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# TIME VARYING AGGLOMERATION EFFECTS ON TOTAL FACTOR PRODUCTIVITY GROWTH 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/or labour productivity trends as indicators to analyse the effect of agglomeration economies on TFP growth. 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 techiques for a dynamic panel are applied finding evidence that specialisation economies and market size have a strong sectorial influence on TFP growth 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.



**Keywords:** Total factor productivity, externalities, dynamic panel

**JEL:** D24, O28, R58

## 1. Introduction

This paper analyses the determinants of productivity growth 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, Total Factor Productivity (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; Barro, 1990). A growing number of 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 conclusive. De Lucio, Herce and Goicolea (1996) and de Lucio, Herce and Goicolea (2002) confirm the presence of urbanisation economies (and specialisation economies from a certain level onwards); Moreno (1996) of both localisation and urbanisation economies; Callejón and Costa (1995 y 1996) of specialisation economies; Esteban, Hernández and Lanaspa (2001) of urbanisation economies; Viladecans (2003) found that external economies were a decisive element, but that the impact of specialisation or diversification depended on the sector. Generally speaking, these papers – with the exception of de Lucio, Herce and Goicolea (2002) – applied a static approach, that is, they explained employment or productivity growth as a function of initial local characteristics (such as specialisation, size or diversification). Results were not conclusive in different countries, periods or sectors either, although such weak and discrepant results could also largely be attributed, as we will see, to the methodology they generally used.

The main point of this research is to analyse why productivity behaves differently in the regions of one same country with similar institutions and market regulations, not to analyse why industries locate in regional clusters, which is the norm in the literature. That is, the objective we seek to achieve is to study what sectoral and local or regional factors are responsible for the differences in TFP trends from on Spanish region to another.

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, not employment, wages or output as proxy variables to capture the presence of external effects on productivity. Only Dekle (2002) and Cingano and Schivardi (2004) have used measures of TFP as a variable. In the second 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. In the third place, to the best of our knowledge it is the first attempt to use a dynamic approach (rather than a cross-section as in Dekle and Cingano and Schivardi), directly employing TFP as a variable. 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 database BD.MORES (De Bustos et al., 2008) 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 presents the evidence on TFP in Spain since the mid 1990s and in the 10 industries and 17 Spanish regions. Section 3 reviews the literature that is most directly related to the approach taken in this paper and concludes by presenting the equation of TFP determinants. Section 4 introduces the methodology used to measure TFP and the data employed. Section 5 presents the econometric specification and comments on the results of the estimation. Finally, Section 6 includes the main conclusions and economic policy recommendations.

## 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 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.

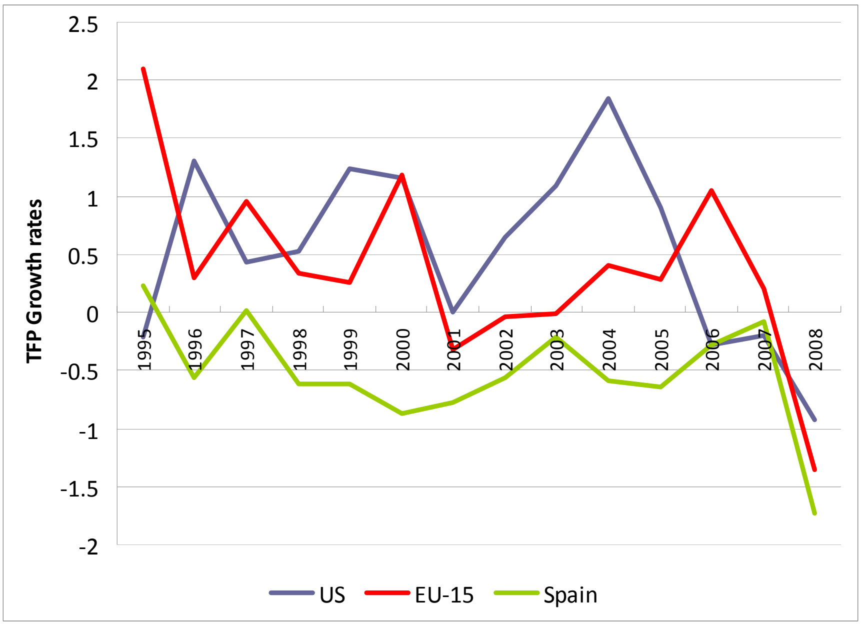


**Figure 1**. TFP Growth. Source: *BD.MORES (2011) and the Conference Board Total Economy Database (2010)*

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. Using the information contained in the database EU-KLEMS[1] 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.

[1]*EU KLEMS Growth and Productivity Accounts: November 2009 Release, Updated March 2011.* http://www.euklems.net/ For a summary overview of the methodology and construction of the EU KLEMS database, please see: O´Mahoni and Timmer (2009). For Table 1, we have selected the manufacturing industry as a whole, construction and services for the analysis in this research, using *BD.MORES and Cambridge Econometrics*. Agriculture and energy were excluded, together with non market services. We have also omitted "other market services", as it was not possible to cover the entire sample period uniformly.

**Table 1. Total Factor Productivity. 2007 (1995=100)**

| | Spain | USA | EU-15 |
|---|---|---|---|
| Total Industries | 92 | 108 | 104 |
| Manufacturing | 95 | 147 | 119 |
| **Food, beverages and tobacco** | 78 | 101 | 100 |
| **Textiles, leather and footwear** | 90 | 121 | 111 |
| **Chemicals + Rubber and plastics** | 88 | 121 | 122 |
| **Electrical, electronic and optical equipment** | 98 | 509 | 162 |
| **Transport equipment** | 106 | 150 | 128 |
| **Other manufacturing industries** | 100 | 113 | 113 |
| **Construction** | 77 | 64 | 92 |
| **Wholesale and Retail trade** | 91 | 143 | 109 |
| **Hotels and Restaurants** | 75 | 103 | 90 |
| **Transport and communication** | 85 | 121 | 130 |
| **Financial intermediation** | 169 | 109 | 121 |

Source: EU-KLEMS (2011)

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 uses the *BD.MORES* database, which contains information that is disaggregated at sector level for each of the 17 Spanish regions.

