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New insights into the development of regional unemployment disparities

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Abstract

Large regional unemployment disparities are a common feature of the labor market in many countries. This study deals with the question whether regional unemployment disparities in western Germany widen, become narrower or remain constant over time. It examines the hypothesis of convergence for regional unemployment rates of western German Federal States and the time period 1968 to 2009 following different concepts of convergence. Western German regional unemployment rates exhibit β-convergence but no σ-convergence. Further, regional unemployment rates show a high degree of intra-distributional dynamics. Panel unit root tests designed for cross-sectional dependent panels are applied to investigate the hypothesis of stochastic convergence. This is necessary because the assumption of cross-sectional independency does not hold. The results do not indicate the existence of stochastic convergence. This is in contrast to previous studies that do not take cross-sectional dependence into account. However, additional robustness checks show that evidence of stochastic convergence depends on the underlying assumption about the shape of the equilibrium relationship between regional unemployment rates and their national counterpart. Western German regional unemployment is not characterized by a catching-up process between high and low unemployment regions. The development of regional unemployment disparities is mainly driven by economic disturbances.

Zusammenfassung

In vielen Ländern ist die Arbeitslosigkeit auf regionaler Ebene sehr unterschiedlich verteilt. Diese Arbeit setzt sich mit der Frage auseinander, ob die Unterschiede zwischen den Arbeitslosenquoten westdeutscher Bundesländer im Zeitraum 1968 bis 2009 zugenommen haben, zurückgegangen sind oder stabil geblieben sind. Dazu werden verschiedene Konvergenzkonzepte herangezogen. Zwar finden sich Hinweise für β-Konvergenz, jedoch nicht für σ-Konvergenz. Die regionale Verteilung der Arbeitslosigkeit zeigt eine hohe Dynamik. Um die Hypothese stochastischer Konvergenz zu prüfen, werden Panel-Einheitswurzeltests für Panels mit abhängigen Querschnitteinheiten verwendet, da die Annahme unabhängiger Querschnitteinheiten nicht erfüllt ist. Im Gegensatz zu existierenden Studien, welche die Abhängigkeit der Querschnitteinheiten nicht berücksichtigen, finden sich keine Hinweise auf stochastische Konvergenz. Wie zusätzliche Analysen jedoch zeigen, werden die Ergebnisse für stochastische Konvergenz von der Annahme hinsichtlich der Art der langfristigen Gleichgewichtsbeziehung von regionaler und nationaler Arbeitslosenquote beeinflusst. Die Arbeit findet keine Hinweise auf einen Aufholprozess zwischen Regionen mit hohen und niedrigen Arbeitslosenquoten. Die Entwicklung regionaler Arbeitslosigkeitsdisparitäten wird in erster Linie von Änderungen des wirtschaftlichen Umfelds bestimmt.

JEL classification: C33, J60; R12

Keywords: Regional unemployment disparities, convergence, panel unit root tests

1 Introduction

Large regional unemployment disparities are a common feature of the labor market in many countries. There are countries where some regions report unemployment rates corresponding to full employment whereas other regions are marked by deep labor market problems (see, for example, OECD 2000, 2005). Furthermore, the magnitude of regional unemployment disparities within countries can be as large as between countries (see, for example, Elhorst 2003).

Regional labor market disparities appear to be less problematic if they simply reflect the preferences of people (see, for example, 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, for example, 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, lower overall unemployment, and could produce substantial social benefits (see, for example, the discussion in Elhorst 2003). Hence, regional (labor market) policy aims to improve the situation of depressed regions and counteract regional labor market disparities.

Not only the existence but also the dynamics of regional labor market disparities are an important issue in this context. The problems associated with the existence of regional labor market disparities reduce or even disappear if regional labor market disparities become smaller or disappear. However, increasing differences between regions induce a more problematic situation not only for high unemployment regions but for the whole country. This leads to the following questions: How stable is the geographical distribution of regional unemployment? Do regional unemployment disparities increase, decrease or remain constant over time?

The question of whether regional labor market disparities become narrower or widen over time is related to convergence. Roughly speaking, convergence means that the differences between regions become smaller or even disappear over time. The analysis of convergence processes has its roots in growth economics. Several concepts of convergence and suitable empirical tests for its existence are provided by the economic growth literature (for an overview see, for example, Islam 2003, Magrini 2004, Durlauf/Johnson/Temple 2005, 2009, or Rey/Le Gallo 2009). Many of these techniques were adopted to examine the evolution of disparities in regional unemployment rates.

According to Baddeley/Martin/Tyler (1998), there are several ways to characterize the temporal evolution of regional unemployment disparities. First, it is possible to investigate the movements in the dispersion of regional unemployment. The concepts of β-convergence and σ-convergence can be applied for this. Regions exhibit β-convergence if unfavorable regions exhibit higher growth rates than favorable regions (see, for example, Barro/Sala-I-Martin 1991, 1992). This is the necessary condition to close the gap between high and low unemployment regions. In contrast, the concept of σ-convergence directly focuses on the inequality among regions (see, for example, Barro/Sala-I-Martin 1991, 1992). Regions exhibit σ-convergence if the dispersion of regional unemployment rates decreases over time.

A second approach is to examine the mobility of individual regions within the distribution of the regional unemployment rates. This procedure refers to the so called distributional approach to convergence. The distributional approach was introduced by Quah (1993a, 1996c,d) and aims to shed light on issues such as mobility, stratification, and polarization of regions.

The third approach is to determine whether and to what extent there is any mean reversion of the differences between regional unemployment rates 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). In the case of stochastic convergence, there has to exist a stable long-run relationship between the regional variables and their national counterpart. Hence, stochastic convergence of regional unemployment rates requires that the deviations of regional unemployment rates from their national counterpart, so called relative regional unemployment rates, follow a stationary process.

The concepts of β-convergence and σ-convergence as well as distributional approach to convergence focus on the cross-sectional behavior of a regional variable. In contrast, the concept of stochastic convergence focuses on the time series behavior of a regional variable. 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 on the convergence process.

The cross-sectional approach considers convergence as a catching-up process between favorable and unfavorable regions. Hence, this approach is appropriate if the regions under consideration are characterized by transition dynamics where the regions tend to converge to their steady state (see Bernard/Durlauf 1996). 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 unemployment disparities are often seen as the result of economic disturbances and sluggish adjustment processes after a region-specific shock (see, for example, Adams 1985, Marston 1985, Topel 1986, or Blanchard/Katz 1992). This in turn implies that regional disparities only disappear if a region-specific shock has temporary effects. Following this point of view, convergence can also be considered as an adjustment process after a region-specific shock. The concept of stochastic convergence deals with this aspect.

