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Counterfactual Distribution Dynamics across European Regions

Abstract

This paper proposes a methodology which combines elements of parametric regression analysis with the nonparametric distribution dynamics approach in order to analyse the role of some variables in the convergence of productivity across European regions over the period 1980-2002. We find that the initial productivity crucially accounts in the convergence process across European regions. Differently, employment growth seems not to play a role, while the Structural and Cohesion Funds seem to play a positive role, even though such effect seems to be very low and statistically significant only at the low bound of the range of initial productivity. The structural change of regional economies plays a positive role, but such effect is statistically significant only for the least productive regions. The output composition of a region in 1980 affects the convergence process of productivity growth in several ways. In particular, the share of non market services on output acts like a source of convergence from 1980 to 2002 but in the long-run it plays a negligible role. Finally, the share of finance acts like a force of divergence across European regions, especially for the least productive regions.

Classificazione JEL: C21; E62; R11; O52

Keywords: European regional policy, structural change, convergence, European regions.

Contents

I. Introduction

Convergence in living standards across European regions has recently attracted the interest of economists and of policy makers of the European Union. At present, no consensus seems to have emerged on whether the regions of Europe are converging in income per capita or in labour productivity (see, e.g, Magrini (2004) 18 for a recent account). The increasing importance of European Union regional policy, indeed, seems to imply that the process of regional convergence needs to be robustly sustained by public intervention.[1]

This paper analyzes the process of convergence in labour productivity for a large sample of European regions in the period 1980-2002, paying attention in particular to the effects of European Union's regional policy. To this purpose, we propose a methodology based on the Quah (1997) 22 and on the counterfactual analysis of convergence which exploits the *counterfactual* distribution dynamics to identify the the impact of a specific explanatory variable on the evolution over time of the distribution of labour productivity across European regions.

In particular, this methodology combines elements of parametric regression analysis with the nonparametric distribution dynamics approach,[2] and allows to detect which variables favour or retard convergence, and which part of the distribution appears to be affected by them.

Our main results are: (i) the impact of initial productivity on the distribution dynamics is such the highest for the lowest values of relative initial productivity and decreasing with initial relative productivity. This is actually what the theory of convergence predicts, that is poor regions will grow faster than rich regions. Our nonparametric methodology shows that such conditional convergence holds for the entire range of initial productivity. (ii) Employment growth does not play a any role in the explanation of the convergence across regional productivity in Europe. This evidence further foster the findings of Puga (1999) **?**, (2002) **?** that labour mobility across European countries (regions) is very low and therefore s not a source of convergence across European regions. (iii) EU regional policy, summarized by the effect on productivity of Structural and Cohesion Funds, plays a positive role in convergence among European regions especially for the regions with a very low initial relative productivity (under 75% of average productivity), but such effect seems to be very low. This low impact is probably due to the generally low amount of European funds with respect to regional output (on average below 0.5% of total output). (iii) The structural change of regional economies captured by the change in agricultural sector plays a positive role even though such effect is statistically significant only for the least productive regions (i.e., below 0.5). (iv) The share of non market services on output acts like a source of convergence from 1980 to 2002 but in the long-run it

[1] In Fiaschi *et al.* (2008) 15 we document that the amount of resources devoted to "cohesion" policies have increased eightfold in relative terms, from about 0.06% to 0.5% of European GVA, across the programming periods between 1975 and 1999.

[2] In a companion paper, Fiaschi *et al.* (2009) 15, we utilize a standard approach based on Barro regressions to study the dynamics of labour productivity in European regions and the effects of EU regional policy.

plays a negligible role. (v) The share of finance on output act like a force of divergence across European regions, especially for the least productive regions.

The paper is organized as follows: Section II. describes our method for the empirical analysis; Section III. presents the results; Section IV. contains our concluding remarks

II. Methodology

Two main approaches to study convergence in per capita income/productivity exist: the "regression approach" (RA) and the "distribution dynamics approach" (DDA). RA studies whether economies are converging towards their steady-state level of per capita income or productivity and, eventually, the speed of convergence. DDA, instead, aims at understanding how the cross-sectional distribution evolves over time, considering also the intra-distribution dynamics.[3]

The most representative examples of RA are the so-called Barro regressions (see Barro (1991) 2 and Barro and Sala-i-Martin (2004) 1). These regressions aim at testing the hypothesis of conditional convergence implied by the neoclassical model of Solow (1956) 27, and the role of various growth determinants, from those suggested by the Solow model itself, namely investment rate and labour force growth, to others such as human capital, institutions, financial development, etc.

In a series of papers, Danny Quah (1996a 20, 1996b 21, 1997 22) has criticized the RA for not being able to capture phenomena like *mobility*, *stratification* and *polarization* in the world income distribution.[4] de la Fluente (2003) **?** extends the convergence equation methodology to overcome this limitations performing an exercise that he calls "convergence accounting". In particular, he decomposes the σ and β convergence measures into sum of partial σ and β measures describing the contribution to observed convergence of each of explanatory variables included in a growth regression.

As an alternative, Quah proposed the DDA, i.e. a study of the evolution in time of the whole cross-section income distribution. In its simplest form, the distribution dynamics of a cross-section of economies can be summarized by a Markov transition matrix and the associated ergodic distribution (Quah, 1993 19). The nonparametric estimate of the stochastic kernel, which represents the continuous version of a transition matrix, avoids the discretization of the income space.

In order to describe how a set of explanatory variables can affect the cross-sectional distribution of income in time, Quah (1997) 22, p. 47 introduces *conditioned* stochastic kernels,

[3]See Quah (1997) 22 for more details, and Durlauf *et al.* (2005) 8 for an exhaustive survey of different empirical methodologies to study economic growth.

[4]In addition to these type of criticism, Bernard and Durlauf (2006) 5 showed that in a growth regression a negative sign of the coefficient of initial income does not necessarily imply convergence in the sense of Solow, i.e. independently from initial conditions, as the data-generating process may be characterized by multiple, locally stable, equilibria.

by means of *conditioning schemes*. Conditioned stochastic kernels map *unconditioned* income levels, i.e. income normalized with respect to the sample average, to *conditioned* income levels, that is incomes normalized with respect to some factor that is suspected to affect the dynamics.[5]

The counterfactual analysis is another methodology aiming at detecting the impact of explanatory variables on distributions. Di Nardo *et al.* (1996) **?** apply a semiparametric procedure that generalized the Oaxaca decomposition in order to analyse the effects of institutional and labour market factors on the distribution of wages in the US over the period 1973-1992. Machado and Mata (2005) **?** using an approach that resembles Di Nardo et. al (1996) ? analyse the changes in the distribution of wages in Portugal from 1980 to 1995. Beaudry *et al.* (2004) 4 apply the counterfactual analysis to study the impact of changes of investment rates over time and their effects on growth on the cross-country distribution of per capita GDP. Finally, Cheshire and Magrini (2005) **?** combine the RA with the use DDA to analyse the factors driving convergence and divergence in the growth dynamics of European urban regions over the period 1978 to 1994. In particular, they estimate a growth model to calculate counterfactual distributions and then analyse the counterfactual distribution dynamics by estimating the stochastic kernels.

Inspired by these contributes, in the present paper evaluates for some relevant variables their impact on the distributions of labour productivity across European regions. The methodology is composed by the following steps: i) the estimation of growth model; ii) the calculation of the counterfactual distributions at the end of the period; iii) the estimation of counterfactual stochastic kernels; iv) the estimation of counterfactual ergodic distributions; v) the estimation of the *marginal effect* of the variable on the distribution at the end of the period.

Step i) provides the basic information to measure the *average effect* of each individual variable on productivity growth rate. Given this information, Steps ii)-iv) show the effect on the distribution of productivity, the *distributional effect*, of each individual variable by comparing the actual and the counterfactual distributions at the end of period, the actual and the counterfactual stochastic kernels and the actual and the counterfactual ergodic distributions. Step v) points out to quantify directly the distributional effect of a given variable by the distribution of marginal growth rate conditional to initial level of productivity. The latter appears to be a more precise measure of the distributional effect of the variable because it is independent of the magnitude of its average effect. Indeed, the distributional effect estimated by Step ii)-iv) can result not statistically significant when the average effect is very low.

As in Cheshire and Magrini (2005) ? we therefore combine the RA with the DDA. Differently from them, we estimate the ergodic distributions (Step iv)) to understand if the estimated distribution dynamics over the sample period has completely exhausted its effect on the distribution at the end of period. Moreover, the estimation of the marginal effect (Step v)) provides

[5]See also Basile (2009) 3 for an application of the conditioning scheme for explaining the productivity polarization across European regions.

a better understanding of the contribution of each variable in the convergence process. Finally, a side-effect of our methodology is a diagnostic test to detect the distribution effect of potential omitted variables in the specification of growth model.

II.A. Decomposing the Growth Rate

Assume there are N regions and define by $y_{i,t}$ labour productivity of region i at time t. The law of motion of $y_{i,t}$ between period 0 and period T can be expressed as:

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

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

Assume that g_i is a function of K explanatory variables ($\mathbf{z}^1$, ..., $\mathbf{z}^K$), whose values in region i are collected in vector $\mathbf{z}_i = \left\{z_i^1, ..., z_i^K\right\}$, and a residual component accounting for unobservable factors, υ_i, that is:

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

Assuming that $\varphi(\cdot)$ is linear, we obtain[6]:

$$\mathbf{g} = \mathbf{Z}\boldsymbol{\beta} + \boldsymbol{\upsilon}, \tag{3}$$

where $\mathbf{g}$ is the vector of growth rates, $\mathbf{Z}$ is the $N \times K$ matrix of explanatory variables including an intercept, $\boldsymbol{\beta}$ is a vector of parameters to be estimated, and $\boldsymbol{\upsilon}$ is the vector of error terms. Because of its linearity, Eq. (3) can be rewritten as:

$$\mathbf{g} = \mathbf{Z}^{-k}\boldsymbol{\beta}^{-k} + \mathbf{z}^k\beta^k + \boldsymbol{\upsilon}; \tag{4}$$

where $\mathbf{Z}^{-k} = \left\{\mathbf{z^1}, ..., \mathbf{z^{k-1}}, \mathbf{z^{k+1}}, ..., \mathbf{z^K}\right\}$ and $\boldsymbol{\beta}^{-k} = \left\{\beta^1, ..., \beta^{k-1}, \beta^{k+1}, ..., \beta^K\right\}$ are respectively the matrix of explanatory factors and the vector of coefficients excluding factor k.

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

$$\begin{aligned} y_i(T) &= y_i(0)e^{\mathbf{z}_i^{-k}\boldsymbol{\beta}^{-k}+z_i^k\beta^k+\upsilon_i} = \\ &= \underbrace{y_i(0)e^{\mathbf{z}_i^{-k}\boldsymbol{\beta}^{-k}}}_{y_i^{-k}(T)}\underbrace{e^{(z_i^k\beta^k)}}_{e^{g_{i,M}^k}}\underbrace{e_i^{\upsilon}}_{e^{g_{i,R}}}, \end{aligned} \tag{5}$$

where $y_i^{-k}(T) = y_i(0)e^{\mathbf{z}_i^{-k}\boldsymbol{\beta}^{-k}}$ is the level of productivity in period T obtained by "factoring

[6]Modelling growth rate g_i by a semiparametric model the methodology proposed in what follows can be easily extended to a more general framework:

$$g_i \quad = \alpha + \textstyle\sum_{k=1}^{K-1}\mu^k(z_i^k) + \upsilon_i.$$

out" the effect of $\mathbf{z}^k$, $g_{i,M}^k = z_i^k \beta^k$ is the part of the growth rate of y_i explained by $\mathbf{z}^k$, capturing the "marginal" effect of $\mathbf{z}^k$ on g, and $g_{i,R} = \upsilon_i$ is the "residual growth" not explained by the explanatory variables in $\mathbf{Z}$.

