A panel technique for the analysis of technology convergence:
The case of the Italian regions

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1. Introduction

Differences in productivity levels represent a major component of the large cross-country differences in per capita income observed in international datasets[1] and even in some regional ones.[2] Nowadays, few economists would dispute neither this finding, nor that differences in productivity reflects – among other things – differences in technology levels.[3] More controversial is the question of whether such differences in technology are stationary or temporary – that is, whether technology convergence is taking place, at what speed, under what conditions. Indeed, as Bernard and Jones (1996) put it, we often do not know "how much of the convergence that we observe is due to convergence in technology versus convergence in capital-labour ratios" (p. 1043).

This state of affairs is the result of two different difficulties faced by the empirical analysis on cross-country differences in per capita income growth rates. The first is that measuring technology levels is not an easy task, and that measuring it at different points in time is even more difficult, given the current availability of data in most of the existing cross-country and cross-region datasets. The second is that the revival of the empirical analysis on growth has been based – partly, at least – on models that rule out technology heterogeneity by assumption [see, among many other, the influential paper by Mankiw, Romer and Weil (1992)].[4]

More recently, things have improved on both the analytical and the empirical side. On the analytical side, simple models in which technology convergence and capital-deepening can be studied within a common framework are now available. In these models the transitional dynamics is simple enough to be useful for empirical analysis [for instance, De la Fuente (2002) and (1997)]. On the empirical side, previous studies have shown that we can test for the presence of technology heterogeneity in cross-country convergence analysis by using an appropriate fixed-effect panel estimator[5]. In particular, Islam (2000) compares the distribution of the estimated fixed effects over two points in time, but the possibility that technology convergence lies behind the observed changes in the distribution is neither discussed nor tested. De la Fuente (2002) deals with technology

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[1] See for instance Hall and Jones (1999) on TFP differences across 127 countries.
[2] Using a sample of 101 EU regions Boldrin and Canova (2001) find that per capita GDP is much more correlated with their measure of TFP than with capital-labour ratios. See also Aiello and Scoppa (2000), and Marrocu, Paci and Pala (2001) for the Italian regions.
[3] See Klenow and Rodriguez-Clare (1997); see also Parente and Prescott (2000), Easterly and Levine (2001), Lucas (2000), on problems concerning technology adoption and various diffusion mechanisms.
[4] In separate, non neoclassical line of research, technology diffusion is regarded as the crucial source of convergence [for instance, Dowrick and Nguyen (1989) and Fagerberg and Verspagen (1996)]. Here the whole observed convergence is typically assigned to one the catch-up mechanism, in a context where the others (capital deepening) are neglected on a priori grounds, rather than tested.
[5] See Islam (1995) and (2000) and Aiyar and Feyrer (2002).

diffusion by means of a fixed effect model, but technology levels are computed independently and then used as a regressor in the convergence equation. As a consequence, the estimated individual intercepts yield a measure of unobservable characteristics other than technology.

The contribution of the present paper is on the empirical side.[6] In this paper we propose a new methodology designed to test whether part of the observed economic convergence is due to technology convergence.[7] Differently from de la Fuente (2002), our methodology can be applied in those cases in which independent indexes of regional technology levels are not available. In our approach, we first use regional GDP per worker to estimate the convergence equation with a Least Squares with Dummy Variable estimator (LSDV) over two sub-periods. Second, we use the values of the individual intercepts to compute an estimate of TFP levels. The robustness of our results is assessed using different specification of the convergence equation and comparing the resulting estimates with that obtained using a difference-GMM (or Arellano and Bond) estimator. Third, we analyse the two series of regional TFP to test whether the observed pattern over time is consistent either with catching-up hypothesis or with the hypothesis that the current degree of technology heterogeneity is at its stationary value.

In this paper we use a panel dataset of Italian regions, 1963-93.[8] There are three main reasons for this choice. We list them from general to specific. First, we use a regional dataset because it deals with areas where various unobservable component are supposed to be far more homogeneous than across countries. In our case, this feature of regional data (as opposed to international ones) represents a distinctive advantage. The reason is that fixed effects in panel regressions reflect all the unobservable components (institutions, geography…), and the more homogeneous are those not directly linked to technology, the closer the fixed effects get to yield a satisfactory measure of technology levels. Second, data comparability is easier. Consider human capital, a crucial variable for convergence analysis. One of the main criticism with cross-country datasets is the limited comparability of the different schooling institutions. The use of a regional dataset allows us to limit this type of problems. Third, we study the Italian case because it is notoriously characterized by a remarkable degree of regional heterogeneity in variables such as per capita income levels and human capital stocks,[9] and because the available time-series are rather

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[6] Companion papers of the present one are Paci and Pigliaru (2002), in which convergence across EU regions is analysed, and Pigliaru (2003), in which the methodology applied in this paper is described and discussed in details.
[7] For instance, Bernard and Jones (1996), De la Fuente (1997) and Lucas (2000).
[8] The length of the dataset is constrained by the human capital variable: we use census data and 2001 observations are not available yet.
[9] Paci and Pigliaru (1995), Di Liberto (2000), Boltho, Carlin and Scaramozzino (1999), among several others.

long, starting from 1960. In spite of being one of the best known cases of regional divide, our paper yields the first explicit analysis of technology convergence across Italian regions[10].

