INNOCENZO GASPARINI INSTITUTE FOR ECONOMIC RESEARCH

Institutional Members: CEPR, NBER and Università Bocconi

WORKING PAPER SERIES

Convergence Across Italian Regions and the Role of Technological Catch-Up

Marco Maffezzoli

Working Paper n. 275

August 2005

IGIER – Università Bocconi, Via Salasco 5, 20136 Milano –Italy
http://www.igier.uni-bocconi.it

Convergence Across Italian Regions and the Role of Technological Catch-Up

Marco Maffezzoli[1]
Università Bocconi and IGIER

This draft: August 1st, 2005

[1]Corresponding address: Istituto di Economia Politica, Università Commerciale "L. Bocconi," Via Gobbi 5, 20136 Milano (Mi), Italy. E-mail: *marco.maffezzoli@unibocconi.it*.
The author is indebted to M.R. Battagion, F. Canova, F. Daveri, M. Ravn, G. Tabellini, and three anonymous referees for their many useful comments, and to seminar participants in Università Bocconi. The usual disclaimers apply.

Abstract

This paper suggests that the main (and possibly unique) source of $\beta-$ and $\sigma-$ convergence in GDP per worker (i.e. labor productivity) across Italian regions over the 1980-2002 period is the change in technical and allocative efficiency, i.e. convergence in relative TFP levels. To obtain this result, I construct an approximation of the production frontier at different points in time using Data Envelope Analysis (DEA), and measure efficiency as the output-based distance from the frontier. This method is entirely data-driven, and does not require the specification of any particular functional form for technology. Changes in GDP per worker can be decomposed into changes in relative efficiency, changes due to overall technological progress, and changes due to capital deepening. My results suggest that: (*i*) differences in relative TFP are quantitatively important; (*ii*) while technological progress and capital deepening are the main, and equally important, forces behind the rightward shift in the distribution of GDP per worker, convergence in relative TFP is the main determinant of the change in its shape.

Keywords: Italian regions, regional convergence, Total Factor Productivity, Data Envelope Analysis.

JEL codes: R1, O4.

1 Introduction

The Italian case is one of the best-known examples of persistent and quantitatively important regional divide, and has attracted attention from economists at least since Myrdal [30]. Historically, the degree of regional inequality in GDP per worker (or per capita) has been significantly higher than in other European countries. Barro and Sala-I-Martin [6] report that regional inequality in Italy remains the highest among all EU countries, and this in spite of the growing efforts on behalf of European institutions to stimulate growth in relatively backward areas. Moreover, as already noted by La Ferrara and Marcellino [27], the Italian microcosm reproduces many of the contrasts and differences existing among European countries, since the productive structure and the level of development of Italian regions varies widely, ranging from the rich and industrialized regions of the North to the relatively poor Southern areas.

The current consensus view is that Italian regions converged in absolute terms quite impressively over the 1960-75 period; this convergence process, however, ended suddenly in 1975, and the 1980s and the beginning of the 1990s witnessed the emergence of a clear pattern of divergence and clustering, in terms of both GDP per capita and, to a certain extent, labor productivity. Some recent contributions - see Ciriaci [15] among others - highlight the ongoing divergence in GDP per capita levels, which contrasts with the convergence in labor productivity that became increasingly evident during the 1990s.[1]

The official Italian regional accounts have been recently reconstructed according to the SEC95 standard, providing us with a set of detailed time-homogenous series covering the entire 1980-2002 period.[2] In this paper, I take advantage of this new dataset to reexamine the process of regional convergence in Italy, focusing on labor productivity, i.e. GDP per worker, which seems to be a better indicator of economic efficiency. The upper part of Figure 1 plots the cross-region distribution[3] of GDP

[1] See, among others, Ascari and Di Cosmo [3], Ciriaci [15], Di Liberto [17], Leonida, Petraglia, and Murillo-Zamorano [28], Mauro and Podrecca [29], Paci and Pigliaru [31], Paci and Saba [33], and Terrasi [35]. Recently, Brugnoli and Fachin [10] find a certain degree of divergence among regional labor productivity levels at the sectoral level. For a recent discussion of convergence (or lack of) across European regions, see Boldrin and Canova [8].

[2] Unfortunately, the existing regional accounts covering the 1960-94 period (1970-94 for regional capital stocks; see Paci and Pusceddu [32]) are not fully comparable with the current official ones, since they come from different sources and have been compiled with different methodologies. Mauro and Podrecca [29] suggest that this lack of homogeneity may be important. In order to avoid these problems, I use the latest and fully time-homogenous data, at the cost of focusing on the 1980-2002 period only.

[3] The densities are estimated using a nonparametric kernel smoothing method. The kernel function is a standard normal, and the bandwidth is the corresponding optimal one. For a detailed description of the data used, see Section 2.3.

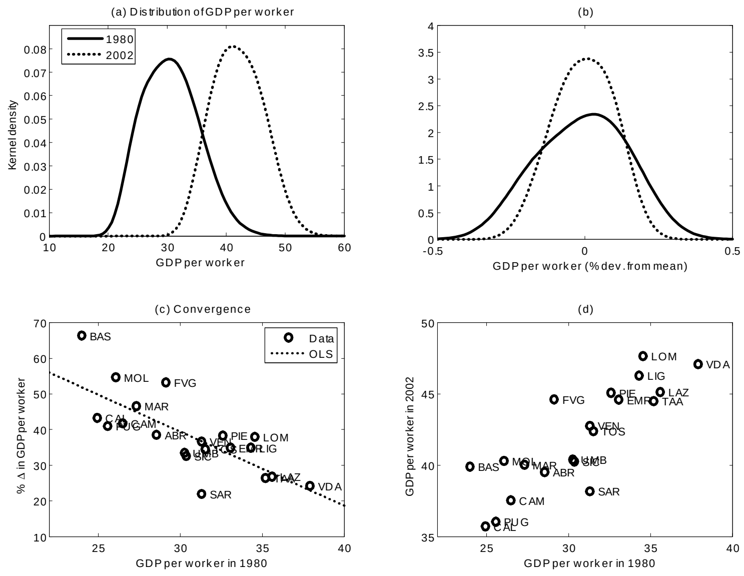

Figure 1: Labor productivity distribution and convergence.

per worker in levels (panel a) and in percentage deviations from the cross-sectional mean (panel b), in 1980 and 2002. In the lower part of the Figure, GDP per worker in 1980 is plotted against its growth rate in percentage terms (panel c), and against its 2002 level (panel d).

Figure 1 reveals clear signs of absolute $\beta-$ and $\sigma-$convergence.[4] Panel (a) shows that the cross-sectional dispersion of labor productivity levels remains quite relevant over the 1980-2002 period, even if a closer look may suggest a certain degree of $\sigma-$convergence, since the mode of the distribution in 2002 is higher than in 1980. The second panel reinforces this impression: when the labor productivity levels are expressed in percentage deviations from their cross-sectional mean, a positive degree of $\sigma-$convergence clearly emerges from the comparison. As far as absolute $\beta-$convergence is concerned, the most compelling evidence comes from panel (c): we hardly need to fit a line to the data to conclude that there is a strong negative relationship between the initial labor productivity level and its subsequent growth rate. Note that the Italian regional divide is evident in panel (d): regions located in the North and in the Center show the highest labor productivity levels, while Southern regions are relegated to the lower-left corner of the graph.

[4] Following Barro and Sala-I-Martin [6], I define as *absolute $\beta-$convergence* the tendency of poor regions to grow faster than rich ones, so that the poor regions tend to catch up with the rich ones in terms of the level of GDP per capita (or per worker). I define instead as *$\sigma-$convergence* the tendency of the cross-sectional dispersion of GDP per capita (or per worker) to decline over time.

The conclusions drawn form this visual inspection of the data are backed up by more formal statistics reported in Table 1. Evidently, GDP per worker displays a positive degree of $\sigma-$convergence, since the cross-sectional coefficient of variation (the cross-sectional standard deviation divided by the cross sectional mean) decreased significantly over the considered time horizon. If we regress the average yearly growth rate of labor productivity on a constant and its 1980 initial level in logs, we obtain a negative, and statistically significant, slope coefficient equal to -0.03, i.e. a 4.6% yearly rate of $\beta-$convergence.[5]

In this paper I attempt to answer the question whether the degree of convergence in GDP per worker across Italian regions evident in Figure 1 and Table 1 can be attributed to convergence in relative TFP levels or to convergence in capital-labor ratios. The answer is that the main (and possibly unique) source of $\sigma-$ and $\beta-$convergence is the change in technical and allocative efficiency, i.e. convergence in relative TFP levels. To obtain this result, I adapt the approach introduced in macroeconomics by Färe *et al.* [20] and extended by Kumar and Russell [26]: I estimate the degree of technical and allocative inefficiency at the regional level by constructing an approximation of the (national) production frontier at different points in time using a deterministic and nonparametric method known as Data Envelope Analysis (DEA), and measuring efficiency as the output-based distance from the frontier.[6] This method is entirely data-driven, and does not require strong assumptions on the functional form of the aggregate production function, on the nature of technological progress, or the structure of product and factor markets. Once estimates of the relative TFP levels are available, changes in GDP per worker at the regional level can be decomposed into changes in relative efficiency, changes due to the overall technological progress, and changes due to capital deepening.

My main results are that: (*i*) differences in relative TFP are quantitatively important determinants of the Italian regional divide (for instance, 54% of the relative gap between the GDP per worker of Latium and Basilicata in 1980 can be attributed to the difference in efficiency); (*ii*) technological progress and capital deepening are the main, and equally important, forces behind the rightward shift in the distribution of GDP per worker, but leave the shape of the distribution totally unaffected;

[5] Note that the t-tests are based on White heteroskedasticity-consistent standard errors and covariance. The same statistics for GDP per capita show almost no sign of either $\sigma-$ or $\beta-$convergence: as discussed in Piacentini and Sulis [34], this is due to the ongoing divergence among labor-force participation rates.

[6] A similar approach is followed in Leonida, Petraglia, and Murillo-Zamorano [28], who focus on the 1970-95 period. Their results seem to contrast sharply with mine: they conclude that Italian regions have diverged at a decreasing rate, and that this divergence is due to technological innovation, i.e. to changes in the shape of the (common across regions) production function.

		$\sigma-$convergence		
		1980	*2002*	
GDP per worker	CV	0.130	0.086	
		$\beta-$convergence		
		Constant	*Slope*	R^2
	Coef.	0.12	-0.03	
GDP per worker	*t-Test*	*(5.48)*	*($-$4.73)*	0.59
	Prob.	*(0.00)*	*(0.00)*	

Table 1: Absolute convergence

(*iii*) convergence in relative TFP contributes little to the rightward shift of the distribution, but is the main determinant of the change in the shape of the distribution.[7] These conclusions remain essentially unaltered even if the analysis is performed at the sectorial level, on a yearly basis, allowing for variable returns to scale, or corrected for differences in human capital stocks.

