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The Determinants of Regional Economic Growth by Quantile

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The Determinants of Regional Economic Growth by Quantile

Abstract (English)

We analyse the robustness of growth determinants across EU regions using quantile regression (QR). We propose using Bayesian Model Averaging (BMA) on the class of QR models to assess the set of relevant covariates allowing for different effects across growth quantiles. The results indicate that the robust growth determinants differ across quantiles. The set of robust variables includes physical investment when taking country fixed effects into account and skill endowment and initial GDP per capita when not. Even when a variable is found to be robust across quantiles its estimated impact on growth is often found to vary across quantiles.

Keywords: Regional Growth, Bayesian Model Averaging, Quantile Regression

JEL Classification: C11, C21, R11

Determinanten regionalen Wachstums nach Quantilen

Abstract (German)

In diesem Beitrag wird die Robustheit von Wachstumsdeterminanten in EU-Regionen mittels Quantilsregressionen analysiert. Dabei wird ein Bayesian Model Averaging (BMA) für Quantilsregressionen verwendet, um die relevanten Kovariaten, die unterschiedliche Effekte in den jeweiligen Wachstumsquantilen aufweisen können, zu ermitteln. Die Resultate zeigen, dass die robusten Wachstumsdeterminanten in den jeweiligen Quantilen tatsächlich unterschiedlich sind. Unter Berücksichtigung von länderspezifischen Effekten ist insbesondere die Variable Anlageinvestitionen ein robuster Erklärungsfaktor regionalen Wachstums; ohne Berücksichtigen dieser Effekte sind Humankapitalausstattung und das Pro-Kopf Einkommen robuste Determinanten. Auch wenn eine bestimmte Variable robust in mehreren oder allen Quantilen ist, sind die ermittelten Effekte auf das Wachstum der Regionen in den jeweiligen Quantilen oftmals unterschiedlich.

Keywords: Regionales Wachstum, Bayesian Model Averaging, Quantilsregressionen

JEL Klassifikation: C11, C21, R11

1. Introduction

A great deal of effort has been expended in to the question of what are the most important determinants of differences in income growth rates across countries. The empirical literature on this subject tends to follow a common approach, regressing a usually small number of variables on output growth rates using a cross-section, or more recently a panel, of countries. The seminal contribution adopting this approach was Barro (1991) which has now been copied and adapted in numerous papers.[i] This literature has included a large number of variables purporting to explain growth. Durlauf et al (2005) for example report more than 40 "general growth theories" and over 130 growth determinants in various cross-country regressions. This has lead researchers to try and find a set of 'robust' variables that are important determinants of growth in a number of different models.

An early attempt at identifying the set of robust growth determinants was Levine and Renelt (1992) who used the Extreme Bounds Analysis (EBA) of Leamer (1978, 1983). In this type of analysis the dependent variable is regressed on the explanatory variable of interest, x_0, including different sets of other explanatory variables. If the maximum and minimum of the resulting coefficients on this variable all have the same sign (and are significant) the relationship is classified as 'robust', in the other case as 'fragile'. Levine and Renelt (1992) report two variables only, initial income and gross fixed capital formation, as robust variables in this particular sense[ii]. Such a criterion has been criticised as being too strong however. Sala-i-Martin (1997) for example, moves away from looking at the maximum and minimum of the coefficients and concentrates instead on the entire distribution of the coefficients from the estimated models. He considers as an evaluation criterion the percentage of times a variable appears significant and of the same sign. Using this definition of robustness and a 95 percent cut-off level, Sala-i-Martin finds a larger set of growth determinants could be considered robust.

A further approach to seeking robust determinants has been to follow some model selection criteria. One such approach is the general to specific methodology often associated with David Hendry, with the paper by Hendry and Krolzig (2004) being one example using this methodology to address the robust determinants of growth. Another approach (see Schneider and Wagner, 2008) uses consistent parameter estimation and model selection procedures based on the Least Absolute Shrinkage and Selection Operator (LASSO) estimator as proposed by Zou (2006). Bayesian Model Averaging (BMA) methods have also become a popular means of identifying the robust set of growth determinants. Examples where BMA has been applied to cross-country growth data include Brock and Durlauf (2001), Brock, Durlauf, and West (2003), Sala-i-Martin, Doppelhofer and Miller (2004), Fernandez et al (2001) and Masanjala and Papageorgiou (2007 and 2008).

The vast majority of the existing empirical growth literature concentrates on cross-country growth rates. There are however a smaller number of papers considering regional growth rates. A number of papers have examined the issue of convergence at the regional level. Barro and Sala-i-Martin (1995) for example present results at the regional level for the US, Japan and the EU. They find evidence in favour of convergence. Boldrin and Canova (2001) and Egger and Pfaffermayr (2006) find evidence of only slow income convergence. Other studies employ spatial techniques: Baumont et al (2002) and Le Gallo et al (2003) for example, examine the importance of convergence after allowing for spatial dependence. Egger and Pfaffermayr (2006) also show that spatial effects exert a non-negligible effect on regional convergence. A smaller number of papers consider the various potential determinants of growth at the regional level. For example, Cheshire and Magrini (2000) consider growth in 122 Functional Urban Regions and find that measures of human capital and economic potential have the strongest impact on growth. Badinger and Tondl (2002) consider data from 128 EU regions and find that capital accumulation and educational attainment are robust determinants of regional growth. Puigcerver-Peñalver (2007) estimates a hybrid growth model which allows for endogenous and exogenous determinants of growth over the period 1989-2000 for 41 Objective 1 regions. Apart from finding convergence, she also finds a significant and positive impact of structural funds. Egger and Pfaffermayr (2006) provide some evidence indicating that the sectoral structure has an impact on regional growth. Fingleton (2001) provides support for one of the main tenets of new economic geography, namely that urbanisation, peripherality, the initial level of technology and across-region spillovers are determinants of regional productivity growth variations, operating via the rate of technical progress and labour efficiency variations. Crespo Cuaresma, Dimitz and Ritzberger-Grünwald (2008) estimate convergence for the EU-15 countries over the period 1960-1998 and find economic integration beneficial for poorer countries, though there are a number of potential factors for this, such as technological spillovers, the stabilisation of the exchange rate, financial transfers (structural funds) etc. Thus there is some uncertainty where these benefits come from.

More closely related to this paper however are contributions searching for robust determinants of growth. LeSage and Parent (2007), LeSage and Fischer (2007) and Crespo Cuaresma, Doppelhofer and Feldkircher (2008) for example all use BMA methods to identify the set of robust growth determinants at the regional level. Crespo Cuaresma et al. (2008b) show that human capital accumulation and convergence forces appear as the most relevant variables in explaining economic growth at the regional level in Europe when model uncertainty is explicitly accounted for in the estimation method.

In this paper we seek to identify the set of robust growth determinants using a dataset of EU regions. The paper builds upon previous work in a number of ways. Firstly, as opposed to the majority of the existing literature we identify the robust growth determinants for a sample of 255 NUTS2 European regions using BMA. Secondly, and most importantly, we combine BMA with Quantile Regressions (QR) by concentrating on a space of econometric models where the effect of growth determinants is allowed to differ across quantiles. Our paper proposes therefore a methodological generalization of BMA which allows us to obtain model averaged estimates based on QR and thus considers alternative sets of robust growth determinants for under- and over-achieving regions.

