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KNOWLEDGE PRODUCTION IN EUROPEAN UNION: EVIDENCE FROM A NATIONAL LEVEL PANEL DATA

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Abstract
The knowledge production function framework is used to understand how territories transform specific inputs into knowledge outputs. This article focuses knowledge production function estimation at European Union with twenty five member-states using a data panel analysis between 1999 and 2003. The importance of different variables in knowledge production is tested. The econometric results underline the role of business R&D giving relevant insights for EU decision-makers, to the creation of a more integrated European Research Area and innovation cooperation within Europe.

Keywords: Knowledge Production Function, Panel Data, European Union

JEL classification: C23, O31, O38

1. Introduction

The creation of a European Research Area requires a strategy and a coherent framework to establish common measures for a territory that should, at least, have some shared features. European policies, in particular since the launching of the Lisbon Agenda in 2000, have been focusing innovation as a central topic for development. One of the crucial debates is the possibility of one size fits all innovation policies at European level and the capacity of different countries and regions to achieve satisfactory results with the same innovation policy instruments.

Knowledge production, the process that a specific territory uses to transform knowledge inputs in knowledge outputs, is particularly valuable to test econometrically hypothesis regarding the existing national specificities. The idea of a Knowledge Production Function (KPF) was popularized with the works of Griliches (1979) and adapted for different contexts. A KPF tries to understand the impacts of input variables, such as R&D expenses, scientific workforce, and qualification of human resources or economic structure, in a measure of knowledge and innovation productivity, commonly patent numbers.

In this article, using a panel data approach - for twenty-five member-states from 1999 to 2003 - two main aspects will be explored: i) firstly, the variables with a major impact in knowledge production will be discussed, and secondly, the analysis of nature of the effects for the KPF estimation will permit some findings about the homogeneity of European countries regarding innovation.

To answer these two issues the article is organized as follows. A first section underlines the relevance of patents as an innovation measure and introduces the knowledge production function framework. A second section is the empirical study. Variable definitions and descriptive statistics are analysed. The section continues with econometric estimations of a pooled least squares model and a fixed effects model. The article concludes with some policy implications.

2. Measuring of innovation dynamics and the knowledge production function

Innovation dynamics is crucial to economic growth and is a central feature in policy formulation. It is in parallel a process that is difficult to understand, quantify or intervene. One of the central difficulties regarding innovation is measurement. In this aspect, patents are important indicators of innovation (OECD, 2006) by providing a measure for output. Patents are relevant to analyse the level of knowledge diffusion across technology areas, countries, sectors, firms, or even the level of internationalisation of innovative activities. Patent indicators are commonly used to measure R&D productivity and efficiency, and to understand the structure and development of specific technologies or sectors. Patents are also used as input indicators as they represent a source of public information for subsequent inventors. The advantages of patent numbers relate to the fact that a patent is based on an invention which has an industrial application. Patent counts may cover a broad range of technologies on which there are often few other sources of data. In parallel, the contents of patent documents are a wealthy source of information. As referred by World Intellectual Property Organization (WIPO, 2008) it is widely accepted that patent statistics are a reliable, although not perfect, indicator of innovative activity. Therefore, it has become standard practice to use patent statistics for monitoring innovative activities and the development of new technologies.

Nevertheless patent indicators remain relevant by being interrelated with scientific research activities that can be converted into commercially successful innovations some restrictions in the usefulness of these indicators can be pointed (WIPO, 2008; Arundel et al; 2006; Godin, 2005). Patents are intermediate indicators; a patent focuses invention rather than innovation. Firms and industries vary in their propensities to file patents, legal systems and policies vary according to country and the patenting process varies in value and expenses, creating diversity in patenting behaviors between firms, sectors, regions and countries. The accuracy of patent measures is bigger in sectors or technologies where a high percentage of the research output is patented such as in pharmaceuticals, medical instruments or biotechnology.

In the US, after the Bayh Dole Act many universities initiated and/or expanded their technology transfer initiatives through patenting and licensing. Even if the Act had not the deep impact as it is usually referred (Rafferty, 2008) and the increase of university patenting activity was also stimulated by other factors and trends occurring in parallel (Berman, 2008; Mowery et al, 2001) the patent numbers rose considerably. Patenting is today increasing world-wide at an unprecedented pace. Official statistics evidence this increase in patent numbers (WIPO, 2008) referring that the number of patents has, in average, increased annually 4.7% since 1995, reaching in 2005 to more than 1.6 million requests.

