The spatial evolution of regional GDP disparities in the 'old' and the 'new' Europe.

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Abstract

This paper studies the evolution of regional income disparities in Europe. Besides using a more complete data set that offers a more detailed look at the evolution of regional incomes in Western Europe than previous studies, it is the first to shed empirical light on regional income differences and their evolution in Eastern Europe during the transition phase from communism towards EU-membership by means of a (spatial) Markov chain analysis. Regional income disparities in Western Europe are found to be decreasing over time and less persistent than reported in earlier studies. In case of Eastern Europe some regions are likely to fall behind in terms of GDP per capita whereas a substantial number of other regions will be able to (slowly) catch up with their Western neighbors. Another interesting find is that whereas in Western Europe localized regional conditions appear to be a main determinant of the observed income differences, in Eastern Europe country-specific factors are of bigger importance.

JEL classifications: C14; D31; F15; R12
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1 Introduction

The evolution of regional income disparities within Europe has received considerable attention in recent years both from an academic and a policy point of view. Ever since the establishment of The European Union in 1957 with the Treaty of Rome, the reduction of regional income disparities has been one of the Union's specific objectives. In order to try and do so it nowadays gives substantial support to so-called Objective I regions, regions with a GDP per capita below 75% of the GDP per capita in the EU as a whole. Recently the eastward expansion of the EU has added a whole new dimension to the issue of regional disparities since the ten new member states that joined the EU are all

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relatively poor in terms of GDP per capita compared to the old member states. The joining of these new member states is likely to cause a shift in the focus of EU regional policy transferring some funds from former Objective I regions to these poorer new member regions. This could in turn have its effect on the spatial distribution of GDP per capita in the regions of the 'old' Europe.

At the same time the academic interest in regional income disparities has seen a substantial increase mostly driven by the availability of more detailed data sets. Arguably the most extensively used method in the empirical literature to identify actual patterns in the evolution of regional income disparities is that of performing (un)conditional growth regressions (Barro and Sala-I-Martin, 1991; Mankiw, Romer and Weil, 1992). The sign of the estimated coefficient on initial income in a regression of economic growth rates on either only initial income (unconditional convergence) or initial income and other variables that characterize the possibly region-varying steady states (conditional convergence), indicates whether regional incomes have become more equal or not. If the estimated coefficient is negative this is interpreted as evidence in favor of convergence. Empirical studies looking for evidence for regional convergence in Europe by means of these growth regression have mostly found evidence in favor of the predictions of the neoclassical growth model, i.e. poorer regions catching up with the richer ones (see e.g. Badinger, Müller and Tondl, 2004).

The use of growth regressions to study convergence has not remained free of criticism however. Besides raising several econometric issues such as heterogeneity and endogeneity problems, these growth regressions may be plagued by Galton's fallacy of regression to the mean (see Quah, 1993b and Friedman, 1992). Also a standard assumption made when estimating these 'standard' growth regressions is that of a region- and time-invariant growth rate of the production efficiency (more commonly referred to as technological development). This questionable assumption[1] (see Lee, Pesaran and Smith, 1998) does not allow for the process of technology adaption and/or catch-up. Finally by the use of a regression framework the focus is on the behavior of a representative economy, and the method is unable to say something about the dynamics of the entire cross-sectional distribution.

The above mentioned caveats, spurred by the development of new theories of economic growth suggesting different types of income dynamics than the gradual one predicted by the neoclassical model (see Aghion and Howitt, 1999 for a good overview), have led to the development of other empirical methods to look at the evolution of income disparities over time. Quah (1993a, 1993b, 1996a, 1996b) suggests an empirical method that models the evolution of the entire cross-section income distribution in terms of a homogeneous Markov Chain process. This method quantifies the evolution of both the entire shape and the internal dynamics of the regional GDP per capita distribution in terms of a transition probability matrix. Hereby not only giving predictions about the long run state of the cross-sectional distribution, but also quantifying the intra-distributional dynamics during the transition towards the long run state and in the steady state itself. This is what makes this approach very suitable (see Fingleton, 1997) for the researcher who wants to draw conclusions about the

[1] Even Solow himself, 2000, mentions this as a major drawback of cross-section growth regressions.

relevance of the predictions following from both the neoclassical and the new growth models. It gives the approach a clear advantage over performing growth regressions where the finding of convergence is not exclusive evidence in favor of the neoclassical growth model (see Cheshire and Carbonaro, 1995). In contrast to the results obtained from the growth regressions, studies that have used this empirical methodology so far (Magrini, 1999; Quah, 1996a; Fingleton, 1997; Le Gallo, 2003) have mostly found, meagre (or even no) evidence for regional income convergence. Hereby giving a more pessimistic view about the persistence of the observed regional income disparities than the earlier mentioned growth regressions, indicating that these disparities are likely to remain present even in the long run.

A caveat applying to all the methods discussed so far is the treatment of spatial interdependence between regions when looking at the evolution of income disparities. All the studies mentioned so far treat regions as if they were 'isolated islands'. Recent theoretical insights from most notably the new economic geography (see e.g. Krugman, 1991; Puga, 1999; Baldwin, Martin and Ottaviano, 2001) literature however suggest that the spatial interdependencies between regions are very important for the evolution of the regional income distribution. Trade between regions, technology and knowledge spillovers, market access, labor (im)mobility, there are very convincing reasons why the relative location of a region matters for its economic performance. The incorporation of spatial dependence in empirical convergence studies thus seems of vital importance (see Rey and Janikas, 2005) and calls for specific spatial econometric methods (see o.a. Anselin, 1988; Rey, 2001; Quah, 1996b). Only a handful of papers have made use of these newly developed methods when looking at the issue of regional income convergence. Most of these studies focus on taking spatial dependence into account when performing growth regressions (Le Gallo and Dall'Erba, 2003; Rey and Montouri, 1999; Badinger et al., 2003) or on providing merely evidence of spatial dependence (López-Bazo et al., 1999; Le Gallo and Ertur, 2003). Papers incorporating spatial dependence directly into a Markov Chain analysis are very few. Rey, 2001 looks at the spatial regional per capita income distribution in the USA and Quah, 1996b and Le Gallo, 2004 study the spatial evolution of European regional income disparities, all giving convincing evidence that space matters indeed.

The aim of this paper is twofold. On the one hand it extends the evidence found in Le Gallo, 2004 and Magrini, 1999 on the (spatial) evolution of regional income disparities in the 'Old' Europe by using a much more extensive data set in terms of both number of regions and number of time periods. Using this larger data set, the evolution of the regional per capita GDP distribution can be characterized in more detail using (spatially conditioned) Markov Chain techniques. The second contribution of this paper is that it is the first to shed empirical light on the evolution of the regional GDP per capita distribution in the 'New' Europe by means of a Markov chain analysis. To do this the paper looks at the evolution of the regional income distribution in four Eastern European countries during the transitional period from their communist past towards their EU-future. Also the impact of the inclusion of these four countries in a subsequent analysis of the total 'Old + New'-distribution is examined.

The main findings of the paper are the following. Regional income differences in the 'Old' Europe are getting smaller (although not likely to entirely disappear), hereby offering a different, more optimistic, picture than the evidence for regional divergence given by Le Gallo, 2004 and Magrini, 1999. Furthermore the observed disparities are quite localized in nature suggesting the importance of regional conditions in explaining the observed disparities. A different picture emerges for regions in the 'New' Europe. During the transition phase from communism towards EU-membership, country-specific and not regional conditions are found to be an important determinant of the observed regional income disparities. Also it is found that not all regions in these former communist countries are likely to catch up with their Western neighbors. Initial country-relative income levels seem to largely determine which regions make this catch up and which ones are left behind.

The paper is organized as follows. Section 2 gives a description of the data used. Section 3 looks at the evolution of the regional income distribution for the 'Old' Europe. Section 4 focusses mainly on the evolution of this same distribution in four former communist countries on their way to EU-membership. It also combines the two distributions to look at the evolution of the whole 'Old + New'-region income distribution. And finally Section 5 concludes.

2 The data

The data in this paper is collected from the Cambridge Econometrics database. From this database, data on the GDP per capita of 208 NUTS2 Western European regions located in 16 different countries is available on a yearly basis for the period 1977-2002. This sample includes more regions (mainly the Austrian, Finnish, Irish, Swiss and Norwegian regions) and more time periods (both at the beginning and at the end of the sample) than previous studies by Le Gallo, 2004 (138 regions, 1980-1995), López-Bazo et al., 1999 (129 regions, 1980-1992) and Magrini, 1999 (122 regions, 1979-1990). The obtained data set thus provides the basis for a more detailed look at the cross-section distribution of regional GDP per capita and its evolution. Besides offering this more detailed data set for regions in the 'Old' Europe the database also contains the GDP per capita of 41 former communist regions (today NUTS2 regions of the EU) in the Czech Republic, Hungary, Poland and East-Germany on a yearly basis for the period 1991-2002. The data on these 41 regions constitutes the basis for the analysis in the second part of this paper.

All GDP series used are expressed in 1995 Euros and a complete description of the regions and countries included in the analysis can be found in the Appendix. NUTS2 regions are used as this is the observational unit on which the EU bases its policy.

3 'Old' Europe, 1977-2002

3.1 Distribution Characteristics

Before going into a more formal description of the evolution of the regional GDP per capita distribution and to fix ideas, Figure 1 shows this distribution[2] in the years 1977, 1982, 1987, 1992, 1997 and 2002.

