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

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***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. Preliminarily, since this approach has been criticized by Dowrick and Rogers (2002) we verify – following these authors – if the conditions are met for the

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use of this methodology. Moreover, since convergence estimations are plagued by the problem of endogeneity of explanatory variables, we also use the Generalized Method of 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. Carmeci and Mauro (2002) use panel data estimators to explore the relationship between the convergence process and the characteristics of Italian labour markets, finding that the imperfections in the working of labour markets (in particular, the centralized wage bargaining mechanism) and the unemployment rate lowers the rate of growth and slow down convergence of less-developed regions.

Di Liberto, Pigliaru and Mura (2007) use panel data with the aim to estimate the role of *technological* convergence across Italian regions between the Sixties and Nineties. They find strong evidence that a process of TFP convergence took place among Italian regions, in particolar up to the mid-seventies.

The common denominator between our paper and those by Carmeci and Mauro (2002) and Di Liberto, Pigliaru and Mura (2007) is the similarity in results concerning the speed of convergence of Italian regions when using analogous estimations techniques. However, we use more recent data (from 1980 up to 2004) while Di Liberto, Pigliaru and Mura (2007) restrict their analysis to the period 1960-1993 and Carmeci and Mauro (2002) use data from the period 1963 to 1995.

More importantly, we focus on the analysis of heterogeneity in TFP across regions, using regional fixed effects to measure the technological level of each region and to obtain implications about the long-run trend of regional income levels.

We will use a new data set (over the period 1980-2004) recently published by the Italian National Statistical Institute (ISTAT, 2005) 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 (around 11-12% 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, Pigliaru and Mura (2007) 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 rather than being 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:

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

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 $\boldsymbol{X_i}$ 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 $\boldsymbol{X}$ 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 year[1].

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%)[2]. 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.[3]

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

[2] 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).

[3] 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.

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

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

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

In eq. [3] the level of technology A grows at the exogenous rate g: $A_t=A_0e^{gt}$, 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] $$\ln(y_t)-\ln(y_0)=-\left(1-e^{-\lambda t}\right)\ln(y_0)+\left(1-e^{-\lambda t}\right)\left(\frac{\alpha}{1-\alpha}\right)\ln\left[\frac{s}{n+g+\delta}\right]+\left(1-e^{-\lambda t}\right)\ln A_0+gt$$

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 $\beta = \left(1 - e^{-\lambda t}\right)$, 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, Pigliaru and Mura, 2007, 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_{t0} 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 preliminary test of common technological growth across regions

Dowrick and Rogers (2002) criticise the recent estimations of cross-country convergence equations that follow the approach proposed by Mankiw, Romer and Weil (1992), because of their assumption of a common rate of technology growth across countries and of the use of a log-linear approximation of the Solow growth model which leads to biased estimations. Alternatively, Dowrick and Rogers (2002) propose a procedure which allows to test rigorously if the rate of technology growth is uniform across countries/regions using capital stock data rather than investment data, as in Mankiw, Romer and Weil (1992).

We follow Dowrick and Rogers (2002) and test at the outset if the rate of technological progress is common across Italian regions. Starting from a standard production function: $Y = K^{\alpha}(AhL)^{1-\alpha}$, dividing by L and taking logs we obtain: $\ln(Y/L) = \alpha\ln(K/L) + (1-\alpha)\ln(h) + (1-\alpha)\ln(A)$. Taking the derivative with respect to time, we arrive at:

[5] $$\frac{\dot{y}}{y} = \alpha\frac{\dot{k}}{k} + (1-\alpha)\frac{\dot{h}}{h} + (1-\alpha)g$$

Using regional data on physical and human capital stocks (ISTAT, 2005), this equation allows us to estimate α and *g*, the rate of technological progress and, more importantly, to estimate if this rate differs across Italian regions. In a panel model we estimate:

[6] $$z_{it} = \alpha\left[\frac{\dot{k}}{k}\right]_{it} + (1-\alpha)\left[\frac{\dot{h}}{h}\right]_{it} + (1-\alpha)g_i + \varepsilon_{it}$$

where z_{it} represents the rate of growth of per worker income of region *i* during period *t*, and g_i represent the regional fixed effects.

