A Stochastic Frontier Analysis of Total Factor Productivity Growth and Convergence among Spanish Provinces

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Catarina Cardoso
Department of Economics, School of Business and Economics,
Loughborough University, LE11 3TU, UK

and

Geetha Ravishankar
Division of Economics, Nottingham Business School,
Nottingham Trent University, NG1 4BU, UK
E-mail: Geetha.Ravishankar@ntu.ac.uk

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Abstract

Using the stochastic frontier analysis methodology, this paper contributes to the literature on regional growth and productivity by providing an assessment of the impact of human capital development on regional efficiency in the Spanish NUTS III regions. Data on physical and human capital over the period 1991-2006 is utilized in a stochastic production function to estimate production inefficiencies. To-date there have been relatively few studies focusing on regional productivity and convergence patterns using stochastic frontiers and even fewer examining that of Spain. This paper addresses this current weakness in the literature and relates it with different educational levels. Overall, the results provide evidence of regional convergence towards the best practice frontier, a process that is beneficially aided by human capital development

Keywords: Regional Growth, Stochastic Production Frontier, Human Capital

1. Introduction

Educational levels in Spain have seen considerable improvement in the last four decades. This improvement over time was particularly striking post 1990 when there was a greater reduction in the gap of average educational levels in Spain vis-à-vis that of the OECD. Spain is known to have significant regional disparities and the availability of a rich regional dataset on physical and human capital has facilitated considerable research on this area (de la Fuente, 2002). In particular, the role of human capital in Spain's regional productivity growth has received considerable attention (de la Fuente, 2002; Di Liberto, 2007; López-Bazo and Moreno, 2007).

The received literature on regional growth (Ang et al, 2011) draws on endogenous growth theory to examine the impact of human capital on economic growth. The positive association between human capital development and economic growth is theorized to occur via external scale economies associated with human capital and the complimentarity between human and physical capital (Sanroma and Ramos, 2007).

However, this literature inherently assumes a production process that efficiently combines human capital and other inputs to produce the maximum feasible output level. In other words, output levels are placed on the production frontier and inefficient production is assumed away so that observed regional output levels are coincident with the maximum (technically efficient) output levels. Estimations of growth that fail to take into account productive inefficiencies may thus generate biased parameters. The importance of accounting for the possibility of inefficient production is illustrated by the findings of Bos et al (2010), Gumbau-Albert (2010a; 2010b). In particular, Gumbau-Albert (2010 a and 2010b) study regional growth in Spain utilizing the SFA approach. A drawback of this latter study is the absence of human capital in their estimations of regional growth. Moreover, the level of regional data is at NUTSII.

By departing from this assumption of technically efficient production, this paper makes the following contributions. First, in contrast to the traditional approaches of convergence studies which estimate average production functions, we adopt the Stochastic Frontier Analysis wherein regional production can deviate from the maximum possible due to both technically inefficient production and random disturbances. This approach enables us to assess the degree to which a given region's observed output deviates from the maximal possible. In doing so, the resulting region specific productive efficiencies are modeled as outcomes of the level of human capital development. As noted by Manca (2011), regional growth is intimately linked with the relative efficiency with which economic agents adopt and implement available technology. Consequently, variations in levels of human capital development impact regional economic growth in a non-trivial manner. Allocative efficiency which captures the degree to which the input mix used within regions is efficient in the sense that input prices are equal to their marginal returns is not considered here due to the lack of data on input prices.

Secondly, with greater development of human capital and the externalities associated with it, the levels of inefficiency are theorized to decline. To assess this, regional efficiencies are utilised to determine the convergence levels thereby providing an understanding of the efficiency growth at the regional level. The application of this methodology leads to new findings on regional efficiency growth in Spain and has direct consequences in informing policies designed to enhance regional development.

Finally, all estimations are deployed on a dataset that identifies the regions and their respective inputs and outputs at a NUTS III level of disaggregation. This affords a richer level of data detail within which to assess regional growth.

To-date there are very few studies that examine Spanish regional efficiency and even fewer that do so at a NUTS III level of disaggregation. One of the closest studies is that of Enflo and Hjerstrand (2009). However the authors use a NUTS II level dataset and adopt the deterministic Data Envelopment Analysis approach to study regional productivity. The aim of the paper is thus to investigate the degree of regional efficiency and trace its links with the level of human capital development. Additionally, the degree to which regions identified as relatively inefficient converge to the best practice regions is also assessed. Policy implications related to these are finally discussed.

