Spatial disparities in productivity in Central and Eastern Europe*

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July 2, 2005

*The authors acknowledge the financial support from MCYT (Project BEC2002-03941).

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Abstract

This paper examines the evolution of territorial imbalances in productivity in 39 Central and Eastern Europe regions between 1992 and 2001. The results obtained show an overall reduction in regional inequality over the study period. This process was compatible with the simultaneous presence of between-country convergence and within-country divergence. In any event, the polarisation of the distribution under consideration is seen to decrease, while the registered level of intra-distribution mobility is relatively low. The analysis also indicates that regional disparities in output per worker in Central and Eastern Europe are closely linked to intrinsic differences between regions. Finally, we investigate the role played in explaining observed dispersion in sectoral productivity levels by the national component, spatial location, agglomeration economies and geographical distance to the economic core of the European Union.

Key words: disparities, productivity, regions, Central and Eastern Europe.

JEL code: R10, R11, P25.

1 Introduction

Throughout the 1990's, the countries of Central and Eastern Europe (CEE) went through a profound economic and political reform process (Gros and Steinherr, 2001), culminating in the adhesion of the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovenia and Slovakia to the European Union (EU) in May 2004¹. This gave rise to an unprecedented increase in the magnitude of regional disparities within the EU. In fact, according to European Commission (2004) estimates, in 2002 only the Czech Republic and Slovenia enjoyed a per capita GDP above 60 per cent of the average of the fifteen EU member states prior to May 2004 (EU15). Estonia, Lithuania and Poland registered figures around 40 per cent of the EU15 average, while the percentage for Latvia was approximately 35 per cent.

When it comes to assessing the implications of this issue, it should be taken into account that the reduction of spatial disparities in development terms relates directly to some of the Union's basic underlying principles, especially since the introduction of the Single Act and the Maastricht agreements. In particular, one of the specific assumptions of the European integration programme is that it will drive the growth of all member states, thereby increasing economic and social cohesion. In fact, article 2 of the Treaty of the EU specifically states that: "The Community shall have as its task (...), to promote (...) a harmonious, balanced and sustainable development of economic activities, (...) sustainable and non-inflationary growth, (...) a high degree of competitiveness and convergence of economic performance (...)". This idea is developed and reinforced in other parts of the same text, which specifies that the economic growth of the EU must go hand in hand with the strengthening of internal cohesion and that the regional aspects of the problem require a commitment to continue and develop the lines of action already

undertaken in the past.

In light of these considerations, this paper analyses the distribution dynamics of regional productivity in CEE from 1992 to 2001. In doing so, we examine the main features of the economic trends in the CEE regions during the period of transition, focusing on inequality, polarisation and regional mobility. Our main purpose is to contribute to the understanding of territorial imbalances in this geographical context in terms of output per worker, a key factor in regional growth processes (López-Bazo *et al.*, 1999; Cuadrado, Mancha and Garrido, 2002)².

It is worth keeping in mind, however, that regional disparities in aggregate productivity might be related, amongst other possible factors, to significant differences in output per worker across the various sectors. If this were the case, significant long-standing disparities in regional productivity might well be perfectly compatible with processes of regional convergence in output per worker in each of the various sectors. In other words, this would mean that regional differences in development terms might basically be due to variability in the industry mix across the sample regions. Indeed, the industry mix in each region would in theory depend on some kind of comparative advantage or historical circumstances (Krugman, 1991). Alternatively, disparities in productivity may be related to intrinsic differences between regions. If this were the case, the main determinants of regional disparities in output per worker would be those aggregate factors, such as infrastructure, human capital and R&D, that have an uniform impact on productivity in all sectors.

Taking this into account, this paper also examines the role played by regional and sectoral factors in the evolution of spatial disparities in output per worker in CEE. With this analysis we hope to draw some type of inference that might be useful for

future regional policy in the EU.

Up to the present moment, as far as we are aware, only Herz and Vogel (2003) have addressed the study of regional disparities for a set of CEE countries³. Specifically, these authors have analysed existing regional disparities in 31 regions of the Czech Republic, Hungary and Poland for the period 1990-2002, by means of the estimation of convergence equations, in an approach made popular by Barro and Sala-i-Martin (1991, 1992) within the framework of the economic growth literature. However, as Quah (1993, 1996a,b; 1997) has repeatedly pointed out, not only does this methodology raise a number of econometric problems (Canova and Marcet, 1995), it also fails to capture a series of potentially interesting features of the dynamics of the distribution in question. In fact, the estimation of convergence equations is based on a model for a single ‘representative’ economy. As a result, this type of analysis provides only a partial view of the observed distribution, since it neglects to consider, for example, the fact that the various regions may shift their relative positions over the study period; thus it completely ignores the possibility of intra-distribution mobility. This methodological approach also fails to inform about the possible existence of distinct clusters of regions with distinguishing features that set them apart from the rest of the population.

In order to overcome the limitations imposed by the use of convergence equations, this paper follows in the main the non-parametric approach proposed by Quah (1993, 1996a,b; 1997) to analyse the evolution of the entire cross-section distribution. Moreover, we explore the origin of regional productivity differences in CEE by means of a methodology combining the shift-share analysis used by Esteban (2000) and various theoretical results obtained in the literature on personal income distribution.

In this paper we use the statistical data supplied by the Cambridge Econometrics

database on the 39 NUTS-2 regions of the eight CEE countries that joined the EU in May 2004⁴. The data provided by Cambridge Econometrics are based mainly on information supplied by REGIO, the Eurostat database. Nevertheless, REGIO is seriously lacking in some respects, especially when it comes to data relating to the early nineties. For this reason, Cambridge Econometrics has opted to complete REGIO data with national statistics for the various countries.

