On the Determinants of Distribution Dynamics: a New Method and an Application to EU Regions

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Abstract

In this paper we provide a novel approach to identify the effect of growth determinants on the distribution dynamics, that integrates the counterfactual analysis of, e. g., Beaudry et al. (2005) with the estimation of conditioned stochastic kernels of Quah (1996b) and Quah (1997). The counterfactuals are constructed from a nonparametric growth regression in which the cross-section heterogeneity in the variable of interest is removed. The methodology also allows for measuring the marginal effect of individual variables on the distribution of per capita income (labor productivity), and to test for the possible presence of distributional effects in the residuals of growth regression, as a means to assess the goodness of fit of the initial growth regression. The methodology is applied to the analysis of productivity dynamics across European regions. We show its capacity to highlight aspects of the identified tendency for polarization, otherwise missed by existing methods.

Keywords: Convergence, polarization, distribution dynamics, counterfactual analysis, European regions.

JEL: *C14; C21; O40; O52; R11*

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1 Introduction

The world income distribution has been largely studied over the last two decades and a new stylized fact appears: the distribution of per capita income has moved from a unimodal shape in the 1960s to a twin-peaks shape in the 1990s (see, e.g., Quah (1996a), and Durlauf et al. (2005)). The same twin-peaked distribution also characterizes the regional distribution of productivity in Europe (see, e.g., Fiaschi and Lavezzi (2007), and Basile (2009)). However, it is still unclear whether these twin-peaks are a persistent phenomenon (see Galor (2007)) and which factors drive the formation of the two peaks.

This paper aims at analyses the factors driving convergence and divergence processes in the growth dynamics. To this purpose, we propose a methodology to measure the *distributional effect* of individual growth determinants, which combines a semiparametric growth regression approach with the approach based on estimation of stochastic kernels, i. e. of the operators that map current distributions into future distributions of income or productivity.[1] Specifically, we exploit the idea of performing a counterfactual analysis (see, e.g. Beaudry et al. (2005)) to evaluate the distributional impact of a given variable. That is, we estimate and compare *actual* and *counterfactual* distributions to estimate short-run effects, and the implied actual and counterfactual *ergodic* distributions to identify long-run tendencies.

In addition, our methodology allows: i) to measure the *marginal effect* of a variable of interest on the distribution, which provides information on the *direction* of the effect of the variable in different ranges of per capita income (or labour productivity) distribution, and ii) to test for the possible presence of distributional effects of the residuals of the growth regression, which we will utilize to assess the specification of the regression model. The advantage of studying the distributional effect of a growth determinant resides in the possibility to identify whether the same factor favors convergence in some range of the per capita income (productivity) distribution and divergence in another, an aspect which cannot be captured by the estimation of a single parameter as in standard growth regressions.

The paper is organized as follows: Section 2 describes the methodology for the empirical analysis and clarifies the relations with existing approaches; Section 3 presents an empirical application to European regions; Section 4 concludes. The appendices contain details on data and on the methodology.

2 Methodology

In this section we present the method for the empirical analysis and clarify the aspects of its novelty with respect to other approaches. Our method can be summarized as follows: we first estimate

[1] See, e.g., Quah (1997) for details.

a semiparametric growth regression, and then utilize the results to estimate counterfactual distributions with respect to individual variables of interest; this allows to identify their contribution to convergence or divergence, that we denote as *marginal growth effect*.

2.1 Related Literature

Two main approaches to study convergence exist in the literature: the "growth regression approach" (GRA) and the "distribution dynamics approach" (DDA). By applying GRA, it is possible to analyze whether economies are, on average, converging towards their steady-state level of per capita income or productivity, and to identify the average effect of growth determinants. The DDA, instead, aims at understanding how the whole cross-sectional distribution evolves over time.[2]

The most representative examples of the GRA are the so-called "Barro regressions" (see, e. g., Barro (1991), and Barro and Sala-i Martin (2004)), which generally found 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 Fluente (2003), in the spirit of the present paper, extends the GRA approach by decomposing the measures of σ and β-convergence (Barro and Sala-i Martin, 2004) into sums of *partial* σ and β-convergence measures, in order to assess the individual contribution to convergence of the explanatory variables included in a growth regression. De La Fluente (2003) defines such methodology "convergence accounting".

The alternative DDA proposed by Danny Quah in a number of papers (see, e. g., Quah (1993, 1996a,b, 1997)) stems from criticism to the GRA for not being able to capture phenomena such as *mobility*, *stratification* and *polarization* in the world income distribution.[3] On the contrary, operators such stochastic kernels (or transition matrices) may reveal information on these aspects of the growth process. A further step, aiming at evaluating the effects of individual explanatory variables on the distribution dynamics is taken by Quah (1996b) and Quah (1997), by introducing *conditioned* stochastic kernels. In particular, in Quah (1996b) conditioned stochastic kernels are based on residuals from two-sided regressions of labor productivity on human capital, physical capital, and country dummies. Differently, Quah (1997) introduces conditioned stochastic kernels as operators mapping *unconditioned* income levels into *conditioned* income levels, that is incomes normalized: "on the basis of incomes relative to one's neighbours appropriately weighted" (Quah, 1997, p. 47), where weights are calculated with respect to a variable suspected to affect the income dynamics.

Another strand of literature proposes counterfactual analysis as an alternative methodology to

[2]See Quah (1997) for a more detailed discussion, and Durlauf et al. (2005) for an exhaustive survey of different empirical methodologies adopted in empirical analyses of economic growth.

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

identify the impact of individual explanatory variables on distributions (see e.g. DiNardo et al. (1996) and Machado and Mata (2005)). In particular, Beaudry et al. (2005) apply this analysis in a study of economic growth. In particular, they analyze in a cross-country setting the distributional effects of some growth determinants over two periods, 1960-1978 and 1978-1998, by estimating 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.

Our methodology is close to that of Cheshire and Magrini (2005), who combine the GRA with the DDA in the analysis of factors driving convergence in 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 a "predicted" stochastic kernel (computed on the basis of fitted values of growth regression) with the "simulated" stochastic kernel (computed on the basis of alternative values of the explanatory variables in the growth regression).

However, we differ from the current literature in two crucial aspects: i) the estimate of "conditioned" stochastic kernels (denoted *counterfactual stochastic kernels*), and ii) of counterfactual distributions. A further difference is that the preliminary step will be based on a semiparametric growth regression, to take into account the presence of nonlinearities which, as many recent studies show, strongly characterize economic growth (see Durlauf et al. (2005), for discussion and references).

In the following we detail our methodology, which is based on six steps: i) estimation of a semiparametric growth regression model (Section 2.2); ii) calculation of counterfactual productivity (Section 2.3.1); iv) estimation of counterfactual stochastic kernels (Section 2.3.1); v) estimation of counterfactual ergodic distributions (Section 2.3.1); vi) evaluation of the distsributional effects of a variable and estimation of its marginal growth effect (Section 2.3.2); ii) test on the distributional effects of growth residuals (Section 2.4).

2.2 Modeling Productivity Growth

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 $T > 0$, therefore, can be expressed as:

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

where g_i is the annual rate of growth of productivity in region i, between periods 0 and T.

