# TECHNOLOGICAL CATCH-UP AND REGIONAL CONVERGENCE IN EUROPE*

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*Abstract:* Our aim is to address the problem of measuring how much of the convergence observed across European regions is due to convergence in technology versus convergence in capital-labour ratios. To this aim, 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 per capita income is due to both capital deepening and catch-up. We use data (1980-93) 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.

JEL: O41, O33,

*Keywords:* Convergence, Growth, Technology Diffusion, Europe

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Contributi di Ricerca CRENoS, 99/9

This version: October 1999

* We would like to thank Adriana Di Liberto, Giovanni Peri, Pasquale Scaramozzino and Giovanni Urga for several useful comments and suggestions. Thanks are also due to partecipants to a seminar held at the 1999 Annual Meeting of the Society for Economic Dynamics. Financial support provided by MURST (Research Project on "European integration and regional disparities in economic growth and unemployment") and by CRENoS is gratefully acknowledged.

## 1. Introduction

As it is now widely recognised, technology differences and diffusion do not receive enough attention in the current empirical literature on economic growth in spite of the fact that they are likely to be important factors in convergence.[1] For instance, a widely used assumption in the literature is that there are no systematic technological differences across economies, so that convergence is entirely due 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),[2] but assume that such differences are stationary, so that again technology diffusion is ruled out 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].[3]

One reason for the insufficient attention given to this specific question is that it is difficult to distinguish empirically between the role of technology diffusion and that of capital deepening, especially in the context of aggregate growth models[4] and in the absence of reliable data on technology levels, as in the case of the European regions. In this paper we addresses this difficulty explicitly. We use a simple model developed in Pigliaru (1999)[5], in which capital accumulation proceeds as in Solow's growth model, while 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 yield 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 technology diffusion.

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

[1] See among many others Bernard and Jones (1996), Parente and Prescott (1994), Jones (1997), de la Fuente (1997) and Lee, Pesaran and Smith (1998). See also the seminal paper by Abramovitz (1986).
[2] See also Islam (1998).
[3] 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.
[4] 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].
[5] As far as the leader economy is concerned, the model is a modified version of Shell (1966).

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 are very similar. We suggest that one way to discriminate between (ii) and (iii) would be 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 the data on patents collected by the European Patent office (EPO). Each patent is then assigned to its region of origin according to the inventors' residence [see Paci and Usai (1999) for details on the adopted methodology]. 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. This evidence is consistent with convergence being (partly) due to technological catch-up.

As for the related literature, a number of paper 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.[6] De la Fuente (1995) 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 sum up the model developed in Pigliaru (1999), in which the long run growth rate of the leader economy depends on its propensity to innovate[7] and the technological catch-up of the follower depends on its own propensity to innovate. 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.

[6] See for instance Fagerberg and Verspagen (1996).

[7] 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).

Since our aim is to evaluate the consequences of technology heterogeneity on convergence, this limited 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:

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

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

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 $0 \leq q < 1$ [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[8]. Countries with similar propensities to innovate but with different levels of per capita output have different innovation rates.

It is easy to show that a stable steady-state exists and that in this steady-state[9] $\tilde{z} = \frac{s}{q}$ and therefore:

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

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.

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[8] 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].

[9] For the sake of simplicity we assume that capita depreciation and population growth are both absent. See Pigliaru (1999) for an analysis in which they are both positive.

## 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:

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

where now * refers to the leader. In the absence of any effort, there are no spillovers to be gained, and no economic growth[10]. In the following we assume that $0 < q \le q^*$. The balance growth of this system is characterised by the following stationary values:

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

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

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

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 $A^*/A$.[11]

A follower economy off its steady-state is generally characterised by $z/z^* < \tilde{z}/\tilde{z}^*$ and $A^*/A > \tilde{A}$. 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.

[10] For a similar assumption in a different context – where technology adoption depends on the level of the stock of human capita – see Benhabib and Spiegel (1994). See also Bernard and Jones (1996).
[11] See Pigliaru (1999).

## 3. Transitional dynamics

In this section, our aim is to assess the influence exerted by the two effects on labour productivity growth in a cross-section or panel of economies. Since our purpose is not to identify the parameters of the model exactly, but rather to show how the presence of catch-up can be detected, in the following we present a simplified version of the transitional dynamics of our model. This version 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.

We first log-linearize the system around the steady-state values of *z* and $A^*/A$, and then find the solution to the resulting differential equations. 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, $s^*$. In this case, $\tilde{A} = q^*/q$ [see (2.5)] and $\tilde{z} = s^*/q^*$ in all economies. We obtain:

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

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. Equation (3.1) can be used to assess the role of heterogeneous propensity to innovate and of technological catch-up in convergence.