Patent numbers are important indicators of economic change because its aggregate number evidences shifts in science and technology (Griliches, 1990). One way to understand the inter-relations in innovation dynamics is trough the creation of a knowledge production function. Usually a KPF associates inputs of innovation, such as R&D human resources or expenses, to outputs, commonly measured by patent counts. Crucial contributions to this stream of literature came from Griliches (1979, 1990) with a three equation system including the KPF and also a production function and another one with the determinants of R&D expenses. The ideas based in KPF were also connected with contributions linking human capital, R&D expenses, innovation dynamics to economic growth (e.g. Romer, 1990).

To estimate a significant KPF each statistical unit should represent the central systemic relation in the innovation process. This regards a central assertion of considering the national level as the main systemic level for knowledge production in EU level. Having, of course evident limitations especially because of the role of geographical proximity in knowledge spill-overs (Paci and Usai, 2009), the nation-states remain a central analytical and political unit mainly because of the relevance of national governments in policy making and institutional building (Hancké, 2009). National innovation systems remain an interesting notion to understand differences in national profiles and competitiveness (Lundvall, 2007).

Using the KPF framework, the analysis of what determines EPO patents per capita in 22 countries in 1980-1999 (Falk, 2005) showed that the specialization in information and communications technologies has a significant and positive impact in patenting. The study also underlined that business R&D was more effective in generating patent applications than public R&D. Sanyal and Jaffe (2004) and Furman et al (2002) also find that business R&D is the crucial variable for patenting dynamics. A broader range of independent variables is currently being added to KPF specifications to test particular hypothesis related with the diversity of industrial specialization, relevance of small companies or participation in knowledge networks. Several applications underline specific aspects of economic process, the relation of knowledge production and total factor productivity (Abdih and Joutz, 2006), the output of innovation activity and quality of education and governmental institutions (Varsakelis, 2006), the efficiency of R&D capital stock and manpower (Wang, 2007), the linkages of international spill-overs and absorptive capacity (Mancusi, 2008), knowledge production and different types of proximity (Marrocu et al, 2011). The main findings are consistent: R&D policies, that increase the stock of knowledge, accelerate innovation and induce economic growth. Firms continue to play the crucial role in innovation dynamics.

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3. Estimating a knowledge production function for EU-25

3.1. Presentation of data

This section intends to comprehend the main drivers of patents by estimating an econometric model that underlines the relations of several science and technology indicators with patents at European national level. Even if patents are not the perfect knowledge production metric, patent-based indicators assume a huge relevance in innovation studies and research evaluation because are based on inventions which have industrial application and cover a broad range of technologies on which there are often few other sources of information. The interest in analysing macro-level variables is crucial as a preliminary approach to understand patenting dynamics. The integration of the model facilitates the understanding of what kind of factors have the central role in patent numbers in Europe in a context characterized by the relevance of patent indicators and its migration from being a means to becoming an end.

This estimation follows from a previous analysis (Pinto and Rodrigues, 2010) where evidences at regional scale in EU were found about the central importance of private R&D to patenting dynamism. In that opportunity the data only permitted a cross-sectional analysis but the interest in taking into account also patterns of relative evolution induced the search for relevant data.

In this way, this new estimation uses RIS - Regional Innovation Scoreboard 2006 database (European Commission, 2006) with twenty five member-states (Belgium, Czech Republic, Denmark, Germany, Estonia, Greece, Spain, France, Ireland, Italy, Cyprus, Latvia, Lithuania, Luxembourg (Grand-Duché), Hungary, Malta, Netherlands, Austria, Poland, Portugal, Slovenia, Slovakia, Finland, Sweden and United Kingdom, between 1999 and 2003. The selected variables (table 1) are related to knowledge workers (HRSTC), life-long learning (LLL), public R&D (PUBRD), business R&D (BERD) med-high tech manufacturing employment (MHTMAN), high-tech services employment (HTSER), and EPO patents (PATENT).

The data collected was indexed in each year to EU average (EU-25=100) in order to eliminate problems related with the diversity of units and to homogenize the understanding of the coefficients. In this way it can be detected variations of relative positions of countries from year to year, understanding the comparative evolution of each member-state.

