

TIME VARYING AGGLOMERATION EFFECTS ON TOTAL FACTOR PRODUCTIVITY IN SPANISH REGIONS (1995-2008)

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Abstract

The lack of capital stock data disaggregated to sector and regional level has led to the utilisation of employment and labour productivity trends as indicators to analyse the effect of agglomeration economies on TFP. This research estimates the direct impact of sector and regional factors on the TFP of regional industry in Spain during the period 1995-2008. Estimation techniques for a dynamic panel are applied finding evidence that specialisation economies and market size have a strong sectoral influence on TFP in both the short and long term. However, human capital and transport and urban infrastructures have a significant effect on TFP trends only in the short term. Our results confirm the doubts created by the use of employment behaviour to capture the influence of agglomeration economies on regional productivity.

Keywords: Total factor productivity, externalities, dynamic panel

JEL: D24, O18, R58

1. Introduction

This paper analyses the determinants of Total Factor Productivity (TFP) in private non-farm and non-energy industries in Spanish regions over a period of 15 years starting in the mid 1990s. This period marked a dramatic change in productivity growth in the Spanish economy. Up to that period, TFP had grown at similar rates to those recorded in other nearby countries and had outpaced TFP growth in the United States (US). But since then, Spain has registered negative TFP growth rates, both during periods of crisis and also expansions, which is more unusual when compared to countries with a similar level of development.

Since the mid 1990s, when productivity growth in Europe began to show signs of weakness, there has been a whole host of studies comparing international TFP growth. Countries and regions were found to be different not only in terms of their endowment of labour and physical capital, but also where productivity and productivity trends were concerned. As a result, it was crucial to analyse the determinants of the differences in the behaviour of TFP from one country or region to another.

At regional level, various approaches had already been taken to address this issue. In the field of regional and urban economics, researchers had already emphasized the importance of dynamic externalities on long term growth. Furthermore, some studies attempted to indirectly capture the influence of geographical proximity on productivity through its influence on employment (Glaeser et al., 1992 and Henderson et al., 1995). Endogenous economic growth models rekindled the interest in spillovers (Romer, 1986 and Lucas, 1988) and the importance of the regional availability of human capital and technology – together with infrastructure (Aschauer, 1989). A growing number of

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theoretical papers in the new economic geography have also given microeconomic grounds to agglomeration phenomena over the last few decades.

In the case of Spain, there have been papers discussing the relative importance of localisation economies (Marshall-Arrow-Romer, known as MAR externalities) or urbanisation economies (Jacobs externalities). The existing empirical evidence regarding our country, as is the case in other countries, is highly varied but not very conclusive¹.

This paper makes a series of contributions in relation to the methodology used in the empirical literature regarding the role played by agglomeration economies. In the first place, the variable to be directly explained is TFP –as in Dekle (2002) and Cingano and Schivardi (2004)– not employment, wages or output as proxy variables to capture the presence of dynamic agglomeration economic effects on productivity². In the second place, to the best of our knowledge it is the first attempt to use a dynamic approach, directly employing TFP as a variable. In the third place, two methods are employed to estimate TFP in each sector in each region: the first and most conventional uses the standard assumptions in the Solow (1957) model and the second estimates elasticities on the basis of a Generalised Leontief cost function. Moreover, although we do include conventional variables to detect the presence of localisation and/or urbanisation economies, we also consider other variables that, according to endogenous growth models, can have an influence on the productivity of the industries in a region, such as the regional availability of infrastructure, human and technological capital.

This research has a panel of data for regional industries in Spain and uses the GMM estimator for dynamic panels. The fact that the BD.MORES database³ has data for all 17 Spanish regions from 1995 to 2008 and for 10 industries, including manufacturing, construction and private services for each makes it possible to use this estimation model. More specifically, the Difference-GMM and System-GMM estimators – Arellano and Bover (1995) and Blundell and Bond (1998) – are applied, which allows us to use the lagged values of the variables as instruments.

The paper is organised as follows. Section 2 very briefly introduces the evidence on TFP in Spain since the mid 1990s and in the 10 industries and 17 Spanish regions. Section 3 presents the empirical model and data. Section 4 discusses the results of the estimation. Finally, Section 5 includes the main conclusions.

2. TFP pattern in Spain, its industries and regions since 1995.

Productivity dynamics is a decisive factor in the maintenance of sustainable growth. During the expansion, until 2007, GDP growth in Spain comfortably outpaced other countries with a similar level of development. That growth was based on a quantitative increase in labour and capital factors, while TFP fell continuously at an annual rate of

¹ See Callejón and Costa (1995), De Lucio, Herce and Goicolea (2002), Viladecans (2003) and Escribá and Murgui (2013).

