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The dispersion of technology and income in Europe: Evolution and mutual relationship across regions

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ABSTRACT

The first part of this article explores whether convergence has occurred in technology and income across EU regions during the period 1990–2002. The second part evaluates whether these two processes of convergence are related to each other. With respect to the first question, we find that all R&D indicators and patents have converged among regions during the 1990s and this has ran parallel to a real convergence in income per capita levels. Regarding the second question, we have identified a strong relationship between the distribution of technology indicators and the distribution of regional income in Europe. Our main result is that convergence in business R&D leads to convergence in patents, which in turn leads to convergence in income per capita. Although, we identify a role for government R&D and higher education spending in this process, the policy implications for these two variables are less clear.

1. Introduction

The 2005 Spring European Council renewed the Lisbon Strategy that was launched 5 years before, and reaffirmed its goal of transforming Europe into the world's most competitive knowledge-based economy. The combination of National Reform Programs at the Member States' level and a reinforcement of the EU funds and programs devoted to R&D&I were the two main tools agreed to achieve this goal.

In all cases, the proliferation and reinforcement of national initiatives to promote R&D&I is based on the strong conviction that public policies can positively affect the long-run growth rate of the economy through economic incentives for the accumulation of various forms of capital and through the promotion of technological innovations.[1]

The logic behind these initiatives is the following (often referred to as the 'linear model'): R&D generates innovation and new technologies, and innovation and new technologies then generate economic growth. This ought to happen because new technologies increase the

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[1] This conviction relies on the postulates of endogenous growth models (Romer, 1986, 1990; Lucas, 1988). While neo-classical growth models (Solow, 1956; Mankiw et al., 1992) consider that economic integration would assure convergence between poor and rich countries (regions) due to capital accumulation in poorer regions that present higher returns to capital, more sophisticated endogenous growth models and new economic geography models (Krugman, 1991; Ottaviano and Puga, 1998) show that income convergence need not occur as a result of economic integration. Consequently, pro-active public policy has a role to play in the promotion of economic convergence between poorer and richer countries or regions. For a more detailed summary of growth theories and the convergence–divergence debate, see Martin and Sanz (2003). For the likely existence of a trade-off economic growth and cohesion, mediated by technology policies, see Peterson and Sharp (1998), Pavitt (1998), and Martín et al. (2005).

productivity of production factors and therefore have a positive supply side effect on the growth potential of the economy.

If this R&D → technology/innovation → growth mechanism holds,[2] then economic policy authorities would be very interested in promoting innovation and technological change through strong investment in R&D. Nevertheless, the relative success of these programs in achieving real innovation and the relative success of these inventions in effectively generating higher rates of economic growth is still a matter of debate in the literature.

While some recent works have found that economic convergence depends on a set of factors among which technology is only one (Paci, 1997; Dunford and Smith, 2000; Tondl, 2001), others have emphasized the decisive role that technology plays for long-run economic convergence (Fagerberg et al., 1997; Paci and Usai, 2000; Fagerberg, 2000; Paci and Pigliaru, 2001). In addition, the relationship between technology and growth might be different for different clusters of regions (Neven and Gouyette, 1995; Quah, 1996; Fagerberg and Verspagen, 1996; Clarysse and Muldur, 1999).

What is clear, in any case, is that technology policies have proliferated across Europe during the last few decades based on the conviction that they will generate economic growth. This proliferation has taken place along different paths in different countries and regions, and has thus generated a moving distribution of technology across Europe. Although, there is abundant literature on the effects of technology on growth, there is very little work on the effects of technology distribution on income distribution across regions in Europe.[3]

Therefore, the first question that this article aims to answer is the following: has the distribution of technology converged or diverged across European regions in the last decade? Our hypothesis is that convergence in both technology indicators and income has taken place between 1990 and 2002.

The second question is a related one: how has that distribution of technology affected the distribution of regional per capita income? In answering this question, we would be shedding light on the issue raised by Bernard and Jones (1996), who claimed that further research was needed to answer how much of the convergence that we observe is due to convergence in technology. Very little work on this specific question has been done since their paper. Therefore, our article tackles this issue directly, and tests our hypothesis that a reduction in the dispersion of technology indicators leads to a reduction in income dispersion. But even if this is confirmed, we want to study how this influence works: is it more important to reduce the dispersion of R&D or patents, in order to reduce regional income per capita? Does public or business R&D make a difference in this respect?

This is thus a paper about how the dispersion in technology affects the dispersion in income. It is not about how technology affects economic growth, which has been widely studied, but about how the distribution of technology affects the distribution in income across European regions. Accordingly, the article is structured as follows. Section 2 offers a descriptive analysis of the evolution of technology indicators in Europe for the period 1990–2002; Section 3 focuses on the causality analysis that relates the distribution of technology indicators to the distribution of income. It also performs a series of robustness checks of the main empirical results. And finally, Section 4 summarizes the main findings and concludes.

2. Spatial distribution of technology indicators since 1990

Technology policies are very difficult to measure quantitatively, and therefore their analysis has to rely on a set of technology indicators that approximate different phases of these policies, assuming that they follow a certain input–output sequence. Following the specialized literature, we use total (gross) R&D expenditures by all sectors as a percentage of GDP (GERD) as the best technology input indicator, and the number of patents per million people (PATENTS) as the best available technology output indicator. In order to enrich our analysis, we also study the evolution of the three components of total R&D investment (GERD), as defined by the European Commission: spending by government (GOVERD), business (BERD) and higher education (HERD). Finally, we also analyze the evolution of regional income per capita (INCOME).

