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The Determinants of Productivity Distribution across European Regions

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The Determinants of Productivity Distribution across European Regions

(Preliminary version. Please do not quote without permission)

Davide Fiaschi, Andrea Mario Lavezzi and Angela Parenti*

June 25, 2010

Abstract

This paper analyzes the determinants of the distribution dynamics of labour productivity of a large cross section of European regions in the period 1992-2002. Initial productivity accounts for a large decrease in the dispersion of productivity. Instead, country unexplained component (country dummies) has an ambiguous effect, benefiting regions around but below the average, but hurting regions far below; while, employment growth has not any distributional effect. Objective 1 and Cohesion Funds have a reducing-dispersion effect, but their very limited size produces a negligible effect on the overall distribution. This also holds for structural change, as measured by the change in the share of Agriculture sector on total GVA, and Wholesales and Retail; on the opposite Hotel and Other Market Services result enhancing-dispersion sectors. Finally, financial sector has an ambiguous effect, mostly benefiting regions with productivity around but below the average. No variable considered in the analysis appears to affect the polarization of productivity, but initial productivity.

Keywords: European regional policy, structural change, convergence, European regions, output composition, distribution dynamics, polarization.

JEL: C21; E62; R11; O52

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1 Introduction

Convergence of income across European regions is still a controversial issue and, at present, no consensus has emerged (see, e. g., Magrini (2004) for a recent survey). Within this discussion, moreover, many scholars wonder whether the European Union regional policy reached its goal of favouring regional competitiveness, and of reducing income disparities across European regions.¹

This paper analyzes the determinants of the distribution dynamics of labour productivity of a large cross-section of European regions in the period 1992-2002. We propose a novel methodology based on the Quah (1997) to measure the distributional impact of individual growth determinants. This method combines a semiparametric growth regression approach with the approach based on estimation of stochastic kernels, i. e. of operators that map current distributions into future distributions. In particular, the distributional impact of a given variable is evaluated by the comparison of *actual* and *counterfactual* distributions, and the related actual and counterfactual stochastic kernels and ergodic distributions. We generate a counterfactual distribution relative to an individual variable by utilizing the results of a growth regression, imposing the sample average value of that variable to all regions. This methodology also allows for measuring the marginal effect of the variable on the distribution, and for testing the possible presence of distributional effects in the residuals of the growth regression.

We find that the initial productivity accounts for a large decrease in the dispersion of productivity. The difference between the Gini indexes of actual and counterfactual distributions is about 3-4 base-points; but polarization appears only slightly affected by initial productivity. Country unexplained component (country dummies) has an ambiguous effect on dispersion, benefiting regions around but below the average, but hurting regions far below the average. The estimate points out the existence of four clusters of countries with a strong geographical pattern. Employment growth instead does not appear to affect productivity distribution.

Objective 1 and Cohesion Funds have a reducing-dispersion effect, but their very limited size produces a negligible effect on the overall distribution. In particular, the effect of funds is the joint results of i) the positive (linear) impact of Objective 1 and Cohesion Funds on productivity growth; and ii) the allocation of funds in favour of poor regions. In this regard EU policy appears to achieve the goals of promoting the competitiveness of European regions (Articles 130(f)-130(p), Single European Act, 1987) and, at the same time, to reduce: “disparities between the levels of development of various regions, and the backwardness of the less-favoured regions” (Article 130(a), Single European Act, 1987).

¹See Fiaschi et al. (2009) for a summary of this debate and references.

Structural change, as measured by the change in the share of Agriculture sector on total GVA, has a reducing-dispersion effect. Also Wholesales and Retail reduces dispersion given i) its positive impact on growth rate; and ii) the negative relationship between the share of Wholesales and Retail sector and the level of productivity. Hotel has instead an enhancing-dispersion effect as result of i) the nonlinear but negative impact of Hotel sector on growth rate; and ii) the negative relationship between the share of Hotel sector and the level of initial productivity. Also Other Market Services enhances dispersion given i) its positive impact on growth rate; and ii) the positive relationship between the share of Other Market Services sector and the level of initial productivity. Finally, financial sector has an ambiguous effect, mostly benefiting regions with productivity around but below the average. The effect is the joint result of i) the nonlinear but positive impact of financial sector on growth rate; and ii) the fact that regions whose productivity is around but below sample average presents on average the highest shares of financial sector.

The paper is organized as follows: Section 2 describes the methodology for the empirical analysis; Section 3 presents the results of empirical analysis; Section 4 contains some concluding remarks.

2 Methodology

Two main approaches to study convergence of income exist in literature: the “growth regression approach” (GRA) and the “distribution dynamics approach” (DDA). GRA studies whether economies are, on average, converging towards their steady-state level of per capita income, and the average effect of growth determinants, while the DDA aims at understanding how the whole cross-sectional income distribution evolves over time.²

The most representative examples of the GRA are the so-called Barro regressions (see Barro (1991) and Barro and Sala-i Martin (2004)), who often showed evidence of conditional convergence across different economies, that is of a negative relation between the growth rate and initial income levels, after controlling for other growth determinants. de La Fuente (2003) extends the GRA approach, decomposing the σ - and β -convergence measures (Barro and Sala-i Martin (2004)) into sums of partial σ and β -convergence measures, to assess the contribution to convergence of each explanatory variables included in a growth regression (de La Fuente (2003) defines such methodology: “convergence accounting”).

The alternative DDA proposed by Danny Quah in a number of papers (e. g. Quah (1993),

²See Quah (1997) for a more detailed discussion, and Durlauf et al. (2004) for an exhaustive survey of different empirical methodologies in growth empirics.

Quah (1996a), Quah (1996b), Quah (1997)) argues that the distribution dynamics of a cross-section of economies can be summarized by a Markov process. The proposal of such approach stems from criticism to the GRA for not being able to capture phenomena such *mobility*, *stratification* and *polarization* in the world income distribution.³ A further step, aiming at evaluating the effects of individual explanatory variables on the distribution dynamics, is taken in Quah (1997, p. 47), who introduces *conditioned* stochastic kernels. In particular, conditioned stochastic kernels map *unconditioned* income levels to *conditioned* income levels, that is incomes normalized “on the basis of incomes relative to one’s neighbours appropriately weighted”, where weights are calculated with respect to some factor that is suspected to affect the dynamics of income.⁴

Another strand of literature proposes counterfactual analysis as an alternative methodology to detect the impact of individual explanatory variables on distributions (see DiNardo et al. (1996) and Machado and Mata (2005)). In particular, Beaudry et al. (2005) analyze in a cross-country setting the distributional effects of some growth determinants in two periods, 1960-1978 and 1978-1998, by estimating standard linear growth regressions. They build counterfactual distributions for the second period by assuming that the variable of interest (a coefficient of the estimated growth regression or the distribution of a variable, e. g., investment rates) maintains in the second period the same value taken in the first.

Close to our methodology is Cheshire and Magrini (2005), who combine the GRA with the DDA in the analysis of factors driving convergence for a large cross-section of European urban regions in the period 1978-1994. In particular, they estimate a linear growth regression model, compute counterfactual distributions under different assumptions on explanatory variables, and compare the “predicted” stochastic kernel (computed on the basis of fitted values of growth regression) to the “simulated” stochastic kernel (computed on the basis of alternative values for explanatory variables in the growth regression).

In the following we will detail our methodology, and clarify the differences with other methods, for the evaluation of the distributional impact of a given variable, which is composed by six steps: i) the estimation of a growth regression model (see Section 2.1); ii) the test on the distributional effects of growth residuals (see Section 2.3); iii) the calculation of the counterfactual distribution (see Section 2.2.1); iv) the estimation of counterfactual stochastic kernels (see Section 2.2.1); v) the estimation of counterfactual ergodic distributions (see Section 2.2.1); vi)

³In addition to these types of criticism, Bernard and Durlauf (1996) showed that, in a growth regression, a negative sign on the coefficient of initial income does not necessarily imply convergence, as the data-generating process may be characterized by multiple, locally stable, equilibria.

⁴See also Basile (2009) for an application of the conditioning scheme for explaining the productivity polarization across European regions.

the estimation of the marginal growth effect (see Section 2.2.2).

2.1 Modeling the Growth of Productivity

Assume there exist N regions, and define by $y_i(t)$ labour productivity of region i at time t . Labour productivity of region i at time T can be expressed as:

$$y_i(T) = y_i(0)e^{g_i T}, \quad (1)$$

where g_i is the (approximate) annual rate of growth of productivity in region i , between time 0 and T .

Assume that g_i is a function of K explanatory variables, whose values in region i are collected in vector $\mathbf{X}_i = (X_{i,1}, \dots, X_{i,K})$, and a residual component accounting for unobservable factors, v_i , that is:

$$g_i = \varphi(\mathbf{X}_i, v_i). \quad (2)$$

Differently from other approaches to counterfactual analysis, we model the growth rate g_i by a semiparametric model, that is:⁵

$$g_i = m(\mathbf{X}_i) + v_i = \alpha + \sum_{k=1}^K \mu_k(X_{i,k}) + v_i \quad (3)$$

where α is a constant term, \mathbf{X}_i is the $1 \times K$ vector of explanatory variables for region i , $\mu_k(\cdot)$ are one-dimensional nonparametric functions operating on each element of the explanatory variables, and v_i is the error term such that $E(v|\mathbf{X}) = 0$, and $var(v|\mathbf{X}) = \sigma^2(\mathbf{X})$ (i.e., the model is allowed to be heteroskedastic). Here we take an alternative explanation of the different marginal impact of explanatory variables, i.e. their nonlinear impact, with respect to Durlauf et al. (2001) which conditions the impact to the initial level of per capita income.

2.2 Distribution Effect of k -th variable

Denote $\mathbf{X}_{i,\underline{k}}$ the vector of all explanatory variables but $X_{i,k}$, i.e.:

$$\mathbf{X}_{i,\underline{k}} = (X_{i,1}, \dots, X_{i,(k-1)}, X_{i,(k+1)}, \dots, X_{i,K})$$

Eq. (3) can be rewritten as:

$$g_i = \alpha + \mu_k(X_{i,k}) + \sum_{j \neq k} \mu_j(X_{i,j}) + v_i. \quad (4)$$

⁵Notation refers to Härdle et al. (2004).

Substituting Eq. (4) in Eq. (1) leads to the following expression for the productivity of individual region i :

$$\begin{aligned} y_i(T) &= y_i(0)e^{[\alpha + \mu_k(X_{i,k}) + \sum_{j \neq k} \mu_j(X_{i,j}) + v_i]T} = \\ &= \underbrace{y_i(0)e^{[\alpha + \sum_{j \neq k} \mu_j(X_{i,j})]T}}_{y_{i,\underline{k}}(T)} \underbrace{e^{\mu_k(X_{i,k})T}}_{e^{g_{i,k}^M T}} \underbrace{e^{v_i T}}_{e^{g_i^R T}}, \end{aligned} \quad (5)$$

where $y_{i,\underline{k}}(T) = y_i(0)e^{[\alpha + \sum_{j \neq k} \mu_j(X_{i,j})]T}$ is the level of productivity in period T obtained by “factoring out” the effect of $X_{i,k}$, $g_{i,k}^M = \mu_k(X_{i,k})$ is the part of the annual growth rate of y_i explained by $X_{i,k}$, capturing the “marginal” effect of $X_{i,k}$ on g_i , and $g_i^R = v_i$ is the annual “residual growth”, not explained by the variables in \mathbf{X}_i .

The modeling of growth in Eq. (5) is the basis for calculating the distributional effect of the k -th variable.