² There is a large body of literature that analyses the behaviour of TFP in the regions but focusing the analysis on convergence (see Bernardini Papalia and Bertarelli, 2010), or the role played by different types of assets and spatial dependence (see Dettori, Marrocu and Paci, 2011).

³ The BD.MORES database (De Bustos et al., 2008) is a Spanish regional database with information disaggregated into 20 branches of activity. This database is compiled by the *Dirección General de Presupuestos del Ministerio de Economía y Hacienda* (Budget General Directorate of the Spanish Ministry of Economic and Financial Affairs in English).

more than 0.5 percentage points. During the period 1995-2008, factor productivity rose in the EU-15 by an annual average of 0.9 points more than in Spain and the gap was even wider when compared to the United States (1.1 points), as illustrated in Figure 1.

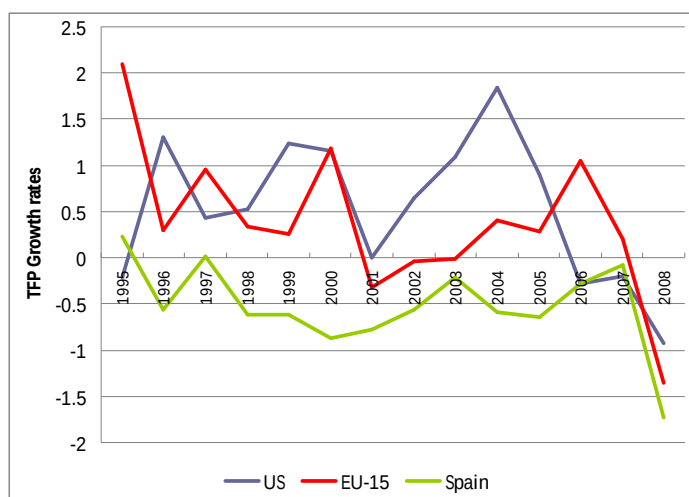


Figure 1. TFP Growth. Source: *BD.MORES (2011) and the Conference Board Total Economy Database (2010)*

The productivity trend in Spain, in comparison to other developed nations, cannot be attributed solely to the economic structure of the Spanish economy, but to the fact that TFP has performed worse than the average in the EU and the United States in the large majority of industries, as can be observed in Table 1 (in Annex). Using the information contained in the database EU-KLEMS as a starting point, and taking 1995 as the base year with a value of 100 for each industry, the productivity trend in Spain is seen to diverge adversely from that observed in the US and the EU-15. The gap in 1995 for the economy as a whole widened to 12 percentage points in regard to the EU-15 and 16 when compared to the United States. That divergence was even greater in the case of manufacturing industries as a whole, at 24 and 52 points, respectively. Spain appears to have a problem with productivity in almost all industries, particularly in services (with the exception of financial intermediation), but also in manufacturing industries. Although the decline in TFP in construction (77) and Hotels and Restaurants (75) has been more pronounced and that the foregoing sectors represent an important share of the Spanish economy, specialisation in those sectors cannot be considered the main culprit of the productivity problem in our country.

The highly negative trend of TFP cannot therefore be attributed to one industry alone, but could it be the result of a group of regions recording performing particularly poorly across all industries and dragging down the national economy as a whole? Although the regions in one same country share its institutional framework to a certain extent, there are specific factors that can negatively affect the growth of industries located in some regions. If this occurs, the poor results registered by a majority of industries in those regions could explain the trend observed in the Spanish economy as a whole, but for reasons that are not necessarily shared at national level. That is, the fall in aggregate

and in many cases cross-sector TFP could be caused by a few regions where performance has been particularly poor. However, an analysis of the trend displayed by this variable at regional level indicates that this does not appear to be the case either. In order to illustrate this point, Figure 2 (in Annex) uses the *BD.MORES* database.

The vertical axis in the graph above represents the average annual growth rate of TFP during the period, while the horizontal axis illustrates the percentage contribution of each region to national GVA. The graph presents two series: one for the sample period (1995-2007) and another for the period 1980-1994 in order to be able to compare the TFP growth trend. The points rank the regions from the highest TFP growth rate to the lowest, such that the accumulated value is equal to aggregate TFP growth. The slope that joins every two points represents TFP growth in a region. Regional patterns do not appear to be disparate, as in that case the lines would be much more curved. The only difference is that some regions have performed exceptionally well, although TFP was much weaker than in the previous period and barely accounts for a quarter of GVA. Furthermore, the negative trend in TFP has been widespread since 1995 in most of the regions with the largest share of national GVA. As is also the case with industrial specialisation, specific regions cannot be blamed for the adverse performance of aggregate TFP either.