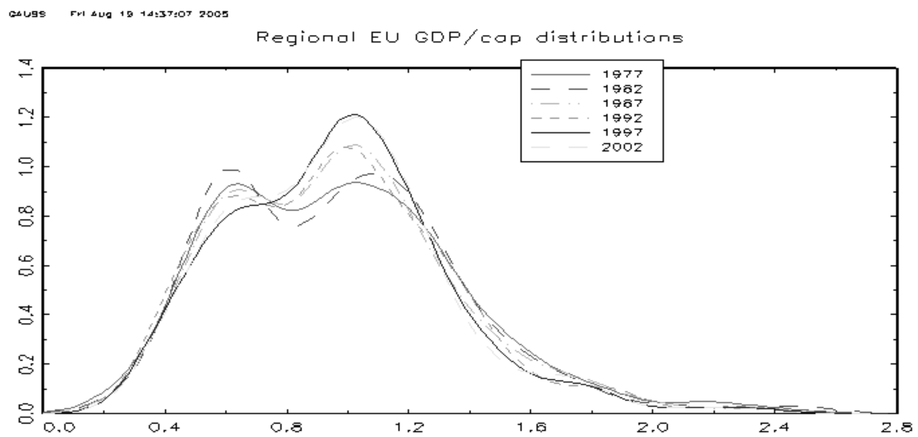

Figure 1

To take account of general Europe-wide trends and business cycle effects, Figure 1 shows the distribution of regional GDP per capita relative to the GDP per capita of the whole sample. This means that 1 on the horizontal axis denotes the European GDP per capita, 0.5 denotes 1/2 times this amount, etc. The figure provides a first look at the evolution of the shape of the regional income distribution. At the beginning of the sample period, 1977-1992, the distribution clearly shows the existence of so-called twin peaks, one located at around 0.6 times the European GDP per capita and one located slightly above the European GDP per capita. Over time however this twin-peakedness becomes less evident, with the distribution in 2002 having less regions located below 0.7 times the European average and more regions with a GDP per capita between 0.75 and 1.25 times the European average. The decline of the peak around 0.6 times the European GDP per capita is however small compared to the increase in the amount of regions located around the European average. Also the distributions at the end of the sample period tend to have somewhat less regions located at the upper and lower end of the distribution when compared with the beginning of the sample period. Overall the kernel estimates in Figure 1 suggest that regional income disparities have decreased over the sample period. This is not to say that they are no longer there, the still substantial amount of regions located below 0.7 times the European average in 2002 shows that regional disparities are maybe less substantial than in 1977, they are not a thing of the past. This decrease of regional disparities contrasts to the findings of Le Gallo, 2004 and López-Bazo et al., 1999 who find that regional disparities have increased during the 80's

[2]The distributions are obtained by kernel estimation methods using a Gaussian kernel with the optimal bandwidth chosen using the method proposed in Silverman, 1986.

and beginning of the 90's. Their results could be due to the fact that Austria, Finland (and in the former study also Ireland), countries with a relatively low initial GDP per capita that have shown strong economic performance over the sample period, are not part of the sample in these studies.

These kernel estimates do however only give some preliminary evidence on the evolution of the shape of the regional GDP per capita distribution. In particular they do not give any information on the intra-distributional dynamics, i.e. they are unable to show whether the same or different regions make up the lower (upper) tail of the distribution when comparing two distributions in different years. This is the aim of the next subsection.

3.2 Quantifying the distributional dynamics

In order to take a better look at the intra-distributional dynamics which are obscured by merely looking at the kernel estimates in Figure 1, the earlier mentioned Markov chain techniques are used. Using these techniques draws upon Quah, 1993a and allows one to quantify the dynamics of the distribution as a whole based on the intra-distributional dynamics of the individual regions that make up the entire cross-section regional income distribution. The use of Markov chain techniques requires the quantification of the distribution by discretizing it. More explicitly one needs to assign each region to one of a predetermined number of groups based on its relative GDP per capita. Letting f_t denote the vector of the resulting discretized distribution at period t and assuming that the distribution follows a homogenous, stationary, first order Markov process, the distributional dynamics can be characterized by the following Markov chain,

$$f_{t+x} = M f_t \tag{1}$$

where M is the so-called x-period transition matrix that maps the distribution at period t into period $t + x$. Each element, m_{ij}, in the transition matrix gives the probability of a region having a GDP per capita that leads it to be allocated in cell j of the distribution in period $t + x$ given its position in the distribution, i.e. cell i, in period t. The estimation of this transition matrix thus requires the discretization of the regional income distribution into a discrete number of groups. Given the number of regions and time periods in our data set the number of groups is chosen to be seven. This is a finer discretization of the regional income distribution than in Le Gallo, 2004 and López-Bazo et al., 1999, who use 5 different income groups, hereby allowing a somewhat more detailed look at the distributional dynamics. In order to be able to assign each respective region to a particular group of the discretized distribution, the boundaries of each of the seven groups has to be chosen. These boundaries are chosen following the recommendation in Quah, 1993a who advises to choose the discretization such that each group initially contains the same number of regions[3]. This results in the following seven income groups: regions with (1)

[3]Magrini, 1999 suggests a different method that reduces the subjectivity in the choice of income groups by chosing the boundaries using criteria designed to minimize a measure of the error made by the approximation. In his paper however using this method of boundary selection leads to having income groups, those describing the tails of the distribution, containing very few observations, shedding serious doubts on the results found in his subsequent Markov

less than 57.5%, (2) between 57.5% and 70%, (3) between 70% and 91%, (4) between 91% and 102%, (5) between 102% and 116%, (6) between 116% and 133% and (7) more than 133% of the European GDP per capita[4].

Having discretized the distribution into the seven above described groups, the transition matrix, M, can be estimated. Having yearly GDP per capita data it is chosen to estimate the 1-yr ($x = 1$) transition matrix. Each transition probability, m_{ij}, in the transition matrix M is estimated by maximum likelihood, i.e.

$$\hat{m}_{ij} = \frac{\sum_{t=1}^{T-1} n_{it,jt+1}}{\sum_{t=1}^{T-1} n_{it}} \tag{2}$$

where $n_{it,jt+1}$ denotes the number of regions moving from group i in year t to group j in year $t+1$, and n_{it} the number of regions in group i in year t. Table 1 shows the resulting estimate of this 1-yr transition matrix, including also the standard errors of the estimated transition probabilities[5]. Earlier studies estimating the evolution of the regional GDP per capita distribution do not report these standard errors (o.a. Le Gallo, 2004; Magrini, 1999; Quah, 1996a) which seems quite strange as they provide a natural way of giving statistical confidence in one's estimates and is quite standard in other field of economics using these Markov chain techniques (e.g. the literature on the evolution of city size distributions, see Black and Henderson, 1999). Omitting them can obscure the fact that the estimated transition probabilities are not very accurate[6]. Finally, following the suggestion in Bickenbach and Bode (2003), Table 1 also reports the p-value of likelihood ratio tests for time homogeneity, i.e. changes in the convergence process, dividing the total sample period in two (1977-1989 and 1989) or three (1977-1985, 1985-1994 and 1994-2002) subperiods.

The estimated transition matrix shows some interesting features. First its diagonal elements are relatively high, especially for the two extreme classes, indicating a high degree of stability in the relative ranking of regions in the total distribution. Another point of interest is the fact that the significant non-zero elements of the matrix are all located directly around the diagonal, which indicates that spectacular 'growth miracles' are not so likely to occur. What is also of interest about the off-diagonal elements is that for regions in the lower income groups the probability of moving upwards in the distribution is usually higher than that of moving downwards and the reverse holds for the higher income groups. This suggests that poorer (richer) regions are more likely to move up (down) in the relative income distribution, hereby providing some rationale for the observed shift in the external shape of the distribution shown in Figure 1.

Drawing conclusions from merely looking at the estimated 1-yr transition matrix gives only evidence of the typical evolution of the discretized distribution over a

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chain analysis and the conclusions drawn from that analysis.

[4]The results of the analysis are qualitatively robust to other (sensible) choices of these boundaries.

[5]These are calculated as follows: $\sqrt{\frac{\hat{m}_{ij}(1-\hat{m}_{ij})}{N_i}}$ with $N_i = \sum_{t=1}^{T-1} n_{it}$.

[6]For example Magrini's, 1999 estimates seem to suffer substantially from small sample bias; some of his estimated probabilities are based on only 5, 4, and even 1 or 2 observations. The report of standard errors and also the number of regions in each income group would have shown this immediately.

Table 1: 'Old' Europe, estimated 1-yr transition matrix

		t+1							
		1	2	3	4	5	6	7	nr obs
	1	0.951	0.049	0	0	0	0	0	730
		(0.008)	(0.008)						
	2	0.044	0.912	0.044	0	0	0	0	792
		(0.007)	(0.010)	(0.007)					
	3	0	0.034	0.914	0.052	0	0	0	736
			(0.007)	(0.010)	(0.008)				
t	4	0	0	0.047	0.879	0.073	0.001	0	744
				(0.008)	(0.012)	(0.010)	(0.001)		
	5	0	0	0.001	0.070	0.869	0.060	0	764
				(0.001)	(0.009)	(0.012)	(0.009)		
	6	0	0	0	0	0.078	0.886	0.036	719
						(0.010)	(0.012)	(0.007)	
	7	0	0	0	0	0.003	0.047	0.950	715
						(0.002)	(0.008)	(0.008)	

Notes: Standard errors between brackets. 1,2,...,7 correspond to the different groups of the discretized distribution. p-value time-homogeneity: 0.45 (subperiods: 1977-1989 and 1989-2002), 0.30 (1977-1985, 1985-1994 and 1994-2002).

period of 1 (!) year. The estimated transition matrix can however also be used to infer interesting things about the long run evolution of the income distribution. From the transition matrix the existence and, if so, the characteristics of the long run steady state of the distribution can be inferred. Moreover interesting things about the path towards this steady state can also be looked at using this matrix. Note the fact that time-homogeneity of the transition matrix over the sample period is not rejected on the basis of the performed likelihood ratio tests (see notes below Table 1), supporting the use of the above mentioned exercises that are all only valid under the assumption of time-homogeneity of the transition probabilities.

First concerning the existence and type of steady state distribution. If one is willing to assume that the distribution continues to evolve according to the estimated 1-yr transition matrix in Table 1, the resulting limiting distribution can be calculated. If such a stable limiting distribution exists, it has to be the case that multiplying this limiting distribution by the transition matrix gives you the limiting distribution back, i.e.:

$$f_\infty = M f_\infty \tag{3}$$

Using this property of the limiting distribution simple linear algebra gives you the formula for the limiting distribution, i.e.

$$(M - I) f_\infty = 0 \tag{4}$$

from which it follows that the limiting distribution corresponds to the (normalised) eigenvector of the transition matrix associated with the eigenvalue equal to one. The condition for such a limiting distribution to exist is that the second largest eigenvalue be smaller than one. If this condition does not hold there exists no limiting distribution adhering to (3). As the second largest eigenvalue of the estimated transition matrix in Table 1 is equal to 0.987 the limiting regional income distribution can be calculated. Table 2 shows this limiting or also called ergodic distribution.