2.2.1 Counterfactual Stochastic Kernel and Ergodic Distributions

The counterfactual productivity, $y_k^{CF}(T)$, represents the productivity that a region would have had at time T if there had not been differences within the sample in terms of the k -th variable (whose values are collected in vector \mathbf{X}_k). In other words, $y_k^{CF}(T)$ captures the effect of the cross-sectional heterogeneous distribution of the k -th variable. Starting from the counterfactual growth rate of region i referred to the k -th variable, $g_{i,k}^{CF}$, calculated by eliminating the cross-sectional heterogeneity in \mathbf{X}_k , that is:

$$g_{i,k}^{CF} \equiv \alpha + \sum_{j \neq k} \mu_j(X_{i,j}) + \mu_k(\bar{X}_k), \quad (6)$$

where $\bar{X}_k = N^{-1} \sum_{i=1}^N X_{i,k}$ is the average value of \mathbf{X}_k across the sample units, and $\hat{\mu}_k(\cdot)$ is the smoothed function relative to \mathbf{X}_k obtained by a semiparametric estimate of Eq. (3), the counterfactual productivity of region i in period T , related to \mathbf{X}_k , is therefore defined as:

$$y_{i,k}^{CF}(T) \equiv y_i(0)e^{g_{i,k}^{CF} T} = y_i(0)e^{[\alpha + \sum_{j \neq k} \mu_j(X_{i,j}) + \mu_k(\bar{X}_k)]T}. \quad (7)$$

The stochastic kernels of real and counterfactual observations are respectively defined as $\phi(\mathbf{y}(T)|\mathbf{y}(0))$ and $\phi^{CF}(\mathbf{y}_k^{CF}(T)|\mathbf{y}(0))$.⁶ The (*actual*) stochastic kernel $\phi(\cdot)$ maps the distribution of (relative) productivity in period 0, to the distribution of (relative) productivity in period

⁶In general, stochastic kernels indicate for each level of productivity in period t its probability distribution in period $t + \tau$, $\tau > 0$. For each stochastic kernel it is possible to estimate its corresponding ergodic distribution following the procedure in Johnson (2005). The ergodic distribution shows if the estimated distribution dynamics over the sample period has completely exhausted its effect on the distribution in the last year of the sample or, otherwise, significant distributional changes are expected in the future. Specifically, the ergodic distribution solves

T . The *counterfactual* stochastic kernel $\phi^{CF}(\cdot)$, instead, maps the distribution of (relative) productivity in period 0, to the distribution of counterfactual relative productivities in period T .

In order to highlight the sources of difference between actual and counterfactual kernels consider the vector of the (log) values of actual productivity at period T , $y_i(T)$, in terms of counterfactual productivity, $y_{i,k}^{CF}(T)$:

$$\log(y_i(T)) = \log(y_{i,k}^{CF}(T)) + [\mu_k(X_{i,k}) - \mu_k(\bar{X}_k)] T + v_i T. \quad (8)$$

The expected value of (the log of) actual productivity at period T conditional to actual productivity at period 0, $E[\log(y_i(T))|y_i(0)]$ actual productivity at period 0", corresponds to the expected value of stochastic kernel with *lag* T ; in particular:

$$E[\log(y_i(T))|y_i(0)] = E[\log(y_{i,k}^{CF}(T))|y_i(0)] + E[\mu_k(X_{i,k}) - \mu_k(\bar{X}_k)|y_i(0)]T + E[v_i|y_i(0)]T,$$

that is:

$$E[\log(y_i(T))|y_i(0)] = E[\log(y_{i,k}^{CF}(T))|y_i(0)] + E[\mu_k(X_{i,k}) - \mu_k(\bar{X}_k)|y_i(0)]T,$$

given that $E[v_i|y_i(0)] = 0$. We therefore observe that the expected values of actual and counterfactual kernels are equal, i.e.:

$$E[\log(y_i(T))|y_i(0)] = E[\log(y_{i,k}^{CF}(T))|y_i(0)] \quad (9)$$

when

$$E[\mu_k(X_{i,k})] = \mu_k(\bar{X}_k). \quad (10)$$

Condition (10) holds for each $y_i(0)$ if:

1. $E[\mu_k(X_{i,k})|y_i(0)] = E[\mu_k(X_{i,k})]$, i.e. $\mu_k(X_{i,k})$ and $y_i(0)$ are independent (the impact of k -th variable is independent of the level of initial productivity); and
2. $E[\mu_k(X_{i,k})] = \mu_k(E[X_{i,k}])$, i.e. $\mu_k(\cdot) = \beta_k \bar{X}_k$ (the expected *marginal* impact of k -th variable is constant).

$f_\infty(z) = \int_0^\infty g_\tau(z|x) f_\infty(x) dx$ where z and x are two levels of the variable, $g_\tau(z|x)$ is the density of z , given x , τ periods ahead. To estimate $g_\tau(z|x) = g(z,x)/f(x)$, the stochastic kernel, we estimated the joint density of z and x , $g(z,x)$, and the marginal density of x , $f(x)$. In the estimation of $g(z,x)$ we followed Johnson (2005), who used the *adaptive kernel estimator* discussed by (Silverman, 1986, p. 100), in which the window of the kernel (Gaussian in our case) increases when the density of observations decreases. Here we adjust the estimate of ergodic distribution for the use of normalized variables (with respect to the average). See Fiaschi and Romanelli (2009).

Therefore, if conditions in point 1. and 2. hold, we have:

$$E[\mu_k(X_{i,k})|y_i(0)] = E[\mu_k(X_{i,k})] = \mu_k(E[X_{i,k}]) = \mu_k(\bar{X}_k). \quad (11)$$

The exact measure of the distributional impact of the k -th variable needs the use of semiparametric growth model. Indeed, assuming $\mu_k(X_{i,k})$ independent of $y_i(0)$ (point 1. listed above), it still could be possible that the marginal impact of the k -th variable depends on its level, i.e. $E[\mu_k(X_{i,k})] \neq \mu_k(E[X_{i,k}])$; point 2. listed above rules out this possibility.

2.2.2 The Marginal Growth Effect

Define the productivity of region i in period T , $y_i(T)$, as:

$$y_i(T) \equiv y_i(0)e^{[\alpha + \sum_{j \neq k} \mu_j(X_{i,j}) + \mu_k(X_{i,k})]T}; \quad (12)$$

and the “factoring out” productivity of region i in period T , referred to k -th variable, as (see Eq. (5)):

$$y_{i,\underline{k}}(T) \equiv y_i(0)e^{[\alpha + \sum_{j \neq k} \mu_j(X_{i,j})]T}. \quad (13)$$

The marginal effect of the k -th variable is therefore defined as:

$$g_{i,k}^M \equiv \log \left(\frac{y_i(T)}{y_{i,\underline{k}}(T)} \right) = \mu_k(X_{i,k}). \quad (14)$$

It may be observed that the estimation of Eq. (3) must include all the explanatory variables in order to avoid omitted-variable problems and therefore obtain unbiased estimates. This feature is one of the main differences with respect to methodology proposed in Quah (1997).

The marginal effect of the k -th variable on distribution is identified by estimating the marginal growth \mathbf{g}_k^M conditioned to the initial level of productivity, i. e. by estimating $\phi^M(\mathbf{g}_k^M | \mathbf{y}(0))$. If the estimate of marginal effect results not (statistically) different from its unconditional mean, i.e. $\phi^M(\mathbf{g}_k^M | \mathbf{y}(0)) = E[\mathbf{g}_k^M] \forall \mathbf{y}(0)$, then the k -th variable has no distributional effects. On the contrary, if $\phi^M(\mathbf{g}_k^M | \mathbf{y}(0))$ is a positive (negative) function of $\mathbf{y}(0)$ (or of some range of $\mathbf{y}(0)$), then the k -th variable is a source of divergence (convergence).

Since the estimation of the marginal effect in semiparametric models is performed through the backfitting technique, it requires as identification assumption $E_{\mathbf{X}_k}[\mu_k(\mathbf{X}_k)] = 0$ (see Härdle et al. (2004, pp. 212-222)); therefore, the unconditional mean of marginal growth will always be equal to zero for the semiparametric terms of growth model in the estimate.

2.3 Test of Distributional Effects of Residual Growth

To our purpose it is important to have a measure of goodness of fit of the growth regression conditioned to the initial level of productivity, i. e. of the presence of possible misspecifications of the model for some ranges of initial productivity. Eq. (5) suggests to consider $\hat{\mathbf{g}}^R$, defined as $\hat{\mathbf{g}}^R \equiv \log \left(\frac{\mathbf{y}(T)}{\mathbf{y}(0)} \right)$, to test that:

$$E[\hat{\mathbf{g}}^R | \mathbf{y}(0)] = E[\hat{\mathbf{g}}^R] \forall \mathbf{y}(0). \quad (15)$$

Moreover, under the hypothesis that estimate of Eq. (3) is unbiased, we have the additional condition:

$$E[\hat{\mathbf{g}}^R] = 0. \quad (16)$$

Finally, if $\mathbf{y}(0)$ is included in the set of regressors, Conditions (15) and (16) ensure that there is no omitted variable inconsistency related to $\mathbf{y}(0)$ (see Wooldridge (2002, pp. 61-63)). Conditions (15) and (16) will be used as a test of misspecification of the growth model.

3 Empirical Results

In this section we study the distribution dynamics of 173 European NUTS 2 regions for the period 1992-2002.⁷ Following Fiaschi et al. (2009), in the estimation of Model (3) the annual average growth rate of per worker GVA of a region is explained by:⁸ i) the share of Structural funds allocated to Objective 1 and of Cohesion Fund over the period 1989-1999, on regional GVA with a three-year lag (which will be indicated as OB1.CF);⁹ ii) the initial productivity level, normalized with respect to sample average (PROD.REL.1992); iii) the average annual investment rate (INV.RATE); iv) the average annual employment growth rate (EMP.GR); v) the average density of economic activity (ECO.DEN), measured by GVA per km², to control for the possible presence of agglomeration effects; vi) a variable to control for the presence of spatial effects (SPATIAL.INDEX);¹⁰ vii) some variables controlling for initial regional

⁷Appendix A contains the regions' list.

⁸Appendix C contains the descriptive statistics of the variables.

⁹Specifically, we consider the yearly average level of OB1.CF in the whole period divided by the level of GVA at the beginning of the period. By using a three-year lag, we assume that funds allocated in 1989 had an effect on growth in 1992, etc.

¹⁰This variable is based on the index proposed by Ord and Getis (1973), and is calculated on the basis of the geographical distance among regions. The index takes on a positive value when high productivity regions are clustered together, while it takes negative values when low productivity regions are clustered. See Fiaschi et al. (2009) for details.

output composition, such as the initial share of GVA in Manufacturing (MAN.1992), Mining (MIN.1992), Construction (COSTR.1992), Non Market Services (NON.MKT.SER.1992), Finance (FIN.1992), Hotel and Restaurants (HOT.1992), Transport (TRANS.1992), Wholesales and Retails (WHOLE.1992), Other Market Services (OTHER.SERV.1992); viii) the change between 1992 and 2002 of the agricultural share on GVA (Delta.SHARE.AGRI)¹¹; finally, ix) country dummies to capture the effects of variables whose dimension is typically national, like political institutions, labour markets, educational systems, etc., for which no data at regional are available.¹²

The average growth rate of employment EMP.GR is augmented by the rate of depreciation of capital according to the Solow model (see Durlauf et al. (2004)),¹³ but not by the long-run trend of productivity (as it would be implied by the Solow model), as the latter is already taken into account by considering productivity normalized with respect to sample average. The composition of output should contribute to a better definition of the initial conditions of a region, while the change in the share of agricultural sector should capture the salient features of structural change taking place in the period.

3.1 Estimates of Growth Model

Results of the estimation of Model (3) are reported in Table (1). See Appendix D for details on the method of estimation and interpretation of results.

¹¹Delta.SHARE.AGRI is calculated as the share of agriculture in 1992 minus the share in agriculture in 2000.

¹²We do not include the country dummy for Germany for avoiding perfect collinearity.

¹³Given that we have no data on capital at regional level, we use the value of 0.03 proposed by Mankiw et al. (1992).

