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ON THE RELATIONSHIP BETWEEN KNOWLEDGE CREATION AND ECONOMIC PERFORMANCE

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Abstract. An empirical two-equation dynamic panel-data model system with fixed effects is proposed to analyze the relationship between knowledge creation and economic performance across regions over time. Estimates of the model for Spanish regions show that (i) knowledge creation depends on local R&D effort, on the amount of knowledge in use, and on knowledge creation in neighboring regions; and (ii) assimilation of new knowledge depends on local knowledge creation and on assimilation of knowledge in neighboring regions. Both processes include region-specific context fixed effects and region-specific time effects, representing region-specific dynamic influences. The results imply that (a) efficiency gains at regional level may be achieved by investing locally in the creation of new knowledge, either technological or organizational; (b) creation of knowledge in a region may be promoted by using greater amounts of already existing knowledge, as well as by increasing local R&D effort; (c) both knowledge creation and knowledge assimilation spread to/from neighboring regions; and (d) regional contexts influence both knowledge creation and knowledge assimilation separately.

Keywords: economic growth, panel-data, R&D, Spanish regions.

JEL Classification: O33, O11, O32, C33.

Introduction

The levels of Gross Domestic Product (GDP) per capita often diverge for long periods across countries and across regions within countries, as is the case for Spain. The disparities are generally explained because of the fact that some economies, either at national or at regional level, are able both to increase the number of people working and to improve their productivity, while others were not (Scarpetta *et al.* 2000). Over the years 1989–2001 remarkable increases both in the size and in the average educational attainment of the labor force were registered

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in Spain. Educational reforms, the rapid expansion of the higher education system, and the increasing participation of women both in post-compulsory education and the labor market played key roles (Vila, Mora 1998). As a consequence, economic growth at national level was relatively high and persistent although its territorial distribution within the country was far from homogenous, leading to rapidly increasing disparities in wellbeing at regional level (Salinas Jiménez 2003). This paper aims at clarifying whether and how the creation and assimilation of knowledge in a region improve its economic performance through efficiency gains in the use of the available resources, which would ultimately result in faster economic growth and higher well-being.

The relationship between knowledge, science, technology and productivity appears to have changed during the last two decades (Giorgio Marrano *et al.* 2009). Innovation, that is, new ideas and recently achieved knowledge that are assimilated and successfully applied to production (e.g. Fomin *et al.* 2012), is now considered more critical to success in business and to the growth of economies (Ezcurra *et al.* 2009), with information and communication technologies playing a capital role in facilitating the diffusion of technological and organizational developments (Kim *et al.* 2011). A number of papers have emphasized the catalyst role of policy regarding the diffusion of knowledge for a rapid adaptation and adoption of better technologies, practices and production processes across firms, regions and countries, highlighting the virtuous cycle between R&D investment, technology stock and growth (Wong, Govindaraju 2012). The contributions made by Foray (2004, 2009) emerge as some of the most relevant. Foray (2004) analyzes the influence of technological progress based on newly achieved knowledge and its diffusion over the production mixture of the economies. Foray (2009) examines several political responses to the recent global and systemic challenges and argues that intense innovation might be the way to manage potential global crises. He concludes that no single policy would serve to overcome the new global risks and also highlights the lack of consensus among economists. Foray's work however focuses on the effects of knowledge creation and dissemination across sectors while the present paper emphasizes the effects of knowledge creation and assimilation from a regional perspective.

According to OECD (2000), increases in efficiency, measured as multi-factor productivity (MFP) gains, are the result of using new technology along with more efficient ways of organizing production. In this environment, education as a source for knowledge creation and assimilation becomes more prominent in explaining divergences in economic growth among territories. The education of the local labor force is at the root of technological and organizational developments generated (Schleicher 2006).

The diffusion of innovation relates as well to the availability of a workforce with sufficient and up-to-date competencies (Knabb, Stoddard 2005; Škare 2011). In particular, higher education relates to labor productivity in several ways via the creation of new knowledge. First, in most countries a substantial proportion of the effort in basic and applied research is done within higher education institutions. Second, the education system provides qualified labor for industry and service sectors, including those who will develop careers in research activities. Third, the flow of graduates entering the labor market each year brings in, along with other components of human capital, the specific capacity to innovate at the workplace. Innovation capacity is not restricted only to entrepreneurs or to those working on research and development (R&D) activities, as many other graduates would have the opportunity to innovate by developing new ideas on the performance of their responsibilities and/or by applying in their jobs knowledge that has been recently discovered and applied by others.

The availability of new knowledge induces changes in the production process leading to increases in the demand for diverse types of highly qualified labor. The distribution of changes in time and space depends on the distribution of inventive effort, which, in turn, relates to the supply of highly qualified individuals. Consequently, regional divergences in income and wellbeing are likely to be explained in terms of regional patters of investment in the creation of new knowledge through research and higher education activities (Bilbao-Osorio, Rodríguez-Pose 2004).

The rest of the article is structured as follows. Section one provides background by summarizing the key features of the literature linking knowledge and economic performance. Section two specifies empirically a two-equation dynamic panel-data system model for knowledge creation and its impacts on economic efficiency when the new knowledge is productively assimilated within a regional framework. Section three describes the data set and the choice of variables and discusses the estimation results. Finally, the last section concludes. An econometric appendix completes the paper.