2. Regional inequality in Italy: summing up

We start with a brief summing up of what is known about regional inequality in Italy. To describe the problem, the best statistics is per capita GDP. When measured by this index, the degree of regional inequality in Italy appears to be significantly higher than in the rest of Europe. For instance, in 1950 it was twice the dispersion calculated for other European countries. Still now, the degree of regional inequality in Italy is higher than in all EC countries[11]. Such high inequality reflects the spread existent between the North and the South of the country.

Among the most influential studies on regional convergence are the Barro and Sala-i-Martin papers (for instance 1995). They examine convergence among US states and European regions and find a speed of convergence of 2 percent in all regional samples examined, including Italian regions[12]. Therefore, they conclude that ".... the south of Italy has not yet caught-up because started far behind the north, and the rate of beta convergence is only 2 percent a year.". In other words, they see no evidence that poor regions, such as those in southern Italy, are being systematically left behind in the growth process: convergence for southern regions seems to be just a question of time. By now many other authors have disputed these somehow optimistic conclusions[13]. The main stylised facts about Italian regional convergence are as follows.

First, the process of regional convergence is not persistent over time periods: decreasing dispersion in regional per capita GDP, while strong during the 60s, all but ceased after 1975[14]. Explanations for this abound. There was a decrease in migration from the South to the North. There were efforts directed towards achieving a uniform wage between the northern and the less productive southern labour force[15]. There was a change in policies directed to foster the development of more backward regions. In particular, the Italian Government's efforts to boost

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[10] Paper close to ours do exist, in that they obtain measures of the cross-region distribution of TFP [Aiello and Scoppa (2000), Marrocu, Paci and Pala (2001)]. However, these papers do not apply the fixed-effect methodology to measure technology levels and, more importantly, do not address the problem of detecting the presence of technology convergence.

[11] See Barro and Sala-i-Martin (1995).

[12] This conclusion is found also with international (or cross-countries) samples. For the Italian case they found an estimated convergence coefficient of $\beta=0.015$, a lower speed of convergence with respect to the rest of Europe.

[13] See Mauro and Podrecca (1994), Paci and Pigliaru (1995), Boltho Carlin and Scaramozzino (1999).

[14] See Mauro and Podrecca (1994), Di Liberto (1994), Boltho, Carlin and Scaramozzino (1999), Paci and Pigliaru (1995) among others.

[15] This policy started officially in 1969.

industrial investment (especially in heavy industries like chemicals and steel) in the South during the 60s and part of the 70s is well documented[16]. After that period, there was a shift in policy from investments to income maintenance in the form of direct transfers and through an expansion of the Public Sector, also associated with an acceleration in the process of administrative decentralisation. All this notwithstanding, non-homogeneity of the convergence process has been found in studies of other countries. For example, the Spanish regions seem to have experienced a similar pattern[17], and many OECD economies experienced a stop in their process of regional convergence somewhere in the mid-1970s[18]. The rapid increase of oil prices in 1973-74 has presumably influenced investments, technology and additional factors that may affect the convergence process internationally.
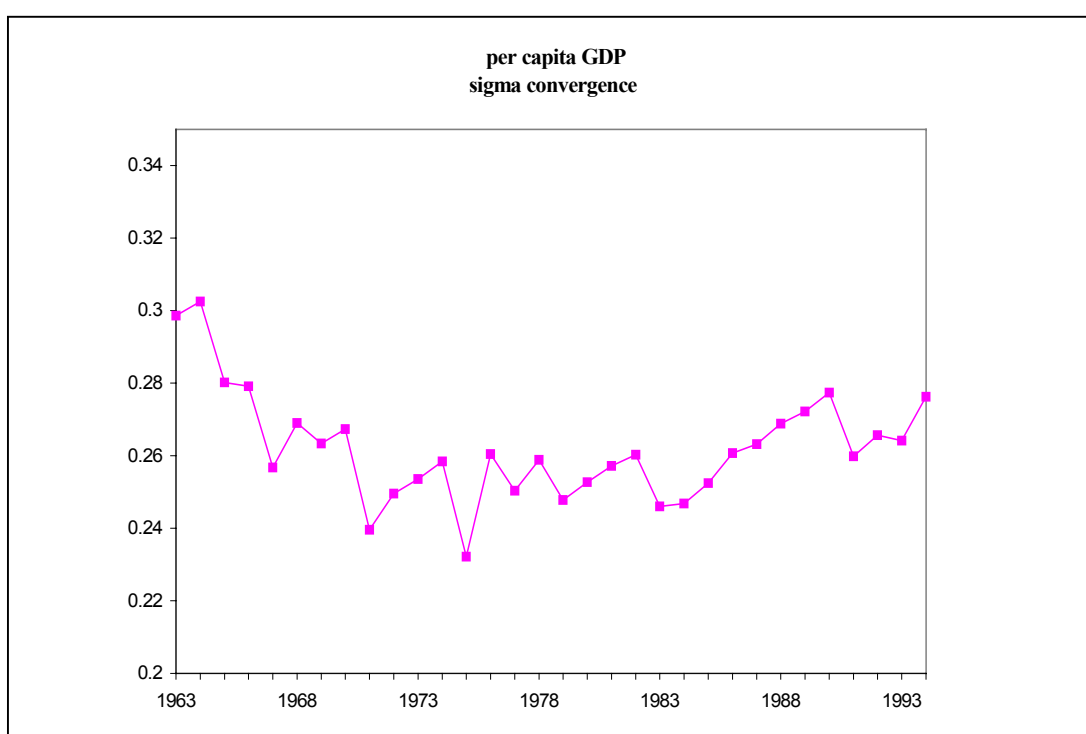
Fig. 1. Time path of the standard deviation of the logarithm of GDP across Italian regions 1963-94.