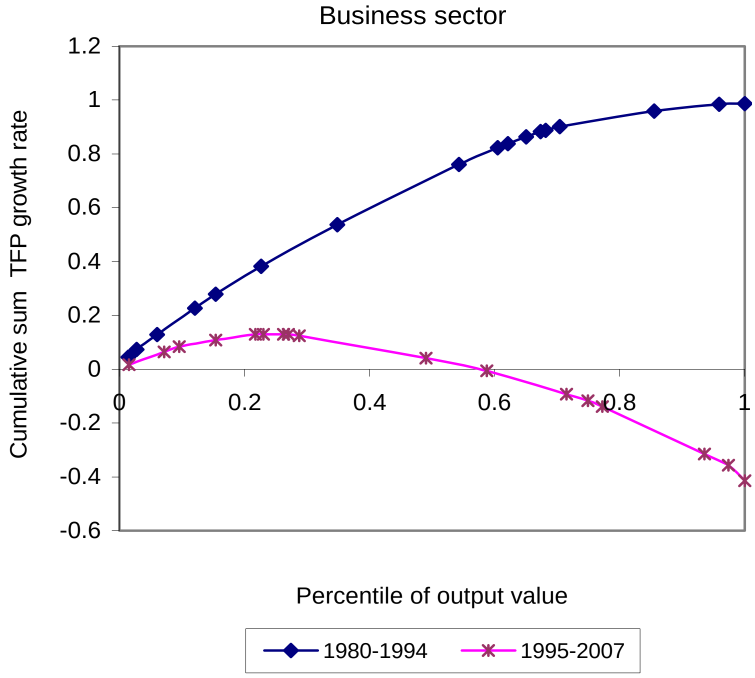


**Figure 2**
Source: BD.MORES

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[2]. 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

[2] This figure is a Sunrise-Sunset diagrams, see Harberger (1998).

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. Although most sectors perform worse than in other countries in the vicinity, not all industries record identical trends from region to region in any country and certainly not in Spain either. Performing studies at sector/regional level can be essential to analyse the determinants of TFP growth.

## 3. Theoretical Framework

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 units[3]. 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 (Arthur, 1986). 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; Otsuka and Yamano, 2008, Brülhart and Mathys, 2008, Escribá and Murgui, 2010)[4]. 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). It is preferable to have information at company level or, if not, at industry level (Combes, 2000; Lee, Sosin and Hong, 2005 and Nefte, 2007) that is as uniform and disaggregated as possible.

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*

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

[4] The survey conducted by Beaudry and Schiffauerova (2009) concentrates on the differences in the geographical units used in the literature and considers from class 1 (regions or provinces) to class 5 (small populated areas or cities), concluding that both Jacobs and Marshall externalities are more intense the smaller the geographical unit.

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

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.

$$A_{ij,t} = A_{i,t} \cdot A_{j,t} \quad (2)$$

The first component captures the general state of technology in branch $i$ in the nation, regardless of location, while the second component reflects the influence of local features on productivity.

Indeed, in order to estimate the presence of agglomeration economies, we must begin by measuring TFP[5]. The most frequently used production function is the Cobb-Douglas function of constant returns, which expressed in terms of growth rates leads to the following specification of the TFP growth rate

$$\hat{A}_{ij,t} = \hat{Y}_{ij,t} - \alpha_{ij}\,\hat{K}_{ij,t} - (1-\alpha_{ij})\hat{L}_{ij,t} \quad (3)$$

Growth in the national technology component occurs at company level at the rate at which productivity grows in industry $i$ in the entire economy (or the entire economy with the exception of that area). The local component grows exogenously to the company depending on various technological spillovers that influence that industry in that area.In order to estimate dynamic externalities, $\hat{A}_{ij,t}$ 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 (4) 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 the levels of specialisation (ESP), diversification (DIV), initial size (SIZ), therefore not taking into account their variation over time. This limitation has been questioned recently (Combes, Magnac and Robin, 2004; Blien, Suedekum and Wolf, 2006; Brülhart and Mathys, 2008; Graham et al. 2010 and Escribá and Murgui, 2010). The foregoing authors believe that in order to correctly estimate dynamic externalities, an expression such as (4´) is required.

$$\frac{1}{t}\ln\left(\frac{A_{ij,t}}{A_{ij,0}}\right) = \sum_{k=1}^{n} \lambda_k \ln X_{ik,0} + \sum_{l=1}^{m} \lambda_l \ln X_{jl,0} \quad (4)$$

$$\ln A_{ij,t} - \ln A_{ij,t-1} = \sum_{k=1}^{n} \lambda_k \ln X_{ik,t} + \sum_{l=1}^{m} \lambda_l \ln X_{jl,t} \quad (4')$$

[5] See Hulten (2001).

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, Henderson et al, 1995 and more recently Usai and Paci, 2003); 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 )[6], or even directly estimating the role of agglomeration economies in employment growth without theoretical structure (Combes, 2000 o 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[7] (Adamson, Clark and Partridge, 2004, di Addario and Patacchini, 2008, Heuerman, 2009, Combes et al., 2010,). Generally speaking, employment growth (or local wage growth)[8], based on making marginal labour productivity equal to real wages, depends on sectoral and regional factors. Expression (5) reflects this

$$\hat{L}_{ij,t} = -\frac{1}{\alpha}\hat{W}_{ij,t} + \frac{1}{\alpha}\hat{A}_{ij,t} + \hat{K}_{ij,t} + \frac{1}{\alpha}\hat{P}_{ij,t} \qquad (5)$$

where $\hat{A}_{ij,t} = g\left(ESP_{ij,0}, DIV_{ij,0}, SIZ_{ij,0}\right)$

When no capital stock is available, it is eliminated either directly or indirectly using MRS. When it comes to estimating, the resulting equation is similar, as the lack of data on the cost of use at local industry level leads researchers to estimate an expression like the one below (6).