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

$$g_i = \varphi(\mathbf{X}_i, \upsilon_i). \tag{2}$$

Differently from other approaches to counterfactual analysis, we model the growth rate g_i by a semi-parametric model, that is:[4]

$$g_i = m(\mathbf{X}_i) + \upsilon_i = \alpha + \sum_{j=1}^{K} \mu_j(X_{i,j}) + \upsilon_i \tag{3}$$

where α is a constant term, $\mu_j(\cdot)$ are one-dimensional nonparametric functions operating on each of the K elements of $\mathbf{X}_i$, and υ_i is an error term with the properties: $E(\upsilon_i|\mathbf{X}_i) = 0$, $var(\upsilon_i|\mathbf{X}_i) = \sigma^2(\mathbf{X}_i)$ (i. e. the model allows for heteroskedasticity).[5]

2.3 Distributional Effects of Individual Variables

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

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

Eq. (3) can be rewritten as:

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

Substituting Eq. (4) into Eq. (1) leads to the following expression for productivity:

$$\begin{aligned} y_i(T) &= y_i(0)e^{[\alpha+\mu_k(X_{i,k})+\sum_{j\neq k}\mu_j(X_{i,j})+\upsilon_i]T} = \\ &= \underbrace{y_i(0)e^{[\alpha+\sum_{j\neq k}\mu_j(X_{i,j})]T}}_{y_{i,\underline{k}}(T)} \underbrace{e^{\mu_k(X_{i,k})T}}_{e^{g^M_{i,k}T}} \underbrace{e^{\upsilon_i T}}_{e^{g^R_i T}}, \end{aligned} \tag{5}$$

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 $X_{i,k}$; $g^M_{i,k} = \mu_k(X_{i,k})$ 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, finally, $g^R_i = \upsilon_i$ is the annual "residual growth", not explained by the variables in $\mathbf{X}_i$. The modelling of growth in Eq. (5) will be the basis for the identification of the distributional effects of the *k-th* variable.

2.3.1 Counterfactual Stochastic Kernels and Ergodic Distributions

We define the *counterfactual productivity* $y^{CF}_{i,k}(T)$, the productivity level that a region would attain at time T if there were no differences within the sample in terms of the *k-th* variable (whose values

[4]Notation refers to Härdle et al. (2004).

[5]Durlauf et al. (2001) consider a growth regression framework in which the impact of the explanatory variables is nonlinear. Specifically, they condition the marginal impact of a variable to the initial level of per capita income (as we do in the following), and find significant nonlinearities. However, the main difference with respect to the present analysis is that Durlauf et al. (2001) do not embed this exercise into a counterfactual analysis of the distribution dynamics of labour productivity.

are collected in the N-dimensional vector $\mathbf{X}_k$). That is, $y_{i,k}^{CF}(T)$ aims at capturing the effect on the productivity distribution of the cross-sectional distribution of the *k-th* variable. To isolate this effect, we will impose to each region the *cross-section average value* of the variable.[6]

Hence, the *counterfactual growth rate* of region i with respect to the k-th variable, $g_{i,k}^{CF}$, is defined as:

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

where $\bar{X}_k = N^{-1} \sum_{j=1}^{N} X_{k,j}$, and $\mu_k(\cdot)$ is the smoothed function relative to the *k-th* variable, obtained from the estimation of Eq. (3). The counterfactual productivity of region i in period T, relative to variable k, is therefore defined as:

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

Counterfactual productivities are the bases to compute *counterfactual stochastic kernels*. Specifically, the *actual* and *counterfactual* stochastic kernels are respectively defined as $\phi(\mathbf{y}(T)|\mathbf{y}(0))$ and $\phi^{CF}(\mathbf{y}_k^{CF}(T)|\mathbf{y}(0))$, where $\mathbf{y}(0)$, $\mathbf{y}(T)$ and $\mathbf{y}_k^{CF}(T)$ are the vectors collecting regional productivities at times 0 and T.[7]

The actual stochastic kernel $\phi(\cdot)$ maps the distribution of (relative) productivity in period 0 into the distribution of (relative) productivity in period T. The counterfactual stochastic kernel $\phi^{CF}(\cdot)$, instead, maps the distribution of (relative) productivity in period 0, into the distribution of counterfactual relative productivities in period T. Therefore, the counterfactual stochastic kernel highlights, for every initial productivity level, the probability distribution over productivity levels at time T if the cross-region heterogeneity in the variable k is suppressed. This implies that the possible differences with respect to the probability distribution based on the actual stochastic kernel depends on the *k-th* variable, in particular on its distribution across regions.

For actual and counterfactual stochastic kernels we estimate the corresponding ergodic distributions, i.e. the *actual* and the *counterfactual ergodic distribution*, following the procedure proposed by Johnson (2005).[8] The ergodic distribution highlights whether the estimated distribution dynamics

[6]Beaudry et al. (2005) isolate the effects of the distribution of a variable by imposing on the second period the values of the variable in the first period.

[7]In general, a stochastic kernel is an operator mapping the density of a variable at time t into its density at time $t+\tau$, $\tau > 0$, and indicates for each level of the variable in period t its the probability distribution in period $t+\tau$. That is, the relation between the densities and the stochastic kernel is: $f_{t+\tau}(z) = \int_0^\infty g_\tau(z|x) f_t(x)\,dx$, where z and x are two levels of the variable, and $g_\tau(z|x)$ is the stochastic kernel. To estimate the stochastic kernel $g_\tau(z|x) = g(z,x)/f(x)$ 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.

[8]Specifically, the ergodic distribution solves $f_\infty(z) = \int_0^\infty g_\tau(z|x) f_\infty(x)\,dx$.

over the period of interest has completely exhausted its effects or, otherwise, significant distributional changes are expected in the future.

2.3.2 The Distributional Effect of Individual Variables and the Marginal Growth Effect

To evaluate the distributional effect of individual variables, we consider two aspects: i) we assess the capacity of an individual variable to make actual and counterfactual stochastic kernels differ; ii) we highlight its *marginal growth effect* with respect to initial productivity. This will allow us to identify whether a variable is as source of convergence or divergence, in particular by identifying which parts of the productivity distribution it affects.

To analyze possible differences between actual and counterfactual kernels, we express the value of (log) actual productivity in period T, $y_i(T)$, in terms of the counterfactual productivity, $y_{i,k}^{CF}(T)$:

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

The expected value of (the log of) actual productivity of region i in period T conditional to actual productivity in period 0, $E[log(y_i(T))|y_i(0)]$, is obtained from the actual stochastic kernel with $\tau = T$. In particular, its relation with the expected value from the counterfactual kernel can be expressed as:

$$E\left[\log\left(y_i(T)\right)|y_i(0)\right] = E[\log(y_{i,k}^{CF}(T))|y_i(0)] + E[\mu_k(X_{i,k}) - \mu_k(\bar{X}_k)|y_i(0)]T. \tag{9}$$

From Eq. (9), we can derive a condition for the equality of the expected values of productivity based on actual and counterfactual kernels. Specifically, these values are equal, i. e.:

$$E\left[\log\left(y_i(T)\right)|y_i(0)\right] = E[\log(y_{i,k}^{CF}(T))|y_i(0)] \tag{10}$$

if:

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

The result in Eq. (11) depends on the fulfilment of the following two conditions:

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, that is the impact of the *k-th* variable on productivity in region i is independent from the initial productivity level.
2. $E[\mu_k(X_{i,k})] = \mu_k(E[X_{i,k}]) = \mu_k(\bar{X})$, i. e. $\mu_k(\cdot) = \beta_k X_{i,k}$, that is the *marginal* impact of the *k-th* variable is constant, i.e. the term $X_{i,k}$ has a linear effect on growth.

Therefore, if Conditions 1 and 2 hold, we obtain the condition in Eq. (11), i. e.:

$$E[\mu_k(X_{i,k})|y_i(0)] = E[\mu_k(X_{i,k})] = \mu_k(E[X_{i,k}]) = \mu_k(\bar{X}_k). \tag{12}$$

Eq. (12) represents a necessary condition for the equality of the actual and counterfactual stochastic kernels and, therefore, for the absence of distributional effects of the *k-th* variable.