Table 2: Steady state and transitional characteristics

Discrete distributions

	1	2	3	4	5	6	7
2002	0.135	0.130	0.163	0.144	0.173	0.144	0.111
ergodic	0.113	0.126	0.164	0.174	0.182	0.140	0.100

Mobility indexes

Transitional		Steady state	
SI	0.107	BI	0.097
HL	51.3	UPLCG	0.113

Notes: 1,2,...,7 correspond to the different groups of the discretized distribution.

Comparing this to the discretized distribution for 2002, which is also shown in Table 2, one can see immediately that the main difference between the 2002 and the ergodic distribution lies in the lowest, highest and the middle relative income groups. The ergodic distribution carries more mass in groups 4 and 5, those groups containing regions with around average European GDP per capita. On the other hand it has less regions in the highest and lowest groups. This movement of both poorest and richest regions towards the middle income groups suggests some tendency for the distribution to become less dispersed. Note however that this movement is far from complete to call it convergence. To give some more evidence on the issue and to also take note of the fact that the discretization of the distribution based on relative GDP per capita obscures to some extent the evolution of the difference in GDP per capita between income groups[7], Figure 2 shows the evolution of the following polarization measure (see Esteban and Rey, 1994) over the sample period:

$$ER = \sum_{i=1}^{k} \sum_{j=1}^{k} f_i^{1+\alpha} f_j |\bar{y}_i - \bar{y}_j| \tag{5}$$

The index is the sum of the difference in the log of the conditional means of GDP per capita, $\bar{y}$, between all possible income groups weighted by their respective frequency, f in the discretized distribution. Furthermore α determines how heavy polarization is weighed with higher values of α resulting in a heavier weighting of polarization[8]. Being a weighted sum of the absolute difference

[7] In an extreme case the transition matrix would be the identity matrix, suggesting no intergroup movement and a stable distribution, whereas the average GDP per capita of these groups diverges.

[8] Following Le Gallo, 2004 the index shown in Figure 2 sets a high weight, $\alpha = 1.5$ on polarization

in average income between income groups, the higher the ER-index the more polarized the income distribution is.

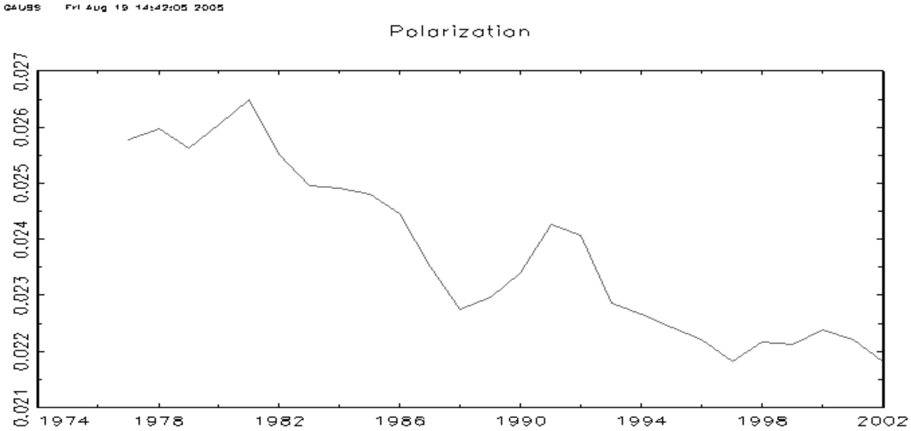

Figure 2

Figure 2 shows that polarization has decreased over the sample period although a short period of increased polarization occurred at the beginning of the 90s. This lends some further support to the notion of the movement towards a somewhat less dispersed regional income distribution. To speak of convergence however is another thing, absolute convergence to the mean would imply all regions moving towards the middle income group in the steady state. The ergodic distribution found here is somewhat more concentrated around the mean than the 2002 distribution, but still a substantial amount of regions (11%,10%) have a regional GDP per capita below 57.5%, above 133% of the European GDP per capita. This shows that although regional income disparities have decreased and are likely to continue to decrease; they will however not entirely disappear.

Besides giving information on the shape of the (discretized) steady state distribution, Table 2 also shows several mobility indexes that can be calculated using the transition matrix in Table 1. These mobility indexes are grouped into those giving an indication of the mobility of regions associated with the movement towards the steady state distribution and those giving an indication of the mobility of regions once this steady state distribution is reached. First the transitional mobility indexes. Shorrocks', 1978, index gives an indication of the mobility across income classes over time and is calculated as $SI = \frac{k-tr(M)}{k-1}$, where k denotes the number of income groups and M is the transition matrix. The index takes on values on the interval $[0, \frac{k}{k-1}]$ with lower values indicating less mobility. The half-life gives an indication of the speed of transition towards the steady state denoting the number of periods it takes for the distribution to move halfway towards the steady state. It is calculated as follows: $HL = -\frac{\ln(2)}{|\lambda_2|}$, where λ_2 is the second largest eigenvalue of the transition matrix. Second the steady state mobility indexes. The Bartholemew, 1982 index is calculated as $BI = \sum_{i=1}^{k} f_i^{\infty} \sum_{j=1}^{k} M_{ij}|i-j|$, it denotes the expected number of group boundaries crossed from one period to the next once in the steady state. The second measure is the unconditional probability of leaving one's current income group once in the steady state, i.e. $UPLCG = \frac{k}{k-1} \sum_{i=1}^{k} f_i^{\infty}(1 - M_{ii})$.

All indexes, shown in Table 2, indicate very low mobility both during the convergence to the steady state distribution and once the steady state distribution is reached. This finding is in line with Le Gallo, 2004 who also reports low mobility between income groups for European regions. The low mobility indexes combined with the estimated transition probabilities in Table 1 indicate that the overall regional income distribution changes very slowly over time. Moreover combining this with the found ergodic distribution suggests that if the evolution of the per capita GDP distribution continues to evolve as it did in the past, the extent of the observed income disparities today will likely continue to decrease, as more regions tend to (slowly) converge towards the relative middle income groups and polarization between the different income groups tends to decrease. They will however not totally disappear and the low mobility between groups moreover suggests that mostly regions with relatively low income per capita today will be the ones with relatively low income per capita tomorrow. This finding of movement towards the mean contrast with the findings in Lóṕez-Bazo et al., 1999 and Le Gallo, 2004 who also look at the NUTS2 GDP per capita distribution. These papers find a tendency of the distribution to move towards a limiting distribution characterized by relatively more poor regions[9]. The fact that the findings in this paper suggest a somewhat brighter picture with the distribution showing a tendency towards more middle income regions, is likely to be due to the more detailed data set used in this paper[10].

3.3 Introducing space

So far the analysis has treated regions as isolated islands, not considering the relative location of regions. The recent new economic geography literature, e.g. Krugman, 1991; Puga, 1999, however views the locational aspect of a region as one of its central features. The developments in neighboring regions are of vital importance for the amount and type of economic activity in a region itself. Also empirically the need to explicitly account for the role of space when considering spatial data has become evident in recent years. A recent paper by Rey and Janikas, 2005 gives a very good overview of the special issues that come to the fore when considering spatial data sets. Several studies at the (European) regional level have already looked at convergence using appropriate spatial statistics and econometric methods (Rey and Montouri, 1999; Le Gallo, 2004 and Fingleton, 1999 are good examples). All of them stress the importance of the spatial context and show the usefulness of taking explicit account of spatial dependence when considering regional data sets. In this subsection, following closely the analysis in Le Gallo, 2004, the impact of taking proper account of the spatial context when doing a Markov Chain analysis is looked at. This is done by using regionally conditioned Markov Chain techniques (Quah, 1996b) and by estimating spatial Markov chains (Rey, 2001).

[9]Magrini, 1999 finds even more extreme evidence of such a 'poverty trap' in his analysis based on NUTS2 data. Not too much attention is paid to his findings however. As mentioned before his results suffer from very inaccurate estimation of the transition probabilities matrix which is subsequently characterized by an absorbing state based on 1 (!) observation that drives the entire result regarding the long run distribution.

[10]As mentioned before the inclusion of the initially relatively low income but afterwards fast growing regions of for example Finland, and in case of Le Gallo, 2004 also Ireland that were not part of the sample in these other papers is a likely explanation for this.

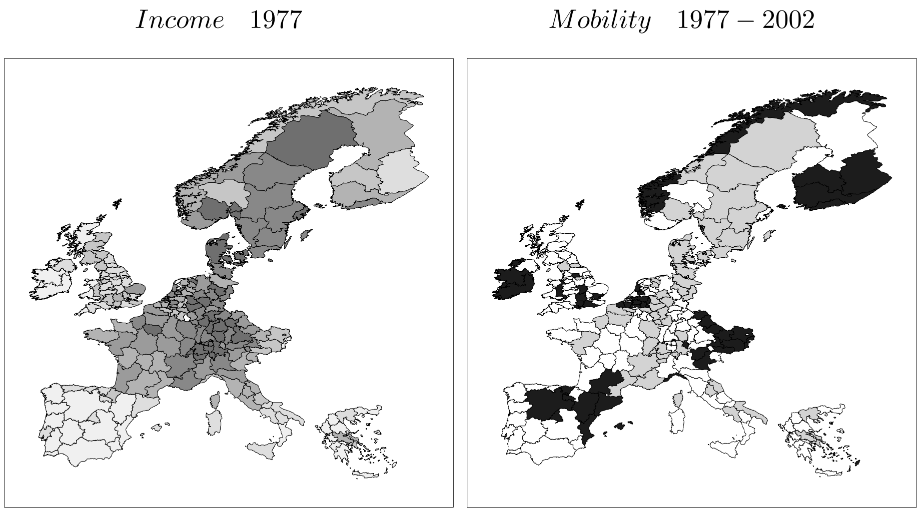

Figure 3: *Income 1977: the darker the region the higher the income group; Mobility 1977-2002: Darkest regions show upward mobility, light regions show downward mobility and no color means no change in income class.*

Before showing the results of these space-incorporating empirical methods, Figure 3 intends to give some preliminary look at the spatial setting of the problem of regional income disparities and their evolution. The figure shows that in 1977 the highest income regions were located in the central and northern regions of Western Europe and that regions in Spain, Portugal, southern Italy, Ireland, Schotland and Finland were the regions with the lowest GDP per capita. Concerning the mobility of regions within the income distribution, Ireland, Spain, Finland, Austria and south-eastern Germany and some regions in the Benelux have shown upward mobility, whereas downward mobility is mainly concentrated in western and northern Germany, France and Sweden. A striking feature of the spatial distribution of mobility is the clustering of regions that move upward and downward respectively. This is also found in Le Gallo, 2004 (although identifying different clusters), suggesting the importance of the economic conditions in neighboring regions for one's own economic development and thus the location of a region within the entire spatial system[11].