	First Specification	Best Specification
Parametric coefficients:	Estimate	Estimate
CONST	0.0131***	0.0048
BE	0.0058***	0.0059***
DK	0.0128***	0.0119***
ES	-0.0016	0.0025
FR	-0.0012	-0.0013
GR	-0.0032	-0.0043
LU	0.0141*	0.0228***
IE	0.0177	0.0015
IT	-0.0049*	-0.0034
NL	0.0037	0.0040
PT	-0.0115*	-0.0101**
UK	0.0072	0.0030
Non parametric coefficients:	EDF	EDF
$\hat{\mu}_1(\log.PROD.REL.1992)$	1.0230***	(-0.0150)***
$\hat{\mu}_2(\log.INV.RATE)$	1.0000*	
$\hat{\mu}_3(\log.EMP.GR)$	6.5640***	8.2530***
$\hat{\mu}_4(\text{SPAT.INDEX})$	1.0000	
$\hat{\mu}_5(\text{OB1.CF})$	2.8680**	(0.1441)***
$\hat{\mu}_6(\log.ECO.DEN)$	1.0000	
$\hat{\mu}_7(\text{Delta.SHARE.AGRI})$	6.9530**	8.3900***
$\hat{\mu}_8(\text{MANU.1992})$	4.4190	
$\hat{\mu}_9(\text{MIN.1992})$	7.4630**	1.8280
$\hat{\mu}_{10}(\text{CON.1992})$	1.0000	
$\hat{\mu}_{11}(\text{NON.MKT.SER.1992})$	2.9280	(-0.0448)***
$\hat{\mu}_{12}(\text{FIN.1992})$	2.1620**	2.7660
$\hat{\mu}_{13}(\text{HOT.1992})$	1.3400**	5.6740***
$\hat{\mu}_{14}(\text{TRANS.1992})$	4.5960***	6.4350***
$\hat{\mu}_{15}(\text{WHOLE.1992})$	1.7840	(0.0604)***
$\hat{\mu}_{16}(\text{OTHER.SERV.1992})$	1.0000***	(0.0622)***
R-sq.(adj)	0.813	0.811
Deviance explained	96.8%	96.5%
GCV score (*10 ⁵)	1.98	1.81
Scale est.(*10 ⁵)	1.31	1.32
Obs.	173	173
Moran Test (B=1000)		I=-0.0302 (p-value=0.11)

Table 1: Estimates of semiparametric Model (3). Significance codes: 0.01*** 0.05** 0.1*. Terms in parenthesis are the coefficients of the variables which enter linearly.

In the best specification, four country dummies result statistically significant at 5% signifi-

cance level, suggesting that some country specific effect is present. There is evidence of conditional convergence, being the coefficient of (the log of) initial productivity ($\log.PROD.REL.1992$) negative and statistically significant. European Structural and Cohesion Funds appear to exert a positive and statistically significant impact with a remarkable magnitude (10% of funds in terms of GVA implies an additional annual growth rate of 1.44%). The impact of employment growth is nonlinear but overall negative, as highlighted by Figure 1. Structural change ($\Delta.SHAARE.AGRI$) shows a nonlinear impact (see Figure 1): negative for values around 0, positive for values above 0.03, and non statistically different from zero in the other ranges.

Initial output composition appears to significantly affect productivity growth. Specifically: a higher initial share of Wholesale and Retails ($WHOLE.1992$), Other Market Services ($OTHER.SERV.1992$), Finance ($FIN.1992$) on GVA determined a higher growth rate, while a higher share of Non Market Services ($NON.MKT.SER.1992$) and Mining ($MIN.1992$) determined a lower growth rate; finally, the initial shares of Hotel ($HOT.1992$) and Transport ($TRANS.1992$) display a U-shaped relationship with the growth rate of productivity, with a negative impact around the middle of range and zero or positive at the bounds of the range (see Figure 1).

Moran's I test cannot reject the null hypothesis of no spatial dependence at 11% confidence level (see Appendix E for the implementation of the test in semiparametric models).

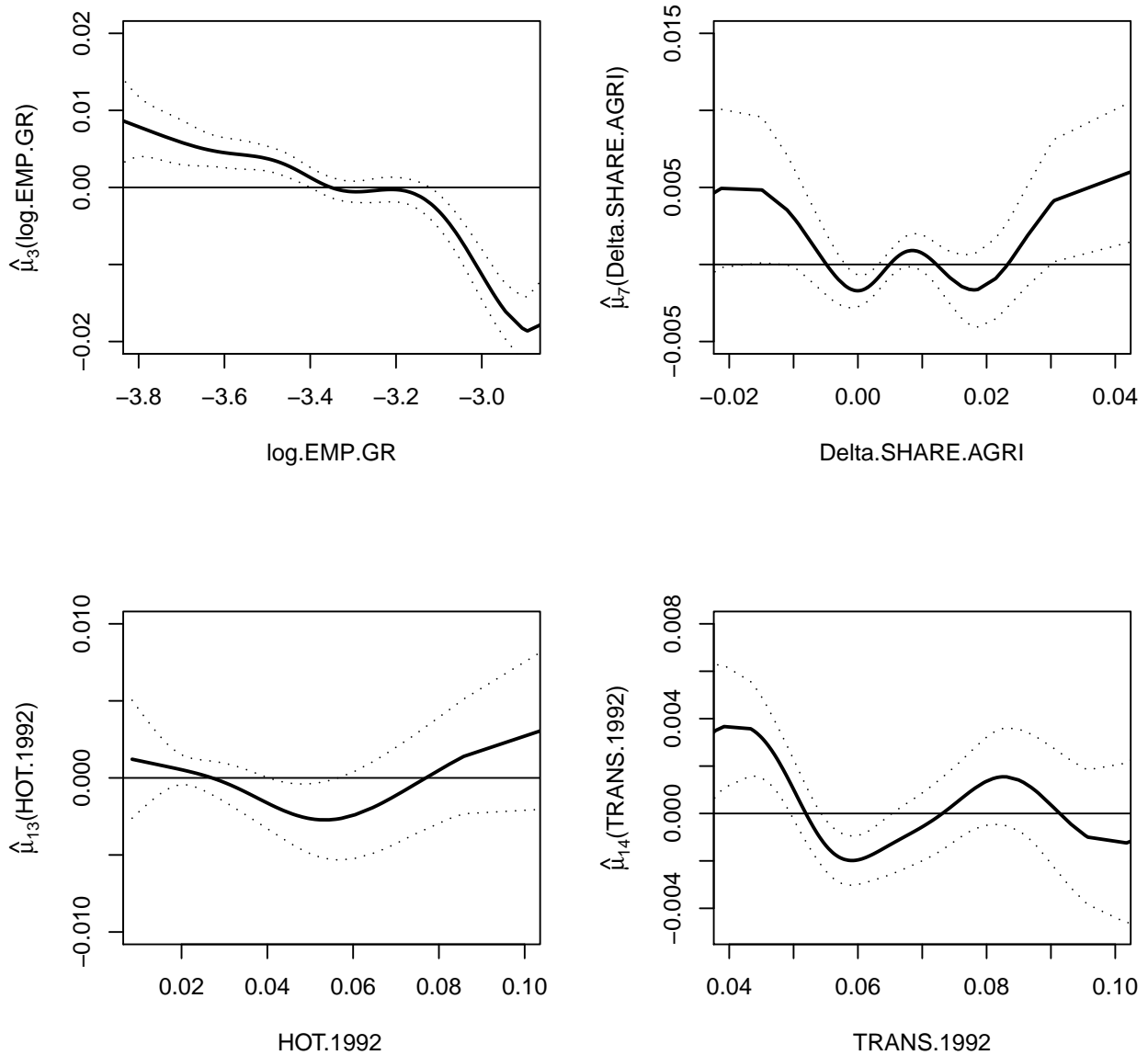


Figure 1: The estimated additive component functions of Model (3) and their confidence bands.

3.2 Distribution Dynamics

All stochastic kernels are estimated considering a time lag of 10 years, i. e. the whole period. In each figure displaying the estimate of the stochastic kernel we report: a solid line representing the estimated median value of productivity at $t + \tau$ conditioned on the value at time t ; the corresponding confidence band at 95% significance level (indicated by dotted lines), obtained

using a bootstrap procedure,¹⁴ and the 45° line.

First of all, we present the actual stochastic kernel of productivity in Figure 2, and the actual distributions (AD) of productivity in 1992 and 2002, along with the actual ergodic distribution (AED) in Figure 3.

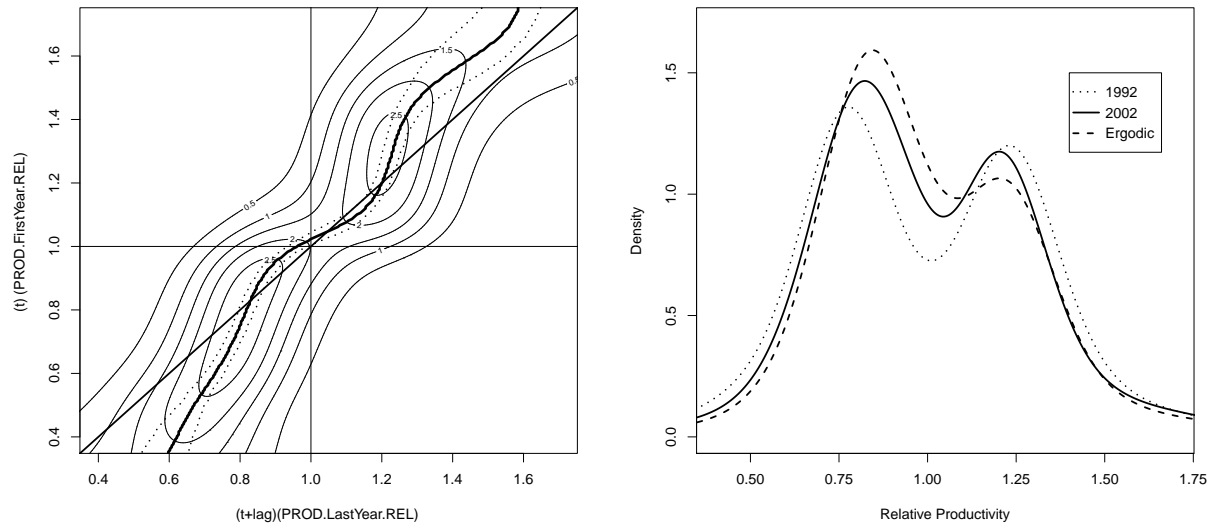


Figure 2: Actual stochastic kernel of productivity. Figure 3: 1992 (dotted line), 2002 (solid line) and Thick line: median of the stochastic kernel; dotted lines: 5% confidence bands. ergodic (dashed line) distributions of productivity

Figure 2 shows that most of the mass is concentrated around the 45° line and, in particular, the median value crosses the 45° line from below in two points, pointing out the presence of two equilibria in the distribution dynamics of relative productivity. This is reflected in the 1992 distribution and even more in the 2002 distribution, where two clusters of regions emerge around the values of 0.8 and 1.2.¹⁵ Accordingly, this tendency is reflected in the ergodic distribution (see Figure 3), which shows the long-run effects of the distribution dynamics implied by the actual stochastic kernel. The presence of two peaks in productivity is consistent with Fiaschi and Lavezzi (2007), which contains further discussion on polarization across European regions.¹⁶

¹⁴The procedure is illustrated in Appendix F.

¹⁵Tests of multimodality show that the null hypothesis of unimodality for both 1992 and 2002 distributions can be rejected at 1% of significance level. Tests of multimodality follow the bootstrap procedure described in Silverman (1986), p. 146, and are performed using 1000 bootstraps.

¹⁶A twin-peaked distribution in the world income distribution is also the result that characterizes most of the

Figure 4 reports the estimated density of the annual residual growth \hat{g}^R conditioned to the initial level of productivity. We also report the conditional mean with the corresponding confidence bands, and a vertical line representing the unconditional mean, which is around zero as expected. Fig. 4 shows that for any initial level of productivity most of the mass of conditional distribution of residual growth is concentrated around the unconditional mean, and that the conditional mean is never statistically different from the unconditional mean. We conclude that the residual growth deriving from the estimation of Model (3) (see Section 2.3), should not present any distributional effect, i.e. the model appears correctly specified, at least according to the initial level of productivity (see Conditions (15) and (16)).