Notice that, given our choice to base counterfactual analysis on cross-section averages, the use of a semiparametric specification that allows for nonlinearities, is necessary to identify possible differences between the actual and counterfactual stochastic kernels, even when the marginal effect of the *k-th* variable is independent of the initial productivity level (i.e. when the condition in Eq. (1) is fulfilled).

As a second step to evaluate the impact of the individual variables on the distribution dynamics, in particular whether it is a source of convergence or divergence, we need to identify the specific relation between the contribution of that variable to productivity growth and initial productivity levels. To this purpose, we define the *marginal growth effect* of the *k-th* variable in Eqq. (3)-(5), i.e. $g_{i,k}^M = \mu_k(X_{i,k})$. It may be observed that the estimation of Eq. (3) must include all the explanatory variables in order to avoid omitted-variable problems and obtain unbiased estimates.

The marginal effect of the *k-th* variable on the distribution dynamics is identified by estimating the marginal growth $\mathbf{g}_k^M$ conditioned on the initial level of productivity, i. e. by estimating $\phi^M(\mathbf{g}_k^M|\mathbf{y}(0))$. If the estimate of the marginal effect does not result 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 statistically different from its unconditional mean and, in particular, it is an increasing (decreasing) function 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 that: $E_{\mathbf{X}_k}[\mu_k(\mathbf{X}_k)] = 0$ (see Härdle et al., 2004, pp. 212-222). Therefore, the unconditional mean of marginal growth will always be equal to zero in the estimation of the semiparametric terms in the growth regression.

Having detailed our methodology, let us finally remark that, with respect to the mentioned existing methods of estimating the effect of individual variables on the distribution dynamics, especially through the estimation of "conditioned" stochastic kernels: i) our method is based on a multivariate analysis to identify the effect of a specific variable, while the method proposed by Quah (1997) is based on the consideration of one variable at the time. Here, by *excluding* the variables of interest one by one, we are able to control more precisely for the effects on growth of other variables, different from the "conditioning" ones, avoiding the omitted variable bias. Quah (1996b), on the contrary, performs a multivariate analysis, but only considers the residuals from this analysis to condition the stochastic kernel, and therefore may only obtain an estimate of the joint effect of these variables; ii) in particular with respect to Cheshire and Magrini (2005), we use a semiparametric method, instead of a linear regression, for the baseline estimation.

2.4 Test of Distributional Effects of Residual Growth

As a final step, we propose a test for the goodness of fit. In particular, we elaborate a measure of goodness of fit of the growth regression conditional on 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 $\hat{\mathbf{g}}^R \equiv log\left(\frac{\mathbf{y}(T)}{\hat{\mathbf{y}}(T)}\right)$, to test that:

$$E[\hat{\mathbf{g}}^R|\mathbf{y}(0)] = E[\hat{\mathbf{g}}^R] = 0 \; \forall \; \mathbf{y}(0). \tag{13}$$

If $\mathbf{y}(0)$ is included in the set of regressors, the condition in Eq. (13) ensures that there is no omitted variable inconsistency related to $\mathbf{y}(0)$ (see Wooldridge, 2002, pp. 61-63). This condition in Eq. (13) will be used as a test of misspecification of the growth model.

3 An Empirical Application to European Regions

To demonstrate the practical use of our methodology, we provide an empirical application to the labour productivity of a sample of European regions already studied in Fiaschi and Lavezzi (2007) and Fiaschi et al. (2011).[9][10]

Specifically, in Section 3.1 we estimate the growth model of Eq. (3); in Section 3.2 we test for the presence of distribution effects in residual growth; in Section 3.3 we study the unconditional distribution dynamics of labour productivity that we will use as benchmark; finally, in Section 3.4 we present the distributional impact of selected regressors.

3.1 The Estimation of a Growth Model for European Regions

Following Fiaschi and Lavezzi (2007) and Fiaschi et al. (2011), in the estimation of Eq. (3) the annual average growth rate of per worker GVA of a region is regressed on:[11] i) the initial productivity level, normalized with respect to sample average (PROD.REL.1992); ii) the average annual investment rate (INV.RATE); iii) the average annual employment growth rate (EMP.GR); iv) the initial density of economic activity (ECO.DEN.1992), measured by GVA per km^2, to control for the possible presence of agglomeration effects; v) the share on regional GVA of EU Structural Funds allocated to Objective 1, and of Cohesion Fund, over the period 1989-1999 (OB1.CF); vii) some variables controlling for the initial regional output composition, such as the initial share of GVA in Agriculture (AGRI.1992), Manufacturing (MANU.1992), Construction (CON.1992), Non Market Services (NON.MKT.SER.1992),

[9]In particular Fiaschi and Lavezzi (2007) show that the distribution dynamics of productivity in 191 European regions over the period 1980-2002 displays polarization, and find that regional output composition crucially accounts for the characterization of twin peaks. Fiaschi et al. (2011), instead, analyses the impact of the European Union regional policy on the productivity growth of a subsample of 173 European regions for the same period 1980-2002, and find that EU funds have a positive and significant effect on productivity growth. Here we use the same variables and sample used in Fiaschi et al. (2011) but we focus on the subperiod 1992-2002 in order to avoid problems of spatial dependence.

[10]A cross-country application can be found in Fiaschi and Parenti (2012)

[11]Appendix A contains the regions' list while Appendix B contains the descriptive statistics of the explanatory variables.

Dep. Var: γ_i	**Preferred Specification**
COUNTRY DUMMIES	YES
Parametric coefficients:	Estimate
CONST	0.0048
$\hat{\mu}_1$(log.PROD.REL.1992)	-0.0095**
$\hat{\mu}_2$(log.INV.RATE)	0.0105***
$\hat{\mu}_7$(MANU.1992)	0.0302***
$\hat{\mu}_{14}$(OTHER.SERV.1992)	0.0960***
Non parametric coefficients:	EDF
$\hat{\mu}_3$(log.EMP.GR)	7.292***
$\hat{\mu}_4$(OB1.CF)	3.961***
$\hat{\mu}_6$(AGRI.1992)	4.127**
$\hat{\mu}_{10}$(FIN.1992)	2.225**
$\hat{\mu}_{11}$(HOT.1992)	2.169***
$\hat{\mu}_{12}$(TRANS.1992)	6.070***
$\hat{\mu}_{13}$(WHOLE.1992)	5.486***
Deviance explained	96.1%
GCV score (*10^5)	1.95
Scale est.(*10^5)	1.41
Obs.	173
Moran Test (B=1000)	
W1, sym	I=-0.0205 (p-value=0.412)
W1, asym	I=-0.0205 (p-value=0.398)
W2, sym	I=0.0021 (p-value=0.320)
W2, asym	I=0.0021 (p-value=0.264)

Table 1: Estimation of Eq. (3). Significance codes: 0.01″***″ 0.05″**″ 0.1″*″.

Finance (FIN.1992), Hotel and Restaurants (HOT.1992), Transport (TRANS.1992), Wholesales and Retails (WHOLE.1992), Other Market Services (OTHER.SERV.1992);[12] finally, viii) 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.[13]

Results of the estimated model are reported in Table 1. The choice of the preferred specification is based on the iterative elimination of nonsignificant terms from the initial specification with all regressors, in order to improve the goodness of fit. All regressors initially enter as nonparametric terms. However, if their effect results to be linear, they are substituted by linear terms.

We also tested for the possible presence of spatial effects across the regions of our sample, as

[12]Data on EU funds come from different publications of the European Commission and represent total Commitments, while data on regional GVA and employment are from Cambridge Econometrics (2004). All data are transformed in 1995 constant prices. See Fiaschi et al. (2011) for details.