The above figures already suggest the presence of positive spatial autocorrelation, the clustering of regions with a similar realization of a random variable (here mobility), in the sample of European regions. To formally test for the presence of such spatial autocorrelation the BB-statistic suggested by Cliff and Ord, 1981 is calculated for both upward and downward mobility. This test statistic is calculated as follows:

[11] Depicting instead the spatial distribution of growth rates to avoid the discretization problem when showing only upward and downward mobility shows a very similar picture. Worth mentioning is only the fact that Portuguese and southern Spanish regions are amongst the fastest growing regions over the period 1977-2002. These high growth rates were apparently not (yet) enough to cause these regions to move up a group in the discretized income distribution but have nonetheless contributed to the fall in polarization (see Figure 2).

$$BB = \frac{1}{2}\sum_i \sum_j w_{ij} d_i d_j \tag{6}$$

where $d_i = 1$ if the region has moved up (down) in the discretized distribution when testing for spatial autocorrelation in upward (downward) mobility. The formula shows that the BB-statistic is a (distance-) weighted sum of the number of times two regions in the sample show a similar movement in the income distribution. To be able to calculate this statistic the weights, w_{ij}, the strength of the spatial interaction between two regions has to be defined. The theoretical economic literature offers different ways through which a region's own economic development depends on characteristics in its neighboring regions, e.g. trade, technological and knowledge spillovers and the mobility of labor. To capture the strength of this spatial interaction between regions, the w_{ij} in (6) are chosen to depend on bilateral distances between the regions in the sample. This reflects the fact that transport costs (see Hummels, 2001) and also the extent of knowledge spillovers (see Audretsch and Feldman, 1996) are empirically found to (still) depend on distance. Distances is also clearly an exogenous measure of the strength of spatial dependencies, giving it an advantage from an econometric point of view over for example trade shares or GDP shares (see Anselin, 1988). To be more specific the weights are constructed as follows:

$$w_{ij} = \begin{cases} 0 & \text{if} \quad i = j \quad or \quad D_{ij} > D_{max} \\ \frac{D_{ij}^{-1}}{\sum_k w_{ik}} & \text{else} \end{cases} \tag{7}$$

where D_{ij} is the distance between the largest cities of region i and j and the direct dependence between regions is limited to regions that are located closer to one's own region than the lower quartile distance of all possible distances between pairs of regions in the sample, D_{max} (about 600 km). It is chosen to use D_{ij}^{-1} as this choice of distance decay function is quite common in empirical studies on trade and economic geography[12]. Finally each of the weights for a specific region is divided by the sum of all the weights of that particular region. The result of doing this is that the spatial interaction with a specific neighboring region depends on that neighboring region's relative (compared to the other neighboring regions) closeness to one's own region.

Using the above described measure of spatial interaction between regions, the BB-statistic is calculated to check for the presence of spatial autocorrelation in both upward and downward mobility. In case of downward mobility the statistic has a value of 9.630 and for upward mobility it takes the value 7.584. The corresponding 5% critical values, obtained by bootstrapping the empirical distribution, are 8.461 and 6.366 respectively, hereby indicating the significant presence of autocorrelation in both upward and downward mobility. These results imply that it is not correct to view the regions in the sample as isolated islands and justifies the use of empirical techniques that take note of the spatial dimension of the regional income distribution.

[12] Choosing the lower quartile distance between regions as the cutoff point and the distance decay function to be D_{ij}^{-1} is still arbitrary. The results are however qualitatively robust with respect to the use of other maximum distances and/or distance functions and are available upon request.

3.3.1 Regional conditioning

The first paper that looked at the relevance of the spatial dimension in a regional data set when using Markov Chain techniques was the paper by Quah, 1996b. That paper suggests the use of regional conditioning. Regional conditioning means that instead of dividing the GDP per capita of each region by that of Europe as a whole, it is divided by a weighted sum of neighboring regions' GDP per capita. Comparing these results to the Europe-conditioned distribution then gives interesting insights in the relevance of the locational aspect of regions in the sample. More specifically the regionally conditioned distributions can be interpreted as the part of GDP per capita that cannot be explained by location-specific factors. Figure 4 below shows the resulting regionally conditioned income distributions. To construct the regionally conditioned series the same weights as in (7) are used when constructing the weighted average of neighboring regions' GDP per capita.

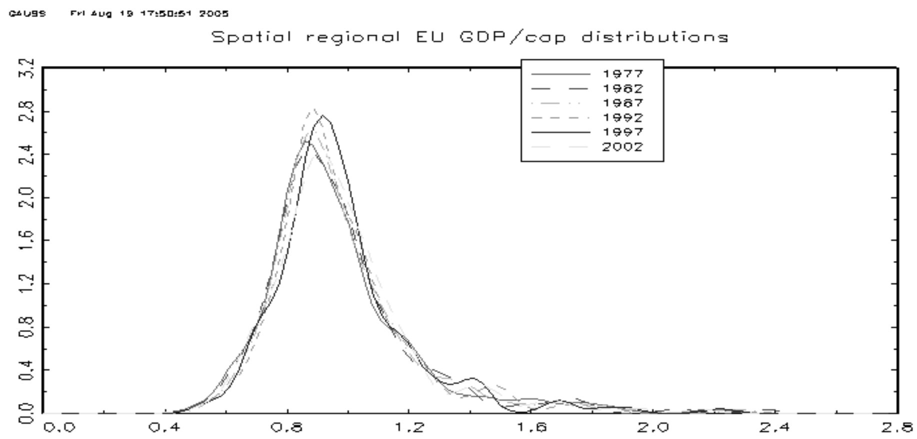

Figure 4

When comparing these regionally conditioned distributions with the Europe relative distributions in Figure 1, one observes a similar picture as in Le Gallo, 2004, namely that these regionally conditioned distributions are much more symmetric and concentrated around 1. This indicates that the economic performance of a particular region is very strongly tied to what happens in its neighboring regions, the locational aspect of the regions in the sample explains to a large extent the level of regional GDP per capita. Note that this appears to be somewhat less so for high income regions given the small bumps in the distribution around 1.4, than for low income regions.

To give some more information on the relevance of the spatial aspect for the GDP per capita distribution, Table 3 shows the transition probabilities between the Europe and the regionally conditioned distribution. This quantifies the differences between the distributions shown in Figure 1 and 4. If the locational aspect of the regions explained nothing about their relative GDP per capita, this matrix should be the identity matrix as this would mean that the distributions are very much the same and also intra-distribution movements do not occur. On the other hand if regional conditioning explained everything, the matrix should contain ones in the column corresponding to the middle income group (4).

Table 3: 'Old' Europe, Europe to Regional relative GDP per capita

		Regional							
		1	2	3	4	5	6	7	nr obs
	1	0.029	0.162	0.546	0.181	0.063	0.013	0.005	758
		(0.006)	(0.013)	(0.018)	(0.014)	(0.009)	(0.004)	(0.003)	
	2	0.011	0.063	0.690	0.148	0.028	0.021	0.039	819
		(0.004)	(0.009)	(0.016)	(0.012)	(0.006)	(0.005)	(0.007)	
E	3	0.008	0.118	0.430	0.216	0.168	0.030	0.031	770
u		(0.003)	(0.012)	(0.018)	(0.015)	(0.013)	(0.006)	(0.006)	
r	4	0	0.018	0.667	0.137	0.102	0.057	0.019	774
o			(0.005)	(0.017)	(0.012)	(0.011)	(0.008)	(0.005)	
p	5	0	0	0.431	0.355	0.159	0.045	0.010	800
e				(0.018)	(0.017)	(0.013)	(0.007)	(0.004)	
	6	0	0	0.025	0.591	0.310	0.072	0.001	749
				(0.006)	(0.018)	(0.017)	(0.009)	(0.001)	
	7	0	0	0	0.018	0.244	0.301	0.438	738
					(0.005)	(0.016)	(0.017)	(0.018)	

Notes: standard errors between brackets. 1,2,...,7 correspond to the different groups of the discretized distribution. p-value time-homogeneity: 0.06 (subperiods: 1991-1989 and 1989-2002), 0.30 (1977-1985, 1985-1994 and 1994-2002).

Looking at the estimated transition probabilities shows that the effects of conditioning neither imply that location is irrelevant nor that it explains everything about the observed regional GDP per capita distribution. The estimated matrix does however show a strong tendency for the highest probabilities to concentrate around the middle column. For example 55% (59%) of the regions with a GDP per capita of less than 57.5% (between 116% and 133%) of the European GDP per capita have a GDP per capita that is between 70% and 91% (between 91% and 102%) of the GDP per capita in their neighboring regions. Only the regions with highest Europe-relative GDP per capita (> 133%) do not show this tendency, 74% of those regions have a regionally conditioned GDP per capita that is more than 1.16 times that of their neighbors[13]. Overall the estimated probabilities formalize what was already suggested when comparing Figures 1 and 4: the (Western) European regional GDP per capita distribution can be characterized by geographically localized clusters of regions with similar GDP per capita levels.

3.3.2 Spatial Markov chains

The results in the previous subsection merely showed (static) evidence of the clustering of regions with similar levels of GDP per capita. Regionally conditioning however does not give any insights about the relevance of the spatial setting of a region for the evolution of its GDP per capita over time. This is the aim of this subsection, which estimates so-called spatial Markov chains, initially

[13]A possible explanation could be that the economies of some of these richest regions (e.g. the financial sector in London, or the ports of Rotterdam and Antwerp) are much more internationally than regionally oriented.

developed by Rey, 2001. These spatial Markov chains estimate the dynamics of the regional GDP per capita distribution conditional on the distance weighted GDP per capita in its neighboring regions. Hereby these estimated conditional probabilities give insights in the role of GDP levels in neighboring regions on the evolution of the per capita GDP in a specific region itself. It can give interesting insights on the relevance of taking the spatial context of a regional data base into account when looking at the issue of interregional convergence, something which cannot be inferred from the estimated unconditional transition matrix in Table 1.