2. Literature Review

The role of human capital in Spanish regional growth has been studied by several authors, but most of them work with the NUTS II level of regional disaggregation and use a different approach. The specifications vary but the most common are either a convergence equation (Barro and Sala-i-

Martin, 1992) according to which the regional growth rate is explained by a set of explanatory variables that includes the initial income per capita or per worker and human capital levels, to an aggregate production function. For example, de la Fuente (2002) concluded that the equalization of education levels contributed to the reduction of productivity disparities over the period 1955-1991 by estimating a convergence equation. Di Liberto (2007) studied the role of human capital in the Spanish NUTS II regions growth over the period 1964-1997 by estimating the convergence equation and divided the regions into two clubs according to the level of GDP per capita and human capital. The average years of total education and the average years of secondary schooling played a positive and significant role only in the rich regions club, in contrast with the significant and positive effect of primary schooling in the poor club.

For a shorter period, 1995-2000, Galindo-Martín and Álvarez-Herranz (2004) proxied human capital by a labour-income measure and by estimating the production function found a positive effect on regional GDP per capita growth. López-Bazo and Moreno (2007) estimated both the private and social returns to human capital in the Spanish NUTS II regions for the period 1980-1995 by using a cost-system in which human capital is included as a factor that shifts the cost function. Higher human capital externalities were found in the regions which were initially in a worse position. The same authors (López-Bazo and Moreno, 2008) distinguished the direct effect of human capital on output from its indirect effect of stimulating investment in physical capital and their findings suggest not only a positive effect of human capital on aggregate productivity but also a significant indirect effect through the stimulation of investment in physical capital.

Only Ramos *et al.* (2010) focus on the human capital effects at the NUTS III level of regional disaggregation and estimate both the production function and the convergence equations by using spatial econometrics. Despite a positive impact of education on productivity growth, no evidence of human capital regional spillovers was found.

3. Methodology

A production unit is considered technically efficient if, using the given technology, it produces the maximum output using a given level of inputs. Developed independently by Aigner *et al.* (1977) and Meeusen and van den Broeck (1977), Stochastic Frontier Analysis (SFA) specifies a production frontier wherein the error term is comprised of producer specific inefficiency and random error. Thus, the production function for a panel of *N* regions in *T* time periods using a vector of *x* inputs, such that $x \in R_{+}^{m}$, to produce the output vector *y* is specified as follows:

$$Y_{nt} = \beta_0 + x'_{nt}\beta + \varepsilon_{nt} \quad [1]$$

$$\varepsilon_{nt} = v_{nt} - u_{nt} \quad [2]$$

where y_{nt} is the nth region's output in log values in the t^{th} period, x_{nt} is the logged value of the inputs and β is a vector of unknown parameters to be estimated. In the context of our study, the input vector consists of physical capital, k_{nt}, and labour, l_{nt}. We additionally specify a time trend variable, *t*, to account for neutral technical change. Technical inefficiency resides in the composed error term ε_{nt}, which is thus specified as $(v_{nt} - u_{nt})$. The v_{nt} represents random error that is *i.i.d* normally distributed and u_{nt} is a non-negative random variable representing technical inefficiency. The Maximum Likelihood Estimation (MLE) procedure used to obtain the parameter values also generates an additional gamma parameter, defined as $\gamma = \sigma_u^2 / \sigma_\varepsilon^2$, where $\sigma_\varepsilon = \sigma_u + \sigma_v$. As the ratio of the variance of inefficiency to that of the composed error term, the gamma parameter, when significant, indicates the presence of technical inefficiency and justifies the use of the SFA approach.