The paper proceeds as follows: Section 2 introduces the theoretical methodology and describes the dataset used in the analysis, Section 3 comments the results, Section 4 discusses some extensions, and Section 5 concludes.

2 Methodology and data

2.1 Data Envelope Analysis

A large and growing literature concerning the measurement of efficiency in production has developed since the seminal contributions of Debreu [16] and Koopmans [25], who provided the basic definitions for technical and allocative efficiency in production. Farrell [21] is the first empirical paper where the problem of measuring efficiency for a set of observed production units is analysed. The Data Envelope Analysis approach, proposed by Farrell [21], was operationalized in linear programming terms by Charnes *et al.* [12] and further extended by Banker *et al.* [4]. Nowadays, DEA is part of a larger family of nonparametric production frontier methods, and is characterized by its assumption of a convex technology set. A fully general exposition of this methodology can be found in Färe *et al.* [19], while recent applications of DEA in the cross-country growth and convergence literature are Färe *et al.* [20] and Kumar and Russell [26].

Suppose that aggregate output at the regional level can be produced using phys-

[7] These results are qualitatively in line with those reported by Di Liberto, Mura, and Pigliaru [18] for the 1963-93 period, and obtained using a panel data econometric approach to estimate traditional growth regression. See also Ascari and Di Cosmo [3].

ical capital and labor via an aggregate production function $Y_t = F_t(K_t, N_t)$, where Y_t, K_t and N_t represent respectively the maximal quantity of output produced, capital and labor employed at date t. We do not need to specify a particular functional form for the aggregate production function, but only to impose an assumption about returns of scale, as well as free input and output disposability.

Since in principle all regions have access to the same technology, the production function itself is not indexed by i; however, regions are allowed to operate at different degrees of technical and allocative efficiency, i.e. different regions with similar capital-labor ratios may produce different amount of output. Formally:

$$Y_{it} = \theta_{it} F_t(K_{it}, N_{it}) \tag{1}$$

where Y_{it}, K_{it} and N_{it} are respectively the output produced, and capital and labor employed in region i at date t, while $\theta_{it} \in [0,1]$ represents region i's *relative* TFP level (to be formally defined in the following).

The DEA approach is a simple nonparametric and data-driven method to jointly estimate θ_{it} and $F_t(\cdot)$. The basic idea is to envelop the data, i.e. the $\langle Y_{it}, K_{it}, N_{it}\rangle_{i=1}^n$ data points in R_+^3, in the smallest possible convex cone; more precisely, under constant returns to scale, the production frontier is approximated by the boundary of the intersection between the convex hull of the data and the free disposal hull. Formally, the approximated technology set, or "Farrell cone," is defined by:

$$\begin{aligned}\Psi_t \equiv & \Big\{\langle Y, K, N\rangle \in R_+^3 \ \mid \\ & Y \leq \sum_{i=1}^n \lambda_i Y_{it},\ K \geq \sum_{i=1}^n \lambda_i K_{it},\ N \geq \sum_{i=1}^n \lambda_i N_{it},\ \lambda_i \geq 0\ \forall i\Big\}\end{aligned} \tag{2}$$

Each observation is interpreted as a unit operation of a linear process, operating at the level λ_i.[8] Hence, every point in the production set is a linear combination of observed data points, or a point dominated by such a linear combination. The approximated technology is therefore a polyhedral cone, with piecewise linear isoquants.

The data points that are dominated by linear combinations of other points represent production processes that are technically inefficient, i.e. that do not operate on the production frontier. Define now the potential output $\hat{Y}_t(K_{it}, N_{it})$ as the maximum output level, i.e. the output level on the production frontier, associated with

[8] Following Afriat [1], non-increasing returns to scale (NIRS) can be imposed by adding the further condition that $\sum_{i=1}^N \lambda_i \leq 1$, while variable returns to scale (VRS) require that $\sum_{i=1}^N \lambda_i = 1$. In this paper we focus mainly on constant returns to scale. However, Section 4.1 discusses how the results are (not) affected by allowing for variable returns to scale.

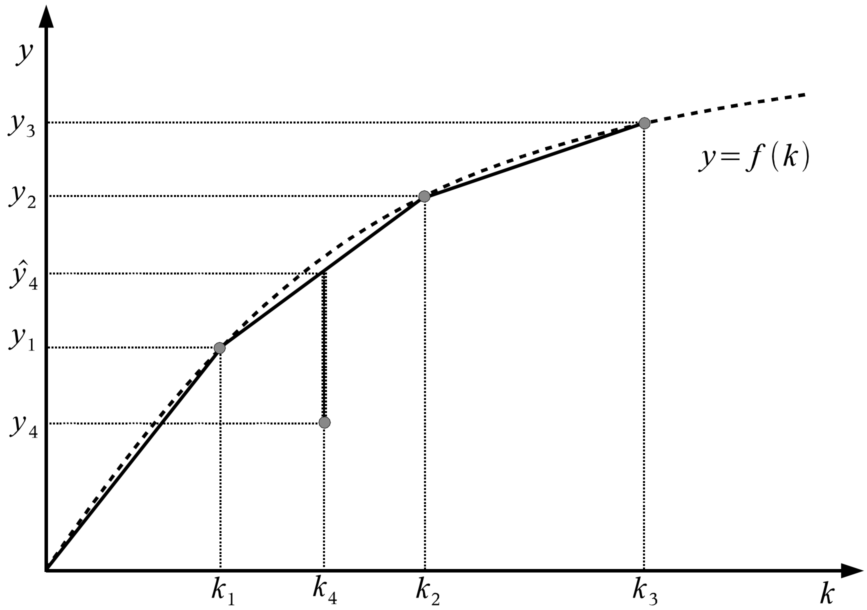

Figure 2: Data Envelope Analysis: a graphical intuition.

the input vector $\langle K_{it}, N_{it} \rangle$ given the technology set Ψ_t; formally:

$$\hat{Y}_t(K_{it}, N_{it}) \equiv \max_{\hat{Y}} \left\{ \hat{Y} \mid \left\langle \hat{Y}, K_{it}, N_{it} \right\rangle \in \Psi_t \right\} \tag{3}$$

The Farrell efficiency index, or score, for region i at date t, i.e. our relative TFP level, is defined as $\theta_{it} \equiv Y_{it}/\hat{Y}_t(K_{it}, N_{it})$, or equivalently as:

$$\theta_{it} = \min_{\theta} \{\theta \mid \langle Y_{it}/\theta, K_{it}, N_{it} \rangle \in \Psi_t\} \tag{4}$$

The Farrell index is less or equal to one, and equals unity only if the production process is efficient, i.e. operates on the frontier. It can be interpreted as the inverse of the maximal proportional increase of output Y_{it} that remains feasible given the technology Ψ_t and the input vector $\langle K_{it}, N_{it} \rangle$. The scores can be easily calculated by solving the following linear program for each observation:

$$\begin{array}{ll} \max\limits_{\{\theta, \lambda_1, \dots, \lambda_n\}} & \theta^{-1} \\ & Y_{it}/\theta \leq \sum_{i=1}^{n} \lambda_i Y_{it} \\ \text{s.t.} & K_{it} \geq \sum_{i=1}^{n} \lambda_i K_{it} \\ & N_{it} \geq \sum_{i=1}^{n} \lambda_i L_{it} \\ & \lambda_i \geq 0 \ \forall i \end{array} \tag{5}$$

A simple example may help to grasp the intuition: consider Figure 2, and the standard concave production function in intensive form represented by the dotted curve $y = f(k)$, where k is the capital-labor ratio. If we were able to observe the input-output combinations for three production units, or regions, operating exactly on the production frontier, the production frontier itself could be roughly approximated by the piecewise linear "best practice" frontier represented by a continuous line in the Figure.[9] The fourth production unit is evidently operating at a lower level of technical efficiency: the observed output y_4 is far below the estimated maximal output $\hat{y}_4$. The Farrell efficiency index in this case corresponds to the ratio $y_4/\hat{y}_4$.

2.2 Decomposition of labor productivity growth

The observed output level at any point in time equals the potential output divided by the corresponding efficiency index: $Y_{it} = \theta_{it}\hat{Y}_t(K_{it}, N_{it})$. In per-worker terms, $y_{it} = \theta_{it}\hat{y}_t(k_{it})$, where $y_{it} \equiv Y_{it}/N_{it}$ and $\hat{y}_{it} \equiv \hat{Y}_t/N_{it}$. Hence, when evaluating the evolution over time of labor productivity, we can decompose its growth rate into the components attributable to growth in efficiency and growth in potential output. At the same time, growth in potential output can be attributed to technological progress or to capital deepening. Formally, the relative change in labor productivity between date 1 and date 2 can be expressed as:

$$\frac{y_{i2}}{y_{i1}} = \frac{\theta_{i2}}{\theta_{i1}}\frac{\hat{y}_2(k_{i2})}{\hat{y}_1(k_{i1})} = \frac{\theta_{i2}}{\theta_{i1}}\frac{\hat{y}_2(k_{i2})}{\hat{y}_1(k_{i2})}\frac{\hat{y}_1(k_{i2})}{\hat{y}_1(k_{i1})} \tag{6}$$

The previous identity decomposes the relative change in labor productivity into: (i) change in efficiency (change in the distance from the frontier); (ii) technological change (the shift in the frontier); (iii) the effect of capital deepening (the movement along the frontier). Note that the previous decomposition measures technological change by the shift in the frontier at the second period capital-labor ratio, and the effect of capital deepening along the first period frontier. An alternative, and equally sensible, decomposition is the following:

$$\frac{y_{i2}}{y_{i1}} = \frac{\theta_{i2}}{\theta_{i1}}\frac{\hat{y}_2(k_{i1})}{\hat{y}_1(k_{i1})}\frac{\hat{y}_2(k_{i2})}{\hat{y}_2(k_{i1})} \tag{7}$$

In this case, technological change is measured by the shift in the frontier at the first period capital-labor ratio, and the effect of capital deepening along the second period frontier.

Being the choice between the two decomposition completely arbitrary,[10] I follow

[9] For the sake of exposition, the best-practice frontier in Figure 2 has been constructed under the assumption of non-increasing returns to scale.