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[16] From Graziani (1978), " The distribution of industrial investments has shifted mainly in favour of the Mezzogiorno, 1970 being a noticeable turning point..... The share of the Mezzogiorno in total industrial investment reached 44% in 1973 against 15% during 1951-59......two important waves of investments have characterised the southern area: the first is in 1959-63 and coincided with a similar phase in the national economy as a whole. The second phase is during the 1969-73 that was peculiar to the south…"

[17] See de la Fuente (1997).

[18] See Sala-i-Martin (1996).

In particular, this pattern could be explained by a different sensitivity to oil shocks among regions due to the different industrial development between north and south. This pattern is confirmed by the σ convergence analysis in Figure 1. The dispersion among Italian regions seems to have decreased until early 70's. Afterward, the dispersion is fairly stable, with some tendency to increase in the last few years.[19] It is then impossible to conclude in favour of a strong and/or continuous process of sigma convergence.

More in details, a measure of the relative (with respect to the Italian average) per capita income reveals that during the 60s, the richest regions, Valle d'Aosta, was 42 percent wealthier than the average Italian region, Lombardia, has 34 percent more income with respect to the Italian average, while poorest regions, Calabria and Basilicata, holds 38 percent less than the Italian average. Even considering that Valle d'Aosta is likely to be an outlier (very small mountainous regions, highly subsidised by the central Government), this is a large regional gap for a relatively small industrialised country. This difference has lowered during the last three decades, but the decrease was neither persistent nor uniform. The reduction of disparities has been effective for the whole sample only during the 1960s. However, there are exceptions even to this rule. For example, Campania and Liguria experienced a constant deterioration of their relative position. Three regions, Abruzzi, Molise and Basilicata had a tendency to narrow their differentials with respect to the national average, even during the last twenty years. These regions seem to have significantly improved their position during the whole period. We also observe changes in the relative positions among richest regions. Northwest (Piemonte, Valle d'Aosta, Lombardia, Liguria), the richest area during the 60s, decreases its relative advantage. The opposite is true for the Northeast part of Italy (Veneto, Friuli Venezia Giulia, Trentino Alto Adige, and Emilia Romagna).

In the following paragraphs we will see whether our measure of TFP levels follows a similar pattern.

3. TFP estimation: the Panel Data approach with technology convergence

As long as technology levels differ across economies, technological diffusion is likely to play a significant role in economic convergence. Our aim is to devise an empirical method to test whether this role is actually present in our dataset or whether the observed convergence is entirely due to other mechanisms such as capital deepening. Therefore, a necessary (but not sufficient, as we will

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[19] The downward peaks in '75 can be explained by the strong negative effect that the oil shock had in the northern, more industrialised, regions.

show presently) tool required for our analysis is an empirical technique capable to detect and measure the degree of technological heterogeneity in the data.