The rest of the paper is organised as follows. Section 2, contains an analysis of regional productivity disparities in CEE, using the information provided by a series of measures commonly used in the traditional literature on inequality. Section 3 investigates the dynamics of the distribution of interest, focusing particularly on polarisation and regional mobility. To further round off the results obtained thus far, section 4 examines the role played in this context by sectoral and regional factors. Finally, section 5 presents the main conclusions.

2 Regional inequality

We begin by examining the evolution of regional productivity disparities in CEE from 1992 to 2001. However, in contrast to the procedure adopted in conventional convergence analysis, this paper will approach the issue by calculating a series of indicators traditionally used to study personal income distribution. Since our unit of reference is the region and not the individual, we will then introduce into the analysis the relative frequencies of each observation. Thus, all the measures calculated will be statistics weighted by the employment share of the different regions. Studies that focus on the convergence hypothesis tend usually to ignore differences in population, output or employment across the various territorial units considered⁵. This omission has important

repercussions in the geographical context under analysis in the present paper, since it means that the same weight is assigned to quite different regions⁶.

Within the literature on personal income distribution, it is a well-known fact that results may differ, at times substantially, according to which measures are used in the analysis. Given the obvious difficulty that arises from the fact that different indicators may give different orderings of the distributions to be compared, it would seem reasonable to check the robustness of our results against different inequality measures. According to this procedure, in this paper we examined regional productivity disparities in CEE by means of the information provided by the Gini index, G , and the measure proposed by Theil (1967) within the information theory context, $T(\beta)$, with $\beta = 0, 1$. Specifically,

$$G = \frac{\sum_{i=1}^n \sum_{j=1}^n e_i e_j |y_i - y_j|}{2\mu} \quad (1)$$

$$T(0) = \sum_{i=1}^n e_i \log \left(\frac{\mu}{y_i} \right) \quad (2)$$

and

$$T(1) = \sum_{i=1}^n e_i \left(\frac{y_i}{\mu} \right) \log \left(\frac{y_i}{\mu} \right) \quad (3)$$

where y_i and e_i denote, respectively, the output per worker and the employment share of region i , with $\mu = \sum_{i=1}^n e_i y_i$. We also took into account the coefficient of variation, CV , and the standard deviation of the logs, $SD \log$, two measures of dispersion that are common in descriptive statistics and widely used in the convergence literature to capture the concept of sigma convergence (Barro and Sala-i-Martin, 1991, 1992). However, in contrast to the procedure adopted in conventional convergence studies, for the purposes of this paper, both statistics were calculated after introducing the corresponding weightings into the analysis. In any event, all the indices selected are independent

of scale and population size and, except for the standard deviation of the logs, they all fulfil the Pigou-Dalton transfer principle for the whole definition domain of the study variable⁷.

Figure 1 presents the evolution of the inequality indices just mentioned. The results point to a decrease in dispersion in the distribution under consideration between 1992 and 2001. Indeed, the various index values fell between 32 and 8 per cent over the ten years contemplated. This does not imply a uniform reduction in disparities throughout the period, however. In fact, no matter which measure of inequality is applied, the main decrease in regional inequality is seen to have taken place between 1992 and 1994, followed by a period of stagnation in the following years. Moreover, though the standard deviation of the logs is not ordinally equivalent to the remaining measures, it can be seen to behave in a qualitatively similar fashion. Note, also, that the Theil indices do not appear to be particularly sensitive to the shares used to weight inequality. This is simply an indication of the positive correlation between output shares and employment shares in CEE⁸. Indeed, the average coefficient of correlation between these two variables for the 1992-2001 period is 0.77.

[INSERT FIGURE 1 AROUND HERE]

From the political and administrative point of view, the sample regions are grouped into various countries. It is therefore reasonable to ask whether, for a given level of inequality in productivity, the territorial imbalances are greater between countries or within countries. To investigate this issue, the relevance of which goes without saying, we consider various theoretical results obtained in the framework of the literature on

personal income distribution, all of which are directly applicable to the analysis of regional disparities.

Thus, let us suppose that we have classified the sample regions, according to the country to which they belong, into G exhaustive and mutually exclusive groups, each formed by n_g regions. In this context, an inequality index is said to be additively decomposable by population subgroups if it can be expressed as the sum of the between-group and within-group components, where: (a) the between-group component is the inequality index value when the output per worker of all group members coincides with the group average, and (b) the within-group component is equal to the weighted average of internal dispersion in productivity in the various groups (Deutsch and Silber, 1999). As shown in Shorrocks (1980, 1984) and Foster (1983), the Theil indices, $T(\beta)$, are the only family of measures that are linearly decomposable in the sense described above, and that also satisfy the properties commonly required of inequality indices⁹. In light of this result, $T(\beta)$ can be written as:

$$T(\beta) = T_0(\beta) + \sum_{g=1}^G \omega_g T_g(\beta) \quad (4)$$

In the above expression $T_0(\beta)$ denotes the Theil index corresponding to $(\mu_1 e_{n_1}, \mu_2 e_{n_2}, \dots, \mu_G e_{n_G})$, where e_{n_g} is an n_g -dimension vector of ones. Likewise, $\omega_g = e_g^{1-\beta} r_g^\beta$, where r_g is the output share of group g . However, it is worth noting that $\sum_{g=1}^G \omega_g = 1$ only when $\beta = 0, 1$. In all other cases the sum of the weightings is not equal to unity. This fact indicates the advisability of using $T(0)$ and $T(1)$ in empirical analysis.

