TFP GROWTH AND ITS DETERMINANTS: NONPARAMETRICS AND MODEL AVERAGING

2011

Michael Danquah, Enrique Moral-Benito
and Bazoumana Ouattara

Documentos de Trabajo
N.º 1104

BANCO DE **ESPAÑA**
Eurosistema

TFP GROWTH AND ITS DETERMINANTS: NONPARAMETRICS AND MODEL AVERAGING(*)

Michael Danquah

SWANSEA UNIVERSITY

Enrique Moral-Benito

BANK OF SPAIN

Bazoumana Ouattara

SWANSEA UNIVERSITY

(*) We would like to thank Atsu Amegashie for helpful comments and suggestions.

Documentos de Trabajo. N.º 1104

2011

The Working Paper Series seeks to disseminate original research in economics and finance. All papers have been anonymously refereed. By publishing these papers, the Banco de España aims to contribute to economic analysis and, in particular, to knowledge of the Spanish economy and its international environment.

The opinions and analyses in the Working Paper Series are the responsibility of the authors and, therefore, do not necessarily coincide with those of the Banco de España or the Eurosystem.

The Banco de España disseminates its main reports and most of its publications via the INTERNET at the following website: http://www.bde.es.

ISSN: 0213-2710 (print)
ISSN: 1579-8666 (on line)
Depósito legal: M. 15403-2011
Unidad de Publicaciones, Banco de España

Abstract

Total Factor Productivity (TFP) accounts for a sizeable proportion of the income and growth differences across countries. Two challenges remain to researchers aiming to explain these differences: on the one hand, TFP growth is hard to measure; on the other hand, model uncertainty hampers consensus on its key determinants. This paper combines a non-parametric measure of TFP growth with model averaging techniques to addess both issues. The empirical findings suggest that the most robust TFP growth determinants are unobserved heterogeneity, initial GDP, consumption share, and trade openness. We also investigate the main determinants of the TFP components: efficiency change (i.e. catching up) and technological progress (i.e. innovation).

Keywords: Productivity, Bayesian Model Averaging, Nonparametric methods.

JEL classification: O47, C11, C14, C23.

Resumen

La Productividad Total de los Factores (PTF) representa una proporción importante de las diferencias de crecimiento económico entre países. Con el objetivo de entender las fuentes estas diferencias dos cuestiones son de vital importancia: por un lado, el crecimiento de la PTF es difícil de medir; por otro lado, la incertidumbre en la especificación del modelo empírico dificulta el consenso sobre sus principales determinantes. Este trabajo combina una medida no paramétrica de crecimiento de la PTF con técnicas de promediado de modelos con el objetivo de abordar ambas cuestiones. Los resultados sugieren que los determinantes más robustos del crecimiento de la PTF son la heterogeneidad no observada, el PIB inicial, la propensión a consumir, y la apertura comercial. También investigamos los determinantes principales de los componentes de la PTF: el cambio de eficiencia (es decir, alcanzar la frontera) y el progreso tecnológico (es decir, la innovación).

Palabras clave: Productividad, promediado Bayesiano de modelos, métodos no paramétricos.

Códigos JEL: O47, C11, C14, C23.

1 Introduction

The view that total factor productivity growth (TFP) plays a pivotal role in explaining overall growth could be traced back to the work of Abramovitz (1956), who was the first to attempt in determining the sources of productivity growth. The author found that the main sources of U.S. productivity growth were still unidentified. This led Abramovitz (1956, p.11) to argue that:

> "*Since we know little about the cause of productivity increase, the indicated importance of this element may be taken to be some sort of measure of our ignorance about the causes of economic growth.*"

Virtually, around the same period Solow (1957) developed the first analytical framework for explaining the existence of an exogenous residual. Solow (1957) went on to show that cross-country differences in technology may generate important cross-country differences in income per capita. This pivotal role of TFP in explaining growth was stressed by subsequent studies (see Romer 1986; 1990 and Lucas 1988, among others). Most empirical studies addressing the issue (see Krugman, 1994; Klenow and Rodriguez-Clare, 1997; Hall and Jones, 1999; Easterly and Levine, 2001) appear to support this prediction. On the other hand, studies in the growth regressions literature implicitly consider all determinants of output growth as inputs. However, as pointed out by Miller and Upadhyay (2000) many of these determinants may affect output only through their effect on the efficiency use of the real inputs, human and physical capital. Therefore, these potential determinants of output growth have a direct effect on total factor productivity. Thus, understanding and modeling the sources of total factor productivity growth is important at least in a policy context.

Over the last decade, several studies have attempted to identify what factors affect TFP and/or its growth. However, the vast majority of the existing literature on the "determinants" of TFP faces three main problems. Firstly, most existing studies use the growth accounting method (following Solow, 1957) which is based on the estimation of Cobb-Douglas production functions. This method, also known as the residual approach derives the value of the residual after the contribution of the inputs of production are determined. The main issue with this approach is it assumes that all the units of production are efficient and no distinction is made between technical progress and changes in technical efficiency. In other words, no separate adjustment for technical improvement (change in efficiency) embodied in labor or capital stock is considered.

Secondly, while there is general consensus that total factor productivity explains output growth, by in large, limited research has be done on its determinants. Indeed, most existing cross-country studies have generally focussed on how specific variables affect productivity. For example, some studies have looked at how human capital affect total factor productivity growth (see Benhabib and Spiegel, 1994, 2005; Vandenbussche et al., 2006). Miller and Upadhyay (2000) explored the effects of openness, trade orientation, and human capital on total factor productivity for a pooled sample of developed and developing countries. Kneller and Stevens (2006) studied the differences in human capital and Research and Development in OECD countries to explain cross-country differences in total factor productivity growth. In short, no attempts has been made to search for the main determinants of total factor productivity growth and its components, by exploring the effects of a rich set of potential explanatory variables.

Thirdly, from an empirical perspective (like with the growth literature) the existing literature faces the problem of model specification uncertainty which arises because of the lacking of theoretical guidance caused by the 'openendedness' of TFP growth theory as no specific model could rule out all others (Brock and Durlauf, 2001).

These three concerns are well summarized in Easterly and Levine (2001, p.179) who argued that "in searching for the secrets of long-run economic growth, a high priority should be placed on rigorously defining the term "TFP", empirically dissecting TFP, and on identifying the policies and institutions most conducive to TFP growth."

In this paper we try to address these three issues. In an attempt to do so, we combine insight from Data Envelopment Analysis — henceforth DEA — approach and Bayesian Averaging technique. First, we depart from the growth accounting method and adopt a frontier technique, using the DEA approach proposed by Färe et al. (1994). This method considers the possible existence of inefficient behavior and rather estimates a production frontier that represents the maximum technically attainable level of production. More importantly, it allows the decomposition of TFP through the channels of technological progress (innovation) and changes in technical efficiency (technological adoption). From a policy perspective it is equally important to understand the factors that drive TFP growth as well as understanding the factors that explain its individual components. Next, we improve on the existing literature by exploring a wider set of explanatory variables that are likely to affect the dependent variables in a panel of developing and developed countries. Finally, on the methodological front we attempt to account for the model uncertainty issue by adopting a model averaging approach to study the determinants TFP growth and its components. More specifically we employ a variant of Bayesian Model Averaging advanced by Raftery (1995) and popularized by Sala-i-martin et al. (1994) in the so-called Bayesian Averaging of Classical Estimates (BACE) approach. In order to apply the method to our panel of countries, we consider the panel data version of the approach discussed in Moral-Benito (2011).

Once these issues are accounted for, the empirical findings indicate that country-specific effects correlated with other regressors play a fundamental role in explaining TFP growth. This result confirms the relevance of time-invariant unobserved heterogeneity taken as given in previous studies (e.g. Miller and Upadhyay, 2000). On the other hand, we also conclude that the main determinants of overall TFP growth are private consumption and a measure of trade openness. Turning to the determinants of the components of TFP growth, the empirical evidence suggests that the main determinants of the efficiency component differ substantially for those of the technological progress component.[1] Moreover, in all cases we find evidence of conditional convergence, i.e., poorer countries tend to have higher rates of growth of overall TFP and its components.

The remainder of the paper is organized as follows. Section 2 provides an in-depth explanation of the methodology used to calculate TFP growth and its components. Section 3 describes the data. In section 4 we discuss the problem of model uncertainty and the model averaging methodology. Section 5 present and discusses the results. Finally, section 6 provides some concluding remarks.