As shown by Islam (1995), a measure of this type can be obtained by using a fixed-effect dynamic panel data technique to estimate convergence in a panel of economies. Islam's empirical methodology extends the MRW's structural approach by allowing technology levels to vary across individual economies, together with saving rates and population growth rates. Consider the "convergence equation" of the standard Solow model around the steady state:

$$(1) \qquad \ln Y_{it2} = (1-\beta)\frac{\alpha}{1-\alpha}\ln(s_{it1}) - (1-\beta)\frac{\alpha}{1-\alpha}\ln(n_{it1}+g+\delta) + \beta \ln Y_{it1} + (1-\beta)\ln A_{i0} + g(t_2 - \beta t_1)$$

where Y_{it_1} is per capita GDP in economy i at time t_1 (initial period, while t_2 is the final one), and s, n, δ and g and are, respectively the saving rate, the population growth rate, the depreciation rate, and the exogenous technological change, the latter assumed to be invariant across individual economies. Moreover, α is the usual capital share of a standard Cobb-Douglas production function. Finally, $\beta \equiv e^{-\lambda\tau}$, where $\lambda = (1-\alpha)(n+g+\delta)$ represents the convergence parameter and $\tau \equiv t_2 - t_1$ the time span considered. This model may be easily augmented to take human capital into account (see below). In their study MRW's assume $\ln A_{i0} = \ln A_0 + \varepsilon_i$, with $\ln A_0$ constant across individuals and ε_i representing a random shock uncorrelated with the explanatory variables such as the initial income level. This assumption is crucial to obtain consistent OLS estimates of (1).

Islam (1995) finds this assumption as far from convincing and stresses the importance of the use of appropriate panel data techniques allowing less restrictive hypothesis on technology. In this framework differences in technology are unobservable but cannot be treated as uncorrelated with other regressors as in MRW. He proposes to use a LSDV estimator, where estimated individual intercepts are interpreted as a measure of the degree of between-individual technology heterogeneity. In a panel data formulation, equation (1.1) is written as follows:

$$(2) \qquad y_{it} = \beta y_{it-1} + \sum_{j=1}^{2}\gamma_j x_{it}^{j} + \eta_t + \mu_i + v_{it}, \qquad j=1,2$$

where the dependent variable is the logarithm of per capita GDP (measured in terms of population working age), η_t is the time trend component, v_{it} is the transitory term that varies across countries, the x's represent respectively:

$$(3) \qquad x_{it}^{1} = \ln(s_{it})$$

(4) $$x_{it}^2 = \ln(n_{it} + g + \delta)$$

and

(5) $$\gamma = (1 - \beta)\frac{\alpha}{1 - \alpha}$$

(6) $$\mu_i = (1 - \beta)\ln A(0)_i$$

and

(7) $$\eta_t = g(t_2 - \beta t_1)$$

where μ_i is a time-invariant component that varies across economies, and η_t is the growth rate of technology assumed (as in MRW) to be constant across individuals. The term μ_i should control for various unobservable factors like institutions or climate, and – crucially for our aim – technology. Since technology is likely to be correlated with standard regressors in (1), in particular, with the lagged per capita GDP, a fixed effect estimator is appropriate.[20] Once we have the estimated individual intercepts, a proxy of TFP and, more generally, of the degree of technology heterogeneity can be easily computed by using equation (6).[21]

At this stage of our analysis, a key question is: What happens if technology *convergence* is at work during the period under analysis (a possibility ruled out by assumption in Islam's approach)? Typically, in this case, lagging economies have the opportunity to experience faster technology growth – an opportunity proportional to the current gap between their technology level and the world technology frontier [De la Fuente (1997), Lucas (2000), Parente and Prescott (2000)]. Let us first define how $\ln A_i$ evolves over time in the presence of a process of technology convergence.

Formally, between periods 0 and t the level of technology in economy i at time t is equal to $\ln A_{it} = \ln A_{i0} + \gamma_i t$, where $\gamma_i t = gt + \rho_i t$, where as before g is the long run rate of technological progress assumed to be constant across economies. In the presence of technology catching up, $\rho_i t$ is generally different from zero, being a positive function of the technology gap at the initial period. On the contrary, if no systematic process of technology diffusion is at work, we would have $\rho_i t = 0$ and $\ln A_{it} = \ln A_{i0} + gt$, with all economies experiencing a common rate of technology growth.

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[20] See Islam (2000).
[21] More generally, the LSDV methodology can be considered an alternative to standard growth accounting methodologies [for a direct comparison, see Islam (2000)].

Comparing these two cases, it is easy to see that they imply different evolutions over time of the distribution of A_i/A^*, where A^* is the technology level the leader region and A_i the same index for a generic follower region. As long as technological convergence is absent, A_i/A^* is constant (abstracting from random shocks); on the contrary, the presence of technological convergence should be reflected in an increasing value over time of A_i/A^* (in this case $\rho_i t > 0$).