In the next section we discuss how the growth rate decomposition showed in Eq. (5) can be utilized to analyze the distribution dynamics conditioned on the *k-th* variable, by estimating the counterfactual distribution and the marginal effect of $\mathbf{z}^k$.

II.B. Counterfactual Distributions and the Marginal Effect of $\mathbf{z}^k$

In this section we discuss how to calculate the counterfactual distribution, which is the basic information for the estimation of counterfactual stochastic kernel and marginal effect of $\mathbf{z}^k$.[7]

II.B.i. Counterfactual Distribution

The counterfactual growth rate of region i referred to the k-th variable, $\hat{g}_{i,CF}^k$, is calculated by eliminating the cross-sectional heterogeneity in $\mathbf{z}^k$, that is:

$$\hat{g}_{i,CF}^k \equiv \mathbf{z}_i^{-k} \hat{\boldsymbol{\beta}}^{-k} + \bar{z}^k \hat{\beta}^k, \tag{6}$$

where $\bar{z}^k = N^{-1} \sum_{i=1}^N z_i^k$ is the average value of $\mathbf{z}^k$ across the sample units, and $\hat{\boldsymbol{\beta}} = [\hat{\boldsymbol{\beta}}^{-k}, \hat{\beta}^k]$ is the vector of parameters obtained by estimating Eq. (3).

The counterfactual productivity of region i in period T, related to the variable $\mathbf{z}^k$, is therefore defined as:

$$\hat{y}_{i,CF}^k(T) \equiv y_i(0) e^{\hat{g}_{i,CF}^k} = y_i(0) e^{\mathbf{z}_i^{-k} \hat{\boldsymbol{\beta}}^{-k} + \bar{z}^k \hat{\beta}^k}. \tag{7}$$

The counterfactual productivity represents the productivity that a region would have had at time T if there had not been differences in terms of $\mathbf{z}^k$ within the sample. In other words, $\hat{\mathbf{y}}_{CF}^k(T)$ captures the effect of the cross-sectional heterogeneous distribution of $\mathbf{z}^k$. In fact, the (log) ratio between the productivity explained by the estimation of Eq. (3) in period T, $\hat{y}_i(T)$, and the counterfactual productivity $\hat{y}_{i,CF}^k(T)$, is equal to:

$$log\left(\frac{\hat{y}_i(T)}{\hat{y}_{i,CF}^k(T)}\right) = log\left(\frac{y_i(0) e^{\mathbf{z}_i^{-k} \hat{\boldsymbol{\beta}}^{-k} + z_i^k \hat{\beta}^k}}{y_i(0) e^{\mathbf{z}_i^{-k} \hat{\boldsymbol{\beta}}^{-k} + \bar{z}^k \hat{\beta}^k}}\right) = (z_i^k - \bar{z}^k)\hat{\beta}^k,$$

[7] Beaudry *et al.* (2005) 4 aim at analyzing the differential effects of some growth determinants in two periods: 1960-1978 and 1978-1998. Thus, they build counterfactual distributions for the second period by assuming that the variable of interest (a coefficient or the distribution of, e.g., investment rates) keeps in the second period same values assumed in the first. So, in their case, the counterfactual analysis is made in the time dimension, while we carry it our in the cross-section dimension. We remark that in that framework the hypothesis of linear impact of a variable on the growth rate, i.e. using linear growth regression, can crucially affects the findings.

which exactly reflects the distribution of $\mathbf{z}^k$ across the units in the sample.

To study intradistribution dynamics we estimate stochastic kernels and ergodic distributions. Stochastic kernels indicate for each level of productivity in period t its probability distribution in period $t+\tau$, $\tau > 0$ (see Quah, 1997 22). For each stochastic kernel we estimate its corresponding ergodic distribution following the procedure in Johnson (2005) 17, adjusted for the use of normalized variables (with respect to the average) in the estimate.[8] 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. This interpretation clearly does not take into account any structural shocks, such as the diffusion of technology and the spread of education worldwide, which might lead to non-stationary processes.[9]

Given our interest in the distribution dynamics, stochastic kernels and ergodic distributions are estimated for relative variables, that is each variable is divided by its own sample average of the period. Denote the normalized variables as:

$$\begin{aligned} \tilde{y}_i(t) &\equiv y_i(t)/\bar{y}(t),\ \forall t = 0, ..., T, \text{ and} \\ \tilde{\hat{y}}^k_{i,CF}(t) &\equiv \hat{y}^k_{i,CF}(t)/\bar{\hat{y}}^k_{CF}(t),\ \forall t = 0, ..., T, \end{aligned}$$

where $\bar{y}(t) = N^{-1}\Sigma_{i=1}^N y_i(t)$, and $\bar{\hat{y}}^k_{CF}(t) = N^{-1}\Sigma_{i=1}^N \hat{y}^k_{i,CF}(t)$, $\forall t = 0, ..., T$.

The stochastic kernels of relative observations and counterfactual relative observations are respectively defined as $\phi(\tilde{\mathbf{y}}(T)|\tilde{\mathbf{y}}(0))$ and $\phi_{CF}(\tilde{\hat{\mathbf{y}}}^k_{CF}(T)|\tilde{\mathbf{y}}(0))$. The stochastic kernel $\phi(\cdot)$ maps the distribution of relative productivities in period 0, to the distribution of relative productivities in period T and can be defined as the *actual* stochastic kernel. The stochastic kernel $\phi_{CF}(\cdot)$, instead, maps the distribution of relative productivities in period 0, to the distribution of counterfactual relative productivities in period T. We define it *counterfactual* stochastic kernel.[10] If the counterfactual stochastic kernel estimating by eliminating the cross-sectional variation in factor k is not different from the actual, then $\mathbf{z}^k$ does not affect the distribution dynamics. Otherwise, $\mathbf{z}^k$ has a distribution effect.

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[8]See Fiaschi and Romanelli (2009) 16.

[9]Specifically, the ergodic distribution solves $f_\infty(z) = \int_0^\infty g_\tau(z|x) f_\infty(x)\, dx$ 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) 17, who used the *adaptive kernel estimator* discussed by 23, p. 100, in which the window of the kernel (Gaussian in our case) increases when the density of observations decreases.

[10]As noticed, Quah (1997) 22 propose an alternative way to detect possible distribution effect of a given variable using the comparison of *unconditioned* and *conditioned* stochastic kernels.

In particular, the actual stochastic kernel $\phi(\cdot)$ can be rewritten as:

$$\begin{aligned}
\phi(\tilde{\mathbf{y}}(T)|\tilde{\mathbf{y}}(0)) &= \phi\left(\frac{\mathbf{y}(T)}{\bar{y}(T)}|\tilde{\mathbf{y}}(0)\right) = \\
&= \phi\left(\frac{\mathbf{y}(0)e^{\mathbf{Z}^{-k}\boldsymbol{\beta}^{-k}}e^{\bar{z}^k\beta^k}}{\bar{\hat{y}}^k_{CF}(T)}\frac{\bar{\hat{y}}^k_{CF}(T)}{\bar{y}(T)}e^{(\mathbf{z}^k-\bar{z}^k)\beta^k}e^{v}|\tilde{\mathbf{y}}(0)\right) = \\
&= \phi\left(\frac{\hat{\mathbf{y}}^k_{CF}(T)}{\bar{\hat{y}}^k_{CF}(T)}\frac{\bar{\hat{y}}^k_{CF}(T)}{\bar{y}(T)}e^{(\mathbf{z}^k-\bar{z}^k)\beta^k}e^{v}|\tilde{\mathbf{y}}(0)\right) = \\
&= \underbrace{\frac{\bar{\hat{y}}^k_{CF}(T)}{\bar{y}(T)}}_{\text{bias composition effect}} \quad \phi\left(\tilde{\hat{\mathbf{y}}}^k_{CF}(T)\ \underbrace{e^{(\mathbf{z}^k-\bar{z}^k)\beta^k}e^{v}}_{\text{distribution effect}}\ |\tilde{\mathbf{y}}(0)\right). \qquad (8)
\end{aligned}$$

Therefore, given unbiased estimates of the parameters $\boldsymbol{\beta}$, the comparison between $\phi(\tilde{\mathbf{y}}(T)|\tilde{\mathbf{y}}(0))$ and the counterfactual stochastic kernel $\phi_{CF}(\tilde{\hat{\mathbf{y}}}^k_{CF}(T)|\tilde{\mathbf{y}}(0))$ show two effects: i) the "distribution effect", since the *k-th* variable is set to sample average and ii) the "bias composition effect", due to possible difference between the average of actual and counterfactual productivities, arising from the adopted exponential growth model in Eq. (1). In order to remove this "bias composition effect" from the comparison of the two kernels, in the representation of counterfactual stochastic kernel the observation in the last period are corrected (i.e., multiplied by the factor $\bar{y}(T)/\bar{\hat{y}}^k_{CF}(T)$).

II.B.ii. The Marginal Effect of $\mathbf{z}^k$

Given the vector of estimated parameters $\hat{\boldsymbol{\beta}}$, we define the "factoring out" productivity of region i in period T, referred to $\mathbf{z}^k$, as (see Eq. (5)):

$$\hat{y}_i^{-k}(T) = y_i(0)e^{\mathbf{z}_i^{-k}\hat{\boldsymbol{\beta}}^{-k}}. \qquad (9)$$

This amounts to factoring out $\mathbf{z}^k$ from the calculation of the fitted growth rate $\hat{g}_i$ (i.e., $\mathbf{z}_i^{-k}\hat{\boldsymbol{\beta}}^{-k} = \hat{g}_i - z_i^k\hat{\beta}^k$).

Defined the "explained productivity" in period T, $\hat{y}_i(T)$, as:

$$\hat{y}_i(T) = y_i(0)e^{\mathbf{z}_i\hat{\boldsymbol{\beta}}}, \qquad (10)$$

the estimated marginal growth rate reflecting the marginal effect of the factored out *k-th* variable is defined as:

$$\hat{g}^k_{i,M} \equiv log\left(\frac{\hat{y}_i(T)}{\hat{y}_i^{-k}(T)}\right) = z_i^k\hat{\beta}^k. \qquad (11)$$

The marginal effect of the *k-th* variable, $\hat{\mathbf{g}}^M_k$, is therefore obtained washing out the effect of all other variables affecting the productivity growth from the estimated growth model. It is worth to remark that the estimation of Eq. (3) must include all the explanatory variables in order to avoid omitted-variable problems and obtain unbiased parameter estimates.

To study the distribution effect of the *k-th* variable, we estimate the marginal growth $\mathbf{g}_M^k$ conditioned to the initial level of (relative) productivity, i.e. $\phi_M(\mathbf{g}_M^k|\tilde{\mathbf{y}}(0))$. The latter indicates for each region with a given level of (relative) productivity at period 0 the annual marginal growth of region's productivity due to $\mathbf{z}^k$.

If $\mathbf{z}^k$ affects the distribution dynamics of $\mathbf{y}$, the counterfactual stochastic kernel is different from the actual. But this also implies that the marginal growth $\mathbf{g}_M^k$ is not independent of the initial level of productivity. Consequently, it is possible to detect the distribution effect of $\mathbf{z}^k$ looking at $\phi_M(\mathbf{g}_M^k|\tilde{\mathbf{y}}(0))$. In particular, if most of the mass in the graph is around a positively (negatively) sloped line, then $\mathbf{z}^k$ is a source of divergence (convergence) for the cross-section distribution. On the contrary, if $\phi_M(\mathbf{g}_M^k|\tilde{\mathbf{y}}(0))$ is increasing (decreasing) in $\tilde{\mathbf{y}}(0))$ then variable k is a source of divergence (convergence).