1. Background

The mechanisms that channel the positive effects of education investment into economic growth have been extensively analyzed for half a century (Temple 1999). Two separate strands of traditional economic theory approached the economic role of knowledge. On the one hand, neo-classical growth theory described a firm's output as a function of two factor inputs, capital and labor, with knowledge operating typically as an exogenous force enhancing labor effectiveness. In particular, neo-classical growth theory (Solow 1956) assumed that technological progress was driven by a scientific process evolving independently from economic forces, and, consequently, long-run growth rates were determined exogenously, from outside the economic system. On the other hand, endogenous growth models (EGM) argued that economic growth is generated within the economic system, as a direct result of internal processes, and, therefore, considered technological progress as endogenous. The endogeneisation of technological progress has been addressed from various perspectives: increasing returns to scale, capital and innovation externalities, learning by doing, human capital accumulation and R&D performance. Additionally, human capital theory predicted that improved knowledge makes individuals more productive, hence they will earn higher wages reflecting their addition to the firm's output. Consequently, the enhancement of a nation's human capital will lead to economic growth by means of the development of new forms of technology and more efficient and effective means of production.

The first version of endogenous growth theory was the so-called AK theory (Romer 1986), which did not make an explicit distinction between capital accumulation and technological progress. AK theory was followed by a second wave of endogenous growth theory, generally known as "innovation-based" growth theory, which recognizes that intellectual ca-pital, the source of technological progress, is distinct from physical and human capital. Physical and human capitals are accumulated through saving and schooling, respectively; however, intellectual capital is accumulated through innovation. The creation of new technological knowledge requires resources to be specifically allocated to R&D activities whereby the new knowledge is generated. In other words, the creation of technological knowledge should be incorporated as an endogenous determinant in economic growth models. A body of literature focused on the economics of innovation offers the means to endogenize the creation of new technological knowledge. The most prevalent model of technological change is the so-called knowledge production function (KPF), where innovative activity is expressed as a function of R&D inputs, human capital inputs and spillovers. The model of technological change can be therefore specified as a two equation dynamic system: one related to the production and the other referring to technological advancement. That two-equation approach is the one developed in this paper.

Although KPF was initially applied to firms' behavior (Griliches 1979), empirical evidence was found to be stronger at broader levels of aggregation such as regions or countries (Pakes, Griliches 1984), which suggested the presence of knowledge-related spatial externalities related to the production of new knowledge. Consequently, EGM models incorporating KPF most often assume that existing knowledge is a non-rival, partially excludable good that may generate external effects at the appropriate aggregation level (Romer 1986, 1990). Summarizing, endogenous growth models focus on knowledge assimilation and the external effects related to the assimilation of knowledge among firms, regions or countries while the literature on knowledge production emphasizes the role of inventive performance and the external effects associated to the production of new useful ideas and knowledge (Acs *et al.* 2012).

Moreover, the so-called "innovation systems" approach (Lundvall 1992) to productivity gains adds to the understanding of innovation dynamics by highlighting the crucial role of physical location regarding innovative performance and economic growth. According to this view, elements such as institutional arrangements, geographic specialization, demographic structure, and other environment or context characteristics should have a decisive influence both on the spatial distribution of inventive performance and on the path of knowledge assimilation in diverse territorial units because endogenous technological change appears as a result of applying resources within a framework defined by the interaction between the social and structural conditions prevalent in a given territory at a given time (Autant-Bernard *et al.* 2013). The main findings related to this approach highlight that the capacity for innovation of diverse territories emerges mainly from individual and corporate interaction in terms of synergies and networks. The influence of technical agencies, research infrastructures, education and training systems, governance structures, and local innovation policies also helps to explain territorial differences in innovative performance (Iammarino 2005).

Consequently, recent empirical research on regional innovation and growth has strived to bring together the diverse approaches to knowledge creation and assimilation found in the literature in order to better understand how new knowledge is generated and applied to production resulting in productivity gains. Within this line, Moreno *et al.* (2005) addressed the spatial distribution of innovative activities and the role of technological spillovers in the process of knowledge creation and diffusion among European regions. Their results highlight the relevance of internal regional factors such as specific R&D effort and agglomeration economies to explain innovative performance, along with knowledge spillovers in the generation of new knowledge from innovative activity performed in other regions. The evidence found also shows that spatial spillovers decay with distance, being mostly constrained by national borders, and that technological similarity between regions is relevant to explain how innovation disseminates at regional level. Under the premise that innovative activities and economic activities are not randomly distributed across space, Usai (2008) describes strong differences in the inventive performance of regions in OECD countries, and estimates a KPF model that includes human capital, R&D, agglomeration effects, country level characteristics and spatial correlation as factor inputs. The outcome of the model confirms that regional inventive performance is directly influenced by the availability of human capital and R&D in the region, shows that inventory capacity is concentrated in specific regions that also tend to cluster together, and provides empirical evidence of national innovation systems strongly influencing the institutional framework within which innovation appears and disseminates at regional level. Rodriguez-Pose and Crescenzi (2011) approach combines R&D, knowledge spillovers and innovation systems approaches in an EGM model build up under the assumption that regional growth models should include human capital as factor input in the production function starting the causal chain between research, innovation and growth. The empirical model includes knowledge-related external effects at regional level to complete the analysis of innovation systems territorially located, where endogenous technological change appears to be influenced by contextual conditions in diverse regions. The results disclose how the complex interaction between local and external research, on the one hand, along with local and external socio-economic and institutional conditions, on the other hand, shape the capacity for innovation of regions, and also point out that proximity plays a key role for the transmission of productive knowledge as estimates of spatial spillovers decay rapidly with distance.