To operationalise the above model, we adopt the Battese and Coelli (1995) SFA model wherein the inefficiency effects are obtained as truncations of a normal distribution with a constant variance but with means that are a function of observable linear variables[1]. This model offers the advantage of modelling the technical inefficiency directly as a function of explanatory variables and is estimated by adapting equation [1], reproduced below, as follows.

$$Y_{nt} = \beta_0 + x'_{nt}\beta + \varepsilon_{nt} \quad [2]$$

$$\varepsilon_{nt} = v_{nt} - u_{nt} \quad [3]$$

$v_{nt} \sim N\left(0, \sigma_\varepsilon^2\right)$ and u_{nt} is obtained by the truncation at zero of a normal distribution with mean $z_{it}\delta$ and variance σ^2. z_{it} is a vector of observed variables that influence inefficiency and δ is vector of unknown parameters to be estimated. In the context of this paper, these z-vectors comprise measures of Human Capital, which thus form the primary determinants of inefficiency. As such, observed regional efficiency levels are attributed to the levels of human capital development.

Having attained the parameter estimates, region specific efficiency at the t^{th} period is obtained following Battese and Coelli (1995) as:

$$TE_{it} = E\left[exp\left(-U_{it}\right)\middle|\varepsilon_{it}\right] \quad [4]$$

These region specific efficiency scores measure the distance of the i^{th} region's observed output levels in time period *t* to its frontier level of output. An efficiency value of unity would thus indicate that the region was on its frontier and utilising available technology to produce the maximum possible output level. An efficiency score lower than 1 would therefore indicate that the region had scope to further increase its output given its observed inputs.

1. β-convergence

Tests of convergence of the efficiency scores are presented next. The concept of β-convergence was proposed by Barro and Sala-i-Martin (1992) and it is defined as an inverse relationship between the growth rate and the initial level of income per capita. In the regional context, this means that poorer regions grow faster, which is explained by the diminishing returns of the physical capital accumulation. Never the less, the concept can be applied to a variety of economic variables. In this case beta convergence tests if the efficiency level grows faster in the less efficient regions than in the most efficient ones suggesting catching-up.

Following Weill (2009) and Mamatzakis (2008), this section estimates the convergence equation using the efficiency scores obtained in the previous section:

$$ln\,Eff_{i,t} - ln\,Eff_{i,t-1} = \alpha + \beta\, ln\,Eff_{i,t-1} + \varepsilon_{i,t} \quad [5]$$

where $\ln \mathrm{Eff}_{i,t}$ is the logged efficiency score of the i^{th} region in the t^{th} time period and $\ln \mathrm{Eff}_{i,t-1}$ is the logged efficiency score of the i^{th} region in the previous time period. A significant and negative β-coefficient indicates convergence in the sense that the most inefficient regions initially are those that exhibit a higher growth rate in the respective efficiency score. In other words, the regions are converging faster. This equation is estimated through the system-GMM in order to control for endogeneity.

[1] A comprehensive review of SFA models is provided in Coelli et al () and Kumbhakar and Lovell (2000).

2. Data

Data on GDP per worker was collected from the Spanish National Institute of Statistics' (INE) Regional Accounts. Before 1995, the GDP nominal values are provided in the country's national currency, Pesetas, and according to the 1986 accounting system. The nominal regional GDP for 1994 is given for both accounting systems (1986 and 1995), so this common year was used to convert the previous years (1991-93) values into a series closer to the 1995 new accounting system. The second step was to convert the GDP value into Euros by using the respective exchange rate at 31 December 1998 (1 Euro=166.66 Pesetas). GDP real values were then calculated using the GDP deflator and 2000 was the base year. The panel integrates the 50 NUTS III Spanish regions which are the provinces. Apart from the capital province, Madrid, which is among the richest regions as expected, all the other richest regions are located at País Vasco (Basque Country) and Cataluña, which are both in the Northeast, and the poorest regions are located in Extremadura, Andalucía and Galicia and tend to remain poor over the period.

Data on physical and human capital at the NUTS III level of regional disaggregation is available from the Fundación BBVA (Banco Bilbao-Viscaya)-IVIE (Instituto Valenciano de Investigaciones Económicas) for the investment in physical capital and the Fundación Bancaja-IVIE for the regional human capital stock. According to de la Fuente (2002), these regional datasets are unique and have important advantages, namely the fact that the data is fully comparable across regions and over time. For each NUTS III region, the IVIE human capital dataset provides the average years of schooling of the total workers employed[2]. The richest regions in terms of GDP per worker tend also to be the richest in human capital.

Region specific inefficiency is modelled as a function of the average levels of primary, secondary and tertiary education. Additionally, the share of agricultural sector in the gross value added is included in order to control for the level of regional development.

