TECHNOLOGICAL CATCH-UP AND REGIONAL CONVERGENCE IN EUROPE*

Raffaele Paci and Francesco Pigliaru
Università di Cagliari and CRENoS, Italy

Abstract: Our aim is to assess, in the absence of TFP data, whether the convergence observed across European regions is due to convergence in technology as well as to convergence in capital-labour ratios. We first develop a growth model where technology accumulation in lagging regions depends on their own propensity to innovate and on technology diffusion from the leading region, and convergence in GDP per worker is due to both capital deepening and catch-up. We use data (1978-93) on 109 European regions. Propensities to innovate are computed by assigning each patent collected by the European Patent Office to its region of origin. Our findings are consistent with the hypothesis that technology differs across regions and that convergence is partly due to technological catch-up.

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Contact author:

Prof. Francesco Pigliaru
DRES
Università di Cagliari
Viale S. Ignazio, 78
09123 Cagliari, Italy
pigliaru@unica.it

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1. Introduction

As it is now widely recognised, technology heterogeneity and the associated process of technological diffusion have not received enough attention in the current empirical literature on economic convergence.[1] For instance, an often used assumption in the literature is that there are no systematic technological differences across economies, so that whole observed convergence is ascribed to capital deepening, as in the influential paper by Mankiw, Romer and Weil (1992). Other papers allow for differences in individual technologies, as in Islam (1995) and (1988), but assume that such differences are stationary, so that again technology catching-up is ruled out by assumption rather than tested. As Bernard and Jones (1996) put it, a consequence of this state of affairs is that we do not know enough about "how much of the convergence that we observe is due to convergence in technology versus convergence in capital-labour ratios" [p. 1043].[2] A corollary of this situation is that there is no consensus concerning what empirical methodology should be used to obtain such a measurement, especially in the absence of reliable data on technology levels.[3]

The first part of this paper addresses this problem explicitly, since our main purpose is to assess the role of technology heterogeneity and catching-up in the convergence in GDP per worker observed across the European regions, for which no TFP data are available.

In order to design an appropriate empirical analysis for our purpose, we use a simple model in which convergence in capital-labour ratios and in technology can occur simultaneously. More specifically, while capital accumulation proceeds as in Solow's growth model, technology accumulation depends on a propensity to innovate, which may vary across economies. Stationary technology gaps can emerge as the result of such differences. The difference between stationary and current gaps generates technology diffusion, which in turn explain part of the growth rate differentials across economies. The influence exerted by capital deepening and catch-up in convergence along the transitional path can be identified.

This model yields the analytical framework we need to test, in the absence of TFP data, whether (i) technology differences play no systematic role in convergence, as in Mankiw et al. (1992); or, in case they exist, whether (ii) they are stationary, as in Islam (1995); or whether (iii) they are an active source of income convergence through a technology catch-up process of the kind discussed by Abramovitz

[1] See among many others Bernard and Jones (1996), Parente and Prescott (1994), Jones (1997), de la Fuente (1997), Lee, Pesaran and Smith (1998) and Hall and Jones (1999). See also the seminal paper by Abramovitz (1986).

[2] Another line of research on convergence in which this question tends to be ignored is represented by papers such as Dowrick and Nguyen (1989) and Fagerberg and Verspagen (1996). Again, the whole observed convergence is assigned to one source (catch-up, in this case) in a context where the other (capital deepening) is neglected on a priori grounds, rather than tested.

[3] As it is well known, simple models of catch-up (in which the sources of technology accumulation are left unexplained) and the Solow model may turn out to yield predictions that are indistinguishable in cross-section and panel data [Barro and Sala-i-Martin (1995), p. 275].

(1986).

The transitional dynamics of our model shows that the main problem for empirical analysis is to assess the precise role played by technological heterogeneity in convergence – that is, distinguishing between hypotheses (ii) and (iii) above. This is so because if individual propensities to innovate determine stationary technological differences, the former may act as a proxy for the latter whenever catch-up is absent or exhausted. As a consequence, the panel data formulations corresponding to the two hypotheses may turn out to be very similar. We suggest that one way to discriminate between (ii) and (iii) is to test whether estimates of fixed-effects in sub-periods show the pattern implied by either hypothesis.

