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Innovation Diffusion: a Sectoral Econometric Approach[1]

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Abstract

This paper aims to study some of the factors that influence the sectoral diffusion of innovation. The final objective is to arrive at a model of innovation diffusion in order to analyse how different economic policies can help to promote it.

In the first place, an exploratory analysis is carried out in which some new statistics such as the sectoral autocorrelation coefficient are used. Secondly, causal analysis is conducted through a sectoral econometric model, where the input-output technical coefficient matrix is used as intersectoral interdependence.

The proposed model is applied to the Spanish economy using data for the periods 1995 and 2001.

[1] (DRAFT VERSION, please do not reference it)

1.- Introduction

In a variety of ways, input-output (I-O) analysis —as originally conceived by Leontief— plays an important role in quantitative economics and is an integral part of econometrics. Sometimes it is used more directly in the form of non-stochastic measurement, although the usual way that the subject is used in econometrics is coupled with statistical inference methods. Nevertheless, the use of I-O analysis ideas in econometrics goes far beyond conventional model building. By analogy, it affects many branches of econometric work and the modelling of intersectoral trade flows (Klein, 1989). In fact, new developments in the study of technical change appear to be particularly promising when they are approached within the framework of I-O analysis.

The original static I-O problem has traditionally been the search for an "equilibrium" output vector for the I-O sectors composing the economic system, in such a way that it could conveniently face the predetermined final demand vector. Particularly, when expressed according to I-O sectors and induced industrial demand, we have that:

$$x = A\, x + f \tag{1}$$

and the solution is the standard demand side Leontief model:

$$x = (I - A)^{-1}\, f \tag{2}$$

where: x is a column vector of output, f is a column vector of final demand, I is the identity matrix, and A is the interindustry matrix of direct input coefficients. The matrix $(I-A)^{-1}$ is usually referred to as the Leontief multipliers matrix and its elements show the direct and indirect requirements of output per unit of final sectoral demand.

Moreover, according to the INFORUM[2] approach to interindustry modelling (Almon, 1991) both real and nominal sides are fully integrated and the original I-O equation can be rewritten (Bardazzi, 1996) as:

$$x = (I - A)^{-1}\, h(x, p, z) \tag{3}$$

where z denotes the variables that are assumed to be exogenous to the model and p represents prices. So, the endogenization of final demand allows prices and quantities to

[2] Interindustry Forecasting Project University of Maryland.

be meaningfully incorporated as endogenous explanatory variables and to explicitly express the vector of sectoral outputs as depending on a bunch of exogenous variables.

Once equation (3) has been reached, new issues must be faced. In particular, topics such as specifying and jointly estimating the model must be addressed. The first topic is dealt with immediately, while an answer to the second one is developed later in the paper. Specifically, a feasible specification for equation (3) could be achieved through an econometric model like the following:

$$x = \beta_1 \ (I - A)^{-1} z_1 + \beta_2 \ (I - A)^{-1} z_2 + \ldots.. + u \qquad (4a)$$

where β_1, β_2, … are the coefficients, z_1, z_2, … are column vectors of regressors, and u is a column vector of random variable.

Equation (4) could be economically interpreted as a linear production function where variables z_1, z_2, z_3 are the inputs (e.g. physical and human capital). However, it shows several limitations, one of which is that this specification does not distinguish between intersectoral and intrasectoral effects. The intersectoral effects are the result of interaction among sectors (interindustrial relationships), while the intrasectoral effects are consequence of each sector's size and efficiency. So, in order to reinterpret equation (4a) to focus on spillovers, the matrix of technical coefficients, A, is decomposed —in equation (4b)— as a sum of two matrices, B and C. B is a null diagonal matrix with off-diagonal elements identical to those in A, and C is the diagonal matrix of internal sectoral technical coefficients, that is C = diag(A). So, we have that:

$$x = \beta_1 \ (I - B - C)^{-1} z_1 + \beta_2 \ (I - B - C)^{-1} z_2 + \ldots.. + u \qquad (4b)$$

which when used in the present case $B \ C \approx 0$, could be approximated by:

$$x \approx \beta_1 \ (I + B(I - B)^{-1} + C(I - C)^{-1}) \ z_1 + \ldots.. + u \qquad (4c)$$

in order to eventually reach the following expression:

$$x \approx \beta_1 \ z_1 + \beta_1 \ B(I - B)^{-1} \ z_1 + \beta_1 \ C(I - C)^{-1} \ z_1 + \ldots.. + u \qquad (4d)$$

which has a very rich interpretation from an economic perspective. Particularly, following van der Linden and Oosterhaven (1995), the first term of the second part of equality is the impact multiplier; the second term captures intersectoral spillovers, while the third term covers intrasectoral spillovers.

Equation (4d), however, which could be observed as a model in reduced form, has significant drawbacks when it comes to being interpreted and estimated that should not be ignored. These include:

- The coefficients of intersectoral and intrasectoral spillovers are equal. This is very rare, as it would imply that both kinds of spillovers would be equally significant.
- It is impossible to distinguish between the effect and the spillover of each factor.
- And, from an econometric viewpoint, equation (4d) has serious multicolinearity problems.

Nevertheless, in this work equation (4) is used a reference and it has been our source of inspiration in order to develop the model that, including intersectoral interdependence, we propose in this manuscript. However, the model will be specified in structural form and the resulting equation will be estimated using a procedure that takes into account intersectoral relationships to deal with the aforementioned problems. Regarding this last issue, we find that spatial econometrics —after the necessary adjustments—, constitutes an excellent tool to tackle this problem, Anselin (1995). So from this point onwards, sectoral econometrics will be called the use of spatial econometrical techniques to analyse intersectoral relationships.

The rest of the paper is organised as follows. Section two introduces the novel concept of sectoral autocorrelation. In Section three develops the econometric model and discusses the alternatives. In section four the model previously suggested is estimated and results are presented. Finally, section five summarises and concludes the paper.

2. Sectoral Autocorrelation: a New Concept

According to the reasoning in the previous section, the proposed model would be characterised by the presence of sectoral interdependence. That is to say, intersectoral relationships should be included. Theoretically speaking, it is logical to assume the existence of sector interdependence, as an increase in production in one sector leads to greater production in the rest of sectors. However, these sectoral relationships are not symmetrical, as an increase in one sector will not affect the rest of sectors equally. Consequently, before the causal specification of an econometric model of sectoral innovation diffusion, which can explain sectoral interdependence clearly, we must let the data talk. This makes studying the univariante sectoral dependence of each variable and analysing the possible presence of sectoral autocorrelation a must.

The concept of dependence or sectoral autocorrelation therefore emerges when there is a relationship between what happens in one sector and what happens in the rest.

That is, the value that a variable takes in one sector not only depends on the sector's own characteristics, but also on the value this variable takes in the rest of sectors.

The concept of sectoral autocorrelation will therefore be developed similarly to that of special autocorrelation. So, sectoral autocorrelation is multidirectional, as is the case with spatial autocorrelation and opposite to temporal autocorrelation, which is unidirectional. Thus, the concept needs a matrix of sector weightings (called a non-stochastic square matrix) to be defined, which has variables that capture the degree of interdependence between pairs of sectors.

Sectoral autocorrelation or the degree of sectoral dependence can be captured by means of the I statistic (Moran, 1948), which is defined as:

$$\mathrm{I} = \frac{N}{\sum_i \sum_j w_{ij}} \; \frac{\sum_{ij} w_{ij} (X_i - \overline{X})(X_j - \overline{X})}{\sum_i (X_i - \overline{X})^2} \tag{5}$$

where X_i and X_j are the observations for sector i and j of the variable of interest, $\overline{X}$ is the sectoral average, N is the number of observations and w_{ij} is the i-j element of the row-standardised W matrix of weights. As the factor $\sum_i \sum_j w_{ij}$ equals N in the case of a row-standardised matrix of weights, the first quotient of (5) is equal to one, so following Cliff and Ord (1981) this statistic has normal-standard distribution under the null hypothesis of sectoral independence in the variable under analysis. The rejection of the null hypothesis indicates that the distribution of the variable among sectors is non-random, and that it follows the patterns defined in the matrix of weights.