We suggest that this difference can be exploited to test for the presence of technology convergence. To sum up, the methodology we propose is the following. We will estimate equation (2) over two sub-periods, in order to obtain a sequence of estimates of individual intercepts which, in turn, will be used to compute the individual values of $\ln A_i$. The evolution such values over two sub-periods will reveal whether the observed pattern is consistent either with catching-up hypothesis or with the hypothesis that the current degree of technology heterogeneity is at its stationary value.[22]

4. Estimation Procedure and Results

In this section we use data on regional GDP per worker[23] to estimate the following equation:

$$(8) \qquad \tilde{y}_{it} = b\tilde{y}_{it-1} + \sum_{j=1}^{2} \gamma_j \tilde{x}_{it-1}^j + \xi \tilde{h}_{it-1} + \mu_i + u_{it}$$

$$(9) \qquad \tilde{y}_{it} = y_{it} - \overline{y}_t, \qquad\qquad \tilde{h}_{it} = h_{it} - \overline{h}_t, \qquad\qquad \tilde{x}_{it} = x_{it} - \overline{x}_t$$

where $\overline{y}_t$, $\overline{h}_t$ and $\overline{x}_t$ are the Italian average in period t, with h being a measure of human capital stock, namely average years of schooling. That is, in equation (8) we augment equation (2) to include a measure of the stock human capital: in fact, when we try to identify TFP differences it is essential to control for one of its most likely determinants[24]. As shown by Figure 2, the relationship between human capital and productivity is clearly a positive one. Secondly, data are taken in difference from the Italian mean, in order to control for the presence of a time trend component η_t and of a likely common stochastic trend (common technology) across regions.

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[22] Finally, notice that estimating equation (2) over short sub-period has an additional advantage. As it is clear from equation (6) and (7), equation (2) is obtained lo-linearizing the Solow model around the steady-state under the assumption of a stationary technology heterogeneity (in our terms, this amounts to assuming that $\rho_i t = 0$).

Consequently, whenever $\rho_i t \neq 0$, equation (1.2) should be regarded as an approximation of the real process, in that it ignores a component of technology growth which does change across individuals as well as time periods. The longer the time span used to estimate equation (1.2), the weaker the approximation obtained.

[23] Since our aim is to obtain TFP estimates from a standard Cobb-Douglas technology, and given that unemployment rates differ greatly across Italian regions, GDP per worker is a more adequate variable than per capita income for our case.
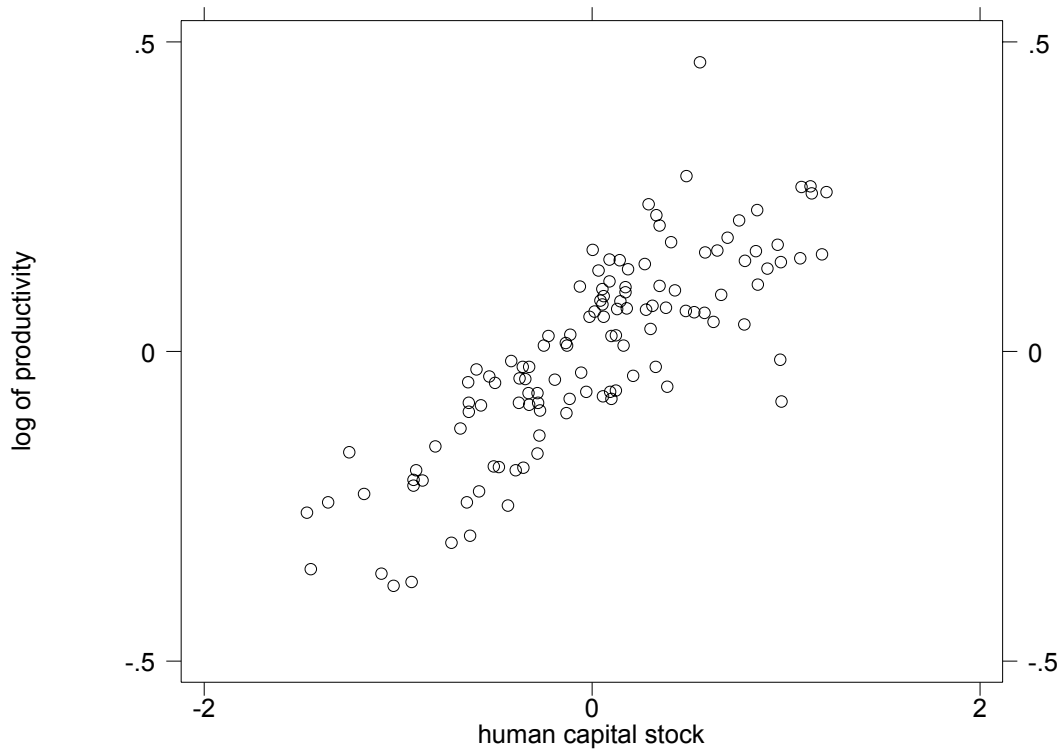
Fig. 2. Relationship between human capital measured as average years of schooling and the logarithm of productivity: 19 regions, 7 observations. Data in deviation from the Italian mean.

Further, we assume $(g+d)=0.05$ for all regions and years, while savings and population growth variables are measured at the start of the period. Finally, we use data in five-year intervals, in order to control for business cycle fluctuations and serial correlation, which are likely to affect the data in the short run[25]. Both the model specification and data transformation are standard in this literature.