### 3.1 Detecting technological catch-up when TFP data are not available

In this case, using (3.1) to distinguish between hypothesis (i) and hypotheses (ii)-(iii) turns out to be simpler than distinguishing between (ii) and (iii).

Since we assume that reliable data on technology levels are not available in the case under analysis, we follow Islam's (1995) methodology in order to allow for individual heterogeneity in those levels. Using the panel data notation we can rewrite equation (3.1) as:

$$
\ln y_{it_2} - \ln y_{it_1} = m_{it_1} + k_{t_1} - b \ln y_{it_1} + j \ln q_{it_1} + w_{it_1}, \tag{3.2}
$$

where

$$
\begin{aligned}
& j \equiv 1 - e^{-\tilde{g}^* t} \\
& m_{it_1} \equiv \left(e^{-\tilde{g}^* t} - e^{-(1-a)\tilde{g}^* t}\right)\ln A(t_1) \\
& k_{t_1} \equiv \tilde{g}^* t + \left(1 - e^{-\tilde{g}^* t}\right)\ln A^*(t_1) + \left(1 - e^{-(1-a)\tilde{g}^* t}\right) a \ln s^* - \left(2 - e^{-\tilde{g}^* t} - e^{-(1-a)\tilde{g}^* t}\right)\ln
\end{aligned}
$$

One general problem with this approach is that, if hypothesis (iii) is true, then $m_{it_1}$ cannot properly defined as a strictly time-invariant individual fixed-effect. The reason is that under hypothesis (iii) technology growth rates differ along the transitional path leading to their common steady-state value. Proper fixed-effects can be obtained under hypothesis (ii), as in Islam (1995). We will come back to this problem later.

Clearly, hypothesis (i) implies that the propensity to innovate is irrelevant for convergence analysis, and therefore predicts that the coefficient of such a variable is zero. Consequently, distinguishing between hypothesis (i) and hypotheses (ii)-(iii) turns out to be a simple task, at least in principle.

As for distinguishing between hypotheses (ii) and (iii), this task is far less simple. Indeed, while a statistically significant positive value of $j$ is consistent with the catch-up hypothesis, it does not corroborate it unambiguously[12]. To see why, let us consider explicitly the alternative hypothesis (ii) in which technological differences are at their stationary values. In this case, convergence is due entirely to capital-deepening. More specifically, $A^*(t)/A(t) = \tilde{A} = q^*/q$ in each period of time (including $t$=0) [13], $\ln A(t_1) = \ln A(0) + \tilde{g}^*(t_1)$, so that:

(3.3) $$\ln y_{it_2} - \ln y_{it_1} = r_i + c_{t_1} - b \ln y_{it_1} + v_{it_1}$$

where

$$\begin{aligned} b &\equiv 1 - e^{-(1-a)\tilde{g}^* t} \\ r_i &\equiv \left(1 - e^{-(1-a)\tilde{g}^* t}\right) \ln A(0) \\ c_{t_1} &\equiv \tilde{g}^* \left(t_2 - e^{-(1-a)\tilde{g}^* t} t_1\right) + \left(1 - e^{-(1-a)\tilde{g}^* t}\right) a \ln\left(s^*/q^*\right) \end{aligned}$$

and $v_{it_1}$ is the error term with mean equal to zero. Notice that $r_i$ is a proper fixed-effect that incorporates the not available index of technology level at time zero.

The problem of discriminating between (ii) and (iii) depends on the fact that, since in steady-state $\tilde{A} = q^*/q$, in principle $A(0)$ and $q$ are perfectly correlated across economies. As a consequence, a statistically 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.

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[12] 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.

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

To discriminate between the two hypotheses, therefore, we have to search for other testable implications of the two models. Consider again the term $m_{it_1}$ associated with hypothesis (iii). We have already noticed that $m_{it_1}$ cannot be regarded as a proper fixed-effect, so that we cannot obtain reliable indirect measures of it by means of the individual intercepts in LSDV estimates over a long period of time. However, suppose that splitting the whole period under observation in several sub-periods made $m_{it_1}$ a semi-permanent term in (3.2). This is a crucial assumption for our purposes, because in this case we could obtain LSDV estimates of (3.2) for properly defined sub-periods, and then use the estimated individual intercepts to test the following implications of the model.

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, the correlation between the individual intercepts and the growth rates of *y* is positive under hypothesis (ii) [Islam (1995)], and negative under hypothesis (iii). Third, under hypothesis (iii) the correlation between the fixed-effects and the propensity to innovate should increase over time, as the system approaches its balanced growth path.