2 Measurement of Productivity

Due to the lack of reliable data on quantity and prices, economists often compute productivity indices to measure productivity change instead of estimating technology and shifts in technology directly (Färe et al., 1994). Along this line, we use the DEA (Data Envelopment Analysis) approach, a non parametric frontier method, to calculate the output-based Malmquist indices of total factor productivity change, technological change, and technical efficiency change. The DEA approach does not require any functional specification for the relationship between inputs and outputs or for the inefficiency error term. In other words, using this approach allows us to circumvent various specifications and estimation problems.[2]

The Malmquist productivity index measure was originally introduced by Caves et al. (1982a, b), and named after Sten Malmquist, who had earlier proposed the idea of constructing quantity indices as ratios of distance functions (Coelli, 1996). The Malmquist productivity index (Malmquist, 1953) allows changes in productivity to be broken down into changes in efficiency and technical change. It does not require any assumptions regarding efficiency and functional form, and is therefore able to distinguish between the factors causing changes in productivity.[3] The Malmquist index is defined in terms of output distance functions. Färe et al. (1994) propose the usage of a distance function to spot whether the growth in productivity is the result of the catching up effect (described as enhancements in performance) or whether this growth is due to a shifting out of the

[1] Only the country-specific effects are robust determinants of both TFP components.

[2] The parametric Stochastic Frontier Approach (SFA) is another alternative to the DEA. One of the main differences between the two lies in the fact that SFA assumes, a priori, that the structure of the production possibility set and the data generation process are known, except for the value of a finite set of unknown parameters.

[3] For further details, see Färe et al. (1994).

technological frontier at a country's given set of inputs. These functions measure the raw distance between a given output vector and maximal potential output (which belongs to the boundary of the reference or frontier technology). The distance function is defined as:

$$D_0^t(x^t, y^t) = \inf \theta : (x^t, y^t/\theta) \in S^t = (\sup \theta : (x^t, y^t/\theta) \in S^t)^{-1} \tag{1}$$

where $S^t = (x^t, y^t)$ is the production technology.[4] Under constant returns to scale (CRS) production technology, maximum feasible output is only achieved when average productivity y/x is maximized. This maximum is the benchmark country, i.e. with the highest level of productivity. For the other countries composing the sample, decreasing distances suggest catching up to the maximum productive frontier (i.e. improving technical efficiency).

The Malmquist productivity index provides distance functions with respect to time (to explain growth trends across periods) as: $D_0^t(x^{t+1}, y^{t+1}) = \inf \theta : (x^{t+1}, y^{t+1}/\theta) \in S^t$ where $D_0^t(x^{t+1}, y^{t+1})$ measures the maximal proportion change in output that ensures that (x^{t+1}, y^{t+1}) is feasible.[5] Denoting by $D_0^{t+1}(x^t, y^t)$ the maximal proportional change in output which is needed to guarantee the feasibility of (x^t, y^t) at $t+1$, Färe et al. (1989) define the productivity index in time t and $t+1$ respectively as:

$$M^t = \frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \tag{2}$$

and

$$M^{t+1} = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^t, y^t)} \tag{3}$$

Following Färe et al. (1989), the Malmquist (output-oriented) TFP change index between period t (the base period) and period $t+1$ under CRS is defined as:

$$M_0\left(x^{t+1}, y^{t+1}, x^t, y^t\right) = \left[\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \times \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^t, y^t)}\right]^{1/2} \tag{4}$$

Equation (4) can be arranged to show that the TFP change index is equivalent to the product of a technical efficiency change index and an index of technical change:

$$M_0\left(x^{t+1}, y^{t+1}, x^t, y^t\right) = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \times \left[\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D_0^t(x^t, y^t)}{D_0^{t+1}(x^t, y^t)}\right]^{1/2} \tag{5}$$

where efficiency change and technical change are represented by Equations (6) and (7), respectively:

$$\frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \tag{6}$$

[4] x^t produces y^t.

[5] Färe et al. (1994) show that at time t, (x^{t+1}, y^{t+1}) is feasible.

$$\left[\frac{D_0^t(x^{t+1},y^{t+1})}{D_0^{t+1}(x^{t+1},y^{t+1})}\times\frac{D_0^t(x^t,y^t)}{D_0^{t+1}(x^t,y^t)}\right]^{1/2} \tag{7}$$

The efficiency change is a ratio of two distance functions, which measures the change in the output-oriented measure of the technical efficiency between period t and $t+1$. A value of the efficiency term greater than, equal to or less than one indicates whether the producer is moving closer to, unchanging or diverging from the production frontier, respectively. The square root technical change term represents a measure of the technical change in the production technology. It is an indicator of the distance covered by the efficient frontier from period t to period $t+1$ and, therefore, an indicator of technological improvements between the two periods. The square root of the technical change term is greater than, equal to or less than one implying that technological best practice is advancing, remaining unchanged, or deteriorating, respectively.

The availability of the different indices *viz*, technical change and efficiency change in the Malmquist TFP index is an interesting part of this paper. It allows us, not only to investigate the robust determinants of productivity growth, but also to find out what (robust) factors drive these different components. From a policy perspective, this can have important implications in decision-making; and from a knowledge angle it could improve our overall understanding of productivity growth.

As previously mentioned, the main advantage of DEA method is that it makes no assumptions about the functional forms. However, its main disadvantage is that, because it is an extreme bound method, it is sensitive to outliers. The Stochastic Frontier Approach (SFA) method, which requires assuming a particular functional form, can deal with statistical noise in the data; although efficiency estimation as a portion of a composed error term may be affected by the distributional assumptions regarding the error components.[6]

3 Data

Our dataset comprises 67 countries[7] and includes annual information covering the period 1960-2000. Following earlier literature and in order to lessen the problem of serial correlation in the errors we split our sample in five-year periods. Therefore we end up with eight observations for each country, making up a total of 536 observations.

Following the approach in the previous section, we compute Malmquist productivity index using data on levels. In particular, we consider the stock of capital and the stock of labor as inputs, and real GDP as output. The capital stock data is calculated by

[6] The literature on the comparison of these two alternatives is inconclusive on which method outperforms the other (see Bjurek, Hjalmarsson and Forsund, 1990; Ferrier and Lovell, 1990; Hjalmarsson, Kumbhakar and Heshmati, 1996; Gong and Sickles, 1992

[7] The list of countries, which includes 20 OECD and 47 Non-OECD countries, is provided in Table 5 at the end of the paper.

applying a perpetual inventory method, following Nehru and Dhareshwar (1993) with investment data (gross capital formation) taken from the World Development Indicators. Labor force is measured by the economic active population, that is the population aged between 15 and 64 years, and sourced from the World Development Indicators.

In addition to the basic factors of production considered to calculate our TFP measure and its components, we consider data on 19 candidate determinants of TFP growth. The number of regressors suggested in the literature as potential determinants of economic growth is huge, e.g. the Durlauf et al. (2005) survey of the empirical growth literature identifies 145 proposed regressors. In this paper we consider a subset of them to analyze how they affect economic growth through the channel of TFP, which we argue might be a relevant one. More concretely, we use the dataset described in Moral-Benito (2011) because of two main reasons: (i) we aim to work with a panel dataset and data availability in the panel context during the postwar period is smaller than in the cross-sectional case;[8] (ii) Ciccone and Jarocinski (2010), and Moral-Benito (2011) found that the smaller the number of regressors considered the higher the robustness of the results in the model averaging framework, so that we prefer to avoid the inclusion of several variables as proxies of the same theory.[9] The sources, descriptions and descriptive statistics of these 19 candidate determinants of TFP growth are presented in Tables 4 and 5.

4 Model Uncertainty and Model Averaging

Model uncertainty arises because the lack of clear theoretical guidance on the choice of TFP determinants results in a wide set of possible specifications. Therefore, researcher's uncertainty about the value of the parameter of interest in a regression exists at distinct two levels. The first one is the uncertainty associated with the parameter conditional on a given empirical model. This level of uncertainty is of course assessed in virtually every empirical study. What is not fully assessed is the uncertainty associated with the specification of the empirical model. It is typical for a given paper that the specification of the regression is taken as essentially known; while some variations of a baseline model are often reported, via different choices of control variables, standard empirical practice does not systematically account for the sensitivity of claims about the parameter of interest to model choice.

Many researchers consider that one promising approach to account for model uncertainty is to employ model averaging techniques to construct parameter estimates that formally address the dependence of model-specific estimates on a given model. The ba-

[8]For instance, the fraction of GDP in mining and the fraction of Muslim population are only available for the year 1960. We face a similar situation for other candidate regressors that are potentially relevant such as financial development indicators that are not available for the beginning of our sample.

[9]For instance, we only include one indicator of trade openness.

sic idea behind model averaging is to estimate the distribution of unknown parameters of interest across different models. The fundamental principle of model averaging is to treat models and related parameters as unobservable, and to estimate their distributions based on the observable data. In contrast to classical estimation, model averaging copes with model uncertainty by allowing for all possible models to be considered, which consequently reduces the biases of parameters.

Intuitively, model averaging represents an agnostic alternative to the usual approach based on selecting a single regression and deciding which variable is important depending on its associated t-ratio. The key idea of model averaging is to consider and estimate all the possible regressions, and then report a weighted average as the estimate of interest. Therefore, model averaging is an agnostic approach in the sense that a researcher relying on this approach holds the view that the true single model is unknown and probably unknowable. Then, the best she can do is to consider all the possible alternatives instead of basing her conclusions on one probably incorrect regression.

