"Growth, Convergence and Public Investment A Bayesian Model Averaging Approach"

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Abstract: The aim of this paper is twofold. Firstly, we study the determinants of growth among a wide set of potential variables for the Spanish provinces. We include several types of private, public and human capital in the group of growth factors. Moreover, we analyse whether Spanish provinces have converged in economic terms in the past decades. The second objective is to overcome the problems of model uncertainty and robustness of estimated parameters in growth regressions using cross-section and panel data techniques. For this purpose, we will use a Bayesian Model Averaging (*BMA*) approach. The Bayesian methodology constructs parameter estimates as a weighted average of linear regression estimates for every possible combination of included variables. The weight of each regression estimates is given by the posterior probability of each model. This technique allows us to obtain parameter estimates that are robust to model specification.

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1. Introduction

The search for the determinants of economic growth is one of the main puzzles in economics. Many studies, from both a theoretical and an empirical point of view, have focused on finding the main factors that can explain observed growth rates.

From a theoretical point of view, many efforts have been devoted to understand the complex economic processes behind growth. Neoclassical growth models à la Solow (1956) give some hints to identify which factors can play an important role on growth rates. For instance, private investment, population growth, exogenous technological progress and the initial level of income per capita are pointed out as main determinants of the rate of economic growth.

Alternatively, the endogenous growth literature[1] gave an important impulse to single-equation macroeconomic models for cross-section of economies (either countries or regions). These models potentially indicate as a source of growth many factors such as political institutions, economic policy factors, knowledge accumulation or institutional indicators. As a result, theoretical models and empirical evidence give more than 60 variables significantly correlated with growth (Sala-i-Martin, 1997).

In front of such variety of sources of growth, the aim of this paper is twofold. Firstly, we study the determinants of growth among a wide set of potential variables for the Spanish provinces for the period 1965-1995, using both cross-section and panel data techniques. We include several types of private, public and human capital in the group of growth factors. Moreover, we analyse whether Spanish provinces have converged in economic terms in the past decades. The second objective is to overcome the problems of model uncertainty and robustness of estimated parameters in growth regressions using cross-section and panel data techniques. For this purpose, we will use a Bayesian Model Averaging (*BMA*, hereafter) approach. The Bayesian methodology constructs parameter estimates as a weighted average of linear regression estimates for every possible subset of potential regressors. The weight of each regression estimates is given by the posterior probability of each model. This technique allows us to obtain parameter estimates that are robust to model specification.

The paper is organised as follows. Section 2 briefly revises some of the main contributions to the empirics of growth, and highlights some of its drawbacks. Section 3 presents the methodology used in this paper. Section 4 describes the variables and data used to perform the

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[1] The endogenous growth theories were "initially motivated by the apparent inability of earlier neoclassical models to explain some important features of cross-country income and growth data" de la Fuente (1997).

empirical estimations. Section 5 presents the main results obtained. Finally, section 6 concludes.

2. Empirical Growth Regressions

Theoretical models have been accompanied by an ever-growing empirical economic growth literature. "Empirical issues have played a key role in the recent literature on economic growth" (de la Fuente, 1997).

Cross-section regressions were initially proposed by Kormendi and Meguire (1985), and Barro (1991). The basic methodology consists in regressing growth rates of per capita output[2] against a set of possible explanatory variables. However, "the problem faced by empirical growth economists is that growth theories are not explicit enough about what variables belong in the "true" regression" (Doppelhofer, Miller and Sala-i-Martin, 2000).[3]

The inclusion of other variables, a part from those directly derived from theoretical models, has been "justified" because of the presence of the "level of technology", *A*, in the standard production function; it can be interpreted in many ways, and not only as the level of technology present at the economy. Many factors (not embodied in a neoclassical production function) may affect the aggregate level of output. These other factors can range from weather conditions to attitudes toward work; all of them could be included as sources of growth making the decision of which variables to include, in an empirical estimation, very difficult. Moreover, the presence of these variables, which are specific to each of the economies analysed and sometimes are unobservable, raised the problem of the existence of a non-zero correlation between these economy-specific effects and the explanatory variables of the model, implying the possibility of obtaining biased estimated coefficients. To solve this, and other possible problems present in the econometric estimation of growth regressions, Knight, Loayza and Villanueva (1993), and Islam (1995) proposed to use panel data techniques in this framework. Panel data techniques allow capturing individual effects to each of the economies analysed as a fixed or random effect in the econometric estimation.

2.1. Human and Public Capital

Among the numerous variables included in growth regressions two factors have obtained special attention in the theoretical and empirical growth literature: human and public capital.

[2] Normally measured with Gross Domestic Product (*GDP*) or Gross Value Added (*GVA*).
[3] For an extensive review on cross-country growth regressions, see de la Fuente (1997), Durlauf and Quah (1999) or Temple (1999).

We find different ways in which human capital has been introduced in theoretical growth models. Mankiw, Romer and Weil (1992) presented an "extended" neoclassical growth model with human and public capital. Human capital is introduced directly in the production function as another input of production, and therefore, the resulting growth regression includes as growth determinant investment in human capital. However, it has been also introduced in other forms in growth models, Nelson and Phelps (1966) presented the idea that an economy with a higher level of human capital can innovate, implement and adopt new technologies more efficiently, and therefore, obtain a higher growth rate. Models developed under this assumption assume a functional form with labour and private capital as inputs of production, and human capital is introduced as influencing the growth rate of technology of the economy.[4] Growth equations derived from both types of models include two types of human capital variables: investment or stock. Our empirical estimation will take into account these different approaches, and we will introduce different types of human capital variables.

Theoretical literature that includes public services (either as flow or stock variable) is wide. From the seminal work by Barro (1990), many other models have taken into account the flow of services provided by the government. For instance, Futagami et al. (1993) construct a model with public capital and transitional dynamics, Glomm and Ravikumar (1994), and Fisher and Turnovsky (1998) explicitly allowed public capital to be subject to congestion.[5]

Moreover, the empirical estimations performed by Aschauer (1989) and Munnell (1990) on the effect of public capital on private sector productivity open a new stream of research that aimed to assess the relevance of public capital in the economy. Many studies were performed and different, and sometimes contradictory, evidence was found.[6] The key point when assessing the impact of public investment on growth is related to the existing trade off between the positive effects of public capital as input of production in front of the negative effects derived from the way public capital is financed (through taxes).

Finally, we will also include variables related with the sectoral structure of the economies involved in our estimations. Serrano (1999) and de la Fuente and Freire (2000) provided theoretical grounds to the inclusion of sectoral structure in growth regressions, and study the effect of this variable in the Spanish case. Section 4 describes variables and data used in our estimates.

[4] For more details, see Gorostiaga (1999).
[5] Bajo-Rubio (2000) introduces various types of public spending in a growth framework, showing their effects on the growth rate of the economy.
[6] For a review on the empirical estimation of the effect of public capital, see Gramlich (1994) or Button (1998).

