DOCUMENTS DE TREBALL

DE LA DIVISIÓ DE CIÈNCIES JURÍDIQUES ECONÒMIQUES I SOCIALS

Col·lecció d'Economia

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

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* **Acknowlegments**. We would like to 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, and all the participants to the VI Encuentro de Economía Pública (Granada, 2003) for helpful comments. Any remaining errors are ours.

Abstract. The aim of this paper is twofold. First, we study the determinants of economic growth among a wide set of potential variables for the Spanish provinces (NUTS3). Among others, we include various types of private, public and human capital in the group of growth factors. Also, we analyse whether Spanish provinces have converged in economic terms in recent decades. The second objective is to obtain cross-section and panel data parameter estimates that are robust to model specification. For this purpose, we use a Bayesian Model Averaging (BMA) approach. 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 estimate is given by the posterior probability of each model.

JEL classification: 047, H54, C11

Key words: Growth, Convergence, Public Investment, Bayesian Model Averaging

Resum: L'objectiu d'aquest estudi és doble. Primer, estudiem els factors determinants del creixement econòmic entre un ampli ventall de possibles variables per a les províncies espanyoles. Entre aquests determinant s'inclouen diferents tipus de capital privat, públic i humà. A més, s'analitza si les províncies espanyoles han convergit en termes econòmics. El segon objectiu es l'obtenció de estimacions, transversals i amb dades de panell, robustes a l'especificació del model utilitzant una metodologia bayesiana, la qual construeix els paràmetres estimats com una mitja ponderada dels estimadors lineals de totes les possibles combinacions de models donandes les variables tingudes en compte. La ponderació de cada paràmetre estimat bé donada per la probabilitat a posteriori de cada model.

Classificació JEL: 047, H54, C11

Paraules clau: Creixement, Convergència, Inversió Pública, Bayesian Model Averaging

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 principal factors that can explain observed growth rates.

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

From a different standpoint, the endogenous growth literature[1] develops new hypotheses that result in a richer empirical specification of single-equation macroeconomic models for a cross-section of economies (either countries or regions). These models indicate as a potential 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).

Faced with such a variety of sources of growth, the aim of this paper is twofold. First, using both cross-section and panel data techniques we study the determinants of economic growth among a wide set of potential variables for the Spanish provinces (NUTS3) for the period 1965-1995. Among other variables, we include various types of private, public and human capital in the group of growth factors. Also, we analyse whether Spanish provinces have converged in economic terms in recent decades. The second objective is to obtain cross-section and panel data parameter estimates that are robust to model specification. For this purpose, we use a Bayesian Model Averaging (BMA, hereafter) approach. 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 estimate is given by the posterior probability of each model.

The paper is organised as follows. Section 2 briefly revises some of the main contributions to the empirics of growth, and highlights some of their drawbacks. Section 3 presents the methodology used. Section 4 describes the variables and data used to perform the empirical estimations. Section 5 presents the main results obtained. Finally, section 6 concludes.

2 Empirical Growth Regressions

The development of theoretical models of growth has been accompanied by an ever-growing empirical economic growth literature; as de la Fuente (1997) notes: "empirical issues have played a key role in the recent literature on economic growth". For example, cross-section regressions, initially proposed by Kormendi and Meguire (1985) and Barro (1991), consist in regressing growth rates of per capita output[2] against a set of possible explanatory variables.[3] 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 et al. 2000).

The inclusion of other variables, apart 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 in the economy. Therefore, many factors not directly embodied in a neoclassical production function may affect the aggregate level of output. These other factors can range from weather conditions to attitudes towards work; all of them could be potentially 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 usually specific to each of the economies analysed and are sometimes unobservable, raise 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 et al. (1993) and Islam (1995) propose the use of panel data techniques, which allow us to capture the unobserved individual effects in each of the economies analysed.

Growth and "convergence" regressions applied to the Spanish case followed the pioneering work of Dolado et al. (1994) for the Spanish provinces, and Raymond and García-Greciano (1994) who studied convergence across Spanish regions. These works were followed by other regional studies such as de la Fuente (1994, 2002), García-Greciano et al. (1995), Mas et al. (1994, 1995, 1998), Cuadrado et al. (1999) and Salas (1999), among others.