Sectoral autocorrelation can be positive or negative. For example, positive sectoral autocorrelation exists if the presence of a particular phenomenon in one sector favours the diffusion of that same phenomenon to the rest of sectors.

Once the concept of sectoral autocorrelation has been defined and a coefficient for its measurement has been exposed, the next question to be studied is the influence of interindustrial inequalities in the distribution of activity and how this affects sectoral production activity. So, some Spanish economic variables —usually identified in the literature as key explanatory variables— are analysed in this section in order to find out whether they display sectoral autocorrelation. However, the question of what weight matrix could be used is unclear.

Indeed, there are no universal criteria for defining the weight matrix and the use of different matrices could be argued. However, we are of the opinion that sectoral dependence is properly captured by the Leontief technical coefficient, so the internal technical coefficient matrix, A, is used in this paper as a measurement of sectoral interdependence. Nonetheless, despite considering a matrix of weights based on the direct input coefficients among sectors, the distance between two sectors can differ from interindustry distance. Thus, for example, Schumpeter defines a coefficient of innovative contiguity between productive sectors, $w_{ij} = 1$, if the intensity in their commercial relationships is higher than the average.

Table 1 shows the results of computing Moran's I statistic for several variables. In all cases, the null hypothesis of random distribution is rejected and positive evidence of the existence of sectoral autocorrelation among Spanish sectors is thereby obtained. These results mean that productive activity in one sector is correlated to the profitability of other sectors.

Table 1. Sectoral Autocorrelation in Productive Activity
(Moran's I test, normal approximation)

	Moran Index	z-value	Prob
Production	0.243	2.922	0.00
Value added (VA)	0.194	2.381	0.02
% of employees that at least began secondary or higher levels of education	0.355	4.122	0.00
Wage earnings	0.268	3.184	0.00
Overall earnings	0.199	2.446	0.01
Number of employees	0.151	1.911	0.06
Physical Capital	0.138	1.784	0.08

Source: Own elaboration using data fromINE.

3.- The econometric model

Production function framework determinants have been modelled, among others, by Leontief (1951), Chenery and Clare (1959), Arrow et al. (1961), Griliches (1967), Berndt (1991), Intriligator et al. (1997), and Bernstein (1997). Traditionally, capital assets K_i and the labour force L_i have been considered the key factors in the production function, which is:

$$Q_i = \mathrm{f}\,(K_i\,,\ L_i) \tag{6}$$

However, in addition to these elements, other factors have also been taken into account. Klein (1952) set up the extended production function more than 50 years ago after including the intermediate consumptions in the equation. Likewise, other approaches, such as the KLEM and KLEMI production function (see Jorgenson et al. (2000) and Klein et al. (2001)) make it possible to incorporate alternative factors into the model, obtaining an equation like the following:

$$Q_i = \mathrm{f}\,(K_i\ ,\ L_i\ ,\ H_i\ ,\ RD_i\ ,\ldots) \qquad (7)$$

where H_i represents human capital and RD_i denotes research and development expenditures.

Nevertheless, equations (6) and (7) both omit the interrelationships among different productive sectors (interindustrial effects) when these interrelationships could be regarded as the local spillovers of the productive system. Inappropriately omitting these effects when estimating equation (7) would generate sectoral autocorrelated residuals, whichwould result in inefficient parameter estimates and inference problems, similar to what happens in temporal autocorrelation. In this case, sectoral econometric methodology provides techniques to solve these problems.

Therefore, taking these ideas and equation (7) into account, we begin our analysis of innovation determinants by using the following model specification (variables and data sources used in the empirical application carried out in the next section are detailed in Table 2):

$$Q_i = \beta_1 + \beta_2\ K_i + \beta_3\ L_i + \beta_4\ H_i + \beta_5\ RD_i + u_i \qquad (8)$$

$$Q_i = \beta_1 + \beta_2 K_i + \beta_1 K_i + \beta_1 K_i + \beta_1 K_i + u_i$$

where u_i is a random effect that could show sectoral dependence problems.

