

Convergence and Regional Productivity Divide in Italy: Evidence from Panel Data*

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[This version: 13/12/2005]

***Abstract:** Using a panel data model to control for differences in regional technological levels and to take into account endogeneity, we find two key results for the growth of Italian regions. Firstly, we show that the rate of conditional convergence of each region is much higher (from 12% to 18% according to specifications) than that estimated in standard cross-section regressions (2%). Secondly, a large part of productivity gaps across regions cannot be imputed to differences in physical or human capital but it is rather related to relevant differences in Total Factor Productivity (TFP).*

***Keywords:** economic growth, convergence, regional TFP heterogeneity*

***JEL Classification :** O47; R11; O11.*

1. Introduction

Many empirical studies have examined the pattern of growth of Italian regions systematically showing wide differences in the level of output per worker (or per capita) and a slow process of convergence between poor and rich regions (in particular after the mid-Seventies).

Analysing convergence across countries, these works have mainly used cross-section regressions assuming a homogenous aggregate production function for all regions. The use of a common production function is mainly due to the fact that certain variables, such as efficiency, technology, organizational capital, institutions and so on, are hard to observe or measure and, hence, cannot be considered in a cross-sections regression.

As shown by Islam (1995), Caselli, Esquivel and Lefort (1996) and de la Fuente (2002), cross-section estimations are biased because the unobservable level of technology is omitted, or rather it is assumed common among countries. However, a host of evidence shows that technology differs across countries and is correlated to the explanatory variables normally included in growth regressions. As a way out, these authors adopt a panel data approach, in view of the fact that it allows them to deal with unobservable differences in the production function of countries. Their results are remarkably different from previous estimates obtained in cross-sections analysis, in particular as regards the speed of convergence of countries to their own steady state, which is much more elevated than in previous cross-section analyses.

Our aim is to apply the methodology proposed in these studies to Italian regions using a panel data model with regional fixed effects and estimating it with Least Square Dummy Variables (LSDV) to avoid the omitted variable bias. Moreover, since convergence estimations are plagued by the problem of endogeneity of explanatory variables, we also use the Generalized Method of

* The paper is the result of a joint work between the two authors. However, Francesco Aiello is mainly responsible for sections 4, 5 and 6 and Vincenzo Scoppa for sections 1, 2 and 3. We would like to thank Mariarosaria Agostino, Paola Cardamone and Maria De Paola for useful comments on an earlier version. Usual disclaimers apply. Financial support from the MIUR (PRIN n. 2004132703) is gratefully acknowledged.

Moments (GMM) estimators suggested by Arellano and Bond (1991) and Arellano and Bover (1995) to deal with both heterogeneity and endogeneity issues.

Besides overcoming the problems of omitted variable and endogeneity biases typical in cross-section regressions, panel data estimations also enable researchers to estimate a measure of the level of technology or efficiency (TFP) in each region (from individual fixed effects) and can help to shed some light on the characteristics of regional economies.

Panel data have been used for Italian regions only recently.¹ We will use a new data set (over the period 1980-2002) recently published by the Italian National Statistical Institute (ISTAT) built using the new SEC95 methodology. The entire period is split into 4-year time periods.

The use of panel data methodology reveals two important findings. First of all, the rate of convergence to steady state for Italian regions is much higher (from 12% to 18% according to specifications) than the rate estimated in cross-sections analysis, which reached a consensus on a rate of convergence as low as 1% or 2%. Therefore, the results show that regions are close to their own steady states and are not definitely on different points of the same growth path, which would lead, in the long-run, all the regions to the same equilibrium. Secondly, a large part of productivity gaps across regions cannot be imputed to differences in the accumulation of physical or human capital but rather to differences in Total Factor Productivity (TFP). The index of TFP obtained in our panel estimations is in line with the levels of TFP obtained by Di Liberto, Mura and Pigliaru (2004) using panel data estimations or by Aiello and Scoppa (2000) through growth accounting methodology. This finding implies that technology is not a public good and regional efficiency depends on learning by doing, organizational and social capital and so on. This, in turn has relevant policy implications: when one admits differences in regional production functions the scope for policy is amplified, not restricted.

The paper is organized as follows. Section 2 briefly reviews previous estimates of the rate of convergence across Italian regions. Section 3 considers the omitted variable bias arising in cross-section regressions and estimates the convergence regression with panel data, emphasizing the marked differences in the results with respect to cross-section estimates. Section 4 deals with the endogeneity bias. In Section 5, we determine regional TFP levels and discuss the implications of heterogeneity of production function across regions. Section 6 reports some conclusions.

2. Existing studies on the convergence rate of Italian Regions

Following the renewed interest in growth theory and the empirical works on cross-country growth patterns, a large number of papers has analyzed the process of growth of Italian regions and the existence of a tendency to converge in terms of income levels.

The empirical literature on convergence has aimed to determine, among other things, if poor regions are growing faster than rich regions, that is if they are closing the considerable gap in terms of income per capita or labour productivity, converging in the long-run to the same steady state (*absolute convergence*), or if they are converging to different steady states (*conditional convergence*).

The common approach used for evaluating the process of conditional convergence has been the estimation, through Ordinary Least Squares (OLS), of the following cross-region growth equation:

¹ A recent work by Di Liberto, Mura and Pigliaru (2004) also uses panel data for Italian regions. Although they obtain results similar to ours, their main aim is to estimate the role of *technological* convergence across Italian regions between the Sixties and Nineties, while we focus on (a) how the standard speed of convergence is modified when one considers fixed effects and (b) on regional heterogeneity in TFP. Moreover, they restrict the analysis to the period 1960-1993.

$$[1] \quad \ln\left(\frac{y_{i,T}}{y_{i,t_0}}\right) = a + \beta \ln(y_{i,t_0}) + \phi' \mathbf{X}_i + \varepsilon_i$$

where y_{i,t_0} is the output per worker in region i at an initial time t_0 , $y_{i,T}$ is the same variable at the most recent time T , ϕ is a parameters vector and \mathbf{X}_i a vector of structural variables (e.g. investment rate (s), human capital (h), growth of labour force (n), depreciation rate (δ) etc.), ε_i is an error term. In practice, the growth rate of output per worker is regressed on the initial level of output and on a set of explanatory (structural) variables.

The estimation in regression [1] of a statistically significant parameter $\beta < 0$ implies that poor regions are growing faster than rich ones, in line with the predictions of the neoclassical growth model (conditional “beta convergence”).