2.1 Human and Public Capital

Among the numerous variables included in growth regressions two factors have been the subject of much of the theoretical and empirical literature on growth: human and public capital.

The literature on theoretical growth models suggests alternative ways of understanding the effects of human capital. Mankiw et al. (1992) present an "extended" neoclassical growth model with human capital directly introduced into the production function as another input of production, suggesting that *investment* in human capital is a determinant of growth and, therefore, it should be included as an explanatory variable. In contrast, Nelson and Phelps (1966) argue 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 with this approach introduce the *stock* of human capital as a determinant of the growth rate of the economy (for more details, see Gorostiaga, 1999). Hence, growth equations derived from these two alternative approaches include two different types of human capital variables: investment or stock. Our empirical estimations take into account these different approaches by introducing different types of human capital variables.

The theoretical literature that includes public services (either as flow or stock variable) is wide. Since the seminal work of Barro (1990), many models have taken into account the flow of services provided by the government.[4] Moreover, the empirical estimations performed by Aschauer (1989) and Munnell (1990) on the effect of public capital on private sector productivity opened a new stream of research that aimed to assess the relevance of public capital in the economy. Many studies have been conducted and different, sometimes contradictory, evidence has been found.[5] The impact of public investment on growth is subject to controversy because of the trade-off between the positive effects of public capital as an input of production versus the potentially negative effects derived from the taxes necessary to finance public capital.

Recently, Gorostiaga (1999) and González-Páramo and Martínez (2002) have estimated an extended neoclassical growth model with human and public capital and test the existence of convergence for the Spanish regions.[6] They find 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.

2.2 Robustness of Growth Results

The multiplicity of relationships established between so many variables and economic growth presents a wide range of specifications to be empirically tested. Thus, as Sala-i-Martin (1997) or Durlauf and Quah (1999) highlight, empirical economists are inclined to follow theory rather loosely, and simply "try" variables determining economic growth. Also, this multiplicity of relationships implies that econometric problems such as endogeneity of regressors, non-linearity, non-stationarity, model specification, and multicollinearity are likely to appear.[7]

Levine and Renelt (1992) propose 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 consider a wide variety of economic policy, political and institutional indicators; however, they fix a certain number of variables to be included in every model. The factors always included by Levine and Renelt (1992) are the initial level of income, the investment rate, 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 Doppelhofer et al. (2000) point out that 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) moves away from the EBA-type tests and proposes looking at the entire distribution of the estimated coefficients, that is to assign levels of confidence to each variable by computing the cumulative density function for each estimated coefficient. He performs the estimations for 62 variables, keeping 3 always fixed in all regressions[8] and combining the remaining 58 in sets of three. He finds that 22 variables appear to be significantly correlated with economic growth.[9]

Recently, Florax et al. (2002) have 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 the sign and significance of the estimated parameters, the procedure of keeping key variables in every model has important effects on the results (affecting the estimated sizes of the parameters).

Bayesian techniques have been also used in the empirical growth regression literature. Studies by Fernández et al. (2001a) and Doppelhofer et al. (2000) use Bayesian approaches to tackle effectively the problem of model uncertainty in cross-section growth regressions. This is the methodology used in this paper, as we explain in the next section.

3 Methodology

The starting point of our empirical estimation is to "admit that we do not know which model is "true" and, instead, attach probabilities to different models", Doppelhofer et al. (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,..., 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:

$$y_i = \alpha + Z_i^j \beta_j + \varepsilon_i \qquad i = 1, ..., N \tag{1}$$

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 effect of variables not contained in Z_i^j is 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 (Fernández et al., 2000b).

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

$$y_{it} = \alpha_1 d_1 + \alpha_2 d_2 + ... + \alpha_N d_N + Z_{it}^j \beta_j + \varepsilon_{it} \qquad i = 1, ..., N \qquad t = 1, ..., T \tag{2}$$

where the coefficients (α_1, α_2,..., α_N) are the individual effects and d_1, d_2,..., 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 that the individual effects enter in all models, the number of possible models is in the panel data case also equal to 2^k.