Table 1 - Variables included in the estimation process

NAME	DEFINITION	RELEVANCE
HRSTC	Human Resources in Science and Technology – Core (% of population)	A rapidly changing economic environment and a growing emphasis on the knowledge-based economy have seen mounting interest in the role and measurement of skills. Meeting the demands of the new economy is a fundamental policy issue and has a strong bearing on the social, environmental and economic well-being of the population. Data on Human Resources in Science and Technology (HRST) can improve our understanding of both the demand for, and supply of, science and technology personnel — an important facet of the new economy.
LLL	Participation in life-long learning per 100 population aged 25-64)	A central characteristic of a knowledge economy is continual technical development and innovation. Individuals need to continually learn new ideas and skills or to participate in life-long learning. All types of learning of valuable, since it prepares people for "learning to learn". The ability to learn can then be applied to new tasks with social and economic benefits.
PUBRD	Public R&D expenditures (% of GDP)	R&D expenditure represents one of the major drivers of economic growth in a knowledge based economy. As such, trends in the R&D expenditure indicator provide key indications of the future competitiveness and wealth of the EU. Research and development spending is essential for making the transition to a knowledge-based economy as well as for improving production technologies and stimulating growth.
BERD	Business R&D expenditures (% of GDP)	The indicator captures the formal creation of new knowledge within firms. It is particularly important in the science-based sector (pharmaceuticals, chemicals and some areas of electronics) where most new knowledge is created in or near R&D laboratories.
MHTMAN	Employment in medium-high and high-tech manufacturing (% of total workforce)	The share of employment in medium-high and high technology manufacturing sectors is an indicator of the manufacturing economy that is based on continual innovation through creative, inventive activity. The use of total employment gives a better indicator than using the share of manufacturing employment alone, since the latter will be affected by the hollowing out of manufacturing in some countries.
HTSER	Employment in high-tech services (% of total workforce)	The high technology services both provide services directly to consumers, such as telecommunications, and provide inputs to the innovative activities of other firms in all sectors of the economy. The latter can increase productivity throughout the economy and support the diffusion of a range of innovations, in particular those based on ICT.
PATENT	EPO patents per million population	The capacity of firms to develop new products will determine their competitive advantage. One indicator of the rate of new product innovation is the number of patents. This indicator measures the number of patent applications at the European Patent Office.

Source: European Commission (2006: 4-5) adapted

A first glance of descriptive statistics (Table 2) underlines some interesting features.

- The high dispersion of PATENT and BERD variables;
- The lowest dispersion of PUBRD when compared with BERD;
- PATENT, BERD and LLL assume a non-normal distribution.

Table 2 - Descriptive statistics

Variables	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
PATENT	75.85	27	273	0	83.65	0.91	2.54	18.24
HRSTC	102.67	101	176	51	33.28	0.42	2.20	7.03
LLL	104.51	72	363	13	79.79	1.41	3.91	45.41
MHTMAN	84.91	95	167	9	38.09	-0.23	2.34	3.32
HTSER	96.85	94	167	38	31.11	0.26	2.24	4.45
PUBRD	79.57	80	155	20	33.93	0.14	2.35	2.61
BERD	71.57	60	263	1	62.07	1.04	3.76	25.55

Source: Own elaboration

The correlation analysis of the stacked data (Table 3) shows that the variables included have small correlations reducing the risk of multicollinearity. Patenting is correlated positively with the existence of human resources in S&T and with business R&D expenses. The other correlations are not significant but there is the curiosity that PUBRD, MHTMAN and HTSER exhibit negative correlations. BERD is more correlated with the public R&D and life-long learning.

Table 3 - Correlation matrix

Variables	PATENT	HRSTC	LLL	PUBRD	BERD	MHTMAN	HTSER
PATENT	1	0.229	0.003	-0.090	0.130	-0.068	-0.120
HRSTC	0.229	1	0.022	0.117	-0.157	-0.071	-0.058
LLL	0.003	0.022	1	0.089	0.145	-0.115	-0.043
PUBRD	-0.090	0.117	0.089	1	0.155	-0.052	0.100
BERD	0.130	-0.157	0.145	0.155	1	-0.047	0.114
MHTMAN	-0.068	-0.071	-0.115	-0.052	-0.047	1	0.170
HTSER	-0.120	-0.058	-0.043	0.100	0.114	0.170	1

Source: Own elaboration

3.2. Econometric evidences

A preliminary general-to-particular approach, inspired in Hendry´s methodology (Hendry, 1979), permitted the simultaneous insertion of all variables in study and eliminate one-by-one the non significant ones based in a t-test. This approach facilitates the creation of parsimonious parametric relationships that can be understood in its economic significance. This approach is useful to illuminate new paths departing from an encompassing structure of the economic process.

The method used was pooled least squares (PLS) with White heteroskedasticity-consistent standard errors and covariance. The total balanced panel had 125 observations. The final model using homogeneous intercepts and coefficients is synthesized in Table 4[1].