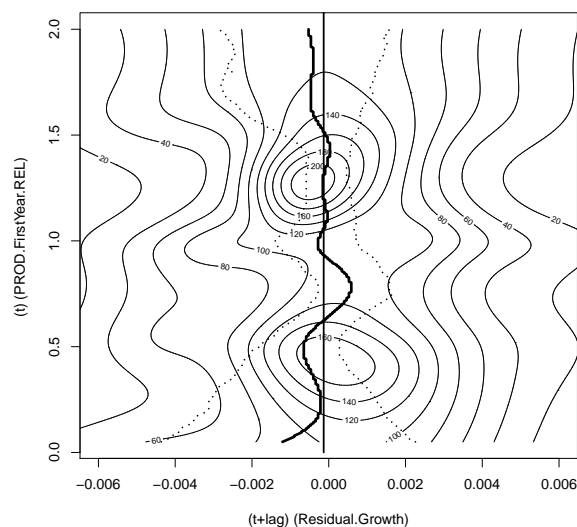


Figure 4: Conditional distribution of residual growth, the conditional mean (thick line), its confidence bands (dotted lines) and the unconditional mean (thin vertical line).

3.3 Conditional Distribution Dynamics

Given the estimation of the growth model in Eq. (3), reported in Table 1, and once controlled for the potential presence of distributional effect in residual growth, the analysis proceeds by calculating and discussing the distributional impact of each variable present in the best specification in Table 1.

studies adopting the distribution dynamics approach. See Durlauf et al. (2004).

3.3.1 Country Dummies

Figure 5 reports: the estimate of marginal growth effect (MGE) of country dummies conditioned on the initial level of productivity $\hat{\phi}_M(\hat{\mathbf{g}}_k^M | \mathbf{y}(0))$, where $\hat{\mathbf{g}}_k^M$ is estimated by Eq. (14); the estimated mean of MGE conditioned to initial level of (relative) productivity (thick solid line), i. e. $E[\hat{\mathbf{g}}_k^M | \mathbf{y}(0)]$, and its confidence bands (dotted lines);¹⁷ the unconditional mean (thin vertical solid line), i. e. $\bar{\mathbf{g}}_k^M$.

For countries with an initial level of productivity below the average, the conditional mean of marginal growth ascribable to country dummies is statistically different from its unconditional mean. In particular, the initially poorer regions (mostly from Greece and Portugal, see Figure 6) have a conditional mean remarkably below the unconditional mean value. Regions with initial productivity below, but closer, to the average (especially regions of Ireland, Spain and UK, see Figure 6) have a conditional mean generally far above its unconditional mean value.¹⁸ Regions with above-average initial productivity display a conditional mean of marginal growth which is generally not statistically different from the unconditional mean (see Figure 5). However, within a large confidence band, regions of France and Germany present conditional slightly below the unconditional mean, while regions of Belgium, Netherlands, Luxembourg and Denmark have conditional mean far above the unconditional mean (see Figure 6).

It may be observed that the clusters of countries emerged in Figure 6 have a strong geographical pattern. In particular, they correspond to the common wisdom of the existence within the European Union of four clusters of countries with very similar institutional characteristics (characteristics that, in our analysis, should be reflected in the unexplained “country” effects).

Starting from the cluster of regions with the lowest country-effect: a first cluster comprises Mediterranean countries, i. e. Greece, Italy and Portugal; the second includes two countries at the core of EU, i. e. France and Germany; a third cluster is composed by Anglo-Saxon countries, i. e. Ireland and UK, and Spain, which represents an exception with respect to the other Mediterranean countries; a fourth cluster, finally, is composed by Northern European countries, i. e. Belgium, Denmark, Luxembourg and Netherlands.

¹⁷Confidence bands are calculated by bootstrap procedure with 300 bootstraps.

¹⁸Figure 6 shows that regions from Italy, albeit having initial conditions similar to those of Ireland, Spain and UK, had a lower marginal growth related to country-wide factors.

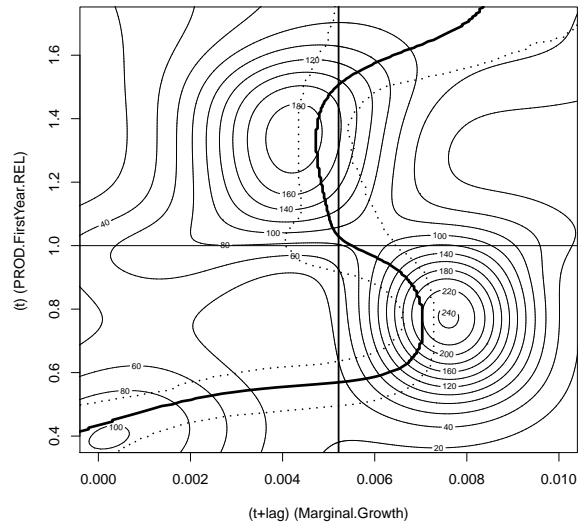


Figure 5: MGE of country dummies conditioned to initial level of (relative) productivity, the estimated mean of MGE conditioned to initial level of productivity (thick solid line), its confidence bands (dotted lines), and the unconditional mean (thin solid vertical line). Counterfactual variable: Country Dummies.

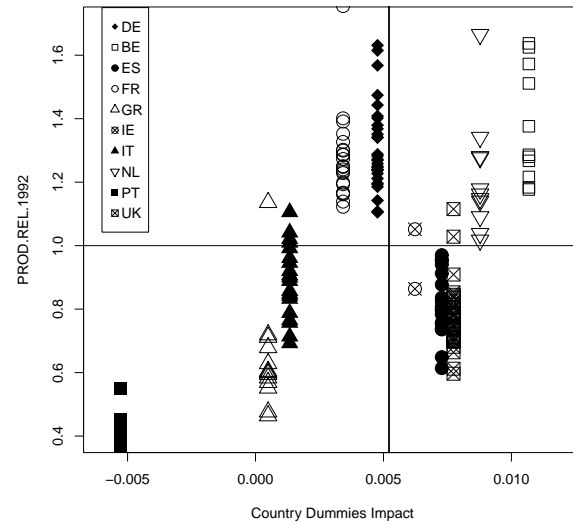


Figure 6: The impact of countries dummies on annual growth rate of regions conditioned to the initial level of productivity and its unconditional mean (solid vertical line). DK and LU are not shown for a better visualization since their values lie at the far-right.

To highlight the country-effects on the distribution, we first of all compare in Figure 7 the ADs in 1992 and 2002, and the CD in 2002.

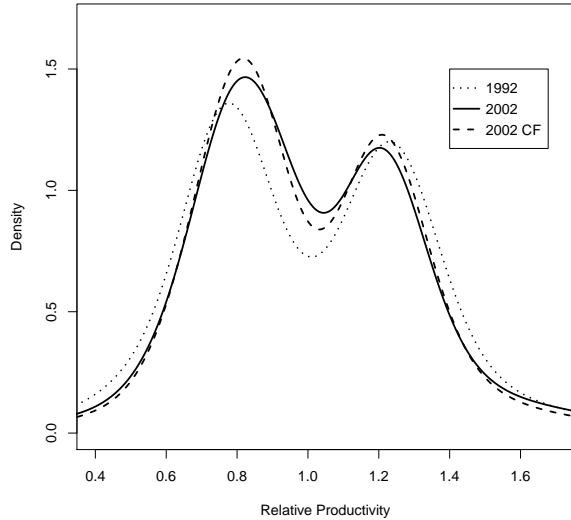


Figure 7: AD in 1992 (dotted line), AD in 2002 (solid line), and CD in 2002 (dashed line). Counterfactual variable: Country Dummies.

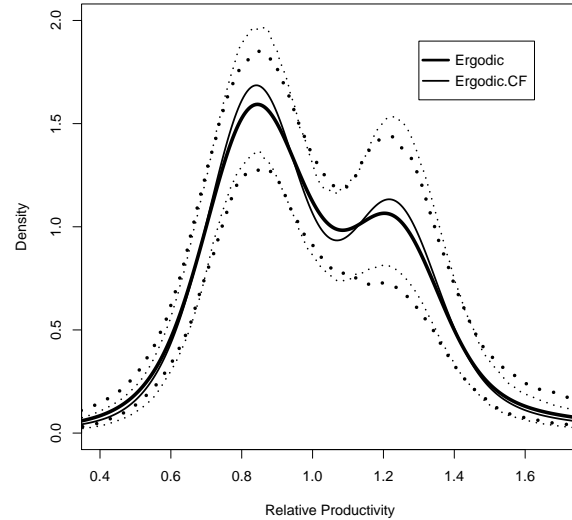


Figure 8: AED (thick line) and CED (thin line) with their confidence bands at 95% level (dotted lines). Counterfactual variable: Country Dummies.

We notice that, in 2002, the CD overlaps with the AD in the tails. However, in the central range of the distribution, we find that the CD displays *more polarization* than the AD, as there is more mass in the peaks and less mass near the mean of the distribution. Hence, country factors seem to favour convergence only in an intermediate range of the productivity distribution. From Figure 6, in fact, we notice that: regions in countries starting at the bottom of the distribution (PT and GR) had the lowest country-effect on growth, regions from some countries starting at the top of the distribution (NL and BE) had the highest effect. For regions in countries closer to the average, we notice that regions from countries starting from above-average productivity, i. e. from FR and DE, had a relatively higher growth effect than regions from countries starting from below-average levels, such as IE, ES and UK. An exception is Italy, with most regions starting from below-average productivity levels, which displays a low country-effect on growth.

This effect is also visible in the long-run, as shown by the actual ergodic distribution (AED) and the counterfactual ergodic distribution (CED) in Figure 8. The differences among the two distributions, however, are not statistically significant, as they are both included in the 95% confidence bands which largely overlap. Hence, we conclude that there is some evidence of a contribution of country-wide factors on convergence in the middle of the productivity distribution only, but this contribution is not statistically significant.¹⁹

¹⁹To find a confirmation of this result is a topic for further research.

	1992	2002	2002.CF	Ergodic	Ergodic.CF
Gini	0.18	0.16	0.16	0.16	0.15
s.e.	(0.008)	(0.008)	(0.007)	(0.035)	(0.031)

Table 2: Gini Indexes and their standard errors of AD, CD, AED and CED. Counterfactual variable: Country Dummies.

3.3.2 Initial Productivity

The pattern of conditional mean reported in Figure 9 points out a clear dynamics of conditional convergence: the conditional mean of MGE is above the unconditional mean for every regions with an initial productivity below the average, while the opposite holds for regions with above-average initial productivity.

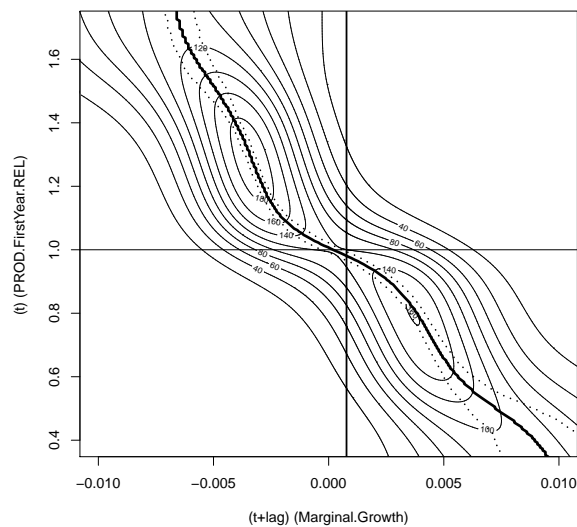


Figure 9: MGE of country dummies conditioned to initial level of (relative) productivity, the estimated mean of MGE conditioned to initial level of productivity (thick solid line), its confidence bands (dotted lines), and the unconditional mean (thin solid vertical line). Counterfactual variable: Initial Productivity.