To date, the vast majority of empirical growth research has relied on the least squares methodology, which models the mean of the growth rate conditional on a set of explanatory variables. Quantile regressions on the other hand model the conditional quantile of the growth rate at any quantile on the conditional growth distribution. In recent years studies have begun to emerge that use QR methods to address the determinants of economic growth across quantiles.[iii] There are a number of reasons for employing QR in the context of growth regressions. One major advantage of QR over standard OLS is that the estimator is robust to outlying observations on the dependent variable. This is a particular advantage in the growth setting where growth rates have been found to be characterised by long right tails and where outlying countries or regions can have a marked effect on OLS results (see Temple, 1999). A further major advantage is that the QR estimator provides one method of capturing parameter heterogeneity across regions. As indicated by Durlauf (2000), amongst others, the assumption of parameter homogeneity is neither an empirical nor a theoretical result. From a theoretical point of view, the fact that economic units which are hit by negative growth shocks may present different economic dynamics which would require the specification of a different data generating process has received a lot of interest in the economic growth literature. Poverty trap models, such as the one put forward originally by Azariadis and Drazen (1990) emphasizing threshold models (see the recent survey by Azariadis and Stachurski, 2004) present a theoretical framework which justifies the need for empirical models with parameter heterogeneity. Barreto and Hughes (2004) argue that by using QR they are addressing the behaviour of countries in which the factors that are not included in the estimated model create an environment that is conducive to high (or low) growth relative to conditions suggested by the variables that are included in the model. As an example, they argue that while investment is often found to be the most important tool to foster improved growth in studies based on OLS, if determinants outside the model are unfavourable, it is conceivable that increased investment will be wasted, resulting in a negligible impact on growth. QR, by potentially providing one solution for each quantile, allows one to assess how policy variables affect regions according to their position on the conditional growth distribution. Parameter heterogeneity is potentially even more relevant in the framework of regional datasets, where unmodelled spatial dependence in the form of geographical polarization of economic growth processes renders standard OLS estimates biased (see for example LeSage and Parent, 2007). Geographical polarization may lead to subsamples of observations being poorly modelled by standard linear regression models and leading to a better fit using QR methods.[iv] A further advantage of QR is that by considering the entire conditional growth distribution it allows one to consider the magnitude of the effects of the explanatory variables at the tails of the conditional distribution, which may be more interesting and useful than finding the magnitude of such effects at the conditional mean.

The paper closest in spirit to ours is the paper of Barreto and Hughes (2004) who combine QR with a variant of both Leamer's (1983) EBA and Sala-i-Martin's (1997) method of determining robustness to consider whether the set of robust growth determinants differ across quantiles. Using cross-country data they find that for under-achieving countries the most significant determinants of growth are latitude, social infrastructure, civil liberties and liquid liabilities, while for over-achieving countries trade, social infrastructure, the share of government expenditure, investment share and prices are the most significant determinants.

To highlight the importance of considering QR in the context of regional growth determinants, the following four figures show five estimated quantile regression lines (i.e. the dotted lines) and the OLS regression line (i.e. the solid line) when considering the relationship between four standard growth determinants and the growth of income per capita across regions.[v] From these figures we can observe that for some of the variables, in particular the share of gross fixed capital formation in value-added and the share of high skilled labour we find a great deal of dispersion in the estimated regression lines, indicating that the response of growth to changes in these variables is sensitive to the quantile considered. In addition, we find that in a number of cases there is quite a difference between the mean (i.e. OLS) and median (i.e. 50^{th} percentile) regression lines, as well as regression lines for other quantiles. These figures are therefore suggestive of parameter heterogeneity and of the importance of considering alternatives to OLS.

<<< Figures 1-4 around here >>>

Combining the BMA approach with QR allows us to simultaneously address the issues of model uncertainty in growth regressions and the presence of heterogeneous effects across different quantiles of the conditional growth distribution. Our results indicate that while some variables appear to be robustly related to growth at all quantiles, examples being initial GDP per capita and a capital city dummy when excluding country effects, others are only found to be relevant at specific quantiles only, in particular human and physical capital variables. Moreover, even when variables are found to be robust across quantiles it is often found to be the case that the coefficients on such variables differ across quantiles. For example, we find that human capital tends to play a more important role for under-performing regions when including country fixed effects, while the opposite is true for physical capital accumulation. The results therefore indicate the problems of trying to draw policy conclusions from OLS regressions, with the impact of particular variables found to depend upon a number of (often unmodelled) characteristics.

The paper is set out as follows. Section 2 discusses the concepts of QR and BMA in further detail and describes how we combine these two approaches. Section 3 discusses the data and Section 4 presents our initial results. Section 5 presents the main results of the paper and Section 6 concludes.

2. Bayesian Averaging of Quantile Regression Models

2.1. Quantile Regressions

Quantile regressions were introduced by Koenker and Bassett (1978), though the history of the Least Absolute Deviations (LAD) model from which quantile methods are derived predates OLS.[vi] Quantile regression analysis has recently received a great deal of attention with extensions to the existing literature that deal with the practical problem of estimating the covariance matrix, that consider the performance of the various estimators in small samples, as well as methods to deal with endogeneity, panel data and heteroscedasticity. Moreover, a growing literature applies such methods to a wide range of economic issues.

Quantile regression models seek to model the conditional quantile functions, in which the quantiles of the conditional distribution of the dependent variable are expressed as functions of observed covariates. The main advantage of QR is that potentially different solutions at distinct quantiles may be interpreted as differences in the response of the dependent variable to changes in the regressors at various points in the conditional distribution of the dependent variable. In the cross-section growth literature therefore it is possible to interpret changing coefficients across the conditional distribution as the result of systematic differences between countries or regions (Canarella and Pollard, 2004).

The quantile regression model, as described by Buchinsky (1998) is

$$y_i = x'_i \beta_\theta + \varepsilon_{\theta i}, \qquad i = 1, \ldots, n$$

where β_θ is the parameter vector associated with the θ_{th} quantile and $\varepsilon_{\theta i}$ is an unknown error term. It is assumed that $\varepsilon_{\theta i}$ satisfies the constraint

$$Quant_\theta(\varepsilon_{\theta i} | x_i) = 0,$$

such that the errors have zero conditional mean though no other distributional assumptions are required.

From a frequentist point of view, the quantile regression estimator of β_θ can be obtained by minimising a weighted sum of absolute errors, where the weights are symmetric for the median regression case ($\theta = 0.5$) and asymmetric otherwise. In general therefore, the linear model for the θ_{th} quantile $(0 < \theta < 1)$ solves the following minimisation problem,

$$\min_{\beta_\theta} \frac{1}{n} \left\{ \sum_{i: y_i \geq x_i' \beta_\theta} \theta |y_i - x'_i \beta_\theta| + \sum_{i: y_i < x_i' \beta_\theta} (1-\theta) |y_i - x'_i \beta_\theta| \right\}$$

As one keeps increasing θ from zero to one, one can trace the entire conditional distribution of y, conditional on the set of regressors. In terms of this paper therefore QR allow us to trace the entire distribution of the growth rate of income per capita, conditional on the regressors included.

The resulting minimisation problem can be solved using linear programming methods. The coefficient for a regressor j can be interpreted as the marginal change in the θ_{th} conditional quantile of y due to a marginal change in j.[vii] The asymptotic theory of QR is provided by Koenker and Bassett (1978). One can use procedures to estimate the asymptotic standard error of the estimators, or alternatively one can use a bootstrap procedure.

The use of QR has a number of benefits. The major benefit being that the entire conditional distribution of the dependent variable can be characterised by using different values of θ. A further benefit relates to the fact that median regression methods can be more efficient than mean regression estimators in the presence of heteroscedasticity (though this problem is also addressed by robust estimation). QR are also robust with regard to outlying observations in the dependent variable. The quantile regression objective function is a weighted sum of absolute deviations, which gives a robust measure of location, so that the estimated coefficient vector is not sensitive to outlier observations on the dependent variable. Finally, when the error term is non-normal, quantile regression estimators may be more efficient than least squares estimators.

2.2. Bayesian Model Averaging

Bayesian Model Averaging (BMA) is a standard Bayesian solution to model uncertainty, and consists of basing prediction and inference on a weighted average of all the models considered, rather than on one single regression model.[viii] Model averaging in general and BMA in particular, are becoming more and more popular, and there are now numerous examples of these techniques being applied in economics. Applications of BMA to economic growth include Min and Zellner (1993), Fernandez et al (2001), Leon-Gonzalez and Montolio (2004), Sala-i-Martin et al (2004), Durlauf et al (2006, 2007), Crespo-Cuaresma and Doppelhofer (2007), Eicher et al (2007), Masanjala and Papageorgiou (2007, 2008), Ley and Steel (2007, 2009).

