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Technological Diffusion, Spatial Spillovers and Regional Convergence in Europe

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TECHNOLOGICAL DIFFUSION, SPATIAL SPILLOVERS AND REGIONAL CONVERGENCE IN EUROPE

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1. Introduction[*]

In this paper we analyze two closely related issues. First, we study the role of technology heterogeneity and diffusion in the convergence in GDP per worker observed across the European regions, in the absence of data on regional total factor productivity (TFP). Second, we study the spatial pattern of the observed regional heterogeneity in technology and the relevance of such a pattern for the econometric analysis of regional convergence in Europe.

As for the first issue, it is well known that studying the role of technology heterogeneity and of the associated process of technological diffusion in growth is not an easy task in general,[1] and that it is even more difficult in cases like ours, with no data on regional TFP available. In the empirical literature such a difficulty is shown by the frequently used assumption that systematic technological differences across economies are absent, so that whole observed convergence is ascribed to capital deepening [see in particular the influential paper by Mankiw, Romer and Weil (1992)].[2] Other papers allow for differences in individual technologies, as in Islam (1995) and (1998), 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].[3]

An implication of the problem highlighted by Bernard and Jones is that we need to go through some detailed analytical work before proceeding with the analysis of the data. In the first part of the paper we discuss a model in which the following alternative hypotheses can be studied and compared:

(i) technology differences play no systematic role in convergence, as in Mankiw *et al.* (1992);

(ii) technology differences exist and are stationary, as in Islam (1995): they co-determine the

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[1] 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].

[2] Important exceptions are, among 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).

[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.

steady-state differences in labor productivity levels;

(iii) technology differences exist, are not stationary, and are an active source of income convergence through a technology diffusion process of the Abramovitz (1986) type.

Our model describes an economy in which hypothesis (iii) is true, with convergence due both to capital deepening and to technology catch-up. The other cases, (i) and (ii), can be studied as special ones by introducing few restrictions. We use this model to design empirical tests that should allow us to identify which hypothesis is true in the case of the European regions. Our analytical discussion highlights the main difficulty to be faced by any empirical analysis that try to assess the precise role played by technological heterogeneity in convergence in the absence of TFP data – namely, distinguishing between hypotheses (ii) and (iii) above is a complex task requiring, among other things, a close inspection of the pattern of the individual intercepts over time. To the best of our knowledge, this problem had not been recognized until now in the empirical literature on convergence.

In the empirical part of the paper we present some evidence on the role of technological differences and catch-up in the observed regional convergence in Europe. We use data on 131 European regions for the 1978-97 period. As a measure for the regions' propensities to innovate, we compute an index based on patent application to the European Patent Office (EPO) 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 correlation (negative and positive, respectively) with the dependent variable measuring the growth of labor productivity. In terms of our model, this evidence corroborates the hypothesis that technological differences are explained by a differences in the regional propensities to innovate, and that they are relevant for the analysis of convergence across European regions. Moreover, we find indications that technological differences are not stable over time. This additional evidence is consistent with convergence being (partly) due to a process of technological catch-up.

As for the second empirical issue addressed in this paper, we study to what extent each region's growth rate is correlated with that of the surrounding regions. Much of the empirical literature on convergence ignores the possibility that the performance of an individual region might be influenced by its geographical location. This limitation of the analysis can be overcome by adopting a number of spatial econometrics techniques [Anselin (1988)]. Our results show, first, that the propensity to innovate of each region does depend on that of the surrounding areas; second, that the intensity of the growth spillovers fades significantly with distance. Taken together, these findings suggest the existence of important localized spillovers of technological knowledge. Finally, we show that the latter are strong enough to play a role that cannot be ignored in the econometric analysis of the convergence process in Europe.

As regard to the relevant 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, in the absence of TFP data. De la Fuente (1995), (1997) develops an approach to convergence analysis very similar to the one used here, but he does not discuss explicitly how to detect technology diffusion with no data on technology levels. Further, some recent papers have employed spatial econometric techniques to analyze regional growth processes among them Rey and Montouri (1999) for the case of the states in the US, Lopez-Bazo *et al.* (1999) and Fingleton (1999) for the European regions.

The rest of the paper is organized 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 sections 4 and 5. Conclusions are in section 6.