Our Italian regional panel includes the period 1963-93 for 19 regions[26]. Given the five-year time span we are left with 7 observations for each region. The sample is then split into two subsample, 1963-78 and 1978-93, each including 4 observations. We firstly apply the LSDV estimator to equation (8), that is, the standard convergence equation of the growth literature, in both sub-samples and save $\hat{\mu}_i$[27]. Table1 shows the regression results. This procedure allows us to obtain two different estimates of regional effects, corresponding to both the 1963-78 interval and the 1978-93. It is worth noticing that these results confirm the stylised facts of the convergence literature reported above: convergence due to factor accumulation, or solovian convergence, while present

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[24] For details on how this variable is constructed see Di Liberto and Symons (2003).

[25] Given the five years time span, our sample includes data for 1963, 1968, 1973, 1978, 1983, 1988, 1993.

[26] Italian regions are 20. We have excluded Valle d'Aosta because it represents an outlier. Nevertheless, results are qualitatively the same when including this region.

[27] As a control, the same procedure has also been applied to the whole sample period, 1963-93 and results shown in the following Tables.

during the sixties and mid-seventies, has disappeared subsequently. The convergence coefficient is significant only in the first subsample, 1963-78, while it is not significant in the second one.

SAMPLE	1963-78	1978-93
beta coefficient	0.402	-0.105
	(0.148)	(0.154)
savings	0.034	-0.045
	(0.054)	(0.053)
(n+g+d)	0.118	-0.008
	(0.086)	(0.152)
human capital	-0.088	-0.025
	(0.059)	(0.059)
adjusted R2	0.94	0.96

Table 1. Data are demeaned. The beta coefficient is the coefficient of the lagged dependent variable. Other regressors are described in the text. Standard errors in parenthesis.

Other explanatory variables are not 10% significant; the non significant negative sign of our human capital indicator may be explained by its extremely high correlation with the lagged dependent variable (correlation coefficient of 0.85). However, the focus of our analysis is on the regional dummies coefficients, $\hat{\mu}_i$, which are almost invariably significant. This is what we need to obtain our regional TFP measures.

To this aim, we firstly use equation (6) and obtain $\hat{A}(0)_i$. Secondly, data are transformed as $\hat{A}(0)_i / \hat{A}(0)_{Lom}$, with $\hat{A}(0)_{Lom}$ being the estimated fixed effect of Lombardia, currently the richest, most industrialised and arguably the most technologically advanced Italian region. Results are shown in Table 2. As expected, northern and richer regions are also the most technologically advanced, with Lombardia being the region with the highest TFP value in the second period of analysis. These data show that the regional relative TFP's values for the two subperiods are significantly different. Therefore, this result contradicts the hypothesis of absence of technological catching up implicit in most models of the solovian convergence literature. Moreover, we observe a decrease in the regional dispersion: the relative TFP variance is much higher in the first period (with

a value of 0.031) than in the second (0.013). Therefore, in the sense of sigma, we observe a process of technological convergence between these two periods.

REGIONS	TFP 1963-93	**A** TFP 1963-78	**B** TFP 1978-93	*Change of Rank A-B*
Piemonte	0.906	0.901	0.902	1
Lombardia	1.000	1.000	1.000	2
Trentino Alto Adige	0.808	0.891	0.813	-2
Veneto	0.855	0.857	0.855	2
Friuli Venezia Giulia	0.933	0.945	0.894	-2
Liguria	1.000	1.059	0.966	-1
Emilia Romagna	0.912	0.901	0.916	4
Toscana	0.859	0.872	0.851	0
Umbria	0.757	0.744	0.769	0
Marche	0.792	0.759	0.794	0
Lazio	0.995	1.056	0.944	-1
Abruzzi	0.734	0.679	0.761	2
Molise	0.591	0.517	0.664	3
Campania	0.690	0.654	0.717	-1
Puglia	0.676	0.578	0.738	2
Basilicata	0.571	0.532	0.606	-2
Calabria	0.580	0.530	0.632	0
Sicilia	0.717	0.686	0.755	0
Sardegna	0.738	0.743	0.735	-3

Table 2. Estimated TFP levels: the initial TFP level correspond to the TFP estimated using the sample 1963-1978, subsequent TFP level correspond to the sample 1978-1993.

However, this process has not been smooth. Regional ranking changed significantly. The fifth column in Table 2 shows the extent of these changes. Only five regions out of nineteen (Toscana, Umbria, Marche, Calabria and Sicilia) remained in the same regional ranking. Seven regions (Sardegna, Basilicata, Campania, Lazio, Liguria, Friuli and Trentino) have seem their relative position worsen during time, while the remaining areas (Piemonte, Lombardia, Veneto, Emilia, Abruzzi, Molise and Puglia) improved their position. Sardegna, loosing three places, has been the worst performer, while Emilia Romagna has been the best, changing from the eighth to the fourth place.