We use this model to obtain preliminary evidence on the role of technological differences and catch-up in the observed regional convergence in Europe. We use data on 109 European regions for the 1978-93 period. As a measure for the regions' propensities to innovate, we compute an index based on patent applications to the European Patent Office (EPO). Each patent is then assigned to its region of origin according to the inventors' residence. Our panel estimates show that both the initial value of regional GDP per worker and the regional propensity to innovate, as defined above, are statistically significant with the expected signs (negative and positive, respectively). In terms of our model, this evidence corroborates the hypothesis that technological differences are explained by propensity to innovate, and that they are relevant for the analysis of convergence across European regions. Moreover, we find that technological differences are not stable over time. This evidence is consistent with convergence being (partly) due to a process of technological catch-up.

As for the related literature, a number of papers deal with the role of technology heterogeneity in European regional convergence but, to the best of our knowledge, no one tries to detect the presence of technology diffusion in a context in which capital-deepening is also considered. De la Fuente (1995), (1997) develops an approach to convergence analysis similar to the one used here, but he does not discuss how to detect technology diffusion with no TFP data.

The rest of the paper is organised as follows. In section 2 we discuss our model. In section 3 we study its transitional dynamics and discuss how to discriminate among the competing hypotheses about the sources of convergence. Our empirical evidence is presented and discussed in section 4. Conclusions are in section 5.

2. A growth model with exogenous propensity to innovate

In this section we discuss the main features of a simple model[4] in which the long run growth rate of the leader economy depends on its propensity to innovate and the technological catch-up of the follower

[4] As far as the leader economy is concerned, the model is a modified version of Shell (1966).

depends on its own propensity to innovate.[5] Stationary differences in technology levels emerge as long as propensity to innovate differs across economies. These differences are taken as given, and no attempt is made to explain how they come about and what policies can modify a given situation. Since our aim is to evaluate the consequences of technology heterogeneity on convergence, this restricted approach suits us well enough.

In the following, we first describe growth in the leader country, and then we turn to the mechanism of catch-up.

2.1 The leader economy

We assume that good Y is produced by means of a Cobb-Douglas technology:

$$Y = K^{a}\left(AL\right)^{1-a}, \tag{2.1}$$

where K is capital, L labour and A an index of technology. Some definitions associated with this production function will be used often in the following. They are as follows:

$y \equiv Y/L = k^{a} A^{1-a} = z^{a} A,\ k \equiv K/L,\ z \equiv K/AL.$

As for how innovation is accumulated, we start with the propensity to innovate, defined as $q \equiv R/Y$, where R is the total amount of the existing resources allocated to innovation, and $0 \le q < 1$ [the further restriction $(s+q) < 1$, where s is the propensity to save, is required for consumption to be allowed in each period]. Technological knowledge increases in proportion to R, according to $\dot{A} = qy$, so that the growth rate of technology is:

$$\frac{\dot{A}}{A} = q\, k^{a} A^{-a} = qz^{a}. \tag{2.2}$$

Technological progress is therefore a function of the per capita amount of resources allocated to innovation in the economy[6]. Countries with similar propensities to innovate but with different levels of per capita output have different innovation rates.

Assuming for simplicity that capital stock depreciation and population growth are both absent, in this model capital accumulation per efficiency takes place according to $\dot{z} = sz^{a} - qz^{a-1}$. It is possible to show that a stable steady-state exists in which the stationary value of z is $\tilde{z} = \frac{s}{q}$, and the stationary value of the growth rate of technology is equal to:

[5] Since in our model technology is regarded as a public good, strictly speaking the differences in the fraction of output allocated to innovation should reflect differences in the policies adopted by the individual economies. See Shell (1966) and Romer (1990).

(2.3) $$\frac{\dot{A}}{A}=q^{1-a}s^{a}.$$

In steady-state the leader economy grows at a constant rate endogenously determined by the parameters that describe the technology and the propensities to invest in physical capital and in innovation.

2.2 The follower economy

Few changes are necessary to characterise the follower economy. In this economy, the flow of technological spillovers accruing from the leader country depends on the resource allocated by the follower to innovate or imitate, as in the following formulation:

(2.4) $$\frac{\dot{A}}{A}=q\left(\frac{A^{*}}{A}\right)z^{a}$$

where now * refers to the leader. In the absence of any effort, there are no spillovers to be gained, and no economic growth[7]. In the following we assume that $0<q\leq q^{*}$. The balance growth of this system is characterised by the following stationary values:

(2.5) $$\tilde{\mathrm{A}}=\frac{q^{*}}{q}\left(\frac{s^{*}}{s}\right)^{\frac{a}{1-a}}.$$

where $\tilde{\mathrm{A}}\equiv A^{*}/A$. Clearly, if all the parameters are uniform across the economies, the stationary value of the gap is one. Moreover,