Thus, Figure 2 presents the decomposition of $T(0)$ according to the expression (4)¹⁰. The results reveal the simultaneous presence of both between-country convergence and regional divergence in output per worker levels in CEE. In fact, there was a substantial decline in average productivity differences between countries during the period 1992

to 2001. At the same time, however, the value of the within-group component rose steadily over the ten-year sample period. With respect to this, however, it is worth noting that, while, at the beginning of the nineties, the between-group component of the index explained 88 per cent of the global inequality, by 2001 this percentage had dropped to 59 per cent. Therefore, if within-group disparities were eliminated at the end of the sample period, while keeping between-group disparities constant, the aggregated inequality would be reduced by 41 per cent. This raises a series of potentially major implications for future regional policy within CEE (European Commission, 2001, 2004). Specifically, the analysis shows that, in 2001, inequality due to the within-group component of the index played a noteworthy role in this context, such that policies aimed at correcting imbalances between countries would have limited impact. In fact, in these circumstances, it would be necessary to reinforce the role of specific redistribution policies within countries.

[INSERT FIGURE 2 AROUND HERE]

Figure 3 shows, in this respect, that there is some variation in inequality levels within the Czech Republic, Hungary, Poland and Slovakia, though regional disparities in productivity rose significantly in all cases over time¹¹. This was due mainly to the strong dynamism experienced by the major urban centres throughout the ten-year sample period, boosted by the presence of a skilled labour force, relatively developed infrastructure, advanced services and, especially, a marked increase in foreign investment during the nineties (Resmini, 2000). It should be noted in this context that the inflow of foreign investment had a decisive impact in improving the productive environment and the diffusion of new technologies in these areas (Tondl and Vuksic, 2003). The remaining

regions of these countries, however, registered, for the most part, slower economic growth rates, since, generally speaking, they underwent the impact of agricultural and industrial decline, which was only partially offset by growth in the services sector (European Commission, 1999).

[INSERT FIGURE 3 AROUND HERE]

3 Polarisation and regional mobility

The above section presents a first analysis of the regional disparities in productivity observed in CEE between 1992 and 2001, using information drawn from several inequality measures. However, the various statistics calculated so far do not supply an accurate description of the output per worker distribution. To overcome this problem, we will now estimate the density functions of the distribution under consideration. Following common practice in the literature, we will use non-parametric estimation techniques, thus avoiding the need to specify any particular functional form beforehand. This kind of approach undoubtedly offers major advantages in the present context, given that parametric approximations lack generality and flexibility.

Figure 4 shows the density functions of the regional distribution of productivity weighted by employment shares¹². The horizontal axis represents regional productivity normalised according to the distribution average, while the associated density appears on the vertical axis. Estimates are based on calculations using Gaussian kernel functions, and the optimal smoothing parameter value is determined in each case following Silverman (1986, p. 47).

[INSERT FIGURE 4 AROUND HERE]

The results reveal some differences in the densities estimated for the sample period. As Figure 4 shows, the CEE regions experienced different growth patterns between 1992 and 2001. Thus, the initial situation did not remain stable over time. In particular, the probability mass concentrated around the average increased during the ten years contemplated. Indeed, in 1992, 55 per cent of total employment was located in regions where the productivity registered values between 75 and 125 per cent of the average, while ten years later the previous percentage had risen to 67 per cent. This, together with the narrowing of the distance between the extreme values of the distribution, is coherent with the preceding analysis and confirms that there was a reduction in regional productivity disparities in CEE throughout the period under consideration. However, it is worth mentioning that in 2001 there still remained an important probability mass below 75 per cent of average productivity. This can be interpreted as an indication of the difficulties of some CEE regions with relatively low output per worker to improve their relative positions at the end of the period analysed.

The estimated density functions, meanwhile, suggest the presence of a certain degree of polarisation in the regional distribution of productivity during the ten years considered. However, it is not possible with a non-parametric analysis to obtain precise quantitative information on polarisation changes over time. To overcome this problem, we will now apply the approach proposed by Esteban and Ray (1994).

According to these authors, it is possible to measure the degree of polarisation of a distribution f partitioned into a number of groups exogenously determined by means of

the following expression:

$$P^{ER}(f, \delta, \rho) = \sum_{j=1}^m \sum_{k=1}^m q_j^{1+\delta} q_k |\mu_j - \mu_k| \quad (5)$$

where, for the purposes of the present study, μ_j and q_j denote, respectively, the average productivity and the employment share of group j . Likewise, $\delta \in [1, 1.6]$ is a parameter that captures the degree of sensitivity of P^{ER} to polarisation¹³. Nevertheless, before applying this measure, it is necessary to define a simplified representation of the original distribution in a series of exhaustive and mutually exclusive groups. This will generate some degree of error, however, as this grouping will result in a certain amount of information loss, depending on the degree of dispersion within each of the groups considered. Following Esteban, Gradín and Ray (1999), in order to establish the dividing line between the various groups, in this paper we used the algorithm proposed by Davies and Shorrocks (1989). In this way, it is possible to obtain the optimal partition of the original distribution that minimises the level of within-group dispersion.

We applied this methodology to examine the evolution of regional polarisation in productivity in CEE between 1992 and 2001. Our aim was to analyse the degree of polarisation that exists after finding the optimal partition that minimises inequality due to within-group dispersion. Figures 5 and 6 report the results obtained when this criterion is used to divide the distribution of interest into two and three groups. In addition, and in order to check the robustness of our conclusions, we introduced different degrees of sensitivity to polarisation into the analysis. Specifically, $\delta = 1, 1.3, 1.6$.

Figure 5 shows a decline in the bipolarisation of the regional distribution of output per worker in CEE over the period as a whole¹⁴. Indeed, the P^{ER} values decreased over the ten years considered by between 7 and 5 per cent, according to the degree of sensitivity to polarisation considered in each case. The evolution of P^{ER} was not uniform

throughout the whole period, however. In fact, irrespective of the δ parameter value, it is possible at first glance to distinguish two distinct stages. Thus, the bulk of the reduction in regional bipolarisation took place in the first years of the study period. This trend changed from 1995 onwards, however, when there began an increase in bipolarisation lasting until 2001, though it did not compensate for the previous reduction.