This study examines the hypothesis of convergence for unemployment rates of western German Federal States considering the time period 1968 to 2009. Möller (1995), Baddeley/Martin/Tyler (1998), Bayer/Jüßen (2007), and Kunz (2012) already analyzed convergence processes of western German regional unemployment rates. Baddeley/Martin/Tyler (1998) follow the concept of σ-convergence and provide results for intra-distributional dynamics for the mid 1980s until the mid 1990s. They find no evidence of σ-convergence. Further, the distribution of regional unemployment is characterized by a high degree of stability over time. In contrast, Möller (1995), Bayer/Jüßen (2007), and Kunz (2012) examine the hypothesis of stochastic convergence. Their results provide evidence of stochastic convergence.

As the different approaches to convergence consider different aspects of a possible convergence process, it is less surprising that examining different concepts of convergence might lead to ambiguous results (see also Barro/Sala-I-Martin 1991 and the examples given in Quah 1996b and Baddeley/Martin/Tyler 1998). To get a complete picture of the evolution of regional unemployment disparities it appears to be reasonable not to follow solely one approach to convergence. However, especially convergence analysis considering both the cross-sectional behavior and the time series behavior of regional unemployment rates are scarce (exceptions are the studies by Martin 1997 and Gray 2004 for the UK as well as Tyrowicz/Wójcik 2010b for the Czech Republic, Poland, and Slovakia). The aim of this study is to close this gap for western Germany. This study follows the concepts of β-convergence and σ-convergence, provides results for intra-distributional dynamics of regional unemployment rates, and examines the hypothesis of stochastic convergence.

As the findings following the concepts of β-convergence, σ-convergence, and the distributional approach show, western German regional unemployment rates are not characterized by a transition process. There is a high degree of intra-distributional dynamics especially in the 1980s. However, the results following the concept of σ-convergence show that the development of regional unemployment disparities is mainly driven by cyclical movements and economic disturbances. Hence, the concept of stochastic convergence is more appropriate in this case. This study investigates two issues in detail the existing literature about stochastic convergence of regional unemployment rates pays less attention to: cross-sectional dependence of the regions under considerations and the underlying assumption about the shape of the long-run relationship between regional unemployment rates and their national counterpart.

In general, unit root tests are applied to examine the hypothesis of stochastic convergence. However, the choice of an appropriate unit root test is not trivial. The low power of univariate unit root tests with regard to distinguish the unit root hypothesis from the stationarity alternative hypothesis is well known (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. However, the literature shows that the results from panel unit root tests designed for cross-sectional independent panels, so called first generation panel unit root tests (see Breitung/Pesaran 2008), might be misleading if the assumption of cross-sectional independence does not hold (see, for example, O'Connell 1998 and Baltagi/Bresson/Pirotte 2007). For example, Carrion-I-Silvestre/German-Soto (2009) investigate the hypothesis of stochastic convergence in terms of economic growth. First generation panel unit root tests find evidence of the existence of stochastic convergence. In contrast, second generation panel unit root tests relaxing the independency assumption reject the hypothesis of stochastic convergence. These results show that the underlying properties of the cross-sectional units of the panel are essential for the choice of an appropriate test procedure to investigate the hypothesis of stochastic convergence. Moreover, the findings by Costantini/Lupi (2006) testing the hypothesis of stochastic convergence for Italian regional unemployment rates show that assuming cross-sectional independence is critical. Therefore, existing results of stochastic convergence of western German regional unemployment rates have to be interpreted with caution. Möller (1995), Bayer/Jüßen (2007), and Kunz (2012) use first generation panel unit root tests but do not investigate whether the assumption of cross-sectional independence holds. Hence, it is necessary to re-investigate the hypothesis of cross-sectional dependence when examining the hypothesis of stochastic convergence for western Germany.

This study examines the cross-sectional independency assumption in detail. The spacing test provided by Ng (2006) is used to picture the shape of cross-sectional dependence. The results confirm the necessity to take cross-sectional dependence into account. Hence, the PANIC (Panel Analysis of Nonstationarity in Idiosyncratic and Common Components) approach provided by Bai/Ng (2004) for cross-sectional dependent panels is applied to test the hypothesis of stochastic convergence. In contrast to previous studies using first generation panel unit root tests, the findings here provide no evidence of stochastic convergence. As the results show, common shocks with a disproportional impact on particular regions have long-lasting effects and cause regional unemployment disparities. In contrast, shocks that specifically affect a particular region appear to have rather temporary effects and do not trigger a rise in regional unemployment disparities.

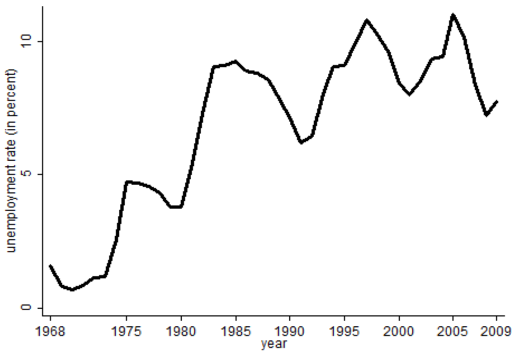
The hypothesis of stochastic convergence requires a stable long-run relationship between the regional unemployment rates and the national unemployment rate. In general, it is assumed that this long-run relationship is characterized by stable absolute differences between the regional variable and its national counterpart. However, it is also possible to assume stable ratios or stable weighted differences between these two measures in the long run (see, for example, Martin 1997 and Baddeley/Martin/Tyler 1998). Therefore, additional robustness checks are presented to examine how sensitive evidence of stochastic convergence is with respect to the underlying assumption about the shape of the long-run relationship between regional unemployment rates and the national unemployment rate. As the results show, this assumption affects whether regional unemployment rates exhibit stochastic convergence.

The remainder of this paper is as follows. The first section introduces the data and provides some stylized facts about the development of regional unemployment in western Germany. Section 3 presents findings following the concepts of β-convergence and σ-convergence. Section 4 investigates the intra-distributional dynamics of regional unemployment rats. The hypothesis of stochastic convergence is examined in section 5. The final section concludes.

2 Data and some stylized facts

Information on unemployment rates of the ten western German Federal States (excluding Berlin) is gathered from the Statistic Service of 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 time series covers the period from 1968 to 2009.