Rather than selecting just one model, the Bayesian approach suggests averaging the results from different model specifications. 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. Fernández et al. (2001b) show that the procedure leads to consistent estimates, even when the errors are not normally distributed.

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 $\pi(\theta_j)$ be the prior density for the set of parameters θ_j. The parameter vector θ_j includes the slope parameters and variance parameters in model M_j ($\theta_j = \beta_j$, σ). In the case of fixed effects panel data models, θ_j would also include the individual effects ($\theta_j = \beta_j$, σ, α_1, α_2,..., α_N).

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

$$\pi(\theta_j \mid y, M_j) = \frac{\pi(\theta_j)\,\pi(y \mid \theta_j, M_j)}{\pi(y \mid M_j)}, \tag{3}$$

where the normalising constant

$$\pi(y \mid M_j) = \int \pi(\theta_j)\,\pi(y \mid \theta_j, M_j)\,d\theta, \tag{4}$$

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

$$\pi(M_i \mid y) = \frac{\pi(M_i)\,\pi(y \mid M_i)}{\sum \pi(M_j)\,\pi(y \mid M_j)}. \tag{5}$$

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:

$$B_{ij} = \frac{\pi(y \mid M_i)}{\pi(y \mid M_j)}. \tag{6}$$

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. Let θ denote the vector containing all parameters. The posterior density for θ takes into account the different possible specifications,

$$\pi(\theta \mid y) = \sum_{j=1}^{m} \pi(\theta \mid y, M_j)\, \pi(M_j \mid y). \tag{7}$$

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

$$E(\theta \mid y) = \sum_{j=1}^{m} E(\theta \mid y, M_j)\, \pi(M_j \mid y), \tag{8}$$

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:

$$Var(\theta \mid y) = \sum_{j=1}^{m} Var(\theta \mid y, M_j)\, \pi(M_j \mid y) + \sum_{j=1}^{m} \left(E(\theta \mid y, M_j) - E(\theta \mid y)\right)^2 \pi(M_j \mid y) \tag{9}$$

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

We use the prior density recommended by Fernández et al. (2001b). They conduct a Monte Carlo study to assess the finite sample properties of different prior densities in the context of model uncertainty. Let Z_j be the $N \times k_j$ matrix which contains the k_j regressors which enter into model M_j. For the constant term and variance parameter the prior is improper and non-informative:

$$\pi(\alpha) \propto 1 \qquad\qquad \pi(\sigma) \propto \sigma^{-1} \tag{10}$$

The prior of α implies that all values for α, from minus infinity to infinity, are equally plausible a priori. Similarly, the prior for σ implies that all values for $\ln(\sigma)$ are given equal prior weight. The prior for the slope parameters β_j in model M_j is a normal density with zero mean and covariance matrix equal to:

$$\sigma^2 \left(g_0 Z_J^T Z_J\right)^{-1}, \tag{11}$$

where

$$g_0 = \min\left\{\frac{1}{N}, \frac{1}{k^2}\right\}. \tag{12}$$

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

In the panel data case, let $\overline{Z}_j = (Z_j, d_1, d_2, ..., d_N)$ be a $NT \times (k_j + N)$ 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:

$$\sigma^2 \left(g_0 \left(\overline{Z}_J\right)^T \left(\overline{Z}_J\right)\right)^{-1}, \tag{13}$$

where

$$g_0 = \min\left\{\frac{1}{(NT)}, \frac{1}{(k+N)^2}\right\}. \tag{14}$$

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

$$\pi(\sigma) \propto \sigma^{-1}. \tag{15}$$

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

Fernández et al. (2001b) 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 (8) and (9) 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 computation time, we follow the algorithm proposed by Madigan and York (1995). This 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 (8) and (9).

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:

- 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.

- Fix M^{n+1} equal to M_j with probability $\gamma = (1, B_{js})$, 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 growth rates for each province is reduced. Many of the variables used in cross-country growth regressions are not appropriate when analysing the Spanish case. However, the consideration of different types of human and public capital, and a measure of sectoral structure, increases the number of potential determinants of growth.

