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A Bayesian factor-augmented productivity model on panel data

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How important is innovation? A Bayesian factor-augmented productivity model on panel data.

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Abstract - This paper proposes a Bayesian approach to estimate a factor augmented productivity equation. We exploit the panel dimension of our data and distinguish individual-specific and time-specific factors. On the basis of 21 technology, infrastructure and institution indicators from 82 countries over a 19-year period (1990 to 2008), we construct summary indicators of these three components and estimate their effect on the growth and the international differences in GDP per capita.
Keywords: Bayesian factor-augmented model, innovation, MCMC, panel data, productivity.

JEL classification: C23, C38, O47

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1 Introduction

Why growth rates differ, what explains differences in productivity and what are the conditions for economic development, those are fundamental questions that continue to preoccupy economists (see Easterly and Levine (2001)). Besides the traditional inputs (labor and capital), some other variables like technology, infrastructures and institutions are often advanced to explain the evolution and the country gaps in productivity. How exactly those explanatory variables affect the total factor productivity residual requires some structural, multi-equation, modeling. This is not the purpose of this paper. Our goal in this paper is to try and ascertain the importance of these "explanations" of the residual on the basis of a certain number of indicators that supposedly capture those broad explanations. To take the example of innovation, instead of including separately measures such as R&D, the number of new products, the number of patent applications or grants, the number of trademark applications, the number of publications, ... could we not create some kind of index of innovation on the basis of which we could compare the performance and the contribution to productivity in different countries?
To construct these indexes we use panel data on 21 indicators, for 82 countries and 19 periods, to identify common factors, which pertain to technology, infrastructures and institutions. We generalize in the panel dimension the approach of common factors that has been proposed a long time ago (see Bartholomew, Deary and Lawn, 2009) and received new attention in recent years in the literature on common features (Anderson, Issler and Vahid, 2006). We then apply these common factors to the explanation of international differences in productivity. The idea behind factor analysis is to summarize various indicators into a limited number of common factors that explain most of the correlations between the individual indicators so as to reduce the dimension of the analysis. Here are a few examples of applications of this procedure. In macroeconomics, Hecq, Palm and Urbain (2006) identify two or three common cyclical features to explain comovements in annual GDP series of 5 Latin American countries over a 50-year period. In analysing the quality of patents, Lanjouw and Schankerman (2004) estimate by factor analysis a patent quality index common to four quality indicators (claims, citations, family size and technology area). Fagerberg and Srholec (2008) use factor analysis on pooled data for 115 countries, 25 indicators and 2 periods (average values for 1992-1994 and for 2002-2004) to isolate four types of indicators, which they interpret as capabilities: the development of

the innovation system, the quality of governance, the political system and the openness of the economy.

Compared to the previous studies we innovate in two respects. On the one hand, we allow for two kinds of common factors, those in the cross-sectional dimension and those in the time series dimension. It is like replacing the cross-sectional specific and the time series specific errors in the two-way error components model by common factors in the two respective dimensions. On the other hand, instead of estimating first the common factors and inserting them afterwards in a factor-augmented regression (FAR) on productivity, we propose a more robust Bayesian approach based on uninformed priors and Markov Chain Monte Carlo simulation where all equations are estimated simultaneously.

The paper is organized as follows. We first briefly review a number of growth models proposed in the literature (section 2). Then, in section 3 we present the background on FAR. In section 4, we propose two ways to estimate, on panel data, a factor-augmented productivity model with multiple indicators: the frequentist approach and the Bayesian approach. After presenting the data in section 5, we analyze in section 6 the results, the individual and time factor scores and the estimated factor-augmented productivity equations. Last, we conclude on the effects of these indicators on the total factor productivity using FAR on panel data (section 7).