[13]In the definition of country dummies, we consider Germany as the benchmark.

growth at regional level is likely to be characterized by spillovers, in particular technological (see, among others, Fingleton and López-Bazo (2006) and Dall'erba et al. (2009)).[14] In order to do this we compute a bootstrap Moran's I test with two different specifications for the spatial weights matrix ($\mathbf{W1}$, based on geographical contiguity and $\mathbf{W2}$, based on the inverse of the distance between regions)[15], and two different auxiliary distributions for the wild bootstrap (symmetric and asymmetric), (see Appendix C for details on the implementation of the test in semiparametric models). From Table 1 we see that the Moran's I test can never reject the null hypothesis of no spatial dependence at the usual levels of confidence.

3.2 Test of Residual Growth

Figure 1 reports the estimated density of the annual residual growth $\hat{\mathbf{g}}^R$ conditioned on the initial level of productivity. We also report the conditional mean (thick line) with the corresponding confidence bands, and a vertical line representing the unconditional mean, which is approximately zero as expected. Figure 1 shows that for any initial level of productivity most of the mass of the 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 2.4) has not significant distributional effects, i.e. the model appears correctly specified, at least conditioning on the initial level of productivity (see Eq. 13).

[14]In Fiaschi et al. (2011) we find that over the subperiod 1992-2002 spatial dependence only appears in the form of spatial lags in the exploratory variables for two out of four models. Therefore, here we decided to estimate a semiparametric model without spatial lags in the explanatory variables and to conduct a test on the residuals for the possible presence of spatial effects.

[15]See Appendix C and Fiaschi et al. (2011) for details.

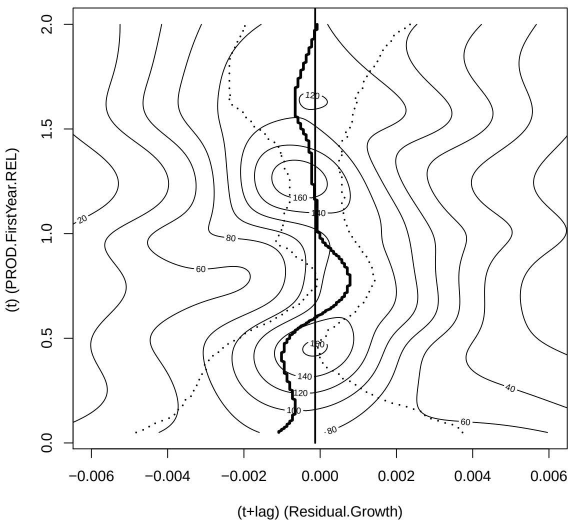

Figure 1: Conditional distribution of residual growth, the conditional mean (thick line), its confidence bands (dotted lines) and the unconditional mean (thin vertical line).

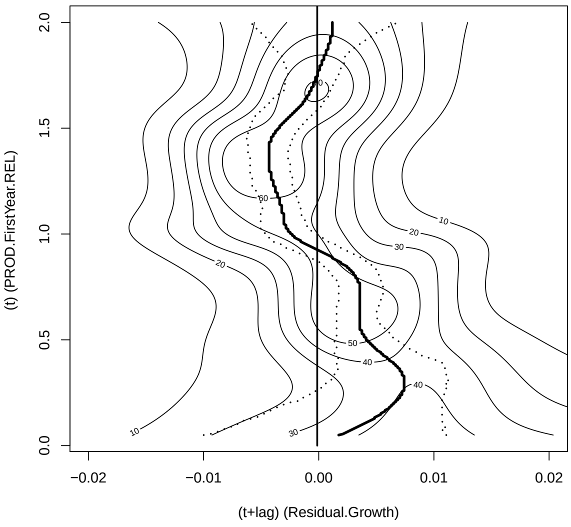

Figure 2: Conditional distribution of residual growth with *bias*, the conditional mean (thick line), its confidence bands (dotted lines) and the unconditional mean (thin vertical line).

In Figure 2 we report the result of the test for the case where regressiors include only a constant, which represents the extreme omitted-variable case; as expected the test suggests the presence of omitted variables which have a different impact on growth conditioned to the level of initial productivity.

3.3 The Unconditional Distribution Dynamics

As benchmark, in this section we study the unconditional distribution dynamics of labour productivity. 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 productivity level at time t; the corresponding confidence band at 95% significance level (indicated by dotted lines) obtained by a bootstrap procedure,[16] and the $45°$ line.

First of all, we present the actual stochastic kernel of productivity in Figure 3, and the actual distributions (AD) of productivity in 1992 and 2002, along with the actual ergodic distribution (AED) in Figure 4.

[16]The procedure is illustrated in Appendix D.

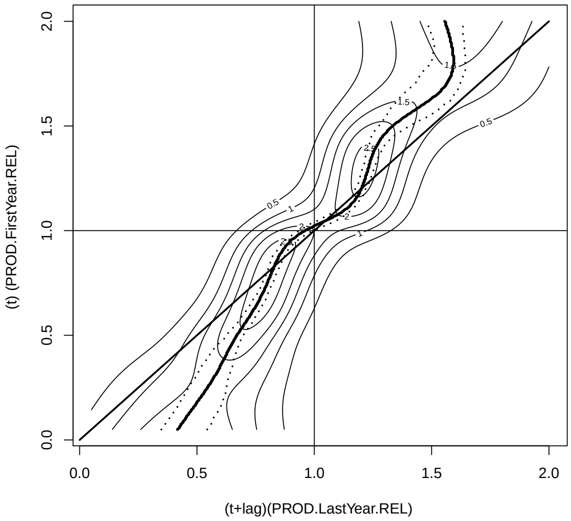

Figure 3: Actual stochastic kernel of productivity. Thick line: median of the stochastic kernel; dotted lines: 5% confidence bands.

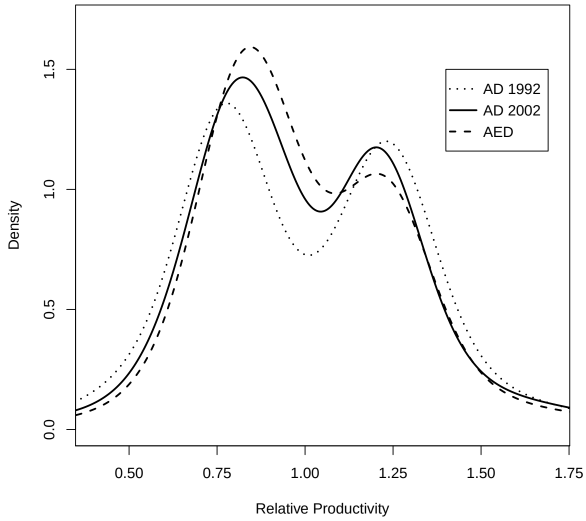

Figure 4: AD 1992 (dotted line), AD 2002 (solid line) and AED (dashed line) distributions of productivity

Figure 3 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. This is reflected in the 1992 distribution and even more in the 2002 distribution, showing two peaks in the proximity of the values of 0.8 and 1.2.[17] Accordingly, this tendency is apparent in the ergodic distribution (see Figure 4), which shows the long-run effects of the distribution dynamics implied by the actual stochastic kernel. The presence of two peaks in productivity and the evidence of strong persistence of the initial levels of productivity is consistent with a multiple equilibria model.[18]

In the following sections we examine the effects on the distribution dynamics of selection of explanatory variables.

3.4 Conditional Distribution Dynamics

Given the results of the estimation of the growth model in Eq. (3), reported in Table 1, and once controlled for the potential presence of distributional effects in residual growth, the analysis proceeds by calculating and discussing the distributional impact of some variables present in the preferred specification of Table 1. In particular we present the results on variables of different nature: country

[17]Tests 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.