As this problem affects all sectors and regions, we must search for the origin of the trend in macroeconomic determinants related to the technological and human capital deficit, as postulated by the modern growth theory, institutional factors, the regulatory framework and structural defects in the factor market (especially in the labour market) and goods market. All the previous factors would be lacking or inefficient in Spain in relation to other countries with a similar level of development.

Many of those factors affect all the regions in a country to the same extent, as they share the same type of institutions and market regulations. Nevertheless, not all Spanish regions have the same endowment of infrastructures, the same level of public R&D investment, or the same labour force in terms of qualifications and training. Part of the reason for Spain performing worse than other countries can be traced back to the relative difference in the performance of some regions in regard to others. Omitting the more institutional factors from the determinants of the general gap in TFP in regard to other countries, the regional level is a good scenario to study the different patterns of TFP in each industry in their different locations within the same country. Not only in terms of the differences in public factor and human capital endowments, but also in terms of how production is organised on a regional scale: whether a region specialises in certain activities or diversifies, whether its activity is concentrated in large cities or is spread throughout the region. Furthermore, differences in regional TFP trends can also be determined by their industrial specialisation. The regions in a country do not have the same economic structure. In fact, there is a high degree of regional specialisation in the Spanish economy. Performing studies at sector/regional level can be essential to analyse the determinants of TFP growth.

3. The empiric model and Data.

This section includes the main features that characterise the studies that have been undertaken to estimate the regional (local) and sectoral factors the influence the presence

of dynamic spillovers and therefore the efficiency of productive units⁴. Such externalities arise as a result of the interaction between nearby economic organisations, either in terms of the type of industrial activity they perform, geographically or past relations, as history matters. In general, such interaction is more intense the closer organisations are in geographical terms, so most studies have focused their estimates on cities and metropolitan areas, although large geographical areas have also been addressed, including regions (Ciccone, 2002, Combes and Overman, 2004, Brülhart and Mathys, 2008, Escribá and Murgui, 2013). Moreover, as the intention is to capture the effect of external factors on a productive entity, the greater the disaggregation of such entities at micro level, the easier it is to represent optimising behaviour and the greater the variability of the data (Melo, Graham and Noland, 2009).

By definition, external economies entail changes – which the literature assumes to be neutral as does Hicks – in the production function of company f in industry i or simply in industry i . For this reason, the literature uses a production function at company or industry level i in each region j

$$Y_{ij,t} = A_{ij,t} \cdot F(L_{ij,t}, K_{ij,t}) \quad (1)$$

Where Y is the private output of company (or industry) i in region j in year t , L and K denote employment and capital respectively and A includes the state of technology that in line with Glaeser et al (1992), has a national and local component in the industry in the region.

In order to estimate dynamic externalities, the TFP growth rate ($\hat{A}_{ij,t}$) is modelled as a function of regional factors. Particularly in agglomeration literature, the following are used as arguments: specialisation, diversification, local size and/or company size, variables which represent localisation and/or urbanisation economies (MAR, Jacobs and Porter externalities). Most studies have made $\hat{A}_{ij,t}$ depend on the initial values of the arguments, as in equation (2) below. The aim is to explain the average growth rate – of employment more than $\hat{A}_{ij,t}$ – between the initial moment in time ($t=0$) and the moment in time (t) depending on different variables X ; the levels of specialisation, diversification, initial size, therefore not taking into account their variation over time. This limitation has been questioned recently (Blien, Suedekum and Wolf, 2006; Brülhart and Mathys, 2008; Graham et al. 2010 and Escribá and Murgui, 2013). The foregoing authors believe that in order to correctly estimate dynamic externalities, an expression such as (2') is required.

$$\frac{1}{t} \ln \left(\frac{A_{ij,t}}{A_{ij,0}} \right) = \sum_{k=1}^n \lambda_k \ln X_{ik,0} + \sum_{l=1}^m \lambda_l \ln X_{jl,0} \quad (2)$$

$$\ln A_{ij,t} - \ln A_{ij,t-1} = \sum_{k=1}^n \lambda_k \ln X_{ik,t} + \sum_{l=1}^m \lambda_l \ln X_{jl,t} \quad (2')$$

⁴Recent overviews of agglomeration economies can be found in Rosenthal and Strange (2004) and Melo et al. (2009), but none of the foregoing papers focuses on TFP as a variable to be explained.