Given data on a dependent variable, Y, a number of observations, N, and a set of candidate regressors $X = x_1, \ldots, x_z$ the variable selection problem is to find the best model, or the most appropriate subset of regressors $x_1, \ldots, x_k$ out of the total set of candidate regressors. In what follows we sketch out the basic intuition behind BMA methods.[ix]

We begin by denoting $\mathcal{M} = \{M_1, \ldots, M_M\}$ the set of all models considered, where each model represents a subset of the candidate regressors, $x^{(m)}$. Model M_m has the form,

$$y_i = x_i^{(m)} \beta^{(m)} + \varepsilon_i$$

where $x^{(m)}$ is a subset of X, $\beta^{(m)}$ is a vector of regression coefficients to be estimated and ε is the standard iid error term. We denote by $\vartheta_m = (\beta^{(m)}, \sigma)$ the vector of parameters in M_m. Taking into account model uncertainty, Bayesian inference about the parameter attached to x_j, a variable in X, is,

$$\Pr(\beta_j | Y) = \sum_{m=1}^{M} \Pr(\beta_j | Y, M_m) \Pr(M_m | Y) \tag{1}$$

i.e. the average of the posterior distributions under each model weighted by the corresponding posterior model probabilities. This is what is termed Bayesian Model Averaging (BMA). The posterior probability of model M_m is,

$$\Pr(M_m|Y) = \frac{\Pr(Y|M_m)\Pr(M_m)}{\sum_{l=1}^{M}\Pr(Y|M_l)\Pr(M_l)}, \quad (2)$$

where,

$$\Pr(Y|M_m) = \int \Pr(Y|\vartheta_m, M_m)\Pr(\vartheta_m|M_m)d\vartheta_m \quad (3)$$

is the integrated likelihood of model M_m, $\Pr(\vartheta_m|M_m)$ is the prior density of ϑ_m under model M_m, $\Pr(Y|\vartheta_m, M_m)$ is the likelihood, and $\Pr(M_m)$ is the prior probability that M_m is the true model (assuming that one of the models considered is true). The posterior model probabilities can thus be obtained as the normalised product of the marginal likelihood for each model $(\Pr(Y|M_m))$ and the prior probability of the model $(\Pr(M_m))$. Notice that for the simple case $M = 2$ the posterior odds for a model against the other can be readily written as the product of the Bayes factor and the prior odds. Further assuming equal priors across models, the posterior odds are equal to the Bayes factor.

The posterior mean and variance of a regression coefficient, β_j, are then given by,

$$E(\beta_j|Y) = \sum_{m=1}^{M} \beta_j^{(m)}\Pr(M_m|Y), \quad (4)$$

$$\mathrm{Var}(\beta_j|Y) = \sum_{m=1}^{M}\left(\mathrm{Var}(\beta_j|Y, M_m) + \left(\beta_j^{(m)}\right)^2\right)\Pr(M_m|Y) - E(\beta_j|Y)^2 \quad (5)$$

Here $\hat{\beta}_j^{(m)}$ denotes the posterior mean of β_j under model M_m, and is equal to zero if x_j is not included in M_m. The posterior mean is therefore the weighted average of the model-specific posterior means, where the weights are equal to the model's posterior probabilities.

The posterior variance reflects both the weighted average of the within-model posterior variances, and the between-model variation of the model-specific posterior means. In addition to the posterior means and standard deviations, BMA provides the posterior inclusion probability of a candidate regressor, $\Pr(\beta_j = 0|y)$, by summing the posterior model probabilities across those models that include the regressor.

If all possible subsets are considered as potential models then the cardinality of the set is $\mathcal{M} = 2^Z$. As such, even with a moderate number of regressors we have an extremely large number of models and estimating all is typically not feasible (e.g. with 30 regressors we have around one billion models and with 40 about two trillion). A number of approaches have been developed to help deal with this problem, examples including a Markov Chain Monte Carlo Model Composition algorithm (Madigan and York, 1995) and a branch-and-bound algorithm developed by Raftery (1995).

2.3. Combining Quantile Regression with BMA

In order to consider whether the set of robust growth determinants differs across quantiles we need to combine QR with BMA. To do this we can write model M_m for the θ_{th} conditional quantile of y conditional on $x^{(m)}$ as,

$$q_\theta(y_i|x_i) = x_i^{(m)}\beta^{(m)}(\theta) + \varepsilon_i$$

where $q_\theta(\psi)$ is the θ_{th} quantile of (ψ) and $\beta^{(m)}(\theta)$ is a set of parameters at the θ_{th} quantile to be estimated. Bayesian inference about the parameter attached to x_j at the θ_{th} quantile is given by rewriting equation (1) as,

$$\Pr(\beta_j(\theta)|Y) = \sum_{m=1}^{M} \Pr(\beta_j(\theta)|Y, M_m)\Pr(M_m|Y),$$

where $\Pr(M_m|Y)$ are the posterior model probabilities given by equation (2).

The likelihood function is thus of central importance when implementing the BMA approach, which creates a problem when implementing BMA on QR. Following Koenker and Machado (1999) and Yu and Moyeed (2001) the marginal likelihood for a quantile regression model can be computed however by assuming that y is distributed according to an asymmetric Laplace distribution, so that,

$$\Pr(Y|M_m) = \theta^N(1-\theta)^N \exp\left\{-\sum_{i=1}^{N} \rho_\theta(y_i - x_i^{(m)}\beta^{(m)}(\theta))\right\} \qquad (6)$$

where $\rho_\theta(u) = u[\theta I(u > 0) - (1-\theta)I(u \le 0)]$. The use of the asymmetric Laplace distribution for y implies that under the assumption of an improper uniform prior distribution on the parameter vector, β can be estimated by maximising,

$$\Pr(\beta_j^{(m)}|Y, M_m) \propto \exp\left\{-\sum_{i=1}^{N} \rho_\theta(y_i - x_i^{(m)}\beta^{(m)}(\theta))\right\},$$

which is just the minimisation problem proposed by Koenker and Basset (1978) for estimating quantile regression models in a frequentist framework. Yu and Moyeed (2001) show that this likelihood function and an improper uniform prior on β lead to a proper posterior distribution of the parameter vector.

Consider the case of two competing models, M_1 and M_2, the posterior odds for model 2 against model 1 can be readily written as the product of the Bayes factor and the prior odds.

Further assuming equal priors across models, the posterior odds are equal to the Bayes factor, $\left(\frac{\Pr(Y|M_1)}{\Pr(Y|M_2)}\right)$, which in turn can be approximated using the Laplace method as,

$$\frac{\Pr(Y|M_2)}{\Pr(Y|M_1)} \approx (2\pi)^{\frac{p_2-p_1}{2}} \frac{|\Psi_2|^{\frac{1}{2}}\Pr\left(Y\middle|M_2,\hat{\beta}_2\right)}{|\Psi_1|\Pr\left(Y\middle|M_1,\hat{\beta}_1\right)} \frac{\Pr\left(\hat{\beta}_2\middle|M_2\right)}{\Pr\left(\hat{\beta}_1\middle|M_1\right)}$$

where p_j is the dimension of β_j, $-\Psi_j$ is the inverse Hessian of the likelihood and $\hat{\beta}_j$ is the maximum likelihood estimator of β_j. Equation (2) can be further operationalised using Schwarz's (1978) approximation (see Raftery, 1995) as

$$\frac{\Pr(Y|M_2)}{\Pr(Y|M_1)} = \exp\left\{\frac{\left[\chi^2_{1,2} - (p_2 - p_1)\log N\right]}{2}\right\}$$

where $\chi^2_{1,2}$ is the standard likelihood ratio test statistic for the choice between model 1 and 2 based on the likelihood function given in equation (6). We use this approximation in order to calculate the posterior model probabilities. In our setting, the approximation based on the Schwarz criterion has the advantage that it does not require the explicit specification of priors over the parameter space (see also Kass and Raftery, 1995) and thus can be easily implemented using frequentist estimation methods.