2 Growth models

As noted by Easterly and Levine (2001), starting with Solow (1957) a growing body of research has suggested that after accounting for physical and human capital accumulation, "something else" accounts for the majority of cross-country differences in both the level of Gross Domestic Product (GDP) per capita and the growth rate of GDP per capita. The term "Total Factor Productivity (TFP)" is used to refer to the "something else" (besides physical factor accumulation) that accounts for economic growth differences. Usually, the assumption of a Cobb-Douglas aggregate production function leads to the following estimating equation:

$$Y_{it} = K_{it}^{\alpha} L_{it}^{1-\alpha} A_{it} \ , \ i = 1, ..., N, \ \ t = 1, ..., T \tag{1}$$

where Y_{it} represents national output per person for country (i) at time(t) (see Easterly and Levine (2001)). K_{it} is the physical capital stock per person and

L_{it} is the number of units of labor per person. A_{it} is the TFP, also known as the Solow residual.
Whereas TFP has been viewed by Abramowitz (1956) as a "measure of our ignorance", different theories have provided alternative conceptions of TFP: variations in technology, externalities, changes in the sector composition of production, adoption of lower cost production methods, scale economies, variations in capacity utilization, institutions to name only a few. Empirical evidence of the relative importance of each of these explanations is far from unanimous. There is even a controversy between those like Mankiw *et al.* (1992) who argue that growth is mainly driven by factor accumulation and those like Easterly and Levine (2001), who argue that there is something else besides factor accumulation that explains differences in economic growth.
Easterly and Levine (2001) argue that TFP growth with increasing returns to technology is more consistent with divergence than models of factor accumulation with decreasing returns, no scale economies, and some fixed factor of production. They observe that, over the past two centuries, the difference between the richest countries and poorest countries has been growing. Moreover, rich countries keep growing, and returns to capital are not falling. However, empirical works do not yet decisively distinguish among the different theoretical conceptions of "total factor productivity growth". So, Easterly and Levine (2001) recommend that economists should devote more effort towards modeling and quantifying total factor productivity.
In this paper, we propose to estimate a Cobb-Douglas production function with no specific assumption on technical progress and returns to scale. Beside the two factors, capital and labor, we include several indicators $Z_{j,it}$ $(j = 1, .., K_Z)$ that we associate with technology, infrastructures and institutions.

$$Y_{it} = K_{it}^{\alpha} L_{it}^{\beta} A_{it} = K_{it}^{\alpha} L_{it}^{\beta} \left[B_{it}. \prod_{j=1}^{K_Z} Z_{j,it}^{\omega_j} \right] \; , \, i = 1, ..., N, \; t = 1, ..., T. \qquad (2)$$

So, TFP is the product $\left[B_{it}. \prod_{j=1}^{K_Z} Z_{j,it}^{\omega_j}\right]$ where B_{it} is supposed to be different over countries and over time:

$$\begin{aligned} B_{it} &= B_0.e^{\alpha_i}.e^{\xi_t} & (3) \\ \text{or } B_{it} &= B_0.e^{\alpha_i}.\exp\left(g_B.t\right) & (4) \end{aligned}$$

The country specific effect $\alpha_i \sim N\left(0, \sigma_i^2\right)$ and the time specific effect $\xi_t \sim N\left(0, \sigma_\xi^2\right)$ could be fixed or random (*i.e.*, correlated or non correlated with

K_{it}, L_{it} and $Z_{j,it}$. If we use eq.(3) for B_{it}, we get a two-way random (or fixed) effects model. With eq.(4) for B_{it}, we get a one-way random (or fixed) effects model with trend. The Z_{it} may be potentially large and may have elements correlated with K_{it} and L_{it}.
Estimation of such a specification with a large number of components of Z_{it} on a panel of countries with usual panel data estimators (FE, RE or LSDV) leads to the curse of dimensionality if we try to include them all in one shot. Moreover, we are confronted with the "*incidental parameter problem*" leading to inconsistency of α_i and ξ_t at least under fixed T. As emphasized by Moral-Benito (2012), the main area of effort since a decade in the empirical growth literature has been to select appropriate variables to include in linear growth regressions. Using Bayesian model averaging (BMA) techniques, some authors have selected variables proposed as growth determinants among a total of more than 140 variables (see also Durlauf *et al.* (2005), Fernandez *et al.* (2001)). If K is the number of potential explanatory variables, there are 2^K possible models and BMA, using MCMC model composition, selects the "best" model. But, one major disadvantage with BMA is that some important variables such as capital stock, R&D, education, ... are eliminated in favor of other variables such as life expectancy, cultural or religions variables. BMA, that can be described as a generalized stepwise method, may leave the reader doubtful about the interpretation of the resulting model in the absence of the usual economic variables such as capital or labor. So, here we propose to use factor-augmented regressions (FAR) to avoid these problems since econometric models, such as the semi-parametric models or the FAR models, focus the attention on the small number of variables of interest such as K and L and consider the other factors Z merely as controls.