The requisite SFA model, as detailed in equation [2], is run in conjunction with these variables along three model specifications. In Model 1, capital and labour is used to determine the GDP per worker and a time trend is incorporated to capture movement of the frontier over time. The inefficiency terms are determined by the average years of primary, secondary and tertiary education with the share of the agricultural sector on gross value added. This forms our baseline model. Model 2, additionally, incorporates the time trend variable as a determinant of inefficiency, thereby providing an indication of the temporal evolution of inefficiency. A negative and significant time trend variable would thus indicate a fall in inefficiency over time. Finally, Model 3, includes an interaction between the capital and time trend.

4. Results

Maximum likelihood estimates of the model parameters are provided in Table 1. As can be seen from the same, all variables have the expected signs. The time trend variable, however, is not found to be significant.

[Insert Table 1]

The presence of inefficiency in the composed error term is evidenced by the gamma parameter, which is significant at the 1% level. Defined as the ratio of the variance of the inefficiency component to that of the composed error term, a value of 0.974 for gamma indicates that nearly all of the variation in the composed error term is attributable to the inefficiency component.

[2] Población Ocupada

Physical capital is found to be positive and significant, as expected, thereby indicating that regions with greater stocks of physical capital experience greater economic growth. As can be seen from its positive and significant coefficient, the greater the share of the agricultural sectors in GVA, the lower the efficiency of the region. The agricultural sector usually presents as relatively less productive and efficient (Bos et al, 2010) and this is borne out in the present study.

Turning to the human capital proxies, upon which regional inefficiencies are contingent, Table 1 shows that increasing levels of human capital development is associated with lower regional inefficiency. This is evidenced by the significant and negatively signed coefficient values for the average levels of primary, secondary and tertiary education. All the levels of education contributed to reduce the inefficiency levels, however secondary schooling played a stronger role than primary and even higher education. The share of agriculture in total Gross Added Value was introduced as a proxy for the level of development of the region. As expected, the less developed is a region the higher is the level of inefficiency. An examination of the region specific inefficiencies would serve to assess the degree to which the above factors impact the productive capabilities of the regions. Table 2, thus, reports the regional efficiency scores.

[Insert Table 2]

As expected, the most efficient regions are simultaneously the richest in terms of GDP per worker and are those in the Basque country (Álava, Guipúzcoa, Vizcaya), Navarra and Comunidad de Madrid.

[Insert Figures 1 and 2]

Figure 1 illustrates the spatial distribution of the efficiency scores (obtained according to model 1) across the Spanish provinces. The darkest regions represent the most efficient in the beginning and at the end of the period. Apart from the capital region, Madrid, which is among the most efficient regions as expected, the other regions are Navarra and those located at Basque Country, which are all in the Northeast. The less efficient are located in Extremadura. While, there is a tendency is for persistency in levels of inefficiency over the period, there are a few cases of regional mobility such as the decline of the islands (Canary and Balears) and the provinces that integrate Andalucía (Granada, Almeria, Jaén, Sevilla and Córdoba which is the most dramatic case).

The analysis proceeds with the estimation of the convergence equation in order to detect to what extent the evolution of a region's efficiency level is determined by its initial level. The results are reported in Tables 3, 4 and 5. Both one and two-step GMM estimator is applied and the diagnostics confirm the validity of the instruments in both cases.

The results obtained provide evidence of β-convergence as the β-coefficient is always negatively significant. Therefore, the regional growth effects are linked with efficiency improvements. And in particular, the lower the region's initial efficiency level, the higher its growth rate over the period.

The beneficial impact of human capital development as evidenced by the negative and significant association between the human capital proxies and regional inefficiencies, coupled with the evidence of beta convergence, suggests that the development of human capital positively aids in regional growth towards the best practice frontier.

5. Conclusion

Using a NUTSIII level data set on Spanish regional growth, this paper utilises the Stochastic Frontier Analysis approach to assess the degree to which regional growth is impacted by human capital development. Unlike the approach typically adopted in convergence studies, SFA accounts for instances where regional production can deviate from the maximum possible due to both technically inefficient production and random disturbances. In addition, the resulting region specific productive efficiencies are modeled as direct outcomes of the level of human capital development. Overall, these results provide evidence of regional convergence towards the best practice frontier, a process that is beneficially aided by human capital development.