These contributions addressed the economic role of knowledge at regional level by means of single-equation models that combined diverse internal (human capital, R&D and social context) and external factors (diverse types of knowledge-related spatial spillovers) that interact as determinants of the innovative capacity of regions, which, in turn, guided economic growth of regions. Particularly, the models focused on the creation of new technological knowledge only, thus neglecting the role of new organizational knowledge in explaining the assimilation of innovation at regional level. None of them, however, consider separately the processes of knowledge creation, on the one hand, and knowledge assimilation, on the other, which limits the analysis of how the diverse determinants, both local and external, operate and interact to explain invention, innovation and productivity gains at regional level over time. Nonetheless, productive innovation requires, first, that some new knowledge should be generated and made available and, second, that the newly-available knowledge should be assimilated into production of economic output with productivity gains. In the next section we propose a two-equation system model to represent the two inter-related processes whereby new technological and new organizational knowledge are created and, once available, they are assimilated and transformed into efficiency gains at regional level. The model's regional scope determines that the external effects involved in both activities, that is, in the creation of new knowledge and in the assimilation of newly available knowledge, should be treated as separate spatial spillovers. Accordingly, the effects due to the local environment, or context conditions, regarding the creation of new knowledge are treated in the model separately from its effects of on the assimilation of newly available knowledge to increase efficiency.

2. Empirical model specification

Economic theory suggests that regional economic performance is likely to be influenced by the amount of knowledge already in use and by the flow of new knowledge available in the region, as well as by contextual, region-specific conditions. Additionally, knowledge-related inter-regional external effects may appear both in the creation of new knowledge and in its application for the production of goods and services. People create and accumulate knowledge through a wide variety of activities including trial and error, formal education, on-the-job training, learning by doing, and scientific research, among others. Furthermore, the whole production system may be regarded as the result of using a certain amount of previously achieved knowledge: materials, processes, products, technology, infrastructures and organizations, all emerged from what people discovered, created, and developed in the past. The distinction between the technological, or explicit, and the organizational, or tacit, components of knowledge in the economy is relevant to the case because the two components emerge largely from different types of activities and are accumulated, and accounted for, in different ways. Technological, explicit knowledge emerges primarily from research and development, and it is stocked as physical capital in the economy. Organizational, or tacit knowledge, exists in people's brains and organizations in the forms of human ability, ideas, skills, competence, know-how and networking; it is generated mainly through formal education in interaction with work, business and general life experience, and is accounted for in terms of human capital. The amount of already existing knowledge (both explicit and tacit) that is used in the economy is, in turn, a factor input for the development of new useful knowledge. Research and development activities create new explicit knowledge on the basis of existing organizational and technological knowledge. The newly-achieved explicit knowledge will increase the amount of knowledge available for the future in two ways. First, it would be assimilated into the production process as productive innovation, thus increasing the amount of knowledge used; and second, the newly-achieved useful knowledge will be learned by people at schools and universities, thus improving the amount of future organizational, tacit knowledge through increased quality of human resources. Figure 1 represents the relationship between technological and organizational knowledge and productive innovation. Inventions, that is, explicit new knowledge, may either be protected by patents or remain free. Both patented and not patented inventions may either be applied to production or remain unused. Innovative performance, then, is the result of using inventions, patented or not patented, as well as new non-tech, or organizational knowledge.

Within this conceptual framework, a two-equation dynamic panel-data model system is specified to estimate the influence of knowledge creation and accumulation on economic efficiency at regional level over time. The equations in the model system refer to the inventive