The empirical estimations in this study are performed with both cross-section and panel data techniques for the period 1965-1995. Our main interest is the analysis of long-run determinants of provincial growth rates (10 years average). However, we also perform also short-run estimations for both cross-section and panel data models (results are presented in the appendix). Each model (cross-section and panel data) is estimated in two forms; first, we include the aggregates of private and public capital; second, these variables are introduced divided into various types (for definitions see below).

The dependent variable in our estimates is the *Growth Rate of per capita Gross Domestic Product*. Provincial GDP series are expressed at 1986 constant prices, with biannual observations, and are obtained from the Fundación BBV[10] (FBBV, hereafter). Population series are obtained from the Instituto Nacional de Estadistica (INE) and cover the relevant data span. These series have also been used to compute the *Population Growth* rate, another variable introduced into 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 the FBBV. Moreover, we split this variable into 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 the FBBV. Following the empirical literature, we consider only productive public investment (*Total Public Investment*), which is decomposed as investment in *Highways* and *Roads*, *Hydraulic Infrastructures (*water and sewer systems*)*, *Urban Structures*, *Ports* and *Airports*.

4.3 Human Capital

There is no unique measure of human capital. Different proxies have been used in the empirical literature. First, we use proxies of human capital as proposed by Mankiw et al. (1992), which have been 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 is obtained from the human capital series elaborated by the IVIE; additional information can be obtained from Mas et al. (1995) and Serrano (1999). We have used four measures (proxies) of human capital: H_1 is the share of working age population with no studies (illiteracy), H_2 is the share for workers with primary school education, H_3 with secondary studies, and finally H_5 is the share of working age population with a higher university degree.[11]

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 use them in our estimations because we wish to evaluate whether these variables should be included in a growth regression, 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 we use to construct this additional human capital variable builds on Mincer's (1974) function of returns on education, which relates the salary obtained by a worker to her level of education. From Mincer's specification, we can obtain a measure of human capital as follows (see Jones, 1997):

$$H_i = e^{\gamma S_i} L_i, \tag{16}$$

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.[12] Furthermore, S_i is calculated as follows:

$$S_i = \sum_j n_j \frac{W_{ij}}{L_i}, \tag{17}$$

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 the IVIE we have considered five levels of education (j), each one with its corresponding number of years of study necessary to obtain that level (n_j): illiteracy (0), primary school (3,5), secondary school (11), university (16), and higher degrees among university or college graduates (17). Finally, we have used the estimations of Alba-Ramírez and San Segundo (1995) of returns on schooling in Spain. The authors calculate the Mincerian specification of earnings equation in Spain, obtaining a value of 8.36% ($\gamma = 0.0836$). This overall rate of return value is very close to the value obtained by Psacharopoulos (1994) for Europe (8.5%).

4.4 Sectoral Structure

We also include variables with information on the sectoral structure of the Spanish provinces. Serrano (1999) and de la Fuente and Freire (2000) provide theoretical grounds for the inclusion of sectoral structure variables in growth regressions. In our case, the variables constructed are the provincial *Share in Agriculture* and *Share in Industry* with respect to total GVA in the province. We have omitted the services share of GVA to avoid problems of multicollinearity.

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 of 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 convergence across Spanish provinces, and the initial share of working population with primary and secondary school. We have called these variables *Initial Primary Enrolment* and *Initial Secondary Enrolment* respectively. A variable that indicates the *Area* of each province (Km^2) has been introduced to study whether there are scale effects that can affect growth rates (see Escot and Galindo, 2000), as well as a dummy variable that indicates the *Localization* of each province (north versus south).[13] Finally, a variable of *Fertility*, the provincial gross birth rate, has also been introduced in the cross-section estimates.

5 Results

This section is devoted to presenting the main results obtained in this study. The algorithm presented in section 3.3 is run with 50000 iterations, and the first 3000 are 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 is sufficient.

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.[14] Each table contains four columns: name of the variables, posterior Bayesian probability of inclusion, posterior mean of slope coefficient ($\beta's$), and posterior standard deviation for each parameter. The posterior probability of inclusion gives the probability that a variable should be included in the model. In other words, it is the probability that the effect of the variable is different from zero. The results are ordered by posterior probability of inclusion.