(2.6) $$\frac{\tilde{z}^{*}}{\tilde{z}}=\left(\frac{s^{*}}{s}\right)^{\frac{1}{1-a}}.$$

As for $\tilde{g}$, $\tilde{g}=q^{*1-a}s^{*a}=\tilde{g}^{*}$. To sum up, in the long run, the two economies grow at the same rate (with the growth rate of the follower converging to that of the leader). Differences in the propensity to innovate ($q^{*}>q$) translate into the leader having a stationary technological advantage over the follower. Finally, economies with different propensities to innovate, but similar propensity to save, end up with the same stationary value of k/A. The system is globally stable around its intertemporal equilibrium defined by the above stationary values of z, z^{*} and of A^{*}/A.

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6 The flow of innovation depends on *y* rather than on the absolute value of output to avoid the counterfactual growth effect associated to the scale of the labour force, which is typical of this class of models [see Barro and Sala-i-Martin (1995) p. 151-2].

7 For a similar assumption in a different context – where technology adoption depends on the level of the stock of human Benhabib and Spiegel (1994). See also Bernard and Jones (1996).

A follower economy off its steady-state is generally characterised by $z/z^* < \tilde{z}/\tilde{z}^*$ and $A^*/A > \tilde{\mathrm{A}}$. As a consequence, its convergence path is influenced simultaneously by the capital deepening mechanism emphasised by the Solow model, and by the technological catch-up process. In the following section, we use a log-linear approximation of the system to assess the role of each component along the transitional path.

3. Transitional dynamics

In this section we log-linearize the system around the steady-state values of *z* and A^*/A, and find the solution to the resulting differential equations.[8] In addition to this, we simplify the notation by assuming that the propensity to save in all economies is equal to the leader's one, s^*, so that $\tilde{\mathrm{A}} = q^*/q$ [see (2.5)] and $\tilde{z} = s^*/q^*$ in all economies. We obtain:

$$\text{(3.1)}\quad \begin{aligned} \ln y(t_2) - \ln y(t_1) = {} & \tilde{g}^* t + \left(1 - e^{-\tilde{g}^* t}\right)\ln\left[A^*(t_1)/A(t_1)\right] + \left(1 - e^{-(1-a)\tilde{g}^* t}\right)\ln A(t_1) + \\ & + \left(1 - e^{-(1-a)\tilde{g}^* t}\right) a \ln\left(s^*/q^*\right) - \left(1 - e^{-(1-a)\tilde{g}^* t}\right)\ln y(t_1) - \left(1 - e^{-\tilde{g}^* t}\right)\ln\left(q^*/q\right) \end{aligned}$$

where t_1 is an initial point of time, $t_2 > t_1$, $t \equiv t_2 - t_1$. In cross-section, t_2 and t_1 are respectively the final and the initial period. In panel data formulation, t defines the length of the time spans in which the total period of observation is divided.

Our next task is to discuss how the econometric evidence based on equation (3.1) can be used to discriminate among the hypotheses (i)-(iii) listed above. To start with, let us notice that, in the absence of reliable data on technology levels, we are forced to follow Islam's (1995) methodology in order to allow for individual heterogeneity in those levels across economies. Let us rewrite equation (3.1) using a panel data formulation:

$$\text{(3.2)}\qquad \ln y_{it} - \ln y_{i,t-1} = m_{it} + k_t - b \ln y_{i,t-1} + j \ln q_{i,t-1} + w_{it},$$

where $k_t \equiv \tilde{g}^* t + \left(1 - e^{-\tilde{g}^* t}\right)\ln A^*(t_1) + \left(1 - e^{-(1-a)\tilde{g}^* t}\right) a \ln s^* - \left(2 - e^{-\tilde{g}^* t} - e^{-(1-a)\tilde{g}^* t}\right)\ln q^*$, $\ln y_{it} \equiv \ln y(t_2)$, $\ln y_{i,t-1} \equiv \ln y(t_1)$, $b \equiv 1 - e^{-(1-a)\tilde{g}^* t}$, $j \equiv 1 - e^{-\tilde{g}^* t}$ and $m_{it} \equiv \left(e^{-\tilde{g}^* t} - e^{-(1-a)\tilde{g}^* t}\right)\ln A(t_1)$. In this formulation, k_t varies across time periods and is constant across individual economies, m_{it} describes the degree of technology heterogeneity at a certain point in time, and w_{it} is the error term with mean equal to zero. For the time being let us assume that fixed-effect (LSDV) estimates of (3.2) can be