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Table 1 Estimation Results for Battese and Coelli (1995) SFA Model

VARIABLES	Model 1 lngdppw	Model 2 lngdppw	Model 3 lngdppw
lnCapital	0.386*** (0.0218) [a]	0.375*** (0.0225)	0.314*** (0.0488)
Time trend	0.000003 (0.00002)	-0.00004 (0.00003)	-0.000002 (0.00002)
lnCapital Time trend			0.000183* (0.000107)
Constant	0.208*** (0.00900)	0.225*** (0.0146)	0.219*** (0.0127)
ln Average primary education	-0.143*** (0.0220)	-0.144*** (0.0220)	-0.140*** (0.0213)
ln Average secondary education	-0.277*** (0.0466)	-0.285*** (0.0472)	-0.273*** (0.0450)
ln Average tertiary education	-0.105*** (0.0207)	-0.105*** (0.0209)	-0.102*** (0.0200)
Share of agricultural sector	0.621*** (0.0892)	0.616*** (0.0892)	0.648*** (0.0875)
Time trend		-0.00007** (0.00004)	
Constant	0.743*** (0.0835)	0.783*** (0.0864)	0.741*** (0.0812)
Gamma [b]	0.974*** (0.014)	3.583*** (0.496)	3.704*** (0.740)
Observations	800	800	800

[a] Standard errors are reported in parentheses.
[b] Gamma, $\lambda = \sigma_u / \sigma_v$, ratio of the standard deviation of the inefficiency component to the standard deviation of the random error.
*** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

Table 2 Average Regional Efficiency (AVRE)

REGION	Model 1	Model 2	Model 3
	AVRE	AVRE	AVRE
Álava	0.96	0.95	0.96
Albacete	0.76	0.74	0.73
Alicante	0.75	0.74	0.75
Almería	0.88	0.87	0.86
Asturias	0.8	0.79	0.79
Ávila	0.72	0.72	0.72
Badajoz	0.70	0.69	0.68
Barcelona	0.89	0.88	0.88
Burgos	0.9	0.89	0.89
Cáceres	0.63	0.63	0.63
Cádiz	0.90	0.89	0.89
Cantabria	0.81	0.81	0.81
Castellón de la Plana	0.86	0.86	0.86
Ciudad Real	0.78	0.78	0.77
Comunidad de Madrid	0.96	0.96	0.96
Córdoba	0.8	0.8	0.79
Cuenca	0.76	0.75	0.75
Girona	0.79	0.79	0.79

REGION	Model 1	Model 2	Model 3
	AVRE	AVRE	AVRE
Granada	0.79	0.78	0.78
Guadalajara	0.75	0.75	0.75
Guipúzcoa	0.94	0.94	0.93
Huelva	0.84	0.83	0.83
Huesca	0.74	0.74	0.73
Jaén	0.82	0.81	0.81
La Coruña	0.79	0.79	0.78
La Rioja	0.91	0.91	0.9
León	0.76	0.77	0.76
Lleida	0.90	0.90	0.89
Lugo	0.67	0.67	0.67
Malaga	0.77	0.77	0.76
Murcia	0.8	0.8	0.79
Navarra	0.97	0.97	0.96
Orense	0.65	0.65	0.65
Palencia	0.83	0.84	0.82
Pontevedra	0.75	0.75	0.75
Salamanca	0.75	0.76	0.74

REGION	Model 1	Model 2	Mode3
	AVRE	AVRE	AVRE
Segovia	0.79	0.8	0.78
Sevilla	0.88	0.89	0.88
Soria	0.78	0.79	0.77
Tarragona	0.85	0.87	0.83
Teruel	0.85	0.86	0.83
Toledo	0.75	0.76	0.75
Valencia	0.81	0.82	0.81
Valladolid	0.91	0.92	0.91
Vizcaya	0.95	0.96	0.94
Zamora	0.75	0.76	0.74
Zaragoza	0.89	0.91	0.89
Baleares	0.9	0.92	0.89
Las Palmas	0.88	0.9	0.88
Santa Cruz de Tenerife	0.76	0.78	0.75

Table 3 System GMM Results for the β-Convergence Equation

Dependent Variable: Efficiency score from Model 1		
	GMM 1	GMM 2
α	-0.05** (-2.48)	-0.07*** (-2.72)
Eff_{it-1}	-0.19** (-2.48)	-0.28*** (-2.73)
No. Observations	750	750
No. Instruments	30	30
Arellano-Bond test for AR(2)	-0.30 (0.77)	-0.35 (0.73)
Sargan test	18.38 (0.19)	18.38 (0.19)
Hansen test	14.85 (0.39)	14.85 (0.39)

Notes: t-statistics based on robust standard errors in brackets, except for the diagnostic tests which are the *p*-values. *, ** and *** indicate statistical significance at 10%, 5% level and 1% level.