[10] If technical change is Hicks neutral, the proportional vertical shift in the frontier is independent

Färe *et al.* [20] in adopting the "Fisher ideal" decomposition:[11]

$$\frac{y_{i2}}{y_{i1}} = \underbrace{\frac{\theta_{i2}}{\theta_{i1}}}_{E_i} \underbrace{\left[\frac{\hat{y}_2(k_{i2})}{\hat{y}_1(k_{i2})}\frac{\hat{y}_2(k_{i1})}{\hat{y}_1(k_{i1})}\right]^{\frac{1}{2}}}_{T_i} \underbrace{\left[\frac{\hat{y}_1(k_{i2})}{\hat{y}_1(k_{i1})}\frac{\hat{y}_2(k_{i2})}{\hat{y}_2(k_{i1})}\right]^{\frac{1}{2}}}_{F_i} \tag{8}$$

The methodology applied in this paper differs in one important aspect from the standard DEA approach. Kumar and Russell [26] obtain some results that could be interpreted as evidence of technological regress: for some countries in their sample, technological change seems to have a negative effect on the growth of GDP per worker. They warn the reader that these results should be taken with the due discernment, since it is unclear how the production frontier could actually implode at some capital-labor ratios, in particular over relatively short time horizons. Technological degradation detected by standard DEA should probably be classified as due to approximation errors, since the frontier of the Farrell cone can be a very imperfect representation of the true production frontier, in particular when the data points are clustered. Figure 3 depicts such a situation. Two production units, a and b, are observed in two periods, 1 and 2; technological progress occurred between the two periods, and the production frontier at date 2 is higher for all capital-labor ratios. The "best-practice" frontiers are represented by continuous, piecewise linear, curves. Note that, if technological change is measured by the shift in the frontier at the first period capital-labor ratio, we may conclude that technological progress contributed *negatively* to the output growth of the first unit, and *positively* to the output grow of second one. This result is simply due to the approximation error involved in using a piecewise linear "best-practice" frontier.

In order to avoid this possibility, I rule technological regress out by assumption, and construct the "best-practice" frontier in year 2002 using all the data points available for both years, 1980 and 2002. In other words, I assume that in 2002 it should have been possible to produce *at least* the same output level obtained in 1980 when using the same vector of inputs.[12] As discussed in the next Sections, some of the quantitative results, but not the main point of the paper, depend on this assumption.

---

of the value of the capital-labor ratio. In general, the proportional shift in the frontier varies in unspecified ways.

[11] Note that the first part of the decomposition, i.e. $E_i \cdot T_i$ corresponds to the geometric mean of the period t and $t+1$ output-oriented Malmquist productivity indexes.

[12] I'm adapting to my needs the approach developed by Banker and Morey [5] for the study of categorical inputs and outputs; a similar procedure, known as "window analysis," is also discussed in Charnes *et al.* [13].

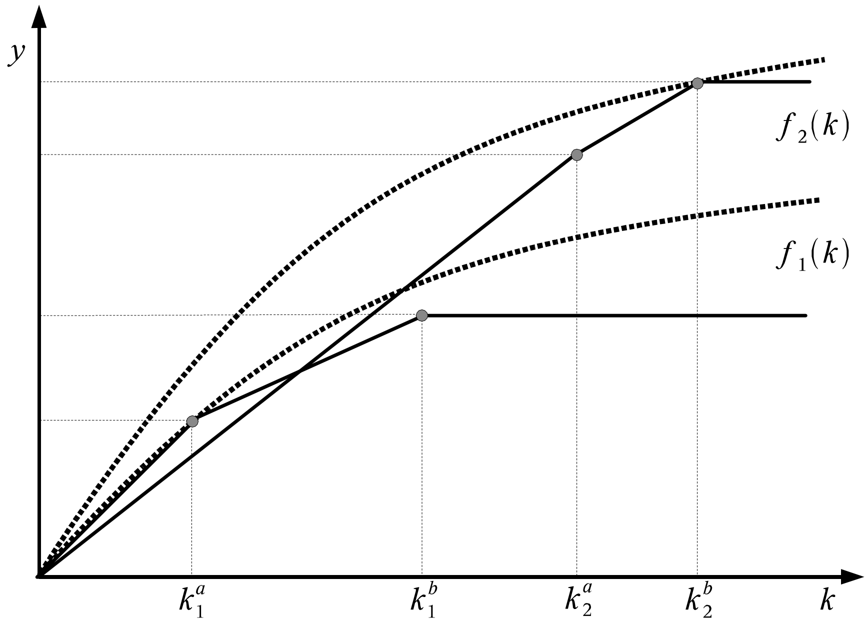

Figure 3: Example of "technological regress."

2.3 Why not standard growth accounting?

The DEA approach is essentially a growth accounting exercise with a few twists of novelty. To understand what they are for, let us quickly review the primal standard growth accounting procedure, as described in Barro and Sala-I-Martin [6]. The starting point is a neoclassical production function of the form $Y = F(A, K, N)$. The growth rate of output can be decomposed into three components, associated with factor accumulation and technological progress:

$$g_Y = \frac{F_A A}{Y} g_A + \frac{F_K K}{Y} g_K + \frac{F_N N}{Y} g_N \tag{9}$$

where g_i is the growth rate of variable i. If the technological factor appears in a Hicks-neutral way, i.e. if $Y = A\tilde{F}(K, N)$, then $(F_A A)/Y = 1$. Furthermore, if factors are paid their social marginal contribution, then the previous relationship can be rewritten as:

$$g_Y = g_A + s_K g_K + s_N g_N \tag{10}$$

where $s_K = (rK)/Y$ and $s_N = (wN)/Y$ are respectively the (possibly time-varying) capital and labor shares in income. Hence, as long as technological progress is Hicks neutral, and factors are paid their social marginal contribution, g_A can be calculated as a residual. If these assumptions are violated, the standard approach will measure the contribution of technology with a bias, as discussed in Barro and

Figure 4: The labor share in Italy.

Sala-I-Martin [6]. Even if the assumptions hold,[13] without specifying a functional form for the production function we cannot recover the TFP levels, and therefore the kind of cross-regional comparisons of efficiency levels discussed in the paper becomes unfeasible. Furthermore, it remains unclear how to decompose observed TFP growth rates at the regional level into changes due to technological progress, which should be common to all regions, and catching-up in terms of relative efficiency.

The next step is usually to assume a "Cobb-Douglas" aggregate production function of the form $Y = AK^{\alpha}N^{1-\alpha}$.[14] In this case it is well known that, if factors are paid their marginal social product, the capital and labor shares in income will be constant over time and respectively equal to α and $1-\alpha$. The value of the "Cobb-Douglas" parameter is then easily calibrated to replicate the long-run labor share in income constructed from national accounts. Since the labor share is rarely constant in the data, the "long-run share" is simply taken to be the average share over a possibly long period of time. As long as the short-run labor share fluctuates randomly around its long-run mean, i.e. there is not systematic trend, this simple approach allows us to decompose the output level into its main components.

Figure 4 plots the labor share in Italy for the 1970-2003 period. Both the raw labor share and the labor share adjusted for self-employment are reported.[15] The

[13] Some recent empirical results in Antràs [2] suggest that technological progress, at least in the US, has not been of the Hicks-neutral type.

[14] See Caselli [11] for a survey of level accounting methods.

[15] The data are taken from the official ISTAT national accounts: more details in the next Section. The raw labor share is simply the ratio between total compensations of employees in current

adjusted labor share reaches its peak in 1975 and then decreases steadily over time: the overall variation amounts to almost 17 percentage points. The raw share displays a similar dynamics. This evidence suggests that the labor share in Italy can hardly be considered constant over time.[16]

There are many possible interpretations: the elasticity of substitution between capital and labor is not equal to one; Italian factor or product markets are not perfectly competitive, so that factors are not paid their social marginal contribution; technological progress has not been Hicks-neutral; and so on. To sum up, in all cases one or more of the basic assumptions behind the standard approach would be violated.[17]

The DEA methodology, instead, being entirely data-driven, is not based on strong assumptions on the functional form of the aggregate production function, the nature of technological progress, or the structure of product and factor markets. We simply need to impose an assumption about returns of scale, as well as free input and output disposability. However, DEA is clearly not a perfect substitute for the standard growth accounting exercise: since a sufficiently large number of observations on independent productive units is needed to construct the production frontier, the DEA approach is mostly useful in cross-sectional analysis, as the one performed in this paper.

2.4 Data

I take advantage of two recently updated official ISTAT datasets: the regional economic accounts, currently available for the 1980-2002 period, and the data on gross fixed investments, depreciation, and net capital stocks at the national level, available for the 1970-2003 period.[18] From these sources I collect data on real GDP, real gross fixed investment, and total employment, measured in Standard Units of La-

prices and nominal GDP; formally: $s_N = COMP/Y$. The adjusted labor share is based on the assumption that self-employed workers obtain on average the same compensation as the employees: formally, $\tilde{s}_N = [COMP/EMP * (EMP + SELF)]/Y$, where EMP is the number of employees and $SELF$ that of self-employed workers (in Standard Units of Labor, see next Section). See Gollin [23] for more details on this procedure.

[16] As Caselli [11] points out, the results obtained from the standard decomposition procedure are highly sensitive to changes in the capital share used. Hence, an imprecise calibration of the "Cobb-Douglas" parameter can be misleading.

[17] We could of course extend the basic framework by assuming a different functional form for the aggregate production function, but the simplicity of the standard approach would be lost, and the econometric techniques necessary to estimate the production function parameters should have to take into account the well-known endogeneity issues discussed in Barro and Sala-I-Martin [6]. Antràs [2] suggests that the US aggregate production cannot be approximated by a "Cobb-Douglas" function.

[18] Both datasets have been revisited according to the SEC95 standard. Data for capital stocks are available only for the 1980-2003 sub-period.

bor,[19] for each of the twenty Italian regions, and data on real gross fixed investment, real depreciation, and the real net capital stock at the national level. All variables, except employment, are expressed in constant 1995 prices.

Unfortunately, ISTAT does not publish official estimates of capital stocks at the regional level. Paci and Pusceddu [32] use a regional dataset for the period 1960-94, based for the 1960-79 sub-period on non-ISTAT data (in particular, on data collected by SVIMEZ and Istituto Tagliacarne), to construct estimates of the national and regional gross capital stocks for the 1970-94 period, following the approach introduced by Gleed and Rees [22].[20] To build my own estimates of the regional net capital stocks for the 1980-2002 period, I apply the following procedure: first of all, to pin down the initial distribution of capital stocks, I focused on 1980 and calculated the regional distribution of capital stocks from the data reported in Paci and Pusceddu [32]:[21] the resulting shares are used to distribute across regions the official ISTAT estimate of the national capital stock in 1980. Then, I obtain a time series for the actual nation-wide depreciation rate using data on depreciation and net capital. Finally, I used the regional series for gross fixed investment and the previously estimated common depreciation rate to construct the time series for the regional net capital stocks, using the standard accumulation equation.[22]

Of course, this procedure is far from perfect. In particular, there are two possibly important sources of measurement error: (i) there is still a certain degree of uncertainty about the initial distribution of capital stocks across regions; (ii) the use of a common depreciation rate may introduce a bias that is difficult to quantify without regional data on the actual composition of gross fixed investment. However, given the current constraint on data availability, this procedure seems a good compromise between simplicity and accuracy, since it makes use of all available information.