[8] For the sake of simplicity, the transitional dynamics discussed below is obtained by ignoring the interaction between *z* and the gap along the transitional path. While some precision is lost, the picture we get is sufficiently detailed for our purpose.

obtained,[9] with the individual intercepts yielding an approximate measure of m_{it}, although this term is not strictly time-invariant.[10]

For the sake of our discussion on how to distinguish among the various hypotheses, let us consider a case in which the signs of the coefficients of the explanatory variables are significant and in accordance with the predictions of the model. This type of evidence can be interpreted as follows. First, since hypothesis (i) implies that the propensity to innovate is irrelevant for convergence analysis, it predicts that its coefficient is zero. So we can rule out hypothesis (i) in favour of the other hypotheses. Second, since (3.2) is obtained under hypothesis (iii), the latter is clearly supported by this type of evidence. However, the same evidence does also corroborate hypothesis (ii).[11] To see how this problem arises, let us evaluate our model under hypothesis (ii) – i.e., with the process of technology diffusion exhausted and convergence due entirely to capital-deepening. Under this hypothesis, $A^*(t)/A(t) = \tilde{A} = q^*/q$ in each period of time (including t=0), $\ln A(t_1) = \ln A(0) + \tilde{g}^*(t_1)$, and the following panel data formulation can be obtained:

$$\text{(3.3)} \qquad \ln y_{it} - \ln y_{i,t-1} = r_i + c_t - b \ln y_{it-1} + v_{it}$$

where $r_i \equiv \left(1 - e^{-(1-a)\tilde{g}^* t}\right) \ln A(0)$, $c_t \equiv \tilde{g}^*\left(t_2 - e^{-(1-a)\tilde{g}^* t} t_1\right) + \left(1 - e^{-(1-a)\tilde{g}^* t}\right) a \ln\left(s^*/q^*\right)$ and v_{it} is the error term with mean equal to zero. Notice that under hypothesis (ii) we obtain proper time-invariant individual intercepts, defined by r_i [see also Islam (1995), p. 1149]. More importantly, since technological differences are supposed to be at their stationary values $\tilde{A} = q^*/q$ [12], then in principle $A(0)$ and q are perfectly correlated across economies. As a consequence, a significant positive value of j does not yield clear-cut evidence in favour of the hypothesis that technology diffusion is part of the observed convergence.[13] At this stage all we could say is that technology heterogeneity, due to differences in propensity to innovate, is relevant for convergence analysis.

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[9] The use of LSDV estimates for convergence analysis has been criticised by Durlauf and Quah (1999) on the grounds that allowing $A(0)$ to differ across economies makes it particularly difficult to understand whether *b*-convergence implies a reduction of the gap between the poor and the rich (p. 52-3). This criticism does not necessarily apply to our case, in which we concentrate on how to discriminate between two sources of convergence.

[10] Under hypothesis (iii) the initial degree of technology heterogeneity cannot be regarded as strictly time-invariant. The reason is that technology diffusion is present, technology growth rates differ along the transitional path leading to their common steady-state value. Consequently, m_{it} includes the term $A(t_1)$ and cannot be properly defined as an individual intercept. We will come back to this point below.

[11] To the best of our knowledge, up to now this problem has not yet been discussed in the empirical literature on convergence.

[12] Recall that we are assuming that the propensity to save is uniform across all economies.

[13] More generally, finding that a technological variable such as R&D or patents exert a statistically significant positive effect on growth does not offer indisputable evidence that catch-up is part of the observed convergence. See Fagerberg, Verspagen and Caniels (1997) and Fagerberg and Verspagen (1996), among many others, for a different viewpoint on the interpretation of evidence of this type.

Therefore, in order to evaluate whether technology convergence is present, we have to search for testable implications of the model that could allow us to discriminate between the two competing hypotheses. To this aim, consider again the term m_{it} in (3,2), associated with hypothesis (iii). We have already noticed that m_{it} cannot be regarded as a proper fixed-effect, while the opposite is true for r_i in equation (3.3). This difference can be exploited empirically as follows.