We determine regional capital stock on the basis of the perpetual inventory method using data on total investment at constant prices, by setting the depreciation rate at $\delta = 4.18\%$, the effective depreciation rate as calculated by ISTAT along the considered period. We estimate the model first with only capital stock (to make easier comparisons with Dowrick and Rogers' estimations) and then with both physical and human capital. Results are shown respectively in columns 1 and 2 of Table 2.

The main result we obtain is that regional fixed effects are not significantly different from zero at any conventional level (p-values are 0.17 and 0.52 in column 1 and 2, respectively). This implies that there is no heterogeneity across regions in the growth rate of technology.

Although regions are very heterogeneous in the *level* of per worker income, the results obtained using the methodology of Dowrick and Rogers (2002) reassure us that Italian regions have a common rate of technological growth and therefore that following Mankiw, Romer and Weil and using log-linearization does not lead to biased estimations.

As robustness exercise on capital stock data, we also use Italian regional data from CRENOS which start from 1960 in order to calculate the data on the initial capital stock (1980). Results are very similar and are not reported.

Table 2. Panel estimation of the production function (Dowrick and Rogers, 2002).
Dependent variables: regional growth of per worker income over the period 1980-2004.

	(1) Only Physical capital	(2) Physical and human capital
$\dot{k}/k$	0.578***	0.305***
	(0.076)	(0.076)
$\dot{h}/h$		2.221***
		(0.339)
Constant	0.014**	-0.034***
	(0.006)	(0.009)
Regional Fixed Effects	YES	YES
Observations	120	120
Number of regions	20	20
R-squared	0.372	0.563
F test that all g_i =0	F(19, 99) = 1.35	F(19, 98) = 0.95
p-value that fixed effects are equal	0.1706	0.5195

Source: ISTAT (2005), Conti Economici Regionali, Anni 1980-2004 (available on-line).
Standard errors in parentheses. ** significant at 5%; *** significant at 1%

3.3. 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:

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

where, in particular, $\beta = -\left(1-e^{-\lambda\tau}\right)$; $\mu_i = \left(1-e^{-\lambda\tau}\right)\ln\left(A_{i,0}\right)$ 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 made available in 2005 a dataset of Regional Economic Accounts for the 1980-2004 period (ISTAT, Conti Economici Regionali, Anni 1980-2004). We split the whole period 1980-2004 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 7 observations for each region (1980-1982; 1983-86; 1987-90; 1991-94; 1995-98; 1999-02; 2003-04), and the first observation is devoted to determine the level y_{t0} and the growth rate[4].

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 1980-2004; δ is equal to 4.18% and represents the Italian average depreciation rate in the considered period, calculated as the ratio between capital depreciation and the existing capital stock[5].

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.

Alternatively, we have used the rate of return of human capital estimated by Ciccone (2004) (see also Ciccone, Cingano, Cipollone, 2006). In order to take into account the fact that regions may differ in their rates of return on education, the stock of human capital has been calculated using the function $h_i = e^{r_i S_i}$, where r_i represents the specific rate of return on schooling for region *i* calculated by Ciccone (2004). However, estimation results regarding human capital contribution are not very different from those obtained using the uniform rate of return and we choose to not report these results to avoid cluttering the tables.

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 $\lambda = 2.36\%$ ($\lambda = 2.72\%$ when absolute convergence is estimated) (Table 3, 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 3 (column 4) 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 $\beta = -0.127$ we can determine the implied speed of convergence $\lambda = 3.40\%$ which is similar to the estimation obtained above in the single cross-section regression and to many other empirical studies on Italian

[4] 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.

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

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 3.