[19] The Standard Unit of Labor series combines raw employment data with national accounting information to obtain the equivalent number of workers effectively employed for a standard unit of time. Unfortunately, data on hours worked are currently unavailable at the regional level.

[20] For other estimates of regional capital stocks in Italy, see Bonaglia and Picci [9].

[21] In other words, I calculate the share of each region as $s_i = K_{i,1980}/\sum_{i=1}^{N} K_{i,1980}$ using the data made kindly available by Paci and Pusceddu [32].

[22] The nation-wide depreciation rate is constructed as $\delta_t = D_t/K_t$, where D_t and K_t are respectively depreciation and the net capital stock at the national level; then, the regional net capital stocks are obtained by iterating on $K_{it+1} = (1 - \delta_t) K_{it} + I_{it}$, where now I_{it} and K_{it} represent investment and capital at the regional level, and $K_{i,1980}$ is given. The full dataset is available from the author on request.

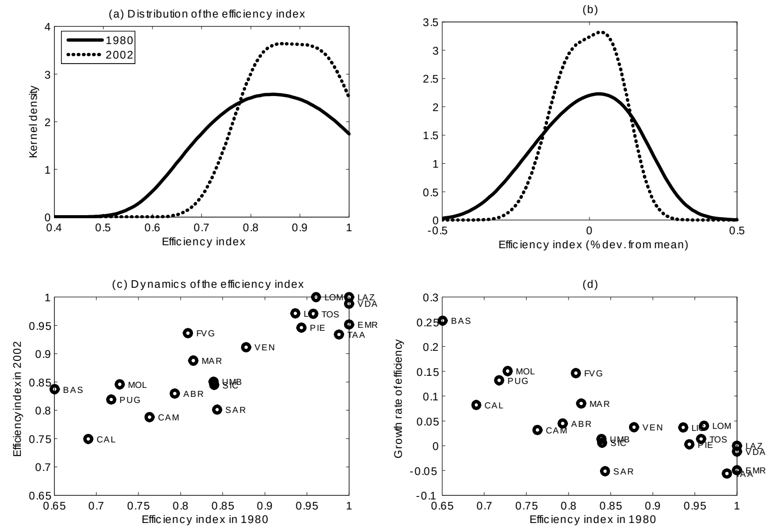

Figure 5: Distribution and convergence of efficiency scores.

3 Results

3.1 Distribution of efficiency scores

Table 2 reports the efficiency scores for the 20 Italian regions in 1980 and 2002, together with their percentage growth rate over the same period and a partition in three broad sub-samples, North, Center, and South, according to an obvious geographical criterion. The regions are ordered according to their efficiency indexes in 1980 (primary key) and 2002 (secondary key). The well-known Italian regional divide is clearly reflected in these results: with some exceptions, the Southern regions are relegated to the bottom of the table. A more careful inspection reveals that the title of most efficient region goes to Latium, since it lies on the "best-practice" frontier in both years. Two Northern regions, Valle d'Aosta and Emilia Romagna lost over time their leadership, while another Northern region, Lombardy, enjoyed an increase in efficiency that took it to the frontier in 2002. The less efficient Northern region in 1980 was Friuli-Venezia Giulia, while the most efficient Southern ones were Sardinia and Sicily. However, while Friuli-Venezia Giulia at least partially recovered his technological gap in 2002, Sardinia and Sicily experienced a significant decrease in their efficiency level.

The results exposed in Table 2 suggest that the efficiency indexes converged across regions over the 1980-2002 period: in fact, note that all regions with low indexes in 1980 experienced a significant improvement in efficiency, while many re-

	Efficiency index			Geographical
	1980	*2002*	*% Change*	collocation
Latium	1.00	1.00	0.0	C
Valle d'Aosta	1.00	0.99	−1.2	N
Emilia-Romagna	1.00	0.95	−4.8	N
Trentino-Alto Adige	0.99	0.93	−5.5	N
Lombardy	0.96	1.00	4.1	N
Tuscany	0.96	0.97	1.4	C
Piedmont	0.94	0.95	0.3	N
Liguria	0.94	0.97	3.7	N
Veneto	0.88	0.91	3.8	N
Sardinia	0.84	0.80	−5.0	S
Sicily	0.84	0.84	0.6	S
Umbria	0.84	0.85	1.3	C
Marche	0.82	0.89	8.9	C
Friuli-Venezia Giulia	0.81	0.94	15.8	N
Abruzzo	0.79	0.83	4.6	S
Campania	0.76	0.79	3.2	S
Molise	0.73	0.85	16.2	S
Apulia	0.72	0.82	14.1	S
Calabria	0.69	0.75	8.5	S
Basilicata	0.65	0.84	28.7	S
Average	**0.86**	**0.89**	**4.9**	

Table 2: Efficiency scores for 20 Italian regions: 1980 and 2002.

gions that were near the frontier in 1980 suffered a decrease in efficiency.[23] This impression is confirmed by Figure 5. Panel (a) plots the estimated distribution of efficiency scores across regions for 1980 and 2002, while panel (b) plots the distribution of their percentage deviations from the cross-sectional mean. There is a clear tendency of the probability mass to shift towards unity, even if the density seems to change form unimodal to bimodal over the period. This positive degree of $\sigma-$convergence among efficiency indexes is more evident in panel (b): a larger probability mass is concentrated around the cross-sectional mean in 2002.

Table 2 seems to suggest that relatively backward regions experienced a faster growth of efficiency. This impression is confirmed by the next two panels: panel (c) plots the indexes in 2002 against the corresponding indexes in 1980, while panel (d) plots the growth in efficiency against the indexes in 1980. In particular, the degree of regional $\beta-$convergence in relative efficiency scores is evident in the last panel:

[23]Please note that, once more, these results have to be taken with the due discernment: the efficiency index is based on distance from the "best-practice" frontier, and not on the distance from the true, and unobservable, production frontier. Hence, approximation errors may be non-negligible.

	GDP per worker	% contribution of:		
	Growth rate %	*Change in*	*Change in*	*Capital*
	(1980-2002)	*efficiency*	*technology*	*deepening*
Abruzzo	38.51	4.58	15.37	14.80
Apulia	41.00	14.09	9.36	13.01
Basilicata	66.36	28.71	21.71	6.20
Calabria	43.28	8.55	16.16	13.64
Campania	41.75	3.21	12.22	22.39
Emilia-Romagna	34.92	−4.84	11.77	26.86
Friuli-V. G.	53.21	15.76	15.41	14.69
Latium	26.81	0.00	10.23	15.04
Liguria	34.93	3.74	20.40	8.03
Lombardy	37.97	4.08	15.31	14.96
Marche	46.57	8.90	10.20	22.13
Molise	54.68	16.23	13.88	16.86
Piedmont	38.32	0.26	12.12	23.05
Sardinia	21.96	−5.03	23.37	4.09
Sicily	32.61	0.59	16.50	13.16
Trentino-A. A.	26.45	−5.49	12.38	19.04
Tuscany	34.49	1.37	8.79	21.95
Umbria	33.49	1.35	16.02	13.52
Valle d'Aosta	24.22	−1.18	25.71	0.00
Veneto	36.64	3.81	12.32	17.19
Average	**38.41**	**4.93**	**14.96**	**15.03**
Yearly average	*1.64*	*0.24*	*0.70*	*0.70*

Table 3: Decomposition of growth in output per worker.

there is a clear negative relationship between the growth rate of efficiency and its initial level.[24]

3.2 Technological catch-up

Table 3 reports the relative contributions (in percentage terms) of changes in efficiency, technological progress, and capital deepening to the growth of GDP per worker, according to the "Fisher ideal" decomposition described in (8).

On average, technological progress and capital deepening are the quantitatively most important determinants of labor productivity growth, while changes in efficiency account for only a tiny 4.9%. Note that the quantitative importance of

[24]If we regress the average yearly growth rate of efficiency on a constant and its 1980 initial level in logs, the estimated slope coefficient is negative and statistically significant, being equal to −0.02 (the vale of the t-test statistic is −4.56, using White heteroskedasticity-consistent standard errors).

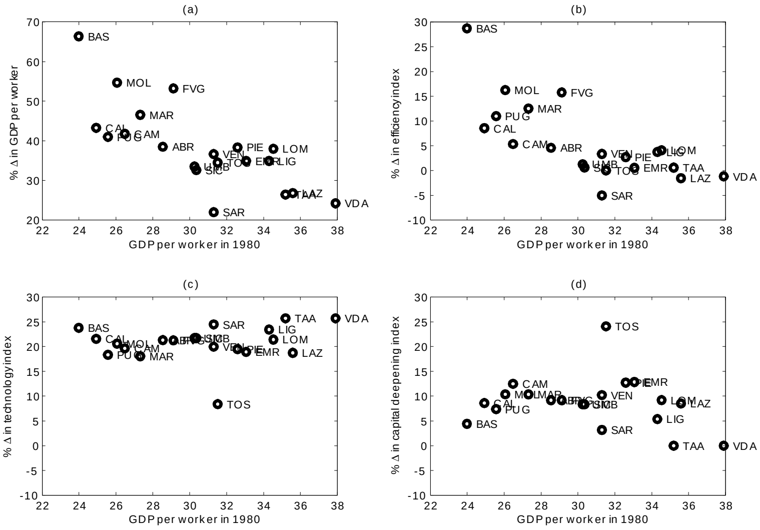

Figure 6: Contributions to absolute $\beta-$convergence.

technological progress and capital deepening is similar.[25] A closer look reveals that four regions in our sample - namely Basilicata, Liguria, Sardinia, and Valle d'Aosta - seem to have benefited from a relatively large (greater than 20%) degree of technical progress and a relatively low (less than 10%) degree of capital deepening. Basilicata enjoyed also a large increase in efficiency, while Sardinia and Valle D'Aosta actually experienced a drop in efficiency. As already noticed, the "best practice" frontier identified by the DEA methodology is just a rough approximation of the real production frontier, hence these three cases may be possibly interpreted as outliers due to approximation errors: in particular, the very high capital-labor ratio of Valle d'Aosta, which isolates this region from the others, may explain the poor performance of DEA in this particular case.