These results may also be summarised using graphical tools. Figure 1 shows the relationship existing between the TFP estimated in the initial interval and the subsequent one. More specifically,

in the X-axis we introduce the relative (to Lombardia) productivity level estimated using the subsample 1963-78, while in the Y-axis we have our relative regional productivity levels for the subsample 1978-93.
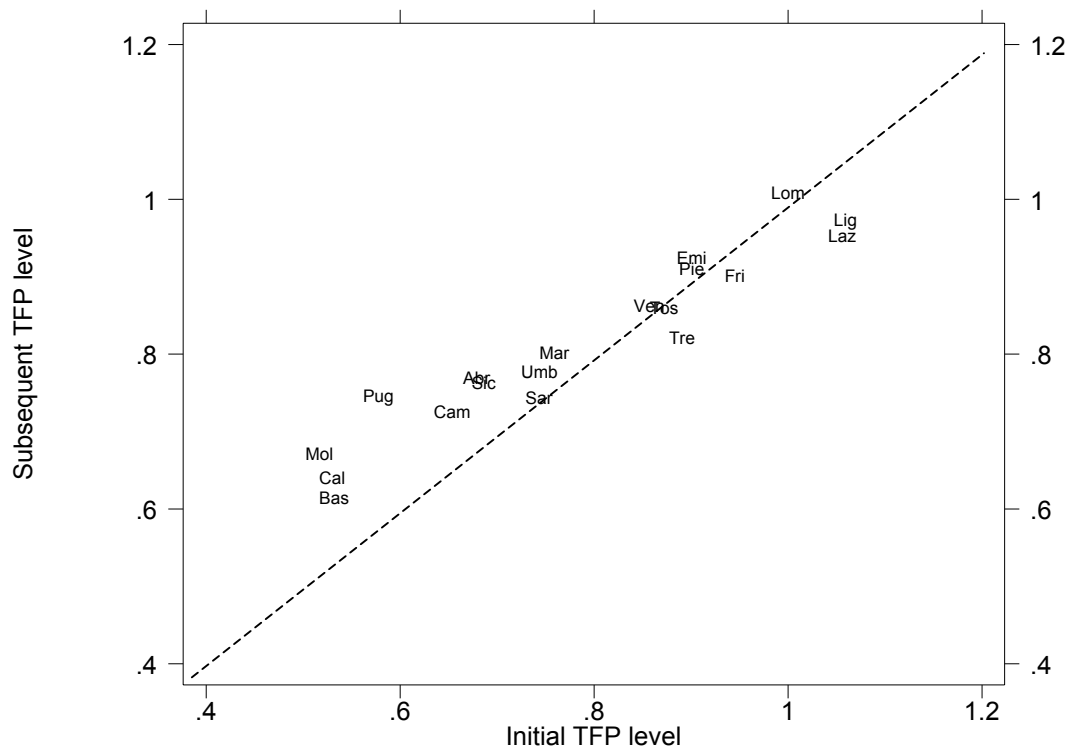
Fig. 3. Estimated TFP levels: the initial TFP level correspond to the TFP estimated using the sample 1963-1978, subsequent TFP level correspond to the sample 1978-1993.

If the relative levels in the two periods were the same we would observe all data along the dashed 45-degree line. Apart from four regions, all regions seem to have in our second period of analysis caught-up with Lombardia. That explains the observed decrease in our dispersion coefficient.