We test the standard assumption that the error terms of our panel data growth model are independent across regions. If there is cross sectional dependence, then the estimates obtained using a fixed effect estimator will be unreliable (Phillips and Sul, 2003). At this aim we employ the test proposed by Pesaran (2004), whose statistics follows a standard normal distribution. Results show that Pesaran's test is -1.547 and, therefore, we can conclude that the process of β-conditional convergence of Italian regions does not suffer from cross-sectional dependence (Table 3).

Table 3. 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)	Cross-section (conditional convergence)	Pooled Regression	LSDV
$\ln(y_{i,t-\tau})$	-0.465** (0.078)	–0.420** (0.096)	-0.351** [0.119]	–0.127** (0.028)	–0.683 ** (0.094)
$\ln(s_{i,t})$		–0.039 (0.085)		–0.031 (0.016)	–0.094** (0.030)
$\ln(s^{private}{}_{i,t})$			0.121 (0.121)		
$\ln(s^{public}{}_{i,t})$			-0.049* (0.025)		
$\ln(n_{it} + g + \delta)$		–0.317* (0.121)	-0.417** [0.121]	–0.027** (0.015)	–0.001** (0.015)
$\ln(h_{i,t})$		0.668 (0.787)	1.355 [0.984]	0.037 (0.081)	1.185** (0.203)
Constant	1.855** (0.261)	0.378 (0.647)	-0.407 [0.816]	0.349 (0.091)	1.625** (0.229)
F-Fisher	35.78	9.52	8.39	14.18	21.31
R-squared	0.596	0.712	0.721	0.271	0.470
					F test ($\mu_i = 0$): F(19, 96)=2.78**
Pesaran Test (p-value in parenthesis)					-1.547 (0.1219)
Implied λ	2.72%	2.36%	1.87%	3.40%	13.01%
Observations	20	20	20	120	120

Source: ISTAT (2005), Conti Economici Regionali, Anni 1980-2004 (available on-line).
Notes: standard errors in parentheses.
*significant at 5% level; ** significant at 1% level.

The value of R^2 is quite high. The coefficient of the lagged output per worker variable is highly significant and, as expected, negative.

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 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. However, the expenditure in investment is not typically transformed into productive capital, especially for the public sector (see Scoppa, 2007, for a similar analysis for Italian regions). Because of agency problems plaguing governments, public actors might follow opportunistic behaviour, such as corruption, “patronage” or simply provide low effort to reduce costs, which create a divergence between the cost of investment and its effective efficiency. Southern regions are particularly affected by these problems (see Golden and Picci, 2005).

Furthermore, private investments are also heavily subsidized by the State, especially in the South. These subsidies to firms could distort investment choice: firms may over-invest or invest in less efficient projects or sectors (i.e., the State might help declining sectors) or the funds could simply be embezzled by entrepreneurs.

On the whole, these considerations help to explain the negative relationship between investment and productivity.

In order to investigate further this aspect, following Carmeci and Mauro (2004) we have splitted the investment in physical capital between public and private investments. Consistently with our explanations, we find that the private investment has a positive effect on regional growth (although not significant), while public capital exerts a strong negative impact (see Table 3, column 3).

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 13.01%. Regional fixed effects are significant (we reject the null hypothesis that all $\mu_i = 0$ at 1% level). Moreover, the important role played by regional dummies is confirmed by the high fraction of variance explained by μ_i (0.76)[6]. As regards the speed of convergence we find that it is about four-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 10 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.