In this section, the purpose is to test the following hypothesis:

H_0. Convergence has occurred in both technology and income across EU regions in the period 1990–2002

H_1. Divergence has occurred in both technology and income across EU regions in the period 1990–2002

Therefore, the use that we make in this section of all these indicators is two-fold: first we just describe their spatial and temporal evolution, and then we report the results of a systematic convergence analysis whereby the common measures of economic and technological convergence are calculated and reported. This includes the sigma-convergence analyses (to test for the existence of convergence) and the bootstrap and jackknife analyses

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[2] The literature uses total expenditures on R&D as a good *input* indicator of technological innovation. As an indicator of technology *output* the literature typically chooses the number of patent applications per million people. "Patents" is not a perfect output technology indicator because they are not awarded for innovations but for inventions, and only a share of them is ever commercialized. This indicator should be interpreted with care, since the number of patents may be determined by non-technology factors, such as patent office staffing and budgets or the legal environment (Wilson, 2003), that may explain why Southern European regions are much less inclined to file patents for innovative products or processes (European Commission, 1997: 349). Nevertheless, this is the best available indicator that we have found among those reported by Eurostat for our sample of European regions. Other studies have also used "Patents" as an output indicator before (see Soete et al., 1983; Paci and Usai, 1997; Grupp, 1998; Grupp and Schmoch, 1998; OECD, 2004; Coupé, 2005; Bhattacharya, 2006).

[3] For references in this respect, see EC (1997, 2002, 2003), Magrini (2004), Segerström (2000), Boldrin and Canova (2001), Acconcia et al. (2003) and especially Clarysse and Muldur (1999).

(to test for different speeds of convergence of different indicators).[4]

2.1. Data and descriptive statistics

Data on R&D expenditure (GERD, BERD, GOVERD and HERD) come from Eurostat Metadata Science and Technology, compiled using the guidelines laid out in the 'Proposed standard practice for surveys of research and experimental development' (Frascati Manual, OECD, 2002). Data on patent applications per million inhabitants come from Eurostat Metadata Patent statistics, and refer to the patent applications to the European Patent Office by year of filing at the regional level. Figures for per capita GDP are based on Eurostat Metadata Gross domestic product indicators, and are computed using Purchasing Power Parities. Note that the regional breakdown used by EUROSTAT is in line with the NUTS II (Nomenclature of territorial units for statistics) level of disaggregation. Hence, we have 177 EU regions.

It is crucial to note that statistics at the regional level show the important disparities between regions that remain hidden in statistics at national level. This is especially true for data on technology indicators. Disparities in technology input (GERD/GDP) and output (patents per million people) are significantly higher at regional than at the national level. If one looks at the distribution of European regions that invested most in total R&D in 2002, we observe important disparities.[5] Among the regions that invested most we find Border, Midlands and West (5.25% of its GDP), Pohjois-Suomi (4.18%), Etelä Suomi (3.72%), Maner Suomi (3.47%) and Wien (3.36%); among those investing least are La Rioja (0.56%), Cantabria (0.54%), Castilla-la Mancha (0.44%), Illes Balears (0.26%) and Aland (0.15%). In 2002, the EU's coefficient of variation among regions was 0.65 with an average regional R&D spending of 1.99% of GDP and a 1.29 standard deviation. The coefficient of variation among the EU-15 member states was 0.50.

The dispersion of patent applications presents even more disparities across regions than the distribution of total R&D expenditures. There are many regions which in 2002 filed less than four patent applications per million people. Among them we find, for example, Notio Aigaio (3.4), Reunion (2.9), Extremadura (2.2), Thessalia (1.8) and Madeira (1.4). On the opposite side, there were many regions that filed more than 400 applications per million people, including Noord-Brabant (1083.8), Stuttgart (748.6), Oberbayern (741.4), Vorarberg (456.3) and Sydsverige (456.6). Such a degree of disparity placed the EU's coefficient of variation at regional level in 1.06 with an average of patent applications per million people in 156.20 and a standard deviation of 165.68 in 2002. The coefficient of variation in patent applications in the EU-15 at the national level in 2002 was only 0.65. It is worth noting that, once controlling for the outliers, the regional disparity in technological development is not so high. This is because patenting activity in Europe is dominated by a small set of regions (an "Archipelago" of 10 regions as suggested by Hilpert, 1992), with all others making only a marginal contribution. When compared to the dispersion of patent applications, the regional distribution of R&D by sector of performance (business, public and higher education as a share of GDP) is also less dispersed. In 2002, the coefficient of variation for BERD was 0.80, 1.00 for GOVERD and 0.67 for HERD.

When compared to the spatial distributions of the two previous technology indicators, the regional distribution of income is less dispersed. Per capita income is computed relative to the EU average. Among the richer regions in the EU in 2002, we find Région de Bruxelles (214.4%), Luxembourg (194.4%), London (173.0%) and Hamburg (171.7%), while among the regions with lower per capita income are Guyane (52.4%), Dytiki Ellada (53.3%), Anatoliki Makedonia, Thraki (54.0%) and Reunion (54.9%). Table 1 shows that in 2002, the EU's coefficient of variation among regions was 0.28 whereas the coefficient of variation among EU-15 member states was 0.25.

Note that technology indicators, and to a lesser extent per capita income, are positively skewed. Above all, patent applications show an important skewed distribution, which might distort the results in the regression estimates presented below. For this reason for most of the paper, we do not use the technological indicators or per capita income but the dispersion of these variables. In the only case where we use the variable itself, Table 10, we make these variables more normally distributed by taking logs. Thus, we follow Cainelli et al. (2004) who take logs of the innovative intensity indicators, transforming them to a more normal shape and avoiding extreme values that might affect the regression estimates of the effects of innovation on firm economic performance.[6]

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[4] We also calculated Tukey's box and whisker plots (to illustrate the evolution of convergence) and Theil and Gini indexes (to check for robustness of all previous results). They are not reported here due to space constraints, but they are available for the interested reader in Martín et al. (2005).

[5] In order to have a homogeneous database, we have chosen a period for which all the variables reflecting technology indicators were available. In this respect, patent applications are the most restrictive variable. The last year available for regional patent applications to the European Patent Office in the Eurostat Metadata is 2002 (Science and Technology: Patent statistics: Patent applications to the EPO by priority year at the regional level). There is some information for the year 2003, but these data are not available for all regions and are highly provisional. In fact, the latest Eurostat publication on "Science, technology and innovation in Europe" issued in March 2007 provides information for EU regional patent applications for 2002 (European Commission, 2007, p. 95).