First, since under hypothesis (iii) technology gaps are not at their stationary values, in general we should expect that $s_m^2 \neq \tilde{s}_m^2$.[14] As a consequence, convergence of s_m^2 to its stationary value should be detectable over subsequent periods if hypothesis (iii) is true – abstracting from random disturbances. On the other hand, under hypothesis (ii) s_r^2 is time-invariant, since – abstracting again from random disturbances – it is assumed to be at its steady-state value $\tilde{s}_r^2$. Second, , under hypothesis (iii) the correlation between the fixed-effects and the propensity to innovate should increase over time, as the current technology gaps approach their stationary values. Consequently, we could split the whole period under observation in several sub-period, obtain LSDV estimates of (3.2) and (3.3), and then use the estimated individual intercepts to test the two above implications of the model.[15]

Finally, a third implication worth noticing is that the correlation between the individual intercepts and the growth rates of *y* is positive under hypothesis (ii) [Islam (1995)], and negative under hypothesis (iii). All these implications will be tested in our empirical analysis, to which we now turn.

4. Empirical evidence

Data. Data on regional GDP and employment are obtained by the CRENoS data set on 109 regions of 12 European countries for the period 1978-93.[16] A more complex problem is how to compute an index of regional propensities to innovate. In our paper, such an index is obtained as follows. First, patent applications collected by the European Patent Office (EPO) are assigned to individual regions by identifying the region of residence of the inventors.[17] Second, the total numbers of patents in a region are divided by the same region's GDP. By doing so, we obtain an index of propensity to innovate at the regional level for the years 1978-93. We use the inventor's residence, rather than the proponent's residence, because the latter generally corresponds to the firms' headquarters, and therefore it might underestimate the peripheral regions' propensity to innovate. For the same reason, the index we use is

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[14] However, in the absence of "absolute convergence" in technology levels the case $s_a^2 = \tilde{s}_a^2$ is not ruled out (similarly, *b*-convergence does not necessarily imply s-convergence unless steady-state values are uniform across individuals).

[15] The problem represented by m_{it} not being a proper time-invariant effect should be less pronounced when shorter time-spans are considered.

[16] The data used in this paper are downloadable at http://www.crenos.unica.it. For details on the data set see Paci (1997).

[17] For the case of patents with more than one inventors, we have proportionally assigned a fraction of each patent to the different inventors' regions of residence.

likely to be more adequate than an alternative one based on expenditure in R&D. Moreover, the correlation between our index and an index based on regional R&D in 1990 turns out to be equal to 0.91.

Our index of the regional propensity to innovate appears to be far from uniform across the European regions. This feature is apparent in Figure 1, where European regions are classified into five groups according to the average value of the index recorded for the period 1978-93. Some clusters of more innovative regions are evident in the Figure, especially in Germany, southern Britain, central France and northern Italy. Moreover, most southern European regions (Portugal, Spain, Greece and southern Italy) show a very low propensity to innovate. In the present paper, we do not try to build this specific spatial feature into our analysis of convergence, but this spatial component is likely to be crucial for future research on European regional convergence. From the point of view adopted in this paper, the major consequence of the observed heterogeneity of our index across regions is that discriminating between (i) and (ii)-(iii) should be possible in spite of the absence of data on TFP.

Estimation results. Our LSDV estimates, based on equation (3.2), are presented in Table 1[18]. We have computed three five-year panels for the sub-periods 1978-83, 1983-88, 1988-93. The dependent variable y is the average growth rate of GDP per worker over each time span. The explanatory variables – labour productivity and propensity to innovate – are included as levels in the initial year of each time span. The regression results for the entire period are shown in Regression 1, Table 1. The initial level of labour productivity has the expected negative coefficient and is highly significant. More importantly, our index of propensity to innovate turns out to be statistically significant with the expected positive sign. In terms of our model, this evidence yields some preliminary support to the idea that technological differences are explained by heterogeneity in propensity to innovate, and that they are relevant for the analysis of convergence across European regions. The relevance of the propensity to innovate as an explanatory variable in the growth equation is confirmed by the regressions included in Table 2, which are explicitly based on the hypotheses (i) and (ii). Their explanatory power appears remarkably lower than in regressions 1-3 in Table 1. More specifically the goodness of fit increases from 2% in the model with only the initial productivity level, to 12% when we add the fixed effects to allow for differences across regions in technological levels, to 51% when we also add our measure of the propensity to innovate.

[18] Since we are dealing with a dynamic model, the LSDV estimator is asymptotically consistent. Given that our panel is characterised by t=3, our estimates are likely to be biased. In particular, the absolute value of the coefficient on capital deepening is likely to be biased upward [see Hsiao (1986)].