[18]See Fiaschi and Lavezzi (2007) for further discussion on polarization across European regions.

dummies, e.g. a typical qualitative variable; initial productivity, and some standard regressors, such as the variables reflecting the accumulation of factors: employment growth and investment rates.[19]

3.4.1 Country Dummies

For the initial productivity level, we highlight the effect for region i of belonging to a certain state. Figure 5 reports: the estimate of the 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 calculated as $\hat{\mathbf{g}}_k^M = \hat{\mu}_k(X_k)$; the estimated mean of MGE conditioned on the initial level of (relative) productivity (thick solid line), i. e. $E\left[\hat{\mathbf{g}}_k^M|\mathbf{y}(0)\right]$, and its confidence bands (dotted lines)[20] and, finally, the unconditional mean (thin vertical solid line), i. e. $\bar{\hat{\mathbf{g}}}_k^M$. Figure 6 displays the effect on growth of country dummies conditional on the initial productivity level, highlighting the membership of regions to a state.

In Figure 5 we notice that for regions 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, Portugal and Italy, see Figure 6) have a conditional mean remarkably below the unconditional mean. 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.[21] Regions with above-average initial productivity display a conditional mean of marginal growth which is generally not statistically different from the unconditional mean. However, within a large confidence band, regions of France and Germany present conditional mean values below the unconditional mean, while regions of Belgium, Netherlands, Luxembourg and Denmark have conditional mean near or above the unconditional mean (see Figure 6).

[19] The results on the distributional impact of the other explanatory variables are available upon request.

[20] Confidence bands are based on 300 bootstraps.

[21] Figure 6 shows that regions from Italy, albeit having initial conditions similar to those of Ireland, Spain and UK, had a lower MGE related to country-specific factors.

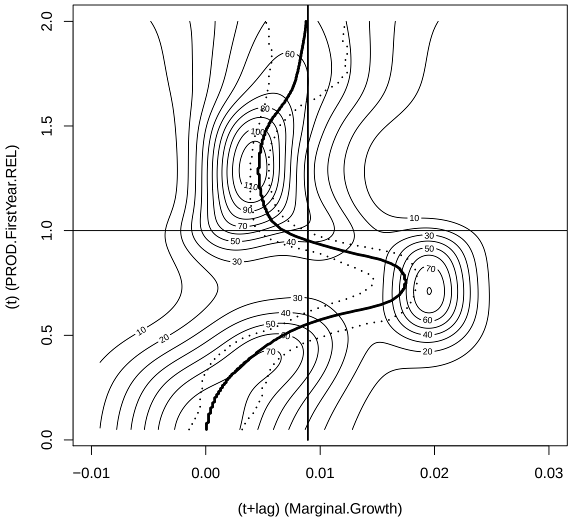

Figure 5: MGE conditioned on the initial level of productivity, estimated mean of MGE conditioned on initial level of productivity (thick solid line), its confidence bands (dotted lines), and unconditional mean (thin solid vertical line). Counterfactual variable: Country Dummies

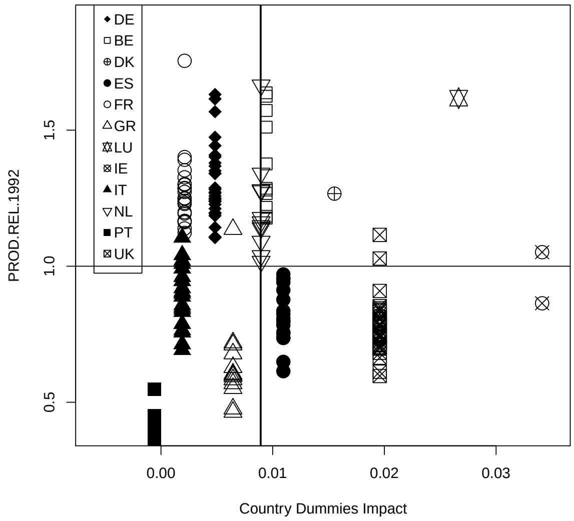

Figure 6: Impact of country dummies on growth, conditioned on the initial level of productivity and its unconditional mean (solid vertical line).

To highlight the country-effects on the distribution dynamics, we first of all compare in Figure 7 the ADs in 1992 and 2002, and the counterfactual distribution (CD) in 2002.[22]

[22]To save space we do not report the estimate of actual and counterfactual kernels. They are available upon request by authors.

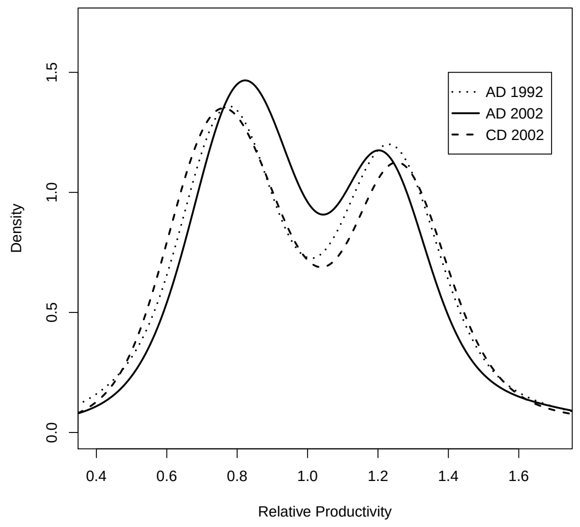

Figure 7: AD in 1992 (dotted line), AD in 2002 (solid line), and CD in 2002 (dashed line). Counterfactual variable: Country Dummies.

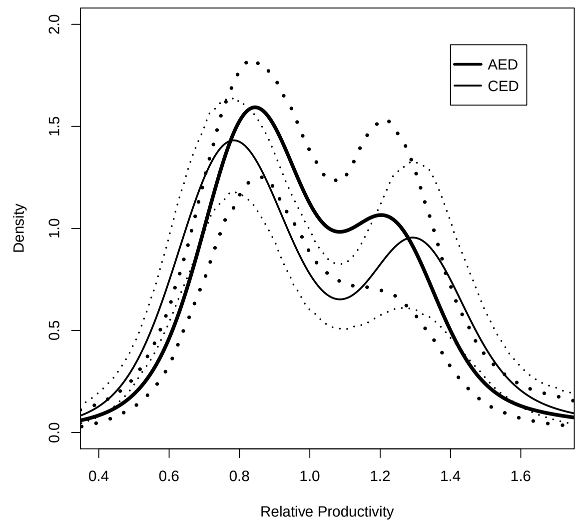

Figure 8: AED (thick line) and CED (thin line) with confidence bands at 95% level (dotted lines). Counterfactual variable: Country Dummies.

We notice that, the ADs in 1992 and 2002 display two peaks, although the distribution in 2002 contains less mass in the tails. In addition, in 2002 the CD overlaps with the AD in the tails which implies that country factors have no significant effects at those productivity ranges. However, in the central part 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 close to the value of one which, given that productivity is normalized with respect to sample average, represents the average productivity level. Hence, country factors seem to favour convergence only in an intermediate range of the productivity distribution.

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 evidence of a contribution of country-wide factors on convergence in the middle range of the productivity distribution only, but this contribution is not statistically significant in the long run.

Finally, computation of the values of a synthetic index of dispersion such as the Gini index, presented in Table 2 confirms these findings. Between 1992 and 2002 overall inequality decreases, although the Gini index is unable to capture the persistence of two peaks in the distribution. The comparison between AD and the CD in 2002, and between the AED and the CED, confirms that the latter displays higher inequality, although the differences are not statistically significant.