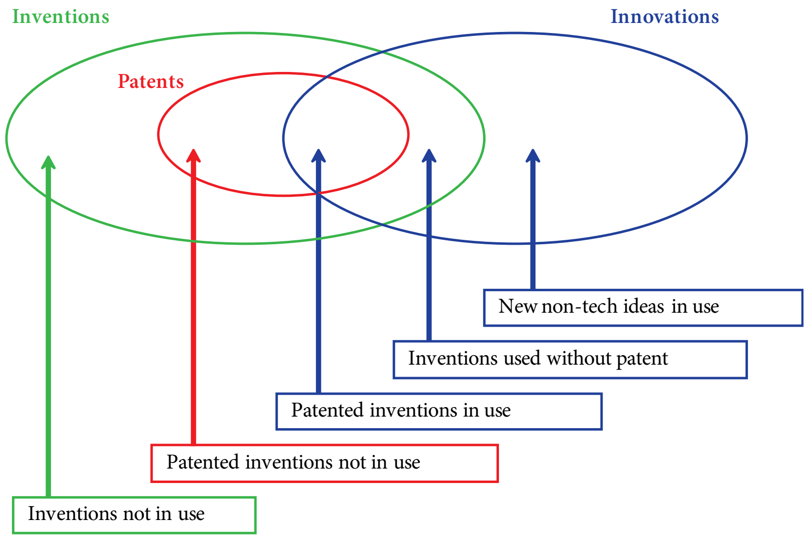

Fig. 1. Structure of inventions, innovations and patents

process and the innovative process respectively. The processes of invention and innovation occur in time and space; consequently, the empirical model shall consider, along with the factor inputs involved, what were the initial conditions (fixed effects) and past evolution (lagged dependent variables) of inventive and innovative performance, and also allow for external effects (spillover terms) for invention and innovation processes. The first equation states a dynamic relationship for the production of new explicit knowledge created in region i at time t ($N_{i,t}$). Assuming that in time the level of explicit knowledge creation in the region depends on its own past values, $N_{i,t-1}$, the factor inputs for the local creation of new tech-knowledge are the effort explicitly devoted to generate it ($R_{i,t}$) and the amount of knowledge already used in the region. As pointed out, knowledge in use resides in people and organizations as tacit, organizational knowledge, $H_{i,t}$, and in capital stock, as formerly achieved tech-knowledge, $T_{i,t}$. Regional heterogeneity in the generation of novel explicit knowledge is accounted for through the inclusion of fixed regional effects term (θ_i) as the capacities of territories to generate new explicit knowledge depend on their level of development and other territory-specific conditions, such as the institutional framework, that evolve slowly enough to be treated as time-invariant. The possibility of external inter-regional effects in the creation of new technological knowledge is allowed by including an additional regressor ($Z_{i,t}$) representing spatial diffusion of the explicit knowledge generated in other regions. The tech-knowledge production equation is written as:

$$N_{i,t} = \beta_1 N_{i,t-1} + \beta_2 R_{i,t} + \beta_3 H_{i,t} + \beta_4 T_{i,t} + \beta_5 Z_{i,t} + \theta_i + \xi_{i,t} , \quad (1)$$

where: $\xi_{i,t}$ stands for a region-specific and time-specific error term for inventive performance.

The second dynamic equation in the model represents the efficiency in the use of the available resources in region i at time t, $P_{i,t}$. Assuming that the regional efficiency path depends on its own past value ($P_{i,t-1}$), productivity gains emerge from the flow of newly achieved knowledge that is assimilated productively, both in its form of technological change and in its form of improved human capacities. Consequently, the factor inputs for efficiency at time t are the tech-innovation locally generated in the previous period ($N_{i,t-1}$) and the new organizational knowledge available in the region ($G_{i,t}$). Regional heterogeneity in efficiency, that is, in the successful assimilation of newly available knowledge, is accounted for by a term of fixed regional effects (φ_i) that represent territory-specific structural conditions and context variables with an influence on the path of knowledge assimilation shaping aggregate productivity. The possibility of external inter-regional effects regarding knowledge assimilation is allowed by an additional term ($X_{i,t}$) expressing the effects of efficiency gains in neighbor regions on local productivity. The equation for productivity is written as:

$$P_{i,t} = \gamma_1 P_{i,t-1} + \gamma_2 N_{i,t-1} + \gamma_3 G_{i,t} + \gamma_4 X_{i,t} + \varphi_i + \varepsilon_{i,t}, \tag{2}$$

where: $\varepsilon_{i,t}$ stands for a region-specific and time-specific error term for productivity gains.

From an econometric viewpoint, Eqs (1) and (2) can be estimated separately and as a dynamic recursive system. The two-equation system defined by Eqs (1) and (2) considered together displays some key features that are relevant for empirical purposes and will be addressed in the next section when discussing the estimation strategy.

3. Data panel, estimation strategy and results

The model described in section 2 is applied to a 17-region, 13-year panel data set to study the influence of knowledge creation and accumulation on economic efficiency at regional level in Spain over the 1989–2001 period. Regional creation of knowledge ($N_{i,t}$) is measured by the number of granted patents per worker in region i at time t. The number of patents proxies for the amount of new knowledge locally created by the research process, although it does not provide a complete count of regional technological innovation, as represented in Figure 1. The assimilation of knowledge ($P_{i,t}$) is measured as MFP in the region representing overall efficiency in the use of the available resources. For empirical purposes it is defined as the fraction of economic growth that remains unexplained by the increases in capital stock and in the number of workers, so MFP has been calculated from Solow's residual within a sources-of-growth accounting framework with capital stock and labor as factor inputs. The resources allocated to research and development activities per worker ($R_{i,t}$) proxies the local effort explicitly devoted to creation of new tech-knowledge in the region. The proportion of workers with post-compulsory education and the ratio capital per worker comprise respectively the amount of tacit ($H_{i,t}$) and explicit knowledge ($T_{i,t}$) already used in the region. New organizational knowledge in the region ($G_{i,t}$) is measured as the increase in the proportion of higher education graduates among the workforce as a proxy for the improvement in aggregate local labor quality. Increases in the share of higher education graduates among the labor force proxy for the amount of newly achieved knowledge learned at universities, and that fresh graduates brought into production every year as they replace retiring workers with lower education levels. The external effects in the production of explicit knowledge ($Z_{i,t}$) and in the assimilation of newly available knowledge ($X_{i,t}$) are built to capture geographical spillovers in the corresponding process. The first one is calculated by weighting a distance matrix among regions with the regional creation of explicit knowledge measured by patents; the second one is obtained by weighting a distance matrix among regions with regional knowledge assimilation as measured by MFP. Details on the definition, measurement, calculation and data sources for the variables included the model are summarized in Table 1.

Table 1. Variables, measurement and data sources

Variable	Measurement and data sources
$N_{i,t}$	Regional technological innovation. Number of patent applications per worker for each region and year. Source: New Cronos Eurostat data base, Spanish Regional Accounts (INE) and Hispalink.
$R_{i,t}$	R&D expenditure per worker for each region and year. Source: INE and own computations.
$H_{i,t}$	Human capital. Percentage of workers who completed any post-compulsory education level. Source: IVIE.
$T_{i,t}$	Capital stock per worker for each region and year. Source: IVIE.
$P_{i,t}$	Efficiency. Multi-Factor Productivity (Solow's residual) for each region and year. Source: INE, IVIE, Hispalink and own computations.
$G_{i,t}$	New organizational knowledge available in the region. Increase in the proportion of higher education graduates in the workforce worker for each region and year. Source: IVE and own computations.
W	Spatial matrix of regional contiguity. Weight matrix.* Source: own computations.
$Z_{i,t} = WN_{i,t}$	Spatial diffusion of technological innovation. Source: own computations with weight matrix.
$X_{i,t} = WP_{i,t}$	Spatial diffusion of productivity. External inter-regional effects. Source: own computations with weight matrix.