$$\hat{L}_{ij,t} = -\frac{1}{\alpha}\hat{W}_{ij,t} + \frac{1}{\alpha}g\left(ESP_{ij,0}, DIV_{ij,0}, SIZ_{ij,0}\right) + \frac{1}{\alpha}\hat{P}_{ij,t} \qquad (6)$$

In keeping with Dekle (2002), when comparing equations (5) and (6), at least three problems can be appreciated. In the first place, unless capital stock is constant ($\hat{K}_{ij} = 0$), omitting this variable results in biased estimates. In the second place, there is no information on the growth of $P_{ij}$ in very small local companies, which means assuming a pattern that is determined, for example, at national level, as in Glaeser et al., (1992) and which is not realistic, particularly in the case of non marketable goods. In the third place, particularly in the early literature, studies have not controlled for how amenities, living and housing costs or the availability of public goods at local level can affect migration decisions.

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[6] Although the problem of data availability remains for measuring the cost of use correctly at local level.

[7] Whereby the wages of workers in activity *i* in region *j* are explained by a set of specific Mincerian variables (education, age, etc.) and agglomeration economies.

[8] Furthermore, when local output data are available, output and even labour productivity have been used as the dependent variable (de Lucio, Herce and Goicolea, 2002). Nevertheless, even though the aforementioned authors use a production function with capital – due to not having data – they substitute it using MRS.

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 variable[9].

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 (Boscá et al. 2010), human capital (Moretti, 2004), technological capital (Fisher, Scherngell and Reismann, 2009), 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 CRENOS[10]. Indeed, their estimations include specific determinants of local industry, region-specific determinants and sectoral factors. We appreciate two basic differences between their work and our approach[11]: in some cases they do not include the determinants of TFP related to agglomeration economies as explanatory variables (Dettori, Marrocu and Paci, 2011), using social, human and technological capital exclusively. However, in those studies it is mainly the growth rate (generally the average for the period) of the dependent variable, TFP, that depends on the initial levels of the determinants (Marrocu, Paci and Usai 2011).

In summary, and taking into account all the possible determinants of TFP, in our research expression (4´) would be modified by incorporating infrastructure and human and technological capital as follows,

$$\ln PTF_{ij,t} - \ln PTF_{ij,t-1} = \gamma_0 + \gamma_1 \ln DIV_{j,t} + \gamma_2 \ln ESP_{ij,t} + \gamma_3 \ln SIZ_{ij,t} + \gamma_4 \ln ASEC_{i,t} + \gamma_5 \ln HUM_{j,t} + \gamma_6 \ln INF_{j,t} + \gamma_7 \ln TEC_{j,t} \quad (7)$$

[9] While they obtain localisation economies when using TFP as a dependent variable, they do not obtain them with employment. Nevertheless, they perform a regression on the average growth rate of the variable dependent on the initial values of the regressors. In fact, the biases are related to capital stock consistency and also to demand elasticity, the effects of agglomeration on the labour supply and the degree of substitutability among factors (Paci and Usai, 2006).

[10] Centro Ricerche Economiche Nord Sud (Universities of Cagliari and Sassari). Marrocu and Paci (2010), Marrocu, Paci and Pontis (2011), Dettori, Marrocu and Paci, (2011) and Marrocu, Paci and Usai (2011).

[11] Graham et al. (2010) take a similar approach to ours for labour productivity and agglomeration economies.

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. The next section explains how these variables are estimated.

## 4. Data and measures of TFP

This research uses a data panel with a sample of 10 industries or branches of the manufacturing and private services sectors in the 17 Spanish regions during the period 1995-2008. All the data used, including employment, output and capital of each regional industry, are from the BD.MORES b-2000 database (De Bustos et al., 2008)[12] and updates performed for this study, with the exception of worker training (Mas et al., 2008). The analysis in this paper is carried out for the manufacturing and construction industries and three branches of services devoted to sales, as defined in *Cambridge Econometrics*. The table below includes the variables that are used in the analysis and shows how they have been estimated.

The sectoral and regional variables are estimated, as can be appreciated in Table 2, 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 closet o each other.

c) In order to capture the size of the market, regional output is used (SIZ) after discounting the regional industry itself[13]. 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 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.

[12]This regional database is available on the following web page: http://www.sgpg.pap.meh.es/SGPG/Cln_Principal/Presupuestos/Documentacion/Basesdatosestudiosregionales.htm

[13] As an alternative to regional employment, Ciccone and Hall (1996) and Ciccone (2002) discuss and use what they define as a density index, that is, local employment divided by geographical area.

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.

**TABLE 2. Determinants of total factor productivity**

| Variable | |
|---|---|
| *Endogenous variable* | |
| Level of TFP ($TFPA_{ij,t}$) | Level of total factor productivity in each industry and region calculated on the basis of assuming constant returns. |
| Level of TFP ($TFPE_{ij,t}$) | Level of total factor productivity in each industry and region calculated on the basis of estimating capital and labour elasticities. |
| *Explanatory variables* | |
| 1. Sectoral TFP (A*SEC*) | Level of total factor productivity of the national industry or sector |
| 2. Specialisation (*ESP* ) | $Esp = \frac{Y_{ij,t} / Y_{j,t}}{Y_{iN,t} / Y_{N,t}}$ |
| 3. Market size (*SIZ)* | $Siz = Y_{j,t} - Y_{ij,t}$ |
| 4. Degree of diversification (*DIV*) | $Div = -\ln\left[\sum_{i=1}^{n}\left(\frac{Y_{ij,t}}{Y_{j,t}}\right)^2\right]$ |
| 5. Worker training (*HUM*) | Average years of schooling of the employed population in each region. |
| 6. Infrastructure (*INF*) | Total capital in transport and urban infrastructure divided by total private productive capital in each region. |
| 7. Technological capital(*TEC*) | Total public capital in R&D divided by total private productive capital in each region. |

Table 3 below presents the average growth rates of the explanatory variables that include the regional characteristics over the sample period: 1995-2008 and Table 4 the descriptive statistics of the series used in the estimation.