Some works have also studied absolute convergence, starting from the assumption that different regions converge to the same steady state, that is, by assuming that the structural variables \mathbf{X} in eq. [1] are equal among regions and thus are not included in the regression. Even though this assumption seems, in general, plausible within a country, it does not apply to Italy where regions are so different in geography, institutions and local policies.

Most of the existing works show a weak conditional convergence process and almost no absolute convergence across Italian regions. The estimation of the speed of convergence (λ), that is the rate at which less developed regions are closing the gap, is about 1-2% per year².

In particular, Barro and Sala-i-Martin (1991) have found that Italian regions (in the period 1950-1985) tend to converge at a rate of about 1.18%, not dissimilar from other European countries (around 2%)³. Sala-i-Martin’s (1996) estimate of λ is even lower (ranging from 1% to 1.5% according to specifications). Paci and Saba (1998) have obtained a rate of conditional convergence equal to 2.37%, while from the estimation of Paci and Pigliaru (1995) the rate is not far from zero. Similar estimates of other studies on Italy are reported in table 1.⁴

Table 1. Results from main empirical works on convergence of Italian regions

	Rate of convergence
Barro and Sala-i-Martin (1991)	1.18%-1.55%
Sala-i-Martin (1996)	1%
Bianchi and Menegatti (1997)	2.46%
Cosci and Mattesini (1995; 1997)	1.1% (3.8%*)
Di Liberto (1994)	3.2% (0.7% after 1975)
Fabiani and Pellegrini (1997)	1.63% (4.02%*)
Ferri and Mattesini (1997)	1.85%
Mauro and Podrecca (1994)	0
Paci and Pigliaru (1995)	0.10%
Paci and Saba (1998)	2.37%*
Cellini and Scorcu (1997)	0.73%
Carmeci and Mauro (2002)	0.09%

* Conditional convergence

² However, when the pre-1975 period is considered the rate of convergence is considerably higher (see, Paci and Saba, 1998).

³ The speed of convergence of 2% per year seems to be “an ubiquitous constant”: most of the existing studies at the international level show estimates of λ around this value (Mankiw, 1995).

⁴ Some of the Italian studies (Mauro and Podrecca, 1994; Paci and Pigliaru, 1995) have made an attempt to take into account different production functions among regions including dummies for macro-regions. However, the cross-section analysis does not allow the authors to consider a sufficient number of variables as the number of regions is too small.

The usual estimate of around 1.5-2% implies a very low process of convergence: at that rate, it would take about 35-45 years to eliminate only half of initial gap in income per worker with respect to the steady state!

3. The speed of convergence: the new estimate through panel data

3.1. Econometric problems in cross-section analysis

In this section, we present the structural equation which is estimated in cross-section regressions and point out the econometric problems plaguing these estimations.

As is well known (see Romer, 2001) starting from the neoclassical growth model and taking a log-linear approximation around the steady state, it is possible to obtain the following equation:

$$[2] \quad \ln(y_t) - \ln(y^*) = e^{-\lambda t} [\ln(y_0) - \ln(y^*)]$$

where y_0 represents the output per worker at an initial period t_0 and y^* is the steady state level and λ indicates the speed of convergence. From the standard Cobb-Douglas production function $Y = K^\alpha (AL)^{1-\alpha}$, the steady state level of income per worker is equal to:

$$[3] \quad y^* = \left(\frac{Y}{L}\right)^* = A \left[\frac{s}{n+g+\delta} \right]^{\frac{\alpha}{1-\alpha}}$$

In eq. [3] the level of technology A grows at the exogenous rate g : $A_t = A_0 e^{gt}$, as the standard growth model states; by taking the logs of eq. [3] and substituting them in the eq. [2], one obtains the following expression:

$$[4] \quad \ln(y_t) - \ln(y_0) = -(1 - e^{-\lambda t}) \ln(y_0) + (1 - e^{-\lambda t}) \left(\frac{\alpha}{1-\alpha} \right) \ln \left[\frac{s}{n+g+\delta} \right] + (1 - e^{-\lambda t}) \ln A_0 + gt$$

Following Mankiw, Romer and Weil (1992), a number of studies has estimated eq. [4] with cross-section data. The investment ratio (s) and growth rate of labour force (n) represent the observable independent variables (taken as averages over the entire sample period), δ is the depreciation rate (assumed constant), while these works assume that the unobservable variable A_0 (which reflects the state of technology at time t_0 or other country specific effects such as institutions, geography etc.) is common among countries, apart from a stochastic specific shock: A_0 is therefore split into two components, one is included in the constant and the other in the error term. Estimation of the speed of convergence λ are recovered from the coefficient of $\ln(y_0)$, denoted with $\beta = (1 - e^{-\lambda t})$, according to the formula: $\lambda = -\ln(1 + \beta)/\tau$, where τ is the time span.

This estimation procedure would be correct if technology were a public good and could be easily applied by all countries – as neoclassical growth model assumes. However, a host of studies (see Hall and Jones, 1998; Klenow and Rodriguez-Clare, 1997; Prescott, 1998, for cross-countries evidence; Aiello and Scoppa, 2000; Di Liberto, Mura, Pigliaru, 2004, for Italian regions) shows that TFP is not homogenous across countries or regions.

More importantly, as shown by Islam (1995) and Caselli, Esquivel and Lefort (1996), if $A_{i,0}$ differs across regions and is correlated with other explanatory variables (physical capital, human capital, etc.), estimates of eq. [4] are biased and inconsistent. In other words, in cross-section regressions there is a problem of omitted variables since it is not possible to take into account the unobservable differences in technology. As a consequence, the convergence coefficient estimated in previous cross-section econometric studies is unreliable. Since the correlation between the omitted variable A and $y_{i,0}$ is reasonably positive, the omission of A determines an upward bias in the

estimate of coefficient of $\ln(y_0)$ in eq. [4] and, as a consequence, the estimate of λ will be downward biased.

In less technical terms, in order to estimate the rate of convergence correctly, it is necessary to take into account the level of steady state of each region: in cross-section regressions this is partly done by introducing the stocks of physical and human capital, but this type of analysis cannot also include the unobservable level of technology, which is a fundamental determinant of long-run prosperity.