Formally, consider a generic representation of an empirical model of the form:

$$\Psi = \theta X + \epsilon \tag{8}$$

where Ψ is the dependent variable of interest (i.e. TFP growth in the present paper), and X represents a set of covariates (i.e. candidate TFP determinants). Imagine that there exist potentially very many empirical models, each given by a different combination of explanatory variables (i.e. different vectors X), and each with some probability of being the 'true' model. This is the starting idea of the Bayesian Model Averaging methodology.

Using the Bayesian terminology, a model is formally defined by a likelihood function and a prior density. Suppose we have K possible explanatory variables. We will have 2^K possible combinations of regressors, that is to say, 2^K different models - indexed by M_j for $j = 1, ..., 2^K$- which all seek to explain y -the data-. M_j depends upon parameters θ^j. In cases where many models are being entertained, it is important to be explicit about which model is under consideration. Hence, the posterior for the parameters calculated using M_j is written as:

$$g\left(\theta^j|y, M_j\right) = \frac{f\left(y|\theta^j, M_j\right) g\left(\theta^j|M_j\right)}{f\left(y|M_j\right)} \tag{9}$$

and the notation makes clear that we now have a posterior, a likelihood, and a prior for each model. The logic of Bayesian inference suggests that we use Bayes' rule to derive a probability statement about what we do not know (i.e. whether a model is correct or not) conditional on what we do know (i.e. the data). This means the posterior model probability can be used to assess the degree of support for M_j. Given the prior model probability $P\left(M_j\right)$ we can calculate the posterior model probability using Bayes Rule as:

$$P\left(M_j|y\right)=\frac{f\left(y|M_j\right)P\left(M_j\right)}{f\left(y\right)} \tag{10}$$

Since $P\left(M_j\right)$ does not involve the data, it measures how likely we believe M_j to be the correct model before seeing the data. $f\left(y|M_j\right)$ is often called the marginal (or integrated) likelihood, and is calculated using (9) and a few simple manipulations. In particular, if we integrate both sides of (9) with respect to θ^j, use the fact that $\int g\left(\theta^j|y,M_j\right)d\theta^j=1$ (since probability density functions integrate to one), and rearrange, we obtain:

$$f\left(y|M_j\right)=\int f\left(y|\theta^j,M_j\right)g\left(\theta^j|M_j\right)d\theta^j \tag{11}$$

The quantity $f\left(y|M_j\right)$ given by equation (11) is the marginal probability of the data, because it is obtained by integrating the joint density of $\left(y,\theta^j\right)$ given y over θ^j. The ratio of integrated likelihoods of two different models is the Bayes Factor and it is closely related to the likelihood ratio statistic, in which the parameters θ^j are eliminated by maximization rather than by integration.

Moreover, considering θ a function of θ^j for each $j=1,...,2^K$, we can also calculate the posterior density of the parameters for all the models under consideration:

$$g\left(\theta|y\right)=\sum\nolimits_{j=1}^{2^K}P\left(M_j|y\right)g\left(\theta|y,M_j\right) \tag{12}$$

If one is interested in point estimates of the parameters, one common procedure is to take expectations across (12):

$$E\left(\theta|y\right)=\sum\nolimits_{j=1}^{2^K}P\left(M_j|y\right)E\left(\theta|y,M_j\right) \tag{13}$$

Following Leamer (1978), we calculate the posterior variance as:

$$\begin{aligned} V\left(\theta|y\right) &= \sum\nolimits_{j=1}^{2^K}P\left(M_j|y\right)V\left(\theta|y,M_j\right) \\ &+ \sum\nolimits_{j=1}^{2^K}P\left(M_j|y\right)\left(E\left(\theta|y,M_j\right)-E\left(\theta|y\right)\right)^2 \end{aligned} \tag{14}$$

Inspection of (14) shows that the posterior variance incorporates both the estimated variances of the individual models as well as the variance in estimates of the θ's across different models. Hence, the uncertainty at the two different levels mentioned above is taken into account. Note also that the number of models to be estimated in order to compute equations (13) and (14) is enormous and might be intractable in practice. We provide in the Appendix a brief summary of the algorithm we employ in this paper in order to overcome this computational issue.

Moreover, the BMA methodology allows constructing a ranking of variables ordered by their *robustness*. In this particular case, *robustness* as TFP determinants. In order to construct our measure of *robustness*, we estimate the posterior probability that a particular variable h is included in the regression, and we interpret it as the probability of that the variable belongs in the true empirical model. In other words, variables with high posterior probabilities of being included are considered as *robust* determinants of default probabilities. This is called the Posterior Inclusion Probability — henceforth PIP — for variable h, and it is calculated as the sum of the posterior model probabilities for all of the models including that variable:

$$\text{posterior inclusion probability} = P\left(\theta_h \neq 0|y\right) = \sum\nolimits_{\theta_h \neq 0} P\left(M_j|y\right) \tag{15}$$

Koop (2003) is an excellent reference for more details on the BMA methodology, and Moral-Benito (2010) provides a recent overview of the model averaging literature and its applications.

4.1 Choice of Priors

Priors on the model space and model-specific priors on the parameter space must be elicited within the BMA framework. For the prior model probabilities we assume that all models are equally probable a priori; given there are 2^K candidate models, the uniform prior on the model space implies $P(M_j) = 1/2^K\ \forall j$. This prior also implies that the prior inclusion probability for each particular regressor is 0.5.

With respect to the priors on the parameter space, Kass and Wasserman (1995) show that the Schwarz asymptotic approximation to the Bayes Factor is the result of considering the Unit Information Prior (UIP) on the parameter space.[10] We make use of the UIP prior on the parameter space and therefore we substitute equation (10) by:

$$P(M_j|y) = \frac{P(M_j) N^{\frac{-k_j}{2}} SSE_j^{-\frac{NT}{2}}}{\sum_{i=1}^{2^K} P\left(M_i\right) \left(NT\right)^{\frac{-k_i}{2}} SSE_j^{-\frac{NT}{2}}} \tag{16}$$

where SSE_j is the sum of squares for model j, N is the number of countries, and T the number of time periods. Eicher et al. (2010) conclude that this UIP combined with the uniform model prior we consider in the paper outperforms any other possible combination of priors previously considered in the BMA literature in terms of cross-validated predictive performance. This combination of priors will also identify the largest set of TFP determinants. For the BMA point estimates, instead of equation (13) we use:

$$E\left(\theta|y\right) = \sum_{j=1}^{2^K} P\left(M_j|y\right) E\left(\theta|y, M_j\right) = \sum_{j=1}^{2^K} P\left(M_j|y\right) \widehat{\theta}_{OLS}^{j} \tag{17}$$

where $\widehat{\theta}_{OLS}^{j}$ is the OLS estimate for model j.[11] Equations (16) and (17) are the basis of the approach described in Raftery (1995) and labeled as Bayesian Averaging of Classical

[10] This prior is a multivariate normal with mean the MLE of the parameters and variance the inverse of the expected Fisher information matrix for one observation.

[11] Equation (17) is true if we either assume diffuse priors on the parameter space for any given sample size, or have a large sample for any given prior on the parameter space.

Estimates (BACE) in Sala-i-Martin et al. (2004) in the context of growth regressions. In this paper we consider not only the BACE approach but also its panel data version with fixed effects described in Moral-Benito (2011).

4.2 Cross-section and Panel Approaches

In order to further describe the empirical approach, let us present the two versions of BACE we consider, namely, BACE with and without country-specific effects. Given equations (16) and (17), we need to obtain the model-specific estimates $\widehat{\theta}^{j}_{OLS}$ together with the model-specific sum of squares SSE_j. Two different alternatives are considered in this paper. First, we apply traditional OLS without country-specific heterogeneity (i.e. pooled OLS); second, we also apply the within-group estimator which incorporates country-specific effects correlated with the regressors.

Formally, under the first alternative, a specific model is as follows:

$$\Psi_{it} = \theta X_{it} + \delta_t + \epsilon_{it} \tag{18}$$

where Ψ_{it} represents TFP growth for country i in year t, X_{it} is a vector of TFP determinants and δ_t captures cross-sectional correlations across the countries in our sample (i.e. a set of time dummies). This represents the most common approach to growth regressions during the nineties. Under independence between the regressors and the shock, $cov(X_{it}, \epsilon_{it}) = 0$, OLS produces consistent estimates of θ. However, this kind of regressions may omit an important country-specific effect and thereby produce biased coefficient estimates (e.g. Easterly and Levine, 2001). It seems reasonable that there is some country-specific unobserved heterogeneity that is time invariant[12] and simultaneously affects the regressors and the dependent variable, TFP growth. This would imply that coefficient estimates in (18) might be biased due to omitted variables. For instance, the quality of institutions is country-specific, time-invariant over the post-war period, and very hard to measure; moreover it is correlated with both TFP and regressors such as investment or trade openness. Therefore, failure to control for the quality of institutions in the form of country-specific effects, a positive coefficient in the regression of TFP growth on, for instance, trade openness, is biased due to omitted variables.