Figure 1: Development of the western German unemployment rate, 1968 – 2009



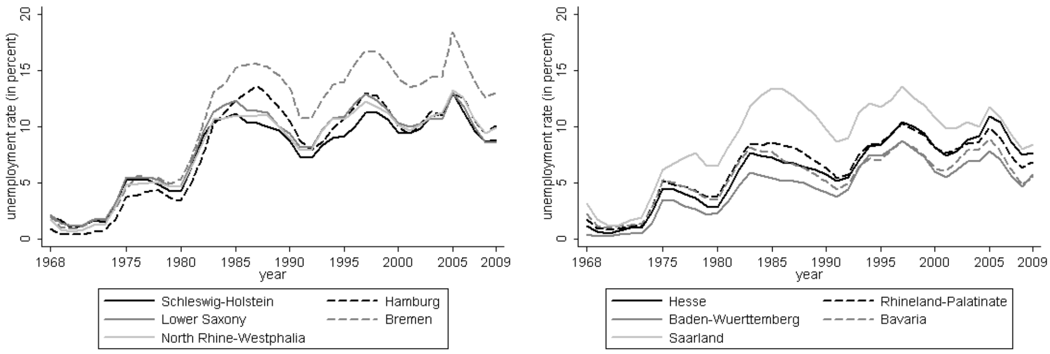
Source: Statistic of the German Federal Employment Agency, own calculations.

Figure 1 reveals a number of stylized facts about the development of the unemployment rate in western Germany. The western German unemployment rate shows an upward trend during the last four decades. The unemployment rate increased from 1.6 percent in 1968 and peaked at 11.0 percent in 2005. Between 2003 and 2005, one of the largest social reforms in Germany took place, the so called Hartz reforms. During this time period, the four laws for modern services at the labour market came into force. These Hartz laws aim to modernize labour market institutions, reduce inflows into unemployment, and improve the transition out of unemployment (see also Klinger/Rothe 2012). Between 2006 and 2008, a decrease of the unemployment rate is observable followed by a slight increase in 2009. In 2009, western Germany reported an unemployment rate of 7.8 percent.

Further, 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. 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 2008. In this year, western Germany reported an unemployment rate of 7.2 percent, 0.8 percentage points lower than in 2001.

Figure 2 shows the development of regional unemployment rates of the western German Federal States. In the late 1960s and the 1970s, the unemployment rate was very low in western Germany. Therefore, also the absolute differences between the unemployment rates of the Federal States was low. However, there were notable relative differences.

Figure 2: Development of regional unemployment rates in western Germany, 1968 – 2009



Source: Statistic of the German Federal Employment Agency.

Comparing figure 1 and figure 2 indicates that the development of the regional unemployment rates and the western German unemployment rate until the 1980s was characterized by similar absolute changes whereas the relative differences decreased.

The Federal States in the south perform better than those in the north. In 2009, the Federal States with the lowest unemployment rates were Bavaria (5.5 percent) and Baden-Wuerttemberg (5.7 percent). The Federal States with the highest unemployment rates were the city states Bremen (13.1 percent) and Hamburg (10.0 percent) followed by North Rhine-Westphalia (9.9 percent).

The fact that city states experience higher unemployment rates compared to the territorial states is usually considered as a common feature of the labor market. However, figure 2 shows that this was not always the case. In 1968, Hamburg reported the second lowest unemployment rate among the western German Federal States with 0.9 percent. Only the unemployment rate in Baden-Wuerttemberg was lower with 0.4 percent. Further, Saarland, Bavaria, and Lower Saxony reported higher unemployment rates in 1968 than Bremen. Starting in the early 1980s, an acceleration of unemployment growth compared to the western German average is observable for the both city states.

As figure 2 shows, there has been a great similarity across the Federal States in terms of the development of their unemployment rates. They mirror the trend and the cyclical behavior of the western German 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, Saarland reported an unemployment rate slightly higher than the western German average and Bavaria was the Federal State with the lowest unemployment rate.

3 The concepts of β-convergence and σ-convergence

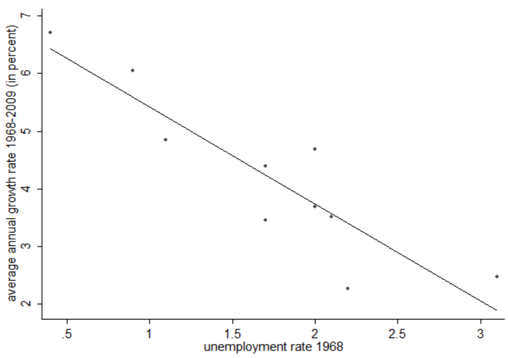
In the case of β-convergence, a negative relationship has to exist between the initial level of the regions' unemployment rates and their corresponding growth rates. This means

Federal States with high unemployment rates should exhibit smaller unemployment rate growth rates than those with low unemployment rates. This is the necessary (but not sufficient) condition that there is some form of catching-up process to close the gap between high and low unemployment regions. Let γ_i^{ur} denote the average annual growth rate between the two points in time 0 and T of the unemployment rate $ur_{i,t}$ for the ith region with $i = 1, \ldots, N$. Further, let $ur_{i,0}$ denote the initial value. The following cross-sectional regression can be used to test the hypothesis of β-convergence for regional unemployment rates:

$$\gamma_i^{ur} = c + \beta ur_{i,0} + \varepsilon_i \qquad (1)$$

A negative value of the coefficient β in equation (1) can be interpreted as evidence of the existence of unconditional β-convergence. This means, the growth rates only depend on the initial values and all regions converge to the same steady state value. In contrast, convergence is called conditional if the average growth rates depend on additional factors and, hence, the steady state value differs among the regions (see, for example, Durlauf/ Johnson/Temple 2009).

Figure 3: Relationship between western German regional unemployment rates in 1968 and their average annual growth rates 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 plots the unemployment rates of western German Federal States against their average annual growth rates between 1968 and 2009. A negative relationship between these two measures is clearly observable. The regression line based on equation (1) has a slope of -1.68 and a R^2 of 0.80. These results can be interpreted as evidence of the existence of unconditional β-convergence.

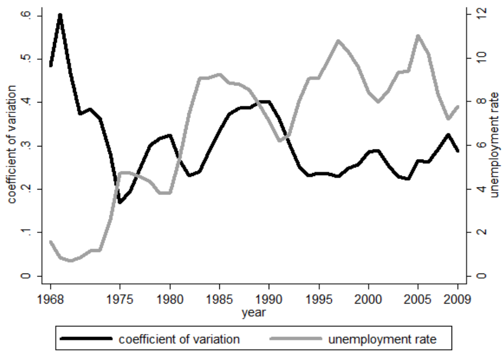
However, the existence of β-convergence is only a necessary but not a sufficient condition for closing the gap between favorable and unfavorable regions and, hence, decreasing regional inequality (see, for example, Barro/Sala-I-Martin 1991, 1992). The mistaken conclusion that regression towards means triggers a reduction of the cross-sectional dispersion is known as Galton's fallacy (see Galton 1886 and Bliss 1999). Therefore, the concept of β-convergence is often criticized.