3.2. A panel data model

The use of panel data allows us to solve the main problems of cross-section regressions, by estimating a growth regression which includes the regional dummy variables to control for unobservable regional technological differences. The estimated equation, based on eq. [4] with the addition of a human capital variable h , is the following:

$$[5] \quad \ln(y_{it}) - \ln(y_{it-\tau}) = \beta \ln(y_{it-\tau}) + c_1 \ln(s_{it}) + c_2 \ln(n_{it} + g + \delta) + c_3 \ln(h_{it}) + \mu_i + \eta_t + \varepsilon_{it}$$

where, in particular, $\beta = -(1 - e^{-\lambda\tau})$; $\mu_i = (1 - e^{-\lambda\tau}) \ln(A_{i,0})$ is the regional fixed effect; η_t is a set of time dummies to take into account exogenous shifts over time of the production function.

Using SEC95 methodology, the Italian National Statistical Institute (ISTAT) has recently made available a new dataset of Regional Economic Accounts for the 1980-2002 period. We split the whole period 1980-2002 into several sub-periods of span τ . The time span we adopt is four years. In the literature a 5-year time interval is frequently used (see Islam 1995, Caselli, Esquivel and Lefort, 1996), but some authors (e.g. de la Fuente, 2002) choose three or two years intervals. The advantage of shorter time periods is the availability of a greater number of data, but the cost is that cyclical or short-run effects can bias the results through serial correlation of the errors. The time span we adopt is four years and, thus, we obtain 6 observations for each region (1980-1982; 1983-86; 1987-90; 1991-94; 1995-98; 1999-02), but the first observation is devoted to determine the level y_{i0} and the growth rate⁵.

The level of output per worker y_{it} is obtained as the ratio between the regional value-added and the total units of labour, s_{it} is the ratio of private and public investment to GDP and n_{it} is the growth rate of employment. y_{it} , s_{it} and n_{it} are calculated as the geometric average over the years in each sub-period. Variables are expressed at constant 1995 prices.

Variables g and δ are considered common for all regions and periods: g is assumed to be equal to 1.44%, which corresponds to the average growth rate of labour productivity for Italy over 1980-2002; δ is equal to 4.18% and represents the Italian average depreciation rate in the period 1980-2002, calculated as the ratio between capital depreciation and the existing capital stock⁶.

In line with Bils and Klenow (2000), the procedure to determine human capital stock is based on the *earnings functions* proposed by Mincer (1974). The stock of human capital per worker for region i , h_i , is assumed to be equal to: $h_i = e^{rS_i}$ where S_i refers to the regional average years of school (in the labor force) and r represents the rate of return for each year of schooling. We assume $r = 5.7\%$, based on the econometric analysis carried out by Brunello and Miniaci (1999) on returns to school of Italian male workers.

⁵ The results are robust to changes in the time-span τ . We have obtained very similar results with both five-year and three-year time interval.

⁶ In cross-countries studies, because of a lack of data on depreciation, it is assumed that $g + \delta = 5\%$.

In order to ensure that differences with previous works do not depend on the data set used, we firstly estimate with OLS a cross-section regression with the new data. Previous results showing slow convergence (see table 1) are largely confirmed, since in our estimation $\lambda = 2.76\%$ ($\lambda = 2.91\%$ when absolute convergence is estimated) (table 2, columns 1 and 2).

For a further comparison with the existing literature, we estimate a pooled regression ignoring differences in individual regions, that is, imposing a common intercept across regions. From table 2 (column 3) it is evident that the panel nature of the data (that is, when data over the entire period are divided in short periods) *per se* does not change the results. From $\beta = -0.1018$ we can determine the implied speed of convergence $\lambda = 2.69\%$ which is very similar to the estimation obtained above in the single cross-section regression and to many other empirical studies on Italian regions. This also confirms that the division into short sub-periods has not introduced business cycle distortions.

At this point, we can properly exploit the nature of panel data in order to control for unobservable regional characteristics. As for the estimation method, since our main concern is the correlation between explanatory variables and the individual specific error component, it is not appropriate to use the “random effects” method, which requires the error to be uncorrelated with the explanatory variables. Therefore, we estimate a fixed effects model using the Least Squares Dummy Variables estimator (LSDV), the results of which are reported in table 2 (column 4).

Table 2. Cross-section, Pooled Regression and Fixed Effects Estimator.
Dependent variable $\ln(y_{it}) - \ln(y_{i,t-\tau})$

Variables	Cross-section (absolute convergence)	Cross-section (conditional convergence)	Pooled Regression	LSDV
$\ln(y_{i,t-\tau})$	-0.4733** (0.0992)	-0.4547** (0.1188)	-0.1018** (0.0281)	-0.5154** (0.1028)
$\ln(s_{i,t})$		-0.0513 (0.0944)	-0.0109 (0.0153)	-0.0527 (0.0296)
$\ln(n_{it} + g + \delta)$		-0.4701* (0.2078)	-0.0887** (0.0164)	-0.0522** (0.0185)
$\ln(h_{i,t})$		0.7325 (0.8105)	0.1836** (0.0764)	1.0357** (0.2160)
Constant	1.8797** (0.3277)	0.0253 (0.8940)	0.0354 (0.0906)	1.0451** (0.2609)
F-Fisher	22.74	8.80	14.18	16.37
R-squared	0.5582	0.7011	0.3738	0.4628
				F test ($\mu_i = 0$): F(19, 76)=2.03*
Implied λ	2.91%	2.76%	2.69%	18.11%
Observations	20	20	100	100

Notes: standard errors in parentheses.

*significant at 5% level; ** significant at 1% level.

The coefficient of the lagged output per worker variable is highly significant and, as expected, negative. The coefficient of the investment rate results negative, at odds with growth theory, but it is not significant at 5% level. The anomalous relationship between investment and growth is not new for Italian regions (see Galli and Onado, 1990). Accumulation of physical capital has been heavily subsidized by the State and is systematically higher in poorer Southern regions.

The variable $\ln(n_{it} + g + \delta)$ has the expected negative sign and is significant. Human capital is positive and highly significant, in line with the new growth theory. The value of R^2 is quite high.

The two most striking results in the LSDV estimations are the relevant differences existing across regional economies and the high speed of convergence λ , which is equal to 18,11%. Regional fixed effects are significant (we reject the null hypothesis that all $\mu_i = 0$ at 5% level). Moreover, the important role played by regional dummies is confirmed by the high fraction of variance explained by μ_i (0.76)⁷. As regards the speed of convergence we find that it is about eight-fold the previous estimate which ignored regional fixed effects. This implies that regional economies converge very rapidly towards their own level of steady states. In this case, it takes about 4 years for regions to close half of their gap.