2. A growth model with exogenous propensity to innovate

In this section we discuss the main features of a simple model[4], fully developed in Pigliaru (1999), 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 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:

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

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

where K is capital, L labor and A an index of technology. Some definitions associated with this production function will be used often in the following. They are as follows:
$y \equiv Y/L = k^{\alpha} A^{1-\alpha} = z^{\alpha} A,\ k \equiv K/L, z \equiv K/AL$.

As for how innovation is accumulated, we start with the propensity to innovate, defined as $\theta \equiv R/Y$, where R is the total amount of the existing resources allocated to innovation, and $0 \le \theta < 1$ [the further restriction $(s+\theta) < 1$, 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 $\dot{A} = \theta y$, so that the growth rate of technology is:

(2.2) $$\frac{\dot{A}}{A} = \theta\, k^{\alpha} A^{-\alpha} = \theta z^{\alpha}.$$

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 $\dot{z} = sz^{\alpha} - \theta z^{\alpha+1}$. It is possible to show that a stable steady-state exists in which the stationary value of z is $\tilde{z} = \frac{s}{\theta}$, and the stationary value of the growth rate of technology is equal to:

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

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 characterize 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:

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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 labor force, which is typical of this class of models [see Barro and Sala-i-Martin (1995), p. 151-2].

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

where now * refers to the leader. The term between parentheses is a measure of the current technology gap, which represents a potential for higher transitional growth in the follower economy. Notice however that, in the absence of any effort, there are no spillovers to be gained, and no economic growth whatsoever[7].

In the following we assume that $0<\theta\leq\theta^{*}$. The balance growth of this system is characterized by the following stationary values:

(2.5) $$\widetilde{A}=\frac{\theta^{*}}{\theta}\left(\frac{s^{*}}{s}\right)^{\frac{\alpha}{1-\alpha}}.$$

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

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

As for $\widetilde{g}$, $\widetilde{g}=\theta^{*1-\alpha}s^{*\alpha}=\widetilde{g}^{*}$.

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 ($\theta^{*}>\theta$) 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.

A follower economy off its steady-state is generally characterized by $z/z^{*}<\widetilde{z}/\widetilde{z}^{*}$ and $A^{*}/A>\widetilde{A}$. As a consequence, its convergence path is influenced simultaneously by the capital deepening mechanism emphasized 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.

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[7] 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).

3. Transitional dynamics

In this section we prepare our empirical analysis by studying the transitional dynamics of the above model. 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 $\widetilde{A} = \theta^*/\theta$ [see (2.5)] and $\widetilde{z} = s^*/\theta^*$ in all economies. We obtain:

$$\ln y(t_2) - \ln y(t_1) = \widetilde{g}^*\tau - \beta_1[\ln y(t_1) - \ln A(t_1)] + \alpha\beta_1 \ln\left(s^*/\theta^*\right) + \beta_2 \ln\left[A^*(t_1)/A(t_1)\right] - \beta_2 \ln\left(\theta^*/\theta\right) \tag{3.1}$$

where $\beta_1 = \left(1 - e^{-(1-\alpha)\widetilde{g}^*\tau}\right)$ e $\beta_2 = \left(1 - e^{-\widetilde{g}^*\tau}\right)$, t_1 is an initial point of time, and $t_2 > t_1$, $\tau \equiv t_2 - t_1$. In cross-section, t_2 and t_1 are respectively the final and the initial period. In panel data formulation, τ defines the length of the time spans in which the total period of observation is divided.

Direct estimation of (3.1) would require the availability of TFP data. Since this condition currently is not met in the case of the European regions, we have to follow Islam's (1995) fixed-effect methodology in order to allow for individual heterogeneity in those levels across economies. Therefore, let us rewrite equation (3.1) using a panel data formulation:

$$\ln y_{it} - \ln y_{i,t-1} = \mu_{it} + \kappa_t - \beta_1 \ln y_{i,t-1} + \beta_2 \ln\theta_{i,t-1} + \omega_{it}, \tag{3.2}$$

where $\kappa_t \equiv \widetilde{g}^*\tau + \beta_2 \ln A^*(t_1) + \alpha\beta_1 \ln s^* - (\alpha\beta_1 + \beta_2)\ln\theta^*$; $\ln y_{it} \equiv \ln y(t_2)$; $\ln y_{i,t-1} \equiv \ln y(t_1)$, and $\mu_{it} \equiv (\beta_1 - \beta_2)\ln A(t_1)$.