3. Data

The data used in the analysis covers 255 NUTS-2 regions in the 27 EU countries. For eight countries the NUTS-2 region is also the country (these countries being Cyprus, Denmark, Estonia, Latvia, Lithuania, Luxembourg, Malta and Slovenia). The maximum number of regions in a country is 39 (Germany). The period of coverage is from 1995-2005, though for some variables a shorter time-period is used due to data availability. The starting point in the dataset ensures that the post-transitional recession in the Eastern European countries had ended, with a rapid catching-up process beginning from 1995 onwards for most, though not all, of these countries. In addition, we are only able to obtain data on most of the explanatory variables we include from 1995 onwards in a comparable and consistent manner. The dataset thus covers the period of strong European integration, beginning with the expansion to 15 members in 1995 and to 25 in 2004, when ten of the twelve Eastern European countries joined the EU (Bulgaria and Romania becoming members in 2007).

The dependent variable in our analysis is the average yearly growth rate of real GDP per capita (*gGDPCAP*) over the period 1995-2005. We use information on 35 potential determinants of growth.[x] Where possible the first year for which data are available is used when measuring the explanatory variables in order to minimise problems of endogeneity.[xi] The variables are listed and described in the appendix. The set of variables included is on the one hand motivated by the various growth theories but also by the availability of comparable data across the 255 regions. It should be noted here that we have to use a balanced dataset in that there are no missing values. In the appendix we have grouped the data into six groups comprising various explanatory variables. For example, one group includes initial conditions and factor accumulation which is particularly emphasised in neoclassical growth theories but also in models emphasising technology gaps and catching-up. The second group includes variables capturing human capital which plays a central role in endogenous growth models by supporting regional innovation and the dissemination of knowledge. Infrastructure and socio-geographic variables are particularly emphasised in economic geography and spatial growth models and capture the effects of proximity to labour and product markets. Variables related to innovation are again related to endogenous growth theories. Finally, a set of employment related variables is included capturing the functioning of labour markets and factor input conditions. The initial unemployment rate captures the sound operation of labour markets and is also related to factor accumulation, regional flexibility and social cohesion. One should note that there is not necessarily a clear link between these sets of variables and a particular growth theory: the same variable can have an important role in different growth theories, while a particular growth theory might emphasize more than one variable. For example, initial conditions – and in particular the initial level of GDP per capita – are particularly emphasised in the neoclassical growth theory where the convergence process is driven by capital accumulation. However, the initial level of GDP per capita (as a proxy for productivity) is also important in theories emphasizing learning capabilities (for example, models emphasising the 'advantage of backwardness' or the 'technology gap').

In each econometric setting (BMA based on OLS and QR) we present the results corresponding to both models with and without country fixed effects. [xii] The use of country fixed effects has an important effect on the interpretation of the resulting parameters. The speed of income convergence, for instance, refers to the convergence process towards a unique, European steady state (after controlling for the other variables in the model) in terms of income per capita in the case without country fixed effects. On the other hand, the income convergence process (and its speed) refers to a country-specific income level for the setting with fixed effects. In principle, we could have included the individual country dummies as regular regressors in the BMA framework. While this is unproblematic from a statistical point of view, it makes the interpretation of results unnecessarily complicated, since the averaged estimates would be composed of some estimates referring to elasticities based on within-country relationships and others referring to differences across regions of different countries.

4. BMA results

As an initial step we implement the BMA approach described above using classical least squares estimates. The BMA approach requires a prior probability of each model and a prior probability distribution over the parameters of each model to compute the weights when averaging over models. We follow the usual approach in the literature and assume a flat prior (i.e. all models are equally likely) in the model space, which implies a prior inclusion probability of 0.5 for each variable. We employ a Markov Chain Monte Carlo Model Composition (MC^3) algorithm using random walk steps as described in Fernandez et al (2001) to deal with the very large model space, which allows us to only visit models that have a non-negligible posterior probability. All reported results are based on 2 million draws of the Markov Chain, after 1 million discarded burn-in draws.[xiii] Tables 1 and 2 report the posterior inclusion probability (PIP), posterior mean, and posterior standard deviation for each of the 35 growth determinants in the Least Squares case. We present two sets of results: the results in Table 1 exclude country effects, while those in Table 2 allow for country fixed effects.

<<< Tables 1 and 2 around here >>>

Despite the very large number of models entertained, a large part of the posterior model probability appears concentrated in a relatively small number of models. The relatively larger number of models visited by the Markov chain in the case of the setting with country fixed effects indicates that uncertainty across models is larger when we consider within-country data. As expected, the results we obtain are found to differ depending on whether country effects are included or not, which implies that the determinants of regional growth between countries are of a different nature as those within countries. The variables with the highest inclusion probability when country dummies are excluded (Table 1) are whether the region hosts the capital city (*CAPITAL)*, the initial GDP per capita (*GDPCAP0)*, the initial share of high educated persons in working age population (*SHSH)* and the initial unemployment rate (*URT0)*. Once country effects are allowed for (Table 2) however the inclusion probability of a number of the variables, in particular *GDPCAP0* and *URT0*, falls dramatically. In this case there are three variables with an inclusion probability above 0.5, indicating that we consider them to be robust growth determinants, namely the share of gross fixed capital formation in gross value added (*SHGFCF)*, *CAPITAL* and *SHSH*.[xiv] The results indicate that an indicator of human capital and a variable capturing whether the region houses the capital city are the most important determinants of regional growth, with physical capital investment (*SHGFCF*) becoming relevant when country effects are included. That human capital and investment are found to be relevant growth determinants is suggestive of the importance of factor accumulation for regional growth. The importance of these variables is also consistent with more recent endogenous growth models that emphasise the importance of learning-by-doing and schooling (Lucas, 1988, Stokey, 1991) and capital accumulation (Romer, 1986). The capital city variable can be interpreted as summarizing several different effects from the effects of agglomeration, infrastructure and the polarization of, for instance, administrative services. The importance of this dummy is however also related to the inclusion of Eastern European countries in our sample, and its effect is less clear-cut if the sample is reduced to old member states[xv], which is in line with the fact that growth in Eastern European countries was concentrated in and around capital cities. The Williamson hypothesis (Williamson, 1965) proposes that there exists a trade-off between economic growth and regional disparities for countries at lower levels of development, and the growth bonus of regions which contain the capital city in Eastern Europe may be capturing this effect.[xvi]

Interestingly, the importance of initial GDP per capita (GDPCAP0) is not found to be strong once we include country effects. The result that initial income is not relevant when country effects are included but is when they are excluded suggests that while countries across Europe appear to be converging, regions within countries do not show robust evidence of income convergence. This finding is again consistent with the above mentioned fact that economic growth has been concentrated in the capital city regions in Eastern European countries. This result is further consistent with the results of De la Fuente and Vives (1995) who show that while convergence has taken place in Europe, regions within countries have either failed to converge or have diverged.

In terms of the posterior means and standard deviations reported in these two tables we see that for the robust variables in each table the posterior mean of the coefficients are of the expected sign. As expected, in this setting we find a positive posterior mean for the parameters attached to *SHSH*, *CAPITAL* and *SHGFCF*, and a negative one for *GDPCAP0*. The posterior standard deviations indicate that the coefficients are well estimated when not including country fixed effects, but obtaining precise estimates of the quantitative effects of variables for regions within countries appears more difficult.

5. Results from the Bayesian Averaging of Quantile Regressions

In this section we report the results from implementing BMA on QR. We implement the BMA approach at each decile from the 10^{th} to the 90^{th} percentile again both including and excluding country effects. Table 3 (4) reports the inclusion probabilities at every decile along the conditional growth distribution when country effects are excluded (included). The variables are ranked according to the mean of the PIP across the quantiles (with variables showing a PIP greater than 0.50 considered robust and highlighted).

