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The effects of externalities on productivity growth in Spanish industry

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Abstract

The paper discusses the role of externalities in promoting industrial growth in Spanish regions. We try to identify whether the so-called dynamic externalities (technological spillovers) come from outside the industry (Jacobs type externalities) or whether they are generated between firms inside the industry (Marshall–Arrow–Romer or MAR type externalities). Moreover, this study attempts to test the effects of competition on innovation and growth (Porter type external effects). Related to earlier work by the authors on static and dynamic externalities analysis, this paper restricts the analysis to dynamic externalities using productivity, instead of labor. The empirical analysis is based on data from the Spanish Industry Survey from 1978 to 1992 for 26 manufacturing branches. We find evidence of dynamic effects due to specialization (MAR) that depend on the level of this variable. While specialization seems to affect productivity growth negatively, once it reaches a certain level, its effect on growth becomes positive due to knowledge sharing. However, we do not find clear evidence on the presence of diversity (Jacobs) and competition (Porter) externalities.

Keywords: Externalities; Knowledge spillovers; Productivity growth

JEL classification: R11; O30; O41

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1. Introduction

This paper applies to Spanish manufacturing data the kind of analysis carried out in Glaeser et al. (1992) and Henderson et al. (1995) to find evidence about the role of dynamic externalities[1] influencing the growth of economic activities in the territory. However, we have overcome various limitations of these papers: firstly we have used productivity instead of labor to measure industrial growth; secondly we have endogenously derived the indexes that measure external effects. Also, we included capital in the production function based model we use and, finally, we do not focus on a few specific industries but on a full range of industries and regions. The empirical analysis is carried out using up to 26 large industrial branches for the 50 Spanish provinces between 1978 and 1992.

In this paper we find mixed evidence on the role of specialization externalities (Marshal–Arrow–Romer or MAR type externalities). If specialization is sufficiently high, it seems to be positive for growth as Henderson (1994) argues. On the other hand, if specialization is low, we find a negative effect on growth, a result that coincides with Glaeser et al. (1992). We do not find clear evidence on the presence of diversity (Jacobs type) and competition (Porter type) externalities.

The rest of the paper is organized as follows. In Section 2.1, we elaborate on the notion of externality as it is not obvious what the appropriate definition is. We propose a simple typology that guides the rest of the paper. Section 2.2 derives the indexes used to identify externalities and presents the model from which estimation equations are obtained. Section 3.1 contains a brief description of the data and a discussion of the province–industry trends that emerge after the first exploitation of this data. In Section 3.2 we discuss the specifications used in our empirical search for externalities. The main results are offered in Section 3.3. Finally, Section 4 provides some concluding comments.

2. Externalities

2.1. *Definitions*

Although the analysis of innovation has usually been confined to the interior of the firm, the idea that external sources of knowledge are important has gradually

[1] In the rest of the paper we will refer to externalities or to dynamic externalities indifferently. Dynamic externalities influence the development of activity along time while static externalities produce contemporaneous once-and-for-all effects on activity. See Glaeser et al. (1992) for a tentative exploration of the presence of static externalities. We used and extended their approach to test for static externalities in de Lucio et al. (1996). There we find evidence of static urbanization economies, we also find evidence of crowding-in between the biggest industries in each territory and the rest of the industries but we fail to find any static localization economies. By localization economies we mean advantages due to the presence of specialized inputs markets while urbanization economies refer to large output markets characterizing urban environments.

gained acceptance. In an uncertain environment, the capacity to innovate is fostered through the transfer of knowledge. Endogenous growth models emphasize the role of knowledge spillovers for growth (Romer, 1986, 1990; Grossman and Helpman, 1991). Additionally, relatively recent literature has emerged that focuses on the geographic dimension of knowledge externalities (Jaffe et al., 1993; Audretsch and Feldman, 1996; Glaeser et al., 1992; Henderson, 1992, 1994; Henderson et al., 1995). This literature suggests that not only do knowledge spillovers generate externalities, but that they also tend to be geographically bounded. In other words, proximity is important for the flow of knowledge. As Henderson (1992) argues, 'close firms engage in networks that facilitate communication and knowledge spilling'. These networks are most often local and are the reflection of interpersonal contacts and mutual trust that develop through the years. Proximity does not guarantee the transmission of knowledge, but it makes it easier.

Although there seems to be widespread agreement on the importance of technological externalities, there is an on-going debate about where this knowledge comes from. One view which Glaeser et al. (1992) attribute to Marshall–Arrow–Romer (MAR), suggests that knowledge comes from firms of the same industry, so we would expect that an increase in an industry's concentration would facilitate knowledge spillovers. On the contrary, Jacobs (1969) argues that the most important knowledge spillovers come from firms in diverse industries. According to Jacobs diversity is better for growth.