INE: Spanish Statistical Institute (www.ine.es); Hispalink (www.hispalink.org);
IVIE: Instituto Valenciano de investigaciones económicas (www.ivie.es).
* Spanish island regions have been treated as contiguous to those regions with ports in the corresponding sea basin. Accordingly, Balearic Islands were considered contiguous to Catalonia, Valencia Region, Murcia and Andalusia, while Canary Islands were treated as contiguous only to Andalusia.

The two-equation dynamic panel-data model system specified to describe the processes of knowledge creation and knowledge assimilation at regional level displays some interesting features regarding estimation. First, the equations are not independent from each other since the dependent variable in Eq. (1) enters as a lagged regressor in Eq. (2). Second, the dependent variable in Eq. (1) is the number of patents per worker, so it is by nature non-negative. Third, both equations are dynamic in the sense that each one has a lagged value of its own dependent variable as a right-hand side regressor, so both ordinary least squares (OLS) and least square dummy variables (LSDV) estimates of the fixed effects equations would be biased and inconsistent because of the correlation between the lagged value and the corresponding first order auto-correlated error term. The first concern, non-independence, is relatively easy to address since the model may be solved recursively. Taking advantage of the non-negative character of innovation, maximum likelihood (ML) asymptotically efficient estimation of a censored normal model (Tobit) for Eq. (1) can be carried out, and, then, the lagged prediction of invention may enter as a pre-determined variable in the estimation of (2). This recursive estimation strategy, however, does not address the correlation between the lagged value of the dependent variable and the error term in Eq. (2). Alternatively, optimal generalized method of moments (GMM) estimators for the whole system may be built up by taking into account all the available moment-restrictions in the definition of the instrument matrices in each case. The details about the design of instruments for the GMM optimal estimation are reported in the Appendix A section.

Consequently, estimation of the model is carried out twice using two different estimation strategies. The first one estimates both equations separately. It uses Tobit estimation for Eq. (1) and LSDV estimation for Eq. (2). The second strategy estimates the two-equation model as a unique system through GMM optimal estimation. The Tobit/LSDV versus GMM estimation results for knowledge creation and assimilation in Spain's regions are shown in Table 2.

Estimation results confirm that all the explanatory variables included in the two-equation model system for knowledge creation and assimilation show statistically significant and robust effects with the predicted signs, irrespectively of the estimation strategy and procedure used. Indeed, due to regional governments are in charge of a great part of the investments in education and R&D in Spain, following reviewers suggestions, alternative specifications focused on the impact of human capital and R&D per worker investments have been analyzed to test the robustness of the estimates by types of regions and no reasons have been found to alter the proposed specification.

Estimation results from Eq. (1), shown in the first and third panels of Table 2, reveal that the creation of new tech-knowledge in a region depends on local factors such the effort devoted to develop it and on the amount of knowledge already existing in the region. Coefficient estimates show that regional inventive performance depends positively on the effort locally devoted to the creation of explicit knowledge, represented by R&D expenditure. Inventive performance depends positively as well on the stock of knowledge that is already used in the region, both as tacit knowledge represented by human capital, and as explicit knowledge expressed by the ratio capital per worker. Inventive performance in a region also benefits from positive external effects from the creation of knowledge in neighbor regions, suggesting that part of the new knowledge locally generated in a region flows to other regions through the interaction of economic agents across borders. Fixed regional effects regarding inventive performance reflect the influence of institutional arrangements and regional innovation systems on the capacity of regions to generate new technological knowledge. Some regions appear as areas where the creation of new tech-knowledge is structurally favored by the environment, while other regions are areas where the environment deters inventive performance. Additionally, the dynamic part of the model reveals that regional innovation depends significantly on its own past values as it was hypothesized in the dynamic part of the model.

Table 2. Estimation results for Creation of knowledge (Eq. (1)) and Assimilation of knowledge (Eq. (2))