3 The background on FAR

As Bai and Ng (2008) pp.114 write "*the motivation for considering factor analysis is to deal with large number of variables. Use of a small number of factors as conditioning variables is a parsimonious way to capture information in a data rich environment, and there should be efficient gains over (carefully) selecting a handful of predictors*".
In the literature on factor-augmented regressions (FAR), the usual specifica-

tion for a time series is:

$$\left\{ \begin{array}{lcl} y_t & = & X_t\beta + \zeta' f_t + u_t \\ z_{tm} & = & \sum\limits_{j=1}^{p_T} \gamma_{mj} f_{tj} + e_{tm} \ , \ m = 1, ..., M, \, t = 1, ..., T \end{array} \right. \tag{5}$$

where y_t is the dependent variable at time t, X_t is a $(1 \times K_X)$ vector of the primary inputs at time t, and $z_t = (z_{t1}, z_{t2}, ...z_{tM})'$ is a $(M \times 1)$ vector of predictors at time t. M may be large. The unobserved regressors f_{tj} : $f_t = (f_{t1}, f_{t2}, ...f_{tp_T})'$ are the common factors and the γ_{mj} are the factor loadings. e_{tm} is an idiosyncratic error term (see Stock and Watson (2002), Bai and Ng (2002), (2006), (2008), Ludvigson and Ng (2009), Gospodinov and Ng (2010), Gonçalves and Perron (2010) to mention only a few).
We can write:

$$\underset{(M\times 1)}{z_t} = \underset{(M\times p_T)}{\Gamma}\underset{(p_T\times 1)}{f_t} + \underset{(M\times 1)}{e_t} \tag{6}$$

So, z_t is the vector of predictors (or control variables), Γ contains the factor loadings and f_t is the vector of factor scores. None of the $\{\gamma_{mj}\}$, $\{f_{tj}\}$ and $\{e_{tm}\}$ are observed, but they can be estimated from the observed panel data set $\{z_{tm}\}$. In particular, with factor analysis, we can obtain estimated factors $\widetilde{f}_t = E[f_t|z_t]$ and run a standard regression of y_t on X_t and on $\widetilde{f}_t$ to estimate β and ζ.
The unobserved common factors f_{tj} are supposed to be *iid* $N(0, 1)$. So, if we stack the z_t vectors into an $(M \times T)$ matrix z, we get:

$$Var\,[z] = E\,[zz'] = \Sigma = \Gamma\Gamma' + \Phi \ , \ Var\,[e] = \Phi \tag{7}$$

and the log-likelihood is given by:

$$\ln L\,(z, \Sigma) = -\frac{MT}{2}\ln 2\pi - \frac{T}{2}\ln|\Sigma| - \frac{1}{2}z'\Sigma^{-1}z \tag{8}$$

Maximization of the log-likelihood gives the ML estimators: $\widehat{\Sigma}$, $\widehat{\Gamma}$ and $\widehat{\Phi}$. The estimates (predictions) of the factor scores are obtained using the Bartlett method:

$$\widetilde{f}_t = E\,[f_t|z_t] = \left(\widehat{\Gamma}'\widehat{\Phi}^{-1}\widehat{\Gamma}\right)^{-1}\widehat{\Gamma}'\widehat{\Phi}^{-1}z_t \tag{9}$$

then, running a standard regression of y_t on X_t and on $\widetilde{f}_t$ allows to estimate β and ζ in:

$$y_t = X_t\beta + \zeta' f_t + u_t \tag{10}$$

Bai and Ng (2006) have shown that the standard errors of the second step parameter estimates $(\beta', \zeta')'$ must account for the estimation error from the first step. Fortunately, no such adjustment is necessary if $\sqrt{T}/M \rightarrow 0$ (*i.e.*, for short panels).
In a panel data context, we may be interested in the estimation of a static linear panel model defined as:

$$y_{it} = X_{it}\beta + Z_{it}\omega + u_{it} \ , \ i = 1, ..., N, \ t = 1, ..., T \tag{11}$$