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

4. Dealing with the endogeneity issue

The hypothesis of strict exogeneity of the regressors of equation (7) ensures the consistency of the results obtained through the use of the LSDV estimator (Hsiao, 2003; Caselli, Esquivel and Lefort, 1996)[7]. But this condition is hard to verify in growth regressions where the usual explanatory variables are endogenous. For example, referring to eq. [7] 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)[8] treating all explanatory variables as potentially endogenous. To this aim, we rewrite eq. [5] in dynamics terms, as follows:

$$[8] \qquad \ln(y_{it}) = \gamma \ln(y_{it-\tau}) + c_1 \ln(s_{it}) + c_2 \ln(n_{it} + g + \delta) + c_3 \ln(h_{it}) + \mu_i + \eta_t + \varepsilon_{it}$$

where $\gamma = 1 + \beta = e^{-\lambda\tau}$. Eq. [8] 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 [8]. 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 [8]). The estimated equation is the following:

$$[9] \qquad \hat{y}_{i,t} - \hat{y}_{i,t-\tau} = \gamma(\hat{y}_{i,t-\tau} - \hat{y}_{i,t-2\tau}) + c_1(\hat{s}_{i,t} - \hat{s}_{i,t-\tau}) + c_2(\hat{n}_{i,t} - \hat{n}_{i,t-\tau}) + c_3(\hat{h}_{i,t} - \hat{h}_{i,t-\tau}) + (\varepsilon_{i,t} - \varepsilon_{i,t-\tau})$$

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

The GMM in first differences (eq. [9]) 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. [8] in levels, whose instruments are the lagged differences of the endogenous variables.

[7] 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.

[8] It is worth noticing that GMM estimators perform well in large samples and that in our case and in all the papers focusing on Italian regions (see, i.e., Carmeci and Mauro 2002; Di Liberto, Pigliaru and Mura 2007) the cross-sections are 20 and T is generally short. Although data limitations imply that GMM results ought to be interpreted with caution, our evidence confirms the outcomes obtained in this paper using other estimation techniques (see table 3) and those obtained in the other above-mentioned studies on the Italian regional economic divide.

Our estimation results are displayed in table 4. The first column (Model A) refers to the GMM-DIFF estimates, while the last two columns summarize the GMM-SYS results. The instrumental variables used in every regression are the lagged values of explanatory variables. To validate our models two types of tests are considered. The Sargan tests on the overindentifying restrictions is conducted to assess the appropriateness of the instruments. Failure to reject Ho 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. Finally, in order to test the hypothesis of cross sectional dependence, we re-estimate the dynamic panel models through a fixed effect estimator and using Pesaran's test. Although Nickell (1981) bias holds, Pesaran's test remains valid for the purposes of testing for cross sectional dependence (Sarafidis and De Hoyos 2006). According to Pesaran's test results, which we report in the last row of table 4, the hypothesis of cross sectional independence cannot be rejected.

An outcome of table 4 is that GMM estimators perform slightly well (the p-value of Sargan test does not reject the model's overidentifying restrictions). 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 5) which is the key variable for detecting TFP heterogeneity across Italian regions.[9] However, the results of table 4 are comparable in all specifications and the parameters have similar values to LSDV estimates (see table 3).

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 significant at 5% level. 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 3).

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 reject the null hypothesis (i.e. H_o: all regional fixed effects are zero) when testing the joint significance: the p-value of the Wald test in model C is 0.0042. 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 method of estimation used (GMM-DIFF or GMM-SYS). For instance, the estimation of this coefficient in model C is 0.641 which implies a speed of conditional convergence equal to 11.12% per year. This rate is lower than that 13%) 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 2.72% to 11.12% per year.

To sum up, after controlling for heterogeneity and endogeneity biases, this section of the paper confirms that the speed of conditional convergence estimated for Italian regions using GMM estimators is extremely high [on this point see also the papers by Carmeci and Mauro (2002) and Di

[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.

Liberto, Pigliaru and Mura (2007)]. 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.