	AD 1992	AD 2002	CD 2002	AED	CED
Gini	0.18	0.16	0.18	0.16	0.19
s.e.	(0.008)	(0.008)	(0.007)	(0.035)	(0.043)

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

3.4.2 Initial Productivity

In Figure 9 we present the MGE for initial productivity. The identified pattern is consistent with conditional convergence, as the result in Table 1: 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.

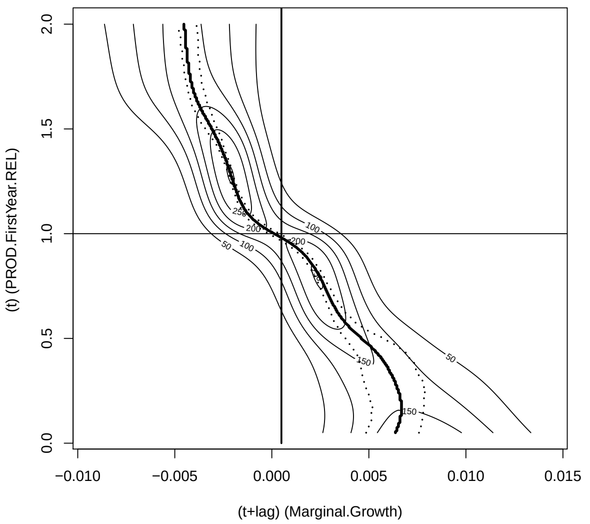

Figure 9: MGE conditioned on the initial level of productivity, estimated mean of MGE conditioned on initial level of productivity (thick solid line), its confidence bands (dotted lines), and unconditional mean (thin solid vertical line). Counterfactual variable: Initial Productivity.

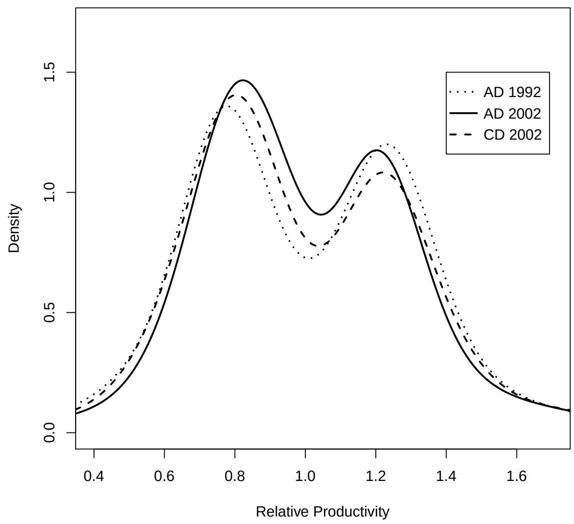

Figure 10: AD in 1992 (dotted line), AD in 2002 (solid line), and CD in 2002 (dashed line). Counterfactual variable: Initial Productivity.

The overall distributional impact seems sizeable, as highlighted by the comparison between the 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 dispersed. This is already evident in the CD in 2002, but it is much more evident in the CED. Gini indexes reported in Table 3 quantify the fall of inequality from 1992 to 2002 in about 2 base points (the difference between indexes related to AD and CD are indeed statistically significant).

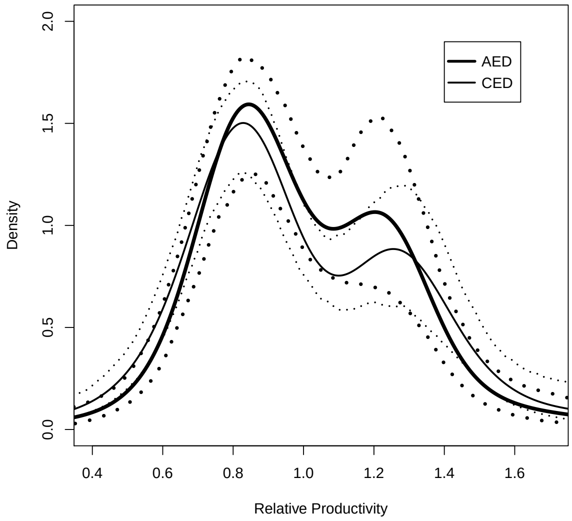

Figure 11: AED (thick line) and CED (thin line) with their confidence bands at 95% level (dotted lines). Counterfactual variable: Initial Productivity.

	AD 1992	AD 2002	CD 2002	AED	CED
Gini	0.18	0.16	0.18	0.16	0.18
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, although initial productivity contributes to reduce inequality, it only slightly affects the tendency towards polarization. That is, the inverse relationship between initial productivity and the growth rate holds on average, as shown also 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 0.8 and 1.2, 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 has not decreased. What decreased was the distance of regions in the tails of the distribution from the average, and the distance between the peaks. This result is in line with the remark of Bernard and Durlauf (1996) on the misleading implications of a negative coefficient of initial productivity in growth regressions, and is consistent with the presence of multiple equilibria.

3.4.3 Employment Growth and Investment Rate

In a cross-country analysis, Beaudry et al. (2005) find that changes in the patterns of accumulation of factors of production, labour 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 and investment rate which have, respectively, a nonlinear negative effect and a linear positive effect on productivity growth (see Table 1).[23]

The conditional mean of MGE of employment growth 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 CD 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. Hence, in the short run, employment growth acts as a force favouring divergence, in particular by pushing some high-productivity regions further above the mean. However, the tendency towards twin-peakedness does not seem to be affected.

This tendency also appears in the CED, shown in Figure 14. The difference in the high-productivity peak is almost significant at 5% confidence level.

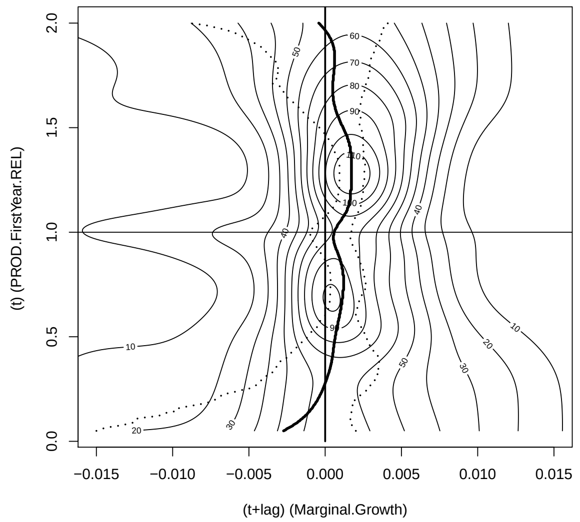

Figure 12: MGE conditioned on the initial level of productivity, estimated mean of MGE conditioned on initial level of productivity (thick solid line), its confidence bands (dotted lines), and unconditional mean (thin solid vertical line). Counterfactual variable: Employment Growth.

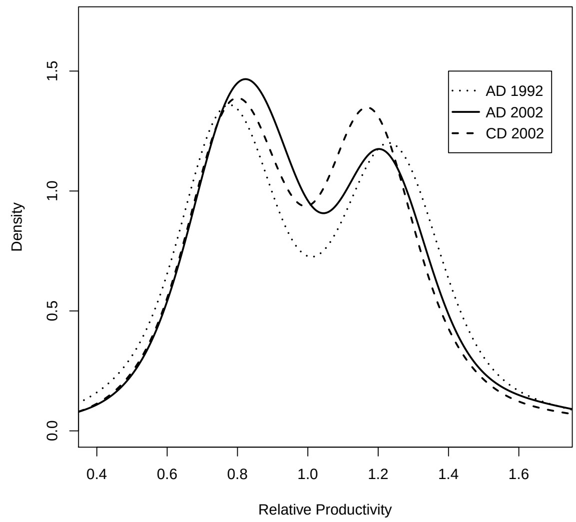

Figure 13: AD in 1992 (dotted line), AD in 2002 (solid line), and CD in 2002 (dashed line). Counterfactual variable: Employment Growth.