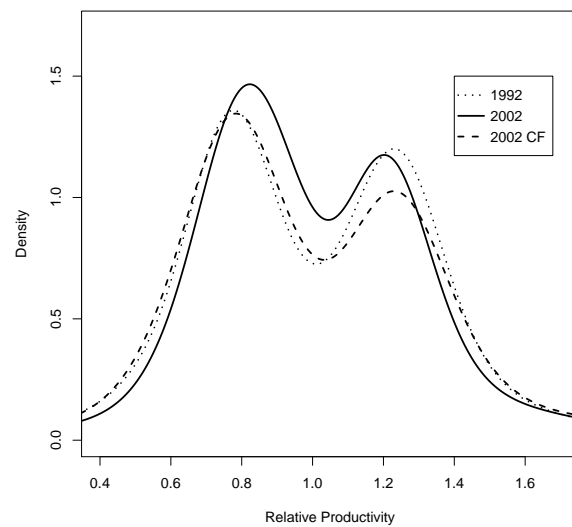


Figure 10: AD in 1992 (dotted line), AD in 2002 (solid line), and CD in 2002 (dashed line). Counterfactual variable: Initial Productivity.

The overall distributional impact is quite strong, as highlighted by the comparison between AD and CD in 2002 (see Figure 10) and the AED and CED (see Figure 11). If each region

had had the same level of productivity in 1992 the distribution would have been more disperse; this is already evident in the CD in 2002, but much more evident in the CED. Gini indexes reported in Table 3 quantify the fall of inequality from 1992 to 2002 in about 3-4 base points (the difference between indexes related to AD and CD are indeed statistically significant).

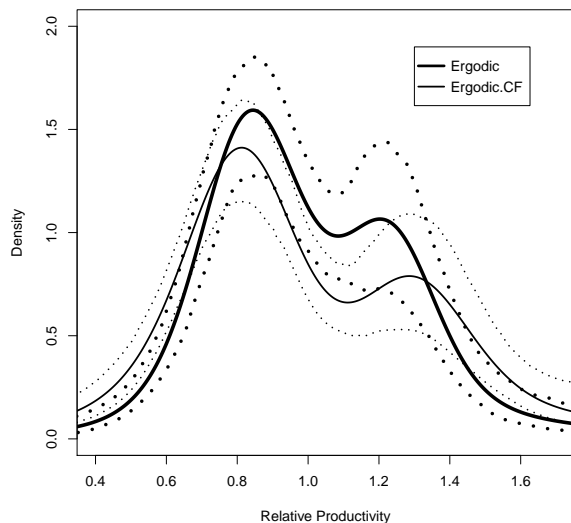


Figure 11: AED (thick line) and CED (thin line) with their confidence bands at 95% level (dotted lines). Counterfactual variable: Initial Productivity.

	1992	2002	2002.CF	Ergodic	Ergodic.CF
Gini	0.18	0.16	0.19	0.16	0.20
s.e.	(0.008)	(0.008)	(0.009)	(0.035)	(0.047)

Table 3: Gini Indexes and their standard errors of AD, CD, AED and CED. Counterfactual variable: Initial Productivity.

Overall, polarization appears only slightly affected by the initial level of productivity. That is, the inverse relation between initial productivity and the growth rate holds on average, as shown in particular by the negative and significant coefficient of PROD.REL.1992 in Table 1. However, as Figure 9 clearly shows, this effect is not constant across different initial productivity ranges. For the two ranges located around the values of 1.2 and 0.8, we observe two peaks in the distribution of MGE in which the slope of the mean MGE is higher than in other productivity ranges. This means that, for regions in those ranges, the marginal growth effect of initial conditions has been similar and, therefore, the distances among them have not decreased. What decreased was the distance of regions in the tails of the distribution from the average, and the distance between the peaks.²⁰ Hence, the overall growth dynamics across regions of Europe appears more consistent with a multiple equilibria model than with a Solovian model.

²⁰This result is in line with the criticism of Bernard and Durlauf (1996) on the misleading implications of a negative coefficient on initial productivity in growth regressions.

3.3.3 Employment Growth

In a cross-country analysis, Beaudry et al. (2005) find that changes in the patterns of accumulation of factors of production, labor and capital, play a very important role in the formation of two peaks in the distribution of productivity. In this section we examine the distributional effect of employment growth.²¹ The conditional mean of MGE is not statistically different from the unconditional mean for the whole range of initial productivity, with the exception of some high-initial productivity regions presenting a conditional mean slightly higher than unconditional mean (see Figure 12). This is reflected in the CF distribution in 2002 (see Figure 13): if all regions had had the same level of employment growth, there would have been more mass in the high-productivity peak near the average. Hence, in the short run, employment growth acts as a force favoring divergence in particular by pushing some high-productivity regions far from the mean. However, the tendency towards twin-peakedness does not seem to be affected.

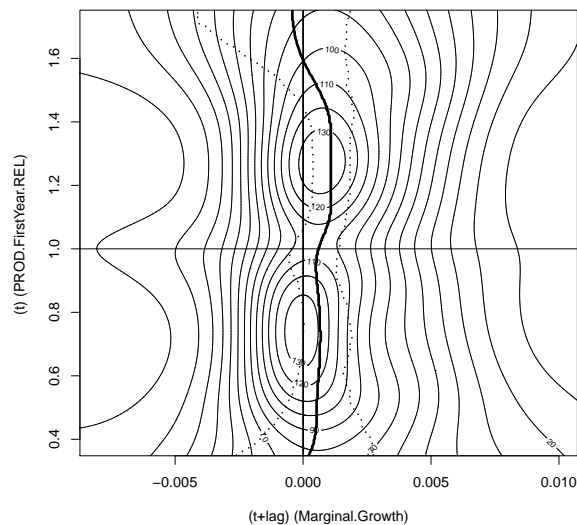


Figure 12: MGE of employment growth conditioned to the initial level of (relative) productivity, the estimated mean of MGE conditioned to initial level of productivity (thick solid line), its confidence bands (dotted lines), and the unconditional mean (thin solid vertical line). Counterfactual variable: Employment Growth.

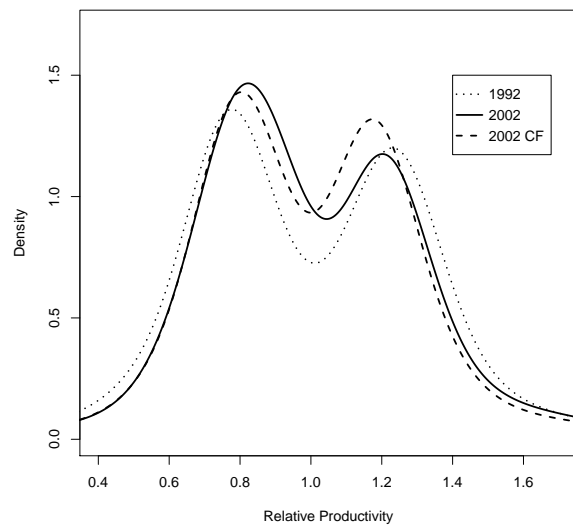


Figure 13: AD in 1992 (dotted line), AD in 2002 (solid line), and CD in 2002 (dashed line). Counterfactual variable: Employment Growth.

This tendency also appears in the CED, shown in Figure 14. The difference in the high-

²¹In Table 1 we showed that investment rates do not enter the preferred specification.

productivity peak is almost significant at 5% confidence level.

Gini indexes of Table 4 confirm the lack of very significant distributional impact of employment growth.

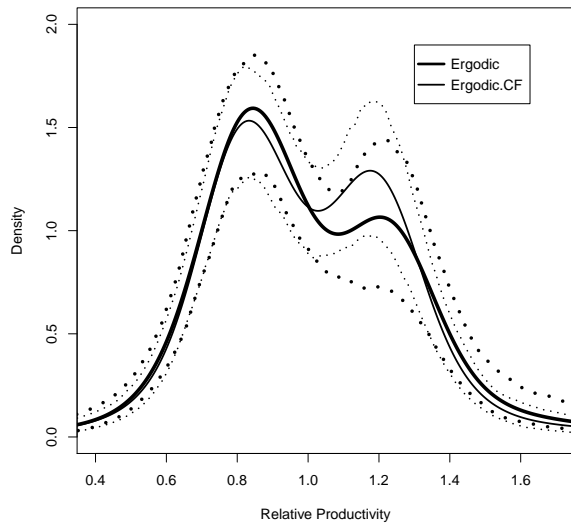


Figure 14: AED (thick line) and CED (thin line) with their confidence bands at 95% level (dotted lines). Counterfactual variable: Employment Growth.

	1992	2002	2002.CF	Ergodic	Ergodic.CF
Gini	0.18	0.16	0.16	0.16	0.15
s.e.	(0.008)	(0.008)	(0.008)	(0.035)	(0.024)

Table 4: Gini Indexes and their standard errors of AD, CD, AED and CED. Counterfactual variable: Employment Growth.

3.3.4 Objective 1 and Cohesion Funds

The limited size of EU funds on GVA (on average 0.6% of GVA) makes difficult to detect possible distributional impact of Objective 1 and Cohesion Funds looking at the overall distribution; indeed, the AD and CD in 2002 and the AED and CED do not display any significant difference (for the sake of brevity we do not report them). However, the estimate of MGE reported in Figure 15 shows that Objective 1 and Cohesion Funds have distributional impact favouring the convergence across European regions. Indeed, the conditional mean is lower than the unconditional mean for level of initial productivity above 1, and higher for levels below 0.7.

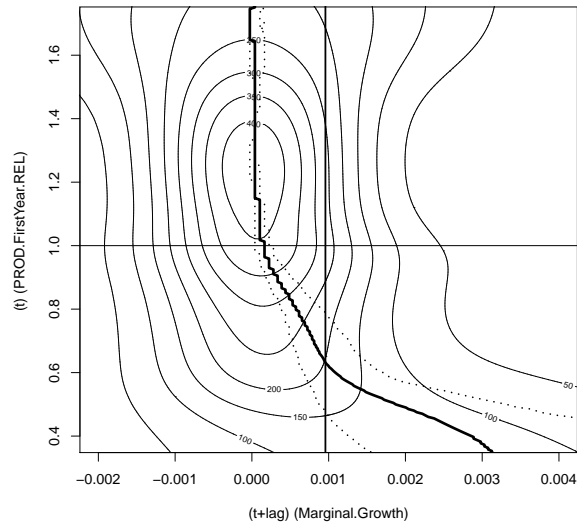


Figure 15: MGE of country dummies conditioned to initial level of (relative) productivity, the estimated mean of MGE conditioned to initial level of productivity (thick solid line), its confidence bands (dotted lines), and the unconditional mean (thin solid vertical line). Counterfactual variable: OB1.CF.

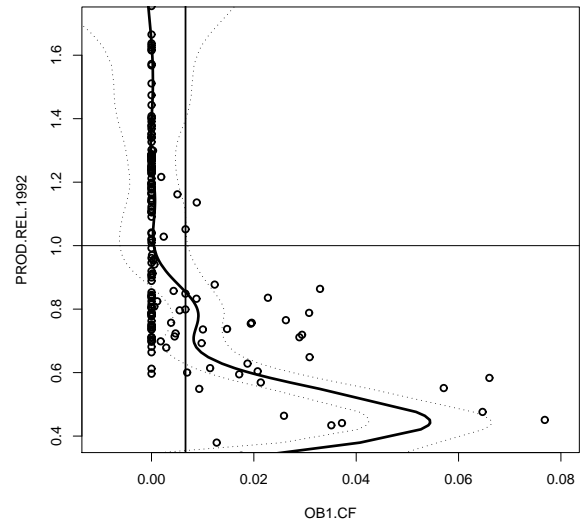


Figure 16: Relationship between OB1.CF and the initial level of productivity (thick solid line), its confidence bands (dotted lines), observations (points) and the unconditional mean (thin solid vertical line).