The concept of σ-convergence focuses directly on the evolution of regional inequality by examining changes in the cross-sectional dispersion of a regional variable over time. Regions exhibit σ-convergence if the dispersion across regions declines over time. If the dispersion increases over time, regions are said to diverge. Please note, that σ-convergence implies β-convergence but not vice versa. Let $\sigma^2_{ur,t}$ denote the dispersion across N regions of the regional unemployment rates $ur_{i,t}$ with $i = 1, \ldots, N$ at time t. σ-convergence occurs between period 0 and period T if:

$$\sigma^2_{ur,0} - \sigma^2_{ur,T} > 0 \tag{2}$$

As western German regional unemployment rates are up to five times higher in 2009 than in 1968, a relative measure of the dispersion seems more appropriate than an absolute measure to take this steady increase of regional unemployment rates into account. Hence, the coefficient of variation is applied as an inequality measure to examine the hypothesis of σ-convergence.

Figure 4: Dispersion of regional unemployment rates in western Germany, 1968 - 2009



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

Figure 4 shows that the coefficient of variation in 1968 was clearly higher than in 2009. These findings are in line with the definition of σ-convergence according to equation (2). However, figure 4 also shows that the coefficient of variation did not follow a steady downward path over time. Between 1968 and 2009, 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.

Baddeley/Martin/Tyler (1998) report a cyclical rise and fall in the dispersion of western German regional unemployment rates considering the time period 1983 to 1995. Figure 4 confirms this feature for the longer time period 1968 to 2009. The coefficient of variation tends to vary directly with the movements in the western German unemployment rate (see figure 4). Usually, the dispersion increases (decreases) if the western German 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, Federal States 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 remain on a below average level.

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 gap between low and high unemployment regions 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 show 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 4 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 for β-convergence is observable or not. Strictly speaking, the test for β-convergence according to equation (1) is only based on two points in time. Equation (1) considers the (average) change of the variable of interest between the initial year and last year of the observation period. What happens between these two points in time is neglected. Thus, the concept of β-convergence might lead to misleading results if the evolution of regional (unemployment) disparities is mainly driven by changes in the economic climate. Similar to the case of σ-convergence, evidence of β-convergence might depend on the initial year and the last year of the observation period (see, for example, the results in Gil-Alana/del Barrio 2009).

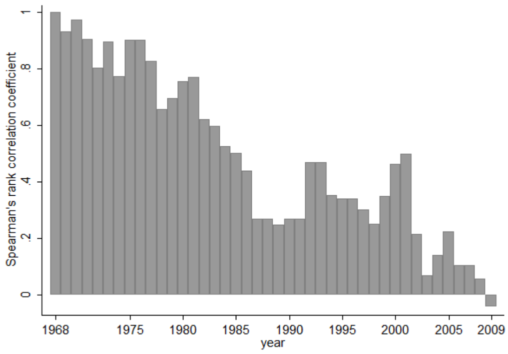
4 Intra-distributional dynamics

The concepts of β-convergence and σ-convergence were criticized because they provide no insights into the dynamics of the entire cross-sectional distribution. Both concepts conceal issues such as mobility, stratification, and polarization of regions (see Quah 1993a,b, 1996a,b,c,d). 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). Hence, the development of the regional dispersion allows no conclusion in terms of the intra-distributional dynamics and vice versa. Therefore, it is important to additionally investigate the mobility of individual regions within the distribution of the regional labor market variable.

Several studies about the evolution of regional unemployment disparities investigate the degree of rank-order stability to get insight into the intra-distribution dynamics (see, for example, Eichengreen 1990, Martin 1997, Baddeley/Martin/Tyler 1998, and Gray 2004).

This study follows this approach too. To examine the degree of rank-order stability of western German Federal States according to their unemployment rates Spearman's rank correlation coefficient is applied. 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 5: Rank-order stability of regional unemployment rates in western Germany, 1968 – 2009



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

Figure 5 presents the development of the rank-order correlation between 1968 and 2009 with 1968 as the reference year. The results clearly show a decline of rank-order stability during the last 40 years. This was, however, not a continuous process. Between 1968 and 1977, the rank order was almost 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 western Germany. However, intra-distributional dynamics of regional unemployment rates appear to be mainly a feature of the 1980s and the time period 2001 to 2009. Moreover, the results show that there is no definite relationship between intra-distributional dynamics of regional unemployment rates and the development of regional inequality in unemployment. For example, the strong degree of intra-distributional dynamics during the 1980s did not go hand in hand with marked and continuous changes in the dispersion of regional unemployment rates (see figure 4).

5 The concept of stochastic convergence

Focusing on the cross-sectional dimension of regional unemployment disparities, there is neither evidence of convergence nor of divergence. A high degree of intra-distributional dynamics is observable for the 1980s and the last decade. Investigating the concept of σ-convergence shows that times of increasing dispersion alternate with times of decreasing dispersion. Economic disturbances in particular appear to be an important driving force of the development of regional inequality.

These results make 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. Therefore, the concept of stochastic convergence appears to be more appropriate.

5.1 The definition 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). For the unemployment rate, the definition of stochastic convergence can be expressed in the following fashion. Let $ur_{i,t}$ denote the unemployment rate of region i at time t. N regions are said to converge if, and only if, a common trend a_t and finite parameters $\mu_1, \ldots, \mu_N$ exist so that:

$$\lim_{t \to \infty} E(ur_{i,t} - a_t) = \mu_i \tag{3}$$

for $i = 1, \ldots, N$ and t denotes the time dimension. Stochastic convergence in the sense of definition (3) occurs if, and only if, the deviations of the regional unemployment rates $ur_{i,t}$ from the joint trend a_t follow a stationary or $I(0)$ process. If all the deviations follow a non-stationary or $I(1)$ process, the regions are said to diverge.

In the framework by 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. Stochastic convergence according to definition (3) does not require that the regions are in a stable equilibrium because the existence of a non-stationary joint trend in the regional unemployment rate $ur_{i,t}$ implies that also the regional variables themselves might follow a non-stationary process. However, it is required that there is a stable equilibrium relationship between the different regions. This is not the case if there is an ongoing catching-up process between high and low unemployment regions. Therefore, the concept of stochastic convergence is not appropriate if the regions under consideration are characterized by transition dynamics. As the results in section 3 show, there is no hint of a transition process for western German Federal States during the time period 1968 to 2009.