	Strategy 1				Strategy 2			
	Eq. (1) TOBIT		Eq. (2) LSDV		Eq. (1) GMM		Eq. (2) GMM	
	Coefficient	Std. Desv.	Coefficient	Std. Desv.	Coefficient	Std. Desv.	Coefficient	Std. Desv.
Creation (t-1)	0.265***	0.055			0.239***	0.050		
R&D per worker	0.090***	0.019			0.086***	0.018		
Human Capital	0.287***	0.087			0.298***	0.081		
Capital per worker	0.214***	0.070			0.249***	0.064		
Creation Spillover	0.008**	0.004			0.009**	0.004		
Assimilation (t-1)			0.679***	0.044			0.723***	0.045
Creation (t-1)			2.709***	0.514			3.940***	0.651
Increase HEG			5.087***	1.547			5.236***	1.483
Assimilation Spillover			0.168***	0.030			0.152***	0.029
Andalusia	−0.037***	0.007	0.328***	0.095	−0.040***	0.007	0.238**	0.094
Aragon	−0.024***	0.008	−0.317***	0.073	−0.025***	0.008	−0.390***	0.073
Asturias	−0.050***	0.009	−0.285***	0.066	−0.054***	0.009	−0.328***	0.065
Balearic Islands	−0.035***	0.011	−0.296***	0.077	−0.039***	0.011	−0.304***	0.074
Castile and Leon	−0.032***	0.008	−0.219***	0.072	−0.053***	0.010	−0.237***	0.069
Castile La Mancha	−0.052***	0.010	−0.230***	0.066	−0.044***	0.008	−0.241***	0.064
Canary Islands	−0.048***	0.011	−0.131*	0.071	−0.035***	0.008	−0.149**	0.068
Cantabria	−0.042***	0.008	−0.075	0.069	−0.055***	0.009	−0.109*	0.066
Catalonia	0.000	0.007	0.262**	0.119	0.001	0.008	0.040	0.134
Valencia Region	−0.020***	0.007	0.044	0.081	−0.022***	0.008	−0.056	0.084
Estremadura	−0.042***	0.009	−0.203***	0.067	−0.046***	0.009	−0.215***	0.064
Galicia	−0.034***	0.006	0.000	0.067	−0.037***	0.007	−0.032	0.065
Madrid	−0.070***	0.011	0.372***	0.108	−0.069***	0.011	0.219*	0.114
Murcia	−0.041***	0.009	−0.207***	0.068	−0.044***	0.009	−0.227***	0.065
Navarre	−0.009	0.007	−0.338***	0.072	−0.007	0.007	−0.422***	0.074
The Basque Country	−0.040***	0.008	−0.223***	0.074	−0.039***	0.009	−0.340***	0.080
Rioja, La	−0.033***	0.008	−0.248***	0.064	−0.036***	0.008	−0.273***	0.062
Residual sum square	2.93E−08		5.41E+12		1.58E−08		5.27E+12	
Variance dependent	1.11E−09		5.32E+11		1.11E−09		5.32E+11	
Mean dependent	3.79E−05		7.45E+05		3.79E−05		7.45E+05	
R^2	0.871		0.946		0.930		0.947	
Adjusted R^2	0.856		0.922		0.907		0.924	
Observations	204		187		204		187	

Note: *, **, and *** denote significance level at 10%, 5% and 1% respectively.

Coefficient estimates from Eq. (2), displayed in the second and fourth panels of Table 2, show that regional efficiency gains emerge from productive innovation, that is, from the assimilation of new knowledge both of technological and of organizational nature. Interpretation of results is straightforward: regional efficiency depends positively on lagged regional inventive performance and on the improvement in local labor quality representing current organizational innovation. Efficiency in a region benefits from positive external effects from efficiency gains achieved in neighbor regions, pointing out that there is positive knowledge spillovers in the assimilation of knowledge successfully used in other regions where efficiency gains have taken place. Fixed effects terms relate to the propensity of regions to assimilate new knowledge productively, suggesting that elements such as specialization, level of development, demographic composition, etc. may foster or limit the impacts on productivity derived from the effective use of newly-achieved knowledge. Additionally, the dynamic part term shows that regional efficiency depends significantly on its own past values as hypothesized.

Generally speaking, GMM optimal estimation of both equations in the system model does not alter the fundamental results since coefficient estimates are close to those obtained using the initial Tobit-LSDV strategy. Nonetheless, GMM estimation yields improved goodness-of-fit measures for both equations, as shown by residual sum of squares and adjusted determination coefficients. Additionally, there is some evidence of systematic reductions in the standard errors of GMM coefficient estimates in the equation representing knowledge assimilation, reflected by larger values for the corresponding z-statistics. This is explained because the Tobit-LSDV estimation strategy includes instruments for innovation but not for the lagged dependent variable, which remains correlated with the error term. Consequently, an additional finding of our analysis is that GMM estimation of the whole system appears to be statistically more efficient that the initial Tobit-LSDV recursive estimation strategy.

Conclusions

The analysis conducted in this paper highlights the relevance of local knowledge creation and assimilation in explaining differences in growth rates among Spanish regions over time. During the 1989–2001 period, economic growth at national level was relatively high and persistent, fostered by remarkable increases both in the size and in the average educational attainment of the labor force. However, its territorial distribution within the country was far from homogenous, leading to increasing disparities in wellbeing at regional level. Regional disparities in R&D and in the supply of educated labor, which translate into inequalities in the amount of available explicit-technological and tacit-organizational knowledge among regions, help to explain regional disparities in the creation of new knowledge, which, in turn, are at the root of divergent economic growth patterns among Spanish regions. The strategy proposed to estimate the two-equation system brings new insight on the topic by separating the process of knowledge creation from that of knowledge assimilation, on the one hand, and by highlighting the distinction between explicit knowledge and tacit knowledge on both processes, on the other hand. The general results are in the line of those found in previous literature on innovation and growth at regional level (i.e. local inventory performance depends on local and external factors, while economic growth depends on local innovation and on external innovation) and provide new evidence on how education and research investments foster regional economic growth.