In order to include country effects in our regressions we also consider a second alternative as follows:

$$\Psi_{it} = \theta X_{it} + \delta_t + \eta_i + v_{it} \tag{19}$$

where now η_i includes country-specific unobserved heterogeneity which is allowed to be correlated with the Xs so that $cov(X_{it}, \epsilon_{it}) \neq 0$ provided $\epsilon_{it} = \eta_i + v_{it}$. The within-group estimator (— henceforth WG —) is appropriate for accommodating this kind

[12] At least during the post-war period considered in this paper over the years 1960-2000.

of unobserved heterogeneity. Note that the WG estimator is simply OLS as in model (18) but including a set of country dummies in the regression. Therefore, given the BMA framework in the paper, we will also be able to estimate the posterior inclusion probability (i.e. the robustness measure) of the country effects as a whole in order to test their relevance in this setting. This might be an interesting result since country-specific effects are typically included in the regression but without previously testing their relevance.

On the other hand, the variability exploited in both alternatives (i.e. including or not country-specific effects) is not the same; if we consider the cross-sectional approach without fixed effects, the focus is on between variation across countries. Instead, considering the panel approach with country effects we implicitly focus on within time variation in the sample. Therefore, the ranking of robust determinants emerging from both alternatives must not necessarily coincide.[13]

5 Empirical Results

We next present the results of applying the BMA methodology to our data on TFP growth and its determinants. We first analyze the main determinants of overall TFP growth, and then of its two components, efficiency change and technological progress.

In the first case we separately present the results with and without country-specific effects. If time-invariant unobserved heterogeneity at the country level is not present in our sample, both results (with and without fixed effects) should be virtually equal. The results should also be the same if country-specific unobserved heterogeneity exists but it is uncorrelated with the rest of regressors. However, we conclude that if the results with and without fixed effects differ, country-specific unobserved heterogeneity correlated with the regressors is relevant in the determination of TFP growth.[14] If this is the case, results without including country dummies will be unreliable due to omitted variables bias.

The main results are as follows: (i) country-specific unobserved heterogeneity is the most important determinant of both TFP growth and its components. While fixed effects are usually included in empirical work, their relevance was not previously tested. The high PIP of the fixed effects confirms that country-specific effects explain a large portion of TFP variation and should be included in empirical TFP regressions; (ii) once we consider fixed effects, the main determinants of overall TFP growth are private consumption and a measure of trade opennes; (iii) we find evidence of conditional convergence, poorer countries tend to have higher TFP growth rates; (iv) regardless of the fixed effects and initial GDP, while efficiency change main determinants are similar to those of overall

[13] Both rankings should coincide only if the fixed effects are independent of the regressors.

[14] We also check this conclusion looking at the posterior inclusion probability of the country dummies as a whole.

TFP growth, this is no longer true for the technological progress determinants; (v) TFP growth determinants are very different across OECD and non-OECD countries.

5.1 Determinants of TFP Growth

The results on the main determinants of TFP growth when applying the BMA approach in its cross-sectional and panel data versions are presented in Table 1. This Table summarizes the posterior distributions of the parameters corresponding to the 19 variables of our data set plus the fixed effects when included. In particular, it reports the posterior inclusion probability, the posterior mean and the posterior standard deviation of these distributions. The first 3 columns correspond to the cross-sectional (or pooled) approach without country-specific effects, and the last 3 columns refer to the approach when unobserved heterogeneity is taken into account.

In the pooled version without fixed effects (columns 1, 2, 3) there is no variable robustly correlated with TFP growth, i.e., no regressor has a posterior inclusion probability larger than the prior inclusion probability of 0.5. However, when fixed effects are included (columns 4, 5, 6), several variables appear to be robustly associated with TFP growth; moreover, the posterior distributions of the parameters are very different from the posteriors in the pooled approach. This is a clear indication that time-invariant unobserved-heterogeneity is vital in explaining TFP growth rates. This conclusion is confirmed and reinforced when looking at the posterior inclusion probability of the fixed effects which is equal to 1, the highest for all the variables in the sample. The relevance of fixed effects (i.e. time-invariant unobserved heterogeneity) in explaining cross-country variation in TFP growth is a reassuring result. Country-specific effects are typically included in cross-country empirical work (e.g Miller and Upadhyay, 2000), but their importance was not previously tested.

Since we argue that country-specific effects correlated with the regressors are present in this application, we expect model-specific pooled OLS estimates (columns 1, 2, 3) to be badly biased. Therefore we focus the rest of the analysis on the panel data version with fixed effects included (columns 4, 5, 6).

Looking at the fixed effects results in columns 4, 5, and 6, we conclude that additionally to unobserved heterogeneity (i.e. fixed effects), three variables could be considered as robust determinants of TFP growth accordingly to the Bayesian robustness check used in this paper: initial GDP, consumption share, and trade openness. Both consumption share and trade openness affect TFP growth with the expected sign: high saving rates (i.e. lower consumption share), and high degrees of openness to the rest of the world

Table 1: Determinants of TFP Growth

	Without Fixed Effects			With Fixed Effects		
	PIP	P. Mean	P. Std.	f	P. Mean	P. Std.
	(1)	(2)	(3)	(4)	(5)	(6)
Fixed Effects	NO	NO	NO	1.00	−0.01	0.15
Initial GDP	0.07	−0.02	0.03	1.00	−0.42	0.09
Consumption Share	0.09	−0.12	0.10	0.82	−0.80	0.25
Trade Openness	0.09	−0.04	0.03	0.75	0.27	0.09
Population under 15	0.33	−0.47	0.22	0.36	−2.26	1.50
Government Share	0.16	−0.30	0.19	0.24	−0.86	0.48
Population Density	0.09	0.15	0.13	0.14	0.26	0.16
Investment Share	0.07	−0.16	0.18	0.11	−0.39	0.31
Population	0.08	0.11	0.10	0.10	0.70	0.58
Labor Force	0.05	0.04	0.26	0.10	−1.33	1.92
Urban Population	0.07	0.07	0.09	0.07	−0.45	0.47
Population Growth	0.10	−2.17	3.20	0.06	2.32	3.51
Secondary Education	0.08	0.17	0.22	0.05	0.28	0.56
Population over 65	0.25	0.98	0.53	0.05	1.16	2.99
Civil Liberties	0.19	−0.19	0.10	0.05	−0.07	0.17
Political Rights	0.14	−0.14	0.09	0.05	−0.06	0.14
Life Expectancy	0.06	−0.10	0.26	0.05	−0.21	0.75
Investment Price	0.08	−0.03	0.03	0.05	0.00	0.04
Primary Education	0.09	0.15	0.13	0.04	−0.06	0.52
Malaria	0.07	−0.04	0.05	0.04	−0.01	0.07
Prior Inclusion Probability		0.5			0.5	
Prior Mean Model Size		9.5			9.5	
Posterior Mean Model Size		2.1			5.1	
Robust Determinants:		-		Fixed Effects, Initial GDP, Cons. Share, T. Openness.		

Notes: PIP refers to the posterior inclusion probability of a particular regressor. Given the prior inclusion probability is equal for all the variables (i.e. 0.5), those variables with PIP higher than 0.5 are labeled as robust determinants of TFP growth. P. Mean refers to the posterior mean conditional on inclusion of a given regressor in the empirical model, which is a weighted average of model-specific coefficient estimates with weights given by the model-specific R-squares. P. Std. is the square root of the posterior variance which is a weighted average of model-specific variances also including the variance of the estimates across different models. The P. Mean and P. Std. estimates corresponding to the Fixed Effects are the averages of the P. Means and P. Stds of each country dummy P. Mean and P. Std. The Prior Mean Model Size refers to the expected model size a priori (in terms of regressors included) implied by the Prior Inclusion Probability of 0.5. The Posterior Mean Model Size is the weighted average of all posterior model sizes with weights given by the posterior model probabilities. The sample is formed by a set of 67 countries with 8 five-year periods for each country over the period 1960 − 2000. This makes a total of 536 observations.

would promote TFP growth. This suggests that long-run TFP growth-promoting policy strategies should, on the one hand, give incentives to save; and, on the other hand, aim to promote openness-enhancing reforms such as reducing trade barriers. Finally, we interpret the negative posterior mean of initial GDP as evidence in favor of the conditional convergence hypothesis, i.e., countries with lower levels of GDP per capita at the beginning of the period tend to have higher TFP growth rates. The posterior mean of the three robust variables is clearly different from zero when looking at the corresponding posterior standard deviations; this fact not only indicates that model-specific coefficients are precisely estimated, but also that these estimates are fairly similar across different models (i.e. with different sets of control variables). More concretely, in the subsequent sections we conclude that a variable has a posterior mean significantly different from zero if its associated ratio of posterior mean to posterior standard deviation is larger than two in absolute value, which in Bayesian terms corresponds to an approximate 95-percent Bayesian coverage region that excludes zero.