To test equation (3) empirically, the common trend a_t is needed. However, a_t is typically unknown and unobservable. To account for the unobservable joint trend, the average of the N regions is defined so that:

$$\lim_{t\to\infty} E(\bar{ur}_t - a_t) = \frac{1}{N}\sum_{i=1}^{N}\mu_i \tag{4}$$

where $\bar{ur}_t = N^{-1}\sum_{i=1}^{N} ur_{i,t}$ is the average value of the unemployment rate across the N regions or the national unemployment rate respectively. Defining the level of the common trend so that $\bar{ur}_t - a_t = N^{-1}\sum_{i=1}^{N}\mu_i = 0$ and subtracting (4) from (3), leads to a definition of stochastic convergence based on the deviation of the regional series from the cross-sectional average:

$$\lim_{t\to\infty} E(ur_{i,t} - \bar{ur}_t) = \mu_i \tag{5}$$

Stochastic convergence in the sense of equation (5) occurs if, and only if, the deviations of the regional unemployment rates from the national unemployment rate, the so called relative regional unemployment rates, follow a stationary process. Only then, there is a stable relationship between these variables in the long run. Therefore, the definition of stochastic convergence implies that region-specific shocks cannot explain the long-run behavior of relative regional unemployment rates or the differences between regions respectively. Absolute convergence requires that all $\mu_1 = \ldots = \mu_N = 0$. Hence, in the case of unconditional or absolute convergence, the regional unemployment rate takes on the same value across all regions. If some $\mu_i \neq 0$ exist, convergence is called conditional.

5.2 Empirical framework to test the hypothesis of stochastic convergence

The unemployment rate is a bounded variable 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 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) unemployment rates can not exhibit divergent behavior in the long run according to the definition of stochastic convergence given in the previous section.

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.[1] If the two barriers limit the excursion of the time series and, hence, induce mean reversion of the time series, this implies that a bounded time series might show a non-stationary behavior if the bounds are sufficiently far apart. Please note, that

[1] 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).

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

Furthermore, 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 unemployment rate and, therefore, relative regional unemployment rates potentially behave like unrestricted $I(1)$ processes (see also Dixon/Shepherd 2001). Therefore, regional unemployment rates might show divergence according to the concept of stochastic convergence.

To test the hypothesis of stochastic convergence it is necessary to compute the deviations of regional unemployment rates from the national unemployment rate and to examine whether these relative regional unemployment rates denoted by $\tilde{ur}_{i,t}$ follow a (non-)stationary process. Unit roots are considered as the main reason why a time series follows a non-stationary process. The literature on time series analysis provides a variety of test procedures to investigate the existence of a unit root. These unit root tests test the null hypothesis of unit root against the alternative hypothesis of stationarity.

According to Pesaran (2007a), one 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 a unit root 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. Nevertheless, unit root tests are widely used to test the hypothesis of stochastic convergence for regional unemployment rates (see, for example, Blanchard/Katz 1992, Decressin/Fatás 1995, Möller 1995, Jimeno/Bentolila 1998, Costantini/Lupi 2006, Bayer/Jüßen 2007, Tyrowicz/Wójcik 2010a,b, or Kunz 2012). Moreover, the existing literature interprets the rejection of a unit root in relative regional unemployment rates as evidence of stochastic convergence. This study follows the literature and also interprets a rejection of the unit root hypothesis as evidence of stochastic convergence.

Several studies use the so called augmented Dickey-Fuller test (ADF test) to examine whether relative regional unemployment rates follow a stationary process (see, for example, Blanchard/Katz 1992, Decressin/Fatás 1995, Jimeno/Bentolila 1998, or Bayer/Jüßen 2007). This univariate unit root test is based on the following regression:

$$\Delta \tilde{ur}_t = \phi \tilde{ur}_{t-1} + \sum_{k=1}^{K} \varphi_k \Delta \tilde{ur}_{t-k} + \varepsilon_t \tag{6}$$

where $\tilde{ur}_t$ denotes the relative regional unemployment rate, $\Delta \tilde{ur}_t = \tilde{ur}_t - \tilde{ur}_{t-1}$, and t denotes the time dimension with $t = 1, \ldots, T$. Lagged differences $\Delta \tilde{ur}_{t-1}, \ldots, \Delta \tilde{ur}_{t-K}$ are added on the right hand side of equation (6) to control for autocorrelation. The error term ε_t is assumed to be independent and identically distributed. The null hypothesis that the time series contains a unit root ($\phi = 0$) is tested against the alternative hypothesis that the time series is stationary ($|\phi| < 0$). It is also possible to allow for deterministic factors in the Dickey-Fuller regression by including an intercept δ and/or a deterministic trend τt. However, as discussed above, the assumption of a deterministic trend appears to be inappropriate in the case of unemployment rates. Moreover, Banerjee/Wagner (2009) show that the definition of stochastic convergence requires identical slopes of a deterministic trend across regions. This implies that computing the deviations of regional variables from their national counterpart would eliminate the identical deterministic trend. Hence, trend stationarity of relative regional variables is not a sufficient condition for stochastic convergence.

In an univariate framework, each time series of relative regional unemployment rates for every sίngle region is tested for a unit root separately. Univariate unit root tests have only low power with regard to distinguish the unit root hypothesis from the stationarity alternative hypothesis. Hence, they often fail to reject the hypothesis of a unit root (see, for example, Campbell/Perron 1991 and 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.

Panel unit root tests were introduced by Levin/Lin/Chu (2002), Im/Peseran/Shin (2003), and Maddala/Wu (1999). They also build on a Dickey-Fuller framework. In a panel framework where i denotes the cross-sectional dimension with $i = 1, \ldots, N$ and t denotes the time dimension with $t = 1, \ldots, T$, the Dickey-Fuller regression can be expressed in the following fashion:

$$\Delta \tilde{ur}_{i,t} = \phi_i \tilde{ur}_{i,t-1} + \sum_{k=1}^{K_i} \varphi_k \Delta \tilde{ur}_{i,t-k} + \varepsilon_{i,t} \tag{7}$$

where $\Delta \tilde{ur}_{i,t} = \tilde{ur}_{i,t} - \tilde{ur}_{i,t-1}$. As in the univariate case, it is possible to include deterministic factors and lagged differences $\Delta \tilde{ur}_{i,t-1}, \ldots, \Delta \tilde{ur}_{i,t-K}$ are included in equation (7) to control for serial correlation.

The so called first generation panel unit root tests assume that the error terms $\varepsilon_{i,t}$ in equation (7) are white noise. This assumption is necessary when deriving the limiting distribution to test the null hypothesis of a unit root against the alternative hypothesis of a stationary process. In a panel framework, this assumption requires that there is no serial correlation and no correlation between the cross-sectional units. Only in this case, 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. Using the panel unit root test provided by Levin/Lin/Chu (2002), O'Connell (1998) shows that the derived limiting distribution is no longer correct and the power diminishes if the off-diagonal elements of Ω are non zero due to cross-sectional correlation. 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 first generation panel unit root tests tend to reject the unit root hypothesis too often if the independency assumption is violated.

Recent developments in panel unit root tests relax the assumption of cross-sectional independence. Second generation panel unit root tests designed for panels with correlated cross-sectional units are provided by Bai/Ng (2004), Moon/Perron (2004), and Pesaran (2007b).