Using fixed effects in panel data model, analogous results are obtained at cross-countries level by Islam (1995) (for OECD countries λ ranges from 6.7% to 10.7% according to the estimation method); Caselli, Esquivel and Lefort (1996) (for non-oil countries $\lambda = 12,8\%$), Canova and Marcet (1995) ($\lambda = 23\%$ for European regions and $\lambda = 11\%$ for OECD countries); de la Fuente (2002) ($\lambda = 12.7\%$ for Spanish regions).

The correction for the omitted variable problem leads to dramatic changes in econometric estimates. The existing consensus on a very slow conditional convergence process is completely overturned by these results. The considerable differences with previous estimates are to be attributed to the relevance of omitted variable bias and to the correlation between unobservable and explanatory variables. In fact, because of the positive correlation between y_0 and A_0 , β was upward biased in cross-section and, therefore, λ downward biased.

However, as pointed out by Caselli, Esquivel and Lefort (1996), growth regressions can also be afflicted by the problem of endogeneity of explanatory variables that we shall face in the next Section using GMM estimators.

4. Dealing with the endogeneity issue

The hypothesis of strict exogeneity of the regressors of equation (5) ensures the consistency of the results obtained through the use of the LSDV estimator (Hsiao, 2003; Caselli, Esquivel and Lefort, 1996)⁸. But this condition is hard to verify in growth regressions where the usual explanatory variables are endogenous. For example, referring to eq. [5] it is likely that the level of investments and the stock of human capital are simultaneously determined with the regional growth rate. The problem is widespread, as Caselli, Esquivel and Lefort (1996) note, extending to the interdependence of virtually all of the relevant growth related variables the “only exception is perhaps the morphological structure of a country’s geography” (p. 365).

In order to tackle the endogeneity issue we use a Generalized Method of Moment (GMM) estimator (Arellano and Bond, 1991; Blundell and Bond, 1998) treating all explanatory variables as potentially endogenous. To this aim, we rewrite eq. [5] in dynamics terms, as follows:

$$[6] \quad \ln(y_{it}) = \gamma \ln(y_{it-\tau}) + c_1 \ln(s_{it}) + c_2 \ln(n_{it} + g + \delta) + c_3 \ln(h_{it}) + \mu_i + \eta_t + \varepsilon_{it}$$

⁷ The correlation among fixed effects and explanatory variables is equal to -0.89, confirming that the “random effects” method is not adequate.

⁸ Caselli, Esquivel and Lefort (1996) discuss the use of LSDV to estimate a dynamic growth model in Islam (1995), Knight, Loayza and Villanueva (1993) and Loayza (1994) and argue that this procedure yields inconsistent results because it does not control for endogeneity. Similar conclusions are in Hsiao (2003), who stresses the special case, as ours, when N is larger than T. It is worth noting that LSDV and GMM are comparable (they are asymptotically equivalent when the residuals of a regression are homoscedastic) when regressors are strictly exogenous. Under this circumstance all the leads and lags of each explanatory variable are valid instruments in GMM estimations.

where $\gamma = 1 + \beta = e^{-\lambda\tau}$. Eq. [6] is a dynamic panel model with fixed effects and a lagged dependent variable. It can be properly estimated through the first differences GMM (GMM-DIFF) estimator proposed by Arellano and Bond (1991). We proceed as follows. First of all, we account for nationwide shocks due to the macroeconomic cycle, by expressing all the variables in each period as deviations from national means, i.e., $\hat{y}_{i,t} = \ln(y_{i,t}) - \frac{1}{20} \sum_{i=1}^{20} \ln(y_{i,t})$. This implies that the year-specific intercept (the term η_t) drops from regression [6]. After obtaining the deviation form of the model, we take the first differences of the variables in order to address the issue of unobserved region specific effects (therefore, the term μ_i drops from regression [6]). The estimated equation is the following:

$$[7] \quad \hat{y}_{i,t} - \hat{y}_{i,t-\tau} = \gamma(\hat{y}_{i,t-\tau} - \hat{y}_{i,t-2\tau}) + c_1(\hat{s}_{i,t} - \hat{s}_{i,t-\tau}) + c_2(\hat{n}_{i,t} - \hat{n}_{i,t-\tau}) + c_3(\hat{h}_{i,t} - \hat{h}_{i,t-\tau}) + (\varepsilon_{i,t} - \varepsilon_{i,t-\tau})$$

where in every period the variables are expressed as deviations from the Italian average.

The GMM in first differences (eq. [7]) uses all the available lags of each independent variable in levels as instruments. However, the levels are poor instruments in growth equations, where variables generally exhibit strong persistence. For this reason, as a test of robustness, we employ a system estimator that rescues some of the cross-sectional variance lost in the differences of the GMM-DIFF estimator. The estimation of the system of equations (GMM-SYS) has been suggested by Arellano and Bover (1995) and implemented by Blundell and Bond (1998). It combines the first differenced regression used in GMM-DIFF and the eq. [6] in levels, whose instruments are the lagged differences of the endogenous variables.

Our estimation results are displayed in table 3. The first three columns (Model A-C) refer to the GMM-DIFF estimates obtained from the different hypotheses on the exogeneity of regressors. The last two columns summarize the GMM-SYS results. The instrumental variables used in every regression are indicated at the bottom of the table. In model A, all the right-hand-side variables (except the one-year lagged dependent variable) are assumed to be exogenous while, in models B and C, regressors are treated as predetermined and endogenous, respectively.

To validate our models two types of tests are considered. The Sargan tests on the overidentifying restrictions is conducted to assess the appropriateness of the instruments. Failure to reject H_0 indicates that the extra instruments are valid and support the model's specification. Moreover, we report the p-values of the tests proposed by Arellano and Bond (1991) to detect first and second-order serial correlation in the residuals. If ε_{it} are not serially correlated, the differenced residuals should show autocorrelation of first-order and absence of second-order serial correlation.

A common outcome of Models A and B is that the instruments used are not valid and that the residuals show serial correlation of second order. Therefore, the corresponding regression findings ought to be interpreted with caution. GMM-DIFF estimator performs slightly better under the endogeneity hypothesis of all the regressors (Model C). In this case, the p-value of Sargan test does not reject the model's overidentifying restrictions. A similar conclusion can be drawn when the GMM-SYS is considered (Model D). Finally, we observe that the Sargan test improves substantially by relaxing the exogeneity and predeterminedness hypotheses of regressors and using all of them as endogenous.