MAR and Jacobs' externalities also differ on the effects of local competition on the transmission of knowledge across firms. From the point of view of the MAR approach, monopoly is better for innovation and growth since it permits the innovator to internalize the benefits derived. On the other hand, Jacobs (1969) argues that a highly competitive climate induces firms to innovate in order to remain competitive. This distinction between the degree of competition leads to a third type of externality we can attribute to Porter (1990) who agrees with Jacobs that competition is better for growth. However, he believes that knowledge spillovers take place mainly among firms belonging to the same vertically integrated industry. In Table 1 a compact classification of the externalities just described is presented.

Table 1
Typology of externalities

		Type of market	
		High competition	Low competition
Predominant source of knowledge	Intra-industry (specialization)	Porter externalities Porter (1990)	MAR externalities Marshall (1890) Arrow (1962) Romer (1986, 1990)
	Inter-industry (diversity)	Jacobs externalities Jacobs (1969)	–

2.2. The model

This section introduces the theoretical framework to study the presence of external effects associated with the economic structure of the industry–territory. Our model includes both capital in the production function and an endogenous derivation of the indexes used to measure externalities, thus going beyond the ad hoc measures used by Glaeser et al. (1992) and de Lucio et al. (1996). We also use productivity instead of employment to measure industry growth. This allows us to compare our results with those of other studies, in order to confirm the effects of knowledge externalities on industry growth measured both by productivity or value added.

We consider a Cobb–Douglas production function. The firms produce Y, or value added, using labor L and capital K, with a technology level given by A:

$$Y_{i,j,t} = A_{i,j,t}\, L^{\alpha}_{i,j,t}\, K^{\beta}_{i,j,t} \tag{1}$$

where i is the industry subscript, j the territory subscript and t stands for time.

Firms, when deciding the amount of capital and labor to use, equal the ratio of capital expenses over the wage bill to the ratio of the production function coefficients of capital, β, and labor, α, in the Cobb–Douglas production function that we assume to be constant:

$$\frac{K_{i,j,t} r_t}{L_{i,j,t} w_{i,j,t}} = \frac{\beta}{\alpha} \tag{2}$$

where r is the interest rate, as a crude proxy for firm's capital user cost, and w is the wage rate. Therefore, the first order condition for profit maximization, as expressed in Eq. (2), provides us with an expression for capital that we can substitute into Eq. (1). Taking logarithms in the resulting equation we have:[2]

$$\ln Y_{i,j,t} = \ln A_{i,j,t} + \alpha \ln L_{i,j,t} + \beta(\ln w_{i,j,t} + \ln L_{i,j,t} + \ln \beta - \ln \alpha - \ln r_t). \tag{3}$$

Because we are interested in looking at the effects of externalities on productivity growth rather than on its level (dynamic externalities), we subtract Eq. (3) from itself lagged one period to obtain the growth rate between 2 consecutive years as:

[2] By doing this, we get rid of a capital stock variable we have not available at industry–province level. In exchange, we include the relative factors price. The consequence of this for the empirical model to be estimated is that factor prices are endogenous. We will come back to this issue in Section 3.2 below.

$$\ln\left(\frac{Y_{i,j,t}}{Y_{i,j,t-1}}\right)=\ln\left(\frac{A_{i,j,t}}{A_{i,j,t-1}}\right)+(\alpha+\beta)\ln\left(\frac{L_{i,j,t}}{L_{i,j,t-1}}\right)+\beta\ln\left(\frac{W_{i,j,t}}{W_{i,j,t-1}}\right)$$
$$-\beta\ln\left(\frac{r_t}{r_{t-1}}\right). \tag{4}$$

Or, in labor productivity terms,[3] as:

$$\ln\left(\frac{Y_{i,j,t}/L_{i,j,t}}{Y_{i,j,t-1}/L_{i,j,t-1}}\right)=\ln\left(\frac{A_{i,j,t}}{A_{i,j,t-1}}\right)-(1-\alpha-\beta)\ln\left(\frac{L_{i,j,t}}{L_{i,j,t-1}}\right)$$
$$+\beta\ln\left(\frac{W_{i,j,t}}{W_{i,j,t-1}}\right)-\beta\ln\left(\frac{r_t}{r_{t-1}}\right). \tag{5}$$

Now, the growth rate of the technology level A_t is assumed to depend on a global component, A_{global} and on a local component A_{local}. The global component captures the exogenous changes in technology that affect industry, so we consider labor productivity growth in any industry outside the territory to be a reliable measure for the global industry technological change:

$$\ln\left(\frac{A_{i,j,t}}{A_{i,j,t-1}}\right)_{\text{global}}=\ln\left(\frac{\dfrac{Y_{i,t}-Y_{i,j,t}}{L_{i,t}-L_{i,j,t}}}{\dfrac{Y_{i,t-1}-Y_{i,j,t-1}}{L_{i,t-1}-L_{i,j,t-1}}}\right). \tag{6}$$

Following the purpose of this paper we will endogenize the local component of the technological factor, A_{local}, using the distribution of economic activity across all industries and regions. Following de Lucio (1997) we build a model of innovation and its diffusion with endogenous determination of the measures of technological external effects. We will thus assume that innovation is distributed according to the distribution of activity both across territories and across industries. Following Grossman and Helpman (1991) and Martin and Ottaviano (1996), we consider that the distribution of innovation is a linear and increasing function of the share of whatever variable of interest we consider that determines innovation, that each firm of an industry–territory has of the total value of this variable in the same industry or region. We will use value-added growth as the proxy variable for the determinants of the innovation process. In accordance with this model, when the firms of a given industry–territory have a greater percentage of the total value added, they will also enjoy a greater share of innovations.