5.3 Testing for cross-sectional independence

The discussion in the previous section shows that the choice of an appropriate test procedure is not trivial. Panel unit root tests appear to be preferable due to their higher power compared to univariate unit root tests. However, the choice of an appropriate panel unit root test depends on whether the assumption of cross-sectional independence is valid. Therefore, it is necessary to test this assumption. Here, the spacing test provided by Ng (2006) is applied to examine whether the hypothesis of cross-sectional independence holds for the residuals form Dickey-Fuller regressions.

Ng (2006) provides a global test on cross-sectional independence 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. This is a great advantage because the null hypothesis that all units are uncorrelated appears to be very extreme. Furthermore, this approach reveals information about the extent and shape of cross-sectional correlation within the sample.

The results of the spacing test presented in this section build on the Pearson's correlation coefficients of the residuals from univariate ADF regressions for relative regional unemployment rates of western German Federal States. In order to isolate serial correlation from cross-sectional correlation, two lags are allowed in the ADF regressions.

The test procedure is as follows. Let $\hat{p}_n$ denote the estimated Pearson's correlation coefficients for the n possible pairs of correlation relationships between the N cross-sectional units with $n = N(N-1)/2$. In a first step, the absolute values of the estimated Pearson's correlation coefficients $\tilde{p}_n$ with $\tilde{p}_n = |\hat{p}_n|$ are calculated. This ensures 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 $\{\tilde{p}_{[1:n]}, \tilde{p}_{[2:n]}, \ldots, \tilde{p}_{[n:n]}\}$.

The spacing test is based on the probability integral transformation of the ordered correlation coefficients. Ng (2006) shows that the spacings of the ordered and transformed correlation coefficients follow a stochastic process with well-defined properties if the sample correlations are zero. Let Φ denote the conditional distribution function of the standard normal distribution. The probability integral transformed ordered correlation coefficients $\bar{\phi}_j$

with $j = 1, 2, \ldots, n$ are defined as $\Phi(\sqrt{T}\tilde{p}_{[j:n]})$ so that $\bar{\phi} = (\bar{\phi}_1, \ldots, \bar{\phi}_n)$. The spacings are defined as $\Delta\bar{\phi}_j = \bar{\phi}_j - \bar{\phi}_{j-1}$.

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:

$$Q_n(\upsilon) = \sum_{j=1}^{|\upsilon n|}(\Delta\bar{\phi}_j - \bar{\Delta}_S(\upsilon))^2 + \sum_{j=|\upsilon n|+1}^{n}(\Delta\bar{\phi}_j - \bar{\Delta}_L(\upsilon))^2 \quad (8)$$

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$_{\upsilon\in(0,1)}Q_n(\upsilon)$. 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 $\bar{\phi}_j$ are not used for determining the breakpoint.

After partitioning the correlations into the two groups S and L, the null hypothesis of no correlation can be tested for the subsamples using the standardized spacings variance ratio test (svr test) provided by Ng (2006). Under the null hypothesis of cross-sectional independence the svr test statistic is standard normally distributed. The correlation coefficients are sorted in ascending order. Hence, a rejection of the null hypothesis for the small correlation sample S will always imply rejection of the null hypothesis for the large correlation sample L.

Table 1 reports the results of the spacing test. Column $\hat{\upsilon}$ contains the share of the n possible correlation relationships in group S, column svr_S contains the test statistic for group S, and column svr_L the test statistic for group L.[2]

Table 1: Results spacing test residuals from ADF regressions

$\hat{\upsilon}$	svr_S	svr_L
0.333	−1.146	2.179*

Source: Own calculations, * denotes rejection of the cross-sectional independence null hypothesis at the five percent level.

The null hypothesis of cross-sectional independence cannot be rejected for group S but is rejected for group L. However, $\hat{\upsilon}$ 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. These findings show the necessity to take cross-sectional dependence into account.

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

Reasons for cross-sectional dependence mentioned in the literature are for instance common trends or cyclical behavior. The spacing test is applied on the regression residuals of relative regional unemployment rates. Usually, relative regional variables are constructed to account for common movements and to examine the region-specific development of a regional variable (see, for example, Blanchard/Katz 1992). Nevertheless, the test provides 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.

5.4 Testing for a unit root in a panel with cross-sectional dependence

The results of the previous section show that relative regional unemployment rates are characterized by cross-sectional dependence. Therefore, 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.

Bai/Ng (2004), Moon/Perron (2004), and Pesaran (2007b) provide panel unit root tests designed for cross-sectional dependent panels. These tests account for the presence of cross-sectional dependence through the specification of approximate factor models. They model cross-sectional dependence via common factors shared by all cross-sectional units and provide test statistics for the cross-sectionally adjusted time series.

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 an $I(1)$ process, while the procedure by Moon/Perron (2004) requires the common factors to be $I(0)$ and the procedure by Pesaran (2007b) allows for one stationary common factor only. Therefore, this paper follows the approach proposed by Bai/Ng (2004).

The basic idea of the procedure provided 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.

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:

$$x_{i,t} = D_{i,t} + u_{i,t} \tag{9}$$

where $D_{i,t}$ denotes the deterministic part of the process that consists of a constant and/or a trend. $u_{i,t}$ denotes the stochastic part. 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. Common factors capture the co-movement of the time series and, hence, the cross-sectional correlation.

Let F_t denote a $r \times 1$ 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:

$$x_{i,t} = D_{i,t} + \xi_i' F_t + e_{i,t} \tag{10}$$

$$(1 - L)F_t = C(L)\eta_t \tag{11}$$

$$(1 - \rho_i L)e_{i,t} = H_i(L)\varepsilon_{i,t} \tag{12}$$

where $C(L) = \sum_{j=0}^{\infty} C_j L^j$ and $H_i(L) = \sum_{j=0}^{\infty} H_{ij} L^j$. Assumptions (11) and (12) imply that the DGP of the r common factors, and the DGP of the idiosyncratic component $e_{i,t}$, can be described as an autoregressive process. The idiosyncratic component $e_{i,t}$ follows an $I(1)$ process if $\rho_i = 1$ and is stationary if $|\rho_i| < 1$. Furthermore, Bai/Ng (2004) assume that r_0 common factors follow an $I(0)$ process and r_1 common factors follow an $I(1)$ 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 $\rho_i = 1$.

This paper considers the case of an intercept as the only deterministic part. Firstly, because trend stationarity is not a sufficient condition for stochastic convergence. Secondly, because the the unemployment rate is a bounded variable and, hence, the assumption of a deterministic trend is inappropriate in the case of the unemployment rate as well as the relative regional unemployment rates (see section 5.2).

If equation (10) contains only an intercept, first differences are taken to eliminate the shift term and the principal component method is applied to the model in first differences. The optimal number of common factors r can be determined by using the information criterions provided in Bai/Ng (2002). Following Banerjee/Wagner (2009), Carrion-I-Silvestre/German-Soto (2009), and Costantini/Lupi (2006), the optimal number of common factors here is determined by the information criterion BIC_3 provided in Bai/Ng (2002).