To calculate these spatial Markov chains this paper takes a different approach then that suggested in Rey, 2001 and also as applied in Le Gallo, 2004. Instead of conditioning on the **absolute** level of spatially weighted GDP per capita in neighboring regions, here the transition probabilities between Europe-relative GDP per capita based income groups are conditioned on a region's GDP per capita **relative to** that of its neighboring regions. Looking merely at how the evolution of a region's own GDP level is affected by the absolute income level in its neighboring regions does not tell you whether or not the region itself is richer, poorer or has a similar income level as its neighbors. Conditioning on neighbor-relative GDP per capita does provide this information and hereby it gives a somewhat more complete (and arguably also more interesting) picture of the effect of the economic conditions in one's immediate surroundings. To estimate these conditional probabilities the regions are first grouped based on the regionally conditioned GDP per capita series for each year in the sample. Next for each of the (here 7) resulting regionally conditioned income groups a 1-year transition matrix based on Europe-relative GDP per capita is estimated. The result is seven 7x7 transition matrices, one for each regionally conditioned income group. Table 4 shows these seven matrices.

The estimated probabilities can be interpreted as follows. Regions that have a GDP per capita that is less than 91% that of their neighbors can be found in the first three transition matrices (upper left, spatial groups 1, 2 and 3). Regions with a similar GDP per capita as their neighbors, i.e. between 91% and 116% that of their neighbors in spatial groups 4 and 5, and finally regions that are rich (GDP per capita of more than 116% that of their neighbors) relative to their neighbors in spatial groups 6 and 7. Comparing the estimated spatially conditioned transition probabilities with each other and with the unconditional probabilities in Table 1 shows some interesting things. The first thing to notice is that the richest Europe-relative regions, those with a GDP per capita of 1.16 or more times the overall European GDP per capita, seem to benefit from being surrounded by relatively poorer regions. For regions in the highest Europe-relative income group the probability of making a downward movement in the discretized distribution decreases from not significantly different from 0 when being substantially richer that one's neighbors (spatial group 7) to 30% when being surrounded by regions with a similar level of GDP per capita (spatial group 4). Similarly for regions in the second highest Europe-relative income group the probability of moving up (down) increases (decreases) the richer a region compared to its neighbors. This finding contrasts with that reported by Le Gallo, 2004 who found the opposite, richer regions benefitting from other

Table 4: ‘Old’ Europe, estimated spatial transition matrices

	t/t+1	1	2	3	4	5	6	7	#
1	1	0.952	0.048	0	0	0	0	0	21
		(0.046)	(0.046)						
	2	0	0.889	0.111	0	0	0	0	9
			(0.105)	(0.105)					
	3	0	0	1	0	0	0	0	6
	4-7	0	0	0	0	0	0	0	-
2	1	0.975	0.025	0	0	0	0	0	118
		(0.014)	(0.014)						
	2	0.060	0.920	0.020	0	0	0	0	50
		(0.034)	(0.038)	(0.020)					
	3	0	0.012	0.976	0.012	0	0	0	85
			(0.012)	(0.016)	(0.012)				
	4	0	0	0.071	0.929	0	0	0	14
				(0.069)	(0.069)				
	5-7	0	0	0	0	0	0	0	-
3	1	0.940	0.060	0	0	0	0	0	402
		(0.012)	(0.012)						
	2	0.042	0.931	0.027	0	0	0	0	548
		(0.009)	(0.011)	(0.007)					
	3	0	0.022	0.893	0.085	0	0	0	318
			(0.008)	(0.017)	(0.016)				
	4	0	0	0.056	0.887	0.054	0.002	0	496
				(0.010)	(0.014)	(0.010)	(0.002)		
	5	0	0	0	0.069	0.880	0.051	0	333
					(0.014)	(0.018)	(0.012)		
	6	0	0	0	0	0.316	0.684	0	19
						(0.107)	(0.107)		
	7	0	0	0	0	0	0	0	-
4	1	0.969	0.031	0	0	0	0	0	129
		(0.015)	(0.015)						
	2	0.026	0.855	0.120	0	0	0	0	117
		(0.015)	(0.033)	(0.030)					
	3	0	0.075	0.912	0.013	0	0	0	159
			(0.021)	(0.022)	(0.009)				
	4	0	0	0.010	0.883	0.107	0	0	103
				(0.010)	(0.032)	(0.030)			
	5	0	0	0.004	0.056	0.881	0.060	0	269
				(0.004)	(0.014)	(0.020)	(0.014)		
	6	0	0	0	0	0.072	0.914	0.014	428
						(0.013)	(0.014)	(0.006)	
	7	0	0	0	0	0	0.308	0.692	13
							(0.128)	(0.128)	

	t/t+1	1	2	3	4	5	6	7	#
5	1	0.978	0.022	0	0	0	0	0	46
		(0.022)	(0.022)						
	2	0.217	0.652	0.130	0	0	0	0	23
		(0.086)	(0.099)	(0.070)					
	3	0	0.025	0.951	0.025	0	0	0	122
			(0.014)	(0.20)	(0.014)				
	4	0	0	0.027	0.827	0.147	0	0	75
				(0.019)	(0.044)	(0.041)			
	5	0	0	0	0.075	0.833	0.092	0	120
					(0.024)	(0.034)	(0.026)		
	6	0	0	0	0	0.078	0.872	0.050	218
						(0.018)	(0.023)	(0.015)	
	7	0	0	0	0	0.006	0.119	0.876	177
						(0.006)	(0.024)	(0.025)	
6	1	0.800	0.200	0	0	0	0	0	10
		(0.126)	(0.126)						
	2	0	0.933	0.067	0	0	0	0	15
			(0.064)	(0.064)					
	3	0	0.045	0.773	0.182	0	0	0	22
			(0.044)	(0.089)	(0.082)				
	4	0	0	0.024	0.929	0.048	0	0	42
				(0.024)	(0.040)	(0.033)			
	5	0	0	0	0.118	0.853	0.029	0	34
					(0.055)	(0.061)	(0.029)		
	6	0	0	0	0	0.037	0.796	0.167	54
						(0.026)	(0.055)	(0.051)	
	7	0	0	0	0	0.005	0.033	0.963	215
						(0.005)	(0.012)	(0.013)	
7	1	0.750	0.250	0	0	0	0	0	4
		(0.217)	(0.217)						
	2	0.033	0.967	0	0	0	0	0	30
		(0.033)	(0.033)						
	3	0	0.042	0.917	0.042	0	0	0	24
			(0.041)	(0.056)	(0.041)				
	4	0	0	0.143	0.643	0.214	0	0	14
				(0.093)	(0.128)	(0.110)			
	5	0	0	0	0.250	0.625	0.125	0	8
					(0.153)	(0.171)	(0.117)		
	6	0	0	0	0	0	0	0	-
	7	0	0	0	0	0	0.006	0.994	310
							(0.005)	(0.005)	

Notes: standard errors between brackets. 1,2,...,7 correspond to the different groups of the discretized distribution. 4-7 for example refers to Europe relative income group 4 to 7. Column 1 and 11 refer to a regionally conditioned income group, whereas column 2 and 12 refer to a Europe-relative income group.

nearby rich regions[14]. Secondly for regions with around average European GDP per capita, those in Europe-relative income groups 4 and 5, the highest (and significant) probabilities of moving upwards in the distribution are found in spatial groups 4 and 5, i.e. when surrounded by regions with a similar level of GDP per capita. Downward movement on the other hand is more likely for these middle-income regions when surrounded by poorer or somewhat richer regions. For regions that have a GDP per capita that is only slightly below (between 0.70 and 0.91 times) the European GDP per capita the conclusions are somewhat less clear cut. Those regions have the highest probability of moving downward in the distribution when surrounded by regions with similar levels of GDP per capita whereas upward mobility is most likely when surrounded by either poorer or somewhat richer regions (spatial group 3 or 6). Finally the conditional probabilities for the poorest Europe-relative regions (GDP per capita of less than 70% that of Europe) show that being poor compared to Europe but rich compared to one's neighbors does not have a significant positive effect on the probability of moving up in the discretized distribution. Instead poor regions surrounded by other poor or somewhat richer regions have the highest probability of moving out of their 'relative poverty'.

Overall the estimated conditional probabilities could be interpreted as giving some evidence in favor of agglomeration theories. The found negative effect of being located close to relatively richer regions on the growth of GDP per capita in the poorer regions (especially income group 2) in Europe could be explained by the fact that well performing regions tend to attract economic activity from the nearby periphery, hereby having a detrimental effect on the development of the periphery itself. Also the found positive effect on richer regions of being surrounded by relatively poor regions could be explained by this reasoning[15]. This interpretation may however be somewhat bold and warrants some further research. Nevertheless the results found still indicate very strongly the importance of a particular region's geographical location, more specifically the level of GDP per capita in its neighboring regions for the evolution of that region's GDP per capita itself compared to the overall trend in Europe as a whole. This clearly shows the importance of taking proper account of regions' relative location and the impact of the spatial interactions between regions when thinking about regional income convergence in Europe, something which is also found in spatial studies looking at β-convergence.

4 'New' Europe, 1991-2002

With the fall of the communist regimes in Eastern Europe in the beginning of the '90's, and the subsequent movement of many of these Eastern European countries towards eventual EU-membership, a whole new dimension has been added to the issue of regional income disparities. The opening up of these countries to the West has resulted in a substantial increase in the amount of foreign direct investment and also to the support these countries have received

[14] Although a closer look at her estimated spatially conditioned transition probabilities seems to shed some doubts on her conclusion.

[15] This would be consistent with the findings of Brakman et al., 2005 who find evidence for localized agglomeration forces in a similar sample of NUTS2 regions.

from Western European countries in the form of for example infrastructure projects and institutional help in the transition process towards an open market-economy. The process of transition has largely been studied at the national level. Papers by for example, Fischer, Sahay and Vegh (1996a, 1996b) and de Melo, Denizer, Gelb and Tenev (2001), see also Campos and Coricelli (2002) for a good overview, try to explain national economic growth differences between transition countries identifying o.a. extent and speed of economic reform, initial conditions (e.g. natural resources, level of industrialization and urbanization and distance to Western Europe) and inflation level as important determinants.