[6] In any case, the estimation of the regression coefficients does not require the dependent, independent variables and residuals to be normally distributed (Rubinfeld, 2000). If this were the case then we would not be able to use dummy variables. Normality in the residuals is only necessary for hypothesis tests to be valid. Nevertheless, the central limit theorem guarantees that linear regressions can perform well in moderately large samples (like the sample we use here) even for extremely non-normal data (Kleinbaum et al., 1998). In any case, we have tested for the normality of the residuals following Hamilton (2006). This author contends that the presence of any severe outlier – defined as an observation further than the 25th percentile minus three times the inter-quartile range or further than the 75th percentile plus three times the inter-quartile range – should be sufficient evidence to reject normality at a 5% significance level. We do not find any severe outliers among the residuals of regressions of Tables 6–10. We do find mild outliers among the residuals – those further than the 25th percentile minus 1.5 times the inter-quartile range or further than the 75th percentile plus 1.5 times the inter-quartile range – which are common in samples of any sizes (Hamilton, 2006). These mild outliers cor-

Table 1
Descriptive statistics

	Unweighted mean	Median	S.D.	Max.	Min.	Obs.
Private spending on R&D	0.85	0.57	0.88	5.60	0.00	2301
Government spending on R&D	0.20	0.10	0.29	2.40	0.00	2301
Higher education spending on R&D	0.32	0.28	0.28	1.98	0.00	2301
Total spending on R&D	1.37	1.03	1.16	7.63	0.00	2301
Patent applications	93.8	60.82	115.5	1083.8	0.00	2301
Per capita income	94.1	93.8	27.8	226.6	27.8	2301

Table 2
Dispersion of R&D indicators and per capita income across EU regions

	1990	1995	2000	2002	% Reduction
Private spending on R&D	1.97	1.61	1.52	1.58	−19.8
Government spending on R&D	1.64	1.50	1.46	1.50	−8.5
Higher education spending on R&D	2.32	1.87	1.83	1.90	−18.1
Total spending on R&D	1.45	1.33	1.29	1.33	−8.3
Patent applications	4.13	3.98	3.42	3.15	−23.7
Per capita income	0.35	0.28	0.28	0.26	−25.7

Table 3
Significance of the reduction in dispersion (sigma-convergence)

	T_3 (1990–2002)	T_3 (1990–1995)	T_3 (1995–2000)	T_3 (2000–2002)
Private spending on R&D	4.490***	4.091***	1.477	–
Government spending on R&D	1.863*	2.629***	1.006	−1.281
Higher education spending on R&D	3.878***	5.029***	0.820	–
Total spending on R&D	2.042**	2.831***	1.082	–
Patent applications	6.064***	0.810	3.269***	2.509**
Per capita income	8.153***	10.695***	1.041	1.002

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

2.2. Convergence analysis

The question is now whether the spatial distribution of the indicators described in the previous section converged, diverged or remained constant in the last decade.[7] We have computed the standard deviation of the logarithm of each of the technological indicators and report the results in Tables 2 and 3 below. This dispersion measure, known as sigma-convergence, explores whether the dispersion among the different measures of technology inputs or outputs and income per capita has been reduced across European regions during the period 1990–2002. It is this measure of dispersion that ensures there has been a convergence process overall (Barro and Sala-i-Martin, 1992).[8] Moreover, we test the hypothesis that the variance decreases over time using the variance ratio test (T_3) proposed by Lichtenberg (1994), but taking into account that the variance in the first year and the variance in the last year are not independently distributed (Carre and Klomp, 1997). This test performs better than the original test proposed by Lichtenberg for short time periods, reducing the probability of committing a type II error.

Results in Tables 2 and 3 reveal that there has been a reduction in the standard deviation of the logarithm of all technology indicators and income per capita during the period 1990–2002 and that this convergence is significant.

However, this convergence is not homogeneous by period and by type of technological indicator. The reduction in dispersion took place between 1990 and 1995. In the second half of the nineties, the standard deviation was reduced but not to a significant level, except in the case of patent applications. Finally, in 2000–2002, it seems that R&D (total and by sectors of performance) started to diverge, whereas

respond to Germany and Finland in the period 1990–1993. Importantly, when running each regression of Tables 6–10 without the observations corresponding to mild outlier residuals, we find fairly similar results.

[7] Xie et al. (1999) elaborate an endogenous growth model based on Barro (1990) and Devarajan et al. (1996), where the production function has private capital and different components of government spending. Assuming a Cobb–Douglas production function, these authors obtain that the growth-maximizing share of a component of government expenditure in total government expenditures is equal to its elasticity divided by the sum of elasticities of all the components. Thus, as long as the elasticity of growth with respect to public R&D spending is similar across countries, we should expect convergence across public R&D spending in EU countries. Indeed, Gemmell and Kneller (2002) show that the long-run growth elasticity of productive expenditures exhibits a high degree of uniformity across OECD countries.

[8] The two most popular convergence measures are *beta*-convergence and *sigma*-convergence. *Beta*-convergence implies that regions devoting fewer resources to R&D or patenting less improve their technological indicators to a higher extent than do technologically advanced regions. However, we have computed only the *sigma*-convergence since this is the only measure that ensures that there has been a convergence process overall. For results on the estimations of *beta*-convergence, see Martín et al. (2005).

Table 4
Test of the speed of reduction in dispersion

	Bootstrap	Jackknife
Private spending on R&D *versus* government spending on R&D	97**	96**
Higher education spending on R&D *versus* government spending on R&D	92*	96**
Private spending on R&D *versus* higher education spending on R&D	63	69
Patent applications *versus* total spending on R&D	100***	100**
Per capita income *versus* total spending on R&D	100***	100***

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

patent applications continued to converge to a significant degree.

To capture these different rhythms of convergence better, we compare the rate of the convergence in R&D to the rates of the reduction in dispersion in income per capita and patent applications. We followed two different procedures: the bootstrap and the jackknife methods.