[23]The figure on the effect of employment growth is omitted for reasons of space and is available upon request.

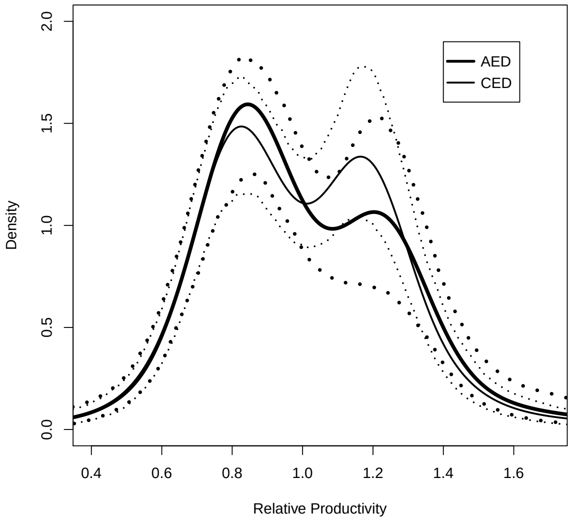

Figure 14: AED (thick line) and CED (thin line) with their confidence bands at 95% level (dotted lines). Counterfactual variable: Employment Growth.

As regards the investment rate Figure 15 shows that its MGE is higher, and statistically significant, only for regions with above-average initial productivity, hence this factor acts a source of divergence. This is confirmed in Figure 16 where we notice that the CD in 2002 displays more mass near the central value of one. This tendency also characterizes the long run (see Figure 17), although the difference between the AED and CED is not statistically significant at 95% confidence level.

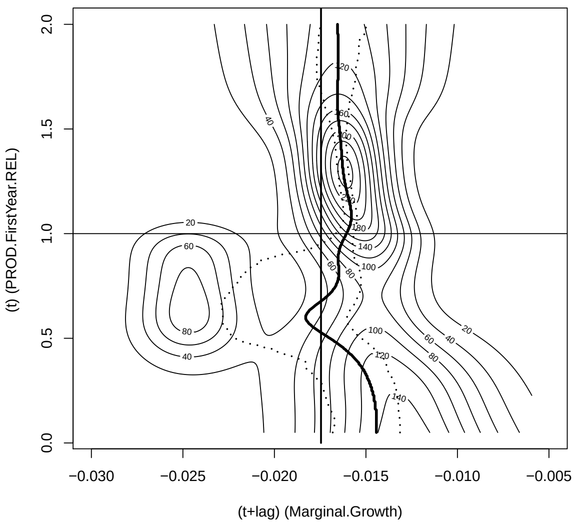

Figure 15: MGE conditioned on the initial level of productivity, estimated mean of MGE conditioned on initial level of productivity (thick solid line), its confidence bands (dotted lines), and unconditional mean (thin solid vertical line). Counterfactual variable: Investment Rate.

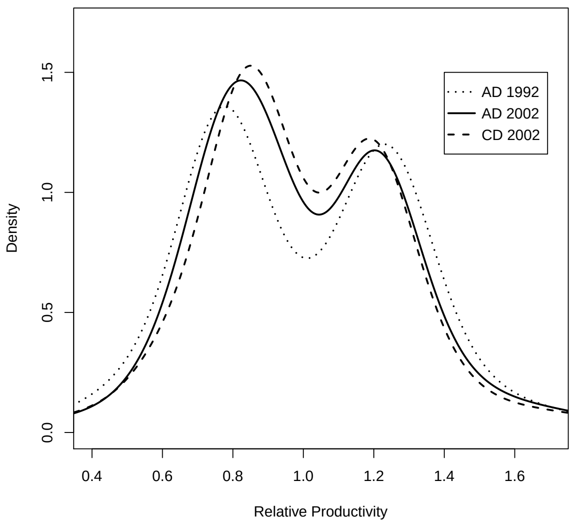

Figure 16: AD in 1992 (dotted line), AD in 2002 (solid line), and CD in 2002 (dashed line). Counterfactual variable: Investment Rate.

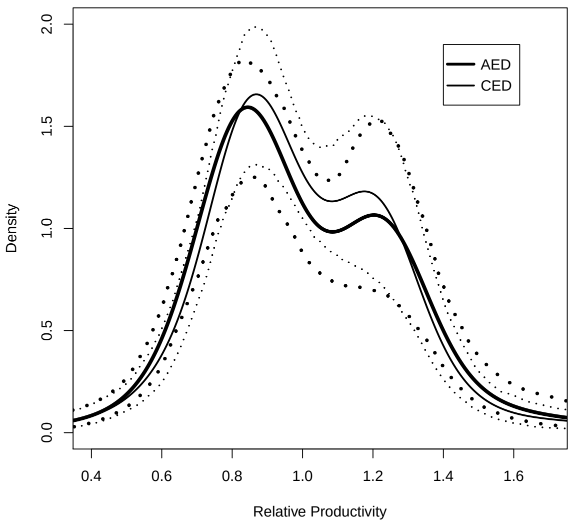

Figure 17: AED (thick line) and CED (thin line) with their confidence bands at 95% level (dotted lines). Counterfactual variable: Investment Rate.

Overall, the effects from the accumulation of factors (labor and capital) is similar: for both variables, regions with higher initial productivity levels had a significant positive effect on growth. This is in stark contrast with the effect suggested by the estimation of the coefficients for the employment growth and investment in Table 1 which are broadly in line with the Solow model which predicts, respectively, a negative and positive effect on growth.[24]

4 Concluding Remarks

In this paper we proposed a method to analyze the factors driving convergence and divergence processes in the growth dynamics. The proposed methodology combines the growth regression approach, albeit allowing for a semiparametric specification, with the distribution dynamics approach. In particular, the potential distributional impact of a given variable is evaluated by the comparison of actual, counterfactual and ergodic distributions (and the related actual and counterfactual stochastic kernels), where counterfactuals are calculated by removing cross-section heterogeneity in the variable of interest through the imputation of sample averages to all the units of the cross-section. The methodology also allows for testing for the possible presence of distributional effects in the residuals of growth regression, as a means to assess the goodness of fit of the estimated model.

We applied our methodology to a sample of European regions, and showed its potential to shed light on the identified tendency for polarization, by the analysis of the distributional effect of country dummies, initial conditions and the accumualation of factors, labor and capital. In all cases it was possible to obtain information otherwise missed by existing methods of investigation of the determinants of distribution dynamics.

[24]This result is in line with Durlauf et al. (2001, p. 934), who find that the effect on growth of population growth and investment is highly sensitive to initial productivity.

