Drifting together or falling apart? 
The empirics of regional economic growth in post-unification Germany

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The objective of this article is to address the question of convergence across German districts in the first decade after German unification by drawing out and emphasizing some stylized facts of regional per capita income dynamics. We achieve this by employing nonparametric techniques which focus on the evolution of the entire cross-sectional income distribution. In particular, we follow a distributional approach to convergence based on kernel density estimation and implement a number of tests to establish the statistical significance of our findings. This article finds that the relative income distribution appears to be stratifying into a trimodal/bimodal distribution.

I. Introduction

When, on 3 October 1990, the 60 million Germans in the West were formally re-united with the 16 million Germans in the East, the two parts could hardly have been more different. Despite a common culture and language, after 40 years of development with radically different economic institutions and incentives, the Federal Republic of Germany and the German Democratic Republic (GDR) were characterized by substantial disparities in physical and human capital, labour productivity, incomes and wealth. According to Sinn and Sinn (1992), Gross Domestic Product (GDP) per person in East Germany in 1989 was only 60\% of the West German level. The West was one of the technologically most advanced and richest countries in the world; the East was economically shattered after four decades of communism and nearly bankrupt. In the years leading up to unification, real GDP growth was steady in the former West Germany and the unemployment rate was stable. After unification, the western states experienced sharper business cycle fluctuations: a modest upturn in 1990–1991 was followed by a sharp recession in 1992–1993, both of which were mainly due to the unification process. The initial economic boom was led by ‘exports’ to the eastern states, where consumers were switching to cheaper and better quality goods produced in the West. The subsequent recession was also closely related to unification. Restrictive measures were implemented to reduce the fiscal deficit and the Bundesbank tightened monetary policy to cap the rising inflation. These policy responses, coupled with a contraction in foreign demand, had a dampening effect on the economy and the post-unification boom gradually turned into a deep recession, with GDP growth rates well below the historical average for West Germany.

The problem of uneven regional developments has been closely monitored in post-unification policy debates and in recent years there has been a surge in...
empirical work on growth and convergence. When considering regional convergence, various empirical approaches have been implemented in the literature: from simple plots of measures of dispersion over time to intra-distributional dynamics using Markov chains applied to GDP per capita. Numerous studies have revealed persistent differences in per capita income among regions. Evidence shows that some regions managed to sustain high per capita income over a long time span while other regions seemed to be trapped in a low income growth path. These persistent differences are strikingly at odds with the standard neoclassical growth model, which predicts that poorer countries usually develop faster than richer ones and that there is a tendency toward convergence in levels of GDP per capita. On the other hand there exists an opposing growth paradigm (see, e.g. Azariadis and Drazen, 1990) explaining multiple steady states in the growth rate of per capita income. According to Azariadis and Drazen (1990) and Aghion and Howitt (1998, Chapter 10), multiple locally stable equilibria can be attributed to differences in initial conditions. Faini (1984) has initially considered multiple steady states in the context of regional development issues. In all these models, different initial conditions may cause regions to get stuck at different self-perpetuating levels of economic activity. As suggested by Quah (1996a,b, 1997) and Paap and van Dijk (1998), this may lead to a polarization into clubs of rich and poor countries or regions.\footnote{The obvious difficulty here is to figure out in the data which countries are in the bad and which ones are in the good equilibrium. Barrier to getting out of such a trap can be the lack of a “big push” (Murphy et al., 1989). Rodrik (1996) has argued that the East Asian miracle may have depended on a state-assisted process of overcoming coordination failure, and a consequent shift between two different equilibrium output levels (or a virtuous circle). It is also worth noting that the possibility of nonuniqueness is discussed informally even in Solow’s (1956) original exposition of the neoclassical growth model.}