The robustness of the trade openness measure as a determinant of TFP growth confirms the result in Miller and Upadhyay (2000). In earlier literature, human capital was also found to positively affect TFP growth (e.g. Benhabib and Spiegel, 1994, 2005; Vandenbussche et al., 2006); however, we find that this result is not robust to uncertainty in the empirical model specification as illustrated by the low PIPs and high posterior standard errors of our human capital variables (e.g. primary and secondary education, life expectancy). On the other hand, to the best of our knowledge private consumption has not been considered in the empirical TFP literature but emerges as a robust determinant of TFP growth according to the Bayesian robustness check used in this paper.

A note of caution is in order at this point. We have labeled as robust determinants of TFP growth those variables with posterior inclusion probability (PIP) larger than their corresponding prior inclusion probability (0.5). Although this comparison has been commonly used in the economics BMA literature, it must be interpreted with care. Even if the posterior inclusion probability is lower than the prior inclusion probability for a given variable, it might be the case that this particular variable is important to decision-makers under some circumstances. For instance, imagine a researcher interested in quantifying the effect of secondary education on TFP growth taking into account model uncertainty; in spite of having a low PIP, she should look at the posterior coefficients of secondary education in Table 1.

5.2 Efficiency Change and Technological Progress

In addition to not requiring information on factor prices, the non-parametric Malmquist TFP index (e.g. Färe et al. 1994) we use in this paper has another important advantage: the change in TFP can be decomposed into two mutually exclusive components, the change of productive efficiency (catching up or imitation) and shifts in technology over time (innovation). This characteristic represents an important gain in informational content. We now turn to the analysis of the main determinants of these two components of TFP.

Table 2: Determinants of Efficiency Change and Technological Progress

	Efficiency Change			Technological Progress		
	PIP	P. Mean	P. Std.	PIP	P. Mean	P. Std.
	(1)	(2)	(3)	(4)	(5)	(6)
Fixed Effects	1.00	−0.08	0.15	1.00	0.07	0.05
Initial GDP	0.92	−0.32	0.09	0.99	−0.10	0.03
Trade Openness	0.89	0.33	0.09	0.97	−0.08	0.02
Consumption Share	0.82	−0.79	0.25	0.07	−0.06	0.08
Population under 15	0.29	−2.18	1.47	0.05	0.02	0.34
Government Share	0.18	−0.80	0.50	0.05	−0.04	0.15
Urban Population	0.11	−0.61	0.49	0.07	0.15	0.16
Investment Share	0.09	−0.35	0.33	0.06	−0.08	0.11
Population over 65	0.08	2.72	3.07	0.22	−1.53	0.90
Population	0.08	0.62	0.61	0.04	0.02	0.19
Labor Force	0.08	−1.03	2.01	0.05	−0.02	0.29
Secondary Education	0.06	0.40	0.57	0.07	−0.14	0.18
Population Density	0.06	0.12	0.18	0.24	0.10	0.05
Population Growth	0.06	2.25	3.60	0.05	0.04	1.01
Primary Education	0.06	−0.39	0.54	0.30	0.34	0.17
Investment Price	0.06	0.03	0.04	0.27	−0.02	0.01
Life Expectancy	0.05	0.04	0.79	0.10	−0.29	0.26
Malaria	0.05	0.01	0.07	0.06	−0.02	0.02
Political Rights	0.04	−0.02	0.14	0.06	−0.03	0.05
Civil Liberties	0.04	−0.05	0.18	0.05	−0.02	0.06
Prior Inclusion Probability		0.5			0.5	
Prior Mean Model Size		9.5			9.5	
Posterior Mean Model Size		5.0			4.7	
Robust Determinants:	Fixed Effects, Initial GDP, T. Openness, Cons. Share.			Fixed Effects, Initial GDP, T. Openness.		

Notes: Columns (1), (2), and (3) refer to the determinants of efficiency change, that is, reductions in the distance to the world technological frontier. Columns (4), (5), and (6) present the results of the technological progress determinants, that is, displacements of the frontier. Given the relevance of unobserved heterogeneity shown in Table 1, country-specific fixed effects are included in the two specifications of this Table. PIP refers to the posterior inclusion probability of a particular regressor. Given the prior inclusion probability is equal for all the variables (i.e. 0.5), those variables with PIP higher than 0.5 are labeled as robust determinants of TFP growth. P. Mean refers to the posterior mean conditional on inclusion of a given regressor in the empirical model, which is a weighted average of model-specific coefficient estimates with weights given by the model-specific R-squares. P. Std. is the square root of the posterior variance which is a weighted average of model-specific variances also including the variance of the estimates across different models. The P. Mean and P. Std. estimates corresponding to the Fixed Effects are the averages of the P. Means and P. Stds of each country dummy P. Mean and P. Std. The Prior Mean Model Size refers to the expected model size a priori (in terms of regressors included) implied by the Prior Inclusion Probability of 0.5. The Posterior Mean Model Size is the weighted average of all posterior model sizes with weights given by the posterior model probabilities. The sample is formed by a set of 67 countries with 8 five-year periods for each country over the period 1960 − 2000. This makes a total of 536 observations.

Table 2 presents the BMA results of separately identifying the main determinants of changes in productive efficiency (columns 1, 2, 3) and technological progress (columns 4, 5, 6). The first interesting result emerging from Table 2 is that, as in the case of overall TFP growth, the country-specific effects and initial GDP are the factors most robustly correlated with both indexes. This result implies that time-invariant country-specific unobservable characteristics are fundamental determinants of both efficiency change and technical change over the post-war period $1960 - 2000$; and, on the other hand, that poorer countries tend to converge to rich countries in terms of efficiency and innovation. However, the posterior mean indicates that the convergence in innovation is much slower than the convergence in efficiency change (-0.10 versus -0.32).

With respect to other policy-relevant determinants, a striking difference arises between the main determinants of catching up to the frontier (i.e. efficiency change) and shifts in the frontier (i.e. technological progress). As in the case of overall TFP growth, in addition to the fixed effects and initial GDP, trade openness and consumption share are the only robust determinants of efficiency change across the countries in our sample. In particular, countries that are more outward-oriented and have higher saving rates catch up faster to the frontier. Nevertheless, only the trade openness measure remains a robust determinant of technological progress; the surprising difference is that in this case, trade openness negatively affects technological progress. According to this result, countries with higher degree of trade openness perform better in terms of catching up to the world technological frontier, but worse in terms of shifting the frontier. This idea implies that the more exposed a country is to the rest of the world the more it imitates but the less it innovates.

5.3 OECD versus non-OECD Countries

Determinants and patterns of development of non-OECD countries may differ in the long run from those of OECD countries. In order to further explore the possibility of different patterns in the determination of TFP growth, we split the countries in our sample in two groups, OECD versus non-OECD, and we repeat the BMA analysis for the two subsamples.

In Table 3 we present the separate results for OECD countries (columns 1, 2, 3) and non-OECD countries (columns 4, 5, 6). The first interesting result emerging from Table 3 is that, again, both the fixed effects and initial GDP are robustly correlated with TFP growth in both subsamples (OECD and non-OECD). This indicates that regardless of the institutional characteristics at the beginning of the sample period (i.e. after the Second World War in 1960) proxied by the OECD versus non-OECD classification, unobserved

Table 3: TFP Determinants: OECD and Non-OECD Countries

	OECD Countries			Non-OECD Countries		
	PIP	P. Mean	P. Std.	PIP	P. Mean	P. Std.
	(1)	(2)	(3)	(4)	(5)	(6)
Fixed Effects	1.00	0.11	0.08	1.00	0.24	0.15
Initial GDP	0.85	−0.31	0.10	0.83	−0.30	0.10
Trade Openness	0.59	0.31	0.12	0.11	0.09	0.09
Consumption Share	0.76	−1.20	0.46	0.28	−0.35	0.19
Population under 15	0.28	1.46	1.04	0.26	−2.46	1.99
Government Share	0.38	−1.32	0.84	0.10	−0.59	0.55
Urban Population	0.18	0.46	0.38	0.09	−0.61	0.65
Investment Share	0.47	−0.89	0.44	0.05	−0.02	0.34
Population over 65	0.09	0.69	1.73	0.47	−10.7	7.34
Population	0.14	1.65	2.52	0.27	1.05	0.57
Labor Force	0.54	−1.42	0.67	0.11	−1.58	2.22
Secondary Education	0.09	0.12	0.27	0.07	−0.81	1.06
Population Density	0.24	1.64	1.33	0.86	0.50	0.16
Population Growth	0.11	2.08	4.33	0.08	2.61	4.61
Primary Education	0.09	0.23	0.41	0.06	0.51	0.85
Investment Price	0.84	0.25	0.08	0.06	−0.03	0.04
Life Expectancy	0.24	2.17	2.07	0.06	0.39	0.85
Malaria	0.10	0.02	0.06	0.05	0.02	0.08
Political Rights	0.13	0.12	0.15	0.05	−0.07	0.16
Civil Liberties	0.19	0.19	0.14	0.05	−0.10	0.22
Prior Inclusion Probability		0.5			0.5	
Prior Mean Model Size		9.5			9.5	
Posterior Mean Model Size		7.3			4.9	
Robust Determinants:	Fixed Effects, Initial GDP, Inv. Price, Consump. Share, T. Openness, Labor Force.			Fixed Effects, Initial GDP, Pop. Density.		