**Table 3. Average growth rates 1995-2008: percentages**

| Region | DIV | SIZ | HUM | INF | TEC |
|---|---|---|---|---|---|
| **Andalusia** | 0.19 | 3.20 | 1.38 | 1.34 | 2.02 |
| **Aragon** | 0.26 | 3.44 | 1.44 | -1.77 | -2.28 |
| **Asturias** | -0.22 | 2.77 | 1.49 | 2.85 | 2.18 |
| **Balearic Islands** | 1.08 | 2.39 | 1.28 | 1.07 | 5.59 |
| **Canary Islands** | 0.53 | 3.17 | 1.02 | -0.57 | 1.49 |
| **Cantabria** | -0.17 | 3.67 | 1.39 | 4.29 | 2.06 |
| **Castile and Leon** | 0.03 | 2.50 | 1.42 | -0.15 | 1.37 |
| **Castile La Mancha** | 0.07 | 3.36 | 1.42 | 0.49 | 6.08 |
| **Catalonia** | -0.27 | 3.15 | 0.94 | 0.63 | 2.98 |
| **Valencia Region** | -0.24 | 3.40 | 1.30 | 1.19 | 4.35 |
| **Extremadura** | -0.01 | 3.32 | 1.71 | -0.59 | 2.45 |
| **Galicia** | 0.21 | 2.71 | 2.10 | 1.00 | 1.86 |
| **Madrid** | -0.14 | 4.34 | 1.05 | -2.06 | -2.47 |
| **Murcia** | -0.26 | 4.03 | 1.49 | 0.03 | -1.17 |
| **Navarra** | -0.10 | 3.44 | 1.10 | 0.31 | 4.00 |
| **Basque Country** | 0.21 | 3.44 | 1.26 | 0.84 | 3.64 |
| **La Rioja** | 0.36 | 2.71 | 1.22 | -2.49 | 8.33 |

**Table 4. Descriptive statistics of the variables in the estimation**

| Variable | Obs. | Mean | Std.Dev. | Min | Max |
|---|---|---|---|---|---|
| **Ln TFPA** | 2380 | 4.547 | 0.359 | 3.332 | 5.877 |
| **Ln TFPE** | 2380 | 4.577 | 0.364 | 3.433 | 5.902 |
| **Ln ASEC** | 2380 | 4.593 | 0.309 | 4.110 | 5.673 |
| **Ln ESP** | 2380 | -0.214 | 0.703 | -3.506 | 1.264 |
| **DIV** | 2380 | 2.126 | 0.244 | 1.410 | 2.470 |
| **Ln SIZ** | 2380 | 9.360 | 0.934 | 7.312 | 11.319 |
| **Ln HUM** | 2380 | 2.386 | 0.069 | 2.188 | 2.542 |
| **Ln INF** | 2380 | -0.716 | 0.423 | -1.518 | 0.141 |
| **Ln TEC** | 2380 | -3.914 | 0.467 | -5.133 | 2.820 |

Total output of all the sectors considered (SIZ) has grown on average over this period. Their productive capital stock has also increased considerably, albeit less than technological capital, the initial values of which were unusually low in most Spanish regions except Madrid. Infrastructures have grown in all regions, but at different rates to private capital. Human capital has also grown across all regions, although at different rates.

*TFP Estimation Procedure*

This paper includes two procedures to estimate TFP for each industry in each region. The first procedure is the most common in the literature: following Solow using a Cobb-Douglas function with two factors, capital and labour. Constant returns, neutrality in the sense of Hicks and perfect competition are assumed. $\alpha_{ij}$ and $(1-\alpha_{ij})$ are used as shares for capital and for labour respectively, that are different in each industry in each region. The information on $\alpha_{ij}$ is extracted directly from the accounts available in the BD.MORES database[14]. The TFP growth rate is calculated as the difference between the output growth rate and the growth in the levels of Divisia inputs. To determine the relative levels of TFP in each regional industry, the methodology in Bernard and Jones (1996) and Harrigan (1997) is used. We call the total factor productivity obtained in this fashion *TFPA.*

The second procedure is based on estimating the elasticities of the two factors using a dual approach through a generalised Leontief cost function (Morrison and Schwartz, 1996). Indeed, despite the Solow residual being the most frequently used procedure to approximate TFP, the assumptions it entails are often considered overly restrictive. In this procedure neither the type of returns or perfect competition are imposed[15]. In order to obtain $\alpha_{ij}$ and $\beta_{ij}$, a cost function has been estimated for each sector *i* obtaining different values in each of the 17 regions. The returns are obtained by summing $\alpha_{ij}$ and $\beta_{ij}$ making any type of returns possible. Let us consider that under increasing returns, for example, the Solow residual would be attributed to TFP growth, which would be a consequence of a movement along the production function (Oh, Heshmati and Lööf, 2009). The procedure followed to calculate both the growth rates and levels of TFP are similar to the procedure described at the beginning of this paragraph and we call the series obtained *TFPE*.

**Table 5. Average values 1995-2008 de $\alpha_i$ and $\beta_i$**

| | First procedure (Accounts) | | Second procedure (Estimates) | |
|---|---|---|---|---|
| **Sector** | $\alpha_i$ | $\beta_i$ | $\alpha_i$ | $\beta_i$ |
| **Food, beverages and tobacco** | 0.336 | 0.664 | 0.304 | 0.678 |
| **Textiles, leather and footwear** | 0.194 | 0.806 | 0.217 | 0.804 |
| **Chemicals + rubber and plastics** | 0.328 | 0.672 | 0.249 | 0.692 |
| **Electrical, electronic and optical equipment** | 0.264 | 0.736 | 0.197 | 0.734 |
| **Transport equipment** | 0.319 | 0.681 | 0.192 | 0.706 |
| **Other manufactured products** | 0.310 | 0.690 | 0.244 | 0.703 |
| **Construction** | 0.230 | 0.770 | 0.083 | 0.779 |
| **Hotels and restaurants** | 0.328 | 0.672 | 0.114 | 0.707 |
| **Transport and communication** | 0.481 | 0.519 | 0.333 | 0.528 |
| **Financial intermediation** | 0.372 | 0.628 | 0.167 | 0.667 |

Table 5 presents the average values of $\alpha_i$ and $\beta_i$, following the two processes to obtain TFP. As Cingano and Schivardi (2004)[16] found, there is no significant discrepancy between the two procedures. As was the case for those authors, the estimated coefficient of capital recorded the greatest difference and was quite a bit lower than that obtained using accounts, which they interpret as a deviation of

[14] The BD.MORES database corrects the gross operating surplus and mixed profits to consider non remunerated work together with the wages.