The second limitation of this literature is due to the lack of local data referring to capital stock (and also output), which makes it impossible to determine levels of TFP and the growth rate, which is the variable to be explained on the basis of sector and regional determinants. Alternatives have considered: a production function depending only on TFP and the labour factor (Glaeser et al, 1992 and Henderson et al, 1995); or a function like equation (1), but substituting K using the Marginal Rate of Substitution (MRS) according to L and the relative price of factors (De Lucio, Herce and Goicolea, 2002 and Combes, Magnac and Robin, 2004), or even directly estimating the role of agglomeration economies in employment growth without theoretical structure (Paci and Usai, 2008). In general, researchers have tried to capture the impact of dynamic externalities on productivity through the effect of marginal labour productivity. Another fairly common practice is to estimate using wage equations (Combes et al., 2010).

As mentioned previously, the aim of this paper is to capture the effect of external factors on a production unit, for which reason it would be preferable to not only have data on entities at the most micro level possible, but also on the closest and smallest local entities possible. Notwithstanding, the opportunity cost is that it would be impossible to estimate TFP as the variable to be explained. Cingano and Schivardi (2004), in a pioneer attempt to use TFP as an explanatory variable at a high level of disaggregation, find contradictory results with regressions on growth in employment and TFP and conclude that a strong bias is incurred by using employment as a variable⁵.

In this research, as we have data on industries at NUTS-2 level, we can address the sectoral and regional determinants of TFP growth, albeit at the cost of the effects of geographical proximity being partly diluted. Notwithstanding, that broader local level allows us to incorporate other regional variables that can affect productivity and which could help to explain the persistent differences in industry productivity trends in different regions within the same country.

Indeed, this paper intends to determine the sectoral and regional factors that explain TFP growth rate heterogeneity among the regions in a country. This objective is thereby connected to other literature that tackles the issue of the regional determinants of TFP, albeit at a higher level of territorial aggregation. Regional availability of infrastructure, human capital, technological capital, and even social capital can intensify the effect of agglomeration economies on company and industry productivity in a region. This eclectic approach has been used recently and fairly frequently by researchers at the Research Centre CRENOS⁶.

In summary, and taking into account all the possible determinants of TFP, in our research expression (2') would be modified by incorporating infrastructure and human and technological capital as follows,

$$\ln A_{ij,t} - \ln A_{ij,t-1} = \gamma_0 + \gamma_1 \ln DIV_{j,t} + \gamma_2 \ln ESP_{ij,t} + \gamma_3 \ln SIZ_{ij,t} + \gamma_4 \ln ASEC_{i,t} + \gamma_5 \ln HUM_{j,t} + \gamma_6 \ln INF_{j,t} + \gamma_7 \ln TEC_{j,t} \quad (3)$$

⁵ While they obtain localisation economies when using TFP as a dependent variable, they do not obtain them with employment.

⁶ Centro Ricerche Economiche Nord Sud (Universities of Cagliari and Sassari).

where *DIV* represents the level of diversification, *ESP* specialisation, *SIZ* size, *ASEC* sectoral total factor productivity, *HUM* human capital, *INF* infrastructure and *TEC* technological capital.

Using equation (3) as a basis, we are going to consider an autoregressive model, such that we assume the total factor productivity of regional industries at a given moment in time will depend on their levels of lagged TFP and a series of past and present sectoral and regional characteristics -the pattern of these characteristics matters when explaining the behaviour of TFP today-. Therefore, the dynamic panel data model to be estimated is expressed generically as

$$a_{ij,t} = \alpha + \sum_{k=1}^n \beta_k a_{ij,t-k} + \sum_{k=0}^n \lambda_k x_{ij,t-k} + \mu_{ij} + d_t + \varepsilon_{ijt} \quad (4)$$

being $a_{ij,t}$ the logarithm of the level of TFP – the endogenous variable⁷ - and $a_{ij,t-k}$ the lagged endogenous variable with lags ($k=1,...,n$), $x_{ij,t-k}$ are the current or lagged values of the series of explanatory variables – in logarithms – included in expression (3) and which were detailed below. The μ_{ij} denote the specific effects of regional industries non varying in time (such as geographical location or idiosyncratic features specific to the region and the industry) and d_t represents the time effects that influence all regional industries (for example, national policy). This paper address such time effects as fixed – unknown constants – by including a series of time dummies in all regressions. ε_{ijt} is the random disturbance.