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.

Appropriate unit root tests for the idiosyncratic and the common components 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 due to common factors, the power of the univariate ADF test remains low. Hence, 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 ith cross-sectional unit, $i = 1, \dots, N$. The BN_N test which parallels the test proposed by Choi (2001) for cross-sectional independent panels is given by:

$$BN_N = \frac{-2\sum_{i=1}^{N} \log p_{\hat{e}}(i) - 2N}{\sqrt{4N}} \sim N(0,1) \tag{13}$$

The BN_{χ^2} test which parallels the procedure proposed by Maddala/Wu (1999) for cross-sectional independent panels is given by:

$$BN_{\chi^2} = -2\sum_{i=1}^{N} \log p_{\hat{e}}(i) \sim \chi^2_{(2N)} \tag{14}$$

For the underlying univariate ADF tests both procedures build on, a heterogeneous lag length is allowed to control for serial correlation. The optimal number of lags are determined by the sequential t-test suggested by Ng/Perron (1995).

Choosing a test for a unit root in the common factor depends on the number of common factors. If there is only one common factor, which means $r = 1$, an univariate ADF test is applied. Bai/Ng (2004) show that the ADF test for the estimated common factor in the intercept only case denoted by ADF$^c_{\hat{F}}$, has the same limiting distribution as the ADF test for the constant only case. If there is more than one common factor in the intercept only case, Bai/Ng (2004) provide the non-parametrical $MQ^c_c(m)$ test and the parametrical $MQ^c_f(m)$ test to determine the number of linearly independent $I(1)$ common trends contained in the common factors.

5.5 Results

In the first step, the principal component method is applied to determine the optimal number of common factors. The maximum number of common factors permitted was set to five. This approach identifies one common factor in relative regional unemployment rates. Table 2 presents the results testing for a unit root in the idiosyncratic components and the common factor. The first two columns report the findings of the BN_N test and the BN_{χ^2} test for the idiosyncratic components. The last column presents the result of the ADF$^c_{\hat{F}}$ test for the identified single common factor.[3]

[3] 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 2: Results unit root tests (PANIC approach by Bai/Ng 2004)

BN_N	BN_{χ^2}	ADF$^c_{\hat{F}}$
2.319^*	34.667^*	-2.117

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

The definition of stochastic convergence requires both the idiosyncratic component as well as the common component to follow a stationary process. The hypothesis of a unit root in the idiosyncratic component is rejected by both the BN_N test and the BN_{χ^2} test. However, the hypothesis of a unit root can not be rejected for the common factor. Hence, the findings provide no evidence of stochastic convergence. This is in contrast to the existing literature using first generation panel unit root tests to examine the hypothesis of stochastic convergence for western German regional unemployment rates. These findings confirm the necessity to take cross-sectional dependence into account.

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 nation-wide shock that has disproportional impact on particular regions can also be considered as region-specific. Common shocks or common movements that affect all regions in the same way are removed by the construction of the relative regional unemployment rates. Hence, the identified common factor 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, this common factor is loaded with a different weight in each time series of the panel. Non-stationarity of western German relative regional unemployment rates occurs due to a pervasive source. This means shocks that specifically affect a certain region appear to have rather temporary effects and do not trigger a rise in regional unemployment disparities. In contrast, common shocks that affect regions in a different way appear to be the main source of regional unemployment disparities.

5.6 Robustness checks

The definition of stochastic convergence according to equation (5) implicitly assumes that the shape of the long-run equilibrium relationship between the regional unemployment rate $ur_{i,t}$ and the national unemployment rate $\bar{ur}_t$ is linear. This means, the absolute difference between the regional unemployment rate and its national counterpart has to be stable in the long run. However, Martin (1997) and Baddeley/Martin/Tyler (1998) point out that alternative assumptions can be made about the shape of the long-run relationship between the two measures $ur_{i,t}$ and $\bar{ur}_t$. Apart from the assumption of stable absolute differences ($ur_{i,t} - \bar{ur}_t = \tilde{ur}^d_{i,t}$), the equilibrium relationship between the regional unemployment rates and the national unemployment rate could also be characterized by stable ratios ($ur_{i,t}/\bar{ur}_t = \tilde{ur}^r_{i,t}$). Finally, it is possible to combine the assumptions of stable ratios and stable differences. This leads to the assumption of stable weighted differences in equilibrium ($ur_{i,t} - \beta_i \bar{ur}_t = \tilde{ur}^{bd}_{i,t}$). Relative regional unemployment rates measured as weighted differences are usually called β-differences (see, for example, Blanchard/Katz 1992).

Making assumptions about the equilibrium relationship between the regional unemployment rates and the national unemployment rate is not trivial (see, for example, Baddeley/Martin/Tyler 1998). The underlying assumption about the long-run relationship between $ur_{i,t}$ and $\bar{ur}_t$ and, therefore, the way relative regional unemployment rates are computed might lead to different pictures for region-specific movements of regional unemployment rates. For example, a change by one percentage point in the regional unemployment rate and the national employment rate does not affect $\tilde{ur}^d_{i,t}$ but $\tilde{ur}^r_{i,t}$. In contrast, a change by one percent in the regional unemployment rate and the national unemployment rate affects $\tilde{ur}^d_{i,t}$ but not $\tilde{ur}^r_{i,t}$.

As Baddeley/Martin/Tyler (1998) point out, this could affect whether changes in regional disparities are observable or not. This in turn implies that the results investigating the hypothesis of stochastic convergence might be sensitive with respect to the underlying assumption about the shape of the long-run relationship between the regional unemployment rates and the national unemployment rate. However, the existing literature does not deal with this issue. This section investigates this aspect in more detail. As an additional robustness checks, the hypothesis of stochastic convergence is examined based on relative regional unemployment rates measured as ratios and relative regional unemployment rates measured as β-differences.[4]

Table 3: Results spacing test for residuals from ADF regressions, relative regional unemployment rate β-differences and ratios

	$\hat{v}$	svr_S	svr_L
β-differences	0.578	2.280^*	–
ratios	0.244	0.865	0.428

Source: Own calculations, * denotes rejection of the cross-sectional independence null hypothesis at the five percent level.