Now let us describe two different time-dependent processes for innovation. On

[3] A better approach should be to use total factor productivity, but the lack of industry–province-specific capital stock measure prevents us from doing so. This applies also to Eq. (6).

the one hand we consider an industry channel and, on the other, a regional channel through which innovations flow. These channels are related to the climate towards innovation existing in a given industry or region. When an industry has a faster rate of innovation, firms belonging to this industry will perform relatively better than others (e.g. information and communication industries). Similarly, when a territory has a dynamic innovation atmosphere, firms located in it will benefit from this stimulating environment (e.g. Silicon Valley). Therefore, firms in a given industry–region will innovate according to their: (i) industry's propensity to innovate (γ_i); (ii) size relative to the industry they belong to ($X_{i,j,t}/X_{i,t}$); (iii) region's propensity to innovate (γ_j); (iv) size relative to the territory they are located in ($X_{i,j,t}/X_{j,t}$). In other words, the innovative performance of a firm depends on the innovation climate of the industry and region it belongs to and on its share at the sectoral and territorial scales:

$$\begin{aligned} \gamma_i N_{i,j,t}\frac{X_{i,j,t}/N_{i,j,t}}{X_{i,t}} &= \gamma_i\frac{X_{i,j,t}}{X_{i,t}} \\ \gamma_j N_{i,j,t}\frac{X_{i,j,t}/N_{i,j,t}}{X_{j,t}} &= \gamma_j\frac{X_{i,j,t}}{X_{j,t}} \end{aligned} \tag{7}$$

where, due to data limitations, we are taking average establishment size on each industry–region, $X_{i,j,t}/N_{i,j,t}$, X being the variable determining innovation and N the number of establishments. Finally, as the unit of analysis is the industry–region, we multiplied this average size by the number of equivalent establishments in each unit.

Additionally we will consider that there is an innovation diffusion process taking place in the considered industry–region, among regions and across industries. We assume that a proportion θ_i and θ_j of the total innovations of the rest of the industries in the region and of the rest of regions in the industry diffuses to any industry–region, respectively. Therefore we have as other components of the innovation process:

$$\begin{aligned} &\theta_i \sum_{k\neq j}\left(\gamma_i\frac{X_{i,k,t}}{X_{i,t}}\right) \\ &\theta_j \sum_{k\neq i}\left(\gamma_j\frac{X_{k,j,t}}{X_{j,t}}\right) \end{aligned} \tag{8}$$

Finally, in order to consider non-linearities or congestion in the process of innovation, and following Henderson (1994), we also include a quadratic effect of the innovation terms mentioned before, with parameters γ_i', γ_j', θ_i', and θ_j'.

According to this model, the local component of labor productivity growth is driven by the generation of innovations and their diffusion, expressed as:

$$\frac{\mathrm{d}A_{i,j,t}}{\mathrm{d}t} = A^{*}_{i,j,i}\left(\gamma_i\frac{X_{i,j,t}}{X_{i,t}} + \gamma_j\frac{X_{i,j,t}}{X_{j,t}} + \theta_i \sum\nolimits_{k\neq j}\left(\gamma_i\frac{X_{i,j,t}}{X_{i,t}}\right) + \theta_j \sum\nolimits_{k\neq i}\left(\gamma_i\frac{X_{i,j,t}}{X_{j,t}}\right)\right.$$
$$+\gamma'_i\frac{X^2_{i,j,t}/N_{i,j,t}}{X^2_{i,t}} + \gamma'_j\frac{X^2_{i,j,t}/N_{i,j,t}}{X^2_{j,t}} + \theta'_i\sum\nolimits_{k\neq j}\left(\gamma'_i\frac{X^2_{i,j,t}/N_{i,j,t}}{X^2_{i,t}}\right)$$
$$\left.+\theta'_j\sum\nolimits_{k\neq i}\left(\gamma'_j\frac{X^2_{i,j,t}/N_{i,j,t}}{X^2_{j,t}}\right)\right). \tag{9}$$