3.2.1 $\beta-$convergence

Figure 6 plots the initial level of GDP per worker (on the horizontal axis) against the growth rate (in percentage terms) of GDP per worker (panel a), the efficiency index (panel b), the technology index (panel c), and the capital deepening index (panel

[25] The relative importance of technological progress and capital deepening is the only result that is quantitatively affected by the assumption that rules out technological regress. Without this assumption, on average the contribution of technical progress drops to 6.26%, while the contribution of capital deepening rises to 26.06%. The estimated changes in relative efficiency, instead, remain almost unchanged. Four cases of technological regress appear in the data, namely Emila Romagna, Latium, Marche, and Tuscany. All other results reported in the following remain essentially unaltered. Detailed tables are available form the author on request.

Dep. Variable:		Average growth rate of:			
		y	E	T	F
	Coef.	-0.03	-0.02	0.00	-0.00
$\ln(y_{80})$	*t-Test*	(-4.73)	(-3.96)	(0.44)	(-0.28)
	Prob.	(0.00)	(0.00)	(0.66)	(0.78)
Correlation with growth rate of y					
Corr. coef.		$-$	0.92	-0.08	0.12

Table 4: Contributions to absolute $\beta-$convergence.

d). The picture reveals a clear negative relationship between the growth rate of GDP per worker and its initial level: this result is not surprising, given our previous discussion. More surprisingly, a similar negative relationship is present between the growth rate of the efficiency index and the initial GDP level, while no relationships at all seem to exist between the growth rates of the technology and capital deepening indexes and initial GDP per worker. The additional fact that panel (b) replicates almost perfectly the pattern observed in panel (a) suggests that convergence among efficiency levels may be the main force behind $\beta-$convergence in GDP per worker.

Table 4 gives a more formal content to this visual inspection. I regress the average growth rates of GDP per worker (y), the efficiency (E), the technology (T), and the capital deepening (F) indexes, on a constant and the logarithm of GDP per worker in 1980. The Table reports the slope coefficients together with the standard t-test statistics (using again White heteroskedasticity-consistent standard errors). As we can see, the efficiency index displays a strong and statistically significant tendency to absolute convergence, and the size of the estimated slope coefficient is quite similar to the coefficient for labor productivity. The other indexes do not show any sign of convergence. Table 4 reports also the cross-sectional correlation coefficients between the growth rate of labor productivity and the growth rate of the efficiency, technology, and capital deepening indexes. Not surprisingly, given our previous results, the growth in efficiency is highly correlated with growth in labor productivity, while the other indexes display a low or even negative correlation coefficient.

3.2.2 $\sigma-$convergence

The six panels of Figure 7 show the *counterfactual* distributions of GDP per worker (in levels and percentage deviation from their cross-sectional mean) obtained by isolating in turn the effects of changes in efficiency, technological progress, and capital deepening, together with the true initial and final distributions of GDP per

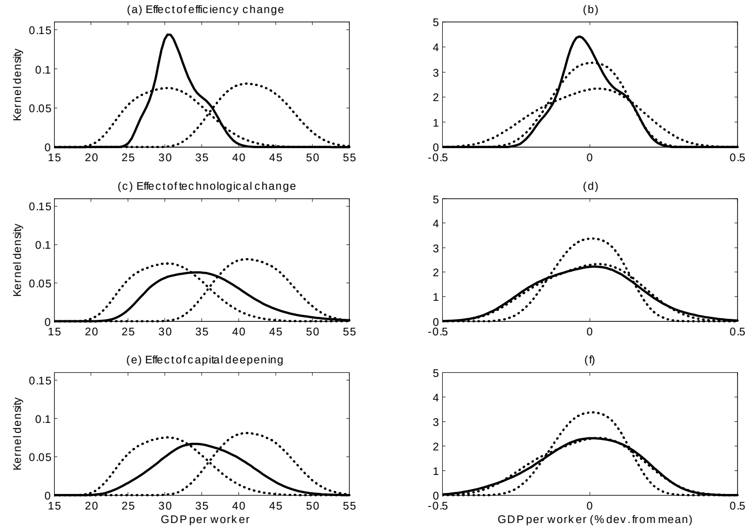

Figure 7: Counterfactual distributions of output per worker.

worker.[26] In other words, the first set of two panels shows the estimated distribution of $\hat{y}_E = E \cdot y_{1980}$, a variable that isolates the effect on the labor productivity distribution of changes in efficiency only. The second set shows the distribution of $\hat{y}_T = T \cdot y_{1980}$, hence isolates the effect of technical change, while the third shows the distribution of $\hat{y}_F = F \cdot y_{1980}$, and therefore isolates the effect of capital deepening. In all graphs the counterfactual distributions are compared to the actual ones.[27]

The picture clearly reveals that while technological progress and capital deepening are both equally responsible for the rightward shift in the distribution, convergence among efficiency indexes is the unique cause of $\sigma-$convergence among GDP per worker levels. In other words, technological progress and capital deepening simply shift the distribution of GDP per worker to the right, without affecting its shape, while convergence in relative TFP levels is responsible for the decrease in the dispersion of labor productivity levels. Note that the quantitative effects of technological progress and capital deepening are extremely similar, almost identical: this parallels the results reported in Table 3.

[26] The distribution of GDP per worker in 2002 can be obtained by successively multiplying the 1980 distribution by each of the three factors, E_i, T_i, and F_i, as defined in (8). Formally, $y_{i,2002} = E_i \cdot T_i \cdot F_i \cdot y_{i,1980}$.

[27] The left-hand side dotted curve is the 1980 actual distribution, while the right-hand dotted curve stands fot the year 2002.

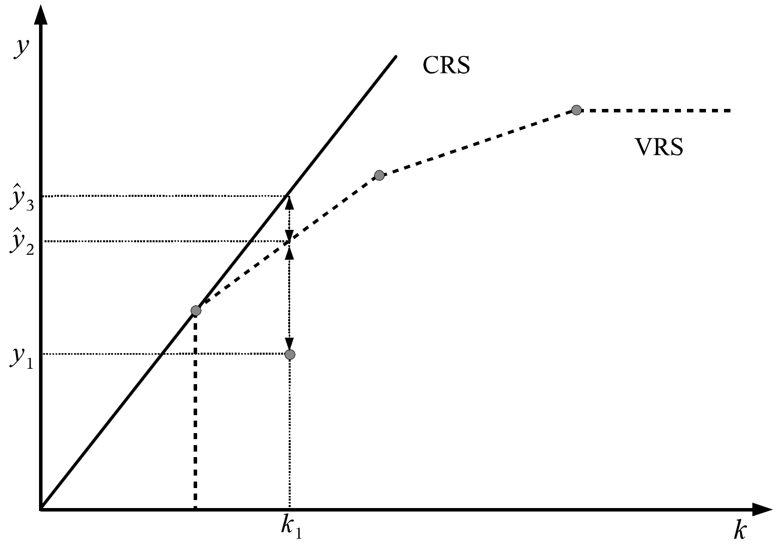

Figure 8: Constant vs. variable returns to scale.

4 Extensions

4.1 Variable returns to scale

The results discussed in the previous Sections are obtained under constant returns to scale. This assumption seems natural in a macroeconomic setting, when the production units under analysis are regions or even countries. Furthermore, Grifell-Tatjé and Lovell [24] have shown that under non-constant returns to scale, the Malmquist productivity index used in this paper does not accurately represent productivity change. However, comparing the results under different assumptions on returns to scale can be a useful robustness check.

We have anticipated that the DEA approach can easily account for non-increasing or variable returns to scale. Following Afriat [1], non-increasing returns to scale (NIRS) can be imposed by assuming that $\sum_{i=1}^{n} \lambda_i \leq 1$, while variable returns to scale (VRS) require that $\sum_{i=1}^{n} \lambda_i = 1$. Figure 8 graphically compares, in the univariate case, the approximated technological sets under constant and variable returns: the frontier under VRS is approximated by a convex hull of intersecting planes which envelops the data more tightly than the CRS conical hull. Hence, the VRS frontier lies weakly below the CRS one, so that the efficiency scores obtained under VRS have to be larger than under CRS. Note that the NIRS frontier is actually a combination of the CRS and VRS ones: it corresponds to the VRS frontier when decreasing returns to scale apply, and to the CRS frontier elsewhere.

	Technical efficiency						Scale efficiency			
	1980			2002			1980		2002	
	CRS	NIRS	VRS	CRS	NIRS	VRS	SE	R	SE	R
Abruzzo	0.79	0.80	0.80	0.83	0.83	0.84	1.00	*C*	0.99	*I*
Basilicata	0.65	0.66	0.66	0.84	0.84	0.84	0.98	*D*	1.00	*C*
Calabria	0.69	0.70	0.70	0.75	0.75	0.75	0.99	*D*	1.00	*C*
Campania	0.76	0.76	0.76	0.79	0.79	0.79	1.00	*C*	1.00	*C*
Emilia-Romagna	1.00	1.00	1.00	0.95	0.95	0.95	1.00	*C*	1.00	*C*
Friuli-V. G.	0.81	0.81	0.81	0.94	0.94	0.94	0.99	*D*	1.00	*C*
Latium	1.00	1.00	1.00	1.00	1.00	1.00	1.00	*C*	1.00	*C*
Liguria	0.94	0.96	0.96	0.97	0.97	0.99	0.97	*D*	0.99	*I*
Lombardy	0.96	1.00	1.00	1.00	1.00	1.00	0.96	*D*	1.00	*C*
Marche	0.82	0.82	0.83	0.89	0.89	0.90	0.98	*I*	0.98	*I*
Molise	0.73	0.73	0.89	0.85	0.85	0.88	0.81	*I*	0.96	*I*
Piedmont	0.94	0.96	0.96	0.95	0.95	0.95	0.99	*D*	1.00	*C*
Apulia	0.72	0.72	0.72	0.82	0.82	0.82	1.00	*C*	1.00	*C*
Sardinia	0.84	0.87	0.87	0.80	0.80	0.80	0.96	*D*	1.00	*C*
Sicily	0.84	0.85	0.85	0.84	0.84	0.85	0.99	*D*	1.00	*C*
Tuscany	0.96	0.96	0.96	0.97	0.97	0.97	1.00	*C*	1.00	*C*
Trentino-A. A.	0.99	0.99	1.00	0.93	0.93	0.94	0.99	*I*	1.00	*C*
Umbria	0.84	0.84	0.84	0.85	0.85	0.88	1.00	*C*	0.97	*I*
Valle d'Aosta	1.00	1.00	1.00	0.99	0.99	1.00	1.00	*C*	0.99	*I*
Veneto	0.88	0.88	0.88	0.91	0.91	0.91	1.00	*C*	1.00	*C*

Table 5: Technical and scale efficiency

Following Banker *et al.* [4], the CRS efficiency level, or *total efficiency* (TE), can be decomposed into *"pure" technical efficiency* (PTE), i.e. the VRS efficiency level, and *scale efficiency* (SE). Scale efficiency is simply defined as the ratio between the two approximated production frontiers. In Figure 8, technical efficiency under CRS is measured by the ratio $y_1/\hat{y}_3$, "pure" technical efficiency is measured by $y_1/\hat{y}_2$, and scale efficiency by $\hat{y}_2/\hat{y}_3$. Hence, $SE = TE/PTE$. The nature of the scale inefficiency for a particular production unit can be determined by comparing the NIRS and VRS efficiency scores: if they are equal, then that particular unit is operating under decreasing returns to scale, while if the scores are different, increasing returns to scale apply.