The sectoral and regional variables are estimated, as can be appreciated in Table 2 (in Annex), as follows:

- a) In order to control for purely sectoral effects, sector TFP (ASEC) is included.
- b) Specialisation (ESP) of a region in an industry or sector is estimated using the share of the regional industry itself in regional output in regard to the share of the output of the sector in total national production. This variable traditionally measures Marshallian externalities, the advantages gained by companies that produce similar goods and are located closed or each other.
- c) In order to capture the size of the market, regional output is used (SIZ) after discounting the regional industry itself⁸. Size is interpreted in small local areas as a reflection of urbanisation economies (size of local demand for intermediate goods, inter-industry linkages and the availability of public services in the area), although it is unclear whether it includes spillovers associated to the cross-fertilisation of ideas (Jacobs).
- d) Ideas and innovation are considered the result of an exchange between different areas of activity and knowledge (Jacobs). A more diversified framework provides different

⁷ In this paper, as mentioned previously, two series of TFP levels have been obtained for regional industries, so the determinants of TFP will be estimated for both series. For more details about TFP estimation procedure can see Annex.

⁸ As an alternative to regional output, Ciccone (2002) discuss and use what they define as a density index, that is, local employment divided by geographical area.

and complementary technological knowhow and therefore fosters growth in each regional industry. Diversity (*DIV*) is estimated by the inverse of the Herfindal-Hirschman index. The existing empirical literature has paid special attention to discriminating between specialisation (localisation) and diversification (urbanisation) as determinants of growth in local industries.

- e) Worker education (*HUM*) is estimated by the average years of study of the population in each region. Human capital is expected to transmit strongly positive externalities and to be a means of absorbing new technologies.
- f) Regional endowment of infrastructure (*INF*) includes both transport and urban infrastructure capital in the region in relation to private productive capital. This variable will have a positive effect on efficiency due to reducing private production costs and to being a public good.
- g) Regional technological capital (*TEC*), which captures capital in R&D provided by the regional public sector in relation to regional private productive capital, is also expected to have a positive effect.

4. Results of the estimation

Table 3 presents the results of estimating some of the determinants of TFP in Spanish regional industries using the specification provided in equation (4) for the period 1995-2008. Different estimation methods are employed, including Ordinary Least Squares (OLS, first column) and Fixed Effects (F.E., second column), which we know will yield biased and inconsistent estimators, and the Generalised Method of Moments (in differences, DIFF-GMM in column [3] and in levels, SYS-GMM in column [4]), which corrects those problems. These estimations do not include all the sectoral and regional determinants in the equation, as the purpose of showing the results of the various estimation methods used is above all to compare the estimated coefficient of the lagged endogenous variable. Bond et al (2001 page 7 suggests this as a test of whether the estimators suffer from “finite sample bias”⁹. An estimate of the lagged endogenous variable will be considered consistent if the coefficient falls between the OLS and Fixed Effects estimations. The well-known reason for this is that the coefficient of the lagged endogenous variable will be overestimated by OLS and underestimated by Fixed Effects.

As can be observed in the table above, the results are derived from the model that includes a lag for the dependent variable and the contemporary value and a lag for the explanatory variables¹⁰. Therefore, an Autoregressive Distributed Lag (ADL(1.1)) model has been specified, as established in Blien et al (2006) and Dauth (2010), although these papers used two lags and employment is the variable under analysis.

The dependent variable considered in the estimations reported in Table 3 is total factor productivity obtained on the basis of the conventional assumptions of perfect competition and constant returns to scale (TFPA)¹¹. As regards the comparison of the

⁹ Bun and Windmeijer (2010) analyse the presence of finite or small sample bias in SYS-GMM and DIFF-GMM estimators.

¹⁰ We select the optimal lag structure using Wald tests. Only the variables lagged one period are significantly different to zero.

¹¹ The results are similar when TFPE is used. Table 4 comments on and compares the results using both measures of TFP with the estimation method finally chosen, namely DIFF-GMM.

lagged endogenous variable, it is positive and highly significant in the various estimations and in the case of the DIFF-GMM estimator, the expected results are obtained, as the coefficient falls between that estimated by OLS (overestimated) and that estimated by Fixed Effects (underestimated). In the case of the SYS-GMM estimator, the coefficient is even higher than that recorded by the OLS estimator, for which reason the Generalised Method of Moments estimating in differences (Difference GMM, Arellano and Bond, 1991) will be considered more appropriate. The rest of coefficients are significant and positive in the case of specialisation, market size and TFP and negative in the case of diversification, but this will be addressed in more detail by the table below.