Research on convergence has accommodated cross-regional heterogeneity in a sequence of stages. At first, conventional cross-section analysis (see, e.g. Barro, 1991; Mankiw et al., 1992) assumed complete homogeneity in steady state growth rates. Recently, Lee et al. (1997, 1998) allowed complete heterogeneity in steady state growth rates. However, as pointed out by Islam (1998), extensions that allow varying growth rates run the risk of robbing the concept of convergence of any economic meaning. Instead of assuming complete heterogeneity, we set a structure of an intermediate form: we advocate techniques which focus on the evolution of the entire cross-sectional distribution in addressing the question of convergence across German districts in the first decade after German unification.\footnote{In this article we add to the contributions of Bianchi (1997), Lopez-Bazo et al. (2004), Corrado et al. (2005), Laurini et al. (2005) and Pittau (2005) testing for “two-club” or “twin-peak” convergence of GDP per capita across countries and EU regions by analysing data which do not overlap with the data of existing papers.} In this context, a convergence process occurs if, for instance, a bimodal density is detected at the beginning of the sample period and over time there is a tendency in the distribution to move towards unimodality. Alternatively, if there already is a unimodal distribution after German unification, convergence occurs when the dispersion of this density and therefore per capita income declines over time. To the best of our knowledge, no papers have attempted to formally test the convergence club hypothesis across East and West German regions after unification.\footnote{Funke and Niebuhr (2005) have demonstrated the existence of two clubs across West German regions prior to unification using threshold estimation techniques.} It is our purpose to detect whether clubs exist and which regions are associated with which clubs. A natural approach to assess the evolution over time of the dispersion of the regional per capita income is to estimate the cross-section distributions by using kernel density estimation.

The remainder of the article is structured as follows. Section II describes the data set used for this study together with the nonparametric estimates of the per capita regional GDP over time. To support the visual impression given by kernel density estimates, and to provide further insight on the features of the underlying density, we have performed multimodality tests, whose results are presented in Section III. Section IV concludes.

II. Data Issues and Empirical Evidence from Nonparametric Density Estimation

The opportunity to assess spatial disparity trends in per capita income indicators is limited by the availability of consistent and comparable data. Long and dense time series for small geographic units are difficult to obtain, and in many cases not existent. In this section, we briefly present the spatial distribution of our data which are at the heart of our analysis. There are three levels of administration in Germany: (1) the Federal Republic at the national level; (2) 16 federal states (Bundesländer) on the
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The distributions have been fitted to the logarithm of real per capita income. In Figs 1 and 2 are plotted the kernel density estimations for the (log) GDP from 1992 to 2001 obtained using the two abovementioned bandwidth selection methods and by transforming the income variable to the original scale. The figures show similar patterns, validating the fact that the estimates are robust with respect to the bandwidth specification. Nevertheless, as expected, the Silverman (1986) rule of thumb returns a slightly larger optimal smoothing parameter and therefore the relative density estimate (Fig. 1) appears over-smoothed compared to the one obtained using the Sheather and Jones (1991) plug-in method (Fig. 2).

A preliminary inspection of the estimated densities reveals several noteworthy aspects. First, the snapshots show pronounced triple peakedness at the beginning of the considered time span. This evidence indicates that the German districts in 1992 can be separated into three groups, poor, rich and middle income. Second, as time passes this triple peakedness becomes less visible as the mode corresponding to low-income level recedes somewhat, without disappearing entirely as Fig. 1 would have us believe. As we will see, this bimodal/trimodal ambiguity recurs later when we utilize statistical tests for multimodality. Either way, this smoothing of the third mode is indicative of an improvement in economic conditions of the German poorest districts. In particular, this smoothing of the initial trimodality supports the notion of a catching-up process of eastern Germany at the beginning of the 1990s, i.e. the poorest districts did not stay as poor as they were immediately after unification. That said, despite the tendency of initially poor units to increase relative incomes, on average, over the considered decade, several districts experienced negative growth rates. Third, there is a visible tendency for the remaining two peaks to move apart, with the third mode moving to the right towards a higher income level. Moreover, the variability of the ‘low-mean distribution’ has been

Nonparametric density estimations can reveal several features of the data and therefore help to capture the stylized facts that need explanation, explaining which specifications match with the data. The kernel estimator for the density function \( f(x) \) at point \( x \) is

\[
\hat{f}(x) = \frac{1}{nh} \sum_{i=1}^{n} K \left( \frac{x_i - x}{h} \right)
\]

where \( x = x_1, x_2, \ldots, x_n \), is an independent and identically distributed sample of random variables from a probability density \( f(x) \) and \( K(\cdot) \) is the standard normal kernel with window width \( h \). The window width essentially controls the degree to which the data are smoothed to produce the kernel estimate. The larger the value of \( h \), the smoother the kernel distribution. A crucial issue is the selection of this smoothing parameter. In order to solve the trade-off between oversmoothing and undersmoothing, i.e. the trade-off between bias and variance, we have first used Silverman’s (1986, p. 48) ‘first generation’ rule-of-thumb for a Gaussian kernel. Additionally, we consider the two-stage direct plug-in bandwidth selection method of Sheather and Jones (1991).