[15]The results of the estimation of the cost function are available upon request.

[16] Although these authors estimate a production function in keeping with Olley and Pakes (1996) and not a cost function as an alternative to Solow's residual.

competitive factor markets. Furthermore, the differences in the coefficients barely change the TFP growth rates and only slightly deviate TFP levels. Consequently, the two methods lead to similar results, as can be verified in the next section of the paper.

## 5.- Econometric specification and Results

Using equation (7) 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

$$a_{ij,t} = \alpha + \sum_{k=1}^{n} \beta_k \ a_{ij,t-k} + \sum_{k=0}^{n} \lambda_k \ x_{ij,t-k} + \mu_{ij} + d_t + \varepsilon_{ijt} \tag{8}$$

being $a_{ij,t}$ the logarithm of the level of TFP – the endogenous variable[17] - 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 (7) and which were detailed in the previous section. The $\mu_{ij}$ 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[18]. $\varepsilon_{ijt}$ is the random disturbance.

Estimating this dynamic panel model entails various econometric problems, such as sample heterogeneity – in our case unobservable variations between regional industries – and the presence of the lags of the endogenous variable as regressors that are correlated to the errors, making the OLS estimator biased and inconsistent.

In order to solve these problems, in line with Arellano and Bond (1991), the Generalised Method of Moments and the estimator in differences – the Difference GMM - can be used. The idea behind the GMM estimator in first differences is to take first differences to eliminate the possible source of inconsistency generated by the presence of $\mu_{ij}$ and to use the levels of the explanatory variables lagged two or more periods as instruments to correct their endogeneity. As a result, expression (8) expressed in first differences would be:

$$\Delta a_{ij,t} = \sum_{k=1}^{n} \beta_k \ \Delta a_{ij,t-k} + \sum_{k=0}^{n} \lambda_k \ \Delta x_{ij,t-k} + \Delta d_t + \Delta\varepsilon_{ijt} \tag{9}$$

However, when there is a high degree of persistence in the series, or in unit root assumptions, and there is a small number of time observations, the estimator in first differences can suffer serious losses of efficiency due to ignoring information about

[17] 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.
[18] Another possibility would be to express the variables in deviations from their average over time.

moment restrictions. That is, the lagged levels of the explanatory variables are weak instruments for first differences[19]. Therefore, in order to solve this problem and following Arellano and Bover (1995) and Blundell and Bond (1998), this paper will employment the system GMM estimator (SYS-GMM hereafter), which yields gains in efficiency in regard to the estimator in differences. This estimator considers the model as a system of equations, one for each period of time. The equations differ in terms of instruments (or conditions of orthogonality). The endogenous variables in first differences are implemented with their levels lagged two or more periods and the endogenous variables in levels use the lagged first differences as instruments.

The consistency of these estimators lies in their compliance with conditions of orthogonality. In other words, the residuals must be serially uncorrelated and the explanatory variables exogenous. In order to verify the validity of the conditions of orthogonality – if the instruments are exogenous – the overidentification test proposed by Sargan (1958) and Hansen (1982) is used. The tests proposed by Arellano and Bond (1991) are also implemented to confirm the presence of residual serial correlation, the null hypothesis of which is no serial autocorrelation[20].

Table 6 presents the results of estimating some of the determinants of TFP in Spanish regional industries using the specification provided in equation (8) 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, as indicated previously, 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 sectorial 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"[21]. 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.

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[19] See Blundell and Bond (1998) and Blundell, Bond and Windmeijer (2000).

[20] That is, first-order autocorrelation is expected, AR(1), $\Delta\varepsilon_{it} = \varepsilon_{it} - \varepsilon_{it-1}$ will be correlated to $\Delta\varepsilon_{it-1} = \varepsilon_{it-1} - \varepsilon_{it-2}$ , but no autocorrelation of a higher order.

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

**Table 6**
**Estimation Results by Sample Period: 1995-2008**

| **Dependent variable** | | $Ln\,TFPA_{ij}$ | | | |
|---|---|---|---|---|---|
| ESTIMATION | | OLS [1] | F.E [2] | DIFF-GMM [3] | SYS-GMM [4] |
| $Ln\,TFPA_{ij}$ | t-1 | 0.967*** | 0.664*** | 0.768*** | 0.975*** |
| | | (0.022) | (0.062) | (0.052) | (0.013) |
| *DIV* | t | -0.321*** | -0.302*** | -0.187* | -0.266*** |
| | | (0.063) | (0.065) | (0.103) | (0.103) |
| | t-1 | 0.324*** | 0.328*** | 0.162* | 0.271*** |
| | | (0.062) | (0.016) | (0.089) | (0.102) |
| *Ln ESP* | t | 0.651*** | 0.656*** | 0.706*** | 0.675*** |
| | | (0.015) | (0.016) | (0.053) | (0.052) |
| | t-1 | -0.644*** | -0.550*** | -0.536*** | -0.669*** |
| | | (0.015) | (0.016) | (0.064) | (0.051) |
| *Ln ASEC* | t | 1.025*** | 1.042*** | 1.026*** | 1.050*** |
| | | (0.032) | (0.033) | (0.039) | (0.041) |
| | t-1 | -0.999*** | -0.799*** | -0.817*** | -1.034*** |
| | | (0.034) | (0.037) | (0.068) | (0.041) |
| *Ln SIZ* | t | 0.268*** | 0.243*** | 0.624*** | 0.353 |
| | | (0.072) | (0.072) | (0.224) | (0.254) |
| | t-1 | -0.264*** | -0.253*** | -0.620*** | -0.350 |
| | | (0.072) | (0.071) | (0.223) | (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 6**: 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.