Discussion. We begin by noticing that our main result in Table 1 (Regression 1) is at odds with hypothesis (i), according to which convergence should not be influenced by variables reflecting systematic differences in technology levels.[19]

As for the other hypotheses, we should recall from our discussion in section 3.1 that a positive and significant coefficient of the propensity to innovate is consistent *both* with convergence being (partly) due to technological catch-up, and with the competing hypothesis (ii), in which technological differences are stationary. Further and more detailed inspection of our results is therefore required in order to identify which hypothesis is better supported by our evidence. As we have maintained above, relevant information can be obtained by carefully analysing the estimated fixed-effects in Regression 1, Table 1.

Our preliminary inspection concerns the interpretation of the individual intercepts adopted in this paper. As we have repeatedly noticed, these coefficients are expected to yield a measure – however indirect – of the technology level of each individual economy.[20] The data shown in Table 3 are clearly consistent with this interpretation. In this Table we report the ten highest and lowest fixed-effect coefficients for the whole period 1978-93. It appears that the European region with highest technology level is Hamburg, followed by Brussels and Ile the France. Among the top ten economies there are also 4 northern Italy regions. All the regions with low technology belong to southern European countries like Portugal (3 regions) Greece (6 regions) and Spain (1 region). We have also reported the average coefficient values for each country (we have excluded the one-region countries). Germany displays the highest value, followed by Belgium, while in the bottom positions we find Spain, Portugal and Greece.

Our next step is to use the estimated individual intercepts to test three implications – discussed in section 3.1 – capable of discriminating between hypothesis (ii) and (iii).

First, hypothesis (iii) implies that the variance of the individual technology levels is not at its stationary value. The opposite is implied by hypothesis (ii), abstracting from random disturbances. The results of our estimates for two sub-periods – 1978-88 and 1983-93 – are reported in Regressions 2 and 3 in Table 1. The variance of the individual intercepts for our 109 European regions shows remarkable changes over time, decreasing from 0.0047 in the first sub-period to 0.0024 in the second one. This result must be interpreted with caution, since there are other random or systematic factors (heterogeneity in the propensity to save and in human capital, for instance) that may affect the variance of the fixed effects over time. Moreover, due to the limited number of time-series observations, we

[19] Our conclusion would be wrong if our measure of the propensity to innovate turned out to be (a) uncorrelated with the (uniform) technology levels, and (b) positively correlated with the (heterogeneous) propensity to accumulate human capital, which we do not include in our regression. While the condition (b) is likely to hold in reality, it is hard to rationalise the existence of such a correlation in a world in which technology growth is exogenous and technology levels are homogeneous across individuals.

[20] In section 3 we have assumed the propensities to invest in physical and human capital to be uniform across all economies. This is not necessarily so in our dataset. As a consequence, the individual intercepts of Regression 1 might reflect these elements as well as the current heterogeneity in technology levels. On this more below.

have estimated our model using only two time spans for each regression, with the overlapping of the central years 1983-88. However, the change over time of the fixed-effect variance is high and this is hardly consistent with the hypothesis of technological differences being stationary over time. The observed decrease in the variance is clearly consistent with the main prediction of the model under hypothesis (iii), since we expect the initial variance in technology levels to be larger than the steady-state one in a typical process of technology catch-up. This result is confirmed when we estimate equation (3.3), which is obtained explicitly under the hypothesis that the differences in technology levels are stationary. In this case too (regressions 7-9 in Table 2) the variance of the individual intercepts decreases over time, contradicting hypothesis (ii).

Second, under hypothesis (iii) the correlation between the individual intercepts and the propensity to innovate should increase over time, as the current technology gaps approach their stationary values. Indeed, such a correlation does increase over time in our sample (from 0.61 to 0.70). This evidence again is consistent with hypothesis (iii) alone.

Third, the correlation between the individual intercepts and the growth rates of y is positive under hypothesis (ii) and negative under hypothesis (iii). Notice that these implications are obtained by assuming homogeneity across individuals of variables such as propensity to save and human capital, which correlate positively with growth but cannot be measured in our current dataset. Therefore, the presence in our sample of some degree of heterogeneity in these variables would be reflected in the estimated individual intercepts. In this case, the above-defined implication associated with hypothesis (ii) would be reinforced in the same direction, while the implication of a negative correlation associated with hypothesis (iii) would be weakened. Our evidence shows that the correlation between individual intercepts and growth rates is not significantly negative for the whole sample, and significantly negative for the lagging regions. We conclude that this piece of evidence too yields additional support for hypothesis (iii) as opposed to hypothesis (ii).