We can reorganize the terms of the previous equation to obtain:

$$\frac{\mathrm{d}A_{i,j,t}}{\mathrm{d}t} = A^{*}_{i,j,i}\left(\theta_i\gamma_i + \theta_j\gamma_j + \gamma_i(1-\theta_j)\frac{X_{i,j,t}}{X_{i,t}} + \gamma_j(1-\theta_i)\frac{X_{i,j,t}}{X_{j,t}}\right.$$
$$+\gamma'_i(1-\theta'_j)\frac{X^2_{i,j,t}/N_{i,j,t}}{X^2_{i,t}} + \gamma'_j(1-\theta'_i)\frac{X^2_{i,j,t}/N_{i,j,t}}{X^2_{j,t}}$$
$$\left.+\theta'_i\gamma'_i\sum\nolimits_{\forall j}\left(\frac{X^2_{i,j,t}/N_{i,j,t}}{X^2_{i,t}}\right) + \theta'_j\gamma'_j\sum\nolimits_{\forall i}\left(\frac{X^2_{i,j,t}/N_{i,j,t}}{X^2_{j,t}}\right)\right). \tag{10}$$

This equation shows that the technology growth rate depends on the within-province specialization of the industry–region, $espp_{i,j,t} = X_{i,j,t}/X_{j,t}$, the within-industry specialization of the industry–region, $espi_{i,j,t} = X_{i,j,t}/X_{i,t}$, the squared of these specialization measures divided by the number of firms, $espp^2_{i,j,t} = X^2_{i,j,t}/(X^2_{j,t}/N_{i,j,t})$ and $espi^2_{i,j,t} = X^2_{i,j,t}/(X^2_{i,t}/N_{i,j,t})$, the firm's diversity in the territory,[4] $div_{j,t} = \Sigma_{\forall i}\big((X^2_{i,j,t}/N_{i,j,t})/X^2_{j,t}\big)$, and the degree of competition the firm faces inside the industry, $com_{i,t} = \Sigma_{\forall j}\big((X^2_{i,j,t}/N_{i,j,t})/X^2_{i,t}\big)$. The last two elements are equivalent to the Hirschman–Herfindahl indexes frequently used in the industrial organization literature to measure the diversity of economic activity in the territory and the level of competition inside an industry. The measure of diversity is similar to the one used by Glaeser et al. (1992). The ratio used by Henderson (1994) to measure specialization is derived endogenously in this model. Finally, the competition measure is not identical to what previously mentioned authors have used, but it captures the same concept of competition.

Integrating (10) and neglecting the industry–region specificity of the γ and θ

[4] Note that this measure of diversity ranks between 0 and 1 and that there is more diversity the lower its value.

parameters, we obtain the value of the local component of the technology on each period as:[5]

$$A_{\text{local } i,j,t} = A_{\text{local } i,j,t-1} \mathrm{e}^{g\left(espi_{i,j,t-1},\ espp_{i,j,t-1},\ espi^{2}_{i,j,t-1},\ espp^{2}_{i,j,t-1},\ com_{i,t-1},\ div_{j,t-1}\right)t}. \tag{11}$$

Note that we have data for a subset, albeit a large one, of the industries that belong to the whole manufacturing sector. This has some consequences; firstly, some indexes (those with squared terms) are only approximations to the real ones and, secondly, the estimated coefficients of regional specialization indexes in the specifications below are linear transformations of the real ones.

We have thus characterized several sources of externalities due to the degree of specialization, diversity and competition present in industries and regions. These externalities are materialized by the innovation processes.

3. The Spanish case

3.1. The data

The data source used in this study is the *Encuesta Industrial* (Industry Survey) produced by the *Instituto Nacional de Estadística* (INE, Spanish Statistical Office). This major source of Spanish industrial information contains reliable data of national totals for 89 manufacturing sectors. However, at the province level, which we use as the geographical unit of observation,[6] this sector disaggregation does not allow for reliable information. INE has provided us with data for 30 manufacturing groupings,[7] which are directly surveyed by the Institute and do not represent the whole industry (some industrial sectors are excluded). The data set contains information on gross value added, production, employment, personnel costs and number of establishments by manufacturing sector and by province. The time

[5]Our main purpose at the empirical level is to clarify which external effects are more important, not to characterize the differences among industries and territories, thus we assume that the parameters in expression (10) are equal across industries and territories. This is clearly a strong assumption and prevents us from exploiting the data to gain a deeper understanding of the role of externalities. This is left to future developments.

[6]The province is the smallest geographical unit for which there are data available. This is probably not the ideal unit of observation for the analysis of local externalities, it would be better to make the analysis with data at the city level or some standard urban economy level. However, provinces can be considered as a proxy of the relevant economic market.

[7]The 30 industry groupings have been taken aggregating sectors that are horizontally integrated to obtain homogeneous industries.

period for the data goes from 1978 through 1992, the longest period available for the homogeneous industrial groupings we have chosen.

The transmission of data from INE to users must comply with the statistical secrecy guaranteed by the survey. Due to the high sectoral and spatial detail of our data there are missing values for a considerable number of observations, those with less than six establishments per unit of observation. The percentage of missing values is thus 27.5% of the total number of observations for 1992, however, these represent only 3.1% of total employment and 4.8% of total value added. A more detailed description of the data set can be found in de Lucio et al. (1996).