where y_{it} is the dependent variable for cross-section i at time t, X_{it} is a $(1 \times K_X)$ vector of the main inputs, Z_{it} is a $(1 \times K_Z)$ vector of predictors where K_Z is large and some Z_{it} may be time invariant or individual invariant. u_{it} is the sum of individual (α_i) and time (ξ_t) specific effects and a remainder term (ε_{it}). The specific effects may be either fixed or random. In the latter case, the disturbance u_{it} is a two-way error component:

$$u_{it} = \alpha_i + \xi_t + \varepsilon_{it} \text{ with } \alpha_i \sim N\left(0, \sigma_\alpha^2\right) \ , \xi_t \sim N\left(0, \sigma_\xi^2\right) \ , \varepsilon_{it} \sim N\left(0, \sigma_\varepsilon^2\right) \tag{12}$$

One way to estimate this model is to use FE (or LSDV with individual and time dummies) or RE specifications. But, taking into account a large number of predictors (i.e, the Z_{it} explanatory variables) leads to the curse of dimensionality if we try to include them all simultaneously. Controlling for fixed effects, by estimating them directly, is not without difficulty and is known as the "*incidental parameter problem*", which manifests itself in biases and inconsistency at least under fixed T (see Chamberlain (1980), and Nickell (1981) to mention a few). In other words, LSDV estimations of α_i are not consistent for short panels.
More radically in the cross-dependence and common factors literature (see Bai and Ng (2008), Eberhardt and Bond (2009), Eberhardt and Teal (2011), Pesaran (2006)), the usual specification avoids gathering information on a large number of predictors Z_{it} and reduces the model to:

$$\left\{ \begin{array}{lll} y_{it} & = & X_{it}\beta + u_{it} \\ u_{it} & = & A_{i,0} + \lambda_i' f_t + \varepsilon_{it} \end{array} \right. \tag{13}$$

In this literature, TFP is viewed as the combination of a country-specific level $A_{i,0}$ and a set of common factors f_t with country-specific factor loadings λ_i. So, TFP is unobserved and, generally, specifications of u_{it} omit the term $A_{i,0} \, (= A_0 + \alpha_i)$ which expresses random differences in TFP levels

across countries. Moreover, the majority of studies in the growth empirics literature estimate convergence regression equations rather than production functions (see Eberhardt and Teal (2011)). The main limitation of this model and the associated estimators (CCME, AMG, ...)[1] is that it needs a large time dimension ($T > 2K_X + 1 + D$) where D is the number of observed common effects (including deterministic ones such as intercepts, dummies, seasonals dummies, time dummies or time trends). The above model with a factor error structure encompasses the two-way fixed effect model. If $u_{it} = \lambda_i' f_t + \varepsilon_{it}$ and if we suppose that there are two common factors ($r = 2$), with $f_t' = (1, \xi_t)$, then $\lambda_i' = (\alpha_i, 1)$ for all i and t. So, the individual effects α_i and the time effects ξ_t enter the model additively instead of interactively. The more general specification of an interactive effects model — as compared to a fixed effects model — is well known for the case of single factor ($r = 1$), (*e.g.*, Holtz-Eakin, Newey and Rosen (1988)). This follows from the fact that when $f_t = 1$ for all t, $\lambda_i f_t = \lambda_i$, and when $\lambda_i = 1$ for all i, $\lambda_i f_t = f_t$. However, the general additive effects $\alpha_i + \xi_t$ being a special case of multiple interactive effects appears to be less noticed. The point is that the class of interactive effect models is much larger than that of additive effect models. For $r > 2$, there exist non-trivial interactive effects.

Owing to potential correlations between the unobservable effects and the regressors, some authors (see Bai (2009)) treat λ_i and f_t as fixed effect parameters to be estimated. This is the basic approach for controlling for unobserved heterogeneity, see Chamberlain (1984) and Arellano and Honore (2001). Indeed, Bai (2009) allows the observable X_{it} to follow

$$X_{it} = \tau_i + \varpi_t + \sum_{k=1}^{r} a_k \lambda_{ik} + \sum_{k=1}^{r} b_k f_{tk} + \sum_{k=1}^{r} c_k \lambda_{ik} f_{tk} + \pi_i' g_t + \eta_{it} \tag{14}$$

where g_t is another set of common factors not influencing u_{it}. Thus X_{it} can be correlated with λ_i alone, or with f_t alone, or simultaneously correlated with λ_i and f_t. In fact, X_{it} can be a nonlinear function of λ_i and f_t.