II.C. Conditional Distribution of Residual Growth

Finally, the proposed methodology allows to develop a diagnostic test to detect potential distribution effects of possible omitted variables in the specification of Model (3) under the assumption that this is the only source of bias. In particular, since in the growth regression the initial level of productivity $\tilde{\mathbf{y}}(0)$ is an explanatory variable, if there is omitted-variable inconsistency the residual growth $\mathbf{g}_R^k$ and the initial level of productivity $\tilde{\mathbf{y}}(0)$ are not conditional mean independent, i.e. $E[\hat{\mathbf{g}}_R|\tilde{\mathbf{y}}(0)] \neq E[\hat{\mathbf{g}}_R]$.[11] Therefore it is possible to discover potential distribution effect by looking at the estimated conditional density $\phi^R(\hat{\mathbf{g}}_R|\tilde{\mathbf{y}}(0))$ and checking if $E[\hat{\mathbf{g}}_R|\tilde{\mathbf{y}}(0)] = 0$ for any level of $\tilde{\mathbf{y}}(0)$. Define the residual growth of productivity as:

$$\hat{g}_{i,R} \equiv log\left(\frac{y_i(T)}{\hat{y}_i(T)}\right), \tag{12}$$

from Eqq. (5) and (9) it follows that:

$$\hat{g}_{i,R} \;=\; log\left(\frac{y_i(T)}{\hat{y}_i(T)}\right) = log\left(\frac{y_i(0)e^{\mathbf{z}_i\boldsymbol{\beta}}e^{\upsilon_i}}{y_i(0)e^{\mathbf{z}_i\hat{\boldsymbol{\beta}}}}\right) = \mathbf{z}_i(\boldsymbol{\beta} - \hat{\boldsymbol{\beta}}) + \upsilon_i.$$

Therefore, if $\hat{\boldsymbol{\beta}}$ are unbiased estimates of $\boldsymbol{\beta}$, then the expected value of conditional residual growth of productivity is zero (i.e., no omitted variables are present), that is:

$$E[\hat{g}_{i,R}] \;=\; E[\mathbf{z}_i(\boldsymbol{\beta} - \hat{\boldsymbol{\beta}}) + \upsilon_i] = \mathbf{z}_i(\boldsymbol{\beta} - E[\hat{\boldsymbol{\beta}}]) - E[\upsilon_i] = 0.$$

[11] See Wooldrigde

Moreover, if $\hat{\boldsymbol{\beta}}$ are unbiased estimates, then in the residual growth rate there are no distribution effects, i.e. $E[\hat{\mathbf{g}}_R|\tilde{\mathbf{y}}(0)] = E[\hat{\mathbf{g}}_R] = 0 \; \forall \tilde{\mathbf{y}}(0)$.

On the contrary, if there is omitted-variable inconsistency then $E[\hat{\mathbf{g}}_R] \neq 0$ and $E[\hat{\mathbf{g}}_R|\tilde{\mathbf{y}}(0)] \neq E[\hat{\mathbf{g}}_R]$. In this case distribution effects could be present in the residuals.

III. Empirical Results

This empirical section studies the distribution dynamics of 173 European NUTS 2 regions for the period 1980-2002.[12] For the estimation of the growth rate of productivity of Eq. (3) we use the preferred specification found in Fiaschi et al. (2009) 15, where the annual average growth rate of per worker GVA of a region is explained by: i) the share of Structural and Cohesion funds on regional GVA with a three-year lag (which, with a slight abuse of notation, will be indicated as $\overline{SCF}$), along with its squared value to capture possible non linear effects;[13] ii) the initial productivity level, normalized with respect to sample average ($PROD.REL_{1980}$); iii) the average annual employment growth rate ($\overline{EMP.GR}$); iv) some variables controlling for regional output composition, such as the initial value of the relative share of GVA in Mining (MIN_{1980}), Construction (CON_{1980}), Non Market Services ($NonMarkertServ_{1980}$), Finance (FIN_{1980}), Transport ($TRANS_{1980}$), Other Services ($OtherServ_{1980}$); v) the change between 1980 and 2002 of the agricultural share on GVA ($\Delta SHARE.AGRI$); finally, vi) 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.[14]

The average growth rate of employment $EMP.GR$ is augmented by the rate of depreciation of capital,[15] 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 leads to a better definition of the initial level of productivity of a region and provides useful information on the role of different sectors and the change in agricultural sector should capture the structural change of the regional economies, on the assumption that a reduction of the agricultural sector should positively contribute to productivity, if workers are reallocated to more productive sectors (e.g. manufacturing).[16]

OLS results of the estimation of Model (3) are reported in Appendix C.

[12] Appendix A contains the regions' list.

[13] Specifically, we consider the yearly average level of SCF in the whole period divided by the level of GVA at the beginning of the period.

[14] In Fiaschi et al. (2009) 15 we controlled for the possible endogeneity and for the presence of spatial dependence.

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

[16] The use of this set of control variables was originally shown to contribute to high levels of goodness of fit in the growth regressions in Fiaschi and Lavezzi (2007) 14.

All stochastic kernels are estimated considering a time lag equal to 23 years (the whole period) and the bootstrap procedure for the calculation of confidence bands of median uses 40 bootstraps. In each figure displaying the estimates of stochastic kernel we report a solid line representing the estimated median value of income at $t+\tau$, conditional on the value at time t with its confidence band at 95% significance level (indicated by dotted lines) obtained using a bootstrap procedure, and the 45° line.[17]

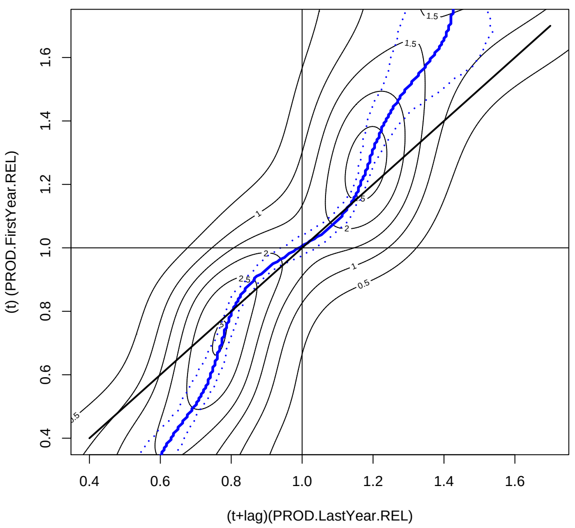

Figure 1: Actual stochastic kernel of productivity

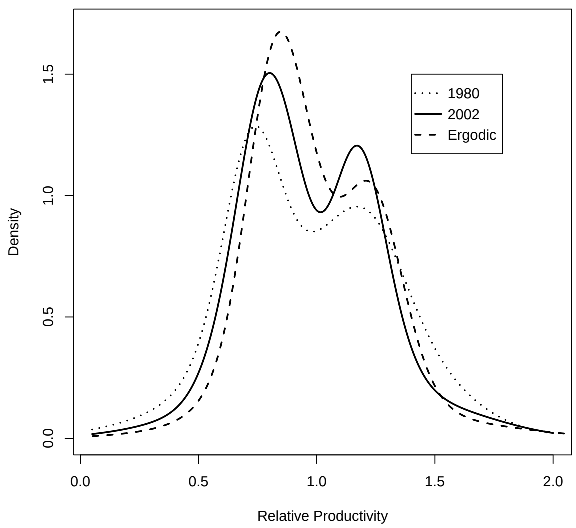

Figure 2: 1980, 2002 and ergodic distributions of productivity

The actual stochastic kernel and the associated ergodic distribution for productivity are reported in Figg. 1 and 2. Fig. 1 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 per worker GVA. This is reflected in the 1980 distribution and even more in the 2002 distribution where two clusters of regions emerge around the values of 0.8 and 1.2.[18] Accordingly, this tendency is reflected in the ergodic distribution (see Fig. 2) which shows the long-run effects of the distribution dynamics implied by the actual stochastic kernel.

Fig. 3 reports the estimated conditional density of the annual residual growth $\hat{g}_R$ for each initial level of productivity in period t, i.e. $\phi_R(\hat{\mathbf{g}}_R|\tilde{\mathbf{y}}(0))$. We also report the estimated conditional median value of the conditional distribution with its confidence band and a vertical

[17] The procedure is illustrated in Appendix D.

[18] Tests of multimodality state that the null hypothesis of unimodality both for 1980 and 2002 distribution in can be rejected at 5% level of significance. Tests of multimodality follow the bootstrap procedure described in Silverman (1986) 24, p. 146 and are performed using 100 bootstrap.

line crossing zero. As discussed in Section II.C., if no further distribution effects are present, then the estimated conditional median should be not statistically different from zero for any initial level of productivity (in figures this means that the confidence band of median must contain zero). Fig. 3 shows that most of the mass is concentrated around zero except below 0.5 and around 1.5, indicating that there may be some omitted variables in the specification of Eq. 3. In particular, regions whose initial level of productivity is below 0.5 have a negative residual growth. This implies that the omitted variables act like a divergence force for very low-productive regions.

In the following analysis we assume that the potential bias in the estimated parameters β is negligible.

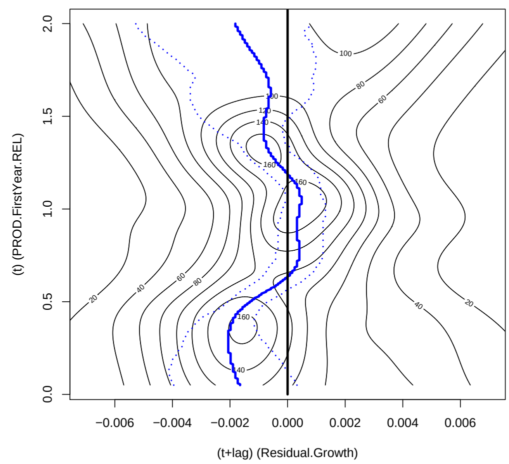

Figure 3: Conditional Distribution of Residual Growth for EU regions

III.A. Conditional Distribution Dynamics

We study the counterfactual distribution dynamics of all the variables used in the growth regression. However, we report only the analysis of the variables we found to play a relevant role in the distribution dynamics of productivity growth of European regions.

III.A.i. Initial Productivity

In order to assess the distribution effect of the initial level of productivity on the convergence processes across European region we use $log(PROD.REL_{1980})$ as factored out and counterfactual variable.

The counterfactual stochastic kernel crosses the 45° line from below around 0.6 and 1.2 (see Fig. 4). These are also the long-run equilibria indicated by the counterfactual ergodic distribution (see Fig. 6), which is flatter than the actual. Indeed it has more probability mass around the peak of low-productive regions and less mass around the peak of high-productive regions.

Fig. 7 reports the estimated conditional density for annual marginal growth. In all the figures relative to $\phi_M(\cdot)$ we also report the estimated median value of the conditional distribution with its confidence band and a vertical line representing the unconditional expected value of marginal growth. The conditional distribution of marginal growth of $PROD.REL_{1980}$ is not concentrated around its unconditional mean. On the contrary, it shows that an initial relative productivity below 1 implies a positive marginal contribution to the growth rate, while the opposite holds for initial relative productivity above 1. This is in line with the hypothesis of (conditional) convergence (in fact, the conditional median of the distribution is negatively sloped). Therefore, initial productivity is a source of convergence because if each region had the same initial conditions there would be more dispersion in terms of productivity across European regions and a higher mass of being a low-productive region in 2002.