In this formulation, κ_t varies across time periods and is constant across individual economies, μ_{it} describes the degree of technology heterogeneity at a certain point in time, and ω_{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 obtained,[9] with the individual intercepts yielding an approximate measure of μ_{it}, although this term is not strictly time-invariant.[10]

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[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.

[9] The use of LSDV estimates for convergence analysis has been criticized by Durlauf and Quah (1999) on the grounds that allowing $A(0)$ to differ across economies makes it particularly difficult to understand whether β-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, μ_{it} includes the term $A(t_1)$ and cannot be properly defined as an individual intercept. We will come back to this point below.

3.1 *Discriminating among hypotheses (i)-(iii)*

We now turn to the problem of how to use panel estimates of equation (3.2) to distinguish among the three hypotheses defined in our Introduction. For reasons that will be soon explained, we will start by comparing the testable predictions associated with hypothesis (iii) to those associated with hypothesis (i) – we will deal with hypothesis (ii) later on.

Under hypothesis (iii) we expect the main predictions of the model to be true – namely, a negative correlation between the dependent variable and the initial value of labor productivity, and a positive correlation with our measure of regional propensity to innovate ($\beta_1 > 0, \beta_2 > 0$). Alternatively, under hypothesis (i) the variable measuring regional differences in the propensity to innovate would be irrelevant for convergence analysis, so that we should find $\beta_1 > 0, \beta_2 = 0$.

Let us now turn to hypothesis (ii). Unfortunately, this hypothesis shares with hypothesis (iii) the same qualitative predictions concerning β_1 and β_2. 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, $A^*(t)/A(t) = \tilde{\mathrm{A}} = \theta^*/\theta$ 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:

(3.3) $$\ln y_{it} - \ln y_{i,t-1} = \rho_i + \chi_t - \beta_1 \ln y_{it-1} + v_{it}$$

where $\rho_i \equiv \beta_1 \ln A(0)$, $\chi_t \equiv \tilde{g}^*\left(t_2 - e^{-(1-\alpha)\tilde{g}^*\tau} t_1\right) + \alpha\beta_1 \ln\left(s^*/\theta^*\right)$ 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 ρ_i; see also Islam, 1995, p.1149). Since technological differences are now supposed to be at their stationary values $\tilde{\mathrm{A}} = \theta^*/\theta$ [11], then in principle $A(0)$ and θ are perfectly correlated across economies. As a consequence, a significant positive value of β_2 does not yield clear-cut evidence in favor of the hypothesis that technology *diffusion* is an active component of the observed convergence. To the best of our knowledge, up to now this problem has not been recognized in the empirical literature on convergence.

To sum up, finding a positive significant value of β_2 in panel estimates of (3.2) allows us to reject the Solovian hypothesis (i) in favor of the idea, shared by the competing hypotheses (ii) and (iii), that technology heterogeneity, explained by differences in propensity to innovate, is relevant for convergence analysis. What the value of β_2 does not tell us is whether the current degree of technology heterogeneity is stationary or is decreasing over time due to the existence of a process of diffusion.

To discriminate between hypotheses (i) and (iii) we should search for testable discriminating implications. In principle, this is not difficult to achieve. Several examples are given in the Appendix 1 at the end of this paper, and one of them is evaluated in the empirical section 4 below. However, in general the empirical testing sketched in the Appendix 1 requires the sample to be split in several sub-period, and the currently available time series for the European regions are rather short for this purpose.

The next section contains our empirical results. Not surprisingly, part of the discussion there reflects the main findings of the present section. As it turns out, it is relatively easy to evaluate the Solovian hypothesis against the alternative ones, and far less easy to generate evidence unambiguously favorable to either hypothesis (ii) or (iii).

4. Empirical evidence: Testing hypotheses (i)-(iii)

Our empirical analysis covers the period 1978-97 and it is based on 131 regions belonging to the 15 members of the EU (excluding the East part of Germany). The list of the regions considered appears in the Appendix 2. Data on employment and value added are from Cambridge Econometrics; value added is in million of ECU 1990 and it has been corrected by PPS. As for the regional propensities to innovate, our measure is based on patent applications to the European Patent Office (EPO) assigned to an individual region by identifying the place of residence of the inventors for each patent.[12] The total numbers of patents in a region are then 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 1978-97. 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. 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 1988-97. Some spatial clusters of innovative areas in northern Europe are evident in the Figure; among the 19 most

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

innovative regions, 5 regions are in Germany, 4 in Sweden, 3 in France and Finland. On the other hand, the group with a very low propensity to innovate includes most southern European regions (Portugal, Spain, Greece and southern Italy). In the next section, we explore this specific spatial feature in more details.