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4 We focus on district-level data because state-level data tend to ‘aggregate away’ important differences between smaller geographic entities within the 16 states. For example, in the dataset that we analyse below, the ratio of GDP per capita between the richest (Hamburg) and the poorest state (Sachsen-Anhalt) was 2.63 in 2001, while the corresponding ratio for the richest (Landkreis München) and the poorest district (Mittlerer Erzgebirgskreis) was 7.30. On the other hand, one has to be aware that district-level GDP per capita figures may be affected by a commuting bias. Especially, commuters could overstate GDP per capita in agglomerations and city regions. Hamburg and Berlin are classified as a single region. This was forced on us because of lack of district-level data for both states. We also run the kernel estimates excluding Berlin and Hamburg. Qualitatively, results are unchanged and the pattern is not much affected.

5 See http://www.statistik-bw.de/Arbeitskreis_VGR/publikationen.asp

6 A ‘mode’ is meant here to be a point on the empirical density estimate around which the tangent to the curve changes its slope from positive to negative.

7 In particular, the growth rates of the real GDP per capita over the decade from 1992 to 2001 were negative in 66 districts. Out of these 66, seven districts (Delmenhorst, Landkreis Holzminden, Landkreis Sigmaringen, Landkreis Solttau-Fallingborstel, Landkreis Unterallgäu, Neustadt an der Weinstrasse, Wilhelmshaven) have even experienced two-digit negative growth rates. Following Jones (1998, p. 4) these districts might be labelled ‘growth disasters’.

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declining over the decade from 1992 to 2001 and in 2001 appears to be considerably smaller than the spread of the 'high-mean distribution'. This evidence reveals that cross regional income disparity has become larger rather than smaller as predicted by absolute convergence. Furthermore, we use the methodology of distributional dynamics to model the evolution of the relative distribution of per capita incomes for German districts. This approach models directly the evolution of relative income distributions by constructing transition probability matrices that track changes over time in the relative position of districts within the distribution. This is an exercise that a number of authors have undertaken (Quah, 1996a, b, 1997). The modelling of distribution dynamics assumes that the density distribution $\phi_t$ has evolved in accordance with the following equation:

$$\phi_{t+1} = M \phi_t$$  \hspace{1cm} (2)

where $M$ is an operator that maps the transition between the income distributions for the periods $t$ and $t+1$. Since the density distribution $\phi$ for the period $t$ only depends on the density $\phi$ for the immediately previous period, this is a first-order Markov process. In our estimates below we have assumed that the distribution $\phi$ has a finite number of states. For the Markov transition matrices we assume that the probability of variable $s_t$ taking on a particular value $j$ depends only on its past value $s_{t-1}$ according to the first-order Markov chain

$$P\{s_t = j | s_{t-1} = i\} = P_{ij}$$  \hspace{1cm} (3)

where $P_{ij}$ indicates the probability that state $i$ will be followed by state $j$. As

$$P_{i1} + P_{i2} + \cdots + P_{in} = 1$$  \hspace{1cm} (4)
we may construct the so-called transition matrix

\[
P = \begin{bmatrix}
P_{11} & P_{12} & \ldots & P_{1n} \\
P_{21} & P_{22} & \ldots & P_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
P_{n1} & P_{n1} & \ldots & P_{nn}
\end{bmatrix}
\] (5)

where line \(i\) and column \(j\) give the probability that state \(i\) will be followed by state \(j\). In our modelling approach, the probability \(P_{ij}\) measures the proportion of districts in regime \(i\) during the previous period that migrate to regime \(j\) in the current period.

The transition probability matrix in Table 1 reports transitions between the 1992 and 2001 distributions of GDP per capita relative to the German average. The main diagonal of the matrix gives the proportion of districts that were in the same range of the distribution immediately after German unification as a decade later. Table 1 also provides information about \(n\), the number of districts that begin their transitions in a given state. Furthermore, we provide the classes that divide up the state space.