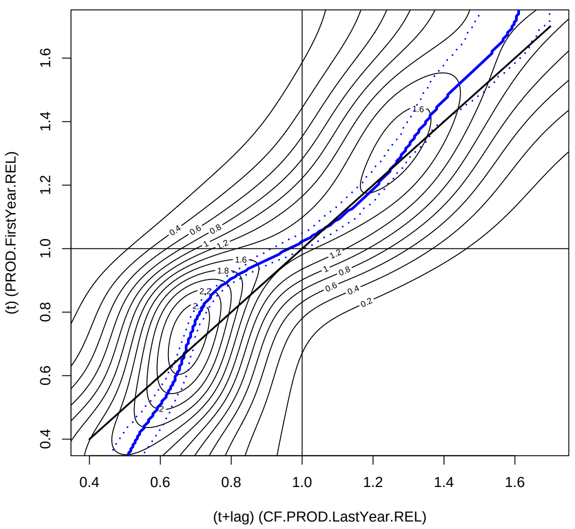

Figure 4: Counterfactual stochastic kernel of productivity (counterfactual variable Initial Productivity)

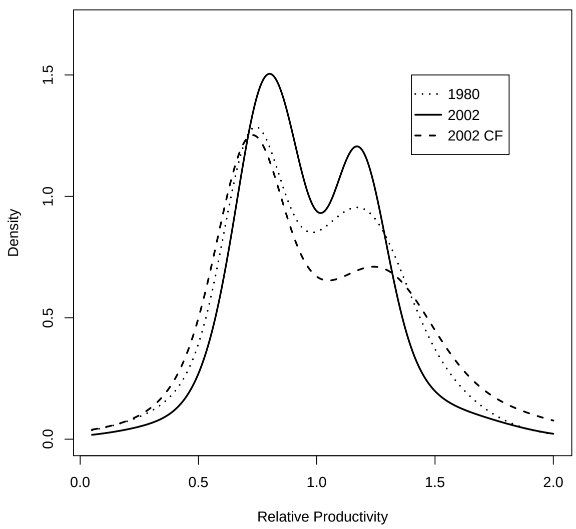

Figure 5: Initial, final and counterfactual final distributions of productivity (counterfactual variable Initial Productivity)

Finally, the Gini indexes calculated for 1980, 2002 and ergodic distributions (see Tab. 1), show that inequality in productivity across European regions is decreasing. On the contrary, without taking into account the differences in the initial productivity the inequality would be higher and increasing.

In order to check if actual and counterfactual distributions in 2002 are statistically different, we perform a bootstrap test of equality of distributions (see Efron and Tibshirani, 1993 9).[19]

[19]We also performed a permutation test that gave very similar results. More detailed of tests are reported in

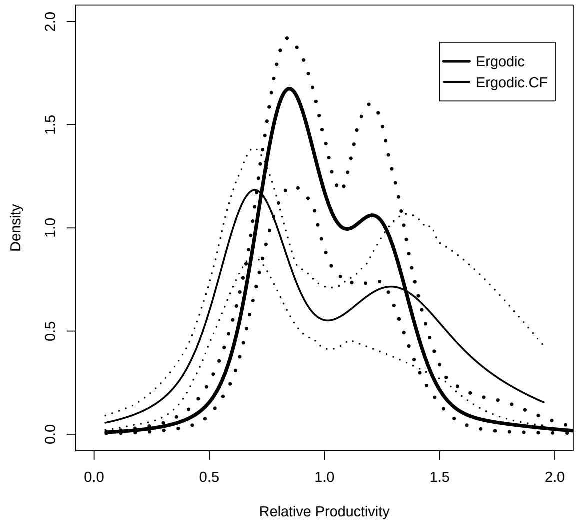

Figure 6: Actual and counterfactual ergodic distributions with confidence bands at 95% level (counterfactual variable Initial Productivity)

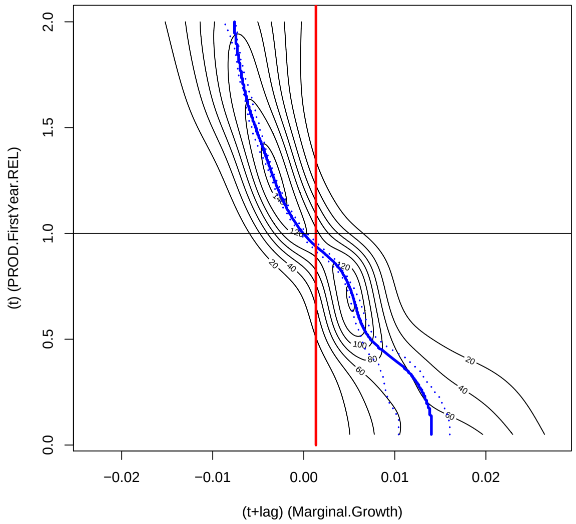

Figure 7: Conditional density of marginal growth (counterfactual variable Initial Productivity)

	1980	2002	2002.CF	Ergodic	Ergodic.CF
σ	0.41	0.28	0.40	-	-
Gini	0.19	0.16	0.22	0.15	0.24
s.e.	(0.010)	(0.008)	(0.010)	(0.005)	(0.013)

Table 1: Standard deviation and Gini Index (counterfactual variable Initial Productivity)

Fig. 8 reports the estimated distributions in 2002 and a reference band which is centered at the average of the two curves and whose width at each point is two standard errors (see Bowman and Azzalini, 1997 6). According to the bootstrap statistic ($t_{obs} = 0.11$, p-value=0) as well as to the reference band in Fig. 8, we can reject the null hypothesis of equality of two distributions.

We also performed a test of equality of actual and counterfactual ergodic distributions using the Kolmogorov-Smirnov test on cumulative densities(see Smirnov 1939 25, 1948 26). From the value of the D-statistic (which is equal to $D = 0.37$ against a critical value of 0.11 at 5% level of significance) we can reject the null hypothesis of equality of actual and counterfactual ergodic distributions at the usual levels of significance. In particular, Fig. 9 shows that actual and counterfactual ergodic distributions are significantly different both for low levels of relative productivity and around 1.[20]

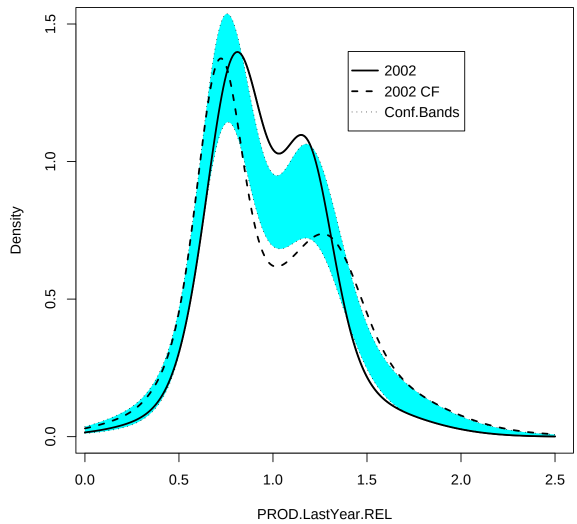

Figure 8: Test of equality of final and counterfactual distributions

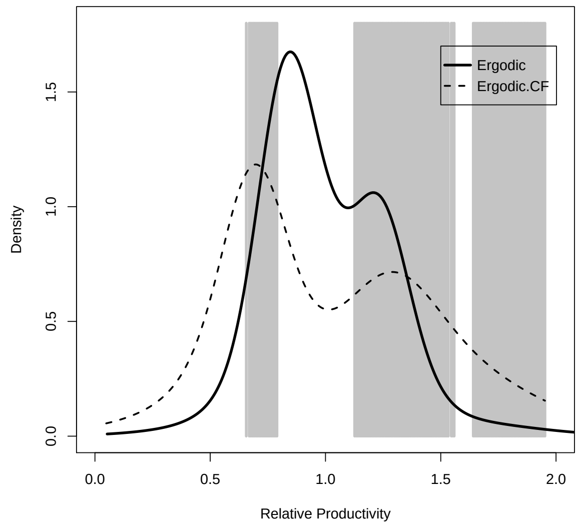

Figure 9: Difference between ergodic distributions. Ranges in grey means non significantly different at 5% level

The evidence provided by the marginal growth rate of initial productivity and the difference between the actual and counterfactual ergodic distributions suggest that the initial level of productivity crucially accounts in the explanation of the convergence of productivity across European regions.

Appendix E.

[20]Ranges where the ergodic distributions are not significantly different at 5% level of significance are indicated by grey areas.

III.A.ii. Employment Growth

In the following we repeat the analysis of the previous section for the employment growth of European regions ($log(\overline{EMP.GR})$).

The counterfactual and actual stochastic kernels are quite similar implying that employment growth has only a marginal effect on the explanation of the convergence dynamics of productivity across European regions (see Fig. 10).[21]This is also showed by the conditional distribution of marginal growth reported in Fig. 13, which is not significantly different from its unconditional mean. Accordingly, the bootstrap statistic ($t_{obs} = 0.02$, p-value=0.56) is such that we cannot reject the null hypothesis of equality of actual and counterfactual distributions in 2002. Moreover, the confidence band reported in Fig. 14 includes both distributions. Morevoer, according to the result of the Kolmogorov-Smirnov test on cumulative densities, we can reject the null hypothesis of equality of actual and counterfactual ergodic distributions at 5% level of significance (the D-statistic is equal to $D = 0.13$ against a critical value of 0.11 at 5% level of significance). However, in Fig. 15 actual and counterfactual ergodic distributions are never significantly different at 5% level.

Finally, the Gini indexes show that without taking into account the differences in the employment growth across regions, the inequality would be the same in 2002 and even lower in the long-run, pointing out that the employment growth does not act like a force toward convergence for productivity.

	1980	2002	2002.CF	Ergodic	Ergodic.CF
σ	0.41	0.28	0.29	-	-
Gini	0.19	0.16	0.16	0.15	0.14
s.e.	(0.010)	(0.008)	(0.007)	(0.005)	(0.004)

Table 2: Standard deviation and Gini Index (counterfactual variable Employment Growth)

Summarizing, employment growth seems not to play a role in the explanation of the convergence across regional productivity in Europe.

III.A.iii. Structural and Cohesion Funds

In the following we repeat the analysis of the previous section for role of SCF on the convergence processes among productivity of European regions ($\overline{\text{SCF}}$).

The estimated counterfactual stochastic kernel is reported in Fig. 16, while the conditional density for marginal growth is reported in Fig. 19. Even in this case the counterfactual stochastic kernel is quite similar to the actual, even if the conditional distribution of marginal

[21]In a cross-country setting, Beaudry *et al.* (2005) 4 find that the different effect of employment growth on productivity growth rate across the two periods they consider, plays a very important role in the formation of two peaks in the distribution of productivity.