Considering the results in Table 3 where country effects are excluded we find that the initial GDP per capita (*GDPCAP0)* and the capital city dummy (*CAPITAL)* have a high inclusion probability across quantiles (with the exception of *CAPITAL* in the first decile). The share of high skilled workers (*SHSH)* tends to become robust at the highest quantiles (though not uniformly), while the variable indicating learning activities (*SHLLL)* is found to be robust at lower quantiles and internet access of firms (*INTF)* at the lowest quantile. Consistent with the least squares results therefore we find that *GDPCAP0* and *CAPITAL* are robust growth determinants, and this appears to be true across the conditional growth distribution. Different to the least squares results however we find additional variables (*SHLLL* and *INTF*) to be robust growth determinants at particular quantiles. Such a result emphasises the relevance of moving beyond considering least squares results only, with potentially different drivers of growth and different policy recommendations needed for under- and over-achievers. In addition, while *SHSH* is again found to be robust, this is only the case for certain quantiles, and the higher quantiles in particular This effect is partly driven by Eastern European regions showing a high share of skilled workers and relatively high rates of economic growth. Such results leads to the nuanced policy conclusions that policies such as promoting higher skills, learning activities and communication facilities are expected to have a differential impact on growth across regions, and are only likely to be beneficial for some regions – namely over-performers.

In Table 4, i.e. when including country fixed effects, we also find that the set of robust determinants differs across quantiles. In particular, we find that the capital city dummy (*CAPITAL)* and the share of gross fixed capital formation (*SHGFCF)* are only found to be robust growth determinants at the higher quantiles (though the latter also at the lowest quantile), while the share of high educated workers (*SHSH)* tends to be robust at lower quantiles. This latter result is compatible with those reported above: when not including country fixed effects the share of highly educated workers is important as this was one of the driving forces behind the high growth rates in Eastern European countries. When including country fixed effects the result implies that human capital is an important factor of growth by enhancing technology adoption. Patenting activities (*TP_0)* are also found to be robust at the lowest quantiles. In this case, no general policy prescriptions can be made as there is no variable found to be robust across quantiles. Investment in physical capital is likely to benefit over-achievers, while investment in human capital is likely to benefit under-achievers.

To summarise: firstly, as with the OLS results we find that there are significant differences in results depending upon whether we include or exclude country effects. Secondly, we find that there are a number of variables that have a high inclusion probability across quantiles. In the case when country effects are excluded these include whether the region is home to the country's capital and the initial per capita GDP. Thirdly, there are also variables that are only found to be robust for certain quantiles. Examples of such variables when country effects are excluded include the indicator of human capital, which is found to be relevant mainly for over-performers, while when country effects are included we find that the variable *CAPITAL* and the investment rate are only relevant for higher quantiles, while the share of high-skilled workers is more relevant at lower quantiles.

<<<Tables 3-6 around here >>>

The final two tables (5 and 6) report the posterior means and standard deviations of the estimated coefficients for the 10th, 30th, 50th, 70th and 90th percentiles of the conditional growth distribution for those variables with a relatively high inclusion probability.[xvii] In terms of the posterior means of the model-averaged parameter, there are no surprises in terms of the signs of the variables. In Table 5 we find a negative mean on *GDPCAP0* and a positive one on the remaining robust variables. There is some variation in the size of the posterior means across quantiles however. For *GDPCAP0* the mean of the coefficient follows a U-shape being slightly larger (in absolute terms) at the lowest and highest quantiles indicating non-linearities in the convergence process. For *CAPITAL* we find that the posterior mean of the parameter increases as we move to higher quantiles, while for the share of high educated workers (*SHSH)* the mean coefficient is highest at the middle and highest quantiles. This is also the case in Table 6 which reports the posterior means and standard deviations when including country fixed effects. We find positive means on all of the robust determinants as expected, but some differences in the size of the mean across quantiles. The mean on *CAPITAL* is again found to be increasing as we move to higher quantiles, as does that on the share of gross fixed capital formation (*SHGFCF)*. For the share of high educated workers (*SHSH)* however the mean is found to be largest at the low and medium quantiles. For under performers the role of human capital endowment seems relatively important having positive effects on technology adoption and learning-by-doing. For high performers however other variables such as investment (i.e. embodied technical progress) become more relevant. From a policy perspective the effects of increasing the human capital stock is therefore expected to be larger for under-performers, whereas for over-performers policy measures geared toward efficient use and complementarities to the existing human capital stock would yield higher returns in terms of growth rates.

6. Conclusions

Growth within European regions in the recent past has been quite uneven. While many of these differences in regional growth can be accounted for by country performance and the convergence process of the Eastern European countries there remain significant differences in regional growth performance even after controlling for country effects. In this paper we seek to understand and identify the set of variables that robustly determine regional growth. The paper differs from the previous literature to understand the robust growth determinants by allowing the set of robust determinants to differ across regions. In particular, we identify the set of robust determinants for both under- and over-achievers defined in terms of their growth performance. To do this we combine quantile regression analysis, which allows us to model regional growth at different points on the conditional growth distribution, and Bayesian Model Averaging (BMA) to select a small number of robust variables from a longer list of potential explanatory variables.

We obtain a number of interesting results from our analysis. Firstly, country specific factors are found to play an important role. The sign, size and significance of many variables differs depending upon whether we account for country effects or not. The list of robust variables we obtain using the BMA analysis (using both least squares and quantile regression models) is also found to differ depending upon whether country effects are accounted for or not. Secondly, we find that there is considerable parameter heterogeneity across quantiles. This is reflected in two sets of results; those showing that the size of the parameters on a specific set of variables varies across quantiles and those showing that the set of robust variables differs across quantiles.

In terms of the robust set of variables we often find that measures of skill endowment (or human capital) are robust determinants, with a higher level of high skilled labour being associated with higher growth. When we account for country effects, investment in physical capital is also found to be a robust determinant of growth with the expected sign. In terms of the quantile results we tend to find that physical capital has a stronger association in over-achievers, with the results on human capital depending upon whether we include country effects or not. While the policy relevance of these variables is clear, other robust variables lead to less clear-cut policy conclusions, in particular geography variables. The dummy for if a region is home to the country's capital city for example is often found to be robust across quantiles, with its association with growth being positive. This is likely to reflect a number of characteristics of capital cities, such as infrastructure, agglomeration economies and so on, but it is not clear how such effects can be replicated. Interestingly, initial GDP per capita which is often found to be relevant in existing studies is not found to be a robust variable when country effects are accounted for.

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Appendix: Data Description

Data used in this study are collected from various sources, in particular: the Eurostat Regio database, Eurostat LFS database, ESPON (for details on these variables see http://www.espon.eu/), and Cambridge Econometrics. The period covered is 1995-2005. Variables capturing initial conditions are taken for 1995 or the first year for which data are available.

<<< Table A1 around here >>>

The distance weighted variables are calculated according to the following formula:

$$dw_{z_i} = \sum_{j=1}^{n-1} \frac{1}{dist_{ij}} z_j \qquad j \neq i$$

Where $z_{i,j}$ is the variable of interest (initial per capita GDP or output density) in country i, j and $dist_{ij}$ is the distance between region i and j .