Nevertheless, if sectoral statistics applied to estimating equation (8) point to the existence of sectoral dependence in the model, it will have to be reformulated and, therefore, sectoral dependence must be explicitly considered in the model's specification. We deem such sectoral autocorrelation in production activity to be a form of intersectoral spillover that can determine the system in the economy. Thus, we specify the model as:

$$Q = \beta_0 + \beta_1\ W_{wd}Q + \beta_3\ K + \beta_4\ L + \beta_5\ H + \beta_6\ RD + u \qquad (9)$$

where Q, K, L, H, RD and u are the vectoral versions of the variables presented in Table 2, and $W_{wd} = A$ - diag(A) is the weight matrix defining the interindustry or trade proximity of sectors and quantifies the intersectoral spillover. Therefore, $W_{wd}Q$ (a weighted sum of interrelation activity in the sectors) represents the sectoral lag for production.

Note that in the way in which equation (9) has been built up, the model does not appear to be especially difficult to estimate by using standard procedures of sectoral econometrics, since the target sector does not take part in the construction of the variable $W_{wd}Q$. However, the flipside of the coin is that this equation fails to capture intrasectoral relationships. Hence, in order to make up for this, model (9) could be generalised to include intrasectoral as well as inter-sector relationships. In order to achieve this, using the main diagonal elements of Leontief technical coefficients W_d = diag(A) as an indicator of intrasectoral features, a supplementary exploratory variable is added to the previous model. Therefore, equation (9) will now read:

$$Q = \beta_0 + \beta_1 W_{wd}Q + \beta_2 W_d Q + \beta_3 K + \beta_4 L + \beta_5 H + \beta_6 RD + u \qquad (10)$$

Estimating equation (10), however, cannot be directly tackled by means of econometric procedures, since the explanatory variable $W_d Q$ included the endogenous variable. So, in order to overcome these limitations, equation (10) could be rewritten, after reorganizing terms, in reduced form as:

$$\left(I - \beta_2 W_d\right) Q = \beta_0 + \beta_1 W_{wd}Q + \beta_3 K + \beta_4 L + \beta_5 H + \beta_6 RD + u \qquad (10.a)$$

or equivalent to:

$$Q = \beta_0 \left(I - \beta_2 W_d\right)^{-1} \ell + \beta_1 \left(I - \beta_2 W_d\right)^{-1} W_{wd}Q + \beta_3 \left(I - \beta_2 W_d\right)^{-1} K$$
$$+ \beta_4 \left(I - \beta_2 W_d\right)^{-1} L + \beta_5 \left(I - \beta_2 W_d\right)^{-1} H + \beta_6 \left(I - \beta_2 W_d\right)^{-1} RD + u \qquad (10.b)$$

where ℓ is a vector of one with proper size.

The endogeneity problems displayed by equation (10) have been solved in equation (10.b) and the model is ready to be estimated by using non-linear procedures. For instance, estimates of (10.b) parameters', conditioned to different values of β_2, could be obtained through either Conditioned Maximum Likelihood or
Least Squares.

Finally, we can obtain an expression that shows some analogy with (4.d) using $\left(I - \beta_2 W_d\right)^{-1}$ = I + $\beta_2 W_d \left(I - \beta_2 W_d\right)^{-1}$ and replacing it in (10.b):

$$Q = \beta_0 + \beta_0 \beta_2 W_d \left(I - \beta_2 W_d\right)^{-1} \ell + \beta_1 W_{wd}Q + \beta_1 \beta_2 W_d \left(I - \beta_2 W_d\right)^{-1} W_{wd}Q$$
$$+ \beta_3 K + \beta_3 \beta_2 W_d \left(I - \beta_2 W_d\right)^{-1} K + \beta_4 L + \beta_4 \beta_2 W_d \left(I - \beta_2 W_d\right)^{-1} L$$
$$+ \beta_5 H + \beta_5 \beta_2 W_d \left(I - \beta_2 W_d\right)^{-1} H + \beta_6 RD$$
$$+ \beta_6 \beta_2 W_d \left(I - \beta_2 W_d\right)^{-1} RD + u \qquad (11)$$

Indeed, when comparing equation (4d), which is derived from input-output analysis and equation (11), we found some similarities between them. The main difference remains the fact that the diagonal matrix of technical coefficients is multiplied by the parameter β_2 in equation (11). Hence, when β_2 = 1, both equation (4d) and (11) are similar to each others in many ways.