The salient characteristics of the transition probability matrix in Table 1 reveal a number of noteworthy behavioural patterns in the distribution of real GDP over time. First, as indicated by the first element of the main diagonal (0.03), districts which originally reside in the lowest range of the distribution (i.e. with a GDP per capital of 50% or less of the German average) appear to be very unlikely to remain in this category at the end of the period in question. Such districts display a strong tendency to either move forward to the second category (0.68) or jump to the third category (0.27). Second, the third and fourth elements of the main diagonal (a real GDP of 65–80% and 80–100% of the German average, respectively) indicate a relatively high probability for the regions within this range to maintain their status quo over the period. That said, regions in the third category appear to be
relatively open to backward or forward movements (with probabilities of 0.13 and 0.22, respectively) while those in the fourth seem decidedly more backward looking, as illustrated by the 0.26 probability of moving a step back but only a mere 0.04 probability of moving forward one step. Finally, the districts residing in the fifth category (with a real GDP of 100–125% of the average) appear to be more likely to either retain this position or fall back by one category. These districts marked inability to move forward (a probability of 0.02) suggests there comes a point where incremental increases in real GDP become harder and harder to sustain.

Furthermore, those districts that reside in the highest income category at the beginning of the time period display a very high probability (0.83) of consolidating their position of affluence.

The aforementioned characteristics support the findings of kernel density estimation, namely: the tendency of the poorest districts to catch-up, the middle income districts retaining their status quo (despite a small number of their ranks back-pedaling), and the consolidation of the richest districts of their position.

In Table 1, the operator $M$ has been constructed by assuming that the distribution $\phi_t$ has a finite number of states. This discrete modelling approach leads to the problem that the researcher has to determine the number of intervals and the limit values of each interval in an arbitrary and ad hoc way. Furthermore, the discretization process may eliminate the property of Markovian dependence in the data, as Bulli (2001) has pointed out. The solution addressing these shortcomings consists of carrying out a continuous analysis of transition, which avoids discretization through the use of conditional densities that are estimated nonparametrically and referred to as stochastic kernels. A stochastic kernel amounts to a transition matrix with an infinite number of infinitely small ranges. The results from this tool are displayed as three-dimensional graphs in Fig. 3 and a two-dimensional contour map in Fig. 4.

The three-dimensional stochastic kernel graph yields a number of valuable insights, which are both additional and complementary to those of the static kernel illustrations of Figs 1 and 2. In order to fully exploit the information content of this construct we firstly adjust the viewer’s perspective by rotating the illustration (Fig. 3, top left and top right). We then provide further insights by tilting the graph downwards, as if looking down on the three-dimensional distribution from above. This ‘aerial view’ is further enhanced by means of contour images of the distribution (Fig. 4). Rotating the graphs in Fig. 3 (top right and top left) highlights two features: the pronounced peaks at the beginning and end of the distribution, and middle section of the distribution which, while relatively lower, still suggests the possibility of either slippage or enhancement of one’s relative position.

This aerial view of the income distribution, highlighting as it does the diagonal pattern of the distribution over time, illustrates the tendency of regions residing in low income categories in 1992 to remain there in 2001, while high income regions retain their affluent status throughout the period in question. That said, a further more subtle nuance can be gleaned from Figs 3 and 4. The hint of concavity visible in both the three-dimensional graph (bottom right) and contour representation are indicative of upward movement in the status of the lower income regions; a finding which is explored further below.

### III. Tests for Multimodality

The discussion above has relied heavily on the visual impression and shape of the nonparametric income densities. In practical terms, looking at Figs 1–4, the first question to ask is: are those districts randomly drawn from a unimodal distribution, a bimodal distribution or is there any kind of trimodality? In order to ascertain the significant number of modes...
present in our estimated density functions, we employ Silverman’s (1981, 1986) nonparametric test for multimodality and peakedness.\textsuperscript{8}

The nonparametric procedure tests the null hypothesis that a density $f$ has $k$ modes (or peaks, bumps) against the alternative that $f$ has more than $k$ modes, where $k$ is a nonnegative integer. The test statistic in this case is the critical window width, defined by

$$h_{\text{crit}}(k) = \inf \{ h \mid \hat{f} \text{ has at most } k \text{ modes} \} \quad (6)$$

For $h < h_{\text{crit}}(k)$, the estimated density has at least $k + 1$ modes. The basic idea of the test is intuitive and simple. Specifically, if the series has $k$ modes, then $h_{\text{crit}}(k - 1)$ should be ‘large’ because substantial

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\textit{Fig. 3. Stochastic kernel estimates, 1992 and 2001}

Notes: In Figs 3 and 4 we have used the region with the highest per capita income as a numeraire. The choice is arbitrary but has no impact upon the qualitative results.