Notes: Columns (1), (2), and (3) refer to the determinants of overall TFP growth in OECD countries while columns (4), (5), and (6) present the results of TFP determinants in non-OECD countries. Given the relevance of unobserved heterogeneity shown in Table 1, country-specific fixed effects are included in the two specifications of this Table. PIP refers to the posterior inclusion probability of a particular regressor. Given the prior inclusion probability is equal for all the variables (i.e. 0.5), those variables with PIP higher than 0.5 are labeled as robust determinants of TFP growth. P. Mean refers to the posterior mean conditional on inclusion of a given regressor in the empirical model, which is a weighted average of model-specific coefficient estimates with weights given by the model-specific R-squares. P. Std. is the square root of the posterior variance which is a weighted average of model-specific variances also including the variance of the estimates across different models. The P. Mean and P. Std. estimates corresponding to the Fixed Effects are the averages of the P. Means and P. Stds of each country dummy P. Mean and P. Std. The Prior Mean Model Size refers to the expected model size a priori (in terms of regressors included) implied by the Prior Inclusion Probability of 0.5. The Posterior Mean Model Size is the weighted average of all posterior model sizes with weights given by the posterior model probabilities. The sample is formed by a set of 67 countries (20 countries in the OECD sample and 47 non-OECD countries) with 8 five-year periods for each country over the period 1960 – 2000.

World War in 1960) proxied by the OECD versus non-OECD classification, unobserved heterogeneity is the key factor in explaining cross-country differences in the TFP growth rate; it also provides evidence in favor of a convergence process in both subsamples of countries.

Initial GDP and unobserved heterogeneity are the two only robust determinants common to OECD and non-OECD countries. Beyond these similarities, some interesting differences arise. With respect to non-OECD countries, the only additional variable robustly correlated with TFP growth is population density. In particular, countries with higher population density are expected to experience higher rates of TFP growth while in the OECD sample this is not the case. We interpret this result as an indication that economies of agglomeration are more relevant in non-OECD or developing countries.

For the sample of OECD countries, in addition to the fixed effects and initial GDP, there are several covariates which appear to be robustly associated with TFP growth, namely, investment price, consumption share, trade openness, and the labor force. Consumption share and trade openness have the same sign as in the case of overall TFP growth for the full sample in Table 1; while consumption negatively affect TFP growth among OECD countries, the effect of trade openness is positive. The posterior mean on the investment price variable is positive and, using non-Bayesian terminology, significantly different from zero according to its posterior standard deviation.[15] This positive sign indicates that the higher the price of investment the higher the TFP growth rate. One possible explanation for this results is that if the price of investment is high, then perhaps firms tend to reallocate resources efficiently and more importantly invest wisely. Labor force represents the last robust determinant of TFP growth in the OECD subsample. Its negative posterior mean indicates that a higher ratio of workers to population is associated with lower levels of TFP growth, which might seem counter-intuitive a priori; however, in a recent paper, Acemoglu (2010) shows that labor scarcity encourages technology adoption or innovation if technology is strongly labor saving.

[15] Sala-i-Martin et al. (2004) note that in most cases, having a ratio of posterior mean to posterior standard deviation around two in absolute value indicates an approximate 95-percent Bayesian coverage region that excludes zero.

6 Concluding Remarks

We investigate the factors that affect total factor productivity growth. To this end, we first start by deriving our measure TFP growth using the nonparametric DEA technique to compute the Malmquist productivity-based index for 67 countries over the period 1960-2000. An advantage of this method is that it allows to decompose TFP into its two components, *viz*, technical efficiency (which reveals whether a country is moving close to the frontier) and technological change (which reveals whether the production function is moving outward). In order to avoid model specific results (bias), we use (Bayesian) model averaging techniques to search for the robust determinants of TFP growth.

We find that the most robust TFP growth determinants are unobserved heterogeneity, initial GDP,[16] consumption share, and trade openness. A split of our sample into OECD and non-OECD countries reveals some interesting findings. We find that initial GDP and unobserved heterogeneity are the only two robust determinants common to OECD and non-OECD countries. For the sample of OECD countries, in addition to the fixed effects and initial GDP, we find that investment price, consumption share, trade openness, and the labor force are robustly correlated to TFP growth. With respect to non-OECD countries, the only additional variable robustly correlated with TFP growth is population density.

Turning to the determinants of the components of TFP, efficiency change and technological change, we also find that (as in the case of overall TFP growth) the country-specific effects and initial GDP are the factors most robustly correlated with both variables. Additionally, the results show that, while trade openness and consumption share can be labeled as robust determinants of efficiency change, only the trade openness measure remains a robust determinant of technological progress across the countries in our sample. With regard to openness, the surprising difference is that it affects negatively technological progress but positively efficiency change; thus suggesting that countries with higher degree of trade openness perform better in terms of catching up to the world technological frontier, but worse in terms of shifting the frontier.

[16] The significant and negative coefficient on initial GDP gives evidence in favor of a convergence effect in the evolution of TFP across countries. Growth rates of TFP in poor countries tend to be higher than in rich countries.

References

[1] Abramovitz, M. (1956) “Resources and Output Trends in the United States since 1870” American Economic Review, Vol. 46, pp. 5-23.

[2] Acemoglu, D. (2010) “When Does Labor Scarcity Encourage Innovation?” Journal of Political Economy, forthcoming.

[3] Benhabib, J. and M. Spiegel (1994) “The Role of Human Capital in Economic Development: Evidence from Aggregate Cross-Country Data” Journal of Monetary Economics, Vol. 34, pp. 143-174.

[4] Benhabib, J. and M. Spiegel (2005) "Human capital and technology diffusion", in P. Aghion and S. Durlauf (Eds.), Handbook of Economic Growth, 4, Amsterdam: North Holland.

[5] Bjurek, H., L. Hjalmarsson and F. Forsund (1990) “Deterministic parametric and nonparametric estimation of efficiency in service production: A comparison” Journal of Econometrics, Vol. 46, pp. 213-227.

[6] Brock, W. and S. Durlauf (2001) “Growth empirics and reality” The World Bank Economic Review, Vol. 15, pp. 229-272.

[7] Caves D., L. Christensen and W. Diewert (1982a) “The Economic Theory of Index Numbers and Measurement of Input, Output and Productivity” Econometrica, Vol.50, pp. 1393–1414.

[8] Caves D., L. Christensen and W. Diewert (1982b) “Multilateral Comparison of Output, Input and Productivity Using Superlative Index Numbers” Economic Journal, Vol. 92, pp. 73-86.

[9] Ciccone, A. and M. Jarocinski (2010) “Determinants of Economic Growth: Will Data Tell?” American Economic Journal: Macroeconomics, Vol. 4, pp. 222-246.

[10] Coelli, T. (1996) “A Guide to DEAP, Version 2.1: A Data Envelopment Analysis (Computer) Program” University of New England, Centre for Efficiency and Productivity Analysis (CEPA) Working paper, 96(08).

[11] Durlauf, S., P. Johnson and J. Temple (2005) “Growth Econometrics” In P. Aghion and S.N. Durlauf, eds., Handbook of Economic Growth, Volume 1A, pp. 555-677, Amsterdam, North-Holland.

[12] Easterly, W. and R. Levine (2001) “It’s Not Factor Accumulation: Stylized Facts and Growth Models” The World Bank Economic Review, Vol. 15, pp. 177-219.

[13] Eicher, T., C. Papageorgiou and A. Raftery (2010) "Default Priors and Predictive Performance in Bayesian Model Averaging, with Application to Growth Determinants" Journal of Applied Econometrics, forthcoming.

[14] Färe, R., S. Grosskopf, S. Norris and B. Lindgren (1989) "Productivity Developments in Swedish Hospitals: A Malmquist Output Index Approach" Discussion Paper no

[15] Färe, R., S. Grosskopf, S. Norris and Z. Zhang (1994) "Productivity growth, technical progress, and efficiency change in industrialized countries" American Economic Review, Vol. 84, pp. 66-83.

[16] Ferrier, G., C. Lovell and A. Knox (1990) "Measuring cost efficiency in banking : Econometric and linear programming evidence" Journal of Econometrics, Vol. 46, pp. 229-245.

[17] Gong, B. and R. Sickles (1992) "Finite sample evidence on the performance of stochastic frontiers and data envelopment analysis using panel data" Journal of Econometrics, Vol. 51, pp. 259-284.

[18] Hall, R. and C. Jones (1999) "Why Do Some Countries Produce So Much More Output Per Worker Than Others?" Quarterly Journal of Economics, Vol. 114, pp. 83-116.

[19] Hjalmarsson, L., S. Kumbhakar and A. Heshmati (1996) "DEA, DFA and SFA: A comparison" Journal of Productivity Analysis, Vol. 7, pp. 303-327.

[20] Kass, R. and L. Wasserman (1995) "A Reference Bayesian Test for Nested Hypothesis with Large Samples" Journal of the American Statistical Association, Vol. 90, pp. 928-934.