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	Rheinhessen-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
BE22	Limburg (B)	ES11	Galicia	FR71	Rhône-Alpes	LU	Luxembourg		and Northamptonshire
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, Worcest.
BE25	West-Vlaanderen	ES21	Pais Vasco	FR82	Prov.-Alpes-Côte d'Azur	NL13	Drenthe		and Warwickshire
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
DE14	Tübingen	ES52	Comunidad Valenciana	GR24	Sterea Ellada	PT11	Norte		and Oxfordshire
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
DE25	Mittelfranken	ES7	Canarias	GR43	Kriti	PT2	Açores		and North Somerset
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	Västsverige	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 Descriptive Statistics

	log.PROD.REL.1992	log.INV.RATE	log.EMP.GR	OB1.CF	
Mean	-0.05	-1.67	-3.33	0.01	
Stand. Dev.	0.33	0.39	0.22	3.04	0.02
	log.ECO.DEN.1992	AGRI.1992	MANU.1992	CON.1992	
Mean	0.86	0.05	0.2	0.06	
Stand. Dev.	1.34	0.04	0.08	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 4: Mean and Standard Deviation of variables used in the growth regressions

	log.PROD.REL.1992	log.INV.RATE	log.EMP.GR	OB1.CF
log.PROD.REL.1992	1.00	0.11	0.01	-0.47
log.INV.RATE	0.11	1.00	0.08	0.33
log.EMP.GR	0.01	0.08	1.00	0.03
OB1.CF	-0.47	0.33	0.03	1.00
log.ECO.DEN.1992	0.49	-0.27	0.07	-0.24
AGRI.1992	-0.51	0.28	-0.01	0.37
MANU.1992	0.26	-0.26	-0.18	-0.45
CON.1992	-0.21	0.24	-0.14	0.21
NON.MKT.SER.1992	-0.07	0.07	0.11	0.37
FIN.1992	0.15	-0.04	0.19	-0.12
HOT.1992	-0.36	0.13	0.17	0.24
TRANS.1992	-0.05	-0.08	0.17	0.19
WHOLE.1992	-0.24	0.11	0.12	0.24
OTHER.SER.1992	0.58	-0.13	-0.09	-0.35

Table 5: Correlations among the variables used in the growth regressions

	log.ECO.DEN.1992	AGRI.1992	MANU.1992	CON.1992
log.PROD.REL.1992	0.49	-0.51	0.26	-0.21
log.INV.RATE	-0.27	0.28	-0.26	0.24
log.EMP.GR	0.07	-0.01	-0.18	-0.14
OB1.CF	-0.24	0.37	-0.45	0.21
log.ECO.DEN.1992	1.00	-0.75	0.23	-0.42
AGRI.1992	-0.75	1.00	-0.14	-0.07
MANU.1992	0.24	-0.35	1.00	-0.14
CON.1992	-0.41	0.28	-0.14	1.00
NON.MKT.SER.1992	-0.04	-0.07	-0.47	-0.02
FIN.1992	0.46	-0.34	-0.15	-0.19
HOT.1992	-0.32	0.27	-0.44	0.00
TRANS.1992	0.28	-0.21	-0.41	-0.05
WHOLE.1992	0.07	0.15	-0.45	-0.11
OTHER.SER.1992	0.51	-0.50	-0.05	-0.19

Table 6: Continued: Correlations among variables used in the 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
OB1.CF	0.37	-0.12	0.24	0.19	0.24	-0.35
log.ECO.DEN.1992	-0.04	0.46	-0.32	0.28	0.07	0.51
AGRI.1992	-0.07	-0.34	0.27	-0.21	0.15	-0.50
MANU.1992	-0.47	-0.15	-0.44	-0.41	-0.45	-0.05
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 7: Continued: Correlations among variables used in the growth regressions

C Bootstrap Procedure to Compute 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 heteroskedasticity.

Given the semiparametric model:

$$\mathbf{g} = \alpha + \sum_{k=1}^{K} \mu_k(\mathbf{X}_k) + \mathbf{u}; \tag{14}$$

where $\mathbf{g}$ is the $N \times 1$ vector of growth rates, α is the $N \times 1$ vector of constant terms, $\mathbf{X}$ is the $N \times K$ matrix of explanatory variables, $\mu(\cdot)$ are nonparametric functions, and $\mathbf{u}$ is the $N \times 1$ vector of error terms such that $E(\mathbf{u}|\mathbf{X}) = 0$ and $var(\mathbf{u}|\mathbf{X}) = \sigma^2(\mathbf{X})$, the bootstrap procedure consists in the following five steps (see Härdle et al. (2004, pp. 127-128)).

1. Estimate Model (14) and obtain the residuals $\hat{\mathbf{u}}$.

2. Compute the observed Morans' I statistics:
$$I_{obs} = \frac{N}{S}\left(\frac{\hat{\mathbf{u}}'\mathbf{W}\hat{\mathbf{u}}}{\hat{\mathbf{u}}'\hat{\mathbf{u}}}\right),$$
where $\mathbf{W}$ is the weight spatial matrix and S is the sum of the elements of $\mathbf{W}$.

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

   (a) draw with replacement N residuals $u_i^* = \hat{u}_i\eta_i$ $(i = 1, ..., N)$ where η_i are independent drawings from one of the following two-point distributions:
   $$\eta = \begin{cases} -1 & \text{with } p = 1/2 \\ 1 & \text{with } 1-p \end{cases} \tag{15}$$
   or,
   $$\eta = \begin{cases} \frac{(1-\sqrt{5})}{2} & \text{with } p = (5+\sqrt{5})/10 \\ \frac{(1+\sqrt{5})}{2} & \text{with } 1-p \end{cases} \tag{16}$$
   We call *symmetric* wild bootstrap the method corresponding to Eq. (15), and *asymmetric* wild bootstrap that corresponding to Eq. (16).

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

   (c) estimate Model (14) using $\mathbf{g}^*$ and take the residuals $\hat{\mathbf{u}}^*$.

4. Compute for each bootstrap sample, $b = 1, ..., B$, the Moran's I statistic I_b^*.

5. Compute the corresponding equal-tail bootstrap P value (see Davidson and MacKinnon (2007)):
$$P^*(I_{obs}) = 2\min\left(\frac{1}{B}\sum_{b=1}^{B}\#\{I_b^* \leq I_{obs}\}, \frac{1}{B}\sum_{b=1}^{B}\#\{I_b^* > I_{obs}\}\right) \tag{17}$$

In our estimates we set B=1000 and we consider two different definitions for the spatial weight matrix (see Anselin (1988)), **W1** and **W2**, respectively based on the distance between regions and on the presence of a common border. Specifically, for two regions (i, j), the values of the elements of $W1$ and $W2$ are respectively given by:

- $w_1(i,j) = w_1^*(i,j)/\sum_j w_1^*(i,j)$ where:
$$w_1^*(i,j) = \begin{cases} 0 & \text{if } i = j \\ d_{ij}^{-2} & \text{otherwise} \end{cases}$$

- $w_2(i,j) = w_2^*(i,j)/\sum_j w_2^*(i,j)$ where:
$$w_2(i,j)^* = \begin{cases} 1 & \text{if } i \text{ and } j \text{ share a common border} \\ 0 & \text{otherwise.} \end{cases}$$

D Bootstrap Procedure to Compute Confidence Intervals

The bootstrap procedure used to calculate the confidence bands for the estimated median of the stochastic kernels and ergodic distributions is respectively based on the procedure in Bowman and Azzalini (1997, p. 44) and in Fiaschi and Romanelli (2009).

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

1. Estimate from sample **Y** the stochastic kernel, the median of the stochastic kernel and the corresponding ergodic distribution $\hat{\psi}$.

2. Select B independent bootstrap samples $\{\mathbf{Y}_1^*, ..., \mathbf{Y}_B^*\}$, each consisting of n data values drawn with replacement from **Y**.

3. Estimate the the stochastic kernel, the median of stochastic kernel and the corresponding ergodic distribution $\hat{\psi}_b^*$ corresponding to each bootstrap sample $b = 1, ..., B$.

4. Use the distribution of $\hat{\psi}_b^*$ about $\hat{\psi}$ to mimic the distribution of $\hat{\psi}$ about ψ.

We set B=500 and in each bootstrap the bandwidth is set equal to the one calculated for the estimation of the density of the observed sample **Y**.

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