Table 3. Estimation Results by Sample Period: 1995-2008

Dependent variable		$LnTFPA_{ij}$			
ESTIMATION		OLS [1]	F.E[2]	DIFF-GMM[3]	SYS-GMM[4]
$LnTFPA_{ij}$	t-1	0.967*** (0.022)	0.664*** (0.062)	0.768*** (0.052)	0.975*** (0.013)
$LnASEC$	t	1.025*** (0.032)	1.042*** (0.033)	1.026*** (0.039)	1.050*** (0.041)
	t-1	-0.999*** (0.034)	-0.799*** (0.037)	-0.817*** (0.068)	-1.034*** (0.041)
$LnESP$	t	0.651*** (0.015)	0.656*** (0.016)	0.706*** (0.053)	0.675*** (0.052)
	t-1	-0.644*** (0.015)	-0.550*** (0.016)	-0.536*** (0.064)	-0.669*** (0.051)
DIV	t	-0.321*** (0.063)	-0.302*** (0.065)	-0.187* (0.103)	-0.266*** (0.103)
	t-1	0.324*** (0.062)	0.328*** (0.016)	0.162* (0.089)	0.271*** (0.102)
$LnSIZ$	t	0.268*** (0.072)	0.243*** (0.072)	0.624*** (0.224)	0.353 (0.254)
	t-1	-0.264*** (0.072)	-0.253*** (0.071)	-0.620*** (0.223)	-0.350 (0.254)
Hansen Test				[0.371]	[0.214]
Difference Hansen test					[0.030]
AR(1) Test				[0.000]	[0.000]
AR(2) Test				[0.237]	[0.254]
R^2		0.98	0.93		
Obs.		2210	2210	2040	2210
Time Dummies		Yes	yes	yes	Yes

Note for Table 3: Standard errors are presented in brackets. A two-step estimator is used for columns [3] and [4] and standard errors are adjusted to correct finite sample bias as in Windmeijer (2005). * values significant at 10%, ** 5% and *** 1%. The figures reported for the Hansen test are p-values for the null hypotheses, valid specification. The figures displayed for the AR(1) and AR(2) tests are the p-values for the null hypotheses zero first-order and second-order autocorrelation respectively. The instruments used to estimate the equations in first differences are the lagged levels of the explanatory variables we consider endogenous two periods and all the lags up to a maximum of five and the exogenous explanatory variables not lagged. Additional instruments used to estimate the equations in levels are the first differences of the endogenous explanatory variables lagged one period and the first differences of the exogenous explanatory variables. Not all the possible lags of variables are used due to the size of the sample and the number of explanatory variables. If more lags were used, the number of instruments would exceed the number of groups.

Table 4 presents the estimation of equation (4) using TFPA (columns [1] and [2]) and TFPE (columns [3] and [4]). Furthermore, columns [1] and [3] include the estimation that considers only the variables typically used in the literature on agglomeration economies, namely, diversification, specialisation, sectoral total factor productivity and market size. Columns [2] and [4] also include regional factor endowments provided by the public sector as explanatory variables, namely, human capital, transport and urban infrastructures and technological capital.

Table 4. Estimation Results by Sample Period: 1995-2008

Two-step DIFF-GMM Estimator					
Dependent Variable		$LnTFPA_{ij}$		$LnTFPE_{ij}$	
		[1]	[2]	[3]	[4]
$LnTFP_{ij}$	t-1	0.768*** (0.052)	0.785*** (0.053)	0.662*** (0.063)	0.643*** (0.075)
$LnASEC$	t	1.026*** (0.039)	1.009*** (0.038)	1.014*** (0.041)	0.979*** (0.042)
	t-1	-0.817*** (0.068)	-0.805*** (0.058)	-0.721*** (0.075)	-0.653*** (0.083)
$LnESP$	t	0.706*** (0.053)	0.713*** (0.046)	0.672*** (0.053)	0.674*** (0.049)
	t-1	-0.536*** (0.064)	-0.539*** (0.057)	-0.439*** (0.073)	-0.427*** (0.074)
DIV	t	-0.187* (0.103)	-0.255*** (0.091)	-0.156 (0.107)	-0.239*** (0.100)
	t-1	0.162* (0.089)	0.284*** (0.084)	0.119 (0.084)	0.242*** (0.087)
$LnSIZ$	t	0.624*** (0.224)	0.327*** (0.098)	0.598*** (0.223)	0.307*** (0.101)
	t-1	-0.620*** (0.223)	-0.265*** (0.096)	-0.554** (0.220)	-0.191* (0.107)
$LnHUM$	t		0.214* (0.119)		0.162* (0.090)
	t-1		-0.287** (0.119)		-0.274** (0.128)
$LnINF$	t		0.202* (0.092)		0.173* (0.093)
	t-1		-0.132 (0.090)		-0.107 (0.097)
$LnTEC$	t		0.019 (0.034)		0.026 (0.032)
	t-1		-0.028 (0.037)		-0.044 (0.036)
Hansen Test		[0.371]	[0.522]	[0.260]	[0.322]
AR(1) Test		[0.000]	[0.000]	[0.000]	[0.000]
AR(2) Test		[0.237]	[0.162]	[0.192]	[0.133]
Obs. and Time Dummies		2040 Yes	2040 yes	2040 yes	2040 yes