Bootstrap analysis applies a non-parametric technique in four steps. In the first step, we estimate the relationship between the logarithm of each variable across EU regions in 1990 and in 2002. Thus, we have 177 observations for each regression. In the second step, 100 bootstrap samples of the residuals are drawn with replacement from the observed residuals of each regression.[9] In the third step, the 100 bootstrap samples of observations for each indicator are constructed by adding a randomly sampled residual to the original predicted value for each region. Finally, we compute the number of times where the convergence is stronger in a variable compared to the convergence in another variable.

The jackknife analysis is equivalent, except for the fact that we draw bootstrap samples of the residuals from a normal distribution with mean zero and the estimated standard deviation of the observed residuals. Results are shown in Table 4. The bootstrap and jackknife procedures show that convergence has been significantly higher for BERD and HERD than for GOVERD. Further, patent applications and income per capita have diminished their standard deviations to a significantly higher extent than aggregate R&D expenditure.

3. How does the dispersion of technology affect the dispersion in income?

From the previous section, we can conclude that during the period 1990–2002 there was a convergence both in technology indicators and income per capita across EU regions. Now the article turns to answer the second question: are these two processes related? If so, how are they related? Is it more important to reduce the dispersion in R&D or the dispersion in patent applications, in order to reduce the dispersion of income per capita?

In this section, the purpose is to test the following hypotheses:

H_0. Convergence in technology has implied convergence in regional per capita income

H_1. Convergence in technology indicators is unrelated to or has implied divergence in regional per capita income

In order to test these hypotheses and to answer these questions, this section has a sequential structure. First, to see whether convergence in technology leads to convergence in income per capita, we regress the dispersion, measured as the standard deviation of the logarithm following the sigma-convergence used in the empirical growth literature, in income per capita in each country by regions against dispersion of technology indicators in each country by regions. Second, since we will find that only some technology indicators are related to convergence in income per capita, we run several models to discover through which mechanism this relationship interacts. This allows us to discern the different roles that business R&D, government R&D and higher education spending play with respect to patent applications, and their overall relationship with income distribution. Finally, we perform a robustness analysis to check if our main findings are confirmed when, instead of limiting the number of observations, we cease regressing the dispersion and exploit the whole panel structure.

3.1. Relationship between convergence in technology and convergence in income

In this subsection, we first regress the dispersion in income per capita in each country by regions against the dispersion of technology indicators in each country by region. Since there are three countries with no regions (Denmark, Ireland and Luxembourg), we end up with a sample of 156 observations (12 countries and 13 years). We conduct simple bivariate regressions between the dispersion in income per capita (as the dependent variable) and the dispersion of each technology indicator. Table 5 shows the results of these bivariate regressions.[10]

Initially, there seems to be a positive and highly significant relationship between the standard deviations of the logarithm of income per capita across EU regions and the standard deviations of the logarithm of all technology indicators. These estimations point towards a positive bilateral relationship between the reduction in the dispersion of technology inputs (R&D variables) and outputs (patents) and the reduction in the dispersion of regional income per capita.

[9] Each of the 100 bootstrap samples are simple random samples of 177 residuals (one for each region) selected with replacement from the residuals of the estimation of the first step. Some of the original residuals are presented two or more times in each bootstrap sample, whereas other residuals are absent. Another possibility is to bootstrap the observations, which is asymptotically equivalent to bootstrapping the residuals. However, this possibility does not maintain the structure of covariates and does not assume the appropriateness of the original model.

[10] Table 5 reports the results of bivariate regressions with the dependent and the independent variables in levels. We have also done this with the variables in first differences and the results are extremely similar.

Table 5
The dispersion of technology indicators and their effect on the dispersion of income. Simple regressions

Dependent variable: standard deviation of log of income per capita (among regions by country)	(1)	(2)	(3)	(4)	(5)
Dispersion BERD	0.173*** (26.36)				
Dispersion GOVERD		0.171*** (20.57)			
Dispersion HERD			0.111*** (29.67)		
Dispersion GERD				0.195*** (19.71)	
Dispersion PATENTS					0.072*** (26.55)
Adjusted R-squared	0.64	0.67	0.54	0.57	0.50
Observations	156	156	156	156	156

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

In order to confirm the validity of these preliminary results, we use a multivariate model to test which technology indicators have more effect on income dispersion. Note that the effects of the reduction of the technology dispersion on income per capita might require some years to kick in. For this reason, we use a dynamic model of this form:

$$\Delta\sigma(\mathrm{INCOME}_{it}) = \beta_1\sigma(\mathrm{INCOME}_{\mathrm{i},t-1}) + \sum_k \beta^k\sigma(\mathrm{TI}^k_{\mathrm{i},t-1}) + \sum_{\mathrm{i}} u_{\mathrm{i}} + \sum_t u_t + \varepsilon_{\mathrm{i}t}; \quad (1)$$

where the dependent variable is the first differences of the dispersion of per capita income (INCOME), the independent variables are the lagged dispersion of per capita income and the lagged dispersion of technology indicators k (TI^k), Δ is the first difference operator, β_1 is the yearly rate at which the dispersion of income per capita returns to the trend line, and i and t are country and year, respectively. We introduce dummy variables for each country (u_{i}) to capture country effects that may be affecting the dispersion of income per capita across regions in each country. This country effect may be reflecting different preferences for income distribution across countries or different fiscal transfer systems.[11] Finally, we take into account common shocks affecting growth in a similar way across countries by including time dummies (u_{t}). As a consequence of this specification, we reduce the sample by 1 year to 144 observations (now 12 countries and 12 years). Note that we also include the lagged value of the independent variables instead of their contemporaneous value. There are two reasons to do so: first, this helps avoiding the likely existence of mutual causality (or endogeneity) in our model, derived from the effect that the dispersion of income per capita may also have on the distribution of technology indicators; second, as suggested by Beck and Katz (1996), with this error correction model we are capturing the long-term relationship between the dispersion of income per capita and the dispersion of technology, by sector of performance. Accordingly, with this model the long-run effect of any independent variable can be obtained from dividing its estimated coefficient by minus the coefficient associated with the lagged dependent variable.