Efficiency gains at regional level appear as a result of the assimilation of newly available knowledge in the region, both in its technological, explicit form (lagged patents) and in its organizational, tacit form (increased labor quality) although local context conditions (fixed regional effects on assimilation) do matter, as does efficiency of neighbor regions (positive assimilation spillover). The creation of technological knowledge, in turn, is the result of applying local R&D effort over the stock of explicit and tacit knowledge already used in the region. Local conditions are relevant to explain local knowledge creation (fixed regional effect on invention) along with inventive performance of neighbor regions (positive spillover for the creation of explicit knowledge). Therefore, regional advances in efficiency would require additional advances in the creation of explicit knowledge, which in turn depends on local R&D effort and on the accumulation of both technological and organizational knowledge, and on improved higher education of the labor force in the region as higher education is the primary source of new organizational knowledge. Those regions that do not generate new knowledge, both tacit and explicit, rapidly enough are at risk of being left behind in the process of economic development. Other things being equal, the lack of a sufficient supply of highly educated workers in some regions may operate as a barrier both to technological innovation and to the creation of new organizational knowledge, thus limiting the possibilities for growth and development.

The main practical implications are that regional policies must be initially addressed to improve the educational level of the labor force as a mean to promote the collaboration between science and industry in the creation of new useful knowledge that can be more easily and more rapidly applied to local production. The analysis highlights the need for local public support for basic scientific research as well as for higher education to increase, respectively, the flows of new technological and of new organizational knowledge endogenously generated in the region in order to improve regional economic performance. Territories do differ in their ability to adapt to new economic conditions depending on the allocated efficiency of their economic agents; therefore, educational and research policies and managerial practice explicitly oriented to the creation and assimilation of new knowledge at regional level appear as key instruments to ease the economic transitions and to develop local innovation systems not only directly, but also indirectly through the spatial diffusion of their effects, so less developed regions may be in position to share the benefits from the new knowledge already generated and already assimilated productively by other regions.

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APPENDIX A

The two-equation panel-data system model in this paper, as often happens when explaining economic relationships, is dynamic in nature: each equation includes its own dependent variable as a right-hand side lagged regressor. The consequences of this characteristic are (following, for instance, Balgati (1995)) that ordinary least square (OLS) estimators will be seriously biased and inconsistent due to the correlation between the lagged dependent variable and the individual specific effects. Moreover, according to Nickell (1981) and Beggs and Nerlove (1988), least square dummy variables (LSDV) estimates will be also biased and inconsistent for small T, although they will be practically unbiased for large T with only a bias of order $1/T$ remaining.

A common solution for dealing with dependent variables that are correlated with the error term is to instrument them with suitable instruments correlated with the dependent variable and not correlated with the error term (Anderson, Hsiao 1981). As a generalization of the instrumental variable method, the Generalized Method of Moments (GMM) was introduced in the panel-data framework by Arellano and Bond (1991). They showed how a more efficient estimator can be obtained when additional instruments based on the orthogonality between lagged values of the dependent variable and errors are used. The selection of the instruments in GMM estimator is based on the information supplied by economic theory and/or on the conditions established over the true moments by the underlying processes. With the proper assumptions, it is possible to construct a GMM estimator that is not only efficient, but also consistent and is asymptotically normally distributed. The GMM estimator is now widely used in the estimation of short dynamic panels.

The optimal instrument matrix for GMM estimation of the fixed effects model with lagged dependent variables as explanatory depends on: a) whether the other explanatory variables in the equations are or not correlated with the fixed effects; and b) whether they are predetermined or strictly exogenous. In the model specified in this paper, $N_{i,t-1}$ is a predetermined regressor in Eq. (2), while $R_{i,t}$, $H_{i,t}$, $T_{i,t}$, $G_{i,t}$, $X_{i,t}$ and $Z_{i,t}$ enter as exogenous, and they are not likely to be correlated with the fixed regional effects of the corresponding equations. Thus, the system of Eqs (1) and (2) is a particular example of a dynamic panel model where r out of the k explanatory variables are predetermined, the rest k–r variables are strictly exogenous and, besides, all of them are not correlated with the fixed effects, θ_i. In particular, equations such as (1) and (2) may be generally expressed as (A.1):

$$y_{it} = \alpha y_{i,t-1} + \beta x_{it} + v_{it} \qquad i = 1,...,N;\ t = 1,....,T, \tag{A.1}$$

where: $x_{it} = \left\{x_{it}^{(r)}, x_{it}^{(k-r)}\right\}$ is a $1 \times k$ vector, being $x_{it}^{(r)} = \left\{x_{1it}, x_{2it},..., x_{rit}\right\}$ the vector of predetermined variables and $x_{it}^{(k-r)} = \left\{x_{(r+1)it},..., x_{kit}\right\}$ the vector of exogenous variables; α is an scalar; β is a $k \times 1$ vector of parameters; and $v_{it} = \theta_i + u_{it}$, with $\theta_i \sim N(0, \sigma_\theta^2)$ and $u_{it} \sim N(0, \sigma_\xi^2)$ are independent of each other and among themselves.

Therefore, inspired on Arellano and Bond (1991) and later works, optimal GMM estimates performing generalized least square (GLS) have been obtained in this paper from:

$$\begin{Bmatrix} \hat{\alpha} \\ \hat{\beta} \end{Bmatrix} = \left[X'WV^{-1}W'X\right]^{-1} X'WV^{-1}W'y, \tag{A.2}$$

being W the matrix of instruments defined as $W = \left[W_1', W_2',...., W_N'\right]'$, where W_i is given by (A.3), X by (A.4), y by (A.5), and V by (A.6):