Figure 1: Initial GDP per capita

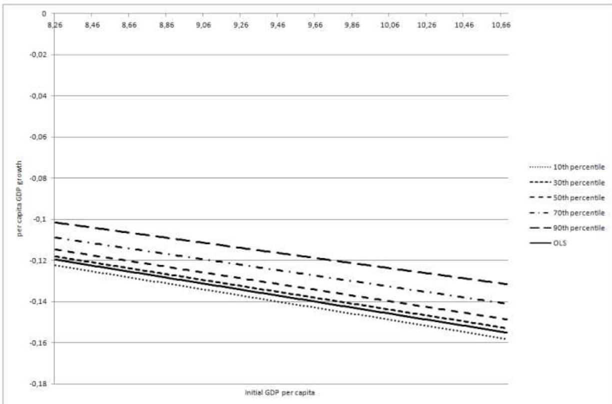

Figure 2: Share of gross fixed capital formation in value-added

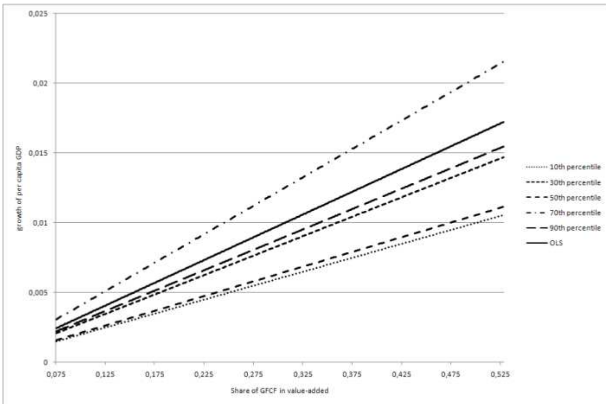

Figure 3: Population growth

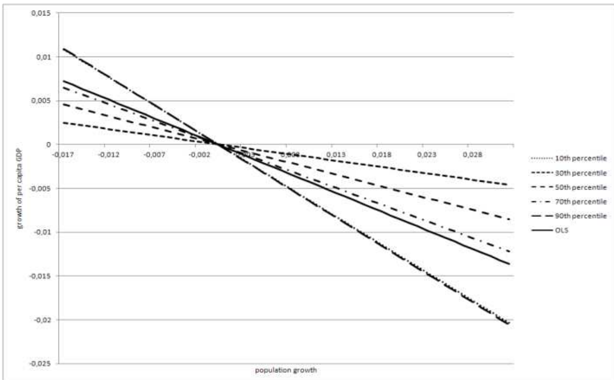

Figure 4: Share of high-skilled labour

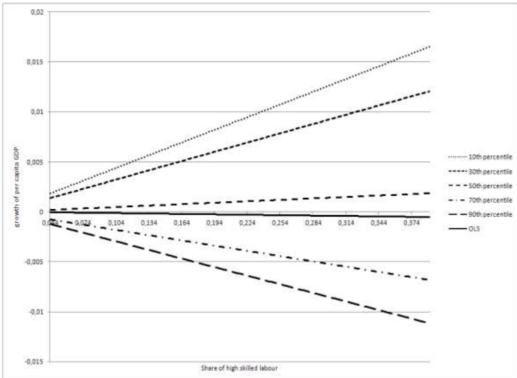

Table 1: BMA on Classical Least Squares Estimates (no country effects)

Variable	PIP	Posterior Mean	Posterior SD
CAPITAL	1.000	0.019	0.002
GDPCAP0	1.000	-0.020	0.002
SHSH	0.881	0.0340	0.017
URT0	0.575	-0.023	0.022
SHLLL	0.122	0.005	0.013
AIRPORTDENS	0.119	0.520	1.531
ERET0	0.079	0.002	0.010
DW_GDPCAP0	0.064	-0.000	0.000
GPOP	0.029	0.006	0.042
SHCE0	0.024	0.001	0.004
INTF	0.017	0.000	0.003
ART0	0.015	-0.000	0.009
SHGFCF	0.014	0.000	0.002
HAZARD	0.009	0.000	0.000
PATENTHT	0.009	0.000	0.004
ACCESSMULTI	0.009	0.000	0.000
PATENTICT	0.007	0.000	0.002
TELF	0.007	-0.000	0.000
ROADDENS	0.007	-0.000	0.000
DISTCAP	0.007	0.000	0.000

CONNECTAIR	0.006	-0.000	0.000
LEVSH	0.006	-0.000	0.000
TELH	0.005	0.000	0.000
REGCOAST	0.004	0.000	0.000
REGBOARDER	0.004	0.000	0.000
PATENTBIO	0.004	0.000	0.008
OUTDENS0	0.004	0.000	0.000
DW_OUTDENS0	0.004	0.000	0.000
PATENTT	0.003	-0.000	0.000
RAILDENS	0.003	0.000	0.001
HRSTCORE	0.002	0.000	0.001
BIOP_0	0.00	0.000	0.000
HTP_0	0.000	0.000	0.000
ICTP_0	0.000	0.000	0.000
TP_0	0.000	0.000	0.000
Number of Models Visited	7958		

PIP stands for posterior inclusion probability. The posterior mean and posterior standard deviation reported refer to the corresponding expressions (4) and (5) in the text.

Table 2: BMA on Classical Least Squares Estimates (country effects)

Variable	PIP	Posterior Mean	Posterior SD
SHGFCF	0.793	0.029	0.018
CAPITAL	0.717	0.006	0.004
SHSH	0.645	0.041	0.035
AIRPORTDENS	0.375	1.693	2.353
ACCESSMULTI	0.247	0.002	0.004
DW_GDPCAP0	0.044	-0.000	0.001
INTF	0.040	0.001	0.006
REGBOARDER	0.030	-0.000	0.000
PATENTT	0.029	0.000	0.003
OUTDENS0	0.028	-0.000	0.000
DW_OUTDENS0	0.028	-0.000	0.000
GDPCAP0	0.026	-0.000	0.002
ART0	0.021	-0.003	0.038
LEVSH	0.019	0.000	0.000
CONNECTAIR	0.014	-0.000	0.000
PATENTHT	0.013	0.000	0.005
PATENTICT	0.011	0.000	0.003
SHLLL	0.010	0.000	0.005
SHCE0	0.009	-0.000	0.002
GPOP	0.009	-0.001	0.017

URT0	0.009	0.001	0.023
ERET0	0.009	0.002	0.039
HAZARD	0.008	0.000	0.000
PATENTBIO	0.008	0.001	0.016
TELF	0.008	0.000	0.000
ROADDENS	0.007	-0.000	0.001
RAILDENS	0.006	-0.000	0.001
HRSTCORE	0.005	0.000	0.001
REGCOAST	0.004	0.000	0.000
TELH	0.003	0.000	0.000
DISTCAP	0.003	0.000	0.000
TP_0	0.002	0.000	0.000
BIOP_0	0.000	0.000	0.000
ICTP_0	0.000	0.000	0.000
HTP_0	0.000	0.000	0.000
Number of models visited		14713	

PIP stands for posterior inclusion probability. The posterior mean and posterior standard deviation reported refer to the corresponding expressions (4) and (5) in the text.

Table 3: Inclusion Probabilities across Quantiles (no country effects)

Variable	10th	20th	30th	40th	50th	60th	70th	80th	90th
GDPCAP0	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CAPITAL	0.220	0.810	0.895	0.988	0.997	0.999	1.00	1.000	1.000
SHSH	0.120	0.158	0.654	0.394	0.378	*0.511*	*0.608*	0.293	0.916
SHLLL	0.057	0.751	0.293	0.543	0.578	0.391	0.104	0.041	0.033
INTF	0.798	0.123	0.084	0.036	0.007	0.007	0.005	0.014	0.011
ERET0	0.015	0.036	0.036	0.068	0.095	0.111	0.055	0.038	0.283
ART0	0.011	0.018	0.029	0.063	0.035	0.032	0.032	0.043	0.093
URT0	0.011	0.014	0.031	0.046	0.057	0.054	0.029	0.017	0.068
AIRPORTDENS	0.087	0.021	0.027	0.037	0.030	0.030	0.012	0.007	0.005
PATENTHT	0.028	0.061	0.037	0.029	0.016	0.019	0.012	0.018	0.004
PATENTICT	0.032	0.052	0.026	0.028	0.016	0.010	0.010	0.012	0.003
TELH	0.003	0.007	0.013	0.017	0.009	0.010	0.024	0.091	0.007