Note for Table 4: Adjusted standard errors (Windmeijer, 2005) are displayed in brackets. * values significant at 10%, ** 5% and *** 1%. The figures reported for the Hansen test are p-values for the null hypotheses, valid specification. The figures displayed for the AR(1) and AR(2) tests are the p-values for the null hypotheses zero first-order and second-order autocorrelation respectively. The instruments used to estimate the equations in first differences are the lagged levels of the explanatory variables we consider endogenous two periods and all the lags up to a maximum of four and the exogenous explanatory variables not lagged.

The estimations consider the lagged endogenous variable and market size as endogenous variables¹². The rest of variables are treated as exogenous.

DIFF-GMM (Arellano and Bond, 1991) is used and as can be observed at the bottom of Table 4, the estimator is consistent as the conditions of orthogonality are accepted as valid (Hansen's overidentification test) and there is no residual autocorrelation. Indeed, looking at the bottom of Table 4, the instruments chosen are accepted as valid with a p-value of 0.371 for column [1], 0.522 for column [2] in the case of TFPA and 0.260 for column [3] and 0.322 for column [4]. It is also accepted that there is no second-order correlation (AR(2) test), with p-values of 0.237, 0.162, 0.192 and 0.133, respectively for the four columns.

Focusing on the results of the estimation for the sample period (1995-2008), the first column reveals positive and significant contemporary coefficients for specialisation, sectorial TFP and market size. All of them register a positive effect on total factor productivity, unlike diversification, which records a negative and significant effect in the case of the contemporary coefficient and also the first lag. These results point in the same direction as the research by Cingano and Schivardi (2004), although these authors took a static approach. The behaviour of these variables is robust to the inclusion of regional human capital, infrastructures and technological capital, as can be observed in column [2] of the aforementioned table. Indeed, all the contemporary coefficients and their lags are statistically significant.

The effect of sectorial TFP is the largest, recording coefficients close to one. This estimated coefficient implies that the regional evolution of TFP in a sector is the same as that of the nation. Therefore, this can be interpreted as an intra-sectorial technological diffusion among Spanish regions. According to our estimated coefficient of specialisation, the increase in regional specialisation in one industry would also have a considerable impact on growth in TFP, the coefficient being in the vicinity of 0.70 and remaining unchanged when variables that capture the regional endowment of strategic factors are included in the estimation. This result has a clear implication: each region should improve and further intensify their activity in the sectors that boast an acquired advantage, which are generally those they have historically specialised in. We find that the TFP regional industry is enhanced by sectorial TFP and sectorial specialization, but not by diversification.

Market size, measured using regional output, also positive affects TFP, with a coefficient of 0.62 that drops to 0.32 when the variables representing regional endowments are included in the estimation. An interpretation is that the way to approximate the market size is by capturing the intensity of infrastructure and human capital in a region.

The coefficient of the lagged endogenous variable is very similar in the first two columns and significantly different to zero. These coefficients (0.76 and 0.78) reveal considerable momentum in TFP.

As regards the role played by human capital, its contemporary effect on TFP behaviour is positive and significant with a coefficient of 0.21. The influence of transport

¹² The estimations have been performed considering possible variable endogeneity and Hansen's Difference Test is only accepted in the case of market size.

and urban infrastructures is also positive with a value of 0.20. In both cases the variables are less significant. However, the coefficients estimated for public technological capital are not significantly different to zero. The results for other countries are more optimistic: technological capital, as well as human capital, is also found to have a positive effect, for example by Jacobs, Nahuiz and Tang (2000), who also use stock as a variable, while Marrocu and Paci (2010) find all types of capital have a positive impact. Notwithstanding, neither of these papers perform a dynamic analysis.

As regards the differences compared to the results presented here, when the dependent variable is TFPE, we can see in columns [3] and [4] that the signs remain unchanged and the estimated variables statistically significant. Differences are observed in the size of the coefficients of the variables, which are always smaller, both when the estimation includes only the variables representing agglomeration economies (column [3]) and also when the explanatory variables capturing the public endowment of strategic factors are included.

In light of the specification used in this research, an Autoregressive Distributed Lag model ADL (1,1) allows us to explore the long term impact of sectoral and regional variables on TFP. Indeed, long term effects can be obtained by calculating the coefficients of each of the explanatory variables as follows:

$$\lambda_{LP} = \frac{\sum_{k=0}^1 \lambda_k}{1 - \sum_{k=1} \beta_k} \quad (10)$$

where λ represents the coefficients of the lagged independent variables and β those of the lagged endogenous variable. The values of the long term effects and the significance of these coefficients (p-values) are presented in Table 5.