Long run cross-section estimates (tables 1a and 1b) suggest that the initial level of GDP is an important growth determinant, with a probability of inclusion of 0.97 and 0.71. The negative sign supports the hypothesis of conditional convergence across Spanish provinces for the whole period analysed (1965-1995).[15] However, the short run estimates conducted with cross-sectional techniques (tables 1c and 1d in the appendix) show that this variable has a probability of inclusion of around 0.5 but with a positive coefficient, indicating the possibility of persistence of income disparities in the short run.[16]

<Insert Table 1a>

Total private investment has a high posterior probability of inclusion (0.91), and a positive coefficient of around 1%. When we analyse the different components of private capital (table 1b), we find that the sectors in which private investment is more likely to have a positive effect are agriculture, construction and services (posterior probabilities of inclusion are between 25% and 35%).

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 the posterior probabilities of inclusion are 0.23 and 0.10. H_2 seems to be marginally correlated with growth rates, with probabilities of inclusion of around 0.18, and a small and positive posterior mean.

<Insert Table 1b>

When public investment is introduced as the total amount of productive spending, it has a very low probability of inclusion (0.06). The disaggregation of this variable causes two types of public investment to have larger 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 are likely to have a zero effect on cross-section growth regressions for the Spanish provinces (the probabilities of inclusion are smaller than 0.1).

Cross-section estimates are likely to be affected by several sources of bias; some of them can be tackled by using panel data techniques. The fact that we introduce a fixed effect for each province accounts for all individual and unobservable effects, allowing them to be correlated with the explanatory variables. Tables 2a and 2b present long run growth regressions using panel data in the BMA approach. When private and public investment are aggregated (Table 2a), human capital variables (H_2 and H_3) obtain the highest probability of inclusion (1) and both have negative estimates. This indicates that a marginal decrease in the proportion of people with primary and secondary studies, accompanied by an increase of the proportion of people with a university degree, results in an increase in the rate of growth (recall that the proportion of people with a university degree is omitted from the equation, and note that the effects of H_1 and H_5 are likely to be zero). The agricultural share of GVA also has a probability of inclusion equal to one and a positive coefficient. Interestingly, public investment has a 0.93 probability of inclusion and a positive and reasonable elasticity of 1.3%, similar to the one obtained for private investment.

<Insert Table 2a>
<Insert Table 2b>

In the disaggregated results (table 2b), there are two types of private investment with a probability of inclusion equal to 1: private investment in industry and construction, with elasticities of 2.3% and 3%, respectively.[17] Population growth has a 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 possibly negative role on growth rates. The other types of public investment are very likely to have a zero effect on growth. In contrast with the cross-section results, two types of human capital have large probabilities of inclusion. H_2 has 0.74 and a negative sign, while H_5 obtains probability around 0.40 and a positive (and small) sign of the effect on growth.

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

6 Conclusions

Some conclusions can be drawn from the analysis conducted in this study. BMA techniques allow us to determine which variables are strongly related to the growth rate of Spanish provinces. Furthermore, they deal with the problem of model uncertainty, which is one of the main problems of empirical growth regressions. We do not restrict ourselves to checking 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 significant correlation with long run growth rates. Among these variables, we find some types of private and public investment, and some human capital proxies. Moreover, we have also found some variables that are very likely to have a zero effect on growth.

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

As expected, private capital plays an important role in determining provincial growth rates. Moreover, private investment in industry and construction seem to be the two types of private investment with highest probability of inclusion in a growth equation. Human capital results are less clear. In the panel data framework, human capital seems to be an important growth determinant: a marginal decrease in the share of working age population with studies up to primary school, accompanied by an increase in the proportion of people with a university degree, seems to have a positive 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%). Except for investment in urban structures, marginal changes in the other types of public investment are likely to have a zero effect on growth. In contrast, a small decrease in public investment in urban structures might be positive for growth.

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 (lower when we introduced them into a cross-section regression). The signs are positive for the provincial agriculture share, and negative for the industry share on GVA.