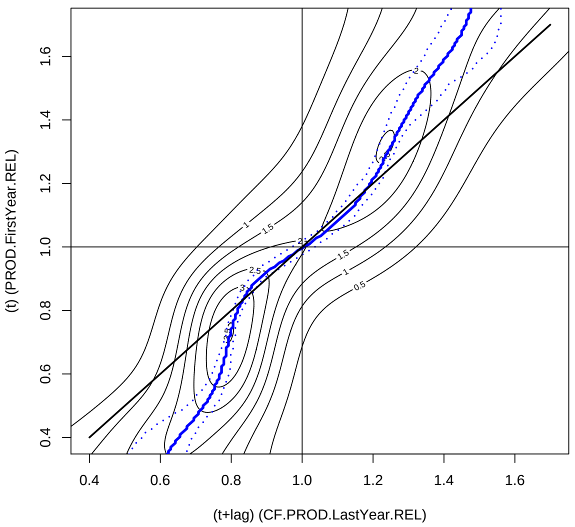

Figure 10: Counterfactual stochastic kernel of productivity (counterfactual variable Employment Growth)

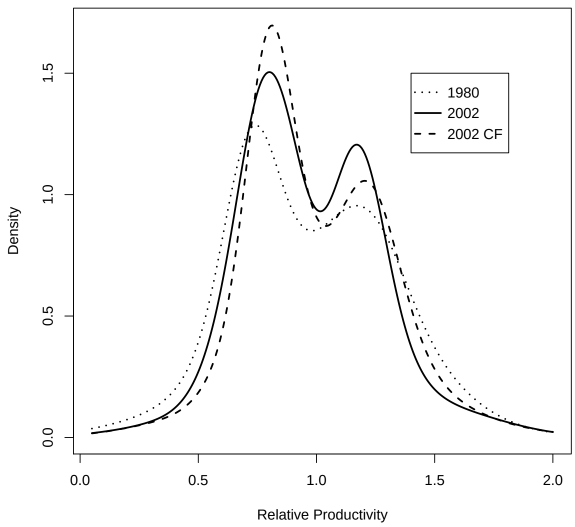

Figure 11: Initial, final and counterfactual final distribution of productivity (counterfactual variable Employment Growth)

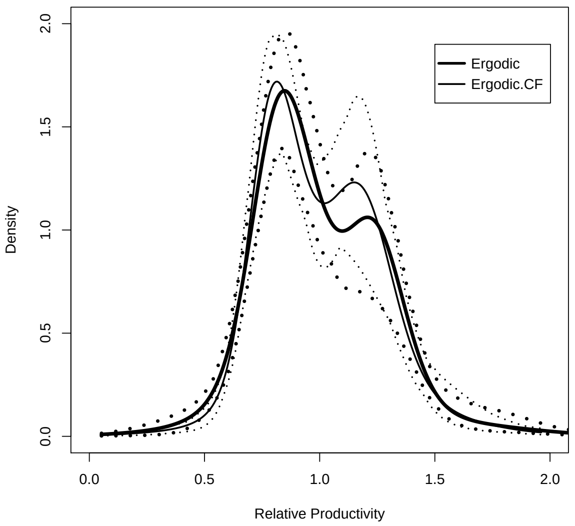

Figure 12: Actual and counterfactual ergodic distributions with confidence bands at 95% level (counterfactual variable Employment Growth)

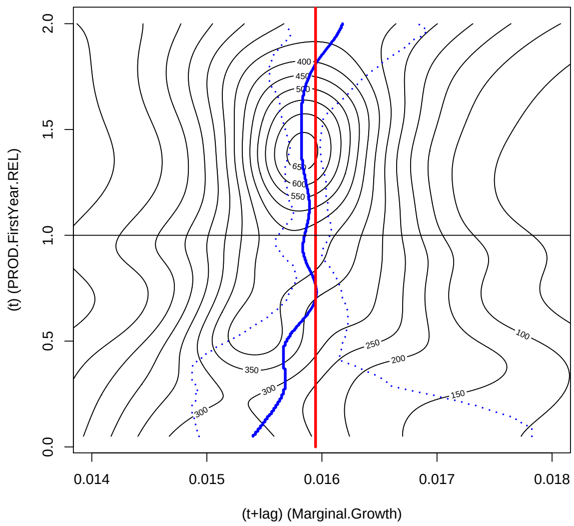

Figure 13: Conditional density of marginal growth (counterfactual variable Employment Growth)

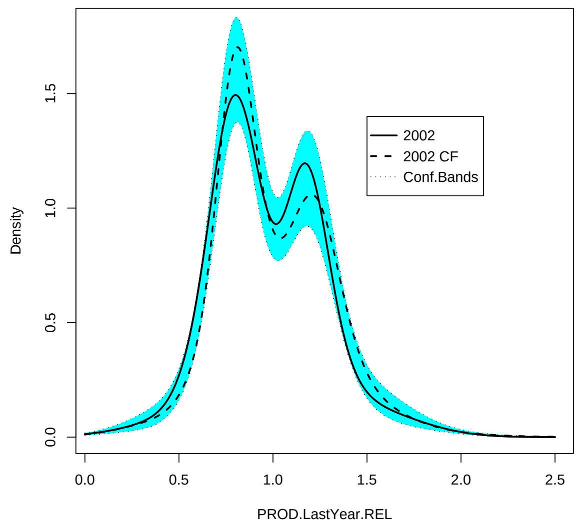

Figure 14: Test of equality of final and counterfactual distributions (counterfactual variable Employment Growth)

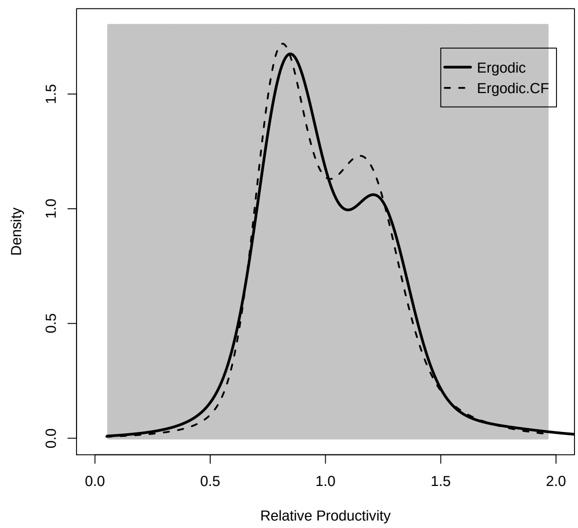

Figure 15: Difference between actual and counterfactual ergodic distributions. Ranges in grey means not significantly different at 5% level (counterfactual variable Employment Growth)

growth relative to SCF is significantly different from its unconditional mean. In particular, regions whose initial level of productivity is higher than 0.7 have an annual marginal growth rate lower than the sample average, while the opposite holds for regions below 0.7; especially, regions with an initial level of productivity lower than 0.5 (i.e, the least productive in the initial period) seem to benefit from the SCF. Moreover, the ergodic counterfactual distribution shows higher a probability mass around the low-productive regions peak with respect to the actual (see Fig. 18). Therefore, SCF acts like a force of convergence for very low-productivity regions in Europe and, consequently, the distribution of productivity across European regions shows less inequality. In fact, according to Gini indexes of counterfactual distributions if each region received the same amount of SCF the inequality in 2002 would be lower than in 1980 and decreasing in the long-run, but it would be higher than the inequality of the actual distribution in 2002.

	1980	2002	2002.CF	Ergodic	Ergodic.CF
σ	0.41	0.28	0.30	-	-
Gini	0.19	0.16	0.17	0.15	0.16
s.e.	(0.010)	(0.008)	(0.008)	(0.005)	(0.005)

Table 3: Standard deviation and Gini Index (counterfactual variable SCF)

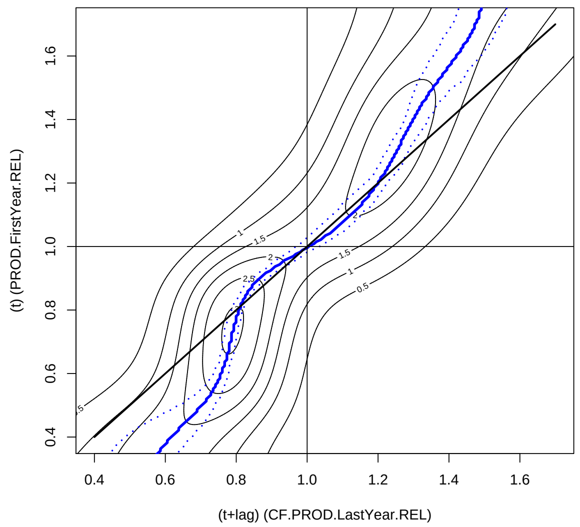

Figure 16: Counterfactual stochastic kernel (counterfactual variable SCF)

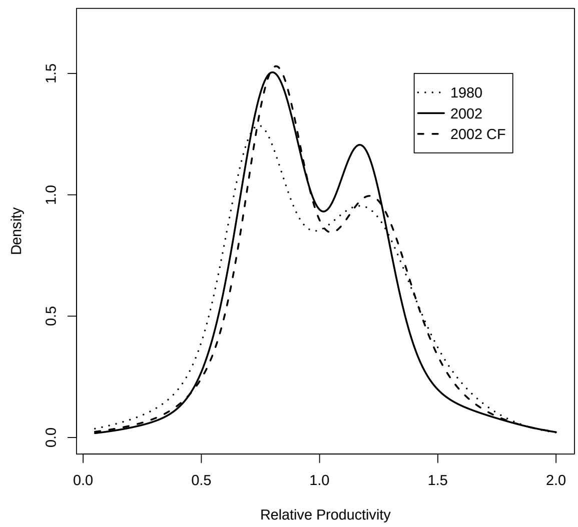

Figure 17: Initial, final and counterfactual final distribution (counterfactual variable SCF)

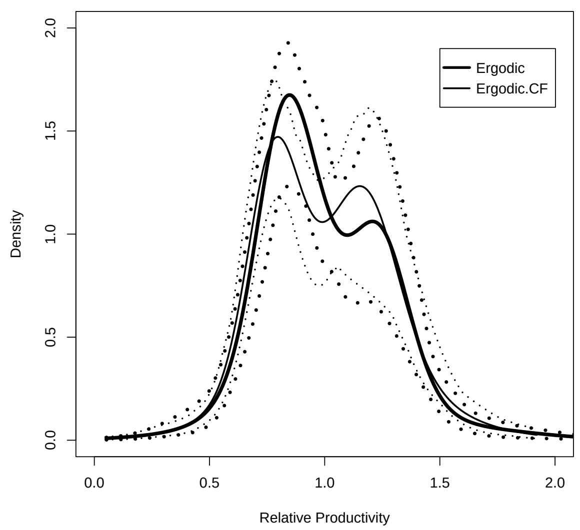

Figure 18: Actual and counterfactual ergodic distributions with confidence bands at 95% level (counterfactual variable SCF)

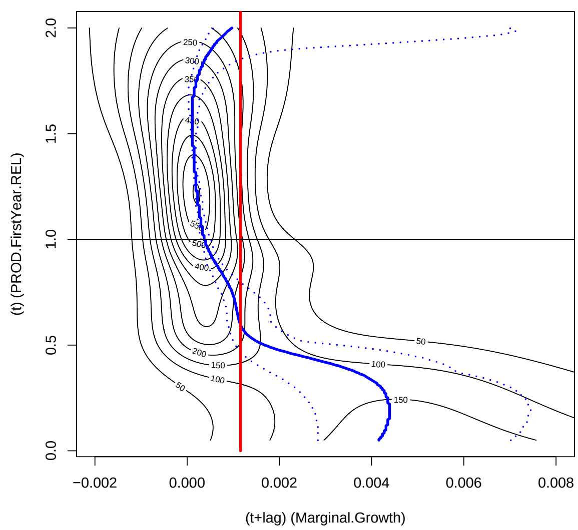

Figure 19: Conditional density of marginal growth (counterfactual variable SCF)

According to the statistics relative to the bootstrap test ($t_{obs} = 0.02$, p-value=0.55) we cannot reject the null hypothesis of equality between actual and counterfactual distributions in 2002. Moreover, the confidence band reported in Fig. 20 is such that both distributions are included in it. The result of the Kolmogorov-Smirnov test on cumulative densities of the actual and counterfactual ergodic distributions can reject the null hypothesis of equality of actual and counterfactual ergodic distribution at 5% level of significance (the D-statistic is equal to $D = 0.12$ against a critical value of 0.11 at 5% level of significance). However, Fig. 21 show actual and counterfactual ergodic distribution are not significantly different at 5% level.