The evolution of regional incomes in these countries both with respect to other Eastern European regions ànd with respect to that of Western European regions during this (still ongoing) process of transition is something which has not been looked at in great detail until recently. Barrios and Tondl (2005) calculate the standard deviation of regional GDP per capita (NUTS-II) for several Eastern European countries over the period 1995-2000, indicating increased regional income inequality in almost all countries. A recent paper by Tondl and Vuksic (2003) is one of the first to provide empirical evidence on possible determinants of factors that are important for regional growth. Using a sample of 36 NUTS-II regions in 6 countries over the period 1995-2000, they find that foreign direct investment, closeness to EU-markets (being a border region), and being home to a country's capital are important determinants of economic growth. This paper tries to shed a different empirical light on the issue by looking at the evolution of regional incomes in four Eastern European (Poland, the Czech Republic, Hungary and East Germany) former communist countries over the period 1991-2002. By applying similar Markov chain techniques as in the previous section, a more detailed picture of the evolution of regional income inequality within these countries is provided than the one shown in Barrios and Tondl (2005). Also the evolution of regional incomes in these countries' regions are compared to that of their Western European counterparts (see previous section).

4.1 Distribution Characteristics

Figure 5 provides a first look at the evolution of the distribution of regional incomes in these countries. It shows the regional income distribution for all (both Eastern and Western European) regions in the sample and also that for only Eastern European regions. Hereby the right panel is a somewhat closer look at the lower tail of the distributions shown in the left panel.

The fact that almost all Eastern European regions are relatively poor in comparison to the Western European regions clearly comes to the fore in the estimated kernels in the left hand panel. The inclusion of these Eastern European regions adds an extra mode to the distribution (compared to Figure 1) containing regions with a GDP per capita of around 1/5 that of the GDP per capita of Europe as a whole (Old + New). Moreover this mode does not disappear over the 12-years of the sample period, but remains evident in 2002. Whereas the rest of the distribution tends to concentrate more around 1.1 times the European GDP per capita reflecting nicely the tendency of the Western European regions found in the previous section, this does not (yet) seem to be the case for the Eastern European regions. The left-hand panel gives a more detailed

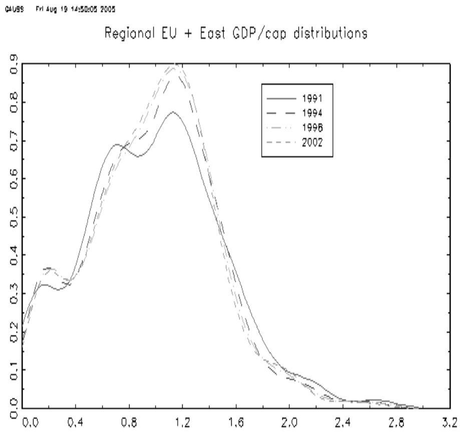

Figure 5a

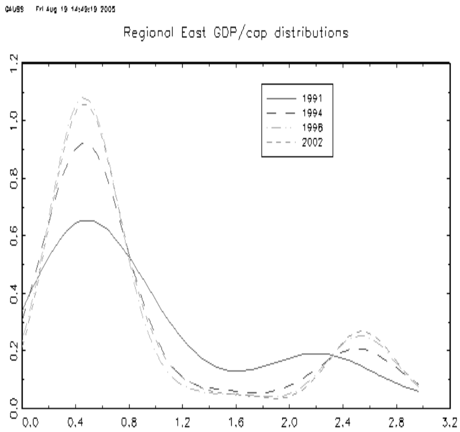

Figure 5b

view on the evolution of the regional incomes in the regions of the four Eastern European countries only. This shows that the distribution increasingly polarized during the first years of the transition period in 2002. It seems a group of regions, mainly East German regions, moved away from the other regions in the sample in terms of GDP per capita[16].

4.2 Quantifying the distributional dynamics

To give more detailed information on the observed evolution of the income distribution and at the same time quantify the intradistributional dynamics, Table 5 and 6 below show the estimated 1-year transition probabilities in case of both all regions and Eastern European regions only[17]. Note that in order to estimate these transition matrices the cutoff points by which the regional income distributions are discretized are different than those in case of Western European regions only. Again they were chosen in such a way that the initial number of observations in each income group is similar across income groups. In case of the 'New + Old'-distribution this resulted in the cutoff points being from high to low: 1.44, 1.23, 1.1, 0.9, 0.69 and 0.45 times the (Eastern + Western) European GDP per capita. And similarly in case of only Eastern Europeans regions (the 'New'-distribution), where given the number of observations the number of income groups has been reduced to five, in the following cutoff points: 2.35, 0.6, 0.46 and 0.375 times the Eastern European GDP per capita. Complementing the estimated transition probabilities in Table 5 and 6, Table 7 shows the mobility indexes and ergodic distributions corresponding to these transition matrices.

The estimated probabilities in Table 5 show some interesting things about the evolution of Eastern European regional incomes relative to the overall European average. First the probability of the poorest regions, all, except for some Portuguese regions, Eastern European regions, to move up in the income dis-

[16]Note that East Germany entered the EU immediately when reuniting with West Germany in 1990, receiving considerable support which may explain some of this effect (see e.g. Fischer et al. (1996a)).

[17]Using the same estimation methods as in the previous section.

Table 5: 'New + Old' Europe, estimated 1-yr transition matrix

		t+1							
		1	2	3	4	5	6	7	nr obs
	1	0.992	0.008	0	0	0	0	0	396
		(0.004)	(0.004)						
	2	0.011	0.931	0.058	0	0	0	0	380
		(0.005)	(0.013)	(0.012)					
	3	0	0.021	0.914	0.065	0	0	0	385
			(0.007)	(0.014)	(0.013)				
t	4	0	0	0.031	0.918	0.048	0.002	0	414
				(0.009)	(0.013)	(0.011)	(0.002)		
	5	0	0	0	0.051	0.900	0.049	0	391
					(0.011)	(0.015)	(0.011)		
	6	0	0	0	0	0.057	0.914	0.029	383
						(0.012)	(0.014)	(0.009)	
	7	0	0	0	0	0	0.062	0.938	390
							(0.012)	(0.012)	

Notes: Standard errors between brackets. 1,2,...,7 correspond to the different groups of the discretized distribution. p-value time-homogeneity: 0.063 (subperiods: 1991-1995 and 1995-2002).

Table 6: 'New' Europe, estimated 1-yr transition matrices

		t+1 (1991-1995)					t+1 (1995-2002)				
		1	2	3	4	5	1	2	3	4	5
	1	0.698	0.302	0	0	0	0.909	0.091	0	0	0
		(0.070)	(0.070)				(0.043)	(0.043)			
	2	0.318	0.545	0.090	0.045	0	0.027	0.920	0.053	0	0
		(0.010)	(0.106)	(0.061)	(0.044)		(0.019)	(0.031)	(0.026)		
t	3	0	0.250	0.750	0	0	0	0.032	0.889	0.079	0
			(0.088)	(0.088)				(0.022)	(0.040)	(0.034)	
	4	0	0	0.146	0.729	0.125	0	0	0.095	0.905	0
				(0.051)	(0.064)	(0.048)			(0.045)	(0.045)	
	5	0	0	0	0.037	0.963	0	0	0	0	1
					(0.036)	(0.036)					

Notes: standard errors between brackets. 1,2,...,5 correspond to the different groups of the discretized distribution. nr. observations per group (1-5): a) 1991-1995: 43,22,24,48,27, b) 1995-2002: 44,75,63,42,63. p-value time-homogeneity 1991-1995: 0.101 (subperiods: 1991-1993 and 1993-1995). p-value time-homogeneity 1995-2002: 0.027 (subperiods: 1995-1999 and 1999-2002).

tribution is almost zero. However, once in the second lowest income class, the probability of moving further up in the distribution increases substantially. The transition probabilities for the 6 highest income groups largely show the same movement as in the analysis on Western European regions only. That is regions with below (above) average relative GDP per capita tend to move up (down) in the distribution suggesting again some movement towards the around European GDP per capita income groups. Table 7 provides additional evidence (note that time-homogeneity of the transition probabilities is not rejected) on this general movement showing that the limiting distribution corresponding to the transition matrix in Table 5 is characterized by relatively few regions in the lowest two income groups. Where in 2002 25% (40%) of the regions were located in the two (three) lowest income groups in the steady state only 10% (20%) can be found in these groups. Moreover the steady state distribution has more regions in the income groups with GDP per capita around or somewhat above that of Europe than the actual 2002 distribution (69% vs. 47%). Besides this the calculated mobility indexes show that there is low mobility of regions within the distribution and also that the speed of the transition process towards the steady state is very low (half life of 110 years). Given this slow speed of the transition process, Table 7 also shows the predicted distribution halfway towards the steady state. It is quite striking to observe that this distribution is almost similar to the ergodic one, except for the lowest income group. Although many of the poorest (more or less the Eastern European) regions will eventually become somewhat richer it is exactly this transition that takes the longest!

Table 7: Steady state and transitional characteristics

Discrete distributions 'Old + New'

	1	2	3	4	5	6	7
2002	0.145	0.116	0.149	0.173	0.136	0.161	0.120
at half life	0.111	0.048	0.116	0.228	0.220	0.192	0.088
ergodic	0.058	0.042	0.116	0.239	0.237	0.211	0.098

Mobility indexes

Transitional		Steady state	
SI	0.082	BI	0.081
HL	109.6	UPLCC	0.094

Discrete distributions 'New'

	1	2	3	4	5
2002	0.146	0.243	0.220	0.171	0.220
ergodic (1991-1995)	0.266	0.252	0.138	0.079	0.265
ergodic (1995-2002)	0.052	0.178	0.300	0.250	0.220

Mobility indexes 1995-2002 (1991-1995)

Transitional		Steady state	
SI	0.094 (0.329)	BI	0.076 (0.326)
HL	14.81 (24.28)	UPLCC	0.095 (0.272)

Notes: 1,2,...,7 correspond to the different groups of the discretized distribution.