To sum up, the evidence discussed so far is likely to be generated by a process that does involve technological catch-up.

5. Conclusions

Building on a simple endogenous growth model, in this paper we carry on an empirical analysis to assess the role of technology heterogeneity and catching-up in the convergence process observed across the European regions during the 1978-93 period. All our results are obtained in the absence of total factor productivity data for the individual economies. Our findings reject the hypothesis that technology is uniform across European regions, and strongly indicate that technology heterogeneity, due to differences in propensity to innovate, is relevant for convergence analysis. Moreover, we provide detailed evidence in favour of the hypothesis that the current differences in technology levels are not stationary and that they are the source of a process of technological catching-up.

One interesting development of the approach proposed in this paper would be to explore the possibility that the stock of human capital take part in the determination of the stationary technology gap – as in Benhabib and Spiegel (1994) –, together with the propensity to innovate. Finally, the possibility that there exist a spatial component in the distribution of the propensity to innovate across individual economies should also be considered within the framework adopted here.

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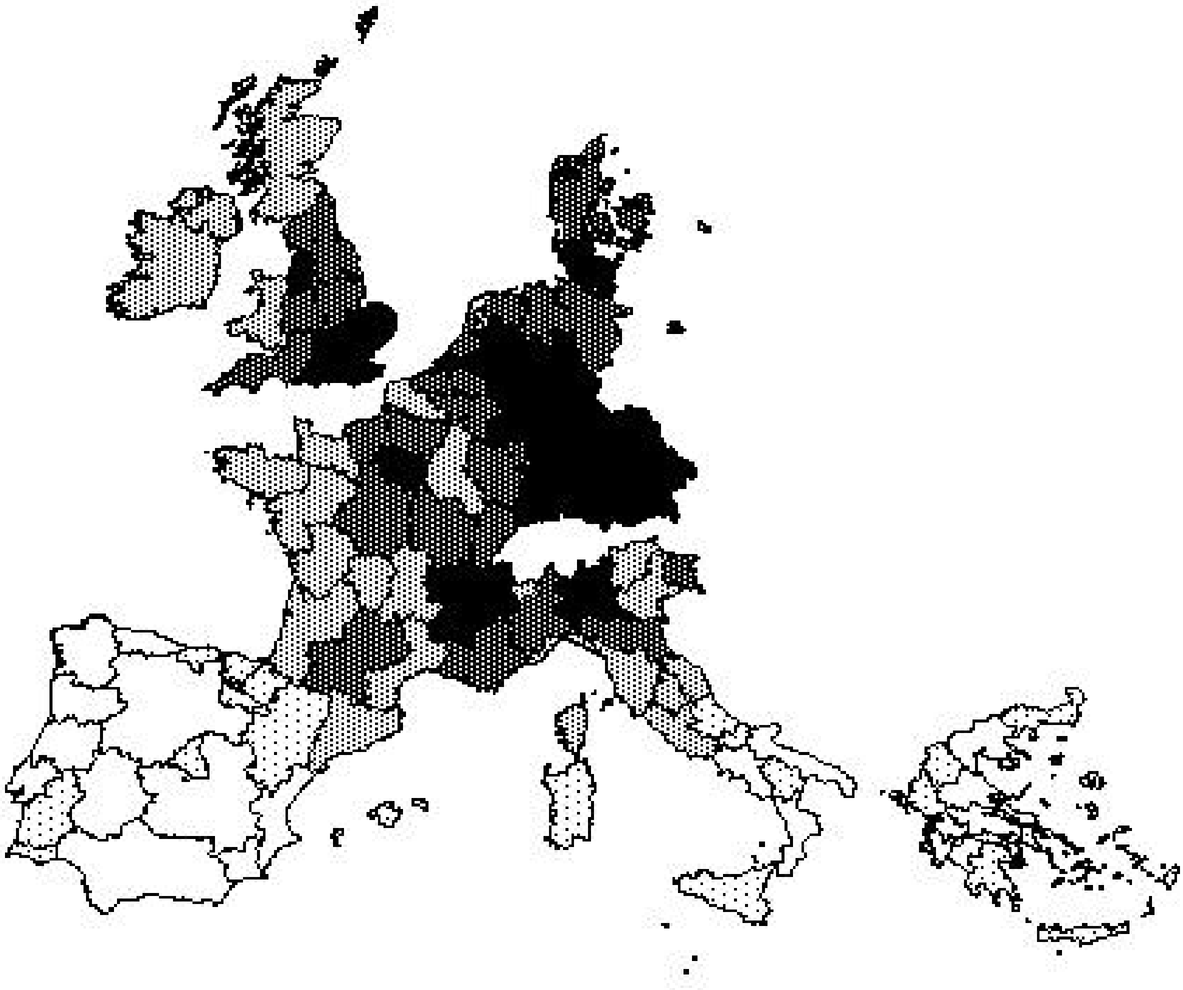
Figure 1. Propensity to innovate across the European regions. 1978-93

q = patents / GDP (in 10.000 units of PPP); annual average



Ranges and (frequency); European Union average: q = 28.6):