2.2. The Spanish Case

Growth regressions have also been applied to the regional (provincial) case. Most of the works have used "convergence equations". In the regional framework, the number of possible variables that can be used as growth determinants is drastically reduced in comparison with regressions involving countries. However, if we include, as we do in this study, measures of different types of human and public capital the number of variables raises substantially. This makes difficult to choose the correct specification to be estimated.

Estimation of convergence equations, directly derived from the neoclassical growth model, allows not only to check the significance of the variables initially included in the model, but also to study the controversial issue of economic convergence across economies.[7]

Pioneering works were Dolado et al. (1994) where the convergence issue was analysed for the Spanish provinces, and García-Greciano and Raymond (1994) who studied regional convergence in Spain. These works were followed by other regional studies such as de la Fuente (1994, 1996), García-Greciano et al. (1995), Mas et al. (1994, 1995, 1998), Cuadrado et al. (1999), Gorostiaga (1999), Salas (1999), García-Greciano and Raymond (1999), among others. Using different specifications and econometric tools, convergence among Spanish regions has been a common result in these works.

Recently, Gorostiaga (1999) and González-Páramo and Martínez (2002) present an extended neoclassical growth model with human and public capital, based on Mankiw, Romer and Weil (1992), and tested for the Spanish regions[8]. They found evidence supporting the conditional convergence hypothesis, however, human and public capital seem to have little or no effect on the growth rate of the economy. However, the Spanish case is not an exception and contradictory results have been found for the effect of human and public capital on growth rates, giving room for further empirical estimations.

2.3. Robustness of Growth Results

The multiplicity of relationships established between many factors and growth bring wide range of specifications to be empirically tested. As Durlauf and Quah (1999) highlighted, empirical economist are inclined to follow theory rather loosely, and simply "try" variables

[7] For a good review of the convergence hypothesis: estimation and drawbacks, see Quah (1993, 1996).
[8] Gorostiaga (1999) performs estimations for Spanish regions (17) for the period 1969-1991, and González-Páramo and Martínez (2002) for the period 1965-1995. Both articles use panel data techniques with instrumental variables (*GMM* estimator proposed by Arellano and Bond, 1991).

determining economic growth (Sala-i-Martin, 1997). Econometric problems such as endogeneity of regressors, non-linearity, non-stationary, model specification, and multicollinearity are likely to appear.[9]

Levine and Renelt (1992) proposed a variant of Leamer's (1983) extreme-bounds analysis (*EBA*, hereafter) to test the robustness of coefficient estimates to alterations in the conditioning set of information. They study a wide variety of economic policy, political and institutional indicators; however, they fix a certain number of variables to be included in all the possible combinations of the others variables. These factors always included by Levine and Renelt (1992) were the initial level of income, the investment rate, the secondary school enrolment and the rate of population growth. They conclude that very few regressors are significant when the *EBA* tests are used. However, Sala-i-Martin (1997), Durlauf and Quah (1999) and Dopperlhofer, Miller and Sala-i-Martin (2000) pointed out how the *EBA* test is too strong for any variable to pass: "if there is one regression for which the sign of the coefficient changes, or becomes insignificant, then the variable is labelled as fragile".

Sala-i-Martin (1997) moved away from the *EBA*-type tests and proposed to look at the entire distribution of the estimated coefficients: the main idea is to assign levels of confidence to each variable by computing the cumulative density function for each estimated coefficient. He performed the estimations for 62 variables, keeping 3 always fixed in all regressions[10] and combining the rest 58 in sets of three. He found that 22 variables appeared to be significant.[11]

Recently, Florax, Groot and Heijungs (2002) highlight the serious limitations of the sensitivity analysis conducted by Levine and Renelt (1992) and Sala-i-Martin (1997). While these "robustness" tests have focused merely on sign and significance of the estimated parameters, and fixing a number of variables to always appear in the regression, Florax, Groot and Heijungs (2002) show that the procedure of keeping key variables constant has important effects on the results (affecting the estimated sizes f the parameters).

Bayesian techniques have been also applied to the empirical growth regression approach. Studies by Fernández, Ley and Steel (2000) and Dopperlhofer, Miller and Sala-i-Martin (2000) use Bayesian approaches to adequately tackle the problem of model uncertainty in growth regressions. This is the methodology used in this paper, and it is explained in next section.

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[9] Many other problems can affect growth regressions such as aggregation problems, economic interpretation of the coefficients or measurement problems in poor economies (see, Durlauf, 1996).

[10] The initial values of income, life expectancy and primary school enrollment.

[11] Among these significant variables, we can find openness, different types of investment, types of economic organization, market distortions, and different regional, political and religious variables.

3. Methodology

This section is devoted to briefly describe the methodology employed to perform our estimations. The main idea is to "admit that we do not know which model is "true" and, instead, attach probabilities to different models", Dopperlhofer, Miller and Sala-i-Martin (2000). The methodology presented allows us to avoid selecting "a priori" a subset of regressors, as in other "robustness" studies; therefore, we obtain the estimated coefficients as an average over models, using the corresponding posterior model probabilities as weights.

3.1. Bayesian Model Averaging

We consider a linear regression with a constant term α and k potential regressors $z_1, z_2, \ldots, z_k$. This gives rise to 2^k possible models, depending on which subset of regressors is included in the model. In the cross-section case, we represent each model M_j by:

$$y_i = \alpha + Z_i^j \beta_j + \varepsilon_i \qquad i=1,\ldots,N$$

where Z_i^j denotes a subset of k_j regressors, and β_j is a vector containing the corresponding slope parameters. Note that in model M_j, the rest of slope parameters not contained in β_j are assumed to be zero. Furthermore, we assume that in every model the error terms are normally and independently distributed, with variance equal to σ. Although normality is not necessary for consistency, it guarantees good finite sample properties.

In the panel data case, model M_j is of the type:

$$y_{it} = \alpha_1 d_1 + \alpha_2 d_2 + \ldots + \alpha_N d_N + Z_{it}^j \beta_j + \varepsilon_{it} \qquad i=1,\ldots,N \qquad t=1,\ldots,T$$

where the coefficients $(\alpha_1, \alpha_2, \ldots, \alpha_N)$ are the individual effects and $d_1, d_2, \ldots, d_N$ are N dummy variables. As before, we assume that the error terms are normally and independently distributed, with variance equal to σ. Since we assume the individual effects enter in all models, the number of possible models is also in the panel data case equal to 2^k.

Rather than selecting just one model, the Bayesian approach suggests to average the results from different model specifications. Bayesian Model Averaging (*BMA*) follows directly from the application of Bayes' theorem and implies mixing over models using the posterior model probabilities as weights. Min and Zellner (1993) show that such mixing over models minimises expected predictive squared error loss, provided the set of models under consideration is exhaustive.