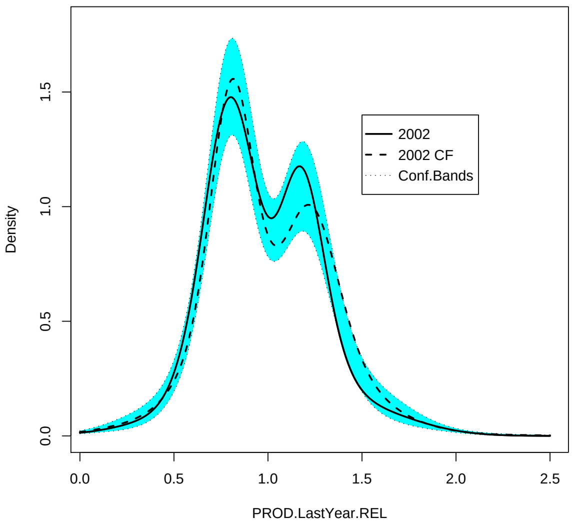

Figure 20: Test of equality of final and counterfactual distributions (counterfactual variable SCF)

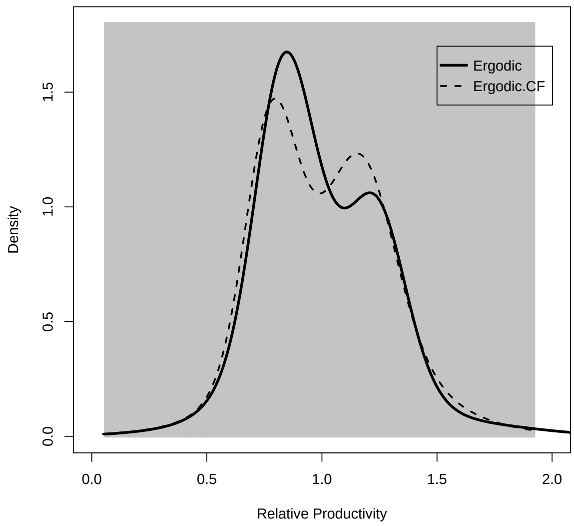

Figure 21: Difference between ergodic distribution at 5% level of significance (counterfactual variable SCF)

Summarizing, SCF seem to play a positive role in the convergence across European regions even though such effect is statistically significant only at the low bound of the range of initial productivity (below 1). From Fig. 19 we see that the marginal effect is below 0.1% of annual growth rate for every region above 0.7 of initial productivity.

III.A.iv. Structural Change

In order to understand the role of the structural change of regional economies captured by the change in agricultural sector, we use $\Delta SHARE.AGRI$ both as factored out and counterfactual variable. It is worth to remember that $\Delta SHARE.AGRI$ is defined as the difference between the share of GVA in agriculture sector in 1980 and that in 2002. Therefore, a positive (negative) value of $\Delta SHARE.AGRI$ implies a decrease (increase) of the agricultural sector of the region.

The counterfactual stochastic kernel reported in Fig. 22 shows the same equilibria of the actual even though the counterfactual distribution in 2002 has more probability mass around the low-productive peak (see Fig. 23). Moreover, the conditional distribution of the marginal growth rate is significantly different from its unconditional mean (see Fig. 25). In particular, it is such that regions with an initial relative productivity lower than 0.5 have a positive marginal growth implied by the change in their agricultural sector. These are the least productive regions, who were expected to benefit more from the structural change of their economy. The Gini indexes show that if each region had have the same change in the agricultural sector there would have been more inequality in 2002, even if in the long-run the inequality would have been the same (see Table 4).

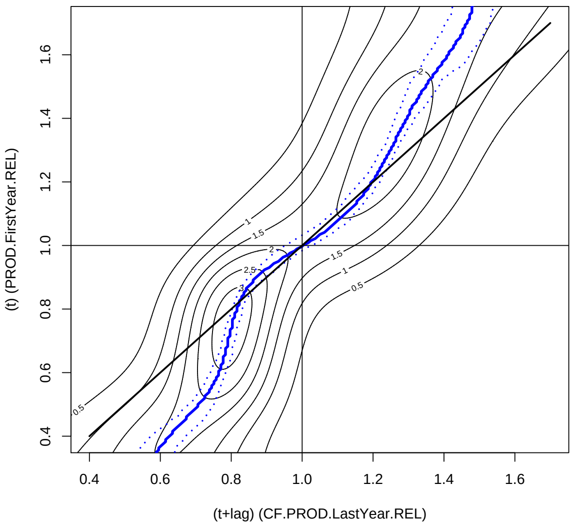

Figure 22: Counterfactual stochastic kernel (counterfactual variable $\Delta SHARE.AGRI$)

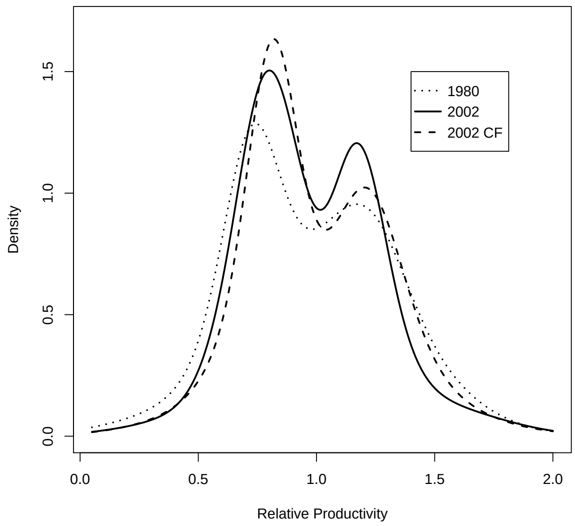

Figure 23: Initial, final and counterfactual final distribution (counterfactual variable $\Delta SHARE.AGRI$)

	1980	2002	2002.CF	Ergodic	Ergodic.CF
σ	0.41	0.28	0.29	-	-
Gini	0.19	0.16	0.17	0.15	0.15
s.e.	(0.010)	(0.008)	(0.008)	(0.005)	(0.005)

Table 4: Standard deviation and Gini Index (counterfactual variable $\Delta SHARE.AGRI$)

According to the bootstrap test of equality of distributions between the actual and counterfactual distributions in 2002 we cannot reject the null hypothesis of equality ($t_{obs} = 0.02$,

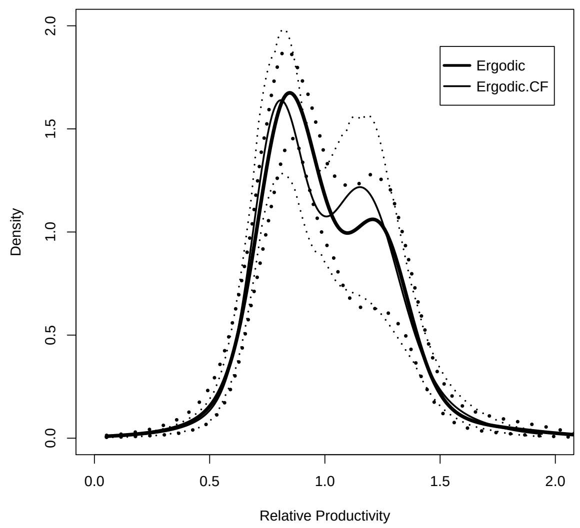

Figure 24: Actual and counterfactual ergodic distributions with confidence bands at 95% level (counterfactual variable $\Delta SHARE.AGRI$)

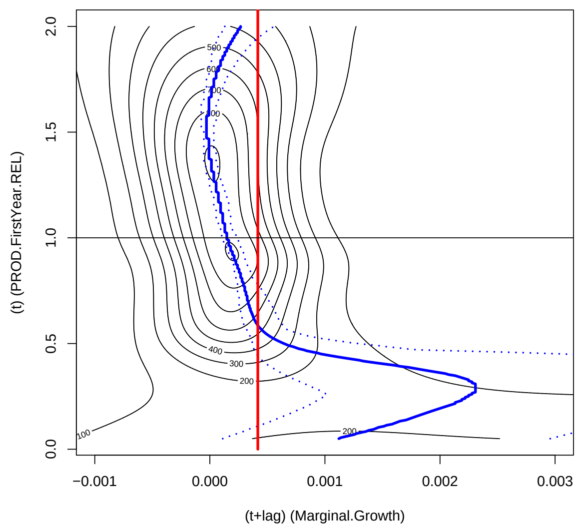

Figure 25: Conditional density of marginal growth (counterfactual variable $\Delta SHARE.AGRI$)

p-value=0.58; see Fig. 26). The result of the Kolmogorov-Smirnov test on cumulative densities can reject the null hypothesis of equality of actual and counterfactual ergodic distribution at 5% level of significance (the D-statistic is equal to $D = 0.13$ against a critical value of 0.11 at 5% level of significance), even if Fig. 27 shows no differences in the distributions at 5% level.

Summarizing, $\Delta SHARE.AGRI$ seem to play a positive role in the convergence process across European regions, even though such effect is statistically significant only for the low bound of the range (i.e., below 0.5).

III.A.v. Share in Non Market Services in 1980, $NonMarketServ_{1980}$

In this section the same methodology is applied by using the share of GVA in non market services in 1980, $NonMarketServ_{1980}$, as factored out and counterfactual variable.

Looking at the counterfactual stochastic kernel (reported in Fig. 28) it is not possible to detect many differences with respect to the actual. However, the estimated counterfactual distribution in 2002 is different from the actual. In particular, it has less probability around the high-productive peak and the latter is shifted on the right. The statistics relative to the bootstrap test is such that we cannot reject the null hypothesis of equality of distributions ($t_{obs} = 0.03$, p-value=0.41), and the confidence band reported in Fig. 32 includes both the distributions.

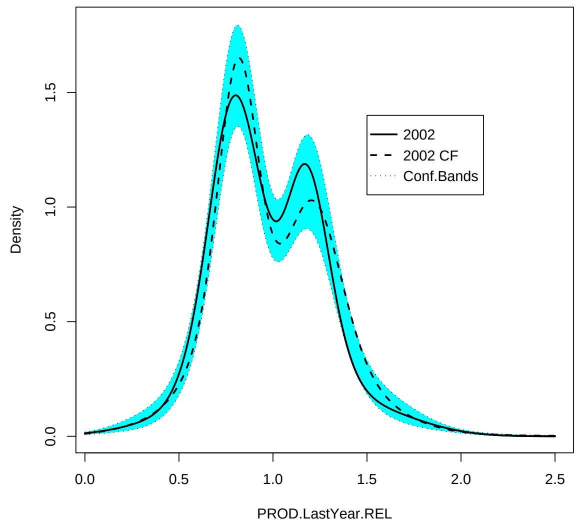

Figure 26: Test of equality of final and counterfactual distributions (counterfactual variable $\Delta SHARE.AGRI$)

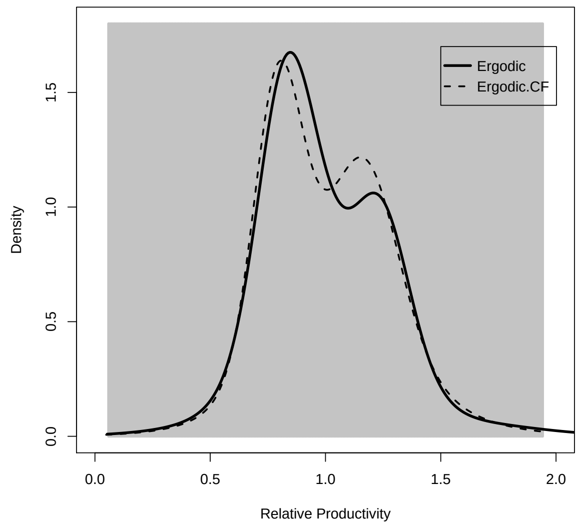

Figure 27: Difference between ergodic distribution at 5% level of significance (counterfactual variable $\Delta SHARE.AGRI$)

On the contrary, the actual and counterfactual ergodic distributions are not statistically different (see Figg. 30 and 33). In fact, the result of the Kolmogorov-Smirnov test on cumulative densities of the actual and counterfactual ergodic distributions is such that we cannot reject the null hypothesis of equality at 5% level of significance (the D-statistic is equal to $D = 0.08$ against a critical value of 0.11 at 5% level of significance).

Accordingly, the Gini indexes show that if all the regions had the the same share in non market services in 1980 there would have been a higher level of inequality in 2002, but not in the long-run.