Table 3 GMM estimates of the extended Solow model for Italy over 1980-2002

Variables	GMM-DIFF			GMM-SYS	
	Model A	Model B	Model C	Model D	Model E
$\ln(y_{it-\tau})$	0.68 (2.62)	0.41 (3.01)	0.62 (2.03)	0.63 (6.86)	0.632 (8.32)
$\ln(s_{i,t})$	-0.0286 (-1.14)	-0.7 (-2.29)	-0.018 (-0.24)	-0.046 (-1.47)	
$\ln(n+g+d)$	-0.03 (-0.61)	-0.029 (-1.08)	-0.142 (-1.45)	-0.025 (-1.93)	
$\ln(h_{i,t})$	-0.065 (-1.95)	1.46 (2.43)	0.07 (1.66)	0.69 (-1.86)	
Regional Dummies	--	--	--	yes	yes
Implied λ	9.64%	22.29%	11.78%	11.55%	11.47%
Sargan test (p-value)	0.0007	0.23	0.67	0.78	0.42
AR(1) (p-value)	0.02	0.04	0.01	0.14	0.12
AR(2) (p-value)	0.01	0.01	0.04	0.72	0.51
Obs.	80	80	80	60	60

Notes:

The t-values are reported in parenthesis and are robust to heteroskedacity. All variable are expressed as deviations from the national means. In model A, each right-hand side variable is treated as exogenous and instrumented by itself. In model B, all right-hand side variables are treated as predetermined and are instrumented by using all lagged values. In model C, all right-hand side variables are endogenous and instrumented by all available lags. In model D and E, the regressors are all endogenous. The instruments are the lagged values of explanatory variables from t-2 back for equation in levels and lags from t-3 back for equation in first differences.

The diagnostic tests (in particular the p-value of the second-order autocorrelation) make GMM-SYS figures more reliable than those obtained with the GMM-DIFF. Furthermore, GMM-SYS procedure yields a direct estimation of the regional fixed effects (shown in table 4) which is the key variable for detecting TFP heterogeneity across Italian regions⁹. However, the results of table 3 are comparable in all specifications and the parameters have similar values to LSDV estimates.

Looking at the estimated coefficients we note that, after controlling for heterogeneity and endogeneity, human capital remains positively and significantly related with the output per worker. The coefficient of investment remains negative, albeit not significant, and that associated with the variable $\ln(n_{it} + g + \delta)$ has the expected sign and is weakly significant. These results confirm, to a great extent, much of the empirical evidence derived from Solow model to explain the difference of productivity across Italian regions and are qualitatively similar to those obtained through the LSDV estimator (see table 2).

As for the main purpose of this paper it is worth noting that GMM estimations confirm the results obtained through LSDV estimators. Indeed, the statistical significance (not shown) of fixed effects is still high: regional intercepts are always significant at 1% or 5% level. Furthermore, we

⁹ Besides better diagnostic tests, we choose the GMM-SYS estimations because they yield direct estimates of the regional fixed effects. On the contrary, in GMM-DIFF the regional fixed effects can be rescued by taking the time average of the residuals of the first-differenced regression (see Caselli, Esquivel and Lefort, 1996). These residuals are a composite error because they include the regional fixed effects, which we are interested in, and the idiosyncratic disturbance which must be left out of the TFP calculations.

reject the null hypothesis (i.e. H_0 : all regional fixed effects are zero) when testing the joint significance: the p-value of the Wald test in model E is 0.0075. This is an evidence of the heterogeneity existing across Italian regions in the efficiency of their economic systems. The second interesting outcome regards the high significance of the one-period-lagged output per worker, whatever the hypotheses on the exogeneity of regressors and whatever the method of estimation used. The estimation of this coefficient in the well-behaved growth model (model D) is 0.63 which implied a speed of conditional convergence equal to 11.55% per year. This rate is lower than that (18.11%) obtained with the LSDV estimator, but is still notably higher than that obtained in all regressions which failed to control for specific regional effects. It is important to emphasise that passing from pooled to GMM-SYS estimations the speed of convergence increases more than fourfold, from 2.69% to 11.55% per year.

To sum up, after controlling for heterogeneity and endogeneity biases, what clearly emerges from our analysis is that the speed of conditional convergence estimated for Italian regions is extremely high. This means that each region converges to its own steady state, which differs significantly from others, but it takes a very short time to close the gap between the observed income level and that associated with its own steady state equilibrium.

5. Fixed Effects and TFP differences across Italian Regions

The results presented above indicate that the regional fixed effects play a crucial role in the analysis of convergence across Italian regions. If they are left out, the speed of convergence is low and estimations are affected by omitted variables problem. On the contrary, their inclusion into the growth equation allows us to control for heterogeneity bias and yields high speed of conditional convergence. The aim of this section is to determine the fixed effects in order to show the heterogeneity in regional TFP and to discuss the long run implications of the regional efficiency divide.

A measure of regional TFP can be obtained from the GMM-SYS estimations of the regional fixed effects (Model D), that is, by using the relationship $\hat{\mu}_i = (1 - e^{-\lambda\tau}) \ln(A_o)$, where A_o is the proxy of the TFP (see eq. 5 and 6). In such a way, a measure of regional economic efficiency is given by $A_o = \exp[\hat{\mu}_i / (1 - e^{-\lambda\tau})]$.

The values of $\hat{\mu}_i$ estimated through GMM-SYS and the resulting figures of A_o are listed in the first two columns of table 4, while the third column reports a measure of TFP dispersion, expressed as the ratio between the index of efficiency of the *i*-th region and that estimated for Lombardia, the region with the highest values of A_o .

Table 4 shows that TFP differs markedly from one region to another: the highest value refers to Lombardia, while the lowest is that estimated for Calabria. TFP distance between these two regions is, in relative terms, about 16%. Valle d'Aosta, Lombardia, Piemonte, Friuli, Trentino Alto Adige and Emilia Romagna appear to be the most efficient regions, whereas Calabria, Puglia, Campania, Sicily, Sardegna are the least. To put it simply, it clearly emerges that the group with the lowest index of efficiency comprises all the Southern regions, whereas the regions of the Centre and the North of Italy compose a more homogenous group with higher indexes of efficiency (table 4).