The probability of each model is determined by the predictive likelihood, $\pi(y)$, which is the normalising constant in the denominator of Bayes' theorem. Let $\pi(\theta)$ be the prior distribution for the set of parameters θ. The parameter vector θ includes slope parameters and variance parameters ($\theta = \beta, \sigma$). In the case of fixed effects panel data models, θ would also include the individual effects ($\theta = \beta, \sigma, \alpha_1, \alpha_2, \ldots, \alpha_N$).

If we denote the likelihood function by $\pi(y|\theta)$, the posterior density is given by Bayes' theorem:

$$\pi(y \mid \theta) = \frac{\pi(\theta)\pi(y \mid \theta)}{\pi(y)}$$

where the normalising constant

$$\pi(y) = \int \frac{\pi(\theta)\pi(y \mid \theta)}{\pi(y)} d\theta$$

is the predictive likelihood, and is used for model comparison. This constant determines the probability that the specified model is correct.

The probabilities for alternative models are evaluated with the predictive likelihood. Given m possible models $\{M_i\}$ and prior probabilities for each model $\pi(M_i)$, the posterior probability for model M_i is

$$\pi(M_i \mid y) = \frac{\pi(M_i)\pi(y \mid M_i)}{\sum \pi(M_j)\pi(y \mid M_j)}$$

The ratio of the probabilities of two models is known as Bayes' factor. Although the posterior probability depends on the number of models m, which is determined a priori, the ratio of the probabilities of two different models does not depend on m. In the case of equal prior probabilities for each model, the Bayes' factor is equal to:

$$B_{i,j} = \frac{\pi(y \mid M_i)}{\pi(y \mid M_j)}$$

For instance, a Bayes' factor equal to 2 would mean that model M_i is 2 times more likely than model M_j, i.e. the probability that model M_i is the true model is 2 times the probability that M_j is the true model. If there were no more models under consideration, the probability of model M_i would be 0.66, and the probability of model M_j 0.33.

The posterior probabilities for each model lead to a procedure to deal with uncertainty about the appropriate model to use. The posterior density for θ takes into account the different possible specifications,

$$\pi(\theta \mid y) = \sum_{j=1}^{m} \pi(\theta \mid y, M_j)\pi(M_j \mid y)$$

The posterior mean for θ is a weighted average of the posterior means in each model,

$$E(\theta \mid y) = \sum_{j=1}^{m} E(\theta \mid y, M_j)\pi(M_j \mid y) \qquad (1)$$

where the weights are the posterior probabilities of each model. An expression for the posterior variance of θ is given by Leamer (1978) and is equal to:

$$Var(\theta \mid y) = \sum_{j=1}^{m} Var(\theta \mid y, M_j)\pi(M_j \mid y) + \sum_{j=1}^{m} \left(E(\theta \mid y, M_j) - E(\theta \mid y)\right)^2 \pi(M_j \mid y) \qquad (2)$$

From this expression, it is clear that the posterior variance of θ incorporates both the variances in individual models as well as the variability in estimates of θ across different specifications, hence taking into account model uncertainty.

3.2. Prior density

Fernández et al. (2001) conduct a Monte Carlo study to assess the properties of different prior densities. We use the prior that they recommend for the cross-section case. Let Z_j be the $N \times k_j$ matrix which contains the k_j regressors which enter in model M_j. For the constant term and variance parameter the prior is improper and non informative:

$$\pi(\alpha) \propto 1 \qquad \pi(\sigma) \propto \sigma^{-1}$$

The prior for the slope parameters β_j in model M_j is a normal density with zero mean and covariance matrix equal to:

$$\sigma^2\left(g_0 Z_j^T Z_J\right)^{-1}$$

with

$$g_0 = \min\left\{\frac{1}{N},\frac{1}{k^2}\right\}$$

The expression for the Bayes' factor with this prior specification is given in Fernández et al. (2001) in expression (2.16), in page 392.

In the panel data case, let $\overline{Z_j} = \left(Z_j, d_1, d_2, ..., d_N\right)$ be a $NT \times \left(k_j + N\right)$ matrix containing k_j regressors and the N dummy variables. The prior for $\left(\beta_j, \alpha_1, ..., \alpha_N\right)$ under model M_j is a normal density with zero mean and covariance matrix equal to:

$$\sigma^2\left(g_0\left(\overline{Z}_j\right)^T\left(\overline{Z}_j\right)\right)^{-1}$$

with

$$g_0 = \min\left\{\frac{1}{(NT)},\frac{1}{(k+N)^2}\right\}$$

The prior for the variance parameter is the same as in the cross-section case:

$$\pi(\sigma) \propto \sigma^{-1}$$

The Bayes' factor with this prior specification can be found in Fernández et al (2001), in expression (2.12) with $m_1=0$.

Fernández et al. (2001) show that these prior specifications lead to Bayes' factors, which are consistent. Hence, as the sample size increases, the probability of the correct model tends to one, and therefore the probabilities of wrong models tend to zero. In addition, this property holds even if the error term is not normally distributed.

3.3. Implementation

When the number of parameters is large, obtaining the posterior mean and variance given in expressions (1) and (2) implies an extremely large number of calculations. This is because the number of models under consideration increases dramatically with the number of potential regressors, at the rate 2^k. In order to reduce the computation time, we follow the algorithm proposed by Madigan and York (1995).

The algorithm constructs a Markov Chain defined over the set of models under consideration. The probability that the Markov Chain visits each of the models is equal to their posterior probabilities. Hence, the posterior probability of each model can be approximated by the relative frequencies of visits in the Markov Chain. Posterior means and variances can be then calculated using these probabilities in expressions (1) and (2).

The Markov Chain is constructed as follows. Let M^n denote the model visited by the Markov Chain in period *n*. The model in period *(n+1)* is determined in the following way:

1. Generate a new candidate model, say M_j, from a Uniform distribution over the subset of models consisting in model M^n and all models containing either one regressor more or one regressor less than M^n.

2. Fix M^{n+1} equal to M_j with probability $\gamma = \min\{1, B_{js}\}$, where B_{js} is the Bayes' factor. And fix M^{n+1} equal to M^n with probability $1-\gamma$.

4. Variables and Data

In the study of the Spanish provinces, the number of specific characteristics that could influence the growth rates for each province is reduced. Many of the variables used in cross-country growth regressions are meaningless when analysing the Spanish case. However, the introduction of human capital, public capital and a measure of sectoral structure as productive factors of production brings more variables to study its growth effects.

The empirical estimations in this study will be performed for cross-sectional regressions as for panel data estimations for the period 1965-1995. Our main interest will be on the analysis of long-run determinants of provincial growth rates, however, we will also perform short-run estimations for both the cross-section and panel data models (results are presented in the appendix).