[INSERT FIGURE 5 AROUND HERE]

Figure 6 reports on the evolution of regional polarisation in productivity when the initial distribution is split into three groups¹⁵. As in the previous case, it is possible to observe an overall decline in regional polarisation during the 1992-2001 period. P^{ER} values, in particular, registered decreases of 14 to 11 per cent over the ten years contemplated, depending on the value assigned to the δ parameter. Note that, when the initial distribution is split into three groups, there is a bigger reduction in polarisation on all indices than with the previous two-group partition. Again, however, this decline was not uniform throughout the study period. Thus, there was a reduction in regional polarisation up until 1994, followed by a marked increase in 1995. Nevertheless, in 1996 there began a new stage characterised by another decrease in polarisation. Other considerations notwithstanding, this pattern over time clearly shows that the evolution of polarisation in CEE did not run parallel to that of regional inequality¹⁶. This highlights the need for separate analyses of the two phenomena, such as we have undertaken in this paper.

[INSERT FIGURE 6 AROUND HERE]

The density functions estimated in Figure 4 give a first impression of the external shape of the distribution for each year of the period analysed. The indices calculated in Figures 5 and 6 likewise inform about the degree and evolution of regional polarisation. This type of analysis, however, is based on a series of cross-sections of the distribution examined, and does not, therefore, take into account that the different economies may, over time, modify their relative positions in terms of productivity. To address this shortcoming and to complete the results obtained so far, we examined mobility dynamics in the distribution of regional output per worker in CEE between 1992 and 2001.

Most of the papers that have studied this issue are based on the information provided by discrete transition matrices, obtained by dividing the distribution into a series of exhaustive and mutually exclusive classes¹⁷. This approach entails a problem, however, since the results it yields are sensitive to the way in which the original distribution is partitioned. Nevertheless, since there is no procedure for determining the optimum number of classes in each case, the researcher must decide arbitrarily (Bulli, 2001; Kremer, Onatski and Stock, 2001). To address this problem, Quah (1996b, 1997) suggests substituting the transition matrix with a stochastic kernel to reflect the probabilities of transition between a hypothetically infinite number of classes, reducing their size infinitesimally (Stockey and Lucas, 1989)¹⁸. Specifically, the stochastic kernel can be obtained by estimating the density function of the distribution over a given period, $t + k$, conditioned on the values of a previous period, t . In other words, the joint density function at moments t and $t + k$ is estimated and then divided by the implicit marginal distribution in order to obtain the corresponding conditional probabilities.

As we can observe, Figure 7 shows the stochastic kernel estimated for the whole sample period ($t = 1992$ and $t + k = 2001$)¹⁹. This three-dimensional graph can be

interpreted as a transition matrix with an infinite number of classes, that informs about the probabilities associated with each pair of values in the first and last years of the study period. In other words, the stochastic kernel gives us, as does a discrete transition matrix, the probability distribution of output per worker in 2001 for regions with a given value in 1992. Thus, if the probability mass is concentrated around the main diagonal, the intra-distribution dynamics are characterised by a high level of persistence in the relative positions of the regions over time and, therefore, low mobility. If, on the other hand, the density is located mainly on the diagonal opposite the main diagonal, this would indicate that regions situated at both ends of the distribution exchange their relative positions over time. Finally, the probability mass could, in theory, accumulate parallel to the t axis. This would reflect a process of convergence in productivity over the study period. In order to aid interpretation of the graph, Figure 7 also includes the related contour plot, on which the lines connect points at the same height on the three-dimensional kernel.

[INSERT FIGURE 7 AROUND HERE]

Figure 7 shows the probability mass concentrated around the main diagonal. This illustrates the limited degree of mobility in the regional productivity distribution during the 1992-2001 period. Thus, the CEE regions tended on the whole to maintain their relative positions throughout the ten years considered. Nevertheless, the estimates also reveal that the various regions differ in their mobility patterns according to their output per worker levels. Thus, regions situated at the upper end of the distribution are characterised by greater persistence in their relative positions over time. By contrast, regions with low and intermediate productivity levels registered a relatively higher de-

gree of mobility over time. In fact, the distribution can also be seen to skew slightly at the lower end. This suggests that the reduction in regional disparities in productivity observed previously was due basically to the dynamics displayed by regions with low output per worker levels at the start of the sample period.

Finally, we estimated the corresponding ergodic distribution by iteration of the stochastic kernel to reach the convergence of the process. Given that this is, by definition, a continuous distribution, it can be represented graphically (Figure 8). As shown, the corresponding ergodic distribution is characterised by a single local maximum located around the average (unimodality)²⁰. Nevertheless, according to our results, the territorial imbalances in output per worker observed during the nineties will persist in the future. However, it is worth mentioning that there is no evidence to suggest that the distribution under study will fragment in the long term into various separate groups of regions differentiated according to their productivity levels²¹.

[INSERT FIGURE 8 AROUND HERE]

4 Explanatory factors of regional productivity differences:

Sectoral and regional elements

In order to complete the results obtained so far, this section aims to examine the causes that lead to regional differences in output per worker in CEE. For this it is important to keep in mind that the aggregate productivity of a region can be expressed as the weighted average of output per worker across the various sectors. Thus, for region

i we can write:

$$y_i = \frac{x_i}{l_i} = \sum_{j=1}^m \left(\frac{x_{ij}}{l_{ij}} \right) \left(\frac{l_{ij}}{l_i} \right) = \sum_{j=1}^m y_{ij} s_{ij} \quad (6)$$

where the subindices i and j denote regions and sectors respectively. In addition, x_i and l_i stand for the output and employment levels, while $\frac{x_{ij}}{l_{ij}} = y_{ij}$ and $\frac{l_{ij}}{l_i} = s_{ij}$.