Table 4 - PLS regression results, Dependent variable PATENT

Variable	C	HRSTC	PUBRD	BERD	R-squared	Adjusted R-squared	S.E. regression	F-statistic
Coefficient	-47.29	0.28	0.29	1.06	0.86	0.86	31.78	246.07
Std. Error	10.61	0.09	0.12	0.086	Mean dep. Var.	S.D. dep. Var.	S.S. resid	Prob (F-statistic)
t-Statistic	-4.46	3.06	1.96	12.48				
Prob.	0.00	0.00	0.05	0.00	75.85	83.65	122193.50	0.00

Source: Own elaboration

The estimated PLS knowledge production function can be written as:

$$PATENT_{it} = -47.29 + 0.28HRSTC_{it} + 0.29PUBRD_{it} + 1.06BERD_{it} \qquad (1)$$

This model underlines the crucial relevance of BERD in the knowledge production. Human resources and public R&D are also statistically significant but have a more limited impact in patent numbers.

For the specific estimation of the panel data model some preliminary steps must be done to assure the reliability of the analysis. It is relevant to confirm the poolability of the data to understand the heterogeneity of the cases, i.e., if we use common intercepts and coefficients, heterogeneous intercepts but common coefficients or if the analysis must be based in conditional variation of some variables. Commonly homogeneous intercepts and coefficients assumption is an unrealistic approach based in a too restrictive condition especially with the preliminary notion about the diversity of national behaviors on patent registration.

The use of pool data methods in this study was validated by an F-test as recommended in Baltagi (2001) and Woolridge (2006). Due to the lack of degrees of freedom two different F-tests were conducted[2]. The nature of effects and the detection of the type of patterns among the intercept and the coefficients in different cases are central in panel data. Taking into account the observations of our dependent variable y in i=1,…, N cases in t=1,..., T periods and k=1, …, K explicative variables defined by a vector K * 1 x, the classic linear regression model assumes the following form:

[1] The software used was E-Views - version 4.1.

[2] F-test 1=A restricted model with homogeneous intercept and coefficients *vs* an unrestricted model with heterogeneous intercept and common coefficients. F-test 2=A restricted model without intercept and homogeneous coefficients: *vs* an unrestricted model without intercept and heterogeneous coefficients. Null hypothesis of homogeneous intercept and coefficients were accepted.

$$y_{it} = a_i + b_i' x_{it} + \varepsilon_{it} \quad (2)$$

The error is independent identically distributed, iid (0, σ2ε). If the intercepts (a_i) are correlated with the explicative variables coefficients (x_{it}) a fixed effect estimation procedure is adequate. If the a_i's are not correlated with the x_{it} a random effect model is more suitable. To understand this correlation a first procedure was to use the previously estimated PLS model and analyze the coefficient covariance matrix (Table 5). In the first column of table it can be observed a relevant relation between the intercept and the coefficients. This analysis suggests that using fixed effects may be more adequate for our data patterns.

Table 5 - Covariance coefficient matrix

C	HRSTC?	LLL?	MHTMAN?	PUBRD?	BERD?	HTSER?
195.1250	-0.900800	0.459857	-0.458026	-0.975404	0.777280	-0.951099
-0.900800	0.016686	-0.002924	0.015175	-0.004010	0.003612	-0.017194
0.459857	-0.002924	0.004755	-0.001126	-0.001042	6.46E-06	-0.005027
-0.458026	0.015175	-0.001126	0.024430	-0.008343	0.006587	-0.028347
-0.975404	-0.004010	-0.001042	-0.008343	0.016569	-0.008846	0.015982
0.777280	0.003612	6.46E-06	0.006587	-0.008846	0.012449	-0.018524
-0.951099	-0.017194	-0.005027	-0.028347	0.015982	-0.018524	0.057233

Source: Own elaboration

To conclude about the nature of the effects it is important to perform a more robust test. The Hausman test, frequently used in the literature for this outcome, verifies given a model and data in which fixed effects estimation would be appropriate, whether random effects estimation would be as good (Hausman, 1978). The Hausman test is a test of hypothesis (H_0: random effects are consistent and efficient versus H_1: random effects are inconsistent when compared to fixed effects). In our case the Hausman statistic supports the rejection of the null hypothesis of the intercept not being correlated with the explicative variable[3]. In this way the individual fixed effects model is the adequate procedure to carry on the estimation. The procedure used was a general-to-specific modelling approach with a Generalized Least Squares Estimator (GLS) and White Heteroskedasticity-Consistent Standard Errors and Covariance. The final model is synthesized in Table 6.

[3] Hausman = 1 785 082.00 compared to a Chi-squared distribution critical value of 12.592 (Sig.=0.05 and six degrees of freedom).