Each model (cross-section or panel data) will be estimated in two forms; first, we will include the aggregates of private and public capital; second, these variables will be introduced divided in various types (for definitions see below).

The dependent variable in our estimates will be Growth Rate of per capita Gross Domestic Product (*GDP*). Provincial *GDP* series are expressed at 1986 constant prices, with biannual observations, and were obtained from *Fundación BBV*[12] (*FBBV*, hereafter). Population series are obtained from *Instituto Nacional de Estadística* (*INE*) and cover the relevant data span. These series have also been used to compute the Population Growth rate, another variable introduced in our regressions.

4.1. Private Investment

We make use of the ratio of private investment to provincial *GDP*. Private Investment series are expressed at 1986 constant prices, and are obtained from *FBBV*. Moreover, we split this variable in five types of private investment: Agriculture, Energy, Industry, Construction and Services. Total Private Investment is the sum of these five types, and therefore, excludes private residential investment.

4.2. Public Investment

This variable reflects the ratio of public investment (undertaken by all public administrations) to provincial *GDP*. Public investment is expressed at 1986 constant prices and is obtained from *FBBV*. Following the empirical literature, we will only consider productive public investment (Total Public Investment), or in other words, investment in Highways and Roads, Hydraulic infrastructures, Urban structures, Ports and Airports.

4.3. Human Capital

There is not a unique measure of human capital. Different proxies have been used in the empirical literature. First, we will use proxies of human capital as proposed by Mankiw, Romer and Weil (1992), and extensively used in the empirical literature: the share of working age population with a certain level of studies over the overall level of workers in each province. Data

[12] *Fundación BBV* has a regional data base on the internet: http://bancoreg.fbbv.es. Alternatively, data can be obtained from *Instituto Valenciano de Investigaciones Económicas* (*IVIE*). Information on construction and exact definitions of variables can be found at Mas et al. (1996).

is obtained from the human capital series elaborated by the *IVIE*[13]; additional information can be obtained from Mas et al. (1995) and Serrano (1999). We have used four measures (proxies) of human capital: *H1* is the share of working age population with no studies (illiteracy), *H2* is the share for workers with primary school, *H3* with secondary studies, and finally *H5* is the share of working age population with high university degree[14].

Some doubts have been raised, in the empirical literature, about the adequacy of these variables as a proxy of human capital (or investment in human capital). However, we will use them in our estimations because we want to evaluate if these variables should be included in a growth regression or not, or in other words, if they are robust as growth determinants. Moreover, we have constructed an additional measure of human capital (H_i).

The procedure to construct the human capital variable starts with Mincer's (1974) function of returns on education, which relates the salary obtained by a worker with her/his level of education.[15] From Mincer's specification, we can obtain a measure of human capital as follows (see Jones, 1997):

$$H_i = e^{\gamma S_i} L_i$$

where H_i is the calculated human capital stock measure, γ are the average returns on schooling, L_i is the overall level of workers in province *i*, and finally S_i is the average years of schooling of the working population in each province.[16] Furthermore, S_i is calculated as follows:

$$S_i = \sum_j n_j \frac{W_{ij}}{L_i}$$

where *j* represents the level of instruction attained, n_j is the number of years necessary to obtain the j^{th} level of education, W_{ij} are the number of workers of province *i* with a level of education *j*.

Following the criteria of *IVIE* we have considered five levels of education (*j*), each one with its corresponding number of years to obtain that level (n_j): illiteracy (0), primary school (3,5), secondary school (11), university (16), and high degrees in university or college graduates (17).

Finally, we have used the estimations of Alba-Ramírez and San Segundo (1995) of returns to

[13] We would like to thank Professor Matilde Mas from *IVIE* for her kindness in providing all the necessary data and information to construct the human capital stock series.

[14] We have omitted the forth classification provided by *IVIE*, which should correspond with *H4* (workers with university), to avoid econometric problems in the empirical estimation.

[15] Also with her/his years of training

[16] Time subscripts have been omitted for clarity.

schooling in Spain. The authors calculate the Mincerian specification of earnings equation in Spain, obtaining a value of 8.36% (γ =0.0836). This overall rate of return value is very close to the value obtained by Psacharopoulos (1994) for Europe (8.5%).

4.4. Sectoral Structure

The variables used to study the effects of the sectoral structure on the growth rates are the provincial Gross Value Added (*GVA*) Share in Agriculture and Share in Industry with respect total *GVA* in the province. We have omitted the services share of *GVA* to avoid possible problems of multicollinearity of the estimates.

4.5. Other variables

The use of panel data techniques allows us to introduce "fixed effects" in growth regressions, or in other words, to account for all those intrinsic characteristics to each province. However, in the cross-section estimates we have introduced other variables that can account for (some) of these individual (to each province) effects. Therefore, we have introduced the logarithm of the Initial Level of per capita *GDP* to analyse the convergence across Spanish provinces, and the initial share of working population with primary and secondary school. We have called these variables Initial Primary Enrollment and Initial Secondary Enrollment respectively. A variable that indicates the Area of each province (Km^2) has been introduced to study if there are scale effects that can affect growth rates (see Escot and Galindo, 2000), a dummy variable that indicates the Localization of each province (north versus south)[17]. Finally, a variable of Fertility, the provincial gross birth rate has been also introduced in the cross-section estimates.

5. Results

This section is devoted to present the main results obtained in this study. The algorithm presented in section 3.3 was run with 50000 iterations, and the first 3000 were not used to compute the posterior means and probabilities. Repeating the analysis with a different initial model yielded very similar results, indicating that the number of iterations was sufficient.

[17] This variable was inspired on the work by Dolado et al. (1994). They estimate growth regressions for different groups of provinces.

Table 1a presents the results for the long run cross-sectional estimates with aggregate private and public capital, while table 1b presents the estimations when private and public investment are disaggregated. Similarly, table 2a and 2b present the results for the panel data estimates.[18] Each table contains four columns: name of variables, posterior Bayesian probability of inclusion, posterior mean of estimated coefficient (β's), and posterior standard deviation for each parameter, respectively. The results are ordered by posterior probability of inclusion.

Table 1a: Cross-section Long-run Estimates. Spanish provinces (1965-1995). Dependent variable: per capita *GDP* growth rate.