Table 5 reports the CRS, NIRS, and VRS efficiency scores, together with the scale efficiency score and an indicator of the implied type of returns to scale, constant (C), decreasing (D), and increasing (I). In general, the scale efficiency scores are only marginally different from unity, and therefore the assumption of constant returns to scale imposed in the previous Sections seems appropriate. The only exceptions are Marche and Molise, which seem to operate under increasing returns to scale in

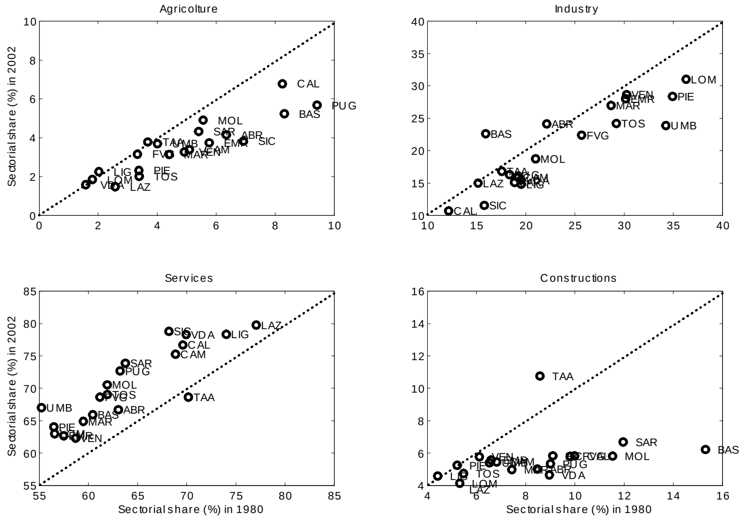

Figure 9: Sectorial shares in Value Added.

both our benchmark years. The results discussed in Section 3.2 remain virtually unaltered if NIRS or VRS are imposed.[28]

4.2 Sectorial decomposition

The productive structure of Italian regions is remarkably variable, ranging from the rich and industrialized regions of the North to the relatively poor and more agricultural regions of the South. Hence, the catching up in relative efficiency at the aggregate level discussed in the previous Sections may have more to do with sectorial reallocations of resources than with pure efficiency gains. In particular, we may conclude that absolute convergence in efficiency scores can be explained by shifts from agriculture to manufacturing or services, i.e. to sectors that are typically more productive. This possibility would change the interpretation of my results, and therefore deserves a closer scrutiny.

The official ISTAT regional accounts report value added in constant 1995 prices and employment (in Standard Units of Labor) at the sectorial level too.[29] I construct four main sectors, namely Agricolture, Industry, Constructions, and Services, and

[28] The results are available from the author on request. Even if under VRS existence of a solution to the linear program in (5) is not guaranteed, in my case a well-behaved solution is reached for all regions. However, decompositions of changes in labor productivity under VRS are subject to the criticism outlined in Grifell-Tatjé and Lovell [24].

[29] The disaggregated sectors are (*i*) Agricolture, forestry, and fishing; (*ii*) Industry in strict sense; (*iii*) Construction; (*iv*) Wholesale and retail trade, hotels and restaurants, repairs, transport and communication; (*v*) Financial intermediation, professional and business services; (*vi*) Other services.

Dep. Variable:			Average growth rate of:			
			v	E	T	F
Agriculture:	$\ln(v_{80})$	*Coef.*	-0.10	-0.03	0.01	-0.01
		Prob.	*(0.01)*	*(0.01)*	*(0.32)*	*(0.36)*
Constructions:	$\ln(v_{80})$	*Coef.*	-0.02	-0.02	0.01	0.00
		Prob.	*(0.29)*	*(0.14)*	*(0.13)*	*(0.74)*
Industry:	$\ln(v_{80})$	*Coef.*	-0.03	-0.03	0.03	-0.01
		Prob.	*(0.09)*	*(0.00)*	*(0.02)*	*(0.26)*
Services:	$\ln(v_{80})$	*Coef.*	-0.03	-0.02	-0.00	-0.00
		Prob.	*(0.03)*	*(0.03)*	*(0.69)*	*(0.73)*
			Correlation with growth rate of v			
			Agri.	*Const.*	*Ind.*	*Ser.*
Change in efficiency (E)			0.89	0.92	0.85	0.99
Technological progress (T)			0.27	0.08	-0.16	0.01
Capital deepening (F)			-0.03	-0.02	0.17	0.10

Table 6: Sectorial contributions to $\beta-$convergence.

use the initial distributions of physical capital stocks at the sectorial level reported by Paci and Pusceddu [32] (constructed for a comparable disaggregation) to build time series for regional and sectorial capital stocks following the procedure outlined in Section 2.4.In the case of Agricolture, the set of production factors is extended to include land availability, and in particular the Utilized Agricultural Area as reported in the Eurostat REGIO database.

Figure 9 plots the sectorial shares in value added in 1980 on the horizontal axis, and the corresponding shares in 2002 on the vertical one. Agriculture is certainly more important for Southern regions, but in general it accounts for a tiny share of regional GDP only, typically less than 9%. The share of agriculture shows a clear tendency to decrease over time, and this in particular for regions with high initial shares, like Apulia, Basilicata, and Calabria. The share of Industry in GDP shows a tendency to decrease over time as well, even if this phenomenon is quantitatively negligible, and some regions like Abruzzo and Basilicata actually enjoyed an increase in the share. Not surprisingly, the Services sector gained importance in almost all regions. Finally, the Constructions sector suffered from a significant contraction in all regions, except Trentino-Alto Adige. Figure 9 clearly suggests that there has been a certain amount of sectorial reallocation during the 1980-2002 period.

Table 6 summarizes absolute $\beta-$convergence, and its determinants, at the sectorial level. For each sector, I regress the average growth rates of value added per worker (v), the efficiency (E), the technology (T), and the capital deepening (F) indexes on a constant and the logarithm of value added per worker in 1980. The upper part of Table 6 reports the slope coefficients together with the standard t-test

	Maximum abs. distance from the dist. of y_{2002}			
Counterfactual distributions:	*Agri.*	*Const.*	*Ind.*	*Ser.*
Distribution of $\hat{y}_E$	0.09	0.19	0.48	0.23
Distribution of $\hat{y}_T$	0.22	0.32	1.92	0.75
Distribution of $\hat{y}_F$	0.16	0.34	1.15	0.88

Table 7: Sectorial contributions to $\sigma-$convergence.

statistics (again, using White heteroskedasticity-consistent standard errors). Labor productivity displays a statistically significant (but for Constructions) degree of absolute $\beta-$convergence even at the sectorial level. Furthermore, the efficiency scores display a strong and significant tendency to absolute convergence too, and the size of the estimated slope coefficient are similar to the coefficient for labor productivity, while other indexes do not show any sign of convergence. Table 6 reports also, for each sector, the cross-sectional correlation coefficients between the growth rate of labor productivity and the growth rate of the efficiency, technology, and capital deepening scores. Once more, the growth in efficiency is highly correlated with growth in labor productivity, while the other indexes display a low or even negative correlation coefficient. These results conform surprisingly well with those obtained at the aggregate level and reported in Table 4.

Finally, Table 7 summarizes the sectorial contributions to $\sigma-$convergence. For each sector, the Table reports the absolute maximum distance between the cross-regional distribution of labor productivity in 2002 (expressed in percentage deviation from the mean) and each of the three counterfactual distributions defined as $\hat{v}_E = E \cdot v_{1980}$, $\hat{v}_T = T \cdot v_{1980}$, and $\hat{v}_F = F \cdot v_{1980}$ (again in percentage deviation from the mean).[30] The counterfactual distribution that summarizes the effect of changes in efficiency alone. i.e. $\hat{v}_E$, is constantly (the only exception being the service sector) the most similar to the final distribution of labor productivity, suggesting that, even at the sectorial level, changes in the shape of the cross-regional distribution of labor productivity are mainly driven by changes in relative efficiency.

4.3 Yearly decomposition

Following Kumar and Russell [26], in the previous Sections I focused on two benchmark years, 1980 and 2002. This allowed me to present a set of relatively clear-

[30] In other words, I am reporting the uniform norm of the difference between the observed labor productivity distribution and each counterfactual distribution in turn: formally, $\|f(y_{2002}) - f(\hat{y}_j)\|_\infty$, where $j \in \{E, T, F\}$. This uniform norm is approximated using 200 equally-spaced points in the $[-2, 2]$ interval. The distributions are estimated as described in footnote 3, p. 1.

	$\beta-$**convergence**		
	Correlation with growth rate of y_t		
	Mean	*Median*	*Std. Dev.*
Change in efficiency (E_t)	0.90	0.95	*0.09*
Technological progress (T_t)	0.12	0.08	*0.19*
Capital deepening (F_t)	0.23	0.17	*0.22*
	$\sigma-$**convergence**		
	Mean of maximum absolute distance		
Counterfactual distributions:	*Dist. of* $\hat{y}_{t+1,E}$	*Dist. of* $\hat{y}_{t+1,T}$	*Dist. of* $\hat{y}_{t+1,F}$
Distribution of y_{t+1}	0.06	0.21	0.20

Table 8: Yearly contributions to absolute $\beta-$ and $\sigma-$convergence.

cutted results. However, data on real GDP, employment, and capital are available for the 1980-2002 period on a yearly basis. Hence, the DEA methodology together with the "Fisher ideal" decomposition can be used to decompose the yearly growth rate of labor productivity into its three components, i.e. catching-up in efficiency, technological progress, and capital deepening.