Table 6 - Fixed effects regression results, Dependent variable PATENT

Method: GLS (Cross Section Weights) Sample: 1999-2003				
Included observations: 5 Number of cross-sections used: 25 Total panel (balanced) observations: 125				
One-step weighting matrix White Heteroskedasticity-Consistent Standard Errors & Covariance				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
BERD?	0.036679	0.016727	2.192816	0.0307
HTSER?	-0.050630	0.011257	-4.497459	0.0000
Fixed Effects				
_BE--C	109.9664			
_CZ--C	11.09115			
_DK--C	162.4061			
_DE--C	226.4813			
_EE--C	10.04904			
_GR--C	8.357278			
_ES--C	22.40376			
_FR--C	110.4908			
_IE--C	63.40595			
_IT--C	65.54430			
_CY--C	13.26070			
_LV--C	7.170732			
_LT--C	4.111195			
_LU--C	147.5707			
_HU--C	16.91240			
_MT--C	14.98725			
_NL--C	183.6835			
_AT--C	127.7238			
_PL--C	4.736078			
_PT--C	5.314075			
_SI--C	28.75519			
_SK--C	7.407898			
_FI--C	252.9892			
_SE--C	249.8249			
_UK--C	98.51552			
Weighted Statistics				
R-squared	0.997539	Mean dependent var		109.3417
Adjusted R-squared	0.996886	S.D. dependent var		128.5728
S.E. of regression	7.174957	Sum squared resid		5045.040
F-statistic	1527.699	Durbin-Watson stat		1.727219
Prob(F-statistic)	0.000000			
Unweighted Statistics				
R-squared	0.990905	Mean dependent var		75.84800
Adjusted R-squared	0.988493	S.D. dependent var		83.65097
S.E. of regression	8.973456	Sum squared resid		7891.245
Durbin-Watson stat	1.433663			

Source: Own elaboration

BERD assumes again the central relevance. It is the main instrument to induce knowledge production. In this approach, human resources in knowledge intensive services have a significant negative coefficient, suggesting that some sort of crowding-out effect between advanced services and patenting propensity may exist.

The different intercepts may also be understood as departure points for EU member-states in knowledge production. Figure 1 show, at least, three different groups of countries. Taking in mind these results with the profiles from the varieties of social systems of innovation and production (Amable and Lung, 2008) we can identify one group of member-states with higher performances (>150) linked with Socio-democrat capitalism (FI, SE, DE, NL and DK), a group of countries with intermediate (50-150) knowledge output (LU, AT, FR, BE, UK, IT, IE), linked with the Anglo-Saxon economies and the Continental capitalism, and finally, a group with modest results (<50) constituted by member-states from Mediterranean and East Europe capitalism.

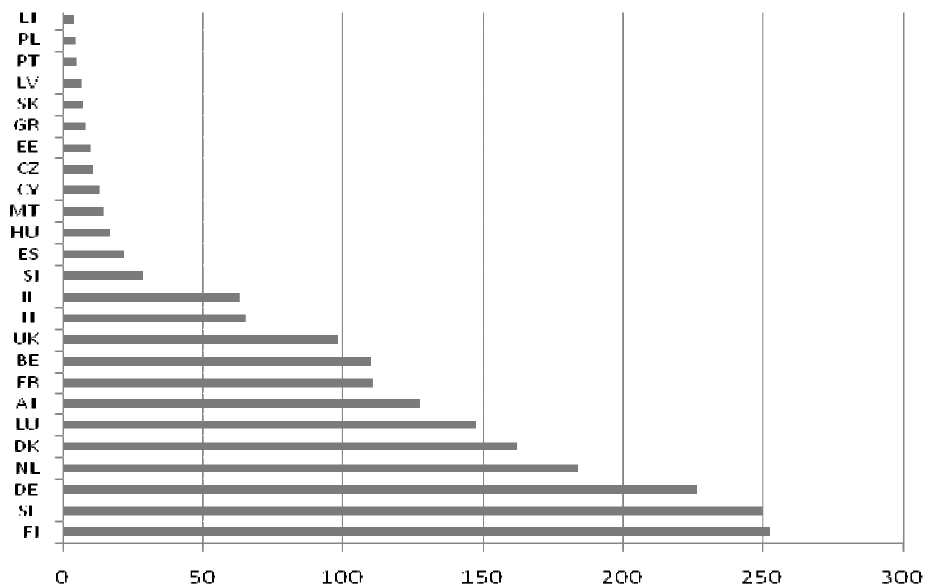

Figure 1- Intercepts of member-states as departure points in knowledge production
Source: Own elaboration (Note: Original variables are expressed relatively to EU-25 annual average=100)