Value added is transformed into real variables using industrial price indexes provided separately by the INE for homogeneous sectors although price indexes are not available for four of our industry groupings in the data set, so these sectors have been omitted. The resulting industrial groupings contained in the data set can be seen in Appendix A. Additionally, personnel costs have been deflated to obtain real labor costs using the nationwide consumer price index. All real variables are set at base year 1990.

The period analyzed in this study is marked by a deep structural change forced by the industrial crisis that lasted until the mid 1980s. During the first part of the period, from 1978 to 1986, 613.4 thousand jobs were lost (−21% of employment in industry). Value added in real terms also decreased slightly (see Fig. 1), although it was less affected than employment. As a result productivity increased considerably. The structural adjustment, together with other factors such as the accession of Spain to the European Community in 1986 and the large inflows of foreign direct investments, resulted in an intense growth in terms of value added as well as employment in the second half of the 1980s. In 1991 manufacturing value-added reached a peak and began descending following a standard cycle. As can be observed in the figure, value added patterns followed by our data set and total manufacturing has been very similar.

Table 2 contains some summary statistics of the distribution of diversity,

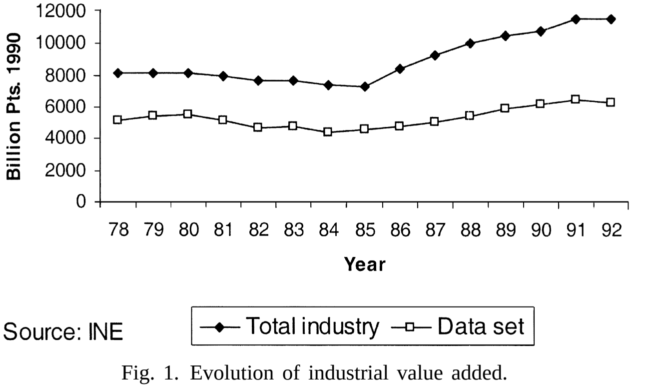

Fig. 1. Evolution of industrial value added.

Table 2
Value-added growth (1978–1992), specialization, diversity and competition in the five fastest and slowest growing Spanish province–industries

	No. establ.	Value added growth[a]	Industrial specialization in 1978	Regional specialization in 1978	Diversity in 1978[b]	Competition in 1978[b]
Five fastest growing province–industries						
Huesca — alcohol and drinks	19	10.2	0.000	0.003	0.001959	0.001695
Toledo — other final cons. chemical products	23	7.7	0.006	0.014	0.000493	0.001863
Alicante — other final cons. chemical products	25	7.0	0.001	0.001	0.000203	0.001863
Leon — alcohol and drinks	105	6.9	0.002	0.018	0.000827	0.001695
Murcia — other final cons. chemical products	48	5.8	0.002	0.002	0.000870	0.001863
Five slowest growing province–industries						
Huelva — alcohol and drinks	7	0.14	0.002	0.017	0.025262	0.001695
Badajoz — agric.-ind. machinery and equip.	93	0.13	0.007	0.148	0.001449	0.000216
Gerona — furniture	164	0.08	0.091	0.153	0.001016	0.000129
Lugo — apparel	420	0.08	0.001	0.038	0.001351	0.000166
Sta. Cruz de Tenerife — apparel	73	0.07	0.001	0.016	0.006058	0.000166
Statistics						
Average	244	1.3	0.038	0.170	0.003	0.001
Standard deviation	386	0.9	0.073	0.076	0.004	0.002
Highest	4183	10.2	0.583	0.637	0.025	0.019
Lowest	6	0.07	0.000	0.001	0.000	0.000

[a] Value added in 1992/value added in 1978.
[b] A higher value of the index means less competition or diversity.

competition and specialization indexes, computed as defined in Section 2.2 above, for the fastest and slowest growing province–industries in the 1978–1992 period. We observe that the relationship between industry growth and diversity, competition and specialization cannot be completely established from the data contained in Table 2, but more diversity (a lower value of the index) seems to be correlated with higher industry growth and more specialization and competition with industrial decline. The indexes in Table 2 have been calculated using value-added, but similar observations can be derived when the indexes are calculated using employment.