Figure 4 introduces the typical convergence graphical representation. In fact, standard analysis of convergence imply a negative correlation between the initial level of per capita GDP and its subsequent growth rate. In figure 4 we have in the X-axis regional TFP in the initial period and in the Y-axis the estimated growth rate in the two period. The presence of technological convergence is easy to detect. Most southern Italian regions correspond to the low initial level-high.growth observations. Molise and Puglia show the highest growth rates. It is not surprising that they have been among our best performers (in terms of ranking) in Table 2.
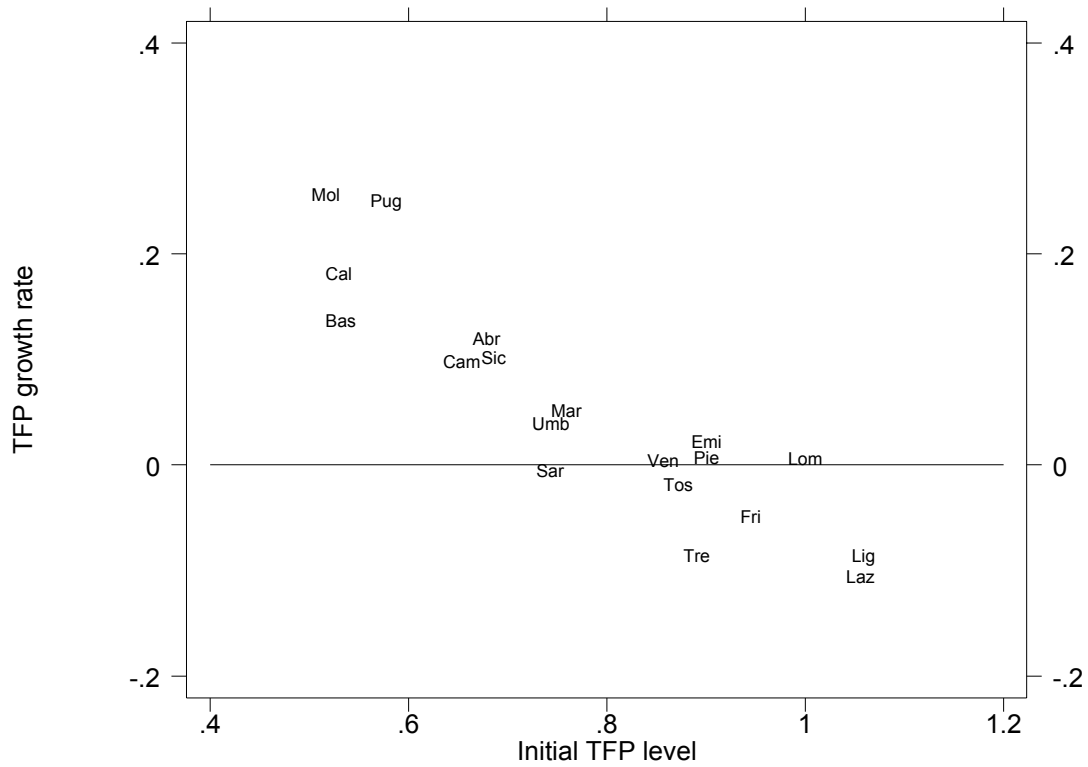
Fig. 4. TFP convergence: growth rate of TFP versus initial level

Regions like Calabria, even though experienced relatively high TFP growth rates, did not improved their relative position because they started by a very low TFP level. Conversely, Emilia Romagna, despite the relatively low TFP growth rate has, nevertheless, improved significantly its relative position. In fact, among the initially technologically advanced areas, it has been the one with the highest TFP growth rate.

These results are robust to different definitions of the sample sub-periods and to the use of a different estimator. We have repeated the above analysis using a four-year time span. In this case we obtained 8 observations for each regions and we've been able to construct two sub-sample with 4 observations each[28]. The results we obtain are very similar to the ones described above, the only difference being represented by an even more clear process of technological catching-up. Therefore, our results do not seem to depend on the definition of the sample. Moreover, preliminary results obtained using a difference-GMM or Arellano-Bond[29] estimator show TFP estimates very similar to the ones presented in Table 2 above. This estimator has been suggested in the literature of convergence because it allows to control for the possible endogeneity of included regressors. Small sample bias in the beta coefficient estimate may also be present using the LSDV estimator. While

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[28] Namely, sub-sample (a) 1963, 1967, 1971, 1975 and sub-sample (b) 1979, 1983, 1987, 1991.
[29] See Arellano and Bond (1991).

we try to take endogeneity problems into account by using regressors at their initial year value, small sample bias is difficult to handle with within this framework and may well also affect difference-GMM estimates[30]. Using this estimator and assuming our human capital indicator as predetermined, we detect a process of technological catching-up similar to the one based on the LSDV estimator. A more comprehensive comparison of the LSDV and GMM results is required at this stage of our research and will be available presently.

5. Conclusion

The aim of this paper was to assess the existence of technology convergence across the Italian regions between 1963 and 1993. We have proposed and applied a fixed-effect panel methodology to distinguish empirically between technology and capital-deepening convergence. Our results yield clear evidence that a significant process of technological convergence has taken place in Italy, and that this process has been a key component of the observed aggregate regional convergence that took place up to the mid-seventies. To the best of our knowledge, this is the first time that evidence on technology convergence across Italian regions has been produced in a context in which the traditional Solovian-type of convergence is simultaneously taken into account.

More generally, our results show that a period of significant convergence in technology has not generated a significant, persistent decrease in the degree of cross-region inequality in per capita income. This puzzling feature is similar to the one emerging from other recent papers such as, for instance, Dowrick and Rogers (2002). In our case, the solution of the puzzle might be a simple one: our evidence shows that technology convergence took place *between* the two sub-periods of our analysis (1963-78 and 1978-93), while nothing can be inferred on what has happened, in terms of technology diffusion, *within* the second sub-period. So, one possibility is that the halt of overall convergence in such sub-period is due to a halt of technology diffusion. More data and research are needed to test this additional hypothesis.

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[30] See Caselli, Esquivel and Lefort (1996), Aiyar and Feyrer (2002) and Bond, Hoeffler and Temple (2001).

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