4. Policy implications and concluding remarks

The econometric results emphasize the crucial impact of business R&D expenditures and the existence of human resources in Science and Technology to the number of patents. Business R&D is the only significant variable in both models, pooled least squares and fixed effects. Patent registration and licensing are important mechanisms to bring to market new ideas and transfer new knowledge across institutional borders. Firms that demonstrate minor capacities to invest in R&D have also a smaller absorptive capacity as suggested by Cohen and Levinthal (1990). In this way the knowledge transfer processes may be ineffective as no linkages between research and economic activities exist. A necessary requirement can be a minimum threshold of human capital operating in private and public bodies, as confirmed by the estimated models, which permits the creation and utilization of new knowledge and its successful share, production and protection for appropriating related benefits. The estimation results follow others underlined by different authors when estimating knowledge production functions using patent numbers as a proxy to innovation and public and private R&D as inputs (inter alia, Jaffe, 1989). Nevertheless the importance of public expenses in research and development activities they seem to have a secondary role in patenting dynamics when compared with the direct impact of private efforts. Firms remain the central actor in appropriating the value of knowledge through the commercialisation of products and to incorporate relevant innovations derived from scientific research and academic institutions.

In sum, the panel data macro level models, even if only a rough approximation and suffering from several limitations, confirm in EU member-states the direct impact of the private expenditures in R&D in the dynamics of innovating, measured by patenting numbers. Firms remain central to transform knowledge in inventions with innovative potential. The model underlines a interesting aspect for an effective ERA structure, even if national level variety exists, proved by the existence of heterogeneous intercepts, a similar capacity to transform innovation inputs in outputs in relative terms, the homogeneous coefficients, subsist. Nonetheless is crucial to understand that for each case the departure point is different and policies need to take into account this diversity that restricts the capacity to produce knowledge outputs.

The results of the current article also increase the interest for the utilization of KPF framework to test the importance of different types of proximities in the knowledge production in European Union. Following the ideas that proximity is not limited to geographical distance (Boschma, 2005 or Torre and Rallet, 2005), the utilization of data panel and spatial econometric techniques can be useful to test, in a future analysis, the relevance of physical distance (measured in kilometres between the capital city's distances), geographical contiguity (a dummy that assumes the value 1 if bordering countries, 0 if not), linguistic distance (differences regarding the percentage of population with English proficiency), institutional proximity (belonging of the similar type of capitalism, e.g., Amable and Lung, 2008), technological distance (differences of knowledge-intensive workers share, and finally, the economic distance (measured by differences in GDP level) in knowledge production and spill-over generation.

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References

Abdih Y, Joutz F (2006). Relating the Knowledge Production Function to Total Factor Productivity: An Endogenous Growth Puzzle. *IMF Staff Papers*. Vol. 53(2).

Amable B, Lung Y (2008). The European Socio-Economic Models of a Knowledge-based society. Main findings and conclusion. *Cahiers du GREThA 2008-26*. Groupe de Recherche en Economie Théorique et Appliquée.

Arundel A, Colecchia A, Wyckoff A (2006). Rethinking science and technology indicators for innovation policy in the twenty-first century. In Louise E, Gault F, (eds) National innovation, indicators, and policy, pp. 167-198 Edward Elgar Publishing.

Baltagi HB (2001). Econometric Analysis of Panel Data. John Wiley & Sons.

Berman EP (2008). Why Did Universities Start Patenting? Institution-Building and the Road to the Bayh-Dole Act. *Social Studies of Science*. 38(6): 835-871.

Boschma R (2005). Proximity and Innovation: A Critical Assessment. *Regional Studies*. 39: 61-74.

Cohen W, Levinthal D (1990). Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly*. 35: 128-152.

European Commission (2006). *European Regional Innovation Scoreboard 2006*. Report prepared by Hugo Hollanders. MERIT – Maastricht Economic and social Research and training centre on Innovation and Technology.

Falk M (2005). What determines Patents per Capita in OECD Countries?. *WIFO Working Papers*, No 242. WIFO.

Furman JL, Porter ME, Stern S (2002). The Determinants of National Innovative Capacity. *Research Policy*. 31(6): 899-933.

Godin B (2005). *Measurement and Statistics on Science and Technology: 1920 to the Present*. Routledge.

Griliches Z (1979). Issues in Assessing the Contribution of Research and Development to Productivity Growth.*Bell Journal of Economics*. The RAND Corporation. 10: 92-116.

Griliches Z (1990). Patent Statistics as Economic Indicators: A Survey. *Journal of Economic Literature*. 28: 1661-1707.

Hancké B (2009). Introducing the Debate. In Hancké B (ed.) *Debating the Varieties of Capitalism – A Reader*. Oxford University Press.

Hausman JA (1978). Specification Tests in Econometrics. *Econometrica*. 46 (6): 1251–1271.

Hendry DF (1979). Predictive failure and econometric modelling in macroeconomics: The transactions demand for money. In Ormerod P (ed.) *Economic Modelling*. Heinemann.