Variable	Bayesian Probability	Posterior Beta	Posterior Std Dev
Constant	--.--	0.0410017	0.014464424
Initial GDP level	0.97097	-0.0119594	0.003555823
Total Private Investment	0.90909	0.0106481	0.00481564
Human Capital (Hi)	0.23115	0.0020429	0.004495447
Agriculture Share	0.20437	0.0003956	0.000977606
H2	0.17164	0.0022715	0.006806195
Initial Primary Enrollment	0.14837	0.0026463	0.009245008
Localization	0.12390	0.0002032	0.000774989
Fertility	0.11655	-0.0004771	0.002053882
H3	0.11210	-0.0002480	0.001971661
Industrial Share	0.09788	-0.0002685	0.001271281
Initial Secondary Enrollment	0.08155	-0.0000716	0.000702331
H5	0.08133	0.0001241	0.000829004
H1	0.07526	-0.0000308	0.000322125
Population Growth	0.07433	-0.0002283	0.002800362
Total Public Investment	0.06206	-0.0000326	0.000663647
Area (Scale Effect)	0.06050	0.0000081	0.000276467

Long run cross-section estimates (tables 1a and 1b) show how the initial level of GDP is strongly supported by the data as a growth determinant, with a probability of inclusion of 0.97 and 0.71. The sign is negative supporting the hypothesis of conditional convergence across Spanish provinces for the whole period analysed (1965-1995). However, the short run estimates conducted with cross-sectional techniques (tables 1c and 1d in the appendix) show how this variable has probability of inclusion around 0.5 but with a positive coefficient, indicating the possibility of persistence of income disparities in the short run.[19]

[18] Similarly, in appendix we report the corresponding results for short-run estimates, cross-section and panel data, in tables 1c 1d, 2c and 2e.

[19] In short run estimations of growth regressions is very difficult to find significant factors. However, our aim in conducting these estimates was to check for the posterior probability of inclusion, and sign of the parameter estimated for the initial level of income: recent empirical works on convergence indicates the likely existence of divergence patterns among Spanish provinces in recent years, see for instance Lamo (2000) or Leonida and Montolio (2001).

Total private investment has a high posterior probability of 0.91, and a positive coefficient of around 1%. When we analyse the different components of private capital (table 1b), we find that private investment in agriculture, construction and services have posterior probabilities of inclusion between 25% and 35% (lower than expected).

Human capital variables show a lower probability of inclusion, ranging from 0.16 to 0.23. Our measure of human capital (H_i) seems to have a positive effect, but it gets posterior probabilities of 0.23 and 0.10. *H2* seems to be marginally correlated with growth rates, with probabilities of inclusion around 0.18,and a small and positive posterior coefficient.

Table 1b: Cross-section Long-run Estimates. Spanish provinces (1965-1995). Dependent variable: per capita *GDP* growth rate.

Variable	Bayesian Probability	Posterior Beta	Posterior Std.Dev.
Constant	--.--	0.0490644	0.029967287
Initial GDP Level	0.70551	-0.0073628	0.005770744
Public Investment Airports	0.45650	-0.0001399	1.75011E-05
Private Investment Agric.	0.35350	0.0009771	0.001524811
Private Investment Const.	0.31565	0.0022014	0.003742031
Public Investment Ports	0.30412	-0.0000096	1.71841E-05
Private Investment Serv.	0.26837	0.0035366	0.007234108
Industry Share	0.18568	0.0016805	0.004211502
H2	0.18437	0.0029589	0.007570217
Agriculture Share	0.18190	0.0004294	0.001114383
H3	0.16426	-0.0008399	0.002629669
Initial Secondary Enrollment	0.14537	-0.0003987	0.001222314
Initial Primary Enrollment	0.12688	0.0030088	0.010287734
Private Investment Energy	0.11366	0.0001144	0.000406733
Public Investment Roads	0.10317	0.0002046	0.000851342
Human Capital (Hi)	0.09410	0.0005846	0.002766518
Localization	0.09406	0.0001285	0.000734253
Private Investment Industry	0.07419	-0.0000714	0.000557162
Public Investment Hydra.	0.07104	-0.0000655	0.000404063
Population Growth	0.06844	-0.0002332	0.003227783
H1	0.06186	0.0000058	0.000343909
Fertility	0.05982	-0.0002151	0.001615647
Public Investment Rail.	0.05619	-0.0000017	1.07874E-05
H5	0.05073	0.0000183	0.000612243
Public Investment Urb.	0.04795	-0.0000470	0.000501923
Area (Scale Effect)	0.03875	-0.0000065	0.000255668

When public investment is introduced as the total amount of productive spending, it has a very low probability of inclusion 0.06. The desaggregation of this variable brings two types of public investment to have higher probabilities (public investment in ports and airports), with negative but very small estimated coefficients.

Finally, the sectoral structure variables obtain a probability of 0.18 of inclusion in the cross-sectional estimates. The rest of the variables introduced seem to have no robust effect on cross-section growth regressions for the Spanish provinces.

Cross-section estimates can have econometrics problems; some of them can be solved by adopting panel data techniques. The fact that we introduced a fixed effect for each province should remove all individual and unobservable effects that can be correlated with some explanatory variables. Tables 2a and 2b present long run growth regressions using panel data in the *BMA* approach. Surprisingly, human capital variables (*H2* and *H3*) obtain the highest probability of inclusion (1) and both have negative estimates, the agricultural share of *GVA* has also 1 as probability of inclusion and a positive coefficient. Interestingly, public investment obtains a 0.93 prob of inclusion and a positive and reasonable elasticity of 1.3%, similar to the one obtained for private investment.

In the disaggregated results (table 2b), we obtain two types of private investment with probability equal to 1: private investment in industry and construction, with elasticities of 2.3% and 3%, respectively[20]. Population growth has posterior probability of inclusion equal to one and shows the expected theoretical sign (negative).

Public investment in roads gets a high probability (0.90) and a positive elasticity of 0.5%, while public investment in urban structures seems to have a possible negative role on growth rates. The other types of public investment get small probabilities of inclusion.

Table 2a: Panel Data Long-run Estimates. Spanish provinces (1965-1995). Dependent variable: per capita *GDP* growth rate.

Variable	Bayesian Probability	Posterior Beta	Posterior Std.Dev.
H2	1	-0.0746035	0.013569448
H3	1	-0.0226618	0.004956876
Agriculture Share	1	0.0340100	0.010013597
Total Public Investment	0.93413	0.0130595	0.005734919
Total Private Investment	0.45508	0.0115163	0.014931574
Population Growth	0.43712	-0.0154031	0.020069702
H5	0.04992	0.000296	0.002719704
H1	0.03393	-0.0002072	0.001579243
Industry Share	0.00598	-0.0001385	0.002341632
Human Capital (Hi)	0	0	0

In contrast with the cross-section results, two types of human capital have large probabilities of inclusion. *H2* has 0.74 and a negative sign, while *H5* obtains probability around 0.40 and a

[20] González-Páramo and Martínez (2002) obtain similar results for total private investment.

positive (and small) sign of the effect on growth.

Finally, both sectoral variables receive probabilities of inclusion above 0.90, and they show opposite signs: *GVA* agriculture share is positive while *GVA* industry share is negative.

Table 2b: Panel Data Long-run Estimates. Spanish provinces (1965-1995). Dependent variable: per capita *GDP* growth rate.