[21] Klenow, P. and A. Rodriguez-Clare. (1997) "The Neoclassical Revival in Growth Economics: Has it gone too far?" NBER Macroeconomics Annual, pp. 73-102.

[22] Kneller, R. and P. Stevens (2006) "Frontier technology and absorptive capacity: evidence from OECD manufacturing industries?" Oxford Bulletin of Economics and Statistics, Vol. 68, pp. 1-21.

[23] Koop, G. (2003) "Bayesian Econometrics" John Wiley and Sons.

[24] Krugman, P. (1994) "The Age of Diminishing Expectations: US Economic Policy in the 1990s" MIT Press.

[25] Leamer, E. (1978) "Specification Searches" New York: John Wiley and Sons.

[26] Lucas, R. (1988) "On the Mechanics of Economic Development" Journal of Monetary Economics, Vol. 22, pp. 3-42.

[27] Madigan, D. and J. York (1995) "Bayesian Graphical Models for Discrete Data" International Statistical Review, Vol. 63, pp. 215-232.

[28] Malmquist, S. (1953) "Index Numbers and Indifference Surfaces" Trabajos de Estadistica y de Investigacion Operativa, Vol. 4, pp. 209–42.

[29] Miller, S. and M. Upadhyay (2000) "The effects of openness, trade orientation, and human capital on total factor productivity" Journal of Development Economics, Vol. 63, pp. 399-423.

[30] Moral-Benito, E. (2010) "Model Averaging in Economics" mimeo.

[31] Moral-Benito, E. (2011) "Determinants of Economic Growth: A Bayesian Panel Data Approach" The Review of Economics and Statistics, forthcoming.

[32] Nehru, V. and A. Dhareshwar (1993) "A new database on physical capital stock: sources, methodology and results" Revista de Analisis Economico, Vol. 8 pp. 37-59.

[33] Raftery, A. (1995) "Bayesian Model Selection in Social Research" Sociological Methodology, Vol. 25, pp. 111-163.

[34] Romer, P. (1986) "Increasing returns and long-run growth" The Journal of Political Economy, Vol. 94, pp. 1002-37.

[35] Romer, P. (1990) "Endogenous Technological Change" The Journal of Political Economy, Vol. 98, pp. S71-S102.

[36] Sala-i-Martin, X., G. Doppelhofer and R. Miller (2004) "Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach" American Economic Review, Vol. 94, No. 4. pp. 813-835.

[37] Solow, R. (1957) "Technical Change and the Aggregate Production Function" The Review of Economics and Statistics, Vol. 39, pp. 312-320.

[38] Vandenbussche, J., P. Aghion, and C. Meghir (2006) "Growth, distance to frontier and composition of human capital" Journal of Economic Growth, Vol. 11 pp. 97-12.

Computational Appendix

For the implementation of the model averaging approach adopted in the paper we need to resort to the algorithms proposed in the literature because of the extremely large number of calculations required for instance when computing the posterior mean in equation (17). This is because the number of potential regressors determines the number of models under consideration, with K potential determinants of TFP growth, the number of models under consideration is 2^K which is usually huge and intractable. These algorithms carry out (Bayesian) model averaging without evaluating every possible model.

Concretely, in this paper we have made use of the Markov Chain Monte Carlo Model Composition (MC^3) algorithm proposed by Madigan and York (1995), which generates a stochastic process that moves through model space. The idea is to construct a Markov chain of models $\{M(t), t = 1, 2, ...\}$ with state space Ξ. If we simulate this Markov chain for $t = 1, ..., N$, then under certain regularity conditions, for any function $h(M_i)$ defined on Ξ, the average

$$\widehat{H} = \frac{1}{N}\sum_{t=1}^{N} h\left(M\left(t\right)\right)$$

converges with probability 1 to $E\left(h\left(M\right)\right)$ as $N \to \infty$. To compute (17) in this fashion, we set $h(M_i) = E(\theta|M_i, y)$.

To construct the Markov chain, we define a neighborhood $nbd(M)$ for each $M \in \Xi$ that consists of the model M itself and the set of models with either one variable more or one variable fewer than M. Then, a transition matrix $\mathbf{q}$ is defined by setting $\mathbf{q}(M \to M') = 0$ $\forall\ M' \notin nbd(M)$ and $\mathbf{q}(M \to M')$ constant for all $M' \in nbd(M)$. If the chain is currently in state M, then we proceed by drawing M' from $\mathbf{q}(M \to M')$. It is then accepted with probability

$$\min\left\{1, \frac{\Pr\left(M'|y\right)}{\Pr\left(M|y\right)}\right\}$$

Otherwise, the chain stays in state M.[17]

After some experimentation with generated data, we were able to verify the proper convergence properties of our GAUSS code which implements the described MC^3 algorithm.

[17] See Koop (2003) for more details on the MC^3 algorithm.

Table 4: Variable Definitions and Sources

Variable	Source	Definition
Dependent Variable 1	This paper	TFP growth over 5-year periods
Dependent Variable 2	This paper	Technical change over 5-year periods
Dependent Variable 3	This paper	Technological progress over 5-year periods
Initial GDP	PWT 6.2	Logarithm of initial real GDP per capita (2000 US dollars at PPP)
Population Growth	PWT 6.2	Average growth rate of population
Population	PWT 6.2	Population in thousands of people
Trade Openness	PWT 6.2	Export plus imports as a share of GDP
Government Share	PWT 6.2	Government consumption as a share of GDP
Investment Price	PWT 6.2	Average investment price level
Labor Force	PWT 6.2	Ratio of workers to population
Consumption Share	PWT 6.2	Consumption as a share of GDP
Investment Share	PWT 6.2	Investment as a share of GDP
Urban Population	WDI 2005	Fraction of population living in urban areas
Population Density	WDI 2005	Population divided by land area
Life Expectancy	WDI 2005	Life expectancy at birth
Population under 15	Barro and Lee	Fraction of population younger than 15 years
Population over 65	Barro and Lee	Fraction of population older than 65 years
Primary Education	Barro and Lee	Stock of years of primary education
Secondary Education	Barro and Lee	Stock of years of secondary education
Political Rights	Freedom House	Index of political rights from 1 (highest) to 7
Civil Liberties	Freedom House	Index of civil liberties from 1 (highest) to 7
Malaria	Gallup et al.	Fraction of population in areas with malaria

Penn World Table version 6.2 data can be found at http://pwt.econ.upenn.edu. WDI 2005 refers to World Development Indicators 2005. Data from Barro and Lee, and Gallup et al. are available at http://www.cid.harvard.edu/ciddata/ciddata.html. Finally, data from Freedom House can be downloaded from http://www.freedomhouse.org.

Table 5: Summary Statistics of the Variables

Variable	Mean	Std. Dev.	Min	Max
TFP	0.999	0.003	0.986	1.023
Efficiency change	0.999	0.003	0.983	1.026
Technical change	1.000	0.001	0.992	1.012
Initial GDP	7166.3	5826.5	616.4	21931.5
Population	47394.6	143075.1	663.2	1206034
Population Growth	0.019	0.011	-0.010	713937
Investment Price	83.28	39.85	31.73	287.1
Trade Openness	1.969	1.236	1.118	8.684
Consumption Share	0.687	0.164	0.446	1.495
Government Share	0.197	0.077	0.075	0.579
Investment Share	0.175	0.083	0.023	0.449
Labor Force	0.417	0.067	0.267	0.553
Life Expectancy	63.57	9.88	41.36	75.64
Population Density	138.7	448.3	1.852	3666.1
Urban Population	0.511	0.240	0.041	1
Malaria	0.424	0.437	0	1
Population under 15	0.365	0.094	0.198	0.515
Population under 65	0.061	0.039	0.024	0.154
Primary Education	3.336	1.662	0.288	7.359
Secondary Education	1.256	0.983	0.056	4.042
Political Rights	3.343	2.142	1	7
Civil Liberties	3.384	1.866	1	7

Table 6: List of Countries

	OECD Sample	
Australia	Austria	Belgium
Canada	Denmark	Finland
France	Greece	Ireland
Italy	Japan	Netherlands
New Zealand	Norway	Portugal
Spain	Sweden	Switzerland
United Kingdom	United States	

	Non-OECD Sample	
Algeria	Argentina	Bolivia
Brazil	Cameroon	Chile
China	Colombia	Costa Rica
Dominican Republic	Ecuador	El Salvador
Ghana	Guatemala	Honduras
India	Indonesia	Iran
Israel	Jamaica	Jordan
Kenya	Malawi	Malaysia
Mali	Mauritius	Mexico
Mozambique	Nicaragua	Pakistan
Panama	Paraguay	Peru
Philippines	Rwanda	Senegal
Singapore	South Africa	Sri Lanka
Thailand	Trinidad&Tobago	Turkey
Uganda	Uruguay	Venezuela
Zambia	Zimbabwe	

BANCO DE ESPAÑA PUBLICATIONS

WORKING PAPERS[1]

0922 GALO NUÑO: Technology, convergence and business cycles.

0923 FRANCISCO DE CASTRO AND JOSÉ LUIS FERNÁNDEZ: The relationship between public and private saving in Spain: does Ricardian equivalence hold?