Estimating (3.2) [and (3.3)] by means of LSDV regressions over different sub-periods should therefore significantly enhance our chances of discriminating between the two hypotheses. In practice, however, implementing this test may turn out to be difficult due to the small number of observations for each individual economy contained in the typical panel data on economic growth (on this more below).[15]

## 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. [see Paci (1997) for details on the data set]. 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, patents collected by the European Patent office (EPO) are

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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 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.

assigned to individual regions by identifying the region of residence of the inventor.[16] 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 likely to be more adequate than an alternative one based on expenditure in R&D [for further discussion see Paci and Usai (1999)]. 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 even in spite of the absence of data on TFP.

*Estimation results.* Our LSDV estimates, based on (3.2), are presented in Table 1[17]. We have defined three five-year panels for the 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.

Regression results for the entire period are shown in Regression 1 of 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, based on the hypotheses (i) and (ii): their explanatory power appears remarkably lower than in regressions 1-3 in Table 1.

[16] 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.

*Discussion*. We begin by noticing that our result is at odds with hypothesis (i). Indeed, to reconcile this specific hypothesis with our evidence, the following conditions are required. First, the technology levels (assumed to be uniform) should be unrelated to the number of patents generated locally; second, propensity to accumulate human capital should differ across regions; third, human capital should be strongly correlated with our measure of the propensity to innovate. In such a context, our technology variable would simply act as a proxy of human capital heterogeneity. While the latter condition is likely to hold in reality[18], 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 space.

As for the other hypotheses, we should note that the positive and significant coefficient of the propensity to innovate is consistent both with convergence being (partly) due to technological catch-up, and with the alternative hypothesis (ii), in which technological differences are stationary.

As we maintained above, it is not easy to distinguish between these two hypotheses on the basis of our regression equation. In the following, we will analyse the pattern of the estimated fixed-effects in order to try to assess whether it is possible to reach a conclusion along the lines suggested in section 3.

In order to assess the stationarity of technological differences included in the fixed effects, we have estimated our model for two sub-periods – 1978-88 and 1983-93. The results are reported in regressions 2 and 3 in Table 1. The variance of the fixed effects for our 109 European regions shows remarkable changes over time; more precisely, it decreases 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 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. Moreover, the observed decrease in the variance is consistent with the main prediction of the model, 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.

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[17] 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)].

[18] To measure the magnitude of this correlation across European regions, we have used the human capital data collected by Lodde (1999) for a sample of 67 regions belonging to Belgium, Italy, France, UK and Germany defined as average number of schooling of the labour force over the eighties. The correlation coefficient between this measure of human capital and our index of propensity to innovate - for the same regions and time period - turns out to be positive and significant (r = 0.65).

This pattern is confirmed when we estimate equation (3.3), which is obtained explicitly under the hypothesis that differences are stationary. In this case too (regressions 7-9 in Table 2) the variance of the individual intercepts decreases over time contradicting hypothesis (ii).

Finally, we find further support for hypothesis (iii) by observing that the correlation between individual intercepts and growth rates is not significatly negative for the whole sample, and significantly negative for the lagging regions; and that the correleation between the individual intercepts and propensities to innovate does increase over time (from 0.61 to 0.70).

All this said, the short time span of our data set does not allow us to reach a clear-cut conclusion regarding hypothesis (ii) v hypothesis (iii). What we can say is that the evidence discussed so far is likely to be generated by a process that does involve technological catch-up. In addition to this, we can offer the following consideration. Transitional dynamics in which technological gaps and factor intensities are *both* off their steady-state values (as in our model) are easy to rationalise – our model being just one particularly simple way among many others. On the contrary, rationalising transitional paths in which factor intensities are off their steady state values, while technology gaps do exist but are stationary, seems to pose a much harder task, and to refer to a much less general case.

*Further evidence on the individual intercepts*. Finally, it is interesting to analyse the estimated fixed-effects coefficients derived from regression 1 in Table 1. Under the (strong) hypothesis that the other elements captured by the fixed effects are uniform across all economies, these coefficients offer a measure of the technology level of each individual economy. In Table 3 we report the ten highest and lowest fixed effects 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.

## 5. Conclusions

In this paper we have developed a simple growth model where technology accumulation in lagging economies depends on their propensity to innovate and on inter-regional spillovers, and convergence is due to both capital-deepening and catch up. We have used the model to show how to generate unambiguous evidence on the role of technology diffusion in the observed convergence.

In the empirical part of the paper, we have used data on 109 European regions for the 1978-93 period. Our findings reject the hypothesis that technology is uniform across European regions, and are consistent with the hypothesis that convergence is partly due to technological catch-up. However, the transitional dynamics of our model shows that, in the absence of data on TFP, it is difficult to discriminate between the catch-up case and the alternative case based on the existence of stationary technology differences. Therefore, additional research on this specific empirical problem is required.