The estimation based on dispersion is based on Bernard and Jones (1996), who claim that some of the convergence in labour productivity that we observe is due to convergence in technology. In fact, these authors compare the evolution the cross-country dispersion in labour productivity to the cross-country dispersion in technology for 14 OECD countries and find that changes in the dispersion of these variables over time are closely correlated (Bernard and Jones, 1996, p. 1041).

Table 6 shows the results of these multivariate regressions. As can be observed from the significance level of the different independent variables, the main conclusion is that the long-run relationship between technology and income occurs through patent applications: regional convergence in the number of patent applications leads to convergence in regional income per capita. On the contrary, all R&D spending indicators fail to have a significant direct long-run effect on income distribution.

In Table 6, columns 1 and 2 reveal that the introduction of total R&D spending (GERD) does not add anything to the explanatory power that the only-patents model has. The irrelevance of GERD to explaining the long-run distribution of income is again confirmed in column 3, when we exclude PATENTS from the right-hand side of the equation. This indicates that the absence of any significant impact of the main input technology indicator (GERD) in column 1 was not due to the simultaneous inclusion of the main output technology variable (PATENTS). From column 4 onwards, we perform some robustness tests to confirm the relevant role of PATENTS in achieving convergence. The diminishing trend in income dispersion may be due to the substantial support given by the EU to regional development. In column 4, we introduce a dummy, which takes the value 1 for countries receiving funds from the main regional pol-

[11] Using dummy variables to estimate individual effects in a dynamic model that includes lagged values of the dependent variable among its regressors is bound to produce biased estimates if the panel time dimension is small (Nickell, 1981). The usual procedure is to instrument the lagged dependent variable after first differencing it. However, Beck and Katz (1995) argue that while the instrumental variable estimators have great asymptotic properties, they may often be inferior to LSDV in the situations commonly faced by researchers when the data span is not so large. In fact, these authors conduct a Monte Carlo simulation and conclude that LSDV outperforms instrumental variables estimators. Furthermore, Beck and Katz (2004) suggest that the inclusion of the lagged dependent variable in levels provides an easy check on the presence of a unit root. If the coefficient associated with the lagged variable is not significant it might be indicating the presence of a unit root. Results show that coefficients associated with lagged variables are highly significant.

Table 6
The dispersion of technology indicators and their effect on the dispersion of income. Multiple regressions

Dependent variable: first differences of standard deviation of log of income	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lagged dispersion of income	−0.232*** (−6.11)	−0.232*** (−6.05)	−0.239 *** (−6.15)	−0.267** (−6.60)	−0.273** (−3.67)	−0.310*** (−3.84)	−0.233*** (−6.11)	−0.250*** (−6.07)	−0.238*** (−6.15)
Lagged dispersion of PATENTS	0.003** (2.37)	0.003** (2.37)		0.003** (2.29)	0.002** (1.97)	0.003** (2.06)	0.003** (2.25)	0.003** (2.07)	0.003** (2.33)
Lagged dispersion of GERD		0.001 (0.15)	0.001 (0.08)	−0.002 (−0.23)	−0.004 (−0.45)	−0.003 (−0.35)			
Dummy countries objective 1				0.011** (2.35)					
Six-year lagged dummy countries objective 1					−0.007** (−2.04)				
Lagged dispersion investment						−0.017 (−0.72)			
Lagged dispersion of BERD							0.003 (0.61)		
Lagged dispersion of GOVERD								−0.007 (−1.12)	
Lagged dispersion of HERD									0.007 (0.84)
Significance of country dummies	F(12,119), 5.89***	F(12,118), 5.46***	F(12,119), 5.11***	F(12,117), 6.31***	F(12,62), 4.36***	F(11,58), 3.49**	F(12,118), 5.77***	F(12,118), 5.99***	F(12,118), 5.92***
Significance of year dummies	F(11,129), 1.08	F(11,118), 1.07	F(11,119), 1.43	F(11,117), 1.23	F(6,62), 1.71***	F(7,58), 2.64**	F(11,118), 2.60***	F(11,118), 1.07	F(11,118), 0.99
Observations	144	144	144	144	84	80	144	144	144
Adjusted R-squared	0.38	0.37	0.35	0.39	0.35	0.31	0.38	0.38	0.38

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

icy instrument of the EU: objective 1. This objective aims at the structural development of the less developed regions and absorbs most of the funding (about 70% of the total structural funds). Data come from the First Cohesion Report (1996) and the Second and Third Report on Economic and Social Cohesion (European Commission: 2001 and 2004). Column 4 shows that, contrary to the expectations, those countries receiving objective 1 structural funds have higher income dispersion than countries outside the objective 1 area. Importantly, the coefficient associated with PATENT applications remains significant and with the same coefficient.

Regions benefiting from objective 1 are decided at the same time as the multi-annual programme of the European Community Budget, the Financial Framework. During the period studied in this paper (1990–2002), there have been three different financial frameworks: 1989–1993, 1994–1999 and 2000–2006. Thus, the positive effect of the objective 1 dummy might be due to reverse causality. Our hypothesis is that it is the high dispersion in income that makes countries having poor regions eligible for objective 1. To test our hypothesis, we introduce the objective 1 dummy 6 years lagged: the years that the financial framework lasts for. In this way, we expect to get rid of the endogeneity: countries having contemporaneous high income dispersion did not necessarily have any EU support in the previous financial framework. By lagging the objective 1 dummy, we lose 5 years more, reducing the sample to 84 observations (12 countries, 7 years). Column 5 shows now a negative and significant effect from the objective 1 dummy: those countries receiving regional policy funds from the EU reduce their income dispersion. We also confirm that even when taking into account the EU funds, there is an effect running from PATENT applications to income dispersion.