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 variables[22]. 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 6 is total factor productivity obtained on the basis of the conventional assumptions of perfect competition and constant returns to scale (TFPA)[23]. As regards the comparison of the 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 7 presents the estimation of equation (9) 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, sectorial 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. The estimations consider the lagged endogenous variable and market size as endogenous variables[24]. 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 7, 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 7, 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 growth, 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),

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

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

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

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. 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. Market size, measured using regional output, also positive affects TFP growth, with a coefficient of 0.62 that drops to 0.32 when the variables representing regional endowments are included in the estimation.

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 growth.

As regards the role played by human capital, its contemporary effect on TFP growth is positive and significant with a coefficient of 0.21. The influence of transport 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. A similar result is obtained for regional industries in Spain for the period 1990-2003[25]. 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, Nahuis and Tang (2000), who also use stock as a variable[26], 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:

[25] See Escribá and Murgui, (2009). This research estimates a Euler equation for investment.

[26] An entire series of papers by CRENOS find evidence for Italy and other European countries that all types of intangible capital have positive effects, including Dettori, Marrocu and Paci (2011). Nevertheless, most research approaches this topic using the regionalised number of patents with the number of researchers or simply using expenditure on R&D as a percentage of GDP.

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

where $\lambda$ represents the coefficients of the lagged independent variables and $\beta$ 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 7[27].

In the long term – see Table 8 – specialisation, sectorial TFP and market size (the latter only when used as an endogenous ETFP variable) have a positive and significant impact on TFP growth. Sectorial TFP has the greatest impact in the long term on TFP growth, 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[28], 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.

[27] Note that the coefficients obtained are non linear combinations of the parameters estimated. Therefore, the null hypothesis is: $H_0 : \lambda_{LP} = 0$ . However, some papers state that when the estimated values of the lagged endogenous variable are near unity, the significance of the long term parameters may not be very reliable. In this case, they test the significance of the numerator in expression (9) using the Wald test. We have performed both tests and results remain unchanged.

[28] The standard deviations of TFP growth rates from on region to another range from 2.78% in Transport Equipment (and 2.10% in Electrical Equipment) to 0.84% in Other Manufactured Products (and 0.86% in Trade and Hotels and Restaurants). As regards the levels of TFP, Transport Equipment once again records the largest deviation (0.393), while Construction registers the smallest (0.105).

**Table 7.**
**Estimation Results by Sample Period: 1995-2008**

| Two-step DIFF-GMM Estimator | | | | | |
|---|---|---|---|---|---|
| **Dependent Variable** | | $Ln\,TFPA_{ij}$ | | $Ln\,TFPE_{ij}$ | |
| | | [1] | [2] | [3] | [4] |
| *Ln TFP*$_{ij}$ | t-1 | 0.768*** | 0.785*** | 0.662*** | 0.643*** |
| | | (0.052) | (0.053) | (0.063) | (0.075) |
| *DIV* | t | -0.187* | -0.255*** | -0.156 | -0.239*** |
| | | (0.103) | (0.091) | (0.107) | (0.100) |
| | t-1 | 0.162* | 0.284*** | 0.119 | 0.242*** |
| | | (0.089) | (0.084) | (0.084) | (0.087) |
| *Ln ESP* | t | 0.706*** | 0.713*** | 0.672*** | 0.674*** |
| | | (0.053) | (0.046) | (0.053) | (0.049) |
| | t-1 | -0.536*** | -0.539*** | -0.439*** | -0.427*** |
| | | (0.064) | (0.057) | (0.073) | (0.074) |
| *Ln ASEC* | t | 1.026*** | 1.009*** | 1.014*** | 0.979*** |
| | | (0.039) | (0.038) | (0.041) | (0.042) |
| | t-1 | -0.817*** | -0.805*** | -0.721*** | -0.653*** |
| | | (0.068) | (0.058) | (0.075) | (0.083) |
| *Ln SIZ* | t | 0.624*** | 0.327*** | 0.598*** | 0.307*** |
| | | (0.224) | (0.098) | (0.223) | (0.101) |
| | t-1 | -0.620*** | -0.265*** | -0.554** | -0.191* |
| | | (0.223) | (0.096) | (0.220) | (0.107) |
| *Ln HUM* | t | | 0.214* | | 0.162* |
| | | | (0.119) | | (0.090) |
| | t-1 | | -0.287** | | -0.274** |
| | | | (0.119) | | (0.128) |
| *Ln INF* | t | | 0.202* | | 0.173* |
| | | | (0.092) | | (0.093) |
| | t-1 | | -0.132 | | -0.107 |
| | | | (0.090) | | (0.097) |
| *Ln TEC* | t | | 0.019 | | 0.026 |
| | | | (0.034) | | (0.032) |
| | t-1 | | -0.028 | | -0.044 |
| | | | (0.037) | | (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. | | 2040 | 2040 | 2040 | 2040 |
| Time Dummies | | Yes | yes | yes | yes |

**Note for Table 7**: 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.

**Table 8. Long Term Effects**

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

Note: *p-values* of coefficient significance are displayed in brackets. The null hypothesis is $H_0 : \lambda_{LP} = 0$

## 6. Conclusions and Economic Policy Recommendations

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.

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, although small regional differences are observed in the TFP growth rate of each individual industry. This research analyses the evolution of TFP in both sectoral and regional terms.

Over the period analysed for Spain, important contemporary impacts on the TFP growth 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. This result is similar to that obtained by Cingano and Schivardi (2004). 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.

The spillovers that allow regional industries to achieve higher levels of efficiency take place between companies that belong to the same branch of activity. Technical change (Arrow, 1962) is the result of experience gained on the production site where companies of the same branch of activity are concentrated, so specialisation and the size of the region boost growth in TFP.