3.2. Empirical specification

Using Eqs. (5) and (10) we derive the following empirical equation:

$$\ln\left(\frac{X_{i,j,t}}{X_{i,j,t-1}}\right) = \beta_0 + \beta_1 \ln\left(\frac{L_{i,j,t}}{L_{i,j,t-1}}\right) + \beta_2 \ln\left(\frac{W_{i,j,t}}{W_{i,j,t-1}}\right) + \beta_3 \ln\left(\frac{Y_{i,t} - Y_{i,j,t}/L_{i,t} - L_{i,j,t}}{Y_{i,t-1} - Y_{i,j,t-1}/L_{i,t-1} - L_{i,j,t-1}}\right) + \beta_4\, Espp_{i,j,t-1} + \beta_5\, Espp^2_{i,j,t-1} + \beta_6\, Espi_{i,j,t-1}$$

$$+ \beta_7\, Espi^2_{i,j,t-1} + \beta_8\, Com_{i,j,t-1}$$
$$+ \beta_9\, Div_{i,j,t-1} + \text{time dummies} \tag{12}$$

where the variable X stands for productivity. Note that the β coefficients are combinations of the γ and θ parameters of the innovation process and that their signs are not necessarily positive

As mentioned in Section 2.2, factor prices may suffer from endogeneity and we need to control for that. If we assume that there is a nationwide capital market where arbitrage opportunities have been exhausted, interest growth rate is constant across regions and industries, consequently, the changes are captured by time dummies. As for wages, endogeneity is controlled for introducing instruments in Eq. (12).

Given the structure of our data set we obtain panel data estimations of Eq. (12). According to MAR and Porter's theories, specialization has a positive effect on growth, so we would expect positive signs for coefficients, β_4 to β_7. A negative β_8 coefficient will confirm the presence of competition externalities given that the corresponding index measures the lack of competition. Finally, if β_9 were negative it would mean that the industrial diversity of a territory explains productivity growth. Under the hypothesis of decreasing returns to scale we also expect to obtain a negative β_1 explaining productivity growth and a positive sign lower than one for β_2. Finally, β_3 is also expected to be positive.

To perform our panel estimations we use the DPD program by Arellano and Bond (1998). This program allows us to use unbalanced panel data sets, increasing considerably the number of observations we can handle. After estimating the model in levels, we have transformed it to first differences to eliminate non-observable individual effects and biases in the estimations. The widespread application of industrial policy at the regional level which might have a permanent effect on productivity growth motivates the inclusion of individual fixed effects. Finally, we use instrumental variables to solve for the possible endogeneity of explanatory variables that would induce correlation between them and the error term making OLS estimations biased.

Using the model introduced in Section 2.2 we consider that technology growth is determined not only by the distribution in the base year but by the industrial composition of the territories in previous years. Consequently we would observe a growth process that is determined by the value of the externality indexes in previous years. Therefore Eq. (12) includes lagged externality indexes. In this way we try to shed light on the dynamic process of externalities or, in other words, the persistence of knowledge external effects.

3.3. Results

Table 3 contains parameter estimates of Eq. (12) using as dependent variable inter-annual productivity growth. All the regressors are measured in the base year

Table 3
Dependent variable: inter-annual productivity growth in Spanish industry–provinces[a]. Sample period: 1978–1992

	Levels	1st differences[b]	1st diff. IV[b]
Intercept	0.026	0.001	−0.01
	(1.99)	(0.06)	(−0.77)
Employment growth	−0.10	−0.18	−0.17
	(−6.41)	(−8.77)	(−3.23)
Wage growth	0.50	0.46	0.58
	(17.79)	(17.84)	(7.02)
Productivity growth outside ind.–prov.	0.11	0.10	0.30
	(3.72)	(3.10)	(4.28)
Industrial specialization	−0.08	−4.72	−4.09
	(−1.58)	(−4.27)	(−6.40)
Industrial specialization^2	−1.04	36.60	32.33
	(−0.35)	(2.33)	(2.99)
Regional specialization	−0.29	−5.71	−1.51
	(−4.77)	(−9.04)	(−2.79)
Regional specialization^2	3.88	40.06	13.36
	(2.81)	(4.39)	(2.49)
Diversity	−0.50	−3.47	−1.41
	(−1.92)	(−1.83)	(−0.82)
Competition	0.90	−5.59	1.86
	(0.95)	(−0.62)	(0.20)
Year dummies	YES	YES	YES
Test 1st order serial correlation	−7.30	−10.15	−8.17
Test 2nd order serial correlation	−1.86	2.38	2.97
Wald joint significance	415.01	549.64	143.68
Wald time dummies	29.60	24.88	18.27
Wald externalities	29.13	129.36	82.08
Sargan test (*P*-value)			0.44
Instruments	NO	NO	$t-3$ to $t-5$

[a] t ratios in parentheses are robust to heteroskedasticity and serial correlation.
[b] One step estimates with robust test statistics.

for each observation of the dependent variable or in growth terms. Before turning to the economic implications of these results we note that the estimates in the three columns are quite different. The first column presents results for levels and the next two columns allow for fixed effects. The difference between column 2 and column 3 is the use of instruments in order to correct for possible endogeneity problems. The third column uses a generalized method of moments estimator of the kind developed by Arellano and Bond (1998) where we use as instruments lagged values of the right hand side variables. In the first differenced estimation we find second order serial correlation in the error term, thus we must take the instruments back one further period to $t-3$. In practice very remote lags are unlikely to be informative instruments, consequently instruments used in column 3 are right hand side variables dated $t-3$, $t-4$, and $t-5$. The Sargan test does not reject the validity of the $t-3$ instruments, so from now on we concentrate on results obtained in column 3 that corrects for endogeneity in a specification that controls for individual fixed effects.[8] In all columns we present results that are robust to heteroskedasticity.