These outcomes suggest it may be rewarding to take a closer look at the relationship between TFP and output per worker, because, if these variables are strongly correlated, then the gap in the level of regional productivity can be ascribed to differences in TFP. This line of investigation may provide meaningful insights because, other things being equal, a region can achieve higher level of income in the long run by improving elements incorporated in A_o . From eq. 3 we expect a positive correlation between TFP and Y/L. Note that our measure of TFP is time invariant, being based on the fixed effects of panel data estimations. Therefore, the relationship between A_o and Y/L

is expected to be insensitive to the year at which it is computed and, thus, it can be explored either by considering Y/L data averaged over 1980-2002 or using data observed in each sub-period analysed.

Table 4 Regional fixed effects and TFP in Italy over 1980-2002

Regions	Regional Fixed Effects	$A_o = \exp\left(\frac{\hat{\mu}_i}{1 - e^{-\lambda\tau}}\right)$	$\frac{A_i}{A_{\text{itk}}}$	Y/L	Y/L (LOMB=1)
	\bar{A}_i			Average 1980-2002	
Piemonte	1.391	4.82	0.98	35.68	0.947
Valle d'Aosta	1.370	4.71	0.96	37.54	0.997
Lombardia	1.408	4.92	1.00	37.67	1.000
Trentino-Alto Adige	1.390	4.82	0.98	35.13	0.933
Veneto	1.369	4.70	0.96	33.35	0.885
Friuli-Venezia Giulia	1.370	4.71	0.96	32.46	0.862
Liguria	1.349	4.59	0.93	35.66	0.947
Emilia-Romagna	1.372	4.71	0.96	34.31	0.911
Toscana	1.367	4.69	0.95	32.83	0.871
Umbria	1.345	4.57	0.93	31.45	0.835
Marche	1.332	4.51	0.92	29.52	0.784
Lazio	1.389	4.81	0.98	36.65	0.973
Abruzzo	1.324	4.47	0.91	30.64	0.813
Molise	1.317	4.43	0.90	29.42	0.781
Campania	1.291	4.31	0.88	29.16	0.774
Puglia	1.302	4.36	0.89	27.48	0.729
Basilicata	1.317	4.43	0.90	27.67	0.735
Calabria	1.255	4.13	0.84	26.26	0.697
Sicilia	1.281	4.26	0.87	31.72	0.842
Sardegna	1.295	4.33	0.88	30.30	0.804
Italy				32.26	0.856
St.Dev. of TFP (A0)				0.22	
St.Dev. of Y/L in 2002				3.26	
St.Dev. of Y/L in Steady State				4.33	
Correlation between Y/L in 1980-1982 and Y/L in 1999-2002				0.82	
Correlation between A0 and Y/L in 1980-1982				0.74	
Correlation between A0 and Y/L in 1999-2002				0.92	
Correlation between A0 and Y/L (average 1980-2002)				0.86	
Correlation between A0 and the growth rate of Y/L				-0.21	
Correlation between A0 and Human capital (1980-2002)				0.42	

Figure 1 The positive relationship between TFP and output per worker (Y/L) over 1980-2002

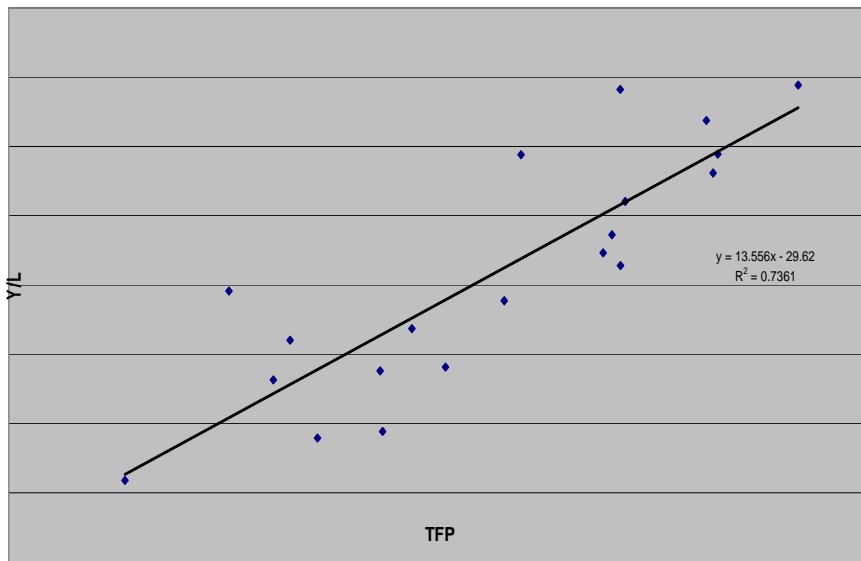
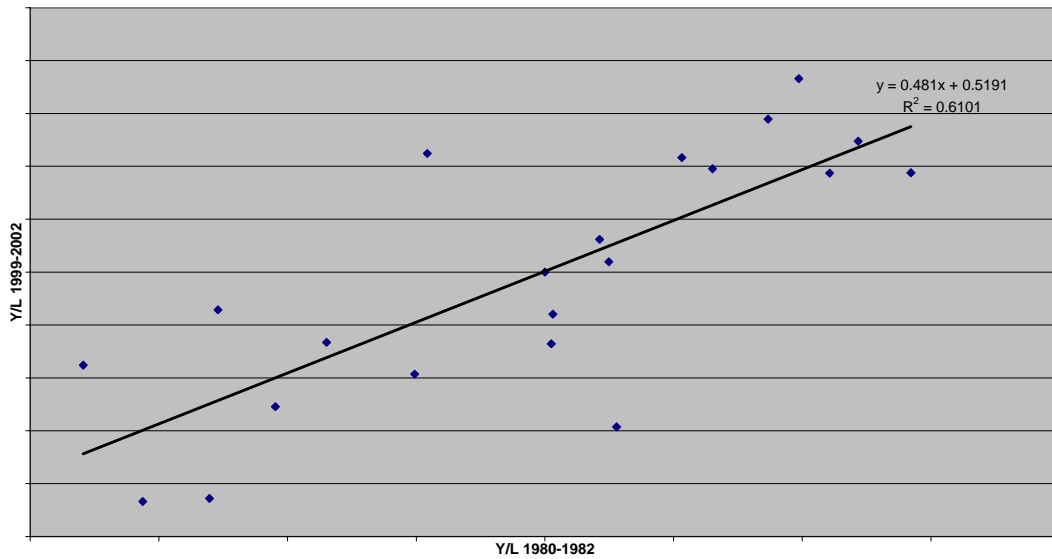


Figure 1 plots A_0 in the horizontal axis and the output per worker registered in the entire span period 1980-2002. It shows a strong positive relationship between output per worker and TFP: the proportion of the variability of output per worker explained only by TFP is 0.73 (figure 1). Similarly, this proportion is 0.54 in the first sub-period considered (1980-1982) and 0.83 in the last period 1999-2002.