Expression (6) states that regional productivity differences can be attributed to two factors (or a combination of them both). Thus, a first possible explanation of regional disparities in productivity might have to do with differences in output per worker in the m sectors considered. Therefore, even in the absence of regional disparities in individual sectors, regions specialised in more productive sectors would register above-average output per worker levels. Alternatively, regional disparities in output per worker may also be a direct result of differences in regional endowments of certain aggregate factors with a uniform effect on productivity across all sectors.

In order to assess the validity of these possible explanations in the CEE setting, it will be necessary to decompose the gap in productivity between each of the regions considered and the average. According to Esteban (2000), a useful technique for an initial exploration of the issue is shift-share analysis. Though this technique was originally proposed by Dunn (1960), it has since been the subject of intense criticism and thorough revision, leading to a considerably improved reformulation of the original. Shift-share analysis was originally designed as a technique for analysing growth in regional employment. It can, however, be directly applied to the study of output per worker. The idea is quite simple. For the case in hand, it is a question of decomposing the productivity gap between a given region and the European average so as to capture the respective roles of three factors: industry mix, region-specific factors with an uniform effect on all sectors and, finally, interaction between the first two elements.

Thus, using the same expression as in the case above, average productivity in CEE can be written as:

$$y = \sum_{j=1}^m s_j y_j \quad (7)$$

where s_j and y_j denote, respectively, sector j 's employment share and its productivity in the whole of CEE. In order to isolate the role played by industry mix in the region, expression (6) can be rewritten as:

$$y_i = \sum_{j=1}^m s_{ij} y_{ij} = \sum_{j=1}^m [(s_{ij} - s_j) + s_j] [(y_{ij} - y_j) + y_j] \quad (8)$$

With some algebra, the above expression will give the productivity differential between region i and the average in any given year. In particular,

$$y_i - y = \sum_{j=1}^m (s_{ij} - s_j) y_j + \sum_{j=1}^m (y_{ij} - y_j) s_j + \sum_{j=1}^m (s_{ij} - s_j) (y_{ij} - y_j) \quad (9)$$

or alternatively,

$$\gamma_i = \varepsilon_i + \rho_i + \alpha_i \quad (10)$$

In other words, the productivity gap between each of the regions considered and the CEE average, γ_i , can be expressed as the sum of three factors. The first of these, ε_i , is known as the structural component, which measures the impact of the difference between the region's industry mix and the average, assuming that output per worker in each sector is the same across all regions. Specifically, ε_i takes positive values if the region is relatively more specialised ($s_{ij} > s_j$) in sectors with high output per worker throughout the whole of CEE. In fact, ε_i reaches its highest value when a region specialises exclusively in the sector with the highest average productivity. The regional or differential component, ρ_i , meanwhile, captures that part of γ_i that can be attributed

to sectoral productivity gaps between region i and the average. In this case the region is assigned an industry mix equal to the average. Therefore, ρ_i takes positive values if region i 's sectoral productivity is higher than the average ($y_{ij} > y_j$). Lastly, the allocative component, α_i , captures the interaction between ε_i and ρ_i , which in turn indicates the region's degree of specialisation in sectors where productivity is higher than the average. It is easy to appreciate that α_i takes positive values if the region is relatively specialised in sectors with above-average productivity. Thus, α_i can be taken as an index of the region's efficiency in allocating resources among the various sectors.

Our initial purpose in this section is to examine the contribution of each of the summands in expression (10) to global inequality in regional productivity differentials in CEE. This is done by decomposing the variance of regional productivity gaps²². At this point, however, it is worth recalling that the variance is not a conventional measure of inequality. Indeed, although it fulfills the condition of independence with respect to population size and the Pigou-Dalton transfer principle, variance is not independent of scale (Cowell, 1995). In order to overcome this problem, we decided to modify expression (10), by dividing each side of the equation by $y = \sum_{j=1}^m s_j y_j$. This done, we have:

$$\gamma'_i = \varepsilon'_i + \rho'_i + \alpha'_i \quad (11)$$

Thus, the index value remains unaltered if the output per worker of each region is modified in the same proportion. Furthermore, taking into account that the CEE regions differ widely in terms of employment, we weighted regional productivity values by employment shares.

We are now ready to analyse the contribution of each of the summands in expression (11) to regional productivity disparities with respect to the average. Specifically, by

applying the inequality measurement described above, we have:

$$\begin{aligned} Var(\gamma') &= Var(\varepsilon') + Var(\rho') + Var(\alpha') + 2[Cov(\varepsilon', \rho') + \\ &\quad + Cov(\varepsilon', \alpha') + Cov(\rho', \alpha')] \end{aligned} \quad (12)$$

As can be appreciated from expression (12), the variance of γ' is not generally equal to the sum of the variances of each of the components considered. Specifically, it is the correlation among the various elements that gives rise to the problems associated with this type of decomposition. Thus, it is necessary to determine how interaction among the various components, expressed in terms of their corresponding covariances, is to be distributed over their individual contributions. However, since there are several ways of making the distribution, it is not possible to find a unique factorial decomposition of $Var(\gamma')$.

To determine the contribution of each component to global inequality it is necessary to establish a rule whereby to distribute the effects of interaction among the various components over their individual contributions. Given that we have, in principle, no further information in this respect, we decided to assign to each component half the covariance by which it is affected, as stated in expression (12). This is what Shorrocks (1982) calls the *natural decomposition* of the variance in the context of the literature on personal income distribution²³. According to this rule, the role of the structural component in global inequality in regional productivity gaps will be given by:

$$\begin{aligned} \overline{Var(\varepsilon')} &= Var(\varepsilon') + Cov(\varepsilon', \rho') + Cov(\varepsilon', \alpha') = \\ &= Cov(\varepsilon', \varepsilon') + Cov(\varepsilon', \rho') + Cov(\varepsilon', \alpha') = \\ &= Cov(\varepsilon', \gamma') \end{aligned} \quad (13)$$