The literature on common factors for panel data is now huge (see Anderson et al (2006)) but many applications concern the FAR (see eq(5)) or the random error model with common factors f_t : $y_{it} = X_{it}\beta + u_{it}$ with $u_{it} = \lambda_i' f_t + \varepsilon_{it}$. For instance, recently Gonçalves and Perron (2010) propose a bootstrapping FAR in a very specific model: $y_t = \beta' W_t + \alpha' f_t + \varepsilon_t$ where the

[1] CCME: cross-correlated mean group estimator, AMG: average mean group estimator (see Pesaran (2006), Eberhardt and Teal (2011)).

unobserved regressors f_t are the common factors in the following panel factor model: $X_{it} = \lambda_i' f_t + \eta_{it}$. Moench, Ng and Potter (2009) propose dynamic hierarchical factors models to characterize within-block and between-block variations as well as idiosyncratic noise in large dynamic panels. Their model is estimated using a Markov Chain Monte-Carlo algorithm that takes into account the hierarchical structure of the factors. Komujer and Ng (2010) propose an indirect estimation of a model with latent error components: $y_{it} = X_{it}\beta + \lambda_i' f_t + \varepsilon_{it}$ with $X_{it} =\lambda_i' g_t + x_{it}$. Kneip, Sickles and Song (2012) estimate time-varying individual effects based on smoothing spline techniques and principal components analysis, etc.
But, a few authors have used FAR on panel data with time invariant common factors. Lanjouw and Schankerman (2004) have estimated the log of research productivity at the firm level on the level of log sales and a time average patent quality index for the firm. This patent quality index was obtained in a first step by factor analysis as the estimated common factor of claims, citations, family sizes and technology areas of patents. Based on an initial screening of data for 175 countries and more than 100 potentially relevant indicators, Fagerberg and Srholec (2008) narrowed down their sample to 115 countries and 25 indicators. With factor analysis, and using 2 subsets of 3-year averages of these 25 indicators on $1992-1994$ and $2002-2004$, they have defined 4 mesures of capabilities (innovation systems, governance, political system and openess). Once these estimated factor scores where obtained, Fagerberg and Srholec (2008) ran a standard factor-augmented regression "*à la Barro*" of the annual growth of GDP per capita on the log of initial GDP per capita and the difference in the capabilities (between the two time periods). Nobody, to our knowledge, has estimated a FAR on panel data with multiple indicator factor models.

4 The factor-augmented regression model: frequentist *versus* Bayesian approaches

Let us suppose that, in the FAR, Z_{it} is a $(1 \times K_Z)$ vector of inputs where K_Z is large, we need to re-write equation (5):

$$\left\{ \begin{array}{lll} y_{it} & = & X_{it}\beta + \zeta' f_t + u_{it} \ , \ u_{it} = \alpha_i + \xi_t + \varepsilon_{it} \\ \begin{pmatrix} Z_{1,it} \\ Z_{2,it} \\ \vdots \\ Z_{K_Z,it} \end{pmatrix} & = & \begin{pmatrix} \lambda_i'^{(1)} & & & \\ & \lambda_i'^{(2)} & & \\ & & \ddots & \\ & & & \lambda_i'^{(K_Z)} \end{pmatrix} (e_{K_Z} \otimes f_t) + \begin{pmatrix} e_{1,it} \\ e_{2,it} \\ \vdots \\ e_{K_Z,it} \end{pmatrix} \end{array} \right. \tag{15}$$

where e_{K_Z} is a $(K_Z \times 1)$ vector of ones. The ideal would be to estimate simultaneously the above system of equations with the matrix of factor loadings $\lambda_i^{(k)}$and the slope parameters β and ζ. The main problem is that to estimate a $(r \times 1)$ vector of common factors f_t we would need a $(T \times NK_Z)$ matrix Z, whereas generally we have only a $(T \times N)$ matrix Z. There is a thus a serious identification problem.