Jaffe A (1989). Real effects of academic research. *American Economic Review*. 79: 957-970.

Lundvall BA (2007) National Innovation Systems – Analytical Concept and Development Tool. *Industry & Innovation*. 14: 95-119.

Mancusi ML (2008). International spill-overs and absorptive capacity: A cross-country cross-sector analysis based on patents and citations. *Journal of International Economics*. 76(2): 155-165.

Marrocu E, Paci R, Usai S (2011). Proximity, Networks and Knowledge Production in Europe. *Working Paper CRENoS 201109*. Centre for North South Economic Research. University of Cagliari and Sassari, Sardinia.

Mowery D, Nelson RR, Sampat BN, Ziedonis A (2001). The growth of patenting and licensing by U.S. universities: an assessment of the effects of the Bayh-Dole act of 1980. *Research Policy*. 30(1): 99-119.

OECD (2006). *Compendium of Patent Statistics*. OECD Publications.

Paci R, Usai S (2009). Knowledge flows across European regions. *The Annals of Regional Science*. 43: 669-690.

Pinto H, Rodrigues P (2010). Knowledge Production in European Regions: The Impact of Regional Strategies and Regionalization on Innovation. *European Planning Studies*. 19(10): 1731-1748.

Rafferty M (2008). The Bayh-Dole Act and university research and development. Research Policy. 37(1): 29-40.

Romer PM (1990). Endogenous Technological Change. *Journal of Political Economy*. 98: 71-102.

Sanyal P, Jaffe A (2004) Peanut Butter Patents Versus the New Economy: Does the Increased Rate of Patenting Signal More Invention or Just Lower Standards?. *Social Science Research Network*. 79-80(April): 1-45.

Torre A, Rallet A (2005). Proximity and Localization. *Regional Studies*. 39: 47-59.

Varsakelis N (2006). Education, political institutions and innovative activity: A cross-country empirical investigation. *Research Policy*. 35(7): 1083-1090.

Wang E (2007). R&D efficiency and economic performance: A cross-country analysis using the stochastic frontier approach. *Journal of Policy Modelling*. 29: 345-360.

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Econ Res Guard 1(2): 72-87

WIPO (2008) *World Patent Report – A Statistical Review*. 2008 Edition. WIPO Publication No. 931(E). World Intellectual Property Organization.

Woolridge JM (2006). *Introdução à Econometria: uma abordagem moderna* [Introduction to Econometrics: A modern approach]. Tradução de Rogério Cezar de Souza, Revisão Técnica de Nelson Carvalheiro, São Paulo, Pioneira Thomson Learning.

Appendix

Table A1 - Initial Pooled Least Squares model before non-significant variable elimination, Dependent variable PATENT

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-47.27719	13.96871	-3.384506	0.0010
HRSTC?	0.211062	0.129175	1.633923	0.1049
LLL?	-0.082621	0.068958	-1.198143	0.2333
MHTMAN?	-0.136112	0.156300	-0.870838	0.3856
PUBRD?	0.315984	0.128719	2.454828	0.0156
BERD?	1.079878	0.111576	9.678447	0.0000
HTSER?	0.198460	0.239234	0.829563	0.4085
R-squared	0.862380	Mean dependent var		75.84800
Adjusted R-squared	0.855382	S.D. dependent var		83.65097
S.E. of regression	31.81132	Sum squared resid		119411.3
F-statistic	123.2389	Durbin-Watson stat		0.157108
Prob(F-statistic)	0.000000			

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Econ Res Guard 1(2): 72-87

Table A2 - Initial GLS model before non-significant variable elimination, Dependent variable PATENT

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HRSTC?	0.052737	0.020034	2.632420	0.0099
LLL?	-0.024499	0.020004	-1.224667	0.2238
MHTMAN?	-0.052774	0.012022	-4.389764	0.0000
PUBRD?	-0.040140	0.022942	-1.749648	0.0834
BERD?	0.061184	0.032302	1.894143	0.0613
HTSER?	-0.052664	0.017314	-3.041619	0.0030
Fixed Effects				
_BE--C	110.9567			
_CZ--C	17.53462			
_DK--C	166.4643			
_DE--C	232.3418			
_EE--C	12.15090			
_GR--C	8.286226			
_ES--C	24.12721			
_FR--C	113.4751			
_IE--C	65.21562			
_IT--C	72.05540			
_CY--C	9.911629			
_LV--C	8.126951			
_LT--C	4.320619			
_LU--C	143.2694			
_HU--C	22.94439			
_MT--C	20.69059			
_NL--C	187.4141			
_AT--C	133.0154			
_PL--C	8.340378			
_PT--C	8.162529			
_SI--C	36.32940			
_SK--C	12.81635			
_FI--C	257.5608			
_SE--C	253.9637			
_UK--C	105.2836			
Weighted Statistics				
R-squared	0.997885	Mean dependent var		104.8917
Adjusted R-squared	0.997210	S.D. dependent var		129.8792
S.E. of regression	6.859669	Sum squared resid		4423.175
F-statistic	1478.612	Durbin-Watson stat		1.629756
Prob(F-statistic)	0.000000			
Unweighted Statistics				
R-squared	0.991122	Mean dependent var		75.84800
Adjusted R-squared	0.988289	S.D. dependent var		83.65097
S.E. of regression	9.052489	Sum squared resid		7703.070
Durbin-Watson stat	1.452147			