[Figure 1 around here]

Our Least Squares Dummy Variable (LSDV) estimates, based on equation (3.2), are presented in Table 1.[13] We have computed four panels for the sub-periods 1978-83, 1983-88, 1988-93 and 1993-97. The dependent variable *y* is the average growth rate of GDP per worker over each time span. The explanatory variables – labor productivity and propensity to innovate – are included as log 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 labor productivity has the expected negative coefficient and is highly significant.[14] 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 2 and 3, which are explicitly based on the hypotheses (i) and (ii). Their explanatory power appears remarkably lower than in regressions 1. More specifically the goodness of fit increases from 6% in the model with only the initial productivity level, to 10% when we add the fixed effects to allow for differences across regions in technological levels, to 26% when we also add our measure of the propensity to innovate.

[Table 1 around here]

Our main result is at odds with hypothesis (i), according to which convergence should not be influenced by variables reflecting systematic differences in technology levels.[15] Our evidence shows that differences in technology levels are clearly relevant for the analysis of the process of European regional convergence.

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[12] 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. See Paci and Usai (2000) for more details.

[13] Since we are dealing with a dynamic model, the LSDV estimator is asymptotically consistent. Given that our panel is characterized by t=4, 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)].

[14] Our result confirms the previous findings on the convergence process across the European regions; see, among many others, Neven and Gouyette (1995), Paci (1997), Tondl (1999), Magrini (1999), Cuadrado-Roura *et al* (2000).

[15] 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 rationalize the existence of such a correlation in a world in which technology growth is exogenous and technology levels are homogeneous across individuals.

As for identifying the exact role played by technological heterogeneity in this process, we are now required to assess whether our evidence is capable to discriminate between the two remaining hypotheses. To start with, let us 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 [hypothesis (iii)], and with the competing hypothesis (ii), in which technological differences are supposed to be 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 shown in the Appendix 1, some relevant information can be obtained by analyzing the estimated fixed-effects.[16] These coefficients are expected to yield a measure – however indirect – of the technology level of each individual economy. Therefore, according to hypothesis (iii) the cross-sectional variance of those levels should not be not at its stationary value. Interestingly for our purposes, the very opposite is implied by hypothesis (ii): abstracting from random disturbances, the variance should be at its stationary value.

The results of our estimates for two sub-periods – 1978-88 and 1988-97 suggest that the variance of the individual intercepts for our 131 European regions changes over time, decreasing from 6.65 in the first sub-period to 5.71 in the second one. This result is 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. All in all, our evidence suggests that technological heterogeneity is important for the analysis of convergence across European regions, and that part of the observed convergence is generated by an on-going process of technology diffusion of the type analyzed by Abramovitz (1986).

However, a word of caution is in order at this stage of our analysis. The evidence supporting hypothesis (iii) must be interpreted with caution. The time series in our dataset are not long enough to allow us to carefully control for 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.

5. Convergence and the spatial pattern of the propensity to innovate

The econometric estimates have shown the important role played by the propensity to innovate in determining aggregate convergence across the European regions. Moreover, in Figure 1 we have remarked that the regional distribution of the propensity to innovate seems to follow a well defined spatial pattern. However the analytical model used so far ignores – similarly to the

[16] 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

convergence literature – the possibility that the growth process of each region can be influenced by its geographical location and thus by the economic performance of its neighbors. This weakness appears particularly relevant when the growth enhancing effect of the technological differentials is under investigation, since it is very likely that they are strongly affected by the spatial dimension.[17] Consequently, it is useful to see how the spatial dimension affects these variables, how we can take account for it, how the econometric estimates for our exogenous variables change once we control for the spatial effects. To this aim we will make use of spatial econometric techniques which, although particularly suitable for this kind of analysis, have been so far neglected by most of the convergence literature.