In the long term – see Table 5 – specialisation, sectoral TFP and market size (the latter only when used as an endogenous TFPE variable) have a positive and significant impact on TFP behaviour. Sectoral TFP has the greatest impact in the long term on TFP dynamic, recording coefficients close to 0.9 in all estimations, using both TFPA and also TFPE. Despite the TFP trends in each sector not being identical in each location, TFP developments in each regional industry are determined in the long term by the overall trend in TFP in that industry. However, the variables that represent regional endowments of human capital, infrastructures and technological capital do not display a significant effect on TFP in the long term.

In the long term, despite the performance of TFP in each sector not being identical in each region, TFP in each regional industry is mainly determined by the overall trend of TFP in that industry. This result suggests there is a need expand the regional approach towards industrial policy in increasingly globalised economies that are subject to international competition. Moreover, TFP will grow more in the long term in the regional industries that specialise the most. The size of the market also affects the long term dynamic of TFP in regional industry, which as in the case of specialisation, suggests that economies of scale have an influence of TFP trends.

Table 5. Long Term Effects

Dependent Variable		$LnTFPA_{ij}$		$LnTFPE_{ij}$	
		[1]	[2]	[3]	[4]
$Ln ASEC$		0.902*** [0.000]	0.947*** [0.000]	0.866*** [0.000]	0.913*** [0.000]
$Ln ESP$		0.734*** [0.000]	0.810*** [0.000]	0.691*** [0.000]	0.692*** [0.000]
DIV		-0.106 [0.686]	0.132 [0.665]	-0.110 [0.555]	0.008 [0.965]
$Ln SIZ$		0.017 [0.742]	0.287 [0.192]	0.129*** [0.002]	0.325* [0.030]
$Ln HUM$			-0.339 [0.556]		-0.312 [0.472]
$Ln INF$			0.325 [0.100]		0.182 [0.227]
$Ln TEC$			-0.044 [0.549]		-0.048 [0.378]

Note: *p*-values of coefficient significance are displayed in brackets. The null hypothesis is

$$H_0 : \lambda_{LP} = 0$$

5. Conclusions.

This research has considered the importance of taking into account time structure to address the determinants of TFP in regional industries in Spain between 1995 and 2008. GMM estimators are used to estimate the dynamic panel model. This model makes it possible to control for bias due to specific unobservable effects and explanatory variable endogeneity.

Over the period analysed for Spain, important contemporary impacts on the TFP of regional industries are obtained. The results show the robustness of the positive and significant coefficients for sectoral TFP, specialisation and size of market, but not for diversification. The coefficients of the determinants typically used in the literature on agglomeration economies remain unchanged both when other variables are included (human capital, infrastructure and technological capital) and also when TFP is estimated using either Solow's assumptions or a cost function.

Results regarding the positive role played by the regional availability of human capital and infrastructure are also robust, while technological capital does not appear to play any role whatsoever in regard to TFP. Policies aimed at improving the general economic environment of the region should focus particularly on enhancing the education of human resources and infrastructure endowment in order to correct the current trend in TFP. Technological capital, at least at the levels currently displayed by Spanish regions will be decisive when it comes to determining the pattern of TFP in regional industries. Furthermore, the role played by regional authorities in terms of technological policy appears to be negligible.

Our results confirm the doubts created by the use of employment behaviour to capture the influence of agglomeration economies on regional productivity. A recent paper of Escribá and Murgui (2013) uses a similar sample of Spanish regional industries for the period 1995-2006. These authors analyse the employment behaviour and obtain opposite results to our study regarding the TFP. In contrast to the positive role played by diversification on the regional employment, our results reflect a negative role. Opposite results are also obtained using as a variable TFP or employment when the analysis was applied to countries (Bucheles and Christiansen, 1999) or local level (Cingano and Schivardi, 2004 for Italian regions or Martin, Mayer and Mayneris, 2011 using French firm and plant-level data).

This period witnesses a highly negative trend in TFP in Spain, considerably worse than that observed in other countries at a similar stage of development. The competitiveness and productivity problem in Spain is widespread across sectors and also regions. Sectoral TFP in the nation and specialization are the main determinants of the evolution of TFP in the region. The problem of negative trend in TFP Spanish regions in this period is general and depends on institutional factors and the functioning of markets affecting all regional industries although with a different intensity in each sector. For future work, it will be interesting to analyse the TFP behaviour in European regions to analyse the role of institutions, the national factors and spatial dependence.

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