Table 4 System GMM Results for the β-Convergence Equation

Dependent Variable: Efficiency score from Model 2		
	GMM 1	GMM 2
α	-0.05** (-2.58)	-0.07*** (-2.85)
Eff_{it-1}	-0.20** (-2.56)	-0.28*** (-2.85)
No. Observations	750	750
No. Instruments	30	30
Arellano-Bond test for AR(2)	-0.24 (0.81)	-0.29 (0.78)
Sargan test	17.75 (0.22)	17.75 (0.22)
Hansen test	13.95 (0.45)	13.95 (0.45)

Notes: t-statistics based on robust standard errors in brackets, except for the diagnostic tests which are the *p*-values. *, ** and *** indicate statistical significance at 10%, 5% level and 1% level.

Table 5 System GMM Results for the β-Convergence Equation

Dependent Variable: Efficiency score from Model 3		
	GMM 1	GMM 2
α	-0.04** (-2.43)	-0.06** (-2.47)
Eff_{it-1}	-0.18** (-2.43)	-0.25** (-2.45)
No. Observations	750	750
No. Instruments	30	30
Arellano-Bond test for AR(2)	-0.35 (0.73)	-0.39 (-0.70)
Sargan test	17.94 (0.21)	17.94 (0.21)
Hansen test	15.45 (0.35)	15.45 (0.35)

Notes: t-statistics based on robust standard errors in brackets, except for the diagnostic tests which are the *p*-values. *, ** and *** indicate statistical significance at 10%, 5% level and 1% level.

Figure 1 EFFS 1 - 1991

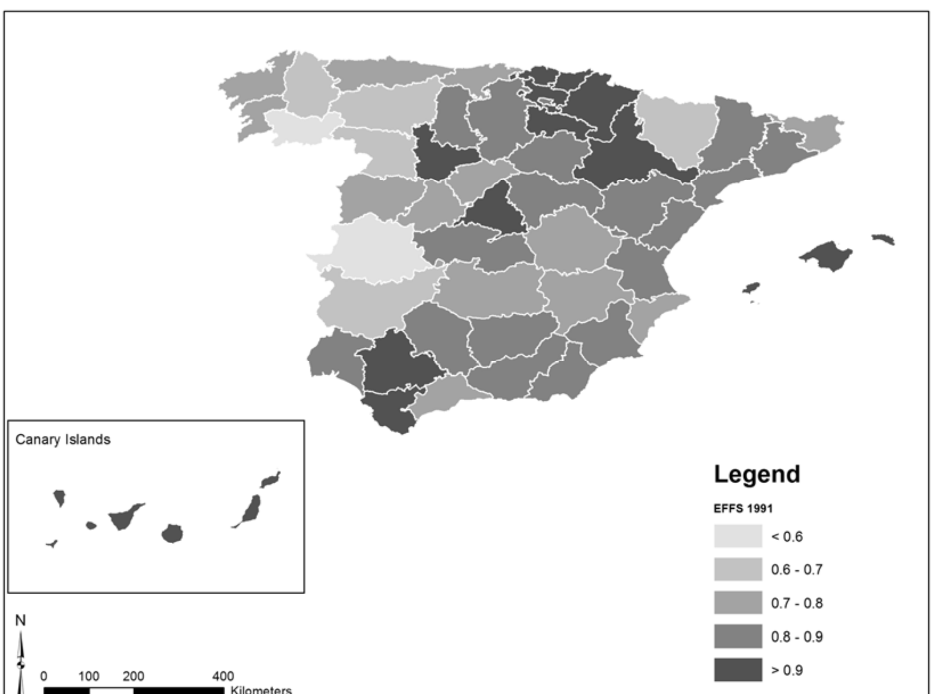

Figure 2 EFFS 1 – 2006