Concentrating on results in column 3, the coefficients obtained for the non-externalities variables have the expected signs. The coefficient on employment growth is negative and significant, which indicates the existence of slightly decreasing returns to scale.[9] The coefficient on wages is positive and significant, indicating that an increase in this variable is positively correlated with productivity growth. Wages may include information on human capital or working hours. An increase in wages may thus indicate a growth of both these variables, since productivity is measured as value added per employee. The positive coefficient obtained for industrial productivity growth at the national scale indicates that a shock experienced at this level has an effect of the same sign in the region.

Moving on to the coefficients on the externalities variables, we observe that specialization seems to affect productivity growth depending on its level. We are not able to find conclusive evidence of diversity externalities and competition does not seem to have any effect on growth. We expected to find a significant and negative sign on both the competition and diversity coefficients, which would imply the existence of Jacob and Porter type externalities, respectively. However, although the coefficient on diversity has the expected negative sign, it is not significant once GMM estimation techniques are used. As can be seen in column 2, however, when instrumentation is not introduced the coefficient on diversity has the expected sign and it is significant at the 10% level.

The effects of specialization are more complex and thus deserve a more detailed explanation. Results indicate that industrial and regional specialization levels have a negative effect on growth, but when the term is squared, specialization becomes positive for growth. Our interpretation of these results is that while low levels of specialization have a negative influence on growth, once it reaches a certain level specialization is good for growth. Given this explanation, different industry–regions will observe different effects depending on their degree of specialization.

Our results also indicate that industrial specialization effects seem to be more relevant than regional specialization for productivity growth. Previous studies centered the specialization externalities at the region rather than at the industry level (Glaeser et al., 1992). These results indicate that indeed regional specializa-

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[8] We have also done estimation using instruments one further period ($t-4$, $t-5$, $t-6$) and the Sargan difference test does not reject the validity of the $t-3$ instruments.

[9] If the dependent variable were VAB instead of productivity, all coefficients would be exactly the same, except for the employment one. In this case the parameter would be equal to the one obtained in the productivity equation plus one.

tion plays an important role, but productivity is also affected by industrial specialization. When a single measure for specialization is used, as commonly done in the literature, the estimated parameter would capture the global effect of specialization and thus we would not be able to disentangle all the different aspects here considered (levels, squared, regional and industrial).

In order to test the persistence of the different external dynamic effects just described, we have introduced a set of lagged specialization, diversity and competition indexes in the equation. The model can be easily extended to accommodate the lagged structure of these effects. We consider that a period of time from 1 to 8 years keeps the structure of the panel and is sufficiently long to analyze the dynamic process of the external effects. As the number of observations per unit diminishes, a larger number of lags would damage the panel, but on the contrary a reduced number of lags would not include enough years to capture the effects like those identified for example by Henderson (1994), and de Lucio et al. (1996). We carry out a first differenced GMM estimation, using like we did previously, right hand side variables dated $t-3$ to $t-5$ as instruments.

The estimation of the extended equation is shown in Table 4 where only the

Table 4
External effects' lagged responses. 1st differences IV[a]. Sample period: 1978–1992. Dependent variable: productivity growth in industry–province

	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8	
Wald test on externalities (df=8)									
Industrial specialization	**−10.60**	0.34	0.59	0.68	0.03	0.54	−0.09	0.27	**52.39**
	−6.97	0.54	1.20	1.28	0.10	1.58	−0.29	0.89	
Industrial specialization^2	**161.72**	31.21	−22.63	**−34.48**	−3.97	**−42.20**	44.36	5.16	**50.78**
	4.62	1.29	−1.12	**−2.11**	−0.18	**−2.13**	1.64	0.23	
Regional specialization	**−4.73**	**−0.81**	**−0.75**	−0.33	**−0.69**	−0.31	−0.48	**−0.59**	**29.45**
	−4.96	**−2.30**	**−3.21**	−1.33	**−2.89**	−1.18	−1.79	**−1.95**	
Regional specialization^2	**21.00**	−0.95	1.40	−13.13	9.23	−0.67	−6.52	0.62	**15.13**
	2.13	−0.15	0.18	−1.00	1.37	−0.08	−0.68	0.05	
Diversity	−1.18	−2.12	0.16	0.74	−1.61	−1.27	0.99	−3.83	5.71
	−0.43	−1.02	0.11	0.35	−0.92	−0.77	0.48	−1.40	
Competition	−3.21	−1.66	10.67	−13.70	4.42	8.72	−5.36	12.19	10.17
	−0.32	−0.14	1.10	−1.17	0.78	1.21	−0.69	1.49	
Wald test on lags (df=6)									
	109.68	8.43	**12.65**	**23.50**	**13.93**	7.81	8.11	8.12	
Year dummies	YES								
Test 1st order serial correlation	−10.42								
Test 2nd order serial correlation	1.51								
Wald joint significance	723.01								
Wald time dummies	9.08								
Wald externalities	8.12								
Sargan test (*P*-values)	56.24								
Instruments	$t-3$ to $t-5$								