The expressions for the regional and allocative components are analogous, such that:

$$\overline{Var(\rho')} = Cov(\rho', \gamma') \quad (14)$$

and

$$\overline{Var(\alpha')} = Cov(\alpha', \gamma') \quad (15)$$

Note that the different terms in $\overline{Var(.)}$ are the sums of the elements in each of the rows (columns) of the matrix of variances and covariances for the various factors into which regional productivity gaps have been disaggregated. Likewise, it is important to note that $\overline{Var(.)}$ are not true indices of inequality. Indeed, the contribution of an individual component may take a negative value when $Cov(.) < 0$. In such cases, the component in question would be exerting a compensatory effect on regional productivity gaps generated by the remaining components. In any event,

$$Var(\gamma') = \overline{Var(\varepsilon')} + \overline{Var(\rho')} + \overline{Var(\alpha')} \quad (16)$$

Next, we applied this methodology to explore the origin of regional disparities in productivity in the CEE regions. For this, we used statistical data corresponding to the following sectors: agriculture, energy and manufacturing, construction, market services and non-market services²⁴. Figure 9 shows the values resulting from the natural decomposition of the variance in CEE regional productivity differentials from 1992 to 2001. Regional productivity disparities decreased in aggregate terms over the ten years considered, given that the value of $Var(\gamma')$ fell from 0.1620 in 1992 to 0.1326 in 2001, which represents a reduction of 18 per cent. The process was not uniform over time, however. In fact, the observed reduction in regional disparities was concentrated in the period between 1992 and 1994, subsequent inequality remaining practically constant

during the following years. It is worth noting that this evolution of $Var(\gamma')$ is consistent with the outcomes obtained in the second section of this paper.

[INSERT FIGURE 9 AROUND HERE]

Figure 9 also reveals that there was no major change in the dispersion of the structural component over time, since $\overline{Var(\varepsilon')}$ only increased by 2 per cent. By contrast, the regional and allocative components shared a similar evolutionary pattern to that of $Var(\gamma')$, which means a decline in inequality over the whole period observed. Indeed, the values for $\overline{Var(\rho')}$ and $\overline{Var(\alpha')}$ decreased respectively by 19 and 59 per cent between 1992 and 2001.

According to Figure 9, the most important impact on global differences in productivity came from the regional component. In fact, the contribution of $\overline{Var(\rho')}$ remained practically constant over time, accounting for 82 per cent of global inequality in 2001. Meanwhile, there was a slight increase over these ten years in the weight of the structural component, which stood at 16 per cent by the end of the period. Finally, the allocative component, with its 2 per cent contribution at the end of the sample period, can be seen to have played a minor role in this context.

In any event, the analysis carried out so far highlights the importance of the regional component when attempting to explain spatial disparities across the CEE regions. What, though, are the determining factors behind the observed disparities in sectoral productivity across the different regions? In an attempt to find an answer to this, we simulated regional productivity levels in a hypothetical situation in which all regions are assigned the same productive structure, such that the sectoral distribution

of employment in each region is equal to the CEE average over the ten years considered.

Under such circumstances, the virtual productivity level of region i would be given by:

$$\hat{y}_i = \sum_{j=1}^m y_{ij} s_j \quad (17)$$

By applying this strategy, we can remove the influence of the sectoral composition of economic activity from the analysis and focus our attention exclusively on sectoral productivity levels.

It is in this context that we examine the role played by different factors in explaining the degree of dispersion in the virtual distribution defined above. In doing so, we consider how far the distribution varies when variables other than $\hat{y}_i$ are included in the analysis.

Since the pioneer study by Molle, Van Holst and Smit (1980), the literature on spatial disparities in the EU has emphasised the importance of the specific features of various countries in regional growth processes (Quah, 1996c; Rodríguez-Pose, 1999). This suggests the need to assess the influence of the national component on sectoral productivity levels in CEE throughout our sample period. In order to analyse the importance of the so-called ‘country effect’, following Quah (1996c), we constructed a conditioned distribution, by normalising each region’s $\hat{y}_i$ value according to the average virtual productivity of the country to which it belongs, excluding the region in question.

Meanwhile, as in the traditional literature on economic convergence, we have so far considered the various regions as isolated units, thus ignoring the strictly spatial dimension. This should raise no major problems, as long as each economy evolves independently of the remaining regions. This does not seem a very realistic assumption, however, if we take into account that geography plays a major role in the distribution of economic activity (Fujita, Krugman and Venables, 1999), such that neighbouring economies are more likely to converge than distant ones. It is of interest, therefore, to

quantify the importance of spatial spillover effects on the evolution of $\hat{y}_i$ in the CEE regions. Various studies have examined the possible presence of spatial dependence in the context of the EU by applying a set of spatial econometric techniques (Fingleton, 1999; López-Bazo *et al.*, 1999; Le Gallo and Ertur, 2003). In this paper, however, we based our analysis of the subject on a new conditioned distribution, obtained in this case by normalising the $\hat{y}_i$ value of each region according to the average virtual productivity of its adjacent regions (Quah, 1996c; Le Gallo, 2004).

In addition to the role played by political-administrative and spatial factors, it is also worth bearing in mind in this context the possible impact of agglomeration economies, which result from market and non-market interactions (spatial externalities), and imply that proximity to larger markets –areas with a higher density of activity– leads to productivity gains (Fujita and Thisse, 2002). In order to approximate the influence of agglomeration effects on sectoral productivity levels in the CEE regions, we introduced employment density into our analysis (Ciccone and Hall, 1996; Ciccone, 2002). In particular, we classified the various regions by quintiles, taking the employment density in each year of the sample period as our reference. We then defined another conditioned distribution, in this case by normalising the virtual productivity of each region according to the average $\hat{y}_i$ of the regions in the same quintile, calculated without considering the region in question²⁵.