Table 2. Variables, Measurement and Data Sources

Variable	Measurement and data sources	Expected sign
Q	Production sectors. Source: Spanish National Accounts INE	
$A = W_{wd} + W_d$	Weight matrix. Interindustry matrix of direct input coefficients. Source: Spanish National Accounts INE	
W_{wd}	Weight matrix. Inte-industry matrix of direct input coefficients. Without the elements of the main diagonal. Source: Spanish National Accounts INE	
W_d	Weight matrix. Intraindustry matrix of direct input coefficients. Only includes elements from the main diagonal. Source: Spanish National Accounts INE	
$W_{wd}Q$	Intersectoral spillovers: sectoral lag for production. Source: self calculations with weight matrix.	+
$W_d Q$	Intrasectoral spillovers: sectoral lag for production. Source: self calculations with weight matrix.	+
K	Capital assets. Source: Fundación BBVA and IVIE.	+
L	Number of employees by sector. Source: Spanish National Accounts and EPA. INE	+
H	Relative number of employees that at least began secondary or higher levels of education by sector Source: Population Census. INE.	+
RD	R&D expenditure by sector. Source: INE.	+

INE: Spanish National Statistical Institute (www.ine.es); Hispalink (www.hispalink.org); IVIE: Instituto Valenciano de investigaciones económicas (www.ivie.es)

*Agriculture, energy, intermediate goods, capital goods, consumption goods, construction, transport and communication services, market services and non market services.

4. Econometric results

In this section we estimate the model proposed in the previous section. The model has also been estimated by generalized least square estimator. After that a a test for the presence of sectoral autocorrelation is specified in equation (8). Table 2 shows the variables used, while the data is divided into 38 productive sectors in the Spanish economy from the 1996 Spanish input-output table.

The econometric results are presented in Table 3. The signs of the outcomes are consistent with the anticipated results (see Table 2). Therefore, we find that both classical production factors (capital assets and labour force) and structural sectoral factors (such as human capital and R&D expenditures) promote each sector's productive activity. So, as can be deduced from the results of equation (8), both human capital and R&D expenditures —taken as a proxy variable of innovation within each sector— make a positive contribution to supporting the sectoral level of production.

Nevertheless, a more detailed observation of the estimation outcomes from Table 3 reveals the presence of an innovation interrelationship among the different sectors. Indeed, when we compare the coefficients obtained for the variable RD in the three models, we find this variable to be significant in equation (8) but not when sectoral autocorrelation is taken into account.

In particular, as the $LM-ERR$ and $LM-LAG$ tests (Anselin 1988) clearly show, as the statistics are significant for both weight matrix A and W_{wd} at a level of 1%, the null hypothesis of sectoral autocorrelation absence is rejected in model (8) and this indicated a misspecification of the model. Thereby a sectoral lag in either disturbances or the endogenous variable should be incorporated. The correction for heterocedasticity is, however, not necessary as the Breusch-Pagan test shows.

Following the "classical" specification search approach adopted in spatial econometrics and given that the value of the $LM-LAG$ statistic is higher than is the case with the $LM-ERR$, for both weight matrices, the estimation of the sectoral lag model is the preferred specification (equations (9) and (10.b)). So, the correct interpretation has to be made based on the sectoral lag model, which removes any misspecification in the form of sectoral autocorrelation.

The sectoral interdependence that Anselin's tests indicated has been included in equation (9) through the lag term $W_{wd}Q$. The estimation of equation (9) confirms that the inclusion of this term capture the sectoral autocorrelation yields a significant coefficient. In this sense, the sectoral autocorrelation variable $W_{wd}Q$ indicates that each sectoral productive power influences the productive activity of the rest of the sectors.

Those spillovers are spread by interindustrial relationships using technical coefficients as multipliers. Moreover, adding the variable $W_{wd}Q$ in equation (9) has prompted R&D expenditures to lose significance. The effect on promoting activity that R&D investment undoubtedly has is swallowed up by the sectoral autocorrelation term which favours each sectoral production through intricate interindustrial relationships.

Table 3. Estimation of production activity with interindustrial relations
Dependent variable: Q_i

Variable	OLS Estimation Equation 8	Bootstrap Equation 9	CLS Estimation Equation 10.b
Constant	-4.850	-5.047***	2.111
$W_{wd}Q$	-	0.659*	-
$(I-\beta_2 W_d)^{-1} W_{wd}Q$	-	-	1.034*
K	0.084*	0.088*	0.036***
L	0.314*	0.291*	0.027*
H	0.214**	0.196***	0.340*
RD	0.059***	0.021	0.033
AIC	1314.6	-	1308.46
$\overline{R}^2$	0.936	0.963	0.947
LM-ERR (W_{wd})	0.126	-	-
LM-LAG (W_{wd})	11.067	-	-
LM-ERR (A)	6.310	-	-
LM-LAG (A)	12.916	-	-
LR Test		7.75*	11.87*
Breusch-Pagan (4 gl)	0.001	-	0.001
JB normality	0.809	-	0.887

Source : Own Elaboration.
NOTE: Significance level indicated as * for 1%, ** for 5% and *** for 10%.
Number observations = 38

In fact, we remember that, from an economic perspective, the variable $W_{wd}Q_i$ could be regarded as a catalytic spillover for the diffusion of interindustrial activity. This fact is coherent with the hypothesis expressed during the model specification and with the econometric results. The coefficient of this variable displays a positive sign and is statistically significant, indicating that the productive power of all sectors is encouraged by general policies aimed at promoting R&D investments.

Model (9) offers very rich outcomes, but does not take into account intrasectoral relationships. Equation (10.b) tries to fill this gap. In this model, where both intersectoral and intrasectoral relationships have been considered, the results bring similar things to light. The coefficient that quantifies both spillovers is significant, though with a higher magnitude. Furthermore, as was the case with equation (9), the R&D variable is insignificant, as the effect of this variable on sectoral production is now captured by intersectoral and intrasectoral interdependence. In fact, we can remember that equation (10.b) could be observed as a final form where the coefficients assess total effects.

5.- Final remarks and Conclusions

The aim of this paper is to analyse how R&D expenditures affect productive activity, and how they are distributed throughout the economic system. That is, to analyse whether R&D expenditure on behalf of a particular sector spills over into the production power of the rest of sectors.

The input-output framework is used as a source of inspiration to reach the theoretical model. Unfortunately, the I-O scheme shows significant rigidity when it comes to quantifying both intersectoral and intrasectoral spillovers. In fact, using the I-O approach both spillovers will display the same coefficient. In order to overcome these limitations, we propose an econometric model that is specified and estimated by means of tools from spatial (sectoral) econometrics. This technology detects sectoral autocorrelation and makes it possible to specify a suitable model with the desired properties from an econometric point of view.

The approach of this paper is completely original as it incorporates intersectoral dependences into the production function through sectoral autocorrelation. Sectoral autocorrelation is a novel concept indeed, which is used for the first time in this paper to measure interindustrial relationships and is explicitly included in the production function.

The first results indicate that the factors typically used to explain production (capital assets and labour force) are once again significant. In addition to these factors, the quantity of qualified workers (human capital) is also a key variable that promotes productive activity. All the results are robust since the values obtained in the three models estimated are quite stable and are in line with our expectations. Moreover, when autocorrelation is not included in the model, sectoral R&D expenditure is recognized as a key variable when it comes to explaining sectoral production power.

Moreover, the estimates obtained when interindustrial interdependences are established in the production function show that both intrasectoral and intersectoral diffusion exists in industrial activity. Spillovers spread by means of intersectoral technical coefficients. To sum up, it is worth noting that the two models that included sectoral autocorrelation draw different coefficients for intersectoral and intrasectoral spillovers, thereby indicating that both types of spillovers have different effects on each sector.

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