Table 8 reports the mean, median, and standard deviation (over time) of the cross-sectional correlation between the growth rate of GDP per worker and each of its three components: change in efficiency, technical progress, and capital deepening. Furthermore, the Table shows the mean (over time) of the absolute maximum distance between the cross-sectional distribution of labor productivity (in percentage deviations from the cross-sectional mean) at date $t+1$, i.e. y_{t+1}, and each of the three counterfactual distributions defined as $\hat{y}_{t+1,E} = E_t \cdot y_t$, $\hat{y}_{t+1,T} = T_t \cdot y_t$, and $\hat{y}_{t+1,F} = F_t \cdot y_t$ (again in percentage deviation from the mean).[31]

The statistics summarized in Table 8 clearly confirm my main results. Even on a yearly base, the growth rate of labor productivity is positively and significantly correlated across regions with changes in efficiency, but not with technological progress nor capital deepening. Hence, my conclusion that $\beta-$convergence is driven exclusively by convergence in relative efficiency levels holds even at the yearly level. Furthermore, it is evident that the counterfactual distribution that isolates the effect of changes in efficiency is consistently more similar to the actual distribution of labor productivity than the other two counterfactual distributions, confirming again that also $\sigma-$convergence is driven by the catching-up process in relative efficiency.

[31] For further details, see footnote 30, p. 23.

4.4 Comparison with standard growth accounting

The yearly "Fisher ideal" decomposition discussed in the previous Section can be easily compared to the standard growth accounting procedure described in Section 2.3. Given data on real output, capital, employment and labor shares at the regional level,[32] we can use the Törnqvist-index formulation of (10) to obtain the growth rate of the Solow residual:

$$g_{t,A} = g_{t,Y} - \left(\frac{s_{t,N} + s_{t-1,N}}{2} \right) g_{t,N} - \left(\frac{s_{t,K} + s_{t-1,K}}{2} \right) g_{t,K} \qquad (11)$$

where $g_{t,x} \equiv \Delta x_t / x_{t-1}$ and $s_{t,N}$ and $s_{t,K}$ are respectively the (time varying) capital share in income. Note that the growth rate of the Solow residual is supposed to measure the growth in TFP, and therefore corresponds to the product of E_t and T_t in our decomposition, i.e. to the geometric mean of the period t and $t+1$ output-oriented Malmquist productivity indexes. Hence, I will compare the growth rate of the Solow residual, $g_{t,A}$, to the corresponding quantity $\hat{g}_{t,A} \equiv E_t \cdot T_t$. Table 9 reports the (geometric) average growth rate of the Solow residual, the correlation coefficient (over time) between the two growth rates, their maximum absolute difference, and the mean and standard deviation of their difference. Note that all values are in percentage terms.

The two measures of productivity growth are clearly positively correlated, being all correlation coefficients greater than 0.9. This is hardly surprisingly, since the determinants of the two variables are similar. However, the maximum absolute deviation is generally quite relevant, and in some cases surprisingly large. Furthermore, the growth rate of the Solow residual tends to underestimate productivity growth by 0.2 percentage points on average. The quantitative differences between the two measures of productivity growth are far from negligible, and actually suggest that one of the two measures is severely biased. Färe *et al.* [20] obtain similar results: the average productivity growth rates obtained using standard growth accounting turn out to be remarkably different from the average Malmquist indexes obtained using DEA analysis. Two possible explanations (non-mutually exclusive) for these surprising deviations come immediately to our mind: (*i*) technological progress may not be Hicks neutral; (*ii*) factors may not be paid their social contributions, i.e. factor shares may not be cost-minimizing shares. However, we have also to remember the main distinguishing characteristic of the DEA methodology: it calculates the Malmquist indexes by comparing each country to a common benchmark, i.e. the

[32] The regional labor shares are calculated using data on nominal GDP and compensation of employees obtained from the official ISTAT regional accounts. The labor shares have been adjusted for self-employment according to the procedure outlined in footnote 15, p. 11.

	Mean of g_A	Correlation between g_A and $\hat{g}_A$	Max. of $\lvert g_A - \hat{g}_A \rvert$	Mean of $g_A - \hat{g}_A$	Std. Dev. of $g_A - \hat{g}_A$
Abruzzo	0.90	0.95	1.47	−0.40	*0.52*
Basilicata	1.85	0.98	1.34	−0.23	*0.46*
Calabria	1.14	0.98	1.25	−0.33	*0.48*
Campania	0.99	0.91	1.99	−0.17	*0.66*
Emilia-Romagna	0.52	0.95	2.46	0.19	*0.67*
Friuli-V. G.	1.39	0.99	1.32	−0.35	*0.32*
Latium	0.52	0.97	0.88	0.19	*0.29*
Liguria	1.06	0.96	1.25	−0.22	*0.39*
Lombardy	0.85	0.99	0.86	−0.31	*0.23*
Marche	1.14	0.96	2.46	0.28	*0.58*
Molise	1.37	0.99	1.32	−0.34	*0.40*
Piedmont	0.58	0.93	1.77	−0.47	*0.59*
Apulia	1.12	0.99	0.87	−0.04	*0.26*
Sardinia	0.52	0.97	1.96	−0.25	*0.52*
Sicily	0.64	0.91	1.29	−0.42	*0.46*
Tuscany	0.71	0.93	2.25	0.52	*0.52*
Trentino-A. A.	−0.05	0.99	1.60	−0.80	*0.35*
Umbria	0.81	0.98	1.22	−0.33	*0.39*
Valle d'Aosta	0.43	0.98	1.89	−0.47	*0.67*
Veneto	0.73	0.98	0.56	−0.02	*0.27*
Average	**0.86**	**0.96**	**1.50**	**−0.20**	**0.45**

Table 9: Comparison with standard growth accounting

world production frontier, while standard growth accounting compares each country only to itself in previous periods, not to a common benchmark.

4.5 Human capital

Ciccone [14] shows that educational attainment of the working-age population in Italy, measured by average years of education, has risen from just above 5 years in 1961 to just below 10 years in 2001. Furthermore, the dispersion in educational attainment across regions has fallen by more than a factor of four over the same period. The evolution of regional educational attainment is obtained by combining data from national censuses and labour force surveys in order to estimate a regional series for average years of education of the population aged 25 to 65, currently available at five-year intervals only for the 1961-2001 period. Ciccone [14] estimates also a set of Mincerian wage equations at the regional level, in order to measure the

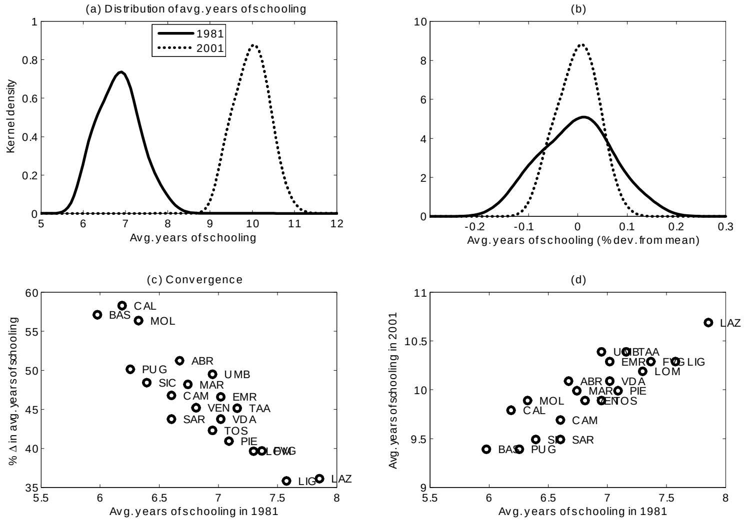

Figure 10: Distribution of average years of schooling.

percentage increase in net wages associated with a one-year increase in attainment.[33]

The upper part of Figure 10 plots the cross-region distribution of the average years of education in levels (panel a) and in percentage deviations from the cross-sectional mean (panel b), in 1981 and 2001. In the lower part of the Figure, the average years in 1981 are plotted against their growth rate in percentage terms (panel c), and against their 2002 level (panel d). The overall increase in the average schooling level and the tendency towards convergence are evident. A visual inspection of Figure 10 immediately suggests that human capital may be the missing factor able to explain regional convergence of efficiency levels.

To test this conlcusion, by borrowing Ciccone's results and following Bils and Klenow [7] we can easily construct estimates of the human capital stock at the regional level. In particular, assuming that labor N_{it} is homogeneous within a region and that each unit of labor has been trained with E_i years of schooling, human capital-augmented labor is given by:

$$H_{it} = e^{\theta_i E_{it}} N_{it} \tag{12}$$

where θ_i represents the time-invariant regional-specific return to schooling estimated in the corresponding Mincerian wage regression (note that an additional year of schooling raises a worker's efficiency proportionally by θ_i).

[33] The estimates of the effect of education on wages are based on the *Survey of Households Income and Wealth* (SHIW) for 1987, 1989, 1991, 1993, 1995, 1998 and 2000. These surveys provide data on the earnings, working hours and personal characteristics for 45398 individuals.

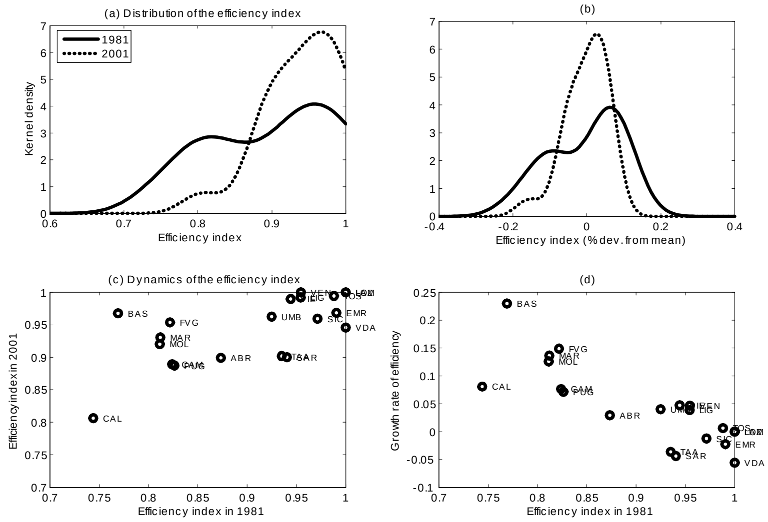

Figure 11: Distribution of efficiency scores (corrected for human capital).

The experiments discussed in Section 3.1 can be easily performed using human capital-augmented labor instead of raw labor. Surprisingly, all main results remain essentially unaltered.

Consider Figure 11, the updated version of Figure 5. Panel (a) plots the estimated distribution of efficiency scores across regions for 1981 and 2001, while panel (b) plots the distribution of their percentage deviations from the cross-sectional mean. As before, the tendency of the probability mass to shift towards unity appears clearly; this time, however, the distribution is evidently *bimodal* in 1981 and becomes *unimodal* in 2001. Panel (c) suggests that correcting for human capital creates two regional clusters in 1981: a group of Southern regions characterized by a relatively low efficiency level, and a group of mainly Northern regions that enjoy efficiency levels near unity (note that Lombardy is now on the frontier in both periods). Finally, panel (d) confirms the strong tendency of efficiency levels to converge: there is a significant negative relationship between the growth rate of efficiency and its initial level.