Finally, another factor that is worth considering when attempting to explain the distribution under consideration is the distance of the CEE regions to the economic core of the EU. In fact, according to Weise *et al.* (2001), the areas of CEE close to the EU15 border began during the nineties to exploit their position within a new political and economic geography. Taking this circumstance into account, we calculated the

geographical distance between Brussels and the different CEE regions contemplated in our paper. Subsequently, following the approach adopted in the rest of this section, we constructed another conditioned distribution, using the same procedure as in the case of employment density described earlier.

The various conditioned distributions thus defined can be intuitively interpreted as that part of the virtual productivity distribution that remains unexplained by the different variables considered. In particular, if the conditioned distributions do not differ from the virtual one, the conclusion should be that the conditioning factors do not explain the characteristics of the distribution under consideration. On the contrary, they contribute to the inequality in the virtual distribution, when dispersion in the conditioned distribution is lower than that in the virtual one²⁶.

[INSERT FIGURE 10 AROUND HERE]

[INSERT FIGURE 11 AROUND HERE]

[INSERT FIGURE 12 AROUND HERE]

[INSERT FIGURE 13 AROUND HERE]

Figures 10, 11, 12 and 13 present the density functions estimated from the original distribution of $\hat{y}_i$ and the four conditioned distributions defined in the preceding paragraphs. As can be observed by comparing the graphs, the national component is the main factor in explaining the degree of dispersion in sectoral productivities across CEE,

despite having decreased in importance over the ten years considered²⁷. Specifically, Figure 10 reveals the existence of relatively substantial differences in the distribution of virtual productivity between any given country and CEE as a whole. This confirms the fact that the observed regional disparities in the levels of $\hat{y}_i$ across CEE are linked to country-specific factors, relating, for example, to historical, social and institutional features.

Additionally, the information provided by Figure 11 shows that in 1992 physically adjacent regions tended, save specific exceptions, to register similar values of $\hat{y}_i$, since the conditioned distribution for that year was clearly more concentrated around the average than the virtual distribution. This suggests that, at the beginning of the study period, sectoral productivity levels were not randomly distributed across space in CEE. However, in the same way as the national component, the spatial dimension decreased in importance in this context over the ten years considered. Despite this evolution, however, in 2001, the regions with the lowest values of $\hat{y}_i$ appeared to be characterised by a greater tendency to cluster geographically than those at the upper end of the virtual distribution.

Finally, Figures 12 and 13 reveal that the rest of the variables included in the analysis played a less prominent role in explaining the regional disparities in sectoral productivity levels in CEE over the ten years contemplated. Thus, conditioning the virtual distribution to employment density and distance to the economic core of the EU does not contribute significantly to reducing dispersion in the distribution of $\hat{y}_i$. Nevertheless, it is worth mentioning that the influence of these two factors on observed differences at each end of the virtual distribution increased throughout the nineties, coinciding with the strengthening of economic ties between CEE and Western Europe.

5 Conclusions

In this paper we have examined the evolution of regional productivity disparities in 39 CEE regions between 1992 and 2001. In order to overcome the limitations of conventional convergence analysis, we have used in the main the non-parametric approach proposed by Quah (1993, 1996a,b; 1997) to study the dynamics of the entire cross-section distribution.

The results of our analysis reveal an overall reduction in regional inequality in output per worker over the study period. However, this process is shown to be compatible with the simultaneous presence of between-country convergence and within-country divergence. The latter finding is due basically to the strong dynamism displayed by the main urban centres. In any event, in relative terms, 88 per cent of global inequality in the early nineties was explained by differences in average productivity across countries. By 2001, however, this percentage had dropped to 59 per cent. Within-country inequality, therefore, emerges as a major source of global inequality in output per worker in CEE by the end of the study period.

Meanwhile, the sample regions present different growth patterns over time. It is worth noting in this respect that the estimated density functions reveal that the probability mass concentrated around the average increased during the ten years contemplated. In fact, regional polarisation in the distribution under consideration diminished over the period irrespective of the number of groups considered in the analysis and the value adopted by the parameter of sensitivity to polarisation in the measure used to quantify this phenomenon.

In addition, we have examined the degree of mobility in the regional productivity distribution. The information yielded by the stochastic kernel and the corresponding

contour plot reveals a relatively low level of intra-distribution mobility. The CEE regions have, therefore, tended on the whole to maintain their relative positions in terms of output per worker over the ten years considered.

In order to complete these results, we have studied the origin of regional disparities in productivity by means of an approach involving a combination of the shift-share analysis used by Esteban (2000), and various theoretical results obtained in the literature on personal income distribution. Our findings reveal that regional disparities in output per worker in CEE are closely linked to intrinsic differences between regions. This being the case, the main factors in determining regional inequality in productivity would be basically those which have an uniform effect on output per worker across all sectors. Industry mix, therefore, appears to have contributed relatively little to regional dispersion in average productivity over the ten years covered by our study. Thus, the relatively minor role played by the structural component supports the relevance of one-sector growth models for examining regional disparities in per capita income in this setting.

Furthermore, our analysis highlights the prominent role played by the national component and the economic behaviour of neighbouring regions in explaining the observed disparities in sectoral productivity levels in CEE, despite the decline in the influence of these factors over the course of the ten-year sample period. According to our results, however, agglomeration economies and geographical distance to the core of the EU are factors of less importance in this context. In any event, it is worth noting that these two variables gained in relevance throughout the nineties, coinciding with the strengthening of economic ties between CEE and Western Europe.

Finally, the empirical evidence provided by our analysis raises some implications of potential importance to regional policy designers in search of ways to increase produc-

tivity in lagging CEE regions. For example, the fact that output per worker differences are linked mainly to region-specific factors seems to suggest the need to focus on policies aimed at encouraging investment in the productive environment, human capital and infrastructure, as well as innovation and technology diffusion. Meanwhile, given that regional disparities are not essentially a matter of differences in industry mix, policies designed to promote restructuring of this nature in lagging regions would seem less recommendable. Likewise, the influence of the national component in explaining regional productivity gaps is a clear indication of the need for custom-made development policies to improve the situation of those CEE countries with low average productivity levels.