0924 GONZALO FERNÁNDEZ-DE-CÓRDOBA, JAVIER J. PÉREZ AND JOSÉ L. TORRES: Public and private sector wages interactions in a general equilibrium model.

0925 ÁNGEL ESTRADA AND JOSÉ MANUEL MONTERO: R&D investment and endogenous growth: a SVAR approach.

0926 JUANA ALEDO, FERNANDO GARCÍA-MARTÍNEZ AND JUAN M. MARÍN DIAZARAQUE: Firm-specific factors influencing the selection of accounting options provided by the IFRS: Empirical evidence from Spanish market.

0927 JAVIER ANDRÉS, SAMUEL HURTADO, EVA ORTEGA AND CARLOS THOMAS: Spain in the euro: a general equilibrium analysis.

0928 MAX GILLMAN AND ANTON NAKOV: Monetary effects on nominal oil prices.

0929 JAVIER MENCÍA AND ENRIQUE SENTANA: Distributional tests in multivariate dynamic models with Normal and Student *t* innovations.

0930 JOAN PAREDES, PABLO BURRIEL, FRANCISCO DE CASTRO, DANIEL GARROTE, ESTHER GORDO AND JAVIER J. PÉREZ: Fiscal policy shocks in the euro area and the US: an empirical assessment.

0931 TERESA LEAL, DIEGO J. PEDREGAL AND JAVIER J. PÉREZ: Short-term monitoring of the Spanish Government balance with mixed-frequencies models.

0932 ANTON NAKOV AND GALO NUÑO: *Oil*gopoly: a general equilibrium model of the oil-macroeconomy nexus.

0933 TERESA LEAL AND JAVIER J. PÉREZ: Análisis de las desviaciones presupuestarias aplicado al caso del presupuesto del Estado.

0934 JAVIER J. PÉREZ AND A. JESÚS SÁNCHEZ: Is there a signalling role for public wages? Evidence for the euro area based on macro data.

0935 JOAN PAREDES, DIEGO J. PEDREGAL AND JAVIER J. PÉREZ: A quarterly fiscal database for the euro area based on intra-annual fiscal information.

1001 JAVIER ANDRÉS, ÓSCAR ARCE AND CARLOS THOMAS: Banking competition, collateral constraints and optimal monetary policy.

1002 CRISTINA BARCELÓ AND ERNESTO VILLANUEVA: The response of household wealth to the risk of losing the job: evidence from differences in firing costs.

1003 ALEXANDER KARAIVANOV, SONIA RUANO, JESÚS SAURINA AND ROBERT TOWNSEND: No bank, one bank, several banks: does it matter for investment?

1004 GABRIEL PEREZ-QUIROS AND HUGO RODRÍGUEZ MENDIZÁBAL: Asymmetric standing facilities: an unexploited monetary policy tool.

1005 GABRIEL JIMÉNEZ, JOSE A. LOPEZ AND JESÚS SAURINA: How does competition impact bank risk-taking?

1006 GIUSEPPE BERTOLA, AURELIJUS DABUSINSKAS, MARCO HOEBERICHTS, MARIO IZQUIERDO, CLAUDIA KWAPIL, JEREMI MONTORNÈS AND DANIEL RADOWSKI: Price, wage and employment response to shocks: evidence from the WDN Survey.

1007 JAVIER MENCÍA: Testing non-linear dependence in the Hedge Fund industry.

1008 ALFREDO MARTÍN-OLIVER: From proximity to distant banking: Spanish banks in the EMU.

1009 GALO NUÑO: Optimal research and development expenditure: a general equilibrium approach.

1010 LUIS J. ÁLVAREZ AND PABLO BURRIEL: Is a Calvo price setting model consistent with micro price data?

1011 JENS HAGENDORFF, IGNACIO HERNANDO, MARÍA J. NIETO AND LARRY D. WALL: What do premiums paid for bank M&As reflect? The case of the European Union.

1012 DAVID DE ANTONIO LIEDO: General equilibrium restrictions for dynamic factor models.

1013 JAMES COSTAIN, JUAN F. JIMENO AND CARLOS THOMAS: Employment fluctuations in a dual labor market.

1014 LUIS M. VICEIRA AND RICARDO GIMENO: The euro as a reserve currency for global investors.

1015 PALOMA LÓPEZ-GARCÍA AND JOSÉ MANUEL MONTERO: Understanding the Spanish business innovation gap: The role of spillovers and firms' absorptive capacity.

---

1. Previously published Working Papers are listed in the Banco de España publications catalogue.

1016 AITOR LACUESTA AND SERGIO PUENTE: El efecto del ciclo económico en las entradas y salidas de inmigrantes en España.

1017 REBEKKA CHRISTOPOULOU, JUAN F. JIMENO AND ANA LAMO: Changes in the wage structure in EU countries.

1018 THOMAS BREUER, MARTIN JANDAČKA, JAVIER MENCÍA AND MARTIN SUMMER: A systematic approach to multi-period stress testing of portfolio credit risk.

1019 LUIS J. ÁLVAREZ AND PABLO BURRIEL: Micro-based estimates of heterogeneous pricing rules: The United States vs. the euro area.

1020 ALFREDO MARTÍN-OLIVER AND VICENTE SALAS-FUMÁS: I.T. investment and intangibles: Evidence from banks.

1021 LUISA LAMBERTINI, CATERINA MENDICINO AND MARIA TERESA PUNZI: Expectations-driven cycles in the housing market.

1022 JULIÁN MESSINA, PHILIP DU CAJU, CLÁUDIA FILIPA DUARTE, NIELS LYNGGÅRD HANSEN AND MARIO IZQUIERDO: The incidence of nominal and real wage rigidity: an individual-based sectoral approach.

1023 ALESSIO MORO: Development, growth and volatility.

1024 LUIS J. ÁLVAREZ AND ALBERTO CABRERO: Does housing really lead the business cycle?

1025 JUAN S. MORA-SANGUINETTI: Is judicial inefficiency increasing the house property market weight in Spain? Evidence at the local level.

1026 MAXIMO CAMACHO, GABRIEL PEREZ-QUIROS AND PILAR PONCELA: Green shoots in the Euro area. A real time measure.

1027 AITOR ERCE AND JAVIER DÍAZ-CASSOU: Creditor discrimination during sovereign debt restructurings.

1028 RAFAEL REPULLO, JESÚS SAURINA AND CARLOS TRUCHARTE: Mitigating the pro-cyclicality of Basel II.

1029 ISABEL ARGIMÓN AND JENIFER RUIZ: The effects of national discretions on banks.

1030 GABRIEL JIMÉNEZ, STEVEN ONGENA, JOSÉ-LUIS PEYDRÓ AND JESÚS SAURINA: Credit supply: identifying balance-sheet channels with loan applications and granted loans.

1031 ENRIQUE MORAL-BENITO: Determinants of economic growth: A Bayesian panel data approach.

1032 GABE J. DE BONDT, TUOMAS A. PELTONEN AND DANIEL SANTABÁRBARA: Booms and busts in China's stock market: Estimates based on fundamentals.

1033 CARMEN MARTÍNEZ-CARRASCAL AND JULIAN VON LANDESBERGER: Explaining the demand for money by non-financial corporations in the euro area: A macro and a micro view.

1034 CARMEN MARTÍNEZ-CARRASCAL: Cash holdings, firm size and access to external finance. Evidence for the euro area.

1035 CÉSAR ALONSO-BORREGO: Firm behavior, market deregulation and productivity in Spain.

1036 OLYMPIA BOVER: Housing purchases and the dynamics of housing wealth.

1037 DAVID DE ANTONIO LIEDO AND ELENA FERNÁNDEZ MUÑOZ: Nowcasting Spanish GDP growth in real time: "One and a half months earlier".

1038 FRANCESCA VIANI: International financial flows, real exchange rates and cross-border insurance.

1039 FERNANDO BRONER, TATIANA DIDIER, AITOR ERCE AND SERGIO L. SCHMUKLER: Gross capital flows: dynamics and crises.

1101 GIACOMO MASIER AND ERNESTO VILLANUEVA: Consumption and initial mortgage conditions: evidence from survey data.

1102 PABLO HERNÁNDEZ DE COS AND ENRIQUE MORAL-BENITO: Endogenous fiscal consolidations.

1103 CÉSAR CALDERÓN, ENRIQUE MORAL-BENITO AND LUIS SERVÉN: Is infrastructure capital productive? A dynamic heterogeneous approach.

1104 MICHAEL DANQUAH, ENRIQUE MORAL-BENITO AND BAZOUMANA OUATTARA: TFP growth and its determinants: nonparametrics and model averaging.

BANCO DE ESPAÑA
Eurosistema

Unidad de Publicaciones
Alcalá 522, 28027 Madrid
Telephone +34 91 338 6363. Fax +34 91 338 6488
E-mail: publicaciones@bde.es
www.bde.es