Column 6 includes the lagged dispersion of investment. However, gross fixed capital formation at NUTS II level is only available since 1995 (Eurostat Metadata, General Statistics, Regional). The sample size is therefore reduced to 80 observations (the United Kingdom has regional investment data available only since 1998). Results show that the dispersion in investment does not affect income dispersion whereas PATENT applications continue to have a remarkably similar and significant coefficient. Columns 7–9 confirm the robustness of PATENTS as an explanatory variable, because of maintaining the same coefficient and significant level, regardless of which other technology indicator (BERD, GOVERD or HERD) is simultaneously included in the estimation.[12] Finally, the strong significance of country dummies in every model confirms the relevance of country effects and institutional factors in the determination of the dispersion of income per capita. In contrast, common time shocks are mostly insignificant; hence, we could leave them out to gain efficiency in the estimations.

[12] We perform the Hansen test (1992) of the null hypothesis of constant parameters through time against the alternative of parameter instability. This test has locally optimal power and does not require a priori knowledge of the sample-split points. The individual statistics for the coefficient associated with PATENTS applications are around 0.03 for all the estimations in Table 6, well below the critical values. Therefore, we do not reject the hypothesis of this parameter being constant over time and over countries.

3.2. Mechanisms by which convergence in patents leads to convergence in income

The results from the previous section clearly highlight the importance that patenting has for economic growth. If poorer regions patent at a faster pace than do richer ones they will also grow faster and the distribution of regional income per capita will be more equal.

These results neglect, however, a role for R&D in reducing income disparities. That is, on the one hand, we have empirical evidence from many studies (referred to in Section 1 above) that shows the importance of R&D for achieving long-run economic growth. But, on the other hand, we find no evidence that a reduction in the dispersion of R&D has any direct effect on the dispersion of income per capita. These two results are not necessarily contradictory. There is a strong possibility that the distribution of R&D may have an indirect effect on the distribution of income, if it leads to a better distribution of patent applications. Or in other words, R&D spending has positive economic effects only when it translates into real innovation (captured by the PATENTS indicator).

To explore this hypothesis, we run a dynamic estimation in which the dependent variable is now the first differences of dispersion of PATENTS, and the independent variables are the same as in Eq. (1), namely the lagged values of all indicators of dispersion of R&D.

$$\Delta\sigma(\mathrm{PATENTS}_{\mathrm{it}}) = \beta_1\sigma(\mathrm{PATENTS}_{\mathrm{i},t-1}) + \sum_k \beta^k \sigma(\mathrm{TI}^k_{\mathrm{i},t-1}) + \sum_{\mathrm{i}} u_{\mathrm{i}} + \varepsilon_{\mathrm{it}}; \quad (2)$$

The results of these new estimations are reported in Table 7. The main finding is that convergence in business R&D (BERD) is crucial to achieving convergence in patents. On the contrary, convergence in government R&D (GOVERD) or in higher education spending (HERD) does not have any significant effect on the distribution of patents.

Moreover, the coefficient associated with the lagged dependent variable shows that the speed of adjustment of patent applications is much higher than in the case of income per capita. A reduction in the dispersion of BERD affects the dispersion of patent applications in the long run and most of the effects kick in just in the first year. Even when the dispersion of the three R&D indicators (GERD, BERD and GOVERD) are included simultaneously, the strength of BERD to explain convergence in patent applications remains. Surprisingly, we find that the dispersion of GOVERD has a negative effect on the dispersion of patent applications. That is, convergence in government R&D increases the dispersion of patent applications. This counterintuitive result might be the result of some GOVERD effects being captured by BERD. Therefore, when both variables are included simultaneously as explanatory variables of the distribution of patents, BERD "wins the race" and GOVERD becomes negative.

Table 7
The dispersion of R&D expenditure and its effect on the dispersion of patents

Dependent variable: first differences of standard deviation of patent applications	(1)	(2)	(3)	(4)
Lagged dispersion of PATENTS	−0.613*** (−7.94)	−0.606*** (−7.82)	−0.599*** (−7.77)	−0.657*** (−8.53)
Lagged dispersion of BERD	0.520** (2.01)			0.784** (2.90)
Lagged dispersion of GOVERD		−0.528 (−1.53)		−0.766** (−2.14)
Lagged dispersion of HERD			−0.667 (−1.49)	−0.731 (−1.64)
Significance of country dummies	F(12,130), 6.60***	F(12,130), 4.21***	F(12,130), 4.34***	F(12,128), 5.05***
Observations	144	144	144	144
Adjusted R-squared	0.27	0.26	0.26	0.30

*Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 8
The dispersion of government R&D and higher education spending on the dispersion of business R&D

Dependent variable: first differences of standard deviation of BERD	(1)	(2)	(3)
Lagged dispersion of BERD	−0.222*** (−5.44)	−0.237*** (−6.15)	−0.233*** (−4.96)
Lagged dispersion of GOVERD	−0.001 (−0.02)		−0.020 (−0.38)
Lagged dispersion of HERD		0.160** (2.40)	0.164*** (4.07)
Significance of country dummies	F(12,130), 3.08***	F(12,130), 4.15***	F(12,129), 3.66***
Observations	144	144	144
Adjusted R-squared	0.25	0.28	0.28

*Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

In Table 8, we study this hypothesis: whether GOVERD and HERD do affect income per capita dispersion in a more indirect way via BERD. Results show that this is the case for HERD but not for GOVERD. We do this by estimating the following equation:

$$\Delta\sigma(\mathrm{BERD}_{it}) = \beta_1\sigma(\mathrm{BERD}_{\mathrm{i},t-1}) + \beta_2\sigma(\mathrm{GERD}_{\mathrm{i},t-1}) + \beta_3\sigma(\mathrm{HERD}_{\mathrm{i},t-1}) + \sum_{\mathrm{i}} u_{\mathrm{i}} + \varepsilon_{it}; \qquad (3)$$

The dispersion of higher education spending (HERD) does significantly affect the dispersion of business R&D (BERD), both when considered alone and when considered together with government R&D (GOVERD). In contrast, the distribution of GOVERD does not seem to have any effect on BERD.