Notes

¹ At the same time, Cyprus and Malta also joined the EU. Readers interested in a more detailed analysis of the last enlargement might consult Avery and Cameron (1998), Grabbe and Hugues (1998) or Weise *et al.* (2001).

²The use of productivity instead of per capita GDP will allow us to remove the influence of commuters on the results of the subsequent analysis. Thus, the relatively noteworthy number of commuters generates important distortions in the per capita GDP figures of some regions. Clear examples of this are Praha in the Czech Republic, or Bratislava in Slovakia.

³However, the issue has been examined in several contributions using country-level data (Campos, 2001; Eichengreen and Ghironi, 2001; Amplatz, 2003), or single country data (Buček, 1999; Nemes-Nagy, 2001; Wostner, 2002).

⁴NUTS is the French acronym for ‘Nomenclature of Territorial Units for Statistics’, a hierarchical classification established by Eurostat to provide comparable regional breakdowns of EU member states. The complete list of regions contemplated in our analysis is included in the Appendix.

⁵There are, nevertheless, some exceptions. See, for example, Salas (2002) or Goerlich (2003).

⁶In employment terms, for example, 2001 figures ranged between 319,000 employed in Lubuskie and over 2,300,000 in Mazowieckie.

⁷The Pigou-Dalton transfer principle is a property commonly required of inequality measures, under which any income transfer from a rich individual (region) to a poorer one that does not invert their relative positions must reduce the inequality. For further details about the properties of the different measures considered, see Cowell (1995).

⁸Note that the output share of region i can be expressed as $\frac{e_i y_i}{\mu}$.

⁹See also Bourguignon (1979) and Cowell (1980).

¹⁰ To check the robustness of our conclusions, we also decomposed $T(1)$. This yielded very similar results, which are omitted for the sake of brevity, but are available from the authors upon request.

¹¹According to the territorial classification used by Eurostat, Estonia, Lithuania, Latvia and Slovenia are defined as one NUTS-2 region. It is therefore impossible to compute internal inequality in these cases.

¹²Though density functions were estimated for each year of the period analysed, for the sake of brevity,

we present only those of 1992 and 2001. The rest are available from the authors upon request.

¹³For further details, see Esteban and Ray (1994).

¹⁴In the two-group case, the optimal partition of the distribution is characterised by the fact that the productivity value that separates the two groups is equal to the average output per worker. When our 39 regions are made to form two groups following this criterion, it is possible on average to account for 66 per cent of the total inequality as measured by the Gini index. The amount of internal inequality left unexplained by the grouping is therefore 34 per cent.

¹⁵The three-group representation explains on average 87 per cent of the global inequality measured by the Gini index, versus the 66 per cent explained by the previous partition. The internal dispersion left unexplained by this grouping is, therefore, 13 per cent. These results show that increases in explanatory power diminish as the number of groups considered increases.

¹⁶For a more detailed discussion of the conceptual differences between inequality and polarisation, see Esteban and Ray (1994).

¹⁷For the EU case, see for example Quah (1996c), López-Bazo *et al.* (1999) or Le Gallo (2004).

¹⁸For a formal definition, interested readers may consult Durlauf and Quah (1999).

¹⁹Gaussian kernel functions were used in all cases, while the smoothing parameter was selected following Silverman (1986, p. 86).

²⁰It is worth noting that comparisons between Figures 4 and 8 should be based only on the shape of the distribution, since there is no point in comparing the level of density that appears on the vertical axis.

²¹It is obvious, however, that the findings obtained from the analysis of Figure 8 are determined by the dynamics of the regional productivity distribution over the whole of the period analysed. We therefore decided to repeat the analysis using only data for the subperiods 1992-1996 and 1997-2001. The results are very similar to those discussed above and, though they are omitted for brevity, are available upon request from the authors.

²²A slightly modified version of this methodology has been applied by Ezcurra *et al.* (2005) to explore the origin of regional disparities in output per worker in the EU15.

²³For further details, see also Shorrocks (1983).

²⁴It is worth underlining the fact that, just as occurs in conventional shift-share analysis, the results obtained by applying this methodology are directly related with the number of productive activities

considered in the analysis. However, despite our best efforts, we were unable to obtain data at a higher level of sectoral disaggregation to cover the entire geographical and temporal scope of the present study.

²⁵The results are very similar if we classify the various regions by deciles.

²⁶The analysis of conditioned distributions was originally proposed in Quah (1996c, 1997). Recent examples of its application to the European case can be found in Overman and Puga (2002) or Le Gallo (2004).

²⁷It is worth noting that this reduction in the relative weight of the country effect over time is coherent with the results obtained previously in this paper.

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Appendix

The 39 territorial units NUTS-2 considered in the paper are:

- *Czech Republic (8)*: Praha, Střední Čechy, Jihozápad, Severozápad, Severovýchod, Jihovýchod, Střední Morava, and Moravskoslezsko.
- *Estonia (1)*.
- *Hungary (7)*: Közép-Magyarország, Közép-Dunántúl, Nyugat-Dunántúl, Dél-Dunántúl, Észak-Magyarország, Észak-Alföld, and Dél-Alföld.
- *Latvia (1)*.
- *Lithuania (1)*.
- *Poland (16)*: Dolnośląskie, Kujawsko-Pomorskie, Lubelskie, Lubuskie, Łódzkie, Małopolskie, Mazowieckie, Opolskie, Podkarpackie, Podlaskie, Pomorskie, Śląskie, Świętokrzyskie, Warmińsko-Mazurskie, Wielkopolskie, and Zachodniopomorskie.
- *Slovakia (4)*: Bratislava, Západné Slovensko, Stredné Slovensko, and Východné Slovensko.
- *Slovenia (1)*.

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