A simple method to assess the effect of spatial proximity in our regional data is to compute an index of spatial autocorrelation which measures the degree of association of the regional distribution of the propensity to innovate over the space. To compute this measure we first need to define a spatial weights matrix where the spatial connections between all pair of observations (in our case the regions) are defined. The simplest (and widely used) matrix is the contiguity matrix W^c, whose characteristic element $w^c{}_{ij}$ takes value 1 if regions *i* and *j* share a common border and value 0 otherwise. Starting from the contiguity matrix W^c it is possible to define higher order spatial matrices. For instance, the second order contiguity matrix identifies, for each region *i*, regions which are adjacent to region *i*'s neighbors. In this way it is possible to examine how the spatial association tends to decline as long as spatial proximity decreases.

[Table 2 around here]

The degree of spatial autocorrelation for the propensity to innovate has been computed by means of the Moran's *I* test up to the third order contiguity matrices for various years. The results are reported in Table 2. Looking at the 1st and 2nd order contiguity, it appears that there is a positive and significant spatial association for all the years considered. It means that the propensity to innovate of each region is highly dependent on the innovative activity performed by the neighbors. Moreover, considering the 3rd order contiguity, the degree of spatial association shows a clear reduction, although it remains statistically significant. In conclusion, technological spillovers play an important role across the European regions; their influence is not strictly restricted to the neighboring regions, but they spread across larger areas, although they do tend to loose their strength as the distance increases. We will come back to this point later.[18]

reflect these elements as well as the current heterogeneity in technology levels. On this more below.

[17] See Quah (1996) for an assessment of these elements for the case of the European regions.

[18] The presence of spatial autocorrelation is found for the other variables of our model, the growth rate and the level of labor productivity. Also in this case the spatial association tends to decline when the distance increases.

The presence of autocorrelation in the spatial distribution of our variables suggests that the econometric estimates presented in the previous session might be affected by spatial dependence; in such a case the classical hypotheses are violated and the OLS estimates are not efficient. To assess this issue, we have estimated our model using a simple pooling of the four periods and introducing national dummies.[19] From regr. 1 in Table 3 we can see, as a preliminary result, that the change of the estimation method leaves the signs and significance of our explanatory variables unaltered with respect to the LSDV estimates of Table 1. This fact ensures that the diagnostic tests for spatial dependence reported in the last rows of Table 3 are relevant for our model. More specifically, two *Robust Lagrange Multiplier* tests are reported; the first (*error*) ascertains the presence of spatial autocorrelation due to the errors (and thus due to an incomplete specification of the model), while the second (*lag*) relates to the spatial autocorrelation of the dependent variable. From regression 1 it appears that both tests are significant indicating the presence of spatial dependence coming from either the errors and the dependent variable. Consequently, it is important to stress that the statistical inference based on the OLS estimates is not correct and therefore it is necessary to control explicitly for the spatial component.

[Table 3 around here]

To this aim we have estimated two additional models in relation to the specific hypotheses on the form of spatial autocorrelation: the spatial error model and the spatial lag model.

The error model yields a better correction for the omission of spatially dependent explanatory variables (regr. 2). The estimates for the autoregressive parameter of the error process turns out to be positive and significant confirming the results of the tests from the OLS estimation. However the LM lag test still indicates the presence of spatial lag after a spatial autoregressive error has been introduced.

In the second case (regr. 3-5) the model is corrected introducing spatial lag dependent variables up to the third order contiguity. The spatial autoregressive coefficients appear all positive and statistically significant, confirming the influence of neighbors' performance in the regional growth rate. Moreover, the LM error test shows that there is no spatial autocorrelation left in the residuals once the spatial lags have been introduced in the equation. This result indicates that, for our case study, the spatial lag model has to be preferred over the error model. It is worth remarking that the value (and the significance) of the coefficients of the lagged variables tends to decline as distance increases. Indeed, if we include in the regression the dependent variable with a 4th order

[19] We have preferred to use a pooling model since there are not yet available reliable tests to assess the presence of spatial autocorrelation in LSDV models with a full set of regional fixed effects. The spatial econometric analysis has been performed using the software *SpaceStat* developed by Luc Anselin. For an introduction to the spatial econometric methods see Anselin (1988).

spatial lag it turns out to be not significant. This means that the higher positive influence on the growth rate of a certain region comes from its closer neighbors. Finally, it is important to notice that the other explanatory variables retain their sign and are still significant.