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.

In the long term, despite the performance of TFP in each sector not being identical in each region, TFP growth 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 growth of TFP in regional industry, which as in the case of specialisation, suggests that economies of scale have an influence of TFP trends.

The industrial policy required must refer to more than exclusively modifying the production model – apart from the necessary reduction of the construction sector in Spain – if that is understood to exclusively entail a change in productive activities. It will be to no avail if our sectoral production structure increasingly resembles that of other more advanced countries if we are less efficient in all branches of industry. It is also natural for regions within a nation to specialise. 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. Growth in TFP will also depend on the interaction between industrial policy and regional policy regarding the endowment of infrastructures and human capital.

## 7. Bibliographical References


Adamson, D.W., D.E. Clark and M.D. Partridge (2004): "Do Urban Agglomeration effects and household amenities have a skill bias?", *Journal of Regional Science*, 44, 201-223

Arellano, M. and S. Bond (1991): "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations", *The Review of Economic Studies* 58, 277-97.

Arellano, M. and O. Bover (1995): "Another look at the instrumental variable estimation of error-components models", *Journal of Econometrics* 68, 29-51.

Arrow, K (1962): "The Economic Implications of Learning by Doing". *Review of Economic Studies* 29, 155-73

Arthur, B. (1986): "Industry location patterns and the importance of history", Stanford University, CEPR Nº 84.

Ascari, G. and V. Di Cosmo (2004): "Determinants of Total Factor Productivity in the Italian Regions", mimeo.

Aschauer, D.A. (1989): "Is public expenditure productive?", *Journal of Monetary Economis*, 23, Marzo, 177-200.

Barro, R. (1990): "Economic growth in a cross section of countries", *The Quarterly Journal of Economics*, 106(2), 407-443.

Beaudry, C. and A, Schiffaurova (2009):"Who´s right, Marshall or Jacobs? The localization versus urbanization debate". *Research Policy*, 38, 318-337.

Bernard, A. and Ch.I. Jones (1996): "Productivity across Industries and Countries: Time Series Theory and Evidence", *Review of Economics and Statistics*. February, pp. 135-146.

Boscá, J.E., F.J. Escribá, F.J. Ferri and M.J. Murgui (2010): "La inversión en infraestructuras públicas: una panorámica y algunas conclusiones para las regiones españolas", Ministerio de Economía y Hacienda. DGP D-2010-11.

Blien, U., J. Suedekum and K. Wolf (2006): "Local employment growth in West Germany: A dynamic panel approach", *Labour Economics*, 13, 445-458.

Blundell, R. and S. Bond (1998): "Initial conditions and moment restrictions in dynamic panel data models", *Journal of Econometrics* 87, 115-43.

Blundell, R., S. Bond and F. Windmeijer (2000): "Estimation in dynamic panel data models: improving on the performance of the standard GMM estimator", *IFS* Working Paper 00/12.

Bond, S., A. Hoeffler and J.Te mple (2001) : "GMM Estim ation of empirical growth models", CEPR Discussion Paper Series, No.3048

Brülhart M. and N.A. Mathys (2008): "Sectoral agglomeration economies in a panel of European Regions", *Regional Science and Urban Economics*, 38, 348-362.

Bun, M and F. Windmeijer (2010): "The Weak Instrument Problem of the System GMM Estimator in Dynamic Panel Data Models", *The Econometrics Journal* 13, 95-126.

Callejón, M. and Costa, M.T. (1995): "Economías externas y localización de las actividades industriales", *Economía Industrial*, 305, 75-86.

Callejón, M. and Costa, M.T. (1996): "Geografía de la producción. Incidencia de las externalidades en la localización de las actividades en España", *Información Comercial Española. Revista de Economía*, 754, 39-49.

Ciccone, A. (2002): "Agglomeration effects in Europe", *European Economic Review*, 46(2), 213-227.

Ciccone, A. and R. Hall (1996):"Productivity and the density of economic activity", *American Economic Review*, 86, 54-70.

Cingano, F. and F. Schivardi (2004): "Identifying the sources of local productivity growth", *Journal of the European Economic Association*, 2 (4), 720-742.

Combes, P. P. (2000): "Economic structure and local growth: France, 1984-1993, *Journal of Urban Economics*, 47(3), 329-355.

Combes, P., G.Duranton, L. Gobillon and S. Roux (2010): "Estimating agglomeration economies with history, geology, and worker effects", CEPR Discussion Papers 6728.

Combes, P. P., T. Magnac and J.M. Robin (2004): "The dynamics of local employment in France", *Journal of Urban Economics*, 56(2), 217-243.

Combes, P. P. and H.G. Overman (2004): The spatial distribution of economic activities in the European Union, in Henderson, J.V. and J.F. Thisse (eds.) *Handbook of Regional and Urban Economics*, Volume 4, Elsevier North-Holland.

De Bustos,A., A. Diaz, A. Cutanda, F.J. Escribá, M.J. Murgui and M.J. Sanz (2008): "La BD.MORES en base 2000: Nuevas estimaciones y variables". Ministerio de Economía y Hacienda. DGAPP. D-2008-08

De Lucio, J.J., J.A. Herce and A. Goicolea (1996): "Externalities and industrial growth: Spain 1978-1992", *FEDEA*. Documentos de trabajo 96.14.

De Lucio, J.J., J.A. Herce and A. Goicolea (2002): "The effects of externalities on productivity growth in Spanish industry", *Regional Science and Urban Economics*, 32, 241-258.

Dekle R. (2002):"Industrial concentration and regional growth: evidence from the prefectures", *The Review of Economics and Stadistics*, 84(2), 310-315.

Dettori, B., E. Marrocu and R. Paci (2011): Total factor productivity, intangible assets and spatial dependence in the European regions", *Regional Studies*, pp. 1-16..

Di Addario, S. and E. Patacchini (2008): "Wages and the city. Evidence from Italy", *Labour Economics*, 15, 1040-1061.