The estimated transition probabilities in Table 6 and the corresponding mobility indexes and long run distribution in Table 7, show a more detailed picture of the evolution of Eastern European regional incomes. Complementing the results in the previous paragraph, they give a more detailed look at the evolution of income disparities between the Eastern European regions themselves. The estimated transition probabilities quantify the observed evolution of the regional income distribution in Figure 4. Instead of one 1-yr transition matrix for the whole period, Table 6 shows two 1-yr transition matrices. The reason for this is that time-homogeneity of the 1-yr transition probabilities, calculated based on the whole sample period, is rejected (p-value of the test based on the subsamples 1991-1995 and 1995-2002: 0.000). As pointed out by Bickenbach and Bode (2003), the rejection of time-homogeneity sheds considerable doubt on the reliability of the estimated transition probabilities. Moreover calculation of the long run distribution and the mobility indices are all only informative under the assumption of time homogeneity. Therefore Table 6 shows one transition matrix for each of the subperiods, i.e. one for 1991-1995 and one for 1995-2002[18]. Note that for each of these two subperiods, time-homogeneity of the transition probabilities is not rejected (at the 10% and 3% respectively). As can be seen from these two transition matrices, they do indeed differ quite substantially. For the period 1991-1995, the probability of moving down in the income distribution is for all income groups higher than the probability of moving up. Also for income groups 2-4 the probability of moving downwards is quite high (ranging from 14.6%-31.8%). On the other hand the poorest regions have quite a high probability, 30%, to move one group up in Eastern European income distribution. However the probability, conditional upon having made this upward movement, that this is followed by a subsequent movement back to the lowest income group is even higher, 31.8%. Only the richest regions, those with GDP per capita larger than 2.35 times the Eastern European average, tend to remain that rich (all Eastern German regions). For the period 1995-1999 a completely different picture emerges. In this period the probability of moving up is, except for income group 4, always significant and higher than the probability of moving down (which is only significant for income group 4). Also the probability of not leaving one's current income group is much higher than in the period 1991-1995, indicating less mobility across income groups (this is confirmed by the mobility indexes in Table 7). The only similarity between the two transition matrices is the fact that also in the period 1995-2002, the richest regions remained the richest regions (suggesting that East Germany when compared to other former communist countries has benefitted substantially from the reunification with West-Germany).

How can we explain these different dynamics in the first and second half of the nineties? A probable explanation is the fact that all Eastern European countries, see e.g. Fischer et al. (2003), experienced deep economic recessions due to the restructuring of the economy required while moving from a planned to to a market economy and a shift towards an economy more oriented to the West. The end of this recession is generally dated around 1994, see e.g. Fischer et al. (1996), after which the Eastern European economies started growing again. The fact that in our sample the richest, i.e. East German, regions seem to be affected much less also gives support to this hypothesis as this country suffered a much less severe recession compared to the other countries in our sample (see Fisher et al. (1996)). Due to the above described change in regional income dynamics, the long run dynamics of the income distribution will be discussed

[18] The results do not change substantially when taking 1994 or 1996 as 'break' date.

on the basis of the 1-yr transition matrix based on the period 1995-2002[19]. The resulting ergodic distribution and mobility indices are shown in Table 7. When comparing the 2002 with the ergodic distribution one can observe that in the steady state more regions can be found in the higher income classes, implying a movement by Czech, Polish and Hungarian regions towards the GDP per capita of their East German counterparts. In 2002 39% (15%) of the regions had a GDP per capita below 0.46 (0.375) times the Eastern European average. In the steady state this percentage has decreased to about 22% (5%) respectively. Moreover, the calculated half life of about 15 years suggests that this transition towards less extremely poor regions can be expected to happen in the not too far future. Note however that still a substantial number of regions, about 50% have a GDP per capita that is 50% less than the overall Eastern European average.

Combining this (quite rapid) expected decline in regional disparities between Eastern European regions with the earlier evidence on the (predicted) evolution of the total ('New + Old') European income distribution, seems to suggest that many Eastern European regions will show some catch-up in terms of GDP per capita with respect to the Western European regions and that this catch-up will happen at a comparable rate across regions. However the process will, besides being slow, most likely not apply to all Eastern European regions leaving some of them behind in relative poverty.

4.3 Introducing space

$Income\quad 1991$ $\qquad\qquad$ $Mobility\quad 1991-2002$

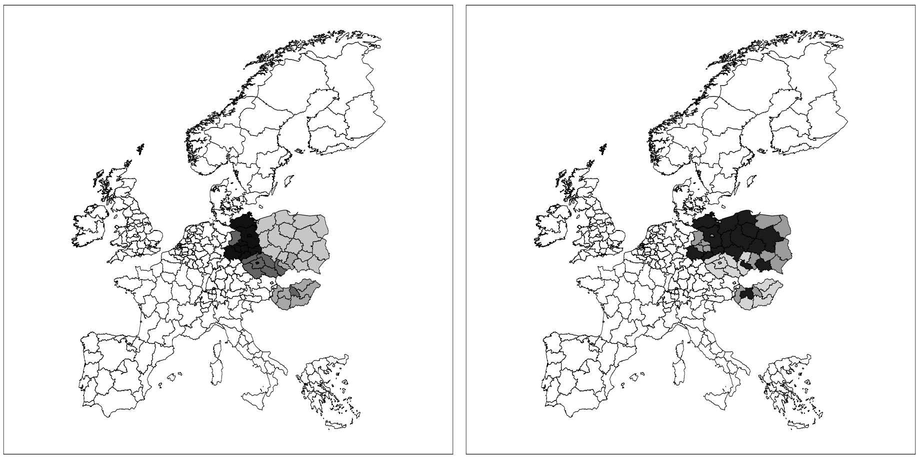

Figure 6: *Income 1977: the darker the region the higher the income group; Mobility 1991-2002: Darkest regions show upward mobility, lightest regions show downward mobility, medium-colored region do not switch income groups and no color means Western European region.*

In case of Western European regions the previous section showed that the observed income disparities could be explained quite well by the (relative) geographical location of a particular region. Hereby suggesting the importance of

[19]The results based on the period 1991-1995 are also shown in Table 7 and show an almost completely different picture.

spatial spillovers coming from e.g. trade, technological development and infrastructure projects. In this section the same techniques are used to look whether a similar conclusion can be found in case of Eastern Europe, hereby focussing on the Eastern European regions in the sample only. Figure 6 shows a first look at the spatial dimension by plotting a map of GDP per capita in 1991 and the mobility of regions over income groups between 1991 and 2002. These two maps already show some interesting things. First the level of regional income in 1991 seems to be largely defined by country borders with the countries ranked from highest to lowest level of GDP per capita: East-Germany, Czech Republic, Hungary and Poland. Within countries there seem to be small differences between region in per capita income level, except maybe for the capital regions in the Czech Republic, East-Germany and Hungary that have higher income levels than the other regions in their country. Concerning the mobility over income groups during 1991-2002, upward mobility is largely concentrated in East-Germany and Poland, whereas all regions in the Czech Republic (except for Praha) and many regions in Hungary (especially the eastern regions) show downward mobility.

To look more closely at the relevance of the spatial dimension, the left hand panel of Figure 7 shows the regionally conditioned distribution where a region's GDP is divided not by the Eastern European average GDP but by a weighted sum[20] of neighboring region's GDP per capita. One can see that regional conditioning does not result in the nicely mean-concentrated distributions as in case of the Western European regions (see Figure 3). The extreme polarization observed in the Eastern European GDP per capita relative distribrution in Figure 4 has smoothed somewhat but to say that regional conditions explain much of the variation is something else[21]. Also over time the regionally conditioned distributions have become less concentrated suggesting that initially similar regions have shown different economic performance in terms of GDP per capita growth. This is confirmed when calculating the Cliff and Ord joint count statistic, see (6). The test statistics for spatial autocorrelation in upward and downward mobility are equal 3.581 and 2.053 respectively. As the corresponding bootstrapped 5% critical values are 3.869 and 2.063 this does not indicate the presence of significant spatial autocorrelation in case of Eastern European regions only[22].

Conditioning a region's GDP per capita instead on the GDP per capita of the country the region belongs to[23], see Figure 7b, leads to much more concentrated distributions except for some regions (mainly the capital regions) with an above country-average GDP per capita. This finding[24] suggests some in-

[20] With weights constructed in the same way as for the Western European regions, see (7).

[21] A similar conclusion follows from looking at the regionally conditioned 'Old + New' Europe distribution (not shown here but available upon request). The distribution becomes more concentrated around the mean except for the mode in the lower tail containing most Eastern European regions.

[22] This seems to contradict the picture shown in Figure 6, but one has to remember that that picture, serving merely illustrational purposes, shows mobility between income groups over 12 years (between 1991 and 2002) whereas the BB-statistic is based on yearly mobility.

[23] Quah, 1996b suggested doing this and found that in case of Western European regions regional conditioning explained more of the income variation that country conditioning. This was also found to be the case for the larger Western European sample used in this paper which is the reason why this was not given much attention in the previous section.

[24] Which is confirmed when quantifying the difference between the regional (country) condi-

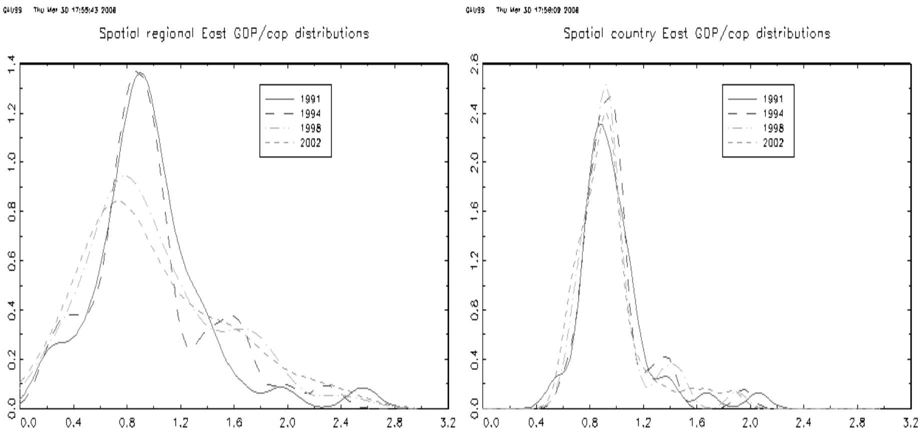

Figure 7a

Figure 7b

teresting things about the nature of regional income disparities in the former communist countries of Eastern Europe. The differences in regional incomes in Eastern Europe seem to be grounded much more in country-specific factors than in regional conditions. This is quite different from what was found in the previous section on Western Europe, where country-specific factors seem to have been largely replaced by regional factors that extend beyond official country borders.