Summing up, what all these results imply is that convergence in higher education spending (which in Europe is mainly done by public universities) leads to convergence in business R&D, which in turn leads to convergence in patents, and then jumps into income per capita convergence.

3.3. *Robustness analysis for the relationship between technology and income*

Finally, in this section we conduct a robustness check of the results from the previous section. To do so, we use a different approach: now we use all the regional data available for the period 1990–2002. In the previous sections, we performed the analyses on the basis of the dispersion, where regional disparities were grouped by countries. This is why we had 144–156 observations in the different estimations.

In this section, we run a model that exploits all data available. This is possible because we introduce in this subsection dependent and independent variables that do not represent any measure of dispersion: now, dependent and independent variables are simply the log of their absolute values. Before estimating the impact of patent applications on income, we test for Granger causality, assessing whether patent applications precede income or vice versa. We apply the modified version of the Granger causality test proposed by Toda and Yamamoto (1995). In this version, the correct lag length (k) is artificially augmented by the maximal order of integration ($d_{\max}$). The Granger causality test is then estimated on the augmented ($k+d_{\max}$) order of VAR, but applying the modified Wald test only on the k coefficients associated with the correct lag length. This version of the Granger causality test ensures that conclusions are valid independently of the order of integration of the variables (Caporale and Pittis, 1999). The optimal lag length is set to 2, because this is the most common lag minimizing the BIC criterion in the 177 regions.[13] Performing the panel data unit root test proposed by Im et al. (2003), we find that both patent applications and income per capita are $I(1)$.[14]

Table 9 shows the results of estimating a two-equation system using the method of seemingly unrelated regressions (SUR) on the pooled data.[15] The first column reveals

[13] Results are remarkably similar when using 1 or 3 lags.

[14] We chose the Im et al. (2003) test, because it has higher power than other panel data unit root tests and performs satisfactory even for small T, as in our case in which we have 13 observations by region.

[15] The SUR estimation does not modify the estimation of the coefficients in the second stage when the dependent variables are the same across the equations in the system (Greene, 2003). Nevertheless, the SUR approach allows us to improve the efficiency.

Table 9
Granger causality test for patent applications and income per capita

Dependent variable	(1) log of income	(2) log of patents
log of income ($t-1$)	1.203*** (56.13)	−2.801*** (2.73)
log of income ($t-2$)	−0.131** (3.93)	2.194 (1.17)
log of income ($t-3$)	−0.091** (4.48)	1.110 (0.97)
log of patents ($t-1$)	−0.010*** (2.65)	0.556*** (24.26)
log of patents ($t-2$)	0.012*** (2.63)	0.167*** (6.65)
log of patents ($t-3$)	0.000 (0.72)	0.174*** (8.05)
Constant	0.086*** (7.26)	−1.794*** (2.69)
H_0: log of patents does not Granger-cause log of income	$\chi^2(2) = 8.96$**	
H_0: log of patents does not Granger-cause log of income		$\chi^2(2) = 6.79$**

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

that the first lag of patent applications affects per capita income negatively, the second has a positive impact, and the third is almost zero. The coefficient associated with the second lag is significantly larger in absolute terms than the first lag coefficient (to a 1% significance level). The Wald test applied to the first and second lag (excluding the augmented third lag) clearly rejects the null hypothesis of patent applications not Granger-causing per capita income. Similarly, the null hypothesis of per capita income not Granger-causing patent applications is rejected. Moreover, the sum of the coefficients associated with the first, second and third lags of per capita income have a significantly positive impact on patent applications. We also run the modified Granger causality test region by region. We find that patent applications Granger-cause per capita income in 134 out of 177 regions whereas per capita income Granger-cause patent applications in 125 regions. All in all, there is Granger causality in both directions: from patent applications to per capita income and vice versa. This result is in line with von Tunzelmann (2004) who finds that patents precede GDP per capita in the long term whereas GDP precedes R&D intensity and (in the short-term) patent applications, in a sample of 18 European countries in the period 1950–1995. Results also mirror Yang (2006), who shows that patent applications Granger-cause GDP and vice versa for the case of Taiwan in the period 1951–2001.

However, Granger analysis does not prove causation in the usual sense. To reach conclusions on the causal relationship of patent applications for per capita income we use the system-GMM (GMM-SYS) estimator suggested by Blundell and Bond (1998). We use an instrumental variables estimator to control for the endogeneity problem shown by the Granger causality analysis. We have 177 regions and 11 years (1 year is lost due to the dynamics introduced in the model and a second year is also lost when using instrumental variables), ending up with 1947 observations. The equation that we estimate in this section is the following:

$$\Delta(\mathrm{INCOME}_{jt}) = \beta_1(\mathrm{INCOME}_{j,t-1}) + \sum_k \beta^k(\mathrm{TI}^k_{j,t-1}) + \varepsilon_{jt}; \quad (4)$$

where j is the region. To estimate Eq. (4), we use the GMM-SYS estimator, which increases efficiency by exploiting all the information available based on estimations in first differences and in levels (Arellano and Bover, 1995).[16] For the estimation in first differences, endogenous variables are instrumented with their own lagged level values. For the equation in levels, endogenous variables are instrumented with their own first differences. Results from the one-step estimates are reported in Table 10, because the standard errors of the two-step estimates tend to be severely downward biased (Arellano and Bond, 1991; Blundell and Bond, 1998).

As can be seen from Table 10, the M2 tests do not reject the null hypothesis of absence of second-order serial correlation. Furthermore, the Hansen test statistic of overidentifying restrictions does not reject the validity of the instruments used. Column 1 corroborates that patent applications are the relevant variable affecting income per capita when considered together with aggregate R&D (GERD). Column 2 shows that this result is robust when introducing a dummy that takes the value 1 if the region receives objective 1 structural funds and 0 otherwise. EU regional policy thus seems to be successful at promoting per capita income growth.[17] Column 3 introduces regional investment, significantly reducing the sample size, since the first year available is 1995. Investment leads to higher growth rates, but it does not remove the significant effect associated with PATENT applications. Column 4 considers R&D by sector of performance (GOVERD, BERD and HERD). Results confirm the robustness of the effect of PATENT applications on economic growth. Column 5 confirms that business R&D (BERD) is the most relevant determinant of patent applications among EU regions.