θ>50 (17)

Table 1.
Propensity to innovate, capital deepening and growth in the European regions

Estimation method: LSDV (least squares dummy variables)
Panels: 1978-83, 1983-88, 1988-93. Cross-section observations:109
Dependent variable: annual average growth rate of labour productivity in each time span
$y_{i\,t1}$ = labour productivity in the initial year of each time span
$\theta_{i\,t1}$ = propensity to innovate in the initial year of each time span
t statistics in parentheses
significance levels: a=1%, b=5%

Explanatory variables	**Regr. 1**	**Regr. 2**	**Regr. 3**
	1978-93	1978-88	1983-93
$y_{i\,t1}$	-0.163	-0.239	-0.167
	(-14.1)[a]	(-11.2)[a]	(-13.2)[a]
$\theta_{i\,t1}$	0.0085	0.0082	0.0026
	(13.1)[a]	(9.27)[a]	(1.14)
adj. R^2	0.51	0.69	0.59
F-test	447[a]	592[a]	416[a]
Fixed effects' variance	0.0019	0.0047	0.0024
Number of panels	3	2	2
Number of observations	327	218	218

Table 2.
Capital deepening and growth in the European regions

Panels: 1978-83, 1983-88, 1988-93. Cross-section observations:109;
Dependent variable: annual average growth rate of labour productivity in each time span
$y_{i\,t1}$ = labour productivity in the initial year of each time span
t statistics in parentheses
significance levels: a=1%, b=5%

	Hypothesis (i)			Hypothesis (ii)		
Explanatory variables	**Regr. 4**	**Regr. 5**	**Regr. 6**	**Regr. 7**	**Regr. 8**	**Regr. 9**
	1978-93	1978-88	1983-93	1978-93	1978-88	1983-93
Constant	0.02 (3.51)[a]	0.02 (2.12)[b]	0.03 (4.69)[a]			
$y_{i\,t1}$	-0.008 (-2.77)[a]	-0.004 (-1.61)	-0.009 (-2.89)[a]	-0.14 (-9.40)[a]	-0.34 (-14.0)[a]	-0.16 (-14.9)[a]
adj. R^2	0.02	0.01	0.03	0.12	0.44	0.58
F-test	7.6[a]	2.6	8.34[a]			
Fixed effects' variance				0.0019	0.011	0.0024
Estimation method:	OLS	OLS	OLS	LSDV	LSDV	LSDV
Number of panels	3	2	2	3	2	2
Number of observations	327	218	218	327	218	218

Table 3.
Descriptive statistics of the fixed effects coefficients from Regr. 1 Table 1.

10 highest coefficients (proxy for high technological levels)			**10 lowest coefficients** (proxy for low technological levels)		
RANK	REGIONS	F.E. COEFF.	RANK	REGIONS	F.E. COEFF.
1	Hamburg	0.487	109	Alentejo	0.259
2	Brussels	0.467	108	Voreio Aigaio	0.260
3	Ile de France	0.462	107	Ipeiros	0.271
4	Bremen	0.455	106	Centro (P)	0.284
5	Valle d'Aosta	0.442	105	Extremadura	0.285
6	Emilia Romagna	0.439	104	Ionia Nisia	0.295
7	Luxembourg	0.437	103	Dytiki Ellada	0.296
8	Lombardia	0.431	102	Algarve	0.301
9	Trentino Alto Adige	0.431	101	Thessalia	0.307
10	Hessen	0.428	100	Kriti	0.308

Ranking of European Countries in decreasing order of estimated fixed effects coefficients

RANK	COUNTRY	F.E. COEFF.
1	Germany	0.411
2	Belgium	0.411
3	Italy	0.394
4	France	0.386
5	United Kingdom	0.374
6	Netherlands	0.370
7	Spain	0.357
8	Portugal	0.310
9	Greece	0.309