Also of interest is the relevance of a region's spatial setting in terms of the evolution of its GDP per capita. In the previous section dealing with Western European regions this was done by estimating a spatially conditioned Markov chain. This would also be very interesting in case of the Eastern European regions. However given the number of transition probabilities that have to be estimated and the much smaller sample at hand when considering only Eastern European regions, doing this does not give much useful insights. Many of the estimated conditional transition probabilities are insignificant which makes it hard to draw any meaningful conclusion from this matrix. Because of this it is decided to not show this matrix here[25]. Moreover, Figure 7 suggested that it is not regional but much more national conditions that matter in the case of Eastern European regions. To still say something about the relevance of a region's spatial setting for the evolution of its income level over time it is therefore decided to show the 1-year transition matrix of the country-conditioned GDP series over time. This matrix, shown in Table 8, gives some insight into the evolution of a region's GDP per capita with respect to the other regions belonging to the same country. It does not provide (as a spatially conditioned Markov chain does) evidence on the relevance of a region's location (here which country it belongs to) for its economic performance relative to all Eastern European countries, but does offer useful insights into the evolution of regional income differences between regions belonging to the same country.

The cutoff points used to discretize the country conditioned distributions are

tioned distributions in Figure 7a (7b) and the Eastern Europe relative distributions in Figure 4b in terms of a transition matrix similar to that in Table 3 (available upon request).

[25]It is available upon request however.

Table 8: 'New' Europe, estimated 1-yr country-conditioned transition matrix

		t+1					
		1	2	3	4	5	nr obs
	1	0.968	0.021	0.011	0	0	94
		(0.018)	(0.015)	(0.011)			
	2	0.103	0.805	0.092	0	0	87
		(0.033)	(0.043)	(0.031)			
t	3	0	0.108	0.763	0.129	0	93
			(0.032)	(0.044)	(0.035)		
	4	0	0	0.169	0.787	0.045	89
				(0.040)	(0.043)	(0.022)	
	5	0	0	0	0.091	0.909	88
					(0.031)	(0.031)	

Notes: standard errors between brackets. 1,2,...,5 correspond to the different groups of the discretized distribution. p-value time-homogeneity: 0.294 (subperiods: 1991-1995 and 1995-2002)

again chosen such that each group initially contains an equal number of regions. They are 1.05, 0.95, 0.885 and 0.79 times the GDP per capita of the country a region belongs to. The estimated transition probabilities show very clearly that regions that are in the lowest country-relative income group do not have a significant chance of catching up with the richer regions in their country. Regions with incomes only slightly below that of their respective country show a much higher probability of moving towards the country-level of GDP per capita. They do however also have a similar probability of moving towards the poorer end of the country-relative distribution. This probability of moving downward is even higher, about 17%, for regions with a GDP per capita similar to that of their country whereas such regions have a much lower probability (4.5%) of becoming even richer in country relative terms. Finally the country-relative richest regions have quite a high probability, 91%, of remaining rich compared to the other regions in their country. The overall impression from Table 5 is thus that especially the poorest country-relative regions are very likely to remain 'trapped in country-relative poverty', that is having a regional income per capita that is 20% lower than what the average person in its home country earns. The opposite, be it to a lesser extent, holds for the richest regions, they are likely to keep their 'privileged' position within their home country in terms of income per capita. Furthermore given the more likely downward movement of regions with a per capita income around or slightly below the country level of GDP per capita, the gap between these high-income regions and their fellow country regions is likely to widen. Combining this with the earlier found evidence on the evolution of the unconditional Eastern European and the total unconditional 'New + Old' European regional income distributions, where it was found that many but not all Eastern European regions tend to have income levels moving towards their Western European neighbors, suggests it is those regions that are already rich in comparison to other regions in their home-country that are most likely to make this move. This may for example be explained by that those regions were (are) best able to attract new foreign investors during the transition phase given their initial advantage compared to other regions in terms of for example market size, available (high skilled) labor and infrastructure, or are home to a country's capital city (see Tondl and Vuksic, 2003).

5 Conclusions

This paper has looked at the (spatial) evolution of regional income disparities in both the 'Old' and the 'New' Europe. To do this it has quantified the dynamics of the regional GDP per capita distribution in the 'Old', the 'New' and the total 'New + Old' Europe, using (spatial) Markov Chain techniques. The paper finds that regional income differences in the 'Old' Europe are getting quite a bit smaller but are not likely to entirely disappear, hereby offering a somewhat brighter picture than other recent studies, e.g. Le Gallo, 2004 and Magrini, 1999 that have found evidence in favor of diverging regional income levels. A different picture emerges for regions in the 'New' Europe where it is found that many regions in these former communist countries are likely to (very slowly) catch up with their Western neighbors, but in the process leave others behind in relative poverty.

Besides offering a clear view on the temporal evolution of the regional GDP per capita distributions, this paper also provides evidence on the importance of the geographical location of a particular region for the evolution of its income level. Where in case of the 'Old' Europe the evolution of regional incomes seems to be determined largely by localized (border-crossing) regional conditions, in the 'New' Europe country-specific conditions are found to be a major determinant. Moreover the way in which a region's location matters seems to provide some evidence in favor of the predictions made by models of the new economic geography. In the 'Old' Europe evidence of localized agglomeration economies is found whereas in the 'New' Europe an initial advantage in terms of country-relative GDP per capita seems to have had a beneficial effect on the economic performance during the transition phase which can be interpreted as being a 'lock-in' effect. The results found in this paper also bring up several interesting questions that should be looked at by future research. Will EU-membership enable not some (as found here) but all regions in Eastern Europe to increase their income levels to be more comparable to those in the 'Old' Europe? Will localized regional conditions eventually replace the country-specific conditions in determining regional income patterns in the 'New' Europe as seems to be the case in the 'Old' Europe? It would be very interesting to see whether or not the increased integration of the Eastern Europe countries with the European Union will change the picture that emerges from this paper's analysis.

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APPENDIX

A Regions included in the analysis

Belgium		
Bruxelles-Brussel	Vlaams Brabant	Liege
Antwerpen	West-Vlaanderen	Luxembourg
Limburg	Brabant Wallon	Namur
Oost-Vlaanderen	Hainaut	
Denmark		
Hovedstadsreg.	O. for Storebaelt	V. for Storebaelt
Germany		
Stuttgart	Schwaben	Dusseldorf
Karlsruhe	Bremen	Koln
Freiburg	Hamburg	Munster
Tubingen	Darmstadt	Detmold
Oberbayern	Giessen	Arnsberg
Niederbayern	Kassel	Koblenz
Oberpfalz	Braunschweig	Trier
Oberfranken	Hannover	Rheinhessen-Pfalz
Mittelfranken	Luneburg	Saarland
Unterfranken	Weser-Ems	Schleswig-Holstein
Greece		
Anatoliki Makedonia	Ionia Nisia	Voreio Aigaio
Kentriki Makedonia	Dytiki Ellada	Notio Aigaio
Dytiki Makedonia	Sterea Ellada	Kriti
Thessalia	Peloponnisos	
Ipeiros	Attiki	
Spain		
Galicia	Aragon	Com. Valenciana
Asturias	Madrid	Baleares
Cantabria	Castilla-Leon	Andalucia
Pais Vasco	Castilla-la Mancha	Murcia
Navarra	Extremadura	
Rioja	Cataluna	
France		
Ile de France	Lorraine	Limousin
Champagne-Ard.	Alsace	Rhone-Alpes
Picardie	Franche-Comte	Auvergne
Haute-Normandie	Pays de la Loire	Languedoc-Rouss.
Centre	Bretagne	Prov-Alpes-Cote d'Azur
Basse-Normandie	Poitou-Charentes	Corse
Bourgogne	Aquitaine	
Nord-Pas de Calais	Midi-Pyrenees	
Ireland		
Border	Southern and Eastern	

Italy		
Piemonte	Emilia-Romagna	Campania
Valle d'Aosta	Toscana	Puglia
Liguria	Umbria	Basilicata
Lombardia	Marche	Calabria
Trentino-Alto Adige	Lazio	Sicilia
Veneto	Abruzzo	Sardegna
Fr.-Venezia Giulia	Molise	
The Netherlands		
Groningen	Gelderland	Zuid-Holland
Friesland	Flevoland	Zeeland
Drenthe	Utrecht	Noord-Brabant
Overijssel	Noord-Holland	Limburg
Austria		
Burgenland	Karnten	Salzburg
Niederosterreich	Steiermark	Tirol
Wien	Oberosterreich	Vorarlberg
Portugal		
Norte	Lisboa e V.do Tejo	Algarve
Centro	Alentejo	
Finland		
Ita-Suomi	Pohjois-Suomi	Etela-Suomi
Vali-Suomi	Uusimaa	Aland
Sweden		
Stockholm	Norra Mellansverige	Smaland med oarna
Ostra Mellansverige	Mellersta Norrland	Vastsverige
Sydsverige	Ovre Norrland	
United Kingdom		
Tees Valley and Durham	Leicester	Hants.
Northumb. et al.	Lincolnshire	Kent
Cumbria	Hereford et al.	Gloucester et al.
Cheshire	Shropshire	Dorset
Greater Manchester	West Midlands (county)	Cornwall
Lancashire	East Anglia	Devon
Merseyside	Bedfordshire	West Wales
East Riding	Essex	East Wales
North Yorkshire	Inner London	North East Scot.
South Yorkshire	Outer London	Eastern Scotland
West Yorkshire	Berkshire et al.	South West Scot.
Derbyshire	Surrey	Highlands and Islands
Norway		
Oslo og Akershus	Agder og Rogaland	Nord-Norge
Hedmark og Oppland	Vestlandet	
Sor-Ostlandet	Trondelag	
Suisse		
Region Lemanique	Zurich	Ticino
Espace Mittelland	Ostschweiz	
Nordwestschweiz	Zentralschweiz	

DDR		
Berlin	Chemnitz	Dessau
Brandenburg	Dresden	Halle
Mecklenburg-Vorpomm.	Leipzig	Magdeburg
Poland		
Dolnoslaskie	Malopolskie	Pomorskie
Kujawsko-Pomorskie	Mazowieckie	Slaskie
Warminsko-Mazurskie	Opolskie	Swietokrzyskie
Lubuskie	Podkarpackie	Lubelskie
Lodzkie	Podlaskie	Wielkopolskie
Zachodniopomorskie		
Hungary		
Kozep-Magyarorszag	Del-Dunantul	Del-Alfold
Kozep-Dunantul	Nyugat-Dunantul	
Eszak-Magyarorszag	Eszak-Alfold	
Czech Republic		
Praha	Severozapad	Stredni Morava
Stredni Cechy	Severovychod	Ostravsko
Jihozapad	Jihovychod	
Severozapad		