Table 4 GMM estimates of the extended Solow model for Italy over 1980-2004

	GMM-DIFF	GMM-SYS	
Variables	Model A	Model B	Model C
$\ln(y_{it-\tau})$	0.598	0.632	0.641
	(2.32)	*(4.21)*	*(4.82)*
$\ln(s_{i,t})$	-0.012	-0.039	
	(-0.87)	*(-1.21)*	
ln(n+g+d)	-0.16	-0.031	
	(-1.65)	*(-2.1)*	
$\ln(h_{i,t})$	0.09	0.32	
	(1.76)	*(1.93)*	
Regional Dummies	--	yes	yes
Speed of Convergence	12.85%	11.47%	11.12%
Sargan test (p-value)	0.597	0.78	0.42
AR(1) (p-value)	0.019	0.154	0.12
AR(2) (p-value)	0.032	0.65	0.51
Pesaran test* (p-value)	-1.547 (0.129)	-1.547 (0.129)	-1.578 (0.115)
Obs.	100	80	80

Notes:
The t-values are reported in parenthesis and are robust to heteroskedacity. All variable are expressed as deviations from the national means. In models A, all right-hand side variables are endogenous and instrumented by all available lags. In model B and C, the regressors are all endogenous and 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 values of Pesaran' test are those obtained by estimating models A-C with a fixed effect estimator.

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 GMMS-SYS estimations of the regional fixed effects (Model C), that is, by using the relationship $\widehat{\mu}_i = \left(1-e^{-\lambda\tau}\right)\ln\left(A_o\right)$, where A_o is the proxy of the TFP (see eq. 7 and 8). In such a way, a measure of regional economic efficiency is given by $A_o = \exp\left[\widehat{\mu}_i / \left(1-e^{-\lambda\tau}\right)\right]$.

The values of $\widehat{\mu}_i$ estimated through GMM-SYS and the resulting figures of A_o are listed in the first two columns of table 5, 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 5 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%. Emilia Romagna, Friuli, Lazio, Lombardia, Piemonte, Trentino Alto Adige, Valle d'Aosta and Veneto 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 5).

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_0 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-**2004** or using data observed in each sub-period analysed.

Table 4 Regional fixed effects and TFP in Italy over 1980-2004

Regions	Regional Fixed Effects $\hat{\mu}_i$	$A_o = \exp\left(\frac{\hat{\mu}_i}{1-e^{-\lambda\tau}}\right)$	$\frac{A_i}{A_{max}}$	Y/L (Average 1980-2004)	Y/L (LOMB=1) (Average 1980-2004)
Piemonte	1.341	4.55	0.98	35.92	0.947
Valle d'Aosta	1.316	4.43	0.95	37.70	0.994
Lombardia	1.357	4.64	1.00	37.92	1.000
Trentino-Alto Adige	1.338	4.54	0.98	35.37	0.933
Veneto	1.317	4.43	0.96	33.59	0.886
Friuli-Venezia Giulia	1.317	4.44	0.96	32.81	0.865
Liguria	1.297	4.33	0.93	35.94	0.948
Emilia-Romagna	1.319	4.44	0.96	34.59	0.912
Toscana	1.316	4.43	0.95	33.07	0.872
Umbria	1.291	4.31	0.93	31.69	0.836
Marche	1.277	4.24	0.91	29.81	0.786
Lazio	1.336	4.53	0.98	36.87	0.972
Abruzzo	1.277	4.24	0.91	30.86	0.814
Molise	1.249	4.10	0.88	29.73	0.784
Campania	1.254	4.13	0.89	29.40	0.775
Puglia	1.249	4.10	0.88	27.71	0.731
Basilicata	1.263	4.17	0.90	27.99	0.738
Calabria	1.201	3.89	0.84	26.52	0.699
Sicilia	1.225	4.00	0.86	31.93	0.842
Sardegna	1.241	4.07	0.88	30.49	0.804
Italy				32.51	0.857
St.Dev. of TFP (A0)				0.21	
St.Dev. of Y/L in 2004				3.26	
St.Dev. of Y/L in Steady State				4.54	
Correlation between Y/L in 1980-1982 and Y/L in 2003-2004				0.80	
Correlation between Ao and Y/L in 1980-1982				0.74	
Correlation between Ao and Y/L in 1999-2004				0.89	
Correlation between Ao and Y/L (average 1980-2004)				0.86	
Correlation between Ao and the growth rate of Y/L				-0.23	
Correlation between Ao and Human capital (1980-2004)				0.43	