Moreover, the conditional distribution of the marginal growth rate is negatively sloped and it is significantly different from its unconditional mean for some ranges of the initial level of productivity (see Fig. 31). In particular, it is lower than the mean for regions whose level of initial relative productivity is between (1.2,1.6), while it is higher for regions having an initial level of relative productivity between (0.3,0.5).

	1980	2002	2002.CF	Ergodic	Ergodic.CF
σ	0.41	0.28	0.29	-	-
Gini	0.19	0.16	0.17	0.15	0.15
s.e.	(0.010)	(0.008)	(0.008)	(0.005)	(0.007)

Table 5: Standard deviation and Gini Index (counterfactual variable $NonMarketServ_{1980}$)

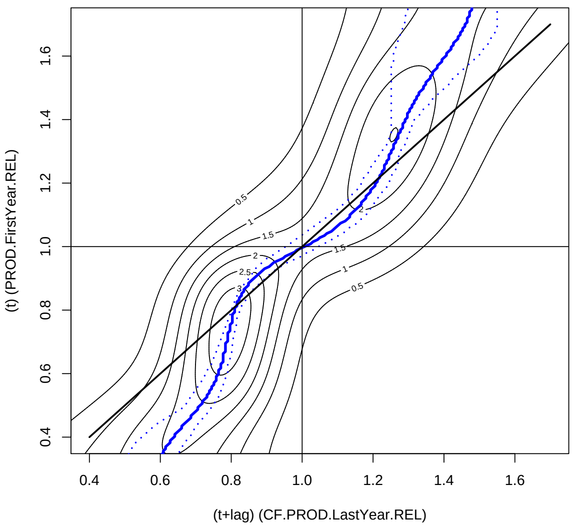

Figure 28: Counterfactual stochastic kernel (counterfactual variable $NonMarketServ_{1980}$)

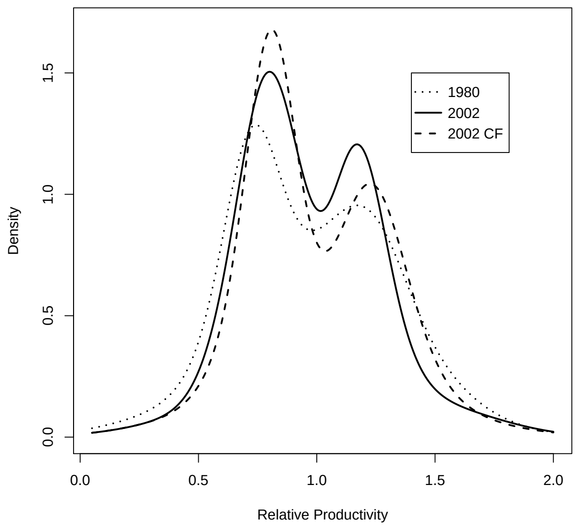

Figure 29: Initial, final and counterfactual final distribution (counterfactual variable $NonMarketServ_{1980}$)

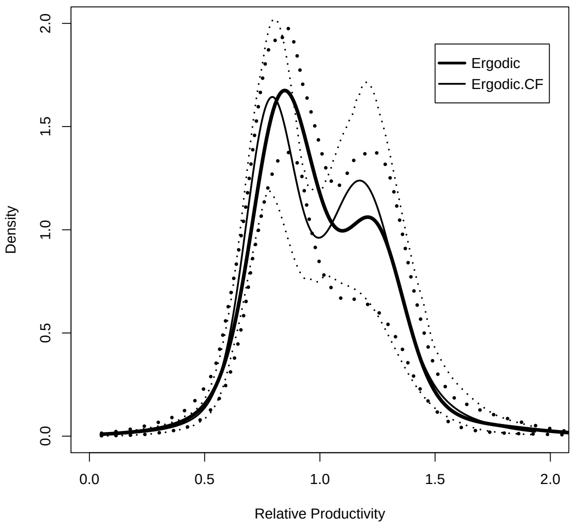

Figure 30: Actual and counterfactual ergodic distributions with confidence bands at 95% level (counterfactual variable $NonMarketServ_{1980}$)

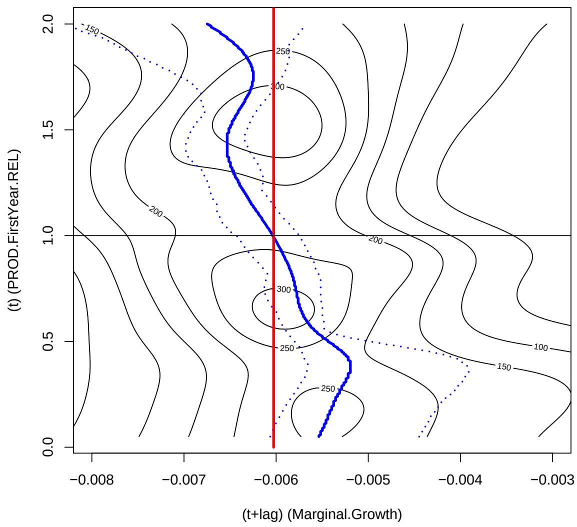

Figure 31: Conditional density of marginal growth (counterfactual variable $NonMarketServ_{1980}$)

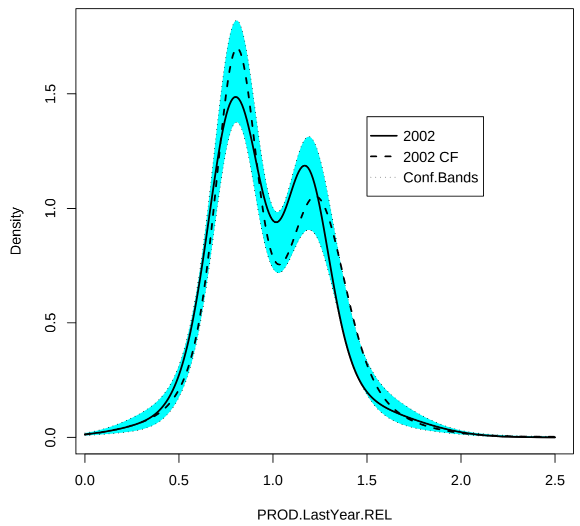

Figure 32: Test of equality of final and counterfactual distributions (counterfactual variable $NonMarketServ_{1980}$)

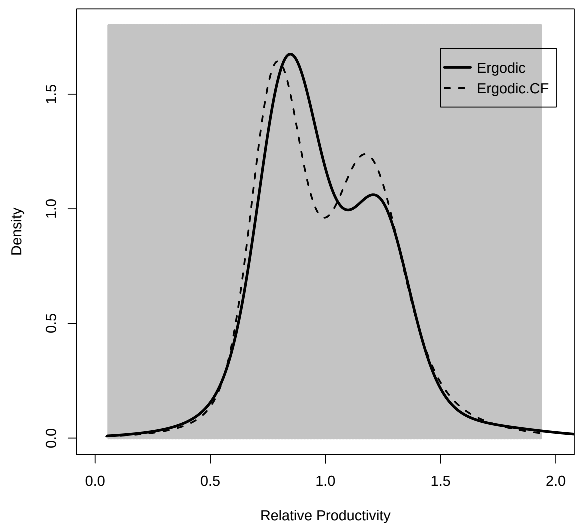

Figure 33: Difference between ergodic distribution at 5% level of significance (counterfactual variable $NonMarketServ_{1980}$)

Summing up, even though $NonMarketServ_{1980}$ from 1980 to 2002 acts like a source of convergence, in the long-run it plays a negligible role in the convergence process of productivity growth across European regions.

III.A.vi. Share in Finance in 1980, FIN_{1980}

A very interesting issue is how the initial share in the finance sector of a region affects its productivity growth rate. To study this impact, we use the share in finance in 1980, FIN_{1980}, as factored out and counterfactual variable.

Also in this case the counterfactual stochastic kernel appears to be very similar to the actual showing the same equilibria (see Fig. 34). However, the counterfactual distribution estimated in 2002 has much more probability mass around the low-productive peak with respect to the actual (see Fig. 35). Also the ergodic counterfactual distribution reflect this tendency (see Fig. 36). Accordingly, the Gini indexes highlight that if all the regions had the same share in the financial sector in 1980 there would have been the same level of inequality in 2002, but in the long-run the inequality would have been lower (see Table 6). This implies that the share in finance is a source of divergence across regions. This result is also implied by the conditional distribution of the marginal growth reported in Fig. 37. In fact, the conditional mean is positively sloped; this means that regions with an initial productivity above (below) the mean have a positive (negative) marginal growth. In particular, the least productive regions (i.e. regions with an initial level of productivity below 0.5) seems to be negatively affected by FIN_{1980}.

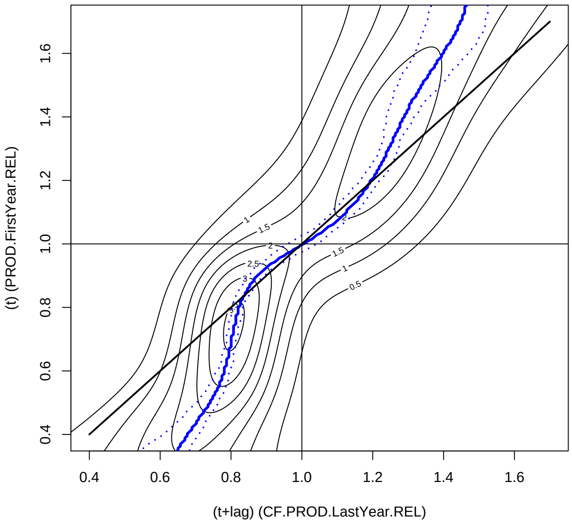

Figure 34: Counterfactual stochastic kernel (counterfactual variable FIN_{1980})

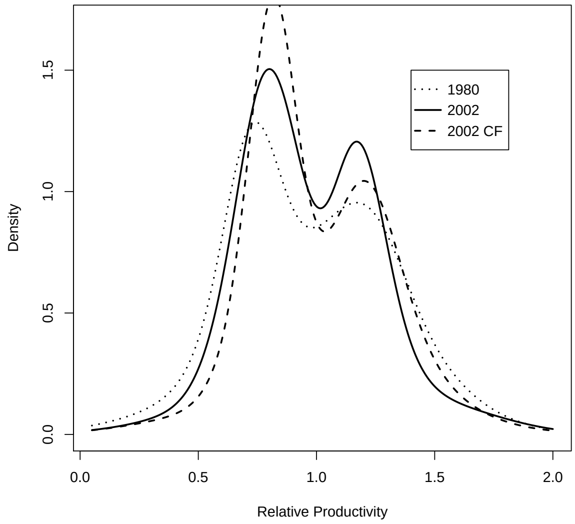

Figure 35: Initial, final and counterfactual final distribution (counterfactual variable FIN_{1980})

	1980	2002	2002.CF	Ergodic	Ergodic.CF
σ	0.41	0.28	0.28	-	-
Gini	0.19	0.16	0.16	0.15	0.14
s.e.	(0.010)	(0.008)	(0.007)	(0.005)	(0.005)

Table 6: Standard deviation and Gini Index (counterfactual variable FIN_{1980})

The statistics relative to the bootstrap test is such that we cannot reject the null hypothesis of equality of distributions in 2002 ($t_{obs} = 0.03$, p-value=0.32), and the confidence band reported in Fig. 38 is such that the two distributions are included in it. On the contrary, according to the Kolmogorov-Smirnov test on cumulative densities we can reject the null hypothesis of equality of actual and counterfactual ergodic distribution at 5% level of significance (the D-statistic is equal to $D = 0.12$ against a critical value of 0.11 at 5% level of significance; see also Fig. 39).

Summarizing, FIN_{1980} seems to play a negative role in the convergence process of productivity growth across European regions.