\textit{Fig. 4. Stochastic kernel contours}

\textsuperscript{8} This test of multimodality has been used by Bianchi (1997) to test the hypothesis of income convergence for a group of 119 countries between the years of 1970 and 1989. Bianchi (1997) rejects the hypothesis of convergence in favour of the formation of convergence clubs.
smoothing is required to generate a \((k - 1)\)-mode density. For example, if the data possess two strong modes, a large value of \(h\) will be needed to obtain a unimodal estimate. An illustrative calculation of the critical window widths \(h\) and the corresponding number of modes (peaks) in the kernel density estimates for the year 1999 is plotted in Fig. 5.

Thus, the technique forms a natural hypothesis-testing framework since large numbers of \(h_{\text{crit}}(k)\) indicate more than \(k\) modes. The crucial question, then, becomes how large is ‘large’ when the chosen bandwidth is concerned. The value of \(h_{\text{crit}}(k)\) is computed through a binary search algorithm, and its significance level can be assessed by the bootstrap test. A sample is taken of the original series (with replacement) and transformed to have the same first two moments. Critical values are then obtained by generating a large number of samples.10 This is not a nested test and its results should therefore be interpreted as a hierarchical set of significance tests.

We execute the Silverman (1981, 1986) test for each year, with null hypotheses of one, two and three modes (hence alternative hypotheses of more than one, more than two and more than three modes).

The results are listed in Table 2, with the first row for any given year indicating the values of \(h_{\text{crit}}(k)\), the \(p\)-values associated with the corresponding critical value widths are given in parentheses, and \(k^*\) representing the number of modes detected. Taken together, the Silverman test suggests a persistent ambiguity between trimodality and bimodality over the time period, consistent with the ‘eye-ball evidence’ drawn from Figs 1–4.

![Fig. 5. Number of modes in the kernel density estimate as a function of the window width size \(h\), 1999](image)

Table 2. Silverman’s multimodality test

<table>
<thead>
<tr>
<th>Year</th>
<th>(h_{\text{crit}(1)})</th>
<th>(h_{\text{crit}(2)})</th>
<th>(h_{\text{crit}(3)})</th>
<th>(k^*)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1992</td>
<td>2490 [0.00]</td>
<td>2240 [0.00]</td>
<td>1780 [0.16]</td>
<td>3</td>
</tr>
<tr>
<td>1994</td>
<td>2530 [0.00]</td>
<td>2170 [0.12]</td>
<td>1600 [0.21]</td>
<td>2</td>
</tr>
<tr>
<td>1995</td>
<td>3120 [0.00]</td>
<td>2960 [0.08]</td>
<td>1590 [0.19]</td>
<td>3</td>
</tr>
<tr>
<td>1996</td>
<td>3760 [0.00]</td>
<td>2640 [0.13]</td>
<td>1810 [0.26]</td>
<td>2</td>
</tr>
<tr>
<td>1997</td>
<td>3060 [0.00]</td>
<td>3200 [0.06]</td>
<td>1930 [0.10]</td>
<td>3</td>
</tr>
<tr>
<td>1998</td>
<td>3910 [0.07]</td>
<td>2570 [0.19]</td>
<td>1860 [0.35]</td>
<td>2</td>
</tr>
<tr>
<td>1999</td>
<td>4660 [0.00]</td>
<td>2700 [0.10]</td>
<td>1860 [0.08]</td>
<td>2</td>
</tr>
<tr>
<td>2000</td>
<td>3875 [0.00]</td>
<td>2530 [0.10]</td>
<td>1710 [0.14]</td>
<td>2</td>
</tr>
<tr>
<td>2001</td>
<td>3620 [0.00]</td>
<td>3130 [0.05]</td>
<td>2710 [0.09]</td>
<td>3</td>
</tr>
</tbody>
</table>

Note: Bootstrapped \(p\)-values in [ ].