But, if we still want to use the two dimensions of the panel data indicators we can introduce additively both p_N individual common factors $q_i = \left(q_{i_1}, ..., q_{i_{p_N}}\right)'$ and p_T time common factors $f_t = (f_{t_1}, ..., f_{t_{p_T}})'$. These individual common factors may be interpreted as capabilities. In our case, the FAR specification becomes:

$$\left\{ \begin{array}{lll} y_{it} & = & X_{it}\beta + \underset{(1\times p_N)}{\delta'} \underset{(p_N\times 1)}{q_i} + \underset{(1\times p_T)}{\mu'} \underset{(p_T\times 1)}{f_t} + \alpha_i + \xi_t + \varepsilon_{it} \\ & = & X_{it}\beta + v_{it} \\ \underset{(L_N\times 1)}{\overline{Z}_i} & = & \underset{(L_N\times p_N)}{\Lambda} \underset{(p_N\times 1)}{q_i} + \underset{(L_N\times 1)}{e_i} \\ \underset{(L_T\times 1)}{\overline{Z}_t} & = & \underset{(L_T\times p_T)}{\Gamma} \underset{(p_T\times 1)}{f_t} + \underset{(L_T\times 1)}{e_t} \end{array} \right. \tag{16}$$

where $\overline{Z}_i = \left(\overline{Z}_{i,1}, ..., \overline{Z}_{i,L_N}\right)'$, $\overline{Z}_t = \left(\overline{Z}_{t,1}, ..., \overline{Z}_{t,L_T}\right)'$. $\overline{Z}_{i,l}$ are the individuals means $\left(= \sum_{t=1}^{T} Z_{it,l}/T\right)$ with $L_N \leq K_Z$ and $\overline{Z}_{t,m}$ are the time means $\left(= \sum_{i=1}^{N} Z_{it,m}/N\right)$ with $L_T \leq K_Z$. Λ (resp. Γ) is a matrix of constants called the individual factor loading matrix (resp. the time factor loading matrix)

such that:

$$\Lambda q_i = \begin{pmatrix} \lambda_{11} & \cdots & \lambda_{1p_N} \\ & \ddots & \\ \lambda_{L_N 1} & \cdots & \lambda_{L_N p_N} \end{pmatrix} \begin{pmatrix} q_{i_1} \\ \vdots \\ q_{i_{p_N}} \end{pmatrix} \text{ and } \Gamma f_t = \begin{pmatrix} \gamma_{11} & \cdots & \gamma_{1p_T} \\ & \ddots & \\ \gamma_{L_T 1} & \cdots & \gamma_{L_T p_T} \end{pmatrix} \begin{pmatrix} f_{t_1} \\ \vdots \\ f_{t_{p_T}} \end{pmatrix} \tag{17}$$

The e_i (resp. the e_t) are assumed to be mutually uncorrelated and multivariate normally distributed. This specification can be viewed as a general factor-augmented two-way error component model.
Such specification allows for the possibility that TFP is in part common to all countries $(\mu^{'} f_t + \xi_t)$, (*i.e.*, representing the global dissemination of scientific knowledge) and in part country-specific $(\delta' q_i + \alpha_i)$. So, it leads to a more interesting economic interpretation than the standard common factor model of eq.(**??**): $y_{it} = X_{it}\beta + \lambda_i' f_t + \varepsilon_{it}$.

4.1 The multi-step frequentist approach

We can use a multi-step estimation method with factor analysis for the first two steps, which give the estimated factor scores for individuals means $\widetilde{q_{ij}}$ $\left(= E\left[q_{ij}|\overline{Z}_{i,l}\right]\right)$ (resp. for time means $\widetilde{f}_t \left(= E\left[f_t|\overline{Z}_{t,m}\right]\right)$). In these two steps, generated regressors $\left(\widetilde{q_{i_1}}, ..., \widetilde{q_{i_{p_N}}}\right)$ and $\left(\widetilde{f_{t_1}}, ..., \widetilde{f_{t_{p_T}}}\right)$ can be obtained as the fitted values from regressions of multiple-indicators $\left(\overline{Z}_{i,l}\right)$ (resp. $\left(\overline{Z}_{t,m}\right)$) related to the individual latent common factors $(q_{i_1}, ..., q_{i_{p_N}})$ (resp. the time latent common factors $(f_{t_1}, ..., f_{t_{p_T}})$). Regression scores will appear as expected values of the factors, given the indicators (see Bartholomew et al. (2009)). The third step uses ML estimator of the two-way error component model.
Since we have not derived the asymptotic properties of this multi-step approach, estimation may lead to biased and inefficient estimators in the third step and we don't know if the condition $\left(\sqrt{T}/N \to 0\right)$ has two equivalents for $\overline{Z}_{i,l}$ and $\overline{Z}_{t,m}$. If we transpose the Bai and Ng (2006) condition for not having to adjust the standard errors at the second step we obtain the conditions$\left(\sqrt{N}/L_N \to 0\right)$ and $\left(\sqrt{T}/L_T \to 0\right)$, which are unlikely to hold for short panels.