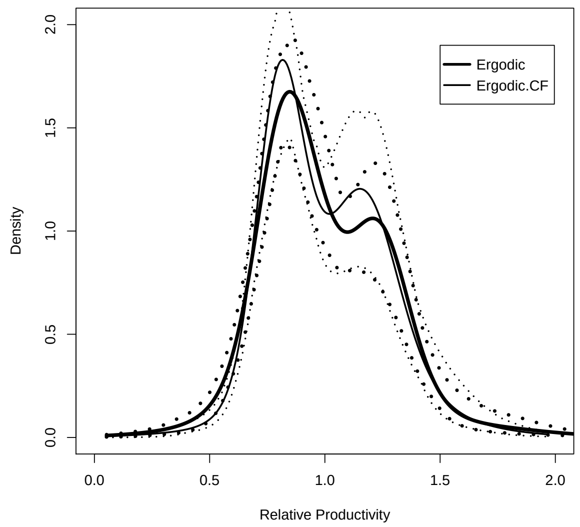

Figure 36: Actual and counterfactual ergodic distributions with confidence bands at 95% level (counterfactual variable FIN_{1980})

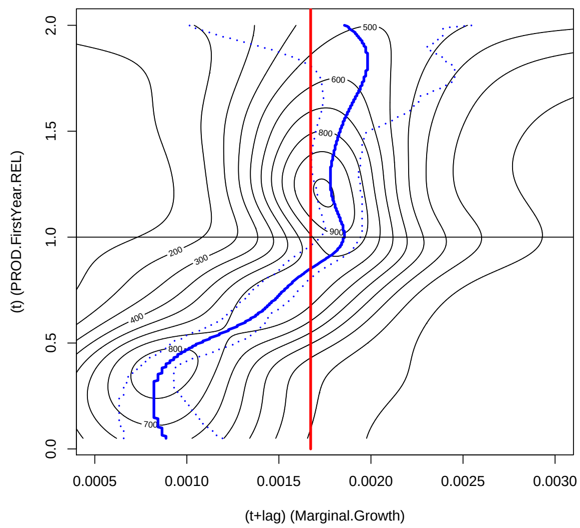

Figure 37: Conditional density of marginal growth (counterfactual variable FIN_{1980})

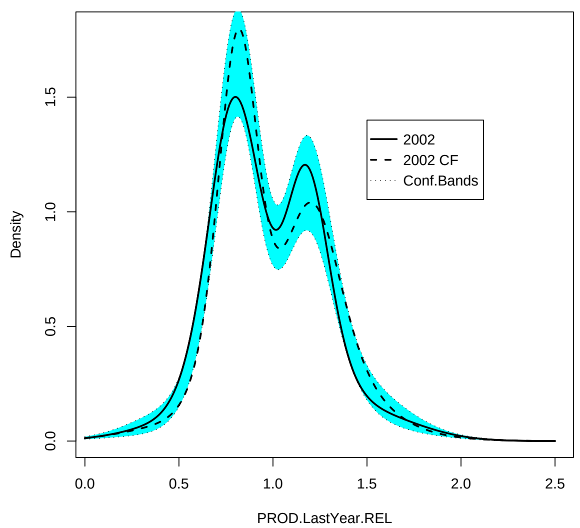

Figure 38: Test of equality of final and counterfactual distributions (counterfactual variable FIN_{1980})

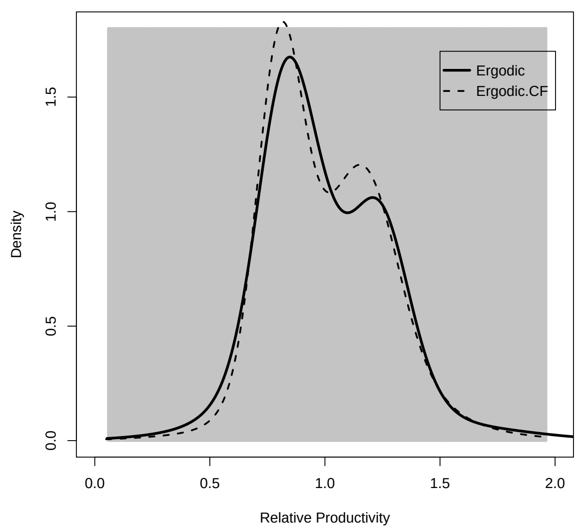

Figure 39: Difference between ergodic distribution at 5% level of significance (counterfactual variable FIN_{1980})

IV. Concluding Remarks

This paper discusses a methodology which combines elements of parametric regression analysis with the nonparametric distribution dynamics approach and allows to detect which variables favour or retard convergence in the productivity growth rate of European regions over the period 1980-2002, and which part of the distribution appears to be affected by them.

We find that the initial productivity crucially accounts in the convergence process across European regions. In particular, the implied conditional distribution of marginal growth is such that starting with a low value of relative initial productivity the marginal growth rate is high and vice versa. This is actually what the theory of convergence predicts, that is poor regions will grow faster than rich regions (in fact, the median of the distribution is negatively sloped). Our nonparametric methodology shows that such conditional convergence holds for the entire range of initial productivity. Differently, employment growth seems not to play a role in the explanation of the convergence across regional productivity in Europe and, even though the Structural and Cohesion Funds seem to play a positive role in the convergence across European regions, such effect seems to be very low and statistically significant only at the low bound of the range of initial productivity. The structural change of regional economies captured by the change in agricultural sector plays a positive role even though such effect is statistically significant only for the least productive regions, who were expected to benefit more from the structural change of their economy.

The output composition of a region in 1980 affects the convergence process of productivity growth in several ways. In particular, Non Market Services $NonMarketServ_{1980}$ acts like a source of convergence from 1980 to 2002 but in the long-run it plays a negligible role. Finally, Finance FIN_{1980} acts like a force of divergence across European regions, especially for the least productive regions.

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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 Data Sources

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

- data over 1975-1988 are from "ERDF in Figures 1989" 10;
- data over 1989-1993 are from "The Fifth Annual Report" 11 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" 12;
- 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" 12 and "The Eleventh Annual Report" 13.

Data represent the total Commitments that European Commission allocated for the entire programming period. Data on total Payments, that is data on sums actually transferred to the regions, are available for the last programming period only. All data are transformed in 1995 constant prices. Data on regional GVA and employment come from Cambridge Econometrics (2004) 7.

C Results of parametric estimation

Results of parametric estimation are reported in Tab. (7).

D Bootstrap procedure for calculating confidence interval

The bootstrap procedure used to calculated the confidence interval for the estimated median of the kernel and the ergodic distribution is based on the procedure in Bowman and Azzalini (1997) 6 for estimated distributions and in Fiaschi and Romanelli (2009) 16 for the estimated long-run (ergodic) distributions.

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

1. Estimate from sample $\mathbf{Y}$ the density $\hat{\phi}$.
2. Select B independent bootstrap samples $\{\mathbf{Y}^{*1}, ..., \mathbf{Y}^{*B}\}$, each consisting of n data values drawn with replacement from $\mathbf{Y}$.
3. Estimate the density $\hat{\phi}^*_b$ corresponding to each bootstrap sample $b = 1, ..., B$.

The distribution of $\hat{\phi}^*_i$ about $\hat{\phi}$ can therefore be used to mimic the distribution of $\hat{\phi}$ about ϕ, that is it it can be used to calculate the confidence intervals for estimates. In our estimates we set B=500 and we take the bandwidth equal to one calculated for the observed sample $\mathbf{Y}$.

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	0.0037	0.0091	0.4117	0.6811
BE	0.0053	0.0013	4.1158	0.0001
DK	0.0042	0.0009	4.7550	0.0000
ES	-0.0090	0.0023	-3.9767	0.0001
FR	0.0006	0.0008	0.6566	0.5123
GR	-0.0123	0.0046	-2.6780	0.0081
LU	0.0115	0.0021	5.5166	0.0000
IE	0.0143	0.0039	3.6381	0.0004
IT	-0.0069	0.0016	-4.4460	0.0000
NL	0.0003	0.0016	0.2168	0.8286
PT	-0.0134	0.0041	-3.2973	0.0012
UK	-0.0035	0.0022	-1.5818	0.1155
$\log(PROD.REL_{1980})$	-0.0158	0.0030	-5.3611	0.0000
$\log(\overline{EMP.GR})$	-0.0047	0.0022	-2.1892	0.0299
$\overline{SCF}$	0.1855	0.0705	2.6298	0.0093
$\overline{SCF}^2$	-0.8677	0.4007	-2.1656	0.0317
$\Delta SHARE.AGRI$	0.0241	0.0158	1.5221	0.1298
CON_{1980}	-0.0309	0.0141	-2.1981	0.0293
MIN_{1980}	-0.0255	0.0077	-3.2886	0.0012
$NonMarketServ_{1980}$	-0.0267	0.0070	-3.8268	0.0002
FIN_{1980}	0.0350	0.0223	1.5660	0.1192
$TRANS_{1980}$	0.0171	0.0149	1.1440	0.2542
$OtherServ_{1980}$	0.0287	0.0164	1.7467	0.0825
	Obs. 173	$\bar{R}^2 = 0.743$		

Table 7: Parametric estimation of equation 3

E *Test for equality of final distributions*

Given two distributions samples of observations $\mathbf{z}$ and $\mathbf{y}$, respectively of size n and m, the computation of the bootstrap test statistic for testing the null hypothesis $f = g$ is given by the following steps:

1. Estimate $\hat{f}(\mathbf{z})$ and $\hat{g}(\mathbf{y})$ using the same smoothing parameter given by the geometric mean of the two optimal bandwidths.

2. Draw B samples of size $n + m$ with replacement from $\mathbf{x}$. Call the first n observation $\mathbf{z}^*$ and for the remaining m observations $\mathbf{y}^*$.

3. Estimate for the first n observations $\hat{f}(\mathbf{z}_b^*)$ and the remaining m observations $\hat{g}(\mathbf{y}_b^*)$, for each drawing $b = 1, ..., B$.

4. Compute for each drawing $b = 1, ..., B$ the statistic

$$t(\mathbf{x}_b^*) = \int \{\hat{f}(\mathbf{u}_b^*) - \hat{g}(\mathbf{u}_b^*)\}^2 du. \tag{13}$$

5. Approximate the achieved significance level by

$$\widehat{ASL}_{boot} = \#\{t(\mathbf{x}_b^*) \geq t_{obs}\}/B \tag{14}$$

   where $t_{obs} = t(\mathbf{x})$ is the observed value of the statistic.

As suggested by Bowman and Azzalini (1997) 6 we also superimpose on the estimates a reference band which is centered on the average of the two curves and whose width at each point is two standard errors. The confidence interval has been estimated using the bootstrap procedure illustrated in the above section.

F *Kolmogorov-Smirnov test for equality of ergodic distributions*

Since we do not have observations for the ergodic distributions, instead of applying the bootstrap test for equality of distributions we performed a Kolmogorov-Smirnov test. This test compares the sample cumulative distribution functions and its test statistic is the difference of greatest magnitude between these two function.

Given two samples respectively of size n_1 and n_2 the hypothesis *H0: two samples come from the same distributions* may be tested again *H1: the distributions have different cumulative distribution functions*. The statistic is given by:

$$D = \max_x |S_1(x) - S_2(x)| \tag{15}$$

where S_1 and S_2 are the empirical cumulative distribution function of the two samples. The null hypothesis is rejected at level β when the observed statistic D is greater than the critical value of the statistic D_β given by:

$$D_\beta = \sqrt{\frac{n_1 + n_2}{n_1 n_2}} c(\beta) \tag{16}$$

where the coefficient $c(\beta)$ is given in the table below for the usual level of significance:

β	10%	5%	1%
$c(\beta)$	1.22	1.36	1.63

Table 8: Coefficient for critical level of Kolmogorov-Smirnov statistic

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