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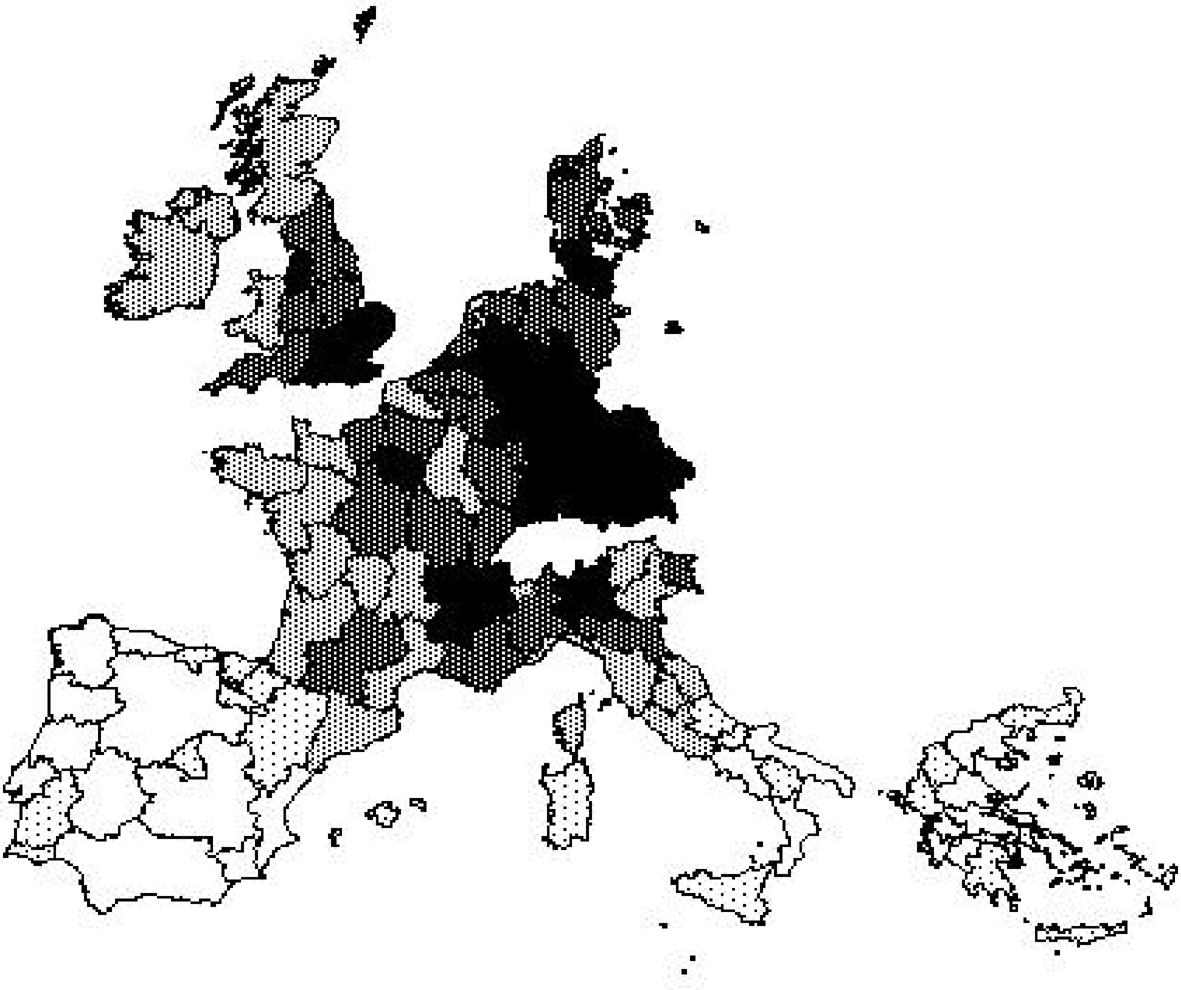
Figure 1. Propensity to innovate across the European regions. 1978-93

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



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

θ<4 (22) 4<θ<10 (19) 10≤ θ<28.6 (26) 28.6<θ<50 (25) 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 [hypothesis (iii)] | 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%

| **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 |
| | | [hypothesis (i)] | | | [hypothesis (ii)] | |
| Constant | 0.02 | 0.02 | 0.03 | | | |
| | (3.51)[a] | (2.12)[b] | (4.69) [a] | | | |
| $y_{i\,t1}$ | -0.008 | -0.004 | -0.009 | -0.14 | -0.34 | -0.16 |
| | (-2.77)[a] | (-1.61) | (-2.89)[a] | (-9.40)[a] | (-14.0)[a] | (-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 | BRUXELLES-BRUSSEL | 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 |