In the light of the above findings, it can be argued that the differences across Italian regions in output per worker are explained by the differences in TFP: northern regions are rich because of the efficiency of their regional economic system and not because of differences in the accumulation of physical or human capital. This evidence is in line with the results of many other authors in similar analyses of productivity disparities in Italy (Aiello and Scoppa, 2000; Di Liberto, Mura and Pigliaru, 2004) or across countries (Easterly and Levine, 2000; Hall and Jones, 1999; Islam, 1995). Although one must be cautious in comparing results because of differences in methods of analysis and in time coverage, it is worth noting that our measure of TFP is highly correlated ($\rho=0.89$) with that obtained by Aiello and Scoppa (2000) in a development accounting exercise aimed to decompose the regional output per worker in 1997. A similar high correlation ($\rho=0.81$) exists between our index of TFP and that obtained by Di Liberto, Mura and Pigliaru (2004) using GMM-DIFF to analyse technological convergence in Italy over the period 1963-1993. We can, therefore, confidently confirm that the persistent differences in TFP play a crucial role in explaining the disparities of income levels in Italy.

The regional differences in TFP are similar to those existing in the levels of output per worker. In 1980-1982, the product per worker in Calabria was 64% of Valle d'Aosta and 68% of Lombardia figures. During the period 1980-2002 a certain degree of convergence took place (see section 2), even if at the end of the period the distance in output levels still remained significant. Indeed, in 1999-2002 the output per worker in Calabria was less than 70% of the value observed in Valle d'Aosta and in Lombardia (table 4). This evidence is summarized in Figure 2, where the regional levels of output per worker in 1980-82 (Y/L_{80-82}) is plotted against the levels of Y/L in 1999-2002, both relative to Italy (the correlation between Y/L_{80-82} and Y/L_{99-02} is 0.82, see table 4). There is a very high degree of persistence in differences in regional productivity: regions below the national average level at the beginning of the period, mainly in the South, are still as far behind the other regions at the end of the period.

Figure 2 The persistence in output per worker gaps in Italy. Linear relationship between Y/L in 1980-1982 and in 1999-2002



Furthermore, following Islam (1995), we investigate the relationship between the levels of regional TFP and the growth rate of output per worker over the period 1980-2002. Our evidence shows that these two variables are inversely correlated: the coefficient of correlation is -0.21 (table 4). This outcome might be driven by a certain degree of technological catching-up which took place over the period under scrutiny. Indeed, in section 3, we have shown that factor accumulation is not the key factor in determining the growth of Italian regions, even when conditional convergence is evaluated with regional dummies. However, the framework of analysis used in this paper does not allow us to provide any direct test of technological convergence because the index of efficiency (A_o) is time invariant and its growth rate is constant over time and does not differ across regions (see equation 3)¹⁰.

Finally, we discuss the two key outcomes of this paper. On the one hand we have shown that the Italian regions converge to their own steady state extremely rapidly; on the other hand TFP has been found to play a significant role in explaining differences in the output per worker. These results can be properly used to derive the level of productivity in steady state. We know that in this equilibrium $y_{i,t} = y_{i,t-\tau} = y_i^*$, where y_i^* is the level of output per worker in steady state. From the specification E of eq. [6], $y_{i,t} = \gamma y_{i,t-\tau} + \mu_i + \varepsilon_{i,t}$, y_i^* can be expressed as $y_i^* = \hat{\mu}_i / (1 - \hat{\gamma})$, where $\hat{\mu}_i$ is the regional fixed effects and $\hat{\gamma}$ is the estimated parameter of the one-period lagged dependent

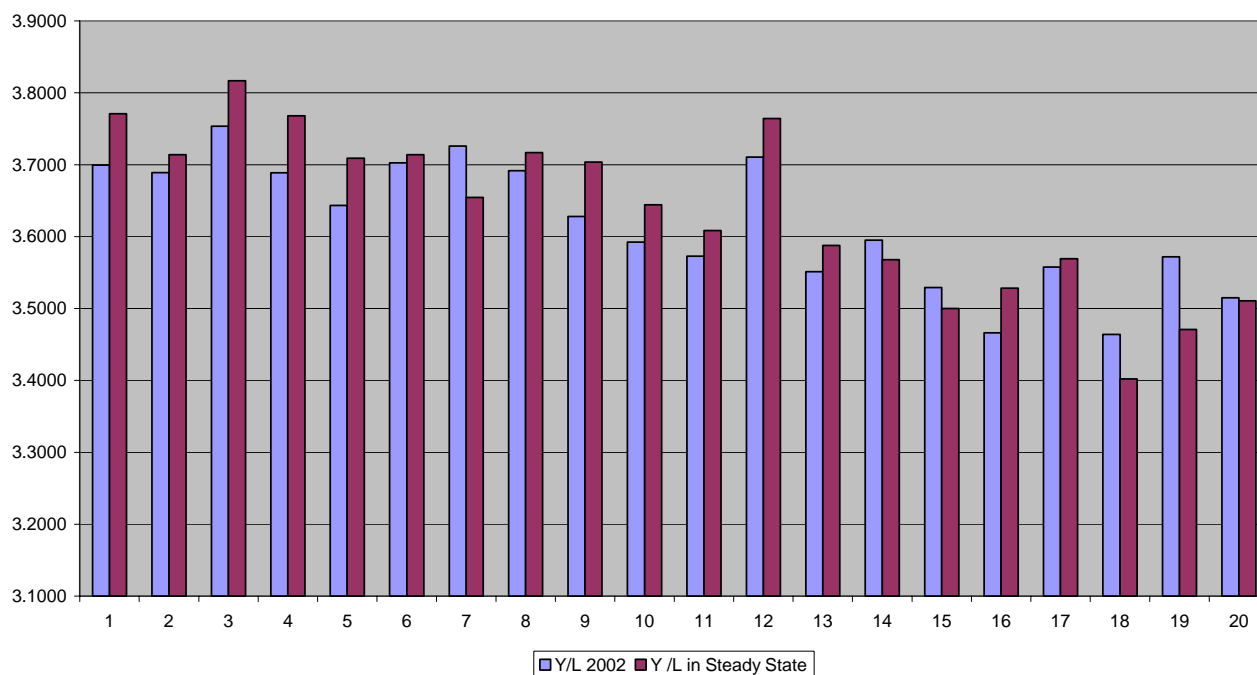
¹⁰ Although we realize that the evidence of technological convergence is indirect and tentative, we can, nevertheless, note that the results are in line with those of some other works specifically aimed at analysing this issue in Italy. In particular, Di Liberto, Mura and Pigliaru (2004) use panel data method on Italian regional data from 1963 to 1993. In order to detect the existence of technology convergence, they run fixed effect regressions on two sub-periods (1963-78, 1978-93) and consider the changes in TFP distributions (reduction in TFP variability from one sub-period to the subsequent one; Southern regions observed an increase of TFP index, while the contrary holds true for Northern regions) as an evidence of TFP convergence. Maffezzoli (2004) uses DEA to decompose the changes in GDP per worker of Italian regions over 1980-2000. The author finds that regions not only converge in TFP but also that this convergence helps to explain the change in the distribution of GDP per worker. Bianchi and Menegatti (2004) show, on the contrary, the non existence of technological convergence across Italian regions over the period 1970-94. This result is based on a conditional β -convergence equation where the distance between the initial TFP of any region and the TFP of the region technological leader is used to gauge the technological catching up. It is worth pointing out that in Bianchi and Menegatti (2004) the coefficient of interest is never significant.