Variable	Bayesian Probability	Posterior Beta	Posterior Std.Dev.
Population Growth	1	-0.0462735	0.010984022
Private Investment Industry	1	0.0258059	0.005148323
Private Investment Const.	1	0.0300594	0.004726612
Industry Share	0.94610	-0.0399281	0.016522953
Agriculture Share	0.93812	0.0189794	0.008001313
Public Investment Roads	0.89620	0.0051801	0.002652676
Public Investment Urb.	0.81636	-0.0067251	0.003986053
H2	0.74451	-0.0205840	0.014170636
H5	0.37325	0.0062023	0.009352125
H3	0.16367	-0.0019553	0.005082086
Public Investment Airports	0.03792	0.0000005	8.31204E-06
Private Investment Energy	0.01596	0.0000345	0.000363982
H1	0.00798	-0.0000446	0.000578246
Private Investment Serv.	0.00798	-0.0001208	0.001671266
Human Capital (Hi)	0	0	0
Public Investment Hydra.	0	0	0
Public Investment Ports	0	0	0
Public Investment Rail.	0	0	0
Private Investment Agric.	0	0	0

6. Conclusions

Some conclusions can be drawn from the analysis conducted in this study. Bayesian Model Averaging techniques allows us to determine what variables are strongly related to the growth rate of Spanish provinces: checking at the same time for robustness and model uncertainty, two of the main problems of empirical growth regressions. We do not restrict ourselves to check robustness with a fixed set of regressors as in other approaches: we allow for all possible combinations of regressors in a wide set of variables, which include, among others, different types of private, human and public capital.

We find that a number of economic variables have correlation with long run growth. Among these variables, we can find some types of private and public investment, and some human capital proxies. Moreover, we have also found some variables that should not be taken into account when estimating growth regressions.

The long run results for cross-section supports the conditional (to a set of variables) convergence hypothesis: the initial level of per capita income has high posterior probability of inclusions and has a negative estimated sign.

As expected, private capital plays an important role in determining provincial growth rates. Moreover, private investment in industry and construction seems to be the two types of private investment with higher probability of inclusion in a growth equation. Human capital results are less clear. In the panel data framework, it seems to be an important growth determinant: the share of working age population with studies up to primary school seems to have a negative effect on growth.

Public investment is significantly correlated with growth when using panel data techniques: with a positive elasticity of around 1%. Public investment in roads and highways is the only type of public investment with a high posterior probability of inclusion and a positive coefficient (0.5%), the other types of public investment showed low probability of inclusion or very small (and very often negative) estimated parameters.

The sectoral structure of the economy seems to have an effect on the growth rate of the economy, both the *GVA* agriculture and industry share have high probabilities of inclusion using panel data techniques (more moderate when we introduced them in a cross-section regression). The signs are positive for the provincial agriculture share, and negative for the industry share on *GVA*.

Finally, some cautions should be raised when interpreting the results. The empirical literature on growth regressions has pointed out some econometric problems of classical growth regressions (either cross-section and panel data approaches), and different econometric techniques have been applied to overcome these problems (for instance, instrumental variables or cointegration techniques). However, the analysis here presented wants to revise model uncertainty and robustness of results in the classical approach, so extensively used. We realise about the problems that the estimation can face in the framework chosen, and we intend, as further research, to include new econometric developments, especially new estimation methods, variables, and data sets, into the Bayesian Model Averaging approach.

7. Appendix

7.1. Testing the Program

In order to test the Gauss code employed in our empirical estimations, the panel data model was estimated with a simulated sample. The sample size was N=50 and T=3. 20 potential regressors were simulated independently from a standard normal distribution. Only ten of the regressors had a non zero effect on the dependent variable. The time variant error term was simulated from independent standard normal distributions. The true values for all individual effects were zero.

Table A shows the true value of the parameters, the Bayesian probability of inclusion, and the posterior mean. For the sake of comparison, we also include the results of a classical fixed effects estimator, which include all potential regressors.

Table A: Testing the Program.

True Beta	Bayesian Probability	Posterior Beta	Posterior Std Dev	Classical Beta	Classical Std Dev	P-Value
0.5	0.66760	0.186824	0.160003	0.2694287	0.1176538	0.025
0.2	0.10855	0.021069	0.071349	0.1283098	0.1197893	0.287
-0.1	0.17335	-0.04038	0.10258	-0.2378842	0.1277064	0.066
0.6	1	0.607512	0.110876	0.6253578	0.1115737	0
0.8	1	0.855306	0.114861	0.8366365	0.119148	0
0.2	0.40512	0.093833	0.131838	0.212296	0.1115722	0.061
0.9	1	0.893852	0.13264	1.025038	0.1420192	0
-1	1	-1.09649	0.115259	-1.142416	0.1201281	0
-0.8	1	-0.69275	0.125855	-0.66614	0.1271563	0
-1	1	-0.91738	0.110228	-0.8790993	0.1149744	0
0	0.05139	-0.00728	0.039495	-0.0986635	0.1095145	0.37
0	0.01166	-0.00014	0.013422	0.0579166	0.1231256	0.639
0	0.01475	-0.00095	0.015977	-0.068095	0.1162278	0.56
0	0.01582	0.000986	0.016618	0.0594687	0.1177793	0.615
0	0.01291	-0.00051	0.013275	0.005232	0.1125725	0.963
0	0.15539	0.035347	0.095619	0.253411	0.1246065	0.045
0	0.02693	-0.00299	0.026924	-0.097417	0.1289101	0.452
0	0.01482	-0.00076	0.014192	-0.0399052	0.1107668	0.72
0	0.03455	-0.00295	0.02636	-0.0447656	0.1187989	0.707
0	0.03417	0.003884	0.02955	0.1491837	0.1142951	0.196

From the results in the table, the probability of inclusion is one when the absolute value of the parameter is larger than 0.5, and it is small otherwise. The error in estimating each parameter is not always smaller with the Bayesian methodology. However, the mean squared error in estimating all parameters is smaller with the Bayesian methodology (0.00885 versus 0.01344).

7.2. Short Run Results

Table 1c: Cross-section Short-run Estimates. Spanish provinces (1965-1995). Dependent variable: per capita *GDP* growth rate (biannual).

Variable	Bayesian Probability	Posterior Beta	Posterior Std. Dev.
Constant	--.--	0.0228768	0.030283234
Initial GDP Level	0.49583	0.0111528	0.013058527
Area (Scale Effect)	0.38696	-0.0026540	0.003902232
Human Capital (Hi)	0.28328	0.0075804	0.014099248
Total Private Investment	0.20237	0.0043680	0.010465076
Localization	0.11417	0.0004663	0.002115955
H1	0.10555	0.0001709	0.000844302
Industry Share	0.09739	0.0006150	0.002829414
Total Public Investment	0.08484	-0.0002381	0.001613804
Agriculture Share	0.07810	-0.0001411	0.000959509
Fertility	0.07650	-0.0005391	0.003442966
Initial Primary Enrollment	0.07066	0.0000873	0.003822989
Initial Secondary Enrollment	0.06804	-0.0003731	0.003185154
H5	0.06666	0.0000774	0.001452272
H2	0.06635	0.0003076	0.00383938
H3	0.06224	-0.0003789	0.004085514
Population Growth	0.06122	-0.0005008	0.006081139

Table 2c: Panel Data Short-run Estimates. Spanish provinces (1965-1995). Dependent variable: per capita *GDP* growth rate (biannual).