$$W_i = \begin{bmatrix} W_i^* & 0 & \cdots & \cdots & 0 \\ 0 & x_{i1}^{(r)}, x_{i2}^{(r)}, x_i^{(k-r)} & 0 & \cdots & 0 \\ \vdots & 0 & x_{i3}^{(r)}, x_i^{(k-r)} & \cdots & \vdots \\ \vdots & \vdots & 0 & \ddots & 0 \\ 0 & 0 & \cdots & 0 & x_{iT}^{(r)}, x_i^{(k-r)} \end{bmatrix}, \tag{A.3}$$

where: $x_i^{(k-r)} = \left\{x_{i1}^{(k-r)}, x_{i2}^{(k-r)},..., x_{iT}^{(k-r)}\right\}$ and W_i^* is the matrix given by the expression:

$$W_i^* = \begin{bmatrix} y_{i1}, x_{i1}^{(r)}, x_{i2}^{(r)}, x_i^{(k-r)} & 0 & \cdots & 0 \\ 0 & y_{i1}, y_{i2}, x_{i1}^{(r)}, x_{i2}^{(r)}, x_{i3}^{(r)}, x_i^{(k-r)} & & \vdots \\ \vdots & 0 & \ddots & 0 \\ 0 & \cdots & 0 & y_{i1}, \cdots, y_{iT-2}, x_{i1}^{(r)}, \cdots x_{iT-1}^{(r)}, x_i^{(k-r)} \end{bmatrix};$$

$$X = \begin{bmatrix} \dot{\Delta} y_{1d} & \dot{\Delta} x_1 \\ \dot{\Delta} y_{2d} & \dot{\Delta} x_2 \\ \vdots & \vdots \\ \dot{\Delta} y_{Nd} & \dot{\Delta} x_N \end{bmatrix}, \tag{A.4}$$

being:

$$\dot{\Delta} y_{id} = \begin{Bmatrix} \Delta y_{id} \\ \ddot{y}_{id} \end{Bmatrix} \quad \Delta y_{id} = \begin{Bmatrix} y_{i2} - y_{i1} \\ y_{i3} - y_{i2} \\ \vdots \\ y_{i,T-1} - y_{i,T-2} \end{Bmatrix} \quad \dot{y}_{id} = \begin{Bmatrix} y_{i2} \\ y_{i3} \\ \vdots \\ y_{i,T-1} \end{Bmatrix};$$

$$\dot{\Delta} x_i = \begin{bmatrix} \Delta x_i \\ \dot{x}_i \end{bmatrix} \quad \Delta x_i{}' = \begin{bmatrix} \Delta x_{1i}{}' \\ \Delta x_{2i}{}' \\ \vdots \\ \Delta x_{ki}{}' \end{bmatrix} \quad \Delta x_{ji} = \begin{Bmatrix} x_{ji3} - x_{ji2} \\ x_{ji4} - x_{ji3} \\ \vdots \\ x_{jiT} - x_{ji,T-1} \end{Bmatrix} \quad \dot{x}_i = \begin{bmatrix} x_{1i2} & x_{2i2} & \cdots & x_{ki2} \\ x_{1i3} & x_{2i3} & \cdots & x_{ki3} \\ \vdots & \vdots & \ddots & \vdots \\ x_{1iT} & x_{2iT} & \cdots & x_{kiT} \end{bmatrix};$$

$$y = \begin{Bmatrix} \dot{\Delta} y_1 \\ \dot{\Delta} y_2 \\ \vdots \\ \dot{\Delta} y_N \end{Bmatrix}, \tag{A.5}$$

being:

$$\dot{\Delta} y_i = \begin{Bmatrix} \Delta y_i \\ \ddot{y}_i \end{Bmatrix} \quad \Delta y_{id} = \begin{Bmatrix} y_{i3} - y_{i2} \\ y_{i4} - y_{i3} \\ \vdots \\ y_{i,T} - y_{i,T-1} \end{Bmatrix} \quad \dot{y}_{id} = \begin{Bmatrix} y_{i2} \\ y_{i3} \\ \vdots \\ y_{i,T} \end{Bmatrix}$$

and

$$V = \sum_{i=1}^{N} W_i{}' \begin{bmatrix} \Delta u_i \Delta u_i{}' & 0 \\ 0 & \dot{u}_i \dot{u}_i{}' \end{bmatrix} W_i, \tag{A.6}$$

being:

$$\Delta u_i = \begin{Bmatrix} \hat{u}_{i3} - \hat{u}_{i2} \\ \hat{u}_{i4} - \hat{u}_{i3} \\ \vdots \\ \hat{u}_{iT} - \hat{u}_{i,T-1} \end{Bmatrix} \quad \dot{u}_{id} = \begin{Bmatrix} \hat{u}_{i2} \\ \hat{u}_{i3} \\ \vdots \\ \hat{u}_{i,T} \end{Bmatrix},$$

where: estimates of the residuals $\hat{u}_{it}$ are obtained from the preliminary one-step consistent estimator of $\{\alpha,\beta\}$ obtained after applying (A.2) with $V = W'(I_N \otimes \dot{G})W$; being I_N the identity matrix of order N, $\otimes$ the Kronecker's product symbol and $\dot{G}$ a $(T-2)(T-1) \times (T-2)(T-1)$ matrix given by:

$$\dot{G} = \begin{bmatrix} G & 0 \\ 0 & I_{T-1} \end{bmatrix} \quad G = \begin{bmatrix} 2 & -1 & 0 & \cdots & 0 & 0 \\ -1 & 2 & -1 & \cdots & 0 & 0 \\ 0 & -1 & 2 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 2 & -1 \\ 0 & 0 & 0 & \cdots & -1 & 2 \end{bmatrix}.$$

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