This outcome is the joint results of i) the positive (linear) impact of Objective 1 and Cohesion Funds on productivity growth (see Table 1); and ii) the allocation of funds to poor regions (in accordance with EU policy, see Figure 16). In this regard EU policy appears to achieve the goals of promoting the competitiveness of European regions (Articles 130(f)-130(p), Single European Act, 1987) and, at the same time, to reduce: “disparities between the levels of development of various regions, and the backwardness of the less-favoured regions” (Article 130(a), Single European Act, 1987).

3.3.5 Structural Change

As for EU funds the distributional impact of structural change (measured by the change in the share of agriculture from 1992 to 2002) on overall distribution is negligible (again, for the sake of brevity, we do not report the AD and CD in 2002 and the AED and CED). But Figure 17 shows that, as expected, structural change is a source of convergence. Figure 18 highlights that structural change was at work for low-productive regions, while is almost absent for all the others.

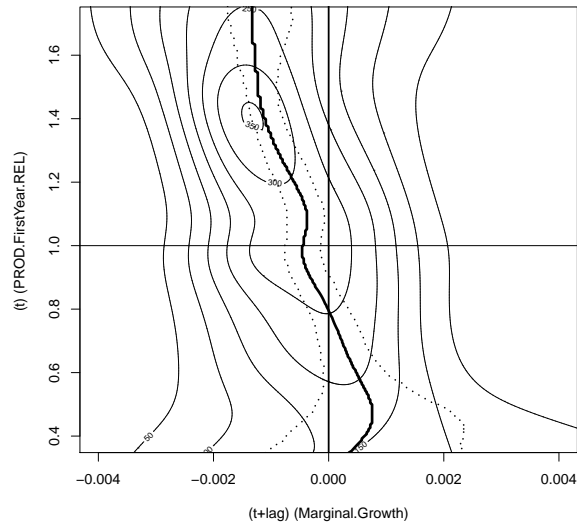


Figure 17: MGE of country dummies conditioned to initial level of (relative) productivity, the estimated mean of MGE conditioned to initial level of productivity (thick solid line), its confidence bands (dotted lines), and the unconditional mean (thin solid vertical line). Counterfactual variable: Delta.SHARE.AGRI.

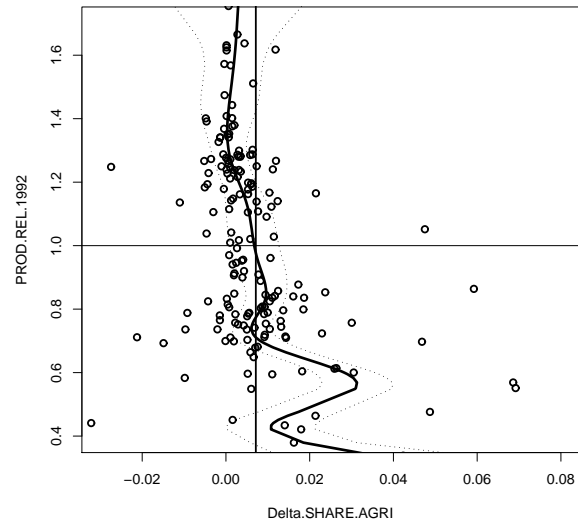


Figure 18: Relationship between Delta.SHARE.AGRI and the initial level of productivity (thick solid line), its confidence bands (dotted lines), observations (points) and the unconditional mean (thin solid vertical line).

3.3.6 Output Composition

Fiaschi and Lavezzi (2007), and the results in Table 1, show that the consideration of the initial output composition has relevant explanatory power in growth regressions for European regions. This section contains the results on the distributional effects of initial output composition. For the sake of brevity we focus on those sectors displaying the most significant MGR (COSA VUOL DIRE "MOST SIGNIFICANT"?), i.e. Finance (FIN.1992), Hotel (HOT.1992), Wholesale and Retails (WHOLE.1992), and Other Market Services (OTHER.SERV.1992).²² As for Objective 1 and Cohesion Funds and structural change we focus on MGR and given the negligible impact on overall distributions of these variables.

Finance Figure 19 shows that the MGR is significantly the highest for regions with initial productivity slightly below the average. For almost all the other regions the conditional mean is significantly below the unconditional mean, an expectation being represented by regions with

²²Results on other sectors are available upon request.

the highest initial level of productivity who had a high, but not significant, MGR. This is the joint result of i) the nonlinear but positive impact of financial sector on growth rate (see Figure 1); and ii) the fact that those regions with initial productivity slightly below the average have on average the highest initial output shares from the financial sector.

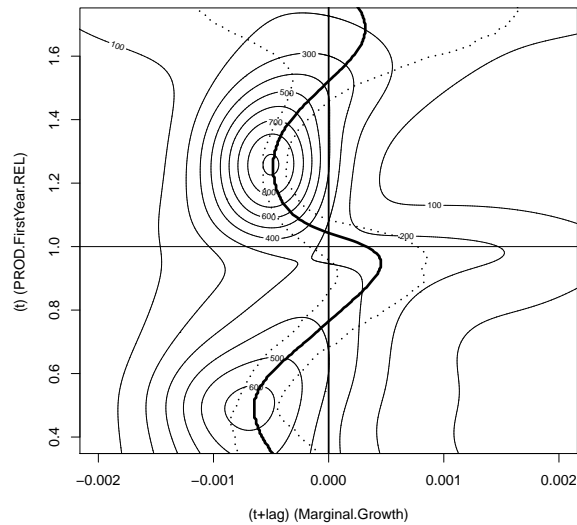


Figure 19: MGE of country dummies conditioned to initial level of (relative) productivity, the estimated mean of MGE conditioned to initial level of productivity (thick solid line), its confidence bands (dotted lines), and the unconditional mean (thin solid vertical line). Counterfactual variable: FIN.1992.

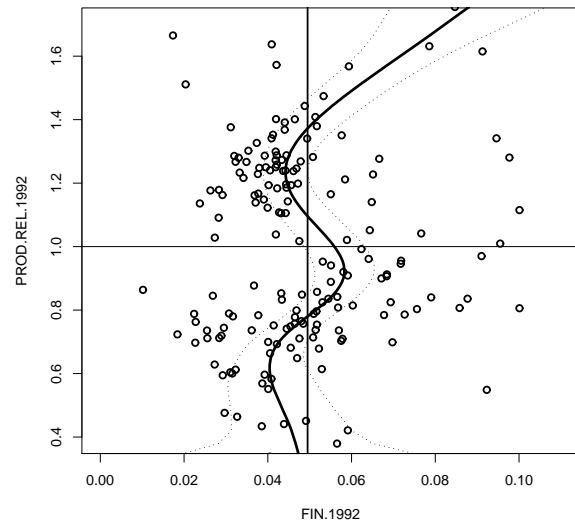


Figure 20: Relationship between FIN.1992 and the initial level of productivity (thick solid line), its confidence bands (dotted lines), observations (points) and the unconditional mean (thin solid vertical line).

Overall the financial sector appears as a factor favouring divergence in the tails of the distribution, in particular considering regions with below-average initial productivity. In this productivity range, the MGR of "richer" regions is significantly positive, while is significantly negative for the other regions. A similar picture emerges for the productivity range above the average: here the MGR of the "richest" regions is not statistically different from zero, while the MGR of the "poorest" regions is significantly below. In the proximity of the middle of the distribution, however, the financial sector acts as force favouring convergence as regions below the average had a MGR significantly higher than regions with above-average initial productivity.

Hotel Figure 21 shows that the MGR is increasing with initial productivity: the conditional mean is significantly below the unconditional mean for regions with productivity below the

average, while the opposite holds for regions with productivity above the average. This is the joint result of i) the nonlinear, but largely negative, effect of the initial share from Hotel sector on the growth rate (see Figure 1); and ii) the substantial negative relationship between the share on GVA from the Hotel sector and the level of initial productivity (see Figure 22): regions with above-average initial productivity have a relatively small initial GVA share from the Hotel sector.

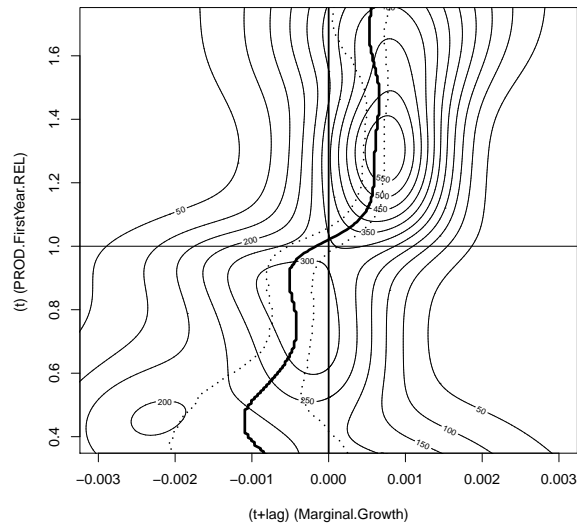


Figure 21: MGE of country dummies conditioned to initial level of (relative) productivity, the estimated mean of MGE conditioned to initial level of productivity (thick solid line), its confidence bands (dotted lines), and the unconditional mean (thin solid vertical line). Counterfactual variable: HOT.1992.

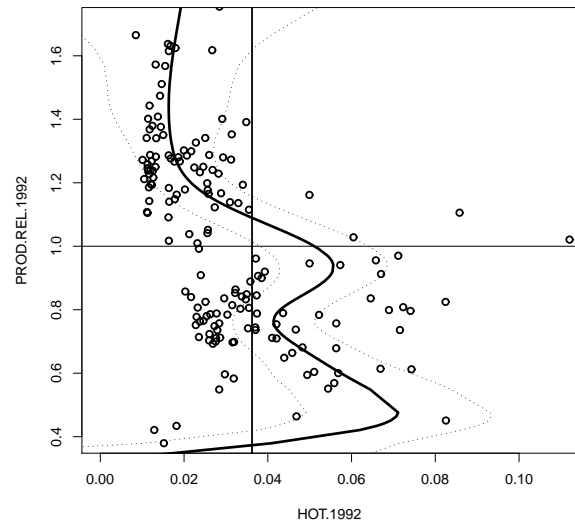


Figure 22: Relationship between HOT.1992 and the initial level of productivity (thick solid line), its confidence bands (dotted lines), observations (points) and the unconditional mean (thin solid vertical line).

Therefore, the Hotel sector acts as a force that increases the dispersion of productivity across regions (see 21).

Wholesales and Retail Figure 23 shows that the MGR is decreasing with productivity: the conditional mean is significantly above the unconditional mean for regions with productivity below the average, while the opposite holds for regions with productivity above (with the exception of few regions with very high productivity). The positive linear impact of the Wholesales and Retail sector on the growth rate (see Table 1), and the negative relationship between the share of Wholesales and Retail sector and the level of productivity (see Figure 24) explain

this finding. Therefore the Wholesale and Retail sector reduces the dispersion of productivity across regions (see Figure 23).

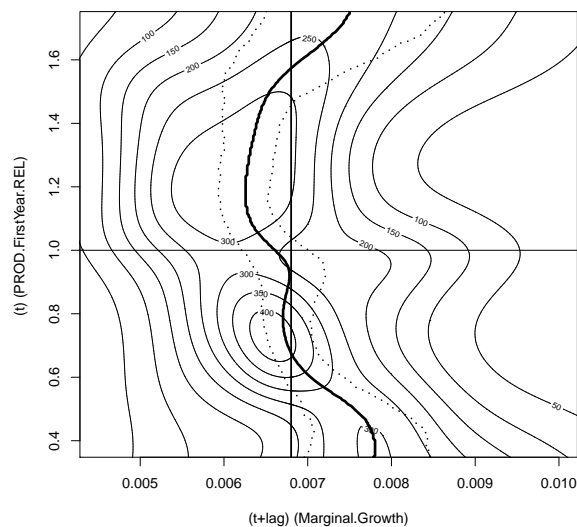


Figure 23: MGE of country dummies conditioned to initial level of (relative) productivity, the estimated mean of MGE conditioned to initial level of productivity (thick solid line), its confidence bands (dotted lines), and the unconditional mean (thin solid vertical line). Counterfactual variable: WHOLE.1992.