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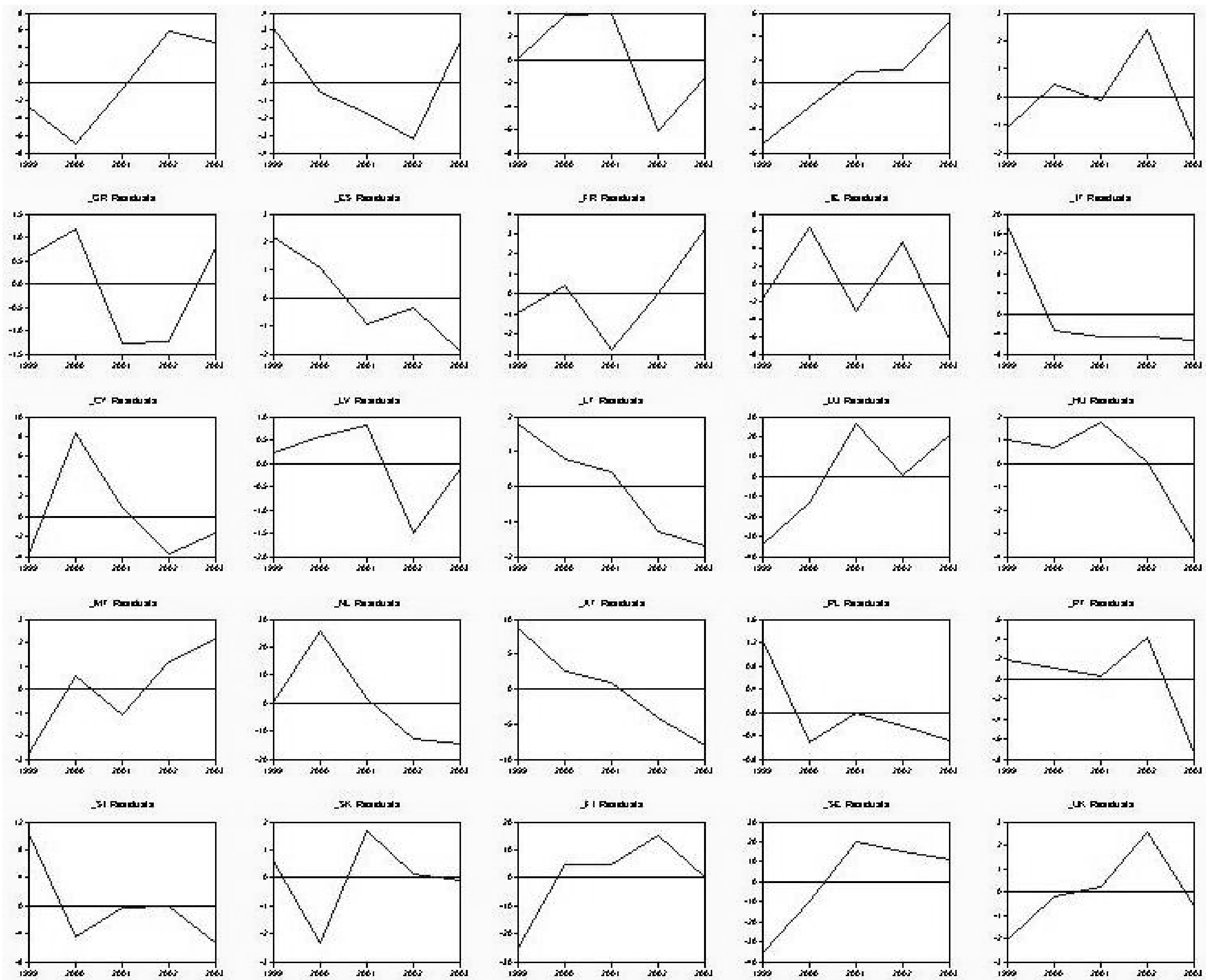

Figure A1 - Residuals of GLS method for cross-sectional units