Variable	Bayesian Probability	Posterior Beta	Posterior Std. Dev.
Population Growth	1	-0.1370811	0.0143147
Agriculture Share	1	0.0399575	0.0042667
H1	0.12418	-0.0003394	0.0011706
H2	0.12395	-0.0010071	0.0035365
H5	0.06329	-0.0002260	0.0015204
Total Private Investment	0.04973	-0.0001571	0.0011223
Industry Share	0.04795	-0.0004146	0.0031869
H3	0.04671	-0.0000517	0.0006182
Human Capital (Hi)	0.04384	0.0006392	0.0046586
Total Public Investment	0.03882	-0.0000166	0.0004474

Table 1d: Cross-section Short-run Estimates. Spanish provinces (1965-1995). Dependent variable: per capita *GDP* growth rate (biannual).

Variable	Bayesian Probability	Posterior Beta	Posterior Std. Dev.
Constant	--.--	0.0149433	0.0397709
Public Investment Ports	0.59181	0.0000475	0.0000463
Initial GDP Level	0.56508	0.0136966	0.0137352
Human Capital (Hi)	0.26655	0.0073887	0.0139524
Population Growth	0.13553	-0.0037893	0.0130363
Area (Scale Effect)	0.13222	-0.0007261	0.0023255
Public Investment Airports	0.11220	-0.0000061	0.0000215
Private Investment Industry	0.09051	0.0003180	0.0013069
Public Investment Hydra.	0.08849	-0.0003500	0.0014409
Localization	0.08311	0.0004066	0.0020713
H1	0.07442	0.0000939	0.0006934
Public Investment Rail.	0.06993	-0.0000061	0.0000306
Industry Share	0.06833	0.0005405	0.0028029
Fertility	0.06807	-0.0006907	0.0037187
Initial Secondary Enrollment	0.06695	-0.0005577	0.0034688
Private Investment Agric.	0.06575	0.0001124	0.0007898
Agriculture Share	0.05935	-0.0000189	0.0009410
Public Investment Roads	0.05513	-0.0000635	0.0008246
Private Investment Const.	0.05467	-0.0001604	0.0015567
Private Investment Energy	0.05364	-0.0000032	0.0000265
H2	0.05135	0.0001641	0.0033868
Private Investment Serv.	0.05062	-0.0004224	0.0036291
H3	0.04047	-0.0004303	0.0039660
Initial Primary Enrollment	0.03753	0.0000149	0.0030828
Public Investment Urb.	0.03655	0.0001051	0.0010919
H5	0.03593	0.0000033	0.0010268

Table 2d: Panel Data Short-run Estimates. Spanish provinces (1965-1995). Dependent variable: per capita *GDP* growth rate (biannual).

Variables	Bayesian Probability	Posterior Beta	Posterior Std. Dev.
Population Growth	1	-0.0674052	0.0095844
Agriculture Share	1	0.0321098	0.0056289
Private Investment Const.	1	0.0155250	0.0023917
Private Investment Serv.	1	-0.0428813	0.0057761
H3	0.98007	0.0112368	0.0028850
Private Investment Energy	0.95347	0.1456270	0.0534894
Private Investment Industry	0.61025	0.0052227	0.0048716
Industry Share	0.35630	-0.0098302	0.0150621
Public Investment Urb.	0.29510	0.0012903	0.0023059
Public Investment Hydra.	0.16622	-0.0005425	0.0014408
H1	0.11724	-0.0004356	0.0014775
Private Investment Agric.	0.04864	0.0029764	0.0307198
H2	0.04467	-0.0002314	0.0019798
H5	0.04089	-0.0000335	0.0013410
Public Investment Roads	0.04040	0.0000016	0.0003277
Public Investment Rail.	0.03973	0.0000007	0.0000224
Human Capital (Hi)	0.03638	0.0001138	0.0031952
Public Investment Airports	0.03358	0.0000002	0.0000067
Public Investment Ports	0.03058	-0.0000007	0.0000166

8. References

Alba-Ramírez, A. and San-Segundo, M. J. (1995), "The Returns to Education in Spain", *Economics of Education Review*, June 1995; 14(2).

Arellano, M. and Bond, S. (1991), "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations", *Review of Economic studies*, April 1991; 58(2).

Aschauer, D. A. (1989), "Is Public Expenditure Productive?", *Journal of Monetary Economics*, March 1989, 23(2).

Bajo-Rubio, O. (2000), "A Further Generalization of the Solow Growth Model: The Role of Public Sector", *Economic Letters*. July 2000; 68(1).

Barro, R. (1990), "Government Spending in a Simple Model of Endogenous Growth", *Journal of Political Economy*, Part 2, October 1990; 98(5).

Barro, R. (1991), "Economic Growth in a Cross Section of Countries", *The Quarterly Journal of Economics*, May.

Button, K. (1998), "Infrastructure Investment, Endogenous Growth and Economic Convergence", *Annals of Regional Science*, February 1998; 32(1).

Cuadrado, J.R., García-Greciano, B. and Raymond, J.L. (1999), "Regional Convergence in productivity and productive structure: the Spanish case", *International Regional Science Review*, vol.22.

de la Fuente, A. (1994), "Inversión pública y desigualdad regional en España 1891-1990", in J. M. Esteban and J. Vives (dirs.), *Crecimiento y convergencia en España y en Europa.* Volumen *II*, Instituto de Análisis Económica, Barcelona.

de la Fuente, A. (1996), "On the Sources of Convergence: A Close Look at the Spanish Regions". *CEPR Discussion Paper*: 1543. December 1996.

de la Fuente, A. (1997), "The empirics of growth and convergence: A selective review", *Journal of Economic Dynamics and Control*, 1997, 21.

de la Fuente, A, and Freire, M. J. (2000), "Estructura Sectorial y Convergencia Regional", *Revista de Economía Aplicada*, Numero 23 (Vol. VIII).

Dolado, J. J.; González-Páramo, J. M. and Roldan, J. M. (1994), "Convergencia económica entre las provincias españolas: Evidencia empírica (1955-1989)". *Moneda y Crédito*; 0(198), 1994.

Doppelhofer, G. Miller, R. I. and Sala-i-Martin, X. (2000), "Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach", *NBER*, Working Paper 7750, June 2000.