be drawn from a rescaled density estimate obtained by setting

\[
x_i^* = \hat{y}^* + \sqrt{1 + \frac{h^2}{\sigma^2}}(y_i^* - \hat{y}^* + \epsilon)
\]

where \(\sqrt{1 + \frac{h^2}{\sigma^2}}\) is the rescaling factor, \(y_i^*\) are sampled with replacement from the original sample, \(\hat{y}^*\) its mean, \(\sigma^2\) its variance and \(\epsilon\) is assumed to be distributed as a standard normal since the kernel is Gaussian.9 In the spirit of the analysis of Hall (1992), the bootstrap method treats the available sample as the population, and through repeated re-sampling of this sample, obtains the distribution of statistics of the test. A sample is taken of the original series (with replacement) and transformed to have the same first and second moments. Critical values are then obtained by generating a large number of samples.10

9 Rescaling is necessary since the kernel estimation artificially increases the variance of the estimate (Efron and Tibshirani, 1993). Since the procedure samples from a smooth estimate of the population, it is called smooth bootstrap.

10 In our simulations we set the number of bootstrap replications to 3000.
In order to geographically illustrate the clusters detected in the Kernel density estimations, we have produced a set of maps, Figs 6 and 7, which create a visual impression of the spatial structure of the real GDP per capita across German districts. The categories are defined such that in each income range there resides an equal number of districts. To be consistent with the results of our empirical analysis we have chosen to identify three and six categories of the real GDP per capita in 1992 and in 2001, the first and the last year of the considered time span. The presented maps provide evidence that spatial clusters do exist for the variable under consideration. In particular, as one would expect, the poorest district are concentrated in East Germany. In 1992, all districts, except Berlin, Kreisfreie Stadt Potsdam and Kreisfreie Stadt Erfurt, belong to the ‘poorest’ group, whereas only 10% of the West districts are included in this low-income cluster. By 2001, the proportion of eastern districts that still reside in this same cluster has shrunk to 80% of the total eastern districts. However, a number of districts have switched to the richer groups, showing an improvement in their relative income level. In particular, the districts Landkreis Teltow-Fläming and Landkreis Dahme-Spreewald in the greater Berlin area have moved from the low- to the middle-income group. Furthermore, 8% of the eastern German districts (Kreisfreie Stadt Dresden, Kreisfreie Stadt Rostock, Kreisfreie Stadt Cottbus, Kreisfreie Stadt Neubrandenburg, Kreisfreie Stadt Jena, Kreisfreie Stadt Erfurt, Kreisfreie Stadt Schwerin, Kreisfreie Stadt Zwickau, Kreisfreie Stadt Potsdam) have gained a foothold amongst the richest elite by 2001.

A further piece of information that can be gleaned from the visual inspection of the maps is that approximately 40% of West Germany belongs to the high-income cluster, both in 1992 and in 2001, with a high concentration of rich districts localized in the Hamburg area to the North, as well as in the

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11 For the correct interpretation of the maps it is important to bear in mind that they are not suitable to assess the absolute growth performance of the 439 German districts: in particular, it is not possible to say whether over the last decade the poorest areas caught up with the richest ones or whether some areas got richer or poorer as they switched from a cluster to another. (The reason for that is that the thresholds defining the identified categories have changed over time). Looking at those thresholds – which all rose considerably – it is indeed possible to state that the average German GDP has risen between 1992 and 2001.

12 Data for Mecklenburg-Vorpommern (18 Kreise) is not available for 1992. However, their per capita income level is found to reside within the lowest income category as soon as these figures become available in 1996.
western and southern parts of West Germany. One surprising feature that emerges is the marked downturn in the fortunes of 24 western districts, which experienced an erosion of their per capita GDP from above 21,300 euros in 1992 to 17,200 euros in 2001.13

All in all, the comparison between 1992 and 2001 shows that the spatial structure of the real GDP per capita of German districts over the last decade has indeed changed. Fig. 6 shows that the relative income position of the East German districts has remained at the bottom of the ranking whereas districts located in the south-west and in the Hamburg area were still included in the richest group. In other words, the relatively ‘poorer’ districts have remained clustered in the eastern part of Germany and the ‘wealthier’ areas have remained localized in the south–west. That said, the emergence of a number of wealthier eastern districts concurrently with the fall-back experienced by a pocket of western regions suggests that the overall picture may be more complex than first thought.