Escribá, F.J. and M.J. Murgui (2009): "Government policy and industrial investment determinants in Spanish regions", *Regional Science and Urban Economics*, 39(4), pp. 479-488.

Escribá F.J. and M.J. Murgui (2010): Crecimiento del empleo regional: un enfoque dinámico". Ministerio de Economía y Hacienda. DGP, D-2010-07.

Esteban, L., J.M. Hernández and L. Lanaspa (2001): "Patrones de localización de la producción y efectividad de la política industrial", *Economía Industrial*, 342, 163-174.

Fisher, M. T. Scherngell and M. Reismann (2009):"Knowledge spillovers and total factor productivity. Evidence using a spatial panel data model" *Geographical Analysis*, 41, 204-220.

Glaeser, E.L., H.D. Kallal, J.A. Scheinkman, and A. Shleifer (1992): "Growth in cities", *Journal of Political Economy*, 100 (6), 1126-1152.

Graham D., P. Melo, P. Jiwattanakulpaisarn and R. Noland (2010): " Testing for causality between productivity and agglomeration economies", *Journal of regional Science*, 50(5), 935-951.

Hansen, L.P. (1982): "Large sample properties of Generalized Method of Moments estimators", *Econometrica*, 50, 1029-1054.

Harberger, A.C. (1998):"A Vision of the Growth Process", *American Economic Review* 88(1), pp 1-32.

Harrigan, J. (1997): "Estimation of Cross-Country Differences in Industry Production Functions", *Journal of International Economics,* 47, 267-293.

Henderson, V., A. Kundoro and M. Turner (1995): "Industrial development in cities", *Journal of Political Economy*, 103(5), 1067-1090.

Heuermann, Daniel F. (2009): "H uman capit al externalities in W estern Germ any", IAAEG discussion paper series, No. 03/2009, http://hdl.handle.net/10419/51389.

Hulten, CH. R. (2001): "Total factor productivity. A short biography", NBER WP. Nº 7471.

Jacobs, B., R. Nahuis and P. Tang (2000): "Human capital, R+D and the assimilation of Technologies in the Netherlands", en Bart Van Ark, S. Knipers y G. Kuper (eds.). *Productivity, Technology and Economic Growth*. Kluwer Academic Publishers.

Lee, B, K, Sosin and S, Hong (2005):"Sectoral manufacturing productivity growth in Korean regions", *Urban Studies* 42, 1201-1219.

Lucas, R. (1988): " On the mechanics of economic development", *Journal of Monetary Economics*, 22, 3-42.

Marrocu E. and R. Paci (2010):"The effects of public capital on the productivity of the Italian regions", *Applied Economics*, 42, 989-1002.

Marrocu E., R. Paci and M. Pontis (2011): "Intangible capital and firm s' productivity". *Industrial and Corporate Change*, pp. 1–26 doi:10.1093/icc/dtr042

Marrocu E. , R. Paci y S. Usai (2011): "P roductivity grow th in the old and the new Europe: the role of agglom eration externalities", Paper provided by ERSA conference papers with number ersa11p200

Mas, M. F. Pérez, L. Serrano, E. Uriel and A. Soler (2008): *Capital Humano. Metodología y series históricas 1964-2007*, IVIE y Fundación Bancaja, Valencia

Melo P.C., D.J. Graham and R.B. Noland (2009): "A meta-analysis of estimates of urban agglomeration economies" *Regional Science and Urban Economies*, 39, 332-342.

Moreno, B. (1996): "Externalities and growth in the Spanish industries", Documento de trabajo 96-17, FEDEA.

Moretti E. (2004):"Workers´ Education, Spillovers, and Productivity: Evidence from Plant-Level Production Functions", *American Economic Review*, 94, 656-690.

Morrison, C. and A. Schwartz (1996): State infrastructure and productive performance", *The American Economic Review*, 1095-1111.

O´Mahony, M and M.P. Timmer (2009):"Output, Input and Productivity Measures at the Industry Level: the EU KLEMS data base" *Economic Journal*, 119 (538) pp.F374-F403.

Nefte, F.M.H. (2007): "Time varying agglomeration externalities. A long term perspective on the changing benefits on agglomeration in UK countries (1841-1971). Section of Economic Geography UTRECHT.

Oh, D., A. Heshmati and H.Lööf (2009): "Technical change and total factor productivity growth for Swedish manufacturing and service industries". CESIS, Electronic WP Series, Nº 193.

Olley, S. and A. Pakes (1996): "The dynamics of productivity in the telecommunications equipment industry", *Econometrica*, 64, 1263-1297.

Otsuka A. and N. Yamano (2008): "Industrial agglomeration effects on regional economic growth: A case of Japanese Regions", Regional Economics Applications Laboratory (REAL) WP.08-T.2

Paci, R. y S. Usai (2008):"Agglom eration economies, spatial dependence and local industry growth", *Revue d'Économie Industrielle*, 123, pp. 87-109.

Romer P, (1986):"Increasing returns and long-run growth". *Journal of Political Economy*, 94, 1002-1037.

Rosenthal, S.S. and W. Strange (2004): "Evidence on the nature and sources of agglomeration economics", in Henderson, J.V. and J.F. Thisse (eds.) *Handbook of Regional and Urban Economics*, Volume 4, Elsevier North-Holland.

Sargan, J.D. (1958): "The estimation of economic relationships using instrumental variables", *Econometrica*, 26, 393-415.

Solow, R. (1957): "Technical change and the aggregate production function", *Review of Economics and Stadistics*, 39(3), 312-20.

*The Conference Board Total Economy Database, September 2010*, http://www.conference-board.org/data/economydatabase/

Usai, S. y R. Paci (2003): "Externalities and local economic growth in manufacturing industries", in *European Regional Growth*, Fingleton B. (ed.). Berlin: Springer-Verlag.

Viladecans, E. (2003): "Economías externas y localización del empleo industrial", *Revista de Economía Aplicada*, 31, 5-32.

Windmeijer, F. (2005): "A finite sample correction for the variance of linear efficient two-step GMM estimators", *Journal of Econometrics,* 126, 25-51.