Durlauf, S. N. (1996), "A Theory of Persistent Income Inequality", *Journal of Economic Growth*, 1.

Durlauf, S. N. and Quah, D. (1999), "The New Empirics of Economic Growth" in *Handbook of macroeconomics Vol. 1*, Taylor and Woodford, eds., North-Holland, Amsterdam, 1999.

Escot, L. and Galindo, M. A. (2000), "Evidencia empírica de la convergencia real", *Papeles de Trabajo del IEF*. 2000.

Fernández, C., Ley, E. and Steel, M. F. J. (2001), "Model Uncertainty in Cross-Country Growth Regressions", *Journal of Applied Econometrics*, 2001, 16.

Fisher, W. and Turnovsky, S. (1998), "Public Investment, Congestion and Private Capital Accumulation", *Economic Journal*, March 1998; 108 (447).

Florax, R. J. G. M., Groot, H. and Heijungs, R. (2002), " The Empirical Economic Growth Literature", *Tinbergen Institute Discussion Paper*, TI 2002-040/3.

Fundación BBV (1999), *Renta nacional de España y su distribución provincial. Serie homogénea 1955-1993. Avance 1994-1997*. Bilbao.

Futagami, K., Morita, Y. and Shibata, A. (1993), "Dynamic Analysis of an Endogenous Growth Model with Public Capital", *Scandinavian Journal of Economics*, December 1993; 95(4).

García-Greciano, B. and Raymond, J. L. (1994), "Las disparidades en el PIB per cápita entre Comunidades Autónomas y la hipótesis de convergencia", *Papeles de Economía Española*, 59.

García-Greciano, B. and Raymond, J. L. (1999), "Las disparidades regionales y la hipótesis de convergencia: Una revisión", *Papeles de Economía Española*, Vol. 80, 1999.

García-Greciano, B., Raymond, J. L. and Villaverde, J. (1995), "Convergencia de las provincias españolas", *Papeles de Economía Española*, 64.

Glomm, G. and Ravikumar, B. (1994), "Public Investment in Infrastructure in a Simple Growth Model", *Journal of Economic Dynamics and Control*, November 1994, 18(6).

González-Páramo, J. M. and Martínez, D. (2002), "Public Investment and Convergence in the Spanish Regions", *Estudios sobre la Economía Española* (*EEE*) *FEDEA*. Working Paper EEE-112

Gorostiaga, A. (1999), "Cómo afectan el capital público y el capital humano al crecimiento?: Un análisis para las regiones españolas en el marco neoclásico", *Investigaciones Económicas*; 23(1), January 1999.

Gramlich, E. M. (1994), Infrastructure Investment: A Review Essay", *Journal of Economic Literature*, September 1994; 32(3).

Islam, N., (1995), "Growth Empirics: A Panel Data Approach", *Quarterly Journal of Economics*, 110.

Jones, C. (1997), "Convergence Revisited", *Journal of economic Growth*, 2, June.

Knight, M., Loayza, N. and Villanueva, D. (1993), "Testing the Neoclassical Theory of Economic Growth. A Panel Data Approach". *IMF Staff Papers*. Vol. 4 (3).

Kormendi, R. C. and Meguire, P. G. (1985), "Macroeconomic Determinants of Growth: Cross-Country Evidence", *Journal of Monetary Economics* September 1985; 16(2).

Lamo, A (2000), "On Convergence Empirics: Some Evidence for Spanish Regions", *Investigaciones Económicas*, Vol. XXIV (3).

Leonida, L. and Montolio, D. (2001), "Inter-Distributional and Intra-Clusters Dynamics, and Territorial Distribution of Growth among Spanish Provinces", *Estudios sobre la Economía Española* (*EEE*) *FEDEA*. Working Paper EEE-109.

Leamer, E. (1978), *Specification Searches*, John Wiley and Sons. New York.

Leamer, E. (1983), "Let's Take the Con out of Econometrics", *American Economic Review*, 1983, 73.

Levine, R. and Renelt, D. (1992), "A sensitivity Analysis of Cross-Country Growth Regressions", *American Economic Review*, Vol. 82, Nº 4, September 1992.

Madigan, D. and York, J (1995), "Bayesian Graphical Models for Discrete Data", *International Statistical Review*, 89.

Mankiw, N. G., Romer, D. and Weil, D. (1992), "A Contribution to the Empirics of Economic Growth", *Quarterly Journal of Economics*, May, 170:2.

Mas, M., Maudos, J., Pérez, F. and Uriel, E. (1994), "Disparidades regionales y convergencia en las CC.AA.", *Revista de Economía Aplicada*, Vol. (4).

Mas, M., Maudos, J., Pérez, F. and Uriel, E. (1995), "Public capital and Convergence in the Spanish Regions", *Entrepreneurship and regional Development*, (7) 4.

Mas, M., Maudos, J., Pérez, F. and Uriel, E. (1998), "Public Capital, Productive Efficiency and Convergence in the Spanish Regions (1964-93)". *Review of Income and Wealth*; 44(3), September 1998.

Maudos, J., Pastor, J. and Serrano, L. (1998), "Convergencia en las regiones españolas: Cambio técnico, eficiencia y productividad", *Revista Española de Economía*, 15(2), 1998.

Min, C. and Zellner, A. (1993), "Bayesian and Non-Bayesian Methods for Combining Models and Forecasts with Applications to Forecasting International Growth Rates", *Journal of Econometrics*, March 1993; 56(1-2).

Mincer, J. (1974), *Schooling, experience and earnings*, New York: Columbia University Press.

Munnell, A. H. (1990), "Why Has Productivity Declined? Productivity and Public Investment", *New England Economic Review*, Jan-Feb 1990.

Nelson, R. and Phelps, R. (1966), "Investment in Humans, Technological Diffusion, and Economic Growth", *American Economic Review: Papers and Proceedings* 61.

Psacharopoulos, G. (1994), "Returns to Investment in Education: A Global Update", *World Development*. September 1994; 22(9).

Quah, D. T. (1993), "Empirical Cross-section Dynamics in Economic Growth", *European Economic* Review 40.

Quah, D. T. (1996), "Empirics for Growth and Convergence", *European Economic Review*, 40.

Sala-i-Martín, X. (1997), "I Just Run Two Million Regressions", *American Economic Review*, 1997, 87.

Salas, R. (1999), "Convergencia, movilidad y redistribución interregional en España: 1981-1996", *Papeles de Economía Española*, Vol. 80, 1999.

Serrano, L. (1999), "Capital humano, estructura sectorial y crecimiento en las regiones españolas", *Investigaciones Económicas*. May 1999; 23(2).

Solow, R., (1956), "A Contribution to the Theory of Economic Growth", *Quarterly Journal of Economics*, 70.

Temple, J. (1999), "The New Growth Evidence", *Journal of Economic Literature*, 1999, 37.