GPOP	0.009	0.005	0.014	0.022	0.024	0.018	0.015	0.010	0.011
HAZARD	0.008	0.007	0.011	0.010	0.007	0.007	0.005	0.012	0.046
PATENTBIO	0.011	0.010	0.008	0.006	0.009	0.012	0.010	0.030	0.008
LEVSH	0.005	0.007	0.011	0.007	0.011	0.006	0.010	0.019	0.027
DW_GDPCAP0	0.006	0.020	0.019	0.010	0.010	0.006	0.005	0.009	0.011
SHCE0	0.003	0.007	0.004	0.004	0.006	0.007	0.002	0.013	0.038
SHGFCF	0.016	0.007	0.008	0.013	0.013	0.007	0.009	0.008	0.003
DISTCAP	0.014	0.007	0.006	0.005	0.006	0.006	0.007	0.014	0.011
OUTDENS0	0.008	0.013	0.009	0.007	0.005	0.007	0.004	0.008	0.006
HRSTCORE	0.006	0.008	0.007	0.004	0.006	0.004	0.007	0.010	0.012
PATENTT	0.009	0.018	0.012	0.005	0.005	0.004	0.003	0.005	0.003
RAILDENS	0.008	0.006	0.005	0.003	0.005	0.003	0.005	0.007	0.016
TELF	0.008	0.005	0.007	0.005	0.005	0.006	0.006	0.005	0.011
CONNECTAIR	0.007	0.008	0.005	0.005	0.006	0.008	0.007	0.008	0.004

ROADDENS	0.007	0.008	0.005	0.004	0.006	0.006	0.006	0.008	0.006
DW_OUTDENS0	0.007	0.007	0.006	0.005	0.003	0.005	0.008	0.005	0.010
ACCESSMULTI	0.010	0.008	0.007	0.003	0.007	0.006	0.003	0.006	0.008
REGBOARDER	0.010	0.007	0.003	0.004	0.007	0.006	0.007	0.006	0.005
REGCOAST	0.010	0.007	0.004	0.006	0.007	0.006	0.005	0.002	0.005
TP_0	0.011	0.002	0.001	0.001	0.000	0.000	0.000	0.000	0.000
HTP_0	0.004	0.004	0.003	0.002	0.001	0.000	0.000	0.000	0.000
ICTP_0	0.005	0.003	0.002	0.000	0.000	0.000	0.000	0.000	0.000
BIOP_0	0.001	0.002	0.001	0.000	0.000	0.000	0.000	0.000	0.000
Number of Models Visited	8424	8577	6914	5850	5544	5731	7160	8366	9057

PIP stands for posterior inclusion probability. The posterior mean and posterior standard deviation reported refer to the corresponding expressions (4) and (5) in the text.

Table 4: Inclusion Probabilities across Quantiles (country effects)

Variable	10th	20th	30th	40th	50th	60th	70th	80th	90th
CAPITAL	0.006	0.004	0.007	0.018	0.139	0.792	0.967	0.995	1.000
SHSH	0.197	0.807	0.880	0.873	0.686	0.189	0.055	0.035	0.178
SHGFCF	0.629	0.137	0.0260	0.018	0.034	0.240	0.640	0.968	0.891
TP_0	0.761	0.114	0.030	0.009	0.007	0.005	0.001	0.001	0.000
PATENTBIO	0.012	0.007	0.007	0.009	0.009	0.024	0.044	0.086	0.416
INTF	0.029	0.007	0.006	0.004	0.006	0.006	0.007	0.008	0.472
GDPCAP0	0.031	0.013	0.013	0.013	0.007	0.010	0.006	0.010	0.367
SHCE0	0.042	0.024	0.037	0.047	0.077	0.060	0.044	0.030	0.0101
LEVSH	0.169	0.035	0.032	0.015	0.010	0.007	0.004	0.004	0.010
AIRPORTDENS	0.032	0.026	0.031	0.030	0.057	0.019	0.008	0.006	0.004
REGBOARDER	0.029	0.015	0.013	0.006	0.008	0.006	0.022	0.040	0.039

SHLLL	0.004	0.024	0.031	0.027	0.031	0.010	0.012	0.009	0.015
ICTP_0	0.055	0.032	0.024	0.012	0.011	0.006	0.002	0.002	0.000
BIOP_0	0.110	0.011	0.008	0.005	0.002	0.004	0.001	0.001	0.001
ACCESSMULTI	0.015	0.021	0.013	0.008	0.010	0.009	0.008	0.009	0.029
HAZARD	0.014	0.006	0.004	0.006	0.005	0.010	0.013	0.010	0.044
PATENTHT	0.008	0.005	0.009	0.014	0.019	0.011	0.011	0.014	0.016
HTP_0	0.047	0.018	0.018	0.008	0.006	0.004	0.001	0.001	0.000
PATENTICT	0.008	0.006	0.007	0.012	0.013	0.011	0.012	0.010	0.006
DW_OUTDENS0	0.007	0.005	0.009	0.003	0.002	0.005	0.005	0.009	0.034
OUTDENS0	0.009	0.007	0.007	0.003	0.004	0.006	0.008	0.008	0.025
DW_GDPCAP0	0.006	0.006	0.018	0.010	0.001	0.010	0.006	0.003	0.007
GPOP	0.006	0.007	0.014	0.013	0.008	0.004	0.005	0.007	0.008
ART0	0.007	0.0045	0.009	0.012	0.011	0.002	0.007	0.006	0.011
REGCOAST	0.005	0.004	0.012	0.016	0.012	0.005	0.004	0.006	0.006

PATENTT	0.011	0.008	0.004	0.004	0.008	0.008	0.006	0.011	0.009
RAILDENS	0.019	0.006	0.006	0.003	0.005	0.004	0.005	0.004	0.011
TELF	0.004	0.003	0.004	0.006	0.005	0.007	0.007	0.011	0.009
DISTCAP	0.008	0.008	0.006	0.007	0.003	0.005	0.006	0.004	0.006
TELH	0.007	0.005	0.004	0.003	0.007	0.008	0.005	0.006	0.008
URT0	0.007	0.007	0.004	0.003	0.005	0.005	0.006	0.005	0.010
ERET0	0.005	0.005	0.005	0.007	0.008	0.004	0.005	0.004	0.009
ROADDENS	0.005	0.005	0.008	0.004	0.006	0.006	0.006	0.004	0.005
CONNECTAIR	0.006	0.008	0.009	0.005	0.005	0.003	0.003	0.004	0.008
HRSTCORE	0.007	0.009	0.005	0.004	0.006	0.004	0.003	0.004	0.004
Number of Models Visited	9898	5712	5866	5132	8228	7706	7265	4384	11607

PIP stands for posterior inclusion probability. The posterior mean and posterior standard deviation reported refer to the corresponding expressions (4) and (5) in the text.

Table 5: Posterior Mean of Regressors across Quantiles (no country effects)

Variable	10th		30th		50th		70th		90th	
	Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D
GDPCAP0	-0.02279	0.00392	-0.01759	0.00252	-0.01893	0.00180	-0.01810	0.00251	-0.02005	0.00346
CAPITAL	0.00281	0.00549	0.01120	0.00514	0.01678	0.00494	0.02881	0.00388	0.03135	0.00548
SHSH	0.00446	0.01316	0.03208	0.02517	0.01834	0.02491	0.03136	0.02703	0.03478	0.01478
SHLLL	0.00215	0.00959	0.01335	0.02171	0.02444	0.02206	0.00364	0.01126	0.00135	0.00872
INTF	0.03249	0.02074	0.00265	0.00947	0.00011	0.00186	0.00000	0.00122	0.00019	0.00300
ERET0	0.00018	0.00196	0.00087	0.00516	0.00305	0.01060	0.00167	0.00759	0.00748	0.01303
ART0	0.00014	0.00192	0.00089	0.00638	0.00118	0.00719	0.00107	0.00665	0.00280	0.01003
URT0	-0.00016	0.00233	-0.00089	0.00571	-0.00221	0.00986	-0.00092	0.00613	-0.00201	0.00841
AIRPORTDENS	0.43450	1.47956	0.13747	0.89176	0.13390	0.83511	0.02449	0.28517	-0.00039	0.13825