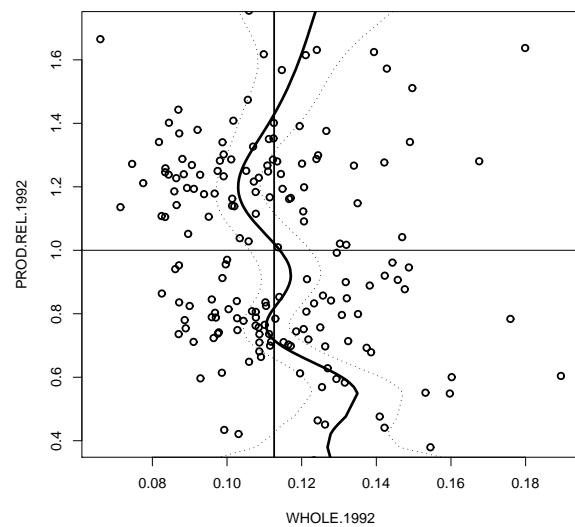


Figure 24: Relationship between WHOLE.1992 and the initial level of productivity (thick solid line), its confidence bands (dotted lines), observations (points) and the unconditional mean (thin solid vertical line).

Other Market Services Figure 25 shows that the MGR is increasing with productivity, being result of i) the positive linear impact of Other Market Services sector on growth (see Table 1); and ii) the positive relationship between the share of Other Market Services sector and the level of productivity (see Figure 26).

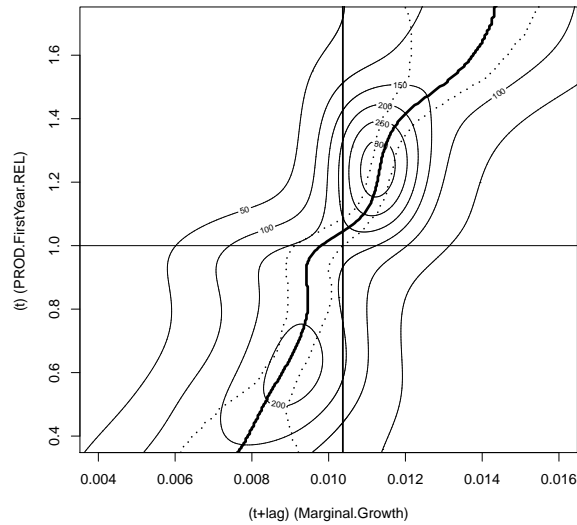


Figure 25: MGE of country dummies conditioned to initial level of (relative) productivity, the estimated mean of MGE conditioned to initial level of productivity (thick solid line), its confidence bands (dotted lines), and the unconditional mean (thin solid vertical line). Counterfactual variable: OTHER.SER.1992.

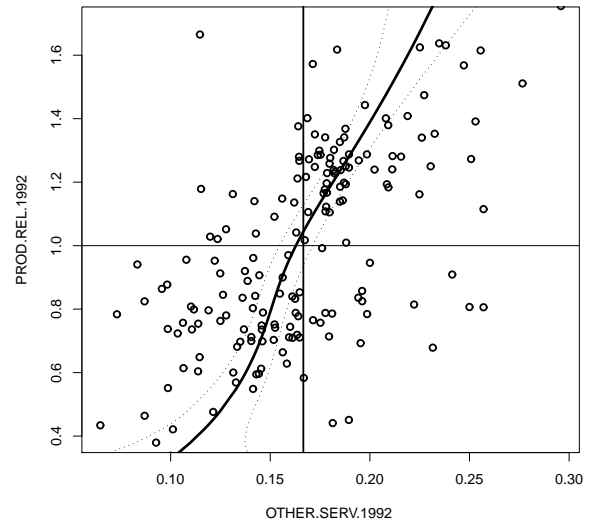


Figure 26: Relationship between OTHER.SER.1992 and the initial level of productivity (thick solid line), its confidence bands (dotted lines), observations (points) and the unconditional mean (thin solid vertical line).

Therefore the Other Market Services sector increases the dispersion of productivity across regions (see 25 and Table 5).

	1992	2002	2002.CF	Ergodic	Ergodic.CF
Gini	0.18	0.16	0.15	0.16	0.14
s.e.	(0.008)	(0.008)	(0.007)	(0.035)	(0.027)

Table 5: Gini Indexes and their standard errors of AD, CD, AED and CED. Counterfactual variable: OTHER.SER.1992.

4 Concluding Remarks

This paper analyzes the determinants of distribution dynamics of labour productivity of a large cross section of European regions in the period 1992-2002. We propose a novel methodology which combines the growth regression approach, but in a semiparametric framework, with the

stochastic kernel approach. In particular, the potential distributional impact of a given variable is evaluated by the comparison of actual and counterfactual distributions and the related actual and counterfactual stochastic kernels and ergodic distributions, where counterfactual distribution is calculated by the estimated growth regression, taking the variable to sample average for all regions. The methodology also allows for measuring the marginal effect of the variable on distribution and for testing for possible presence of distributional effects in the residuals of growth regression.

The analysis can be extended in many respects. Firstly, Objective 1 and Cohesion Funds have a distributional impact favouring the convergence across European regions; future research should be address to a more detailed analysis of the EU policy including for example the other types of Structural Funds. Secondly, country unexplained characteristics have an ambiguous effect on dispersion, and suggest the existence of four clusters of countries with a strong geographical pattern. A natural extension of the analysis should aim at discovering the roots of this unexplained cross-country heterogeneity. Thirdly, we find that some sectors have a reducing-dispersion impact (e.g. and Wholesales and Retail) while others have either an enhancing-dispersion impact (e.g Hotel and Other Market Services) or an ambiguous effect (e.g Finance); a deeper analysis of the dynamics of output specialization across European regions should uncover possible pattern of agglomeration as suggested by the New Economic Geography literature (see Krugman (1991)). Finally, the proposed methodology can be applied to a cross-country setting; this should represent an extension of the Beaudry et al. (2005) analysis taking into account the possibility of a nonlinear impact of individual variables on countries' growth rate.

A List of NUTS2 Regions in the Sample

AT11	Burgenland	DEA1	Düsseldorf	FR26	Bourgogne	IT52	Umbria	UKD1	Cumbria
AT12	Niederösterreich	DEA2	Köln	FR3	Nord - Pas-de-Calais	IT53	Marche	UKD2	Cheshire
AT13	Wien	DEA3	Münster	FR41	Lorraine	IT6	Lazio	UKD3	Greater Manchester
AT21	Kärnten	DEA4	Detmold	FR42	Alsace	IT71	Abruzzo	UKD4	Lancashire
AT22	Steiermark	DEA5	Arnsberg	FR43	Franche-Comté	IT72	Molise	UKD5	Merseyside
AT31	Oberösterreich	DEB1	Koblenz	FR51	Pays de la Loire	IT8	Campania	UKE1	East Riding, North Lincol.
AT32	Salzburg	DEB2	Trier	FR52	Bretagne	IT91	Puglia	UKE2	North Yorkshire
AT33	Tirol	DEB3	Rhein Hessen-Pfalz	FR53	Poitou-Charentes	IT92	Basilicata	UKE3	South Yorkshire
AT34	Vorarlberg	DEC	Saarland	FR61	Aquitaine	IT93	Calabria	UKE4	West Yorkshire
BE1	Rég. Bruxelles	DEF	Schleswig-Holstein	FR62	Midi-Pyrénées	ITA	Sicilia	UKF1	Derbyshire, Nottingh.
BE21	Antwerpen	DK	Danmark	FR63	Limousin	ITB	Sardegna	UKF2	Leicestershire, Rutland and Northamptonshire
BE22	Limburg (B)	ES11	Galicia	FR71	Rhône-Alpes	LU	Luxembourg		
BE23	Oost-Vlaanderen	ES12	Principado de Asturias	FR72	Auvergne	NL11	Groningen	UKF3	Lincolnshire
BE24	Vlaams Brabant	ES13	Cantabria	FR81	Languedoc-Roussillon	NL12	Friesland	UKG1	Herefordshire, Worcester and Warwickshire
BE25	West-Vlaanderen	ES21	Pais Vasco	FR82	Prov.-Alpes-Côte d'Azur	NL13	Drenthe		
BE31	Brabant Wallon	ES22	Comunidad de Navarra	FR83	Corse	NL21	Overijssel	UKG2	Shropshire and Staffordshire
BE32	Hainaut	ES23	La Rioja	GR11	Anatoliki Mak., Thraki	NL22	Gelderland	UKG3	West Midlands
BE33	Liège	ES24	Aragón	GR12	Kentriki Makedonia	NL31	Utrecht	UKH1	East Anglia
BE34	Luxembourg (B)	ES3	Comunidad de Madrid	GR13	Dytiki Makedonia	NL32	Noord-Holland	UKH2	Bedfordshire, Hertford.
BE35	Namur	ES41	Castilla y León	GR14	Thessalia	NL33	Zuid-Holland	UKH3	Essex
DE11	Stuttgart	ES42	Castilla-la Mancha	GR21	Ipeiros	NL34	Zeeland	UKI1	Inner London
DE12	Karlsruhe	ES43	Extremadura	GR22	Ionia Nisia	NL41	Noord-Brabant	UKI2	Outer London
DE13	Freiburg	ES51	Catalua	GR23	Dytiki Ellada	NL42	Limburg (NL)	UKJ1	Berkshire, Buckinghamshire and Oxfordshire
DE14	Tübingen	ES52	Comunidad Valenciana	GR24	Stereia Ellada	PT11	Norte		
DE21	Oberbayern	ES53	Islas Baleares	GR25	Peloponnisos	PT12	Centro (P)	UKJ2	Surrey, East, West Sussex
DE22	Niederbayern	ES61	Andalucia	GR3	Attiki	PT13	Lisboa, Vale do Tejo	UKJ3	Hampshire, Isle of Wight
DE23	Oberpfalz	ES62	Región de Murcia	GR41	Voreio Aigaio	PT14	Alentejo	UKJ4	Kent
DE24	Oberfranken	ES63	Ceuta y Melilla	GR42	Notio Aigaio	PT15	Algarve	UKK1	Gloucestershire, Wiltshire and North Somerset
DE25	Mittelfranken	ES7	Canarias	GR43	Kriti	PT2	Açores		
DE26	Unterfranken	FI13	Itä-Suomi	IE01	Border, Mid., Western	PT3	Madeira	UKK2	Dorset, Somerset
DE27	Schwaben	FI18	Etelä-Suomi	IE02	Southern and Eastern	SE01	Stockholm	UKK3	Cornwall, Isles of Scilly
DE5	Bremen	FI19	Länsi-Suomi	IT11	Piemonte	SE02	Östra Mellansverige	UKK4	Devon
DE6	Hamburg	FI1A	Pohjois-Suomi	IT12	Valle d'Aosta	SE04	Sydsverige	UKL1	West Wales, The Valleys
DE71	Darmstadt	FI2	land	IT13	Liguria	SE06	Norra Mellansverige	UKL2	East Wales
DE72	Gießen	FR1	Île de France	IT2	Lombardia	SE07	Mellersta Norrland	UKM1	North Eastern Scotland
DE73	Kassel	FR21	Champagne-Ardenne	IT31	Trentino-Alto Adige	SE08	Övre Norrland	UKM2	Eastern Scotland
DE91	Braunschweig	FR22	Picardie	IT32	Veneto	SE09	Småland med öarna	UKM3	South Western Scotland
DE92	Hannover	FR23	Haute-Normandie	IT33	Friuli-Venezia Giulia	SE0A	Västssverige	UKM4	Highlands and Islands
DE93	Lüneburg	FR24	Centre	IT4	Emilia-Romagna	UKC1	Tees Valley	UKN	Northern Ireland
DE94	Weser-Ems	FR25	Basse-Normandie	IT51	Toscana	UKC2	Northumberland		

B Data Sources

Data on Structural Funds used in this paper come from different publications of the European Commission. Data cover the two programming periods:

- data over 1989-1993 are from “The Fifth Annual Report” European Commission (1995) and “The impact of structural policies on economic and social cohesion in the Union 1989-99 a first assessment presented by country (October 1996): regional development studies” European Commission (1997);
- data over 1994-1999 are from “The impact of structural policies on economic and social cohesion in the Union 1989-99 a first assessment presented by country (October 1996): regional development studies” European Commission (1997) and “The Eleventh Annual Report” European Commission (2000).