Finally, some caution should be expressed when interpreting the results. The empirical literature on growth regressions has pointed out some econometric problems of classical growth regressions (both 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 presented here aims to revise model uncertainty and robustness of results in the classical approach, which has been so extensively used. We are aware of the problems that 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, in the Bayesian Model Averaging approach.

NOTES

1. Endogenous growth theories are "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).
2. Normally measured by Gross Domestic Product (GDP) or Gross Value Added (GVA).
3. Most of the studies in the growth regression literature have used "convergence equations" directly derived from the neoclassical growth model. This approach allows the estimation of the determinants of growth and also explores the controversial issue of economic convergence across economies. For a good review of cross-country growth regressions and the convergence hypothesis and its drawbacks, and estimation issues, see de la Fuente (1997), Durlauf and Quah (1999) or Temple (1999).
4. For instance, Bajo-Rubio (2000) introduces various types of public spending into a growth framework, showing their effects on the growth rate of the economy.
5. For a review on the empirical estimation of the effect of public capital, see Gramlich (1994) or Button (1998).
6. Both articles use panel data techniques with instrumental variables (GMM estimator proposed by Arellano and Bond, 1991).
7. Many other problems can affect growth regressions, such as aggregation problems, economic interpretation of the coefficients, or measurement problems (see, Durlauf, 1996).
8. The initial values of income, life expectancy and primary school enrolment.
9. Among these significant variables, we can identify openness, different types of investment, types of economic organization, market distortions, and different regional, political and religious variables.
10. The Fundación BBV has a regional data-base on the internet: http://bancoreg.fbbv.es. Alternatively, data can be obtained from the Instituto Valenciano de Investigaciones Económicas (IVIE). Information on construction and exact definitions of variables can be found in Mas et al. (1996).
11. We have omitted the fourth classification provided by the IVIE, which would correspond with H_4 (workers with a university degree), to avoid multicollinearity.
12. Time subscripts have been omitted for clarity.
13. This variable is inspired by the work of Dolado et al. (1994). They estimate growth regressions for different groups of provinces.

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

15. The implied speed of convergence is around 1%.

16. It is difficult to find significant short - run determinants of growth. However, our aim in conducting these cross - section regressions is to estimate the posterior probability of inclusion and the sign of the parameter for the initial level of income: recent empirical studies on convergence indicate the likely existence of persistence of income inequalities and divergence patterns in the short run for Spanish provinces; see for instance Lamo (2000) or Leonida and Montolio (2001).

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

7 Appendix

7.1 Testing the Program

In order to test the Gauss code employed in our empirical estimations, the panel data model is estimated with a simulated sample. The sample size is $N = 50$ and $T = 3$. 20 potential regressors are 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 is simulated from independent standard normal distributions. The true values for all individual effects are 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 include also the results of a classical fixed effects estimator, which include all potential regressors.

<Insert table A>

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

<Insert table 1c>
<Insert table 1d>
<Insert table 2c>
<Insert table 2d>

8 References

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9 Tables

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

Table 1b: Cross-section Long-run Estimates. Spanish provinces (1965-1995)

Dependent variable: per capita GDP growth rate. Disaggregation.

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

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

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 1d: Cross-section Short-run Estimates. Spanish provinces (1965-1995)

Dependent variable: per capita GDP growth rate. Disaggregation.

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 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

Table 2b: Panel Data Long-run Estimates. Spanish provinces (1965-1995)

Dependent variable: per capita GDP growth rate. Disaggregation.

Variable	Bayesian Probability	Posterior Beta	Posterior Std.Dev.
Population Growth	1	-0.0462735	0.010984022
Private Investment Indust	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 Airport	0.03792	0.0000005	8.31204E-06
Private Investment Energ	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

Table 2c: Panel Data Short-run Estimates. Spanish provinces (1965-1995)

Dependent variable: per capita GDP growth rate.

Variable	Bayesian Probability	Posterior Beta	Posterior Std. Dev.
Population Growth	1	-0.1370811	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 2d: Panel Data Short-run Estimates. Spanish provinces (1965-1995)

Dependent variable: per capita GDP growth rate. Disaggregation.

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 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