Table 6: Posterior Mean of Regressors across Quantiles (country effects)

Variable	10th		30th		50th		70th		90th	
	Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D
CAPITAL	0.00001	0.00029	0.00002	0.00037	0.00126	0.00358	0.01315	0.00423	0.02001	0.01535
SHSH	0.01692	0.03759	0.06295	0.02856	0.04245	0.03309	0.00328	0.01541	0.00894	0.02138
SHGFCF	0.03027	0.02455	0.00057	0.00407	0.00089	0.00547	0.02597	0.02046	0.04381	0.02778
TP_0	0.00189	0.00128	0.00003	0.00021	0.00000	0.00007	0.00000	0.00003	0.00000	0.00001
PATENTBIO	-0.00185	0.02763	0.00040	0.01889	0.00210	0.02418	0.01076	0.05178	0.11853	0.17419
INTF	0.00073	0.00540	-0.00004	0.00120	0.00000	0.00095	0.00000	0.00085	0.02743	0.03364
GDPCAP0	-0.00031	0.00216	-0.00006	0.00061	-0.00003	0.00045	-0.00002	0.00045	-0.00623	0.00894
SHCE0	-0.00114	0.00602	-0.00142	0.00783	-0.00272	0.01019	-0.00119	0.00633	-0.00030	0.00353
LEVSH	0.00062	0.00145	0.00005	0.00032	0.00001	0.00012	0.00000	0.00005	-0.00001	0.00015

Table A1: Variable Names and Data Sources

Variable Name	**Description**	**Source**
Dependent variable		
GGDPCAP	Growth rate of real GDP per capita	Eurostat; own calculations
Factor accumulation and initial conditions		
GDPCAP0	Initial real GDP per capita (in logs)	Eurostat; own calculations
GPOP	Growth rate of population	Eurostat; own calculations
SHGFCF	Initial share of gross fixed capital formation (GFCF) in gross value-added (GVA)	Cambridge Econometrics; own calculations
SHCE0	Initial share of NACE C to E (Mining, Manufacturing and Energy) in total GVA	Eurostat; own calculations
Human capital		
SHSH	Initial share of high educated (according to ISCED classification) in working age population	Eurostat LFS
SHLLL	Lifelong learning activities;	Eurostat LFS

	share in total employed persons	
LEVSH	Initial number of high educated (according to ISCED classification) persons (in logs)	
Infrastructure		
INTF	Proportion of firms with own website regression	ESPON (variable PFW03N2)
TELH	A typology of levels of household telecommunications uptake (1 … very low, … 6 … very high)	ESPON (variable Htct02N2); revised scaling
TELF	A typology of estimated levels of business telecommunications access and uptake (1 … very low, … 6 … very high)	ESPON (variable HBctct02N2); revised scaling
ACCESSMULTI	Potential accessibility multimodal, ESPON space = 100	ESPON (variable AcME01N3)
AIRPORTDENS	Airport density	Number of airports (ESPON) divided by area; own

		calculations
ROADDENS	Road density	Length of road network (ESPON variable LRo01N3) divided by area; own calculations
RAILDENS	Rail density	Length of rail network (ESPON variable LR01N3) divided by area; own calculations
CONNECTAIR	Connectivity to commercial airports by car of the capital or centroid representative of the NUTS3 (in hours)	ESPON (variable CCA01N3)
Socio-geographical variables		
REGCOAST	Coastal region; 0 … No coast; 1 … Coast	ESPON (variable COA03N2)
REGBORDER	Border region; 0 … No border, 1 … Border	ESPON (variable BOR03N2)
CAPITAL	Regions hosting capital city: 0 … Regions without capital city, 1 … regions with capital city	
HAZARD	Sum of all weighted hazard	ESPON (variable smwh04);

	values	calculated from NUTS3 using population shares as weights
OUTDENS0	Initial output density	Initial output divided by area
DISTCAP	Distance to capital city	
DW_GDPCAP0	Distance weighted initial GDP per capita of other regions	Own calculations
DW_OUTDENS0	Distance weighted initial output density of other regions	Own calculations

Technology, patenting and innovation variables

PATENTT	Number of total patents per thousand inhabitants	Eurostat; own calculations
PATENTHT	Number of patents in high technology per thousand inhabitants	Eurostat; own calculations
PATENTICT	Number of patents in ICT per thousand inhabitants	Eurostat; own calculations
PATENTBIO	Number of patents in biotechnology per thousand inhabitants	Eurostat; own calculations
BIOP_0	Number of patents in biotechnology (in logs)	Eurostat
HTP_0	Number of patents in high	Eurostat

	technology (in logs)	
ICTP_0	Number of patents in ICT (in logs)	Eurostat
TP_0	Number of patents (in logs)	Eurostat
HRSTCORE	Human resources in science and technology (core)	Eurostat LFS
Employment variables		
ERET0	Employment rate (employed persons divided by working age population)	Eurostat LFS
URT0	Unemployment rate (unemployed divided by employed and unemployed persons)	Eurostat LFS
ART0	Activity rate (employed and unemployed divided by working age population)	Eurostat LFS

[i] For a review of the empirical growth literature, see Temple (1999) and Durlauf and Quah (1999).

[ii] Kalaitzidakis et al (2000) employ the same approach as Levine and Renelt (1992) but allow for potential non-linearities. They find more variables to be robustly related to growth, emphasising the importance of non-linearities in the growth process.

[iii] Examples using cross-country data include Mello and Perrelli (2003), Osborne (2006), Canarella and Pollard (2004) and Foster (2008). All of these papers find evidence of heterogeneous effects of some growth determinants across quantiles.

[iv] BMA using QR may be also embedded in classes of models which assess spatial correlation across variables or errors explicitly, but this falls outside the scope of this study.

[v] The figures are based on simple bivariate regressions of per capita GDP growth on each of the growth determinants.

[vi] Useful surveys of quantile regression methods include Buchinsky (1998) and Koenker and Hallock (2001). A book length treatment of the subject is provided by Koenker (2005).

[vii] Quantile regression coefficients measure the marginal effect of changes in the independent variables on the dependent variable for representative under- and over-achieving countries in terms of growth and not slow and fast growing countries per se. This can be contrasted with OLS which considers the average behaviour of representative countries.

[viii] Overviews of BMA are provided by Raftery et al (1997), Hoeting et al (1999), Clyde and George (2004) and Doppelhofer (2007).

[ix] This section follows closely the description of Raftery (1995) and Raftery et al (1997) who provide a fuller description of BMA techniques.

[x] Originally we started with a slightly larger set of variables. Some of these were dropped however because of issues of multicollinearity.

[xi] Admittedly, endogeneity may still be present in some models despite the (Granger-) causal structure that we have imposed in our specifications by measuring the regressors at the beginning of the period. A more systematic account of the issue of endogeneity in the setting of quantile-BMA falls outside the scope of this piece of research and is proposed as a potentially fruitful avenue for further research. In particular, recent results by Moral-Benito (2009) and Chernozhukov and Hansen (2003) may prove helpful in this respect.

[xii] When country effects are controlled for this is done using the within transformation (i.e. subtracting from each observation the country mean of the relevant variable).

[xiii] We checked the convergence of the MC3 algorithm by computing the correlation between posterior model probabilities based on the Markov chain frequencies and the exact marginal likelihoods (as proposed by Fernández et al. 2001). In all reported results this correlation was above 0.95.

[xiv] We take the prior inclusion probability as the threshold to define robust variables. The intuition for this choice is that it helps us identify variables for which the probability of inclusion in the true model increases after observing the data.

[xv] These results are available from the authors upon request. The robustness of the other variables as growth determinants is not affected by the use of these subsamples.

[xvi] A deeper analysis of the Williamson hypothesis falls outside the scope of this paper. Crespo Cuaresma et al. (2009) investigate this issue further.

[xvii] The full set of results is available upon request.