This section starts with the spacing test by Ng (2006) for residuals from an ADF regressions for relative regional unemployment rate β-differences and relative regional unemployment rate ratios respectively. As table 3 shows, the results are mixed. In the case of the β-differences, 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. For the ratios, the null hypothesis of cross-sectional independence can neither be rejected for group S

[4] The regression results of the cyclical sensitivity model introduced by Thirlwall (1966) and Brechling (1967) are applied to compute the β-differences (see, for example, Decressin/Fatás 1995). The cyclical sensitivity model is based on a regression of the form $ur_{i,t} = \alpha_i + \beta_i \bar{ur}_t + \varepsilon_{i,t}$. The regression is estimated for each region i with $i = 1, \ldots, N$ separately. The β-differences for each region i at date t are calculated as $ur_{i,t} - \hat{\beta}_i \bar{ur}_t = \tilde{ur}^{bd}_{i,t}$. This means that relative regional unemployment rate β-differences correspond to the sum of the estimated constant $\hat{\alpha}_i$ and the error term $\hat{\varepsilon}_{i,t}$.

nor group L. Moreover, the principal component method identifies no common factor in relative regional unemployment rate ratios. These results indicate that the assumption of cross-sectional independence holds in the case of relative regional unemployment rate ratios.

Table 4: Results unit root tests relative regional unemployment rate ratios

Choi (2001)	Maddala/Wu (1999)
5.180^{*}	52.762^{*}

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

According to these results, a first generation panel unit root test is sufficient in the case of relative regional unemployment rate ratios. Here, the panel unit root tests provided by Choi (2001) and Maddala/Wu (1999) for cross-sectional independent panels are applied because they correspond to the BN_N test and BN_{χ^2} test for the idiosyncratic components in the PANIC framework (see also section 5.4). Table 4 presents the results for both tests. The test by Choi (2001) as well as the test by Maddala/Wu (1999) strongly reject the hypothesis of a unit root. This can be interpreted as evidence of the existence of stochastic convergence in the case of relative regional unemployment rate ratios.

Table 5: Results unit root tests relative regional unemployment rate β-differences (PANIC approach by Bai/Ng 2004)

BN_N	BN_{χ^2}	ADF$^{c}_{\hat{F}}$
5.080^{*}	52.129^{*}	-2.491

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

To examine the hypothesis of stochastic convergence for relative regional unemployment rate β-differences the PANIC approach is applied because the assumption of cross-sectional independence is violated. The principal component method identifies one common factor in relative regional unemployment rate β-differences. Table 5 presents the results of the unit root tests for the idiosyncratic components and the common factor. The hypothesis of a unit root in the idiosyncratic components is rejected whereas the hypothesis of a unit root can not be rejected for the common factor. As in the case of relative regional unemployment rates measured as absolute differences, the hypothesis of stochastic convergence has to be rejected due to a pervasive source. Divergence occurs because of shocks common to all regions but with a different impact across regions.

The results show that evidence of stochastic convergence depends on the underlying assumption about the shape of the long-run relationship between regional unemployment rates and their national counterpart. The results for relative regional unemployment rate β-differences are very similar to the results for relative regional unemployment rates measured as absolute differences presented in the previous section. However, evidence of stochastic convergence is found for relative regional unemployment rate ratios. Moreover, the findings of the spacing test in this section show that calculating relative regional unemployment rate ratios appears to be an appropriate way for western German Federal States to capture cross-sectional correlation compared to relative regional unemployment rate absolute differences and β-differences.

6 Conclusion

This paper follows different concepts of convergence to examine the evolution of regional unemployment disparities for western German Federal States. The findings provide evidence of unconditional β-convergence of regional unemployment rates. This means there is a negative relationship between the initial values of regional unemployment rates and their corresponding growth rates. Using the coefficient of variation to examine the hypothesis of σ-convergence shows that the dispersion of regional unemployment rates in 2009 is actually lower compared to the initial year 1968. However, these results following the concepts of β-convergence and σ-convergence should not be interpreted as evidence of a catching-up process between high and low unemployment regions in western Germany.

Considering the development of the coefficient of variation over time 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. 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 higher unemployment rates compared to those with lower 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.

Measuring σ-convergence strongly depends on where the initial year and the last year of the observation period are located during a business cycle because of the strong cyclical behavior of regional inequality. This can easily lead to misleading results. This aspect is also problematic following the concept β-convergence because σ-convergence implies β-convergence. Especially in the case of β-convergence, this issue makes it questionable whether this is is a suitable concept to investigate the evolution regional unemployment disparities.

Furthermore, the findings show considerable changes in the geographic distribution of regional unemployment rates in western Germany over time. Especially the 1980s and the time period 2001 to 2009 are characterized by a high degree of intra-distributional dynamics.

The presence of stochastic convergence requires that the deviation of regional unemployment rates from their national counterpart, so called relative regional unemployment rates, follow a stationary process. Panel unit root tests are applied to examine the hypothesis of stochastic convergence due to their higher power compared to univariate unit root tests. The spacing test by Ng (2006) indicate that the assumption of cross-sectional independency does not hold. Hence, panel unit root tests for panels with independent cross-sectional units applied in the existing literature are inappropriate. These tests tend to reject the null hypothesis of a unit root too often if the independency assumption is violated. To take cross-sectional dependence into account, the PANIC approach provided by Bai/Ng (2004) is applied to test for 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.

In contrast to the previous studies examining the hypothesis of stochastic convergence for western German regional unemployment rates, this study finds almost no evidence of stochastic convergence. This shows the necessity to test the hypothesis of cross-sectional independence and take cross-sectional dependence into account when using panel unit root tests to analyze stochastic convergence of regional unemployment rates.

The hypothesis of stochastic convergence does not hold because the identified common factor contains a unit root. Hence, divergence of regional unemployment rates 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 definition of stochastic convergence implicitly assumes that the shape of the long-run relationship between the regional unemployment rates and the national unemployment rates is characterized by stable absolute differences. However, as Martin (1997) and Baddeley/Martin/Tyler (1998) point out, alternative assumptions about the shape of the long-run relationship between regional unemployment rates and the national unemployment rates are possible such as stable ratios or stable weighted differences. Therefore, this study provides additional robustness checks with respect to the underlying assumption about the shape of the long-run relationship between the regional unemployment rates and their national counterpart. The hypothesis of stochastic convergence is investigated for relative regional unemployment rates measured as the ratio as well as the weighted or β-difference between the regional unemployment rate and its national counterpart. For relative regional unemployment rate β-differences the hypothesis of stochastic convergence has to be rejected. In contrast, evidence of stochastic convergence is found for relative regional unemployment rate ratios. These results show that evidence of stochastic convergence appears to be sensitive in terms of the underlying assumption about the long-run relationship between regional unemployment rates and their national counterpart. Hence, the way relative regional unemployment rates are constructed appears to be a crucial decision and is of great importance analyzing the hypothesis of stochastic convergence.

The results from the different cross-sectional approaches to convergence applied in this study show that western German regional unemployment rates are not characterized by a transition dynamics and a catching-up process between high and low unemployment regions. The evolution of regional unemployment disparities is mainly driven by changes in the economic climate. Hence, the concept of stochastic convergence appears to be the more appropriate to investigate the evolution of regional unemployment disparities in western Germany.

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