Our analysis has shown how the regional growth process is strongly characterized by a spatial pattern, where each region benefits by the positive performance of its neighbors. A second important element is that this positive influence tends progressively to decline with the increase of the distance between the regions.

6. 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 technological catching-up in the convergence process across 131 European regions during the 1978-97 period. All our results are obtained in the absence of total factor productivity data for the individual regions. 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 some preliminary evidence in favor 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.

We have also studied whether each region's propensity to innovate is correlated with that of the surrounding regions. Our results are consistent with the hypothesis that important localized spillovers of technological knowledge do exist, and that they are strong enough to play a role that cannot be ignored in the econometric analysis of the convergence process in Europe. Our econometric estimates show that, given a region's current technology gap, its capacity to profit from it in terms of growth depends – among other things – not only on its individual effort, but on the neighbors' performance too.

One interesting development of the approach proposed in this paper would be to explore the possibility that the stock of human capital takes part in the determination of the stationary technology gaps – as in Benhabib and Spiegel (1994) –, together with the propensity to innovate.

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Appendix 1: Hypothesis (ii) v hypothesis (iii)

First, consider the term μ_{it} in (3.2), associated with hypothesis (iii). In the text, we have noticed that μ_{it} cannot be regarded as a proper fixed-effect, while the opposite is true for ρ_i in equation (3.3). This difference can be exploited empirically as follows. Since under hypothesis (iii) technology gaps are not at their stationary values, in general we should expect that $\sigma_{\mu}^{2} \neq \tilde{\sigma}_{\mu}^{2}$. As a consequence, convergence of σ_{μ}^{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) σ_{ρ}^{2} is time-invariant, since – abstracting again from random disturbances – it is assumed to be at its steady-state value $\tilde{\sigma}_{\rho}^{2}$.

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 (the problem represented by μ_{it} not being a proper time-invariant effect should be less pronounced when shorter time-spans are considered).

Finally, a third discriminating implication 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).

Appendix 2. List of the 131 European regions included

B1 Bruxelles
B2 Vlaams Gewest
B3 Région Wallonne

DK Denmark

D1 Baden-Württemberg
D2 Bayern
D3 Berlin
D4 Bremen
D5 Hamburg
D6 Hessen
D7 Niedersachsen
D8 Nordrhein-Westfalen
D9 Rheinland-Pfalz
D10 Saarland
D11 Schleswig-Holstein

G1 Anatoliki Makedonia
G2 Kentriki Makedonia
G3 Dytiki Makedonia
G4 Thessalia
G5 Ipeiros
G6 Ionia Nisia
G7 Dytiki Ellada
G8 Sterea Ellada
G9 Peloponnisos
G10 Attiki
G11 Voreio Aigaio
G12 Notio Aigaio
G13 Kriti

E1 Galicia
E2 Asturias
E3 Cantabria
E4 Pais Vasco
E5 Navarra
E6 La Rioja
E7 Aragón
E8 Madrid
E9 Castilla y León
E10 Castilla-la Mancha
E11 Extremadura
E12 Cataluña
E13 Com. Valenciana
E14 Baleares
E15 Andalucia
E16 Murcia
E17 Canarias (ES)

F1 Île de France
F2 Champagne-Ardenne
F3 Picardie
F4 Haute-Normandie
F5 Centre
F6 Basse-Normandie
F7 Bourgogne
F8 Nord - Pas-de-Calais
F9 Lorraine
F10 Alsace
F11 Franche-Comté
F12 Pays de la Loire
F13 Bretagne
F14 Poitou-Charentes
F15 Aquitaine
F16 Midi-Pyrénées
F17 Limousin
F18 Rhône-Alpes
F19 Auvergne
F20 Languedoc-Roussillon
Provence-Alpes-Côte
F21 Azur
F22 Corse

IE Ireland

I1 Piemonte
I2 Valle d'Aosta
I3 Liguria
I4 Lombardia
I5 Trentino-Alto Adige
I6 Veneto
I7 Friuli-Venezia Giulia
I8 Emilia-Romagna
I9 Toscana
I10 Umbria
I11 Marche
I12 Lazio
I13 Abruzzo
I14 Molise
I15 Campania
I16 Puglia
I17 Basilicata
I18 Calabria
I19 Sicilia
I20 Sardegna