Figure 1 The positive relationship between TFP and output per worker (Y/L) over 1980-2004

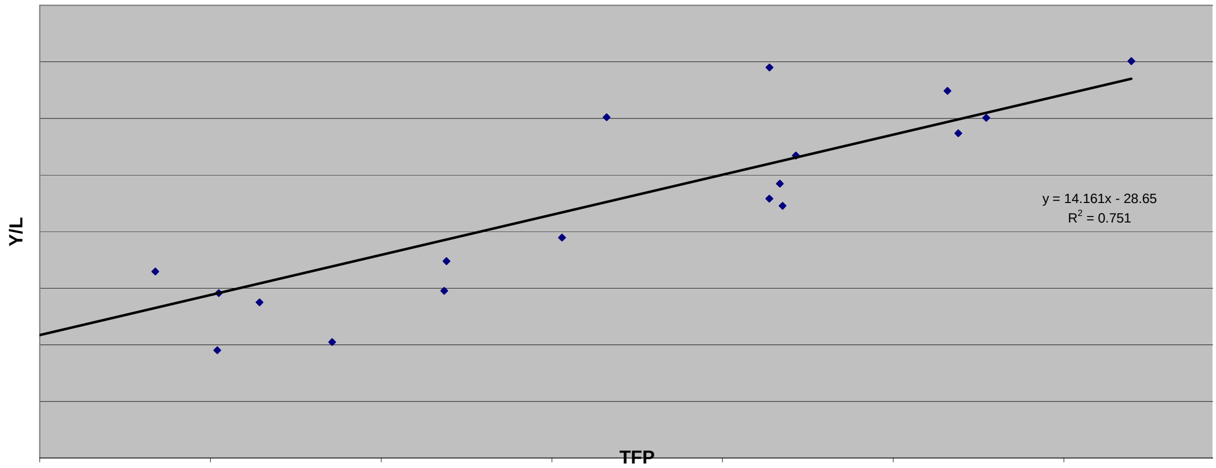
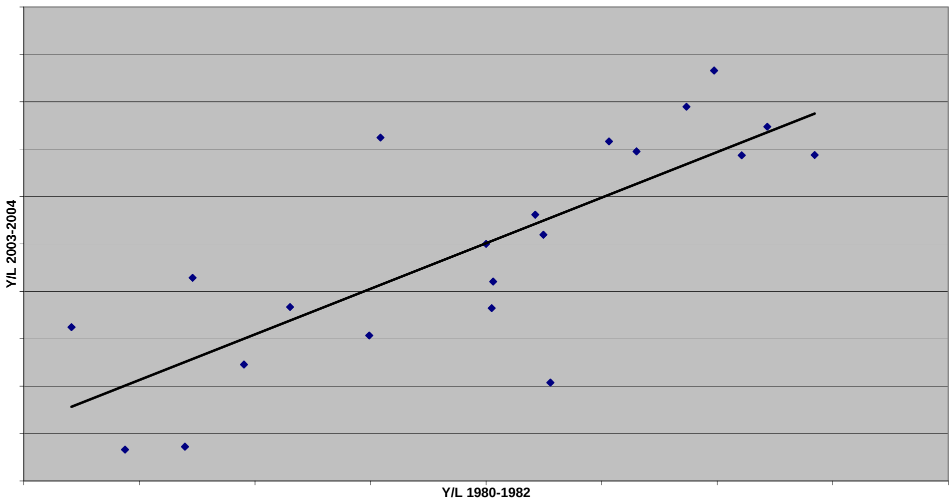


Figure 1 plots A_0 in the horizontal axis and the output per worker registered in the entire span period 1980-**2004**. It shows a strong positive relationship between output per worker and TFP: the proportion of the variability of output per worker explained only by TFP is 0.75 (figure 1). Similarly, this proportion is 0.56 in the first sub-period considered (1980-1982) and 0.81 in the last period 2003-2004.