4.2 The Bayesian approach

One way to avoid these problems in this frequentist multi-step method is to estimate jointly, in one step, the system (16). This can be done using the Bayesian approach (see Press and Shigemasu (1997)). The e_i (resp. the e_t) are assumed to be mutually uncorrelated and multivariate normally distributed as $MN(0, \Psi)$ (resp. as $MN(0, \Phi)$). Ψ and Φ are not assumed to be diagonal. In other words, the probability laws $\ell(.)$ of y_{it}, $\overline{Z}_i$ and $\overline{Z}_t$ are:

$$\begin{cases} \ell\left(y_{it}|X_{it}, \beta, \delta, \mu, \sigma_\varepsilon^2\right) & = & N\left(X_{it}\beta, \sigma_y^2\right) \\ \ell\left(\overline{Z}_i|\Lambda, q_i, \Psi\right) & = & MN\left(\Lambda q_i, \Psi\right) \\ \ell\left(\overline{Z}_t|\Gamma, f_t, \Phi\right) & = & MN(\Gamma f_t, \Phi) \end{cases} \tag{18}$$

with $\sigma_y^2 = \delta'\delta + \mu'\mu + \sigma_\alpha^2 + \sigma_\xi^2 + \sigma_\varepsilon^2$ or equivalently:

$$\begin{pmatrix} y_{it} \\ \overline{Z}_i \\ \overline{Z}_t \end{pmatrix} \sim MN\left(\begin{pmatrix} X_{it}\beta \\ \Lambda q_i \\ \Gamma f_t \end{pmatrix}, \begin{pmatrix} \sigma_y^2 & \delta'\Lambda' & \mu'\Gamma' \\ \Lambda\delta & \Psi & 0 \\ \Gamma\mu & 0 & \Phi \end{pmatrix}\right) \tag{19}$$

Following Lindley and Smith (1972) (see Bresson and Hsiao (2011), Bresson et al. (2011)), we express model (16) in three stages of hierarchy.

1. The first stage of the hierarchy postulates the joint density function of the data $\left(y_{it}, \overline{Z}_i, \overline{Z}_t\right)$ conditional on $(X_{it}, q_i, f_t, \pi, \Lambda, \Gamma)$ such that:

   $$p\left(y_{it}, \overline{Z}_i, \overline{Z}_t|X_{it}, q_i, f_t, \pi, \Lambda, \Gamma\right) \propto p\left(y_{it}|X_{it}, q_i, f_t, \pi\right).p\left(\overline{Z}_i|q_i, \Lambda\right) p\left(\overline{Z}_t|f_t, \Gamma\right) \tag{20}$$

   where $\pi = (\beta', \delta', \mu')'$.

2. The second stage of the hierarchy postulates the prior distributions of $\left(\pi, \Lambda, \Gamma, \sigma_\alpha^2, \sigma_\xi^2, \sigma_\varepsilon^2, \Psi, \Phi\right)$:

   $$p\left(\pi|X_{it}\right) \sim MN\left(\overline{\pi}, \Omega_\pi\right) \tag{21}$$

   $$p\left(\Lambda|\overline{Z}_i\right) \sim MN\left(\overline{\Lambda}, \Omega_\Lambda\right) \tag{22}$$

   $$p\left(\Gamma|\overline{Z}_t\right) \sim MN\left(\overline{\Gamma}, \Omega_\Gamma\right) \tag{23}$$

$$p\left(\Psi^{-1}\right) \sim W_{L_N}\left(\left(