LU Luxembourg

N1 Noord-Nederland
N2 Oost-Nederland
N3 West-Nederland
N4 Zuid-Nederland

P1 Norte
P2 Centro (P)
P3 Lisboa e Vale do Tejo
P4 Alentejo
P5 Algarve

U1 North East
U2 North West
U3 Yorkshire and Humber
U4 East Midlands
U5 West Midlands
U6 Eastern
U7 South East and London
U8 South West
U9 Wales
U10 Scotland
U11 Northern Ireland

A1 Burgenland
A2 Niederosterreich
A3 Wien
A4 Karnten
A5 Steiermark
A6 Oberosterreich
A7 Salzburg
A8 Tirol
A9 Vorarlberg

S1 Stockholm
S2 Östra Mellansverige
S3 Småland Med Öarna
S4 Sydsverige
S5 Västsverige
S6 Norra Mellansverige
S7 Mellersta Norrland
S8 Övre Norrland

FN1 Itä-Suomi
FN2 Väli-Suomi
FN3 Pohjois-Suomi
FN4 Uusimaa
FN5 Etelä-Suomi

Figure 1. Propensity to innovate across the European regions (average 1988-1997)

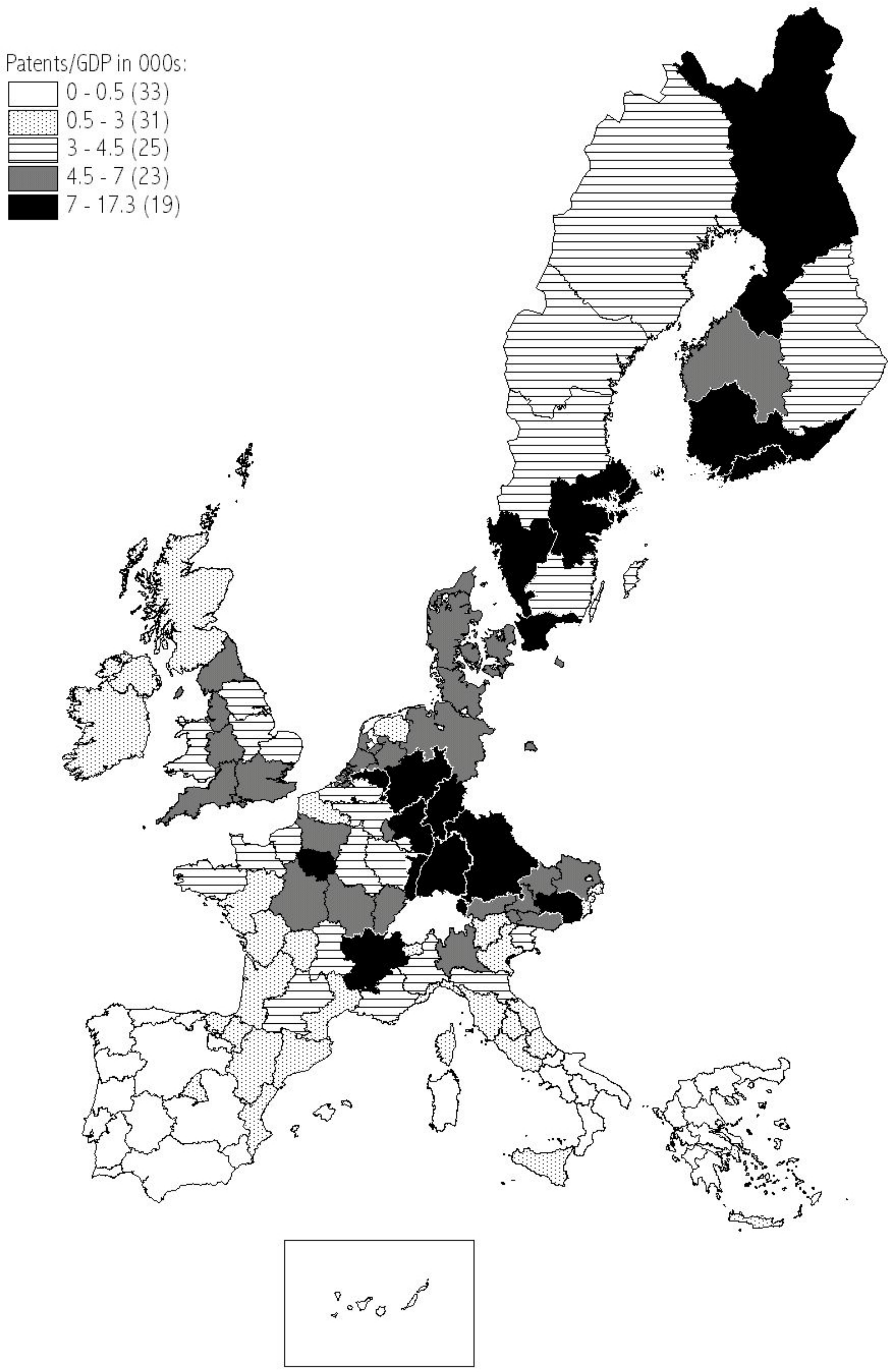

Table 1. Propensity to innovate and growth in the European regions

Panels: 1978-83, 1983-88, 1988-93, 1993-97. Cross-section observations:131
Total observations: 524
Dependent variable $gy_{i\,t}$: annual average growth rate of labor productivity in each time span
$y_{i\,t-1}$ = labor productivity in the initial year of each time span
$\theta_{i\,t-1}$ = 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**
$y_{i\,t-1}$	-11.30 (-14.6)[a]	-1.80 (-6.18)[a]	-8.06 (-10.67)[a]
$\theta_{i\,t-1}$	1.20 (9.08)[a]		
constant		7.80 (7.99)[a]	
adj. R^2	0.26	0.06	0.10
F-test	314[a]	38[a]	
Estimation method	LSDV	OLS-pooling	LSDV

Table 2. Moran test for spatial autocorrelation in the propensity to innovate

Normalized statistics z, probability between parentheses.
131 observations

Years	Contiguity spatial matrix		
	1st order	2nd order	3rd order
1978	9.54	9.77	6.88
	(0.00)	*(0.00)*	*(0.00)*