variable. We use GMM-SYS estimations of eq. [6] considering as conditioning variables the regional dummies only (table 3, model E).

The derivation of the level of Y/L in steady state (y^*) enables us to measure the difference with the level observed at the end of the period analyzed (y_{2002}) and to verify if in the long run the economic divide will still persist among Italian regions. Both variables (y^* and y_{2002}) are plotted in figure 3. Two results, which confirm previous ones, clearly emerge: the first refers to the wide differences in steady state levels across regions, whereas the second illustrates how close regions are to their own steady state equilibrium. Moreover, it is evident that Italian regional gaps are likely to persist in the long run: in equilibrium, the productivity of northern and central regions will be systematically higher than that estimated for the Mezzogiorno¹¹.

Another interesting result is the actual relative position of each region with regard to the steady state level of productivity. Our analysis shows a sharp difference in the behaviour of rich and poor Italian regions. In fact, figure 3 illustrates that the regions of the North and Centre of Italy are behind the equilibrium of steady state (they have still to grow in order to fill their gap of income), whereas the contrary holds for Liguria and for 5 Southern regions (Calabria, Sicily, Sardegna, Campania and Molise)¹². In other words, in equilibrium, the level of income of these regions is even lower than that measured in 2002 and this means, in the absence of any structural shock, that these regions will face the risk in the near future of a further process of impoverishment.

Figure 3 A comparison between the level of labour productivity observed in 2002 and the steady state estimated level (data in logs)



Codes: 1=Piemonte, 2=Valle d'Aosta, 3=Lombardia, 4=Trentino-Alto Adige, 5=Veneto, 6=Friuli-Venezia Giulia, 7=Liguria, 8=Emilia-Romagna, 9=Toscana, 10=Umbria, 11=Marche, 12=Lazio, 13=Abruzzo, 14=Molise, 15=Campania, 16=Puglia, 17=Basilicata, 18=Calabria, 19=Sicilia, 20=Sardegna

¹¹ This result is partially confirmed by the standard deviation of labour productivity which increases from 3.26 to 4.33 passing from the observed value of income per worker in 2002 to that estimated for steady state (table 4).

¹² This is probably due to a relatively high level of accumulation of factors (i.e., physical capital) with respect to the output level.

5. Concluding remarks

In this paper we apply a panel data approach to investigate the neoclassical convergence and the existence of technological heterogeneity across Italian regions. By using a new dataset from ISTAT covering the period 1980-2002, we show that the estimation of a standard cross-region regression produces a speed of conditional convergence of 2,76% per year. From an economic point of view, the slow convergence in cross-section studies depends on the fact that there appears to be almost no negative correlation between the initial output level and the growth rate. Since the level of technology is not controlled for, the steady state levels of rich and poor regions are quite similar. Therefore, it appears that poor regions are growing at a very slow rate with respect to their distant target, resulting in slow convergence.

Our cross-section results regarding slow convergence process are analogous to those of the considerable body of literature explaining the economic divide in Italy, but, as in Caselli, Esquivel and Lefort (1996) and Islam (1995), we argue that much of this work is affected by a misspecification of the growth regression due to problems of omitted variables and endogeneity.

By using different panel data methods to control for technological heterogeneity and for endogeneity, we find a notably higher speed of conditional convergence. Our chosen econometric specification of the growth model is obtained by referring to the GMM-SYS estimator proposed by Arellano and Bover (1995). In this specification, the speed of conditional convergence is 11.55% per year.

The second key result of this paper is the high significance of regional fixed effects which we use to measure the technological level observed in each region over the period under scrutiny. The evidence of a high β -conditional convergence and of marked differences in the aggregate production functions at regional level suggest that regions converge in a very rapid way to their own steady state. The differences observed in the data are not due to the different locations of the regions along the same transitional dynamic path, but rather to very different steady states.

However, these findings are disturbing from a policy perspective because even if, on one hand, regions are converging speedily, on the other hand they predict that, in the long run, regions will reach very different income levels. It is confirmed that the northern and central areas of the country will converge to a much higher level of income than that achievable by the south of Italy. In other words, without structural shocks which provoke shifts of the aggregate regional production function, the Italian economy will be characterised by a dualistic structure also in the long-run equilibrium.

If the gaps between regions persist in the stationary level of income, then the crucial question will be to investigate the determinants of such differences. This study clearly confirms that factor accumulation in Italy does not play an important role in determining regional development. On the contrary, it has been shown that TFP not only significantly differs region-by-region, but also that it is the key variable in explaining regional divide in the steady state equilibrium. The evidence is that the income per capita is high in the northern regions, which are those recording the highest index of economic efficiency, and low in the Southern regions with the lowest values of TFP. Therefore, this paper suggests that in order to foster regional growth in Italy, improvements of conventional variables (i.e., investments in physical and human capital) should not be a priority in the policy agenda; efforts must rather be devoted to all the factors (economic, social and political) which enter into the regional TFP and determine the efficiency of the local economic systems.

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