Figure 7 paints the same picture in greater detail as six different income groups are identified. This 6-category map allows a more precise view of the spatial structure of real GDP per capita across the German districts, while retaining a natural consistency with the 3-category map of Fig. 6. Of the two lowest income ranges, the very poorest range is observed only in East Germany in 1992. By 2001, however, it is apparent from the more detailed 6-category maps that a number of West German states now reside in this lowest category, particularly in the north and south-west. Within the East there is also a discernible movement from the lowest income range to the second lowest, over the period in question. In the middle income ranges there has been a perceptible emergence of middle-income category districts in the East German states over the 1992–2001 time period, whereas in the West those regions residing in the middle income ranges in 1992 have broadly retained their status throughout the period. Similar to the trends observed in Fig. 6, the relatively wealthier regions tend to be concentrated in the west and southern areas of the country in both 1992 and 2001. One can also discern the emergence of a sprinkling of relatively wealthy regions in the East by 2001, due perhaps to real GDP growth associated with urban, commercial areas such as Berlin and Dresden.

Taken as a whole, the visual impression created in Figs 6 and 7 of the spatial structure of the real GDP

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13 In 2001 the share of western districts included in the low-income group over the total number of West German districts rose to 18% (58 out of a total of 326 West German districts) from 10% in 1992.
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per capita leads one to conclude the following: over the period 1992–2001 there has been a noticeable catching-up process in terms of the real GDP of East German regions; West German regions that have been residing in middle income ranges tend to have retained this status throughout the period in question, though as illustrated by the 6-category maps a small number of western regions which were in the lower income categories in 1992 have fallen back somewhat by 2001; the relatively richer clusters in the western and southern areas of the country have consolidated their position over the period in question, while a sprinkling of relatively wealthy regions has also emerged in the East.14

IV. Conclusions and Further Comments

The objective of this article is to address the question of convergence across German districts in the first decade after German unification by drawing out and emphasizing some stylized facts of regional per capita income dynamics, rather than estimating any particular economic model. We achieve this by employing techniques which focus on the evolution of the entire cross-sectional income distribution. In particular, we follow a distributional approach to convergence based on nonparametric kernel density estimation and implement a number of tests to establish the statistical significance of our findings. The visual inspection of the estimated densities indicates the following: the presence of trimodality in 1992; in subsequent years less pronounced trimodality, supporting the notion of a catching-up process of eastern Germany in the early 1990s; and a tendency for the remaining two peaks to move apart, resulting in a swelling of the middle income mode and a more pronounced high income mode.15

An alternative approach to investigating the presence of convergence clubs would be to track in more detail the performance of each geographical unit. This may provide another dimension of disparity that is relevant for economic policy making. From a policy perspective, besides having information about the entire cross-section of observations, it is also important to know how likely is each district to improve its conditions, how many did so and what are their characteristics. In other words, whether or not districts that were rich (poor) a decade ago are the same ones that are rich (poor) now has relevant policy implications. If the poor regions are persistently poor, one may want to consider public programs aimed at enhancing the performance of these districts. On the other hand, if the incomes per capita are rotating over time, one would be less concerned about overall geographical income distribution. Our approach has not conceptualized this alternative mixing or ranking change aspect of disparity. Further consideration should be given to such indicators in future research.

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References


14 These results are consistent with the empirical evidence in Bayer and Jüßen (2007) and Villaverde and Maza (2008) showing moderate speed of β-convergence across German and European regions.

15 The exact nature of multimodality, however, is still surrounded by some degree of uncertainty. At first glance, it might seem promising to consider a growth model with multiple equilibria in the tradition of Drazen and Azariades (1990), Matsuyama (1991), Azariadis (1996) and Aghion and Howitt (1998, Chapter 10) when trying to explain ‘job-poor’ versus ‘job-rich’ growth experiences. In such models, a country may be trapped in a ‘job-poor’ equilibrium when, in principle at least, an alternative and superior equilibrium is also feasible. However, the recent literature has cast doubts on the robustness of multiple equilibria. Frankel and Pauzner (2000) analyse a two sector model with increasing returns, based upon Matsuyama (1991). They show that if the wage is stochastic and arrives as a Poisson process, the multiplicity property may be eliminated because some of the deterministic equilibria are more robust to perturbations than others. A similar conclusion has been established by Herrendorf et al. (2000) for heterogeneous agents. They show that sufficient heterogeneity of agents will lead to a refinement in the set of observable equilibria and uniqueness in models like that of Matsuyama (1991).