1983	12.36	13.37	9.22
	(0.00)	*(0.00)*	*(0.00)*
1988	12.51	13.35	9.23
	(0.00)	*(0.00)*	*(0.00)*
1993	11.99	12.88	8.67
	(0.00)	*(0.00)*	*(0.00)*
1997	11.38	12.64	9.17
	(0.00)	*(0.00)*	*(0.00)*

Table 3. Spatial autocorrelation in the growth process of the European regions.

Estimation method: *pooling* with national dummies
Panels: 1978-83, 1983-88, 1988-93, 1993-97. Cross-section observations:131 Total observations: 524
Dependent variable $gy_{i\,t}$: annual average growth rate of labour productivity in each time span
$y_{i\,t-1}$ = labor productivity in the initial year of each time span
$\theta_{i\,t-1}$ = propensity to innovate in the initial year of each time span
$gy_{it}(Ln)$ = n^{th} order spatial lag dependent variable
λ_{it1} = spatial autoregressive coefficient
t statistics in parentheses significance levels: a=1%, b=5%

Explanatory variables	Regr. 1 OLS	Regr. 2 Spatial error model	Regr. 3	Regr. 4 Spatial lag model (ML)	Regr. 5
Constant	21.99 (12.54)[a]	16.63 (10.08)[a]	15.58 (10.70)[a]	14.71 (10.15)[a]	14.62 (10.18)[a]
y_{it-1}	-6.03 (-11.49)[a]	-4.27 (-8.84)[a]	-4.37 (-10.16)[a]	-4.19 (-9.81)[a]	-4.19 (-9.89)[a]
θ_{it-1}	0.672 (6.55)[a]	0.28 (2.48)[b]	0.470 (5.72)[a]	0.440 (5.43)[a]	0.441 (5.48)[a]
λ_{it1}		0.59 (16.05)[a]			
$gy_{it}(L1)$			0.518 (14.27)[a]	0.301 (6.57)[a]	0.297 (6.40)[a]
$gy_{it}(L2)$				0.397 (7.92)[a]	0.276 (4.14)[a]
$gy_{it}(L3)$					0.177 (2.60)[b]
Adj. R^2	0.25	0.24	0.43	0.51	0.52
F-test	14.4[a]				

Tests for spatial dependence based on contiguity weight matrix, W^c

Robust LM (*error*)	5.65 [b]				
Robust LM (*lag*)	22.17 [a]				
LM on spatial lag dependence		11.85 [a]			
LM on spatial error dependence			6.94 [a]	0.12	0.92