Data represent the total Commitments that European Commission allocated for the entire programming period. All data are transformed in 1995 constant prices. Data on regional GVA and employment come from cam (2004).

C Descriptive Statistic

	log.PROD.REL.1992	log.INV.RATE	log.EMP.GR	SPAT.INDEX	OB1.CF
Mean	-0.05	-1.67	-3.33	0.49	0.01
Stand. Dev.	0.33	0.39	0.22	3.04	0.02
	log.ECO.DEN	Delta.SHARE.AGRI	MANU.1992	MIN.1992	CON.1992
Mean	0.96	0.01	0.2	0.04	0.06
Stand. Dev.	1.34	0.01	0.08	0.03	0.02
	NON.MKT.SER.1992	FIN.1992	HOT.1992	TRANS.1992	
Mean	0.22	0.05	0.04	0.06	
Stand. Dev.	0.05	0.02	0.04	0.02	
	WHOLE.1992	OTHER.SER.1992			
Mean	0.11	0.17			
Stand. Dev.	0.02	0.04			

Table 6: Mean and Standard Deviation of variables used in growth regressions

	log.PROD.REL.1992	log.INV.RATE	log.EMP.GR	SPAT.INDEX	OB1.CF
log.PROD.REL.1992	1.00	0.11	0.01	0.85	-0.47
log.INV.RATE	0.11	1.00	0.08	0.21	0.33
log.EMP.GR	0.01	0.08	1.00	-0.05	0.03
SPAT.INDEX	0.85	0.21	-0.05	1.00	-0.38
OB1.CF	-0.47	0.33	0.03	-0.38	1.00
log.ECO.DEN	0.47	-0.28	0.10	0.39	-0.23
Delta.SHARE.AGRI	-0.37	0.03	0.19	-0.37	0.20
MANU.1992	0.26	-0.26	-0.18	0.32	-0.45
MIN.1992	-0.04	0.06	0.02	-0.13	-0.01
CON.1992	-0.21	0.24	-0.14	-0.19	0.21
NON.MKT.SER.1992	-0.07	0.07	0.11	0.01	0.37
FIN.1992	0.15	-0.04	0.19	0.07	-0.12
HOT.1992	-0.36	0.13	0.17	-0.43	0.24
TRANS.1992	-0.05	-0.08	0.17	-0.15	0.19
WHOLE.1992	-0.24	0.11	0.12	-0.23	0.24
OTHER.SER.1992	0.58	-0.13	-0.09	0.54	-0.35

Table 7: Correlations between variables used in growth regressions

	log.ECO.DEN	Delta.SHARE.AGRI	MANU.1992	MIN.1992	CON.1992
log.PROD.REL.1992	0.47	-0.37	0.26	-0.04	-0.21
log.INV.RATE	-0.28	0.03	-0.26	0.06	0.24
log.EMP.GR	0.10	0.19	-0.18	0.02	-0.14
SPAT.INDEX	0.39	-0.37	0.32	-0.13	-0.19
OB1.CF	-0.23	0.20	-0.45	-0.01	0.21
log.ECO.DEN	1.00	-0.30	0.23	-0.13	-0.42
Delta.SHARE.AGRI	-0.30	1.00	-0.14	-0.07	-0.07
MANU.1992	0.23	-0.14	1.00	-0.12	-0.14
MIN.1992	-0.13	-0.07	-0.12	1.00	-0.07
CON.1992	-0.42	-0.07	-0.14	-0.07	1.00
NON.MKT.SER.1992	-0.04	-0.04	-0.47	-0.08	-0.02
FIN.1992	0.47	-0.13	-0.15	-0.20	-0.19
HOT.1992	-0.31	0.21	-0.44	-0.03	0.00
TRANS.1992	0.29	-0.05	-0.41	-0.14	-0.05
WHOLE.1992	0.08	0.16	-0.45	-0.26	-0.11
OTHER.SER.1992	0.50	-0.36	-0.05	-0.27	-0.19

Table 8: Continued: Correlations between variables used in growth regressions

	NON.MKT.SER.1992	FIN.1992	HOT.1992	TRANS.1992	WHOLE.1992	OTHER.SER.1992
log.PROD.REL.1992	-0.07	0.15	-0.36	-0.05	-0.24	0.58
log.INV.RATE	0.07	-0.04	0.13	-0.08	0.11	-0.13
log.EMP.GR	0.11	0.19	0.17	0.17	0.12	-0.09
SPAT.INDEX	0.01	0.07	-0.43	-0.15	-0.23	0.54
OB1.CF	0.37	-0.12	0.24	0.19	0.24	-0.35
log.ECO.DEN	-0.04	0.47	-0.31	0.29	0.08	0.50
Delta.SHARE.AGRI	-0.04	-0.13	0.21	-0.05	0.16	-0.36
MANU.1992	-0.47	-0.15	-0.44	-0.41	-0.45	-0.05
MIN.1992	-0.08	-0.20	-0.03	-0.14	-0.26	-0.27
CON.1992	-0.02	-0.19	0.00	-0.05	-0.11	-0.19
NON.MKT.SER.1992	1.00	-0.10	-0.07	0.08	0.12	-0.02
FIN.1992	-0.10	1.00	-0.07	0.43	0.15	0.29
HOT.1992	-0.07	-0.07	1.00	0.22	0.16	-0.31
TRANS.1992	0.08	0.43	0.22	1.00	0.25	0.11
WHOLE.1992	0.12	0.15	0.16	0.25	1.00	0.01
OTHER.SER.1992	-0.02	0.29	-0.31	0.11	0.01	1.00

Table 9: Continued: Correlations between variables used in growth regressions

D GAM Estimation

We estimate Model (3) following the method described in Wood (2006), and implemented by the package *mgcv* in R. The estimation is obtained by penalized likelihood maximization. The model is fitted by minimizing:

$$\| \mathbf{y} - \mathbf{X}\beta \|^2 + \sum_{k=1}^K \lambda_k \int_{-\infty}^{+\infty} [\mu_k''(x)]^2 dx \quad (17)$$

where \mathbf{y} is the vector of observations, \mathbf{X} is the matrix of explanatory variables, β is a vector of parameters to be estimated, λ_k , $k = 1, \dots, K$ are smoothing parameters, and the penalty, which controls the smoothness of the estimate, is represented by the integrated square of second derivatives of the smooth terms. The vector of parameters originates from expressing every smooth term in Model (3), $\mu(\cdot)$, as:

$$\mu_k(x) = \sum_{t=1}^q b_t(x) \beta_t \quad (18)$$

where $b_t(x)$ are *basis functions* and q is their number.

Parameters β are chosen to minimize the function in Eq. (17) for given values of the smoothing parameters λ_k . Smoothing parameters are, in turn, chosen by the minimization of the Generalized Cross Validation (GCV) score. Estimation proceeds by penalized iteratively re-weighted least squares, until convergence in the estimate is reached.

In the results of the estimations, we report: 1) the estimated degrees of freedom for each term (EDF). The EDF reflect the flexibility of the model. When the EDF of a term are equal to one, the term can be substituted by a linear function; 2) the adjusted R^2 , having the familiar interpretation; 3) the proportion of deviance explained, a generalization of R^2 ; 4) the Scale parameter estimation, corresponding to the residual variance of the estimation; 5) the GCV score, which provides the fundamental information on the specification of the model. The decision to remove or maintain a term is based on comparison of GCV score; the model minimizing the GCV with the lowest number of terms is assumed to be the best specification.

E Bootstrap procedure for calculating Moran's I test

We apply a bootstrap procedure to perform the Moran's I test for residual spatial dependence of our semiparametric models in presence of general heteroscedasticity.

Given the semiparametric model:

$$\mathbf{g} = \alpha + \sum_{k=1}^K \mu_k(\mathbf{X}_k) + v; \quad (19)$$

where \mathbf{g} is the $N \times 1$ vector of growth rate, α is the $N \times 1$ vector of constant term, \mathbf{X} is the $N \times K$ matrix of explanatory variables, $\mu(\cdot)$ are nonparametric functions, and v is the $N \times 1$ vector error term such that $E(v|\mathbf{X}) = 0$ and $var(v|\mathbf{X}) = \sigma^2(\mathbf{X})$, the bootstrap procedure of testing consists in the following five steps.

1. Estimate Model (19) and calculate the residuals \hat{v} .
2. Calculate the observed Morans' I statistics:

$$I_{obs} = \frac{N}{S} \left(\frac{\hat{v}' \mathbf{W} \hat{v}}{\hat{v}' \hat{v}} \right),$$

where \mathbf{W} is the weight spatial matrix and S is the sum of the element of W .

3. Select B independent bootstrap samples of residuals $\{\hat{\mathbf{u}}^{*1}, \dots, \hat{\mathbf{u}}^{*B}\}$ in two steps:

- (a) draw with replacement N residuals \mathbf{u}^* from the following two-point distribution:

$$u = \begin{cases} (1 - \sqrt{5})/2 & \text{with } p = (5 + \sqrt{5})/10 \\ (1 + \sqrt{5})/2 & \text{with } 1 - p \end{cases}$$

- (b) generate $\mathbf{g}^* = \hat{\alpha} + \sum_{k=1}^K \hat{\mu}_k(\mathbf{X}_k) + \mathbf{u}^*$;

- (c) estimate Model (19) using \mathbf{g}^* and take the residuals $\hat{\mathbf{u}}^*$.

4. Compute for each bootstrap sample, $b = 1, \dots, B$, the Morans' I statistic I_b^* .
5. Approximate the achieved significance level by:

$$\widehat{ASL}_{boot} = \#\{I_b^* \geq I_{obs}\} / B \quad (20)$$

In our estimates we set $B=1000$ and we take a row-standardized weight spatial matrix with a distance cut-off equal to 660.8 km (the third quantile of distribution, the same used for the calculation of SPATIAL.INDEX (see Anselin (1988)).

F Bootstrap procedure for calculating confidence interval

The bootstrap procedure used to calculate the confidence bands for the estimated median of the stochastic kernel and ergodic distribution is respectively based on the procedure in Bowman and Azzalini (1997) and in Fiaschi and Romanelli (2009).

Given a sample of observations $\mathbf{Y} = \{\mathbf{Y}_1, \dots, \mathbf{Y}_m\}$ where \mathbf{Y}_i is a vector of dimension n , the bootstrap algorithm consists of three steps.

1. Estimate from sample \mathbf{Y} the stochastic kernel, the median of stochastic kernel and the corresponding ergodic distribution $\hat{\psi}$.
2. Select B independent bootstrap samples $\{\mathbf{Y}^{*1}, \dots, \mathbf{Y}^{*B}\}$, each consisting of n data values drawn with replacement from \mathbf{Y} .
3. Estimate the stochastic kernel, the median of stochastic kernel and the corresponding ergodic distribution $\hat{\psi}_b^*$ corresponding to each bootstrap sample $b = 1, \dots, B$.

The distribution of $\hat{\psi}_b^*$ about $\hat{\psi}$ can therefore be used to mimic the distribution of $\hat{\psi}$ about ψ . In particular, the confidence interval for the median of the kernel corresponds to the case $\hat{\psi} = m$ which solves:

$$\int_{-\infty}^m \hat{g}_\tau(z|x) dx = 0.5,$$

where $\hat{g}_\tau(z|x)$ is the estimated stochastic kernel, while for the ergodic distribution to the case $\hat{\psi} = \hat{f}_\infty$. We set $B=500$ and in each bootstrap the bandwidth is set equal to the one calculated for the estimate of density of the observed sample \mathbf{Y} .

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