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, Pigliaru and Mura, 2007; Maffezzoli, 2006) 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 (ρ=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 (ρ=0.81) exists between our index of TFP and that obtained by Di Liberto, Pigliaru and Mura (2007) 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 1980-2004 a certain degree of convergence took place (see sections 2 and 3), even if at the end of the period the distance in output levels still remained significant. Indeed, in 2003-2004 the output per worker in Calabria was less than 70% of the value observed in Valle d'Aosta and in Lombardia. This evidence is summarized in Figure 2, where the regional levels of output per worker in 1980-82 ($Y/L_{80\text{-}82}$) is plotted against the levels of Y/L in 2003-2004, both relative to Italy (the correlation between $Y/L_{80\text{-}82}$ and $Y/L_{03\text{-}04}$ is 0.8, 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 2003-2004



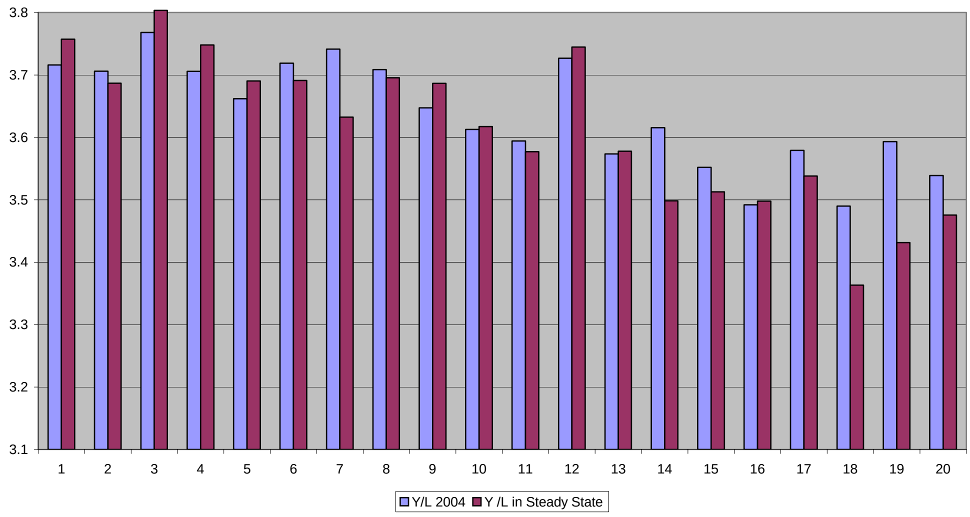
Finally, we discuss the two key outcomes of this paper. On the one hand we have shown that the Italian regions converge to their own steady state extremely rapidly; on the other hand TFP has been found to play a significant role in explaining differences in the output per worker. These results can be 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 C of eq. [8], $y_{i,t} = \gamma y_{i,t-\tau} + \mu_i + \varepsilon_{i,t}$, 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 variable. We use GMM-SYS estimations of eq. [8] considering as conditioning variables the regional dummies only (table 3, model C).

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_{2004}) and to verify if in the long run the economic divide will still persist among Italian regions. Both variables (y^* and y_{2004}) 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 Mezzogiorno.[10]

Another interesting result is the actual relative position of each region with regard to the steady state level of productivity. We find a sharp difference in the behaviour of rich and poor Italian regions. In fact, figure 3 illustrates that many 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 5 Southern regions (Molise, Basilicata, Calabria, Sicily and Sardegna. In other words, in equilibrium, the level of income of these regions is even lower than that measured in 2004 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.

[10] This result is partially confirmed by the standard deviation of labour productivity which increases from 3.26 to 4.54 passing from the observed value of income per worker in 2004 to that estimated for steady state (table 4).

Figure 3 A comparison between the level of labour productivity observed in 2004 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

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 1980-2004, we show that the estimation of a standard cross-region regression produces a speed of conditional convergence of 2,36% 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 11.12% 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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