Figure 12, the updated version of Figure 6, plots the initial level of GDP per worker against its growth rate (panel a), the efficiency index (panel b), the technology index (panel c), and the capital deepening index (panel d). As before, the Figure reveals a negative relationship between the growth rate of the efficiency index and the initial GDP level, while no relationships at all seem to exist between the growth rates of the technology and capital deepening indexes and initial GDP per worker. Again, panel (b) replicates almost perfectly the pattern observed in panel (a), and

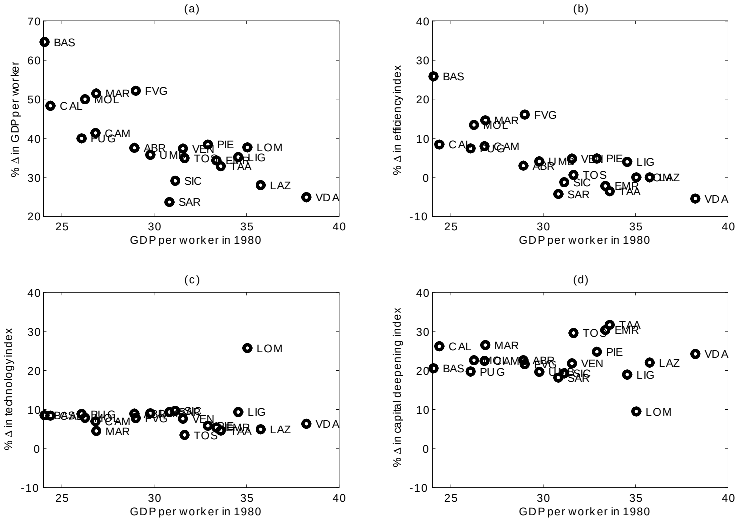

Figure 12: Contributions to $\beta-$convergence (corrected for human capital).

this confirms that convergence among efficiency levels seems to remain the main force behind $\beta-$convergence in GDP per worker.

Finally, Figure 13, the updated version of Figure 7, confirms that, while technological progress and factor accumulation shift the distribution rightwards, convergence among efficiency indexes seems the unique cause of $\sigma-$convergence among GDP per worker levels.

5 Conclusions

In this paper I suggested that the main source of convergence in GDP per worker is the change in technical and allocative efficiency. This conclusion is reached using a deterministic and nonparametric method to measure efficiency as the output-based distance from an estimated "best practice" frontier. More in detail, the main results suggest that differences in relative TFP are important determinants of the Italian regional divide, and that while technological progress and factor accumulation are the main forces behind the rightward shift in the distribution of GDP per worker, convergence in relative TFP determines the change in its shape.

Although these results are, in my opinion, rather stimulating, some of the caveats already discussed in Kumar and Russell [26] apply to my work too. In particular, the DEA methodology used in this paper is simply an alternative approach to growth accounting that does not require neutrality of technical change or strong assumptions about functional forms, and therefore provides no explanations for the phenomena

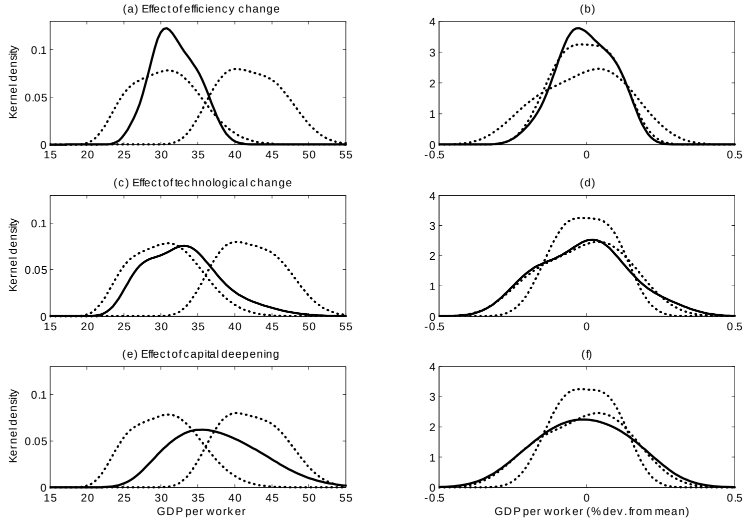

Figure 13: Counterfactual distributions (corrected for human capital).

that are measured. Furthermore, a detailed sector-specific analysis may be more informative about the actual patterns of regional convergence, but is subject to data availability problems, in particular at the regional level. The exploration of these possible extension is left to future research.

References

[1] Afriat, S. (1972): "Efficiency Estimation of Production Functions," *International Economic Review*, 13(3), 568-98.

[2] Antràs P. (2004): "Is the U.S. Aggregate Production Function Cobb-Douglas? New Estimates of the Elasticity of Substitution," *Contributions to Macroeconomics*, 4(1), Article 4.

[3] Ascari, G. and V. Di Cosmo (2004): "Determinants of Total Factor Productivity in the Italian Regions," Atti della XXV Conferenza Italiana di Scienze Regionali, Novara.

[4] Banker, R., A. Charnes, and W. Cooper (1984): "Some Models for Estimating Technical and Scale Inefficiency in Data Envelope Analysis," *Management Science*, 30, 1078-92.

[5] Banker, R., and R. Morey (1986): "The Use of Categorical Variables in Data Envelope Analysis," *Management Science*, 32, 1613-1627.

[6] Barro, R. and X. Sala-I-Martin (2004): *Economic Growth*, 2 ed., New York, McGraw Hill.

[7] Bils, M. and P. Klenow (2000): "Does Schooling Cause Growth?" *American Economic Review*, 90, 1160-1183.

[8] Boldrin, M. and F. Canova (2001): "Europe's Regions: Income Disparities and Regional Policies," *Economic Policy*, 32, 207-53.

[9] Bonaglia, F. and L. Picci (2000): *Il Capitale nelle Regioni Italiane*, DSE Working Paper #374, Università di Bologna, Bologna.

[10] Brugnoli, A. and S. Fachin (2000): "Convergenza e Divergenza della Produttività Settoriale del Lavoro nelle Regioni Italiane, 1980-95," *Rivista di Politica Economica*, forthcoming.

[11] Caselli, F. (2004): *Accounting for Cross-Country Income Differences*, mimeo, Harvard University.

[12] Charnes, A., W. Cooper, and E. Rhodes (1978): "Measuring the Inefficiency of Decision Making Units," *European Journal of Operational Research*, 2, 429-44.

[13] Charnes, A., W. Cooper, B. Golany, L. Seiford, and J. Stutz (1985): "Foundations of Data Envelope Analysis for Pareto-Koopmans Efficient Production Functions," *Journal of Econometrics*, 30, 91-107.

[14] Ciccone, A. (2004): *Human Capital as a Factor of Growth and Employment at the Regional Level: The Case of Italy*, mimeo, Universitat Pompeu Fabra (**??**).

[15] Ciriaci, D. (2001): "Convergenza e Dualismo: Nord e Sud tra il 1970 e il 1999," *Rivista Economica del Mezzogiorno*, XV, 763-802.

[16] Debreu, G. (1951): "The Coefficient of Resource Utilization," *Econometrica*, 19, 273-92.

[17] Di Liberto, A. (1994): *Convergence across Italian Regions*, Working Paper Fondazione ENI Enrico Mattei, n.68.94, Milan.

[18] Di Liberto, A., R. Mura, and F. Pigliaru (2004): *How to Measure the Unobservable: a Panel Tecnique for the Analysis of TFP*, CRENOS Working Paper #2004/05.

[19] Färe, R., S. Grosskopf, and K. Lovell (1995): *Production Frontiers*, Cambridge (UK), Cambridge Univ. Press.

[20] Färe, R., S. Grosskopf, M. Norris, Z. Zhang (1994): "Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries," *American Economic Review*, 84(1), 66-83.

[21] Farrell, M. (1957): "The Measurement of Productive Efficiency," *Journal of the Royal Statistical Society, Series A, General*, 120(3), 253-82.

[22] Gleed, R., and R. Rees (1979): "The Derivation of Regional Capital Stocks Estimates for UK Manufacturing Industries. 1951-1973." *Journal of the Royal Statistical Society*, 142, 330-46.

[23] Gollin, D. (2002): "Getting Income Shares Right," *Journal of Political Economy*, 110, 458-474.

[24] Grifell-Tatjé, E. and C. Lovell (1995): "A Note on the Malmquist Productivity Index," *Economic Letters*, 47, 169-175.

[25] Koopmans, T. (1951): "An Analysis of Production as an Efficient Combination of Activities," in T. Koopmans (ed.), *Activity Analysis of Production and Allocation*, Cowles Commission for Research in Economics, Monograph 13, New York, Wiley.

[26] Kumar, S. and R. Russell (2002): "Technological Change, Technological Catch-up and Capital Deepening: Relative Contributions to Growth and Convergence," *American Economic Review*, 92(9), 527-48.

[27] La Ferrara, E. and Marcellino, M. (2000), *TFP, Costs, and Public Infrastructure: An Equivocal Relationship*, IGIER Working Paper #176, Università Bocconi, Milan.

[28] Leonida, L., C. Petraglia, and L. Murillo-Zamorano (2004): "Total Factor Productivity and the Convergence Hypothesis in the Italian Regions," *Applied Economics*, 36, 2187-93.

[29] Mauro, L. and E. Podrecca (1994): "The Case of Italian Regions: Convergence or Dualism," *Economic Notes*, 3, 447-72.

[30] Myrdal, G. (1957): *Economic Theory and the Underdeveloped Regions*, Duckworth, London.

[31] Paci, R. and F. Pigliaru (1999): "Growth and sectoral dynamics in the Italian regions," in J. Adams e F. Pigliaru (eds), *Economic Growth and Change. National and Regional Patterns of Convergence and Divergence*, Edward Elgar, Cheltenham (UK).

[32] Paci, R. e N. Pusceddu (2000): "Stima dello Stock di Capitale nelle Regioni Italiane," *Rassegna Economica*, *Quaderni di Ricerca*, 97-118.

[33] Paci, R. and A. Saba (1998): "The Empirics of Regional Economic Growth in Italy. 1951-1993," *Rivista Internazionale di Scienze Economiche e Commerciali*, 45, 515-542.

[34] Piacentini, P. and G. Sulis (2000): "Crescita Virtuosa e Crescita Neoclassica nell'Ambito Regionale: Tendenze Recenti per le Aree Europee in Ritardo di Sviluppo," *Rivista Economica del Mezzogiorno*, XIV, 57-98.

[35] Terrasi, M. (1999): "Convergence and Divergence across Italian Regions," *The Annals of Regional Science*, 33, 491-510.