Finally, Column 6 introduces some new findings. First, now there is a weak role for government R&D in stimulating business R&D, which is compatible with its insignificant

[16] We use the system GMM estimator since we now have a much larger simple (1947 observations) and therefore we are able to obtain reliable estimations using instrumental variables.

[17] Note that now we have many observations and thus can instrument the objective 1 dummy by its lagged values as well as lagged values of other explanatory variables, since the eligibility of a region is determined by its per capita income in previous years. Therefore, we do not need to lag the objective 1 dummy itself as in Table 6. Furthermore, the case for endogeneity is less clear. In Table 6, we find that poor regions increase income dispersion in their countries at the same rate as they benefit from objective 1. Now, poor regions do not necessarily have had to record low growth rates in previous years.

Table 10
Direct and indirect effects of technology indicators on income per capita

Dependent variable	(1) log of income (differences)	(2) log of income (differences)	(3) log of income (differences)	(4) log of Income (differences)	(5) log of patents (differences)	(6) log of BERD (differences)
Lagged dependent variable	-0.042^{***} (38.9)	-0.070^{***} (2.75)	-0.074^{**} (-27.18)	-0.062^{***} (-32.67)	-0.352^{***} (12.76)	-0.065^{***} (37.96)
log of GERD	-0.003 (0.75)	-0.002 (0.35)	-0.002 (-0.44)			
log of PATENTS	0.005^{**} (2.41)	0.006^{**} (2.34)	0.006^{**} (2.31)	0.004^{***} (2.67)		
Dummy regions objective 1		0.042^{***} (3.40)				
log of INVESTMENT			0.085^{***} (2.57)			
Six years lagged dummy regions objective 1						
log of BERD				0.001 (0.62)	0.458^{***} (3.70)	
log of GOVERD				-0.001 (-0.76)	0.123 (1.00)	0.037^{*} (1.73)
log of HERD				-0.001 (-0.26)	-0.144 (1.47)	-0.058^{***} (-3.37)
Hansen test of over-identification restrictions	41.04 $\chi(31)$	40.40 $\chi(33)$	23.32 $\chi(17)$	39.39 $\chi(30)$	176.49 $\chi(227)$	176.20 $\chi(262)$
First-order correlation test	-3.20^{***}	-3.34^{***}	-2.40^{***}	-3.24^{***}	-4.85^{***}	-1.53
Second-order correlation test	1.15	1.30	-1.65^{*}	1.14	0.80	0.99
Observations	1947	1947	837	1947	1947	1947

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

role in the previous dispersion analysis.[18] This points towards a possible complementarity between government and business R&D that is so important in the public–private partnerships literature. Second, we find that more spending in higher education may not be the way to increase business R&D. These different but compatible results between what we found in the dispersion analysis and what we find in this robustness check, confirm that there is a role for public initiatives (through either GOVERD or HERD) in the process of reducing income disparities. Nevertheless a complete understanding of the channels through which this influence occurs needs further study.[19]

4. Conclusion

This study of the evolution of the distribution of regional technology indicators during the 1990s has provided some clear and important findings which can be very useful to inform future economic policy debates in the EU.

First of all, both input and output technology indicators have converged among regions during the period studied, and this has ran parallel to a real convergence in income per capita levels. This process of simultaneous convergence has been especially important during the first half of the decade, but weakened between 2000 and 2002.

Second, we have identified a strong relationship between the distribution of technology indicators and the distribution of regional income in Europe. Convergence in output technology indicators (patents) contributes to convergence in regional income. For convergence in patents to occur, technology indicators also have to converge, especially business R&D. And for business R&D to converge, either higher education spending or government R&D might have to converge as well.

These results confirm that there is a relationship between convergence in input technology indicators (based on research and education), convergence in output indicators (through patented innovations) and convergence in per capita income (by means of higher economic growth). Our paper confirms empirically the theoretical hypothesis of Bernard and Jones (1996) regarding the importance that changes in the dispersion of technology have in explaining changes in the dispersion of per capita income over time,

[18] Column 6 indicates that the long-run relationship between business R&D and government and higher education R&D is $\ln(\text{BERD}) = 0.57\ln(\text{GOVERD}) - 0.89\ln(\text{HERD})$. This relationship leads to the following association $\sigma^2(\text{BERD}) = 0.32\sigma^2(\text{GOVERD}) + 0.80\sigma^2(\text{HERD}) - 0.51\text{Cov}(\text{GOVERD, HERD})$. As the covariance between GOVERD and HERD is positive, the evidence in Tables 8 and 9 is compatible.

[19] For example, there is a hypothesis that reconciles the positive influence of the dispersion of HERD in BERD and the negative influence that it shows in the levels analysis. These two results could be showing that higher education R&D in a technologically advanced region crowds out business R&D in that region, but crowds in business R&D in other technologically advanced regions. This might be due to the existence of spillover effects of basic research in higher education institutions that might be benefiting all regions, while the cost relies in the region performing the higher education activities. As a result, the dispersion in higher education R&D increases the dispersion of business R&D. Obviously, to test this hypothesis is beyond the scope of this article, but is a very promising starting point for further studies.

and also sheds some light on the mechanisms by which this influence occurs.

Therefore, while technology policy based on pure excellence and efficiency criteria should remain as a policy tool for economic growth in Europe, this policy should be counterbalanced by community, national and/or regional policies that put these connections between technology and income to work. Only a more balanced distribution of technology across regions will guarantee long-run convergence in per capita income for all European citizens.

Finally, we also find evidence of income Granger-causing patent applications and vice versa. This result indicates that both variables may be reinforcing each other: patent applications increase income, which in turn leads to rises in patent applications. This moves the debate on from the simple 'linear model' to a more complex interaction between technology and incomes.

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