[a] One step estimates with robust test statistics.

external effects coefficients (*t* statistic between brackets) are presented.[10] Bold characters are used to single out those coefficients significant at the 10% level. The interpretation of these coefficients is thus the same as before, however the different lags introduced allow for additional comments related to the persistence of the external effects considered.

By estimating this model with lagged variables, we wanted to check where the externalities had a persistence in time and when each of them reached its maximum effect on productivity growth. As we go back in time we are still not able to find an effect of diversity or competition on productivity growth. The coefficients on specialization with 1 year lag are the largest and the most significant and have the same sign as the ones presented in Table 3. We observe a decreasing effect of these externalities as time passes. In some cases we observe that the specialization coefficient changes its sign, although for all the cases the net effect has the same sign as the one obtained for the first lag.

4. Concluding comments

In this paper we have attempted to test for the presence and persistence of a variety of externalities that may influence the growth of economic activity in the territory, more precisely industrial productivity growth. Our methodology has followed closely that of Glaeser et al. (1992) and Henderson (1994) although we present here some significant improvements. Firstly, using a wide range of manufacturing branches across the Spanish provinces, we have carried out panel data estimations that eliminate the regional–industrial individual effects. Secondly, we have tried to overcome the limitations that arise when using employment to analyze industrial growth. Instead we have used productivity growth. This is particularly relevant when industrial employment has been falling while value added has been increasing. Thirdly, we present a model where the measures that proxy external effects are derived endogenously.

The empirical analysis has been done using data from the Spanish Industry Survey from 1978 to 1992 for 26 manufacturing branches across the 50 Spanish provinces. The evidence presented in the paper suggests that there are dynamic externalities favoring the growth of economic activity as measured by industrial productivity and these are related to the specialization within a region and an industry once a certain level has been reached. However we do not find evidence of the presence of diversity and competition external economies.

According to these results technological spillovers take place when there is a high degree of specialization. Firms belonging to a certain industry and located in a given territory benefit from deep specialization that promotes knowledge sharing.

[10] Results for the other variables of the model do not change our previous interpretation.

This however does not occur if specialization is not sufficiently strong. On the other hand, our evidence on diversity externalities is not conclusive. The positive effect of a larger industrial diversity vanishes when we introduce instrumental variables in order to correct for possible endogeneity problems. Finally, we do not find evidence of the effect that competition has on productivity growth. These results differ from those obtained by, amongst others, Glaeser et al. (1992) and de Lucio et al. (1996), who find that diversity plays a role on growth due to cross fertilization among different industries. On the contrary, they are in line with those obtained by Henderson (1994) who finds evidence of the importance of specialization for growth. The results presented here are robust to whichever variable is used to proxy industry growth: employment or value added, as in previous contributions, or productivity, as it is done in this paper.

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Appendix A

Manufacturing sectors used in the empirical analysis and mean Gini coefficients[11] computed using value-added

Manufacturing sector	GINI
Plastics and synthetic fibers	0.98
Office equipment	0.98
Pharmaceutical products	0.96

[11]The Gini coefficients are based on industry value-added. We take value added in an industry–province and divide it by the economy wide value-added for that industry (q_i). This ratio is normalized by the province's share of total manufacturing (p_i). Then we sort out the provinces in an ascending order. Lastly we compute the Gini coefficient as follows:

$$G_i = \sum_{i=1}^{N-1} (p_i - q_i) / \sum_{i=1}^{N-1} p_i.$$

This index ranges from 0 to 1. The higher the index, the greater the geographic concentration of the industry.

Petrol chemistry, organic and non-organic chemistry	0.92
Electronic materials, precision and optics	0.84
Production and first transformation of metals	0.78
Vegetables and fish preserves	0.71
Other final consumption chemical products	0.70
Other industrial chemical products	0.69
Textiles	0.68
Leather and shoes	0.62
Fertilizers and paintings	0.58
Glass products and ceramics	0.57
Food products and tobacco	0.51
Printing	0.50
Alcohol and drinks	0.42
Agricultural and industrial machinery and equipment	0.41
Electric machinery and materials	0.41
Plastic derivatives	0.36
Paper and derivatives	0.35
Wood, cork and derivatives	0.33
Furniture	0.33
Flour mills, bread and pastry	0.24
Apparel	0.24
Materials for building and construction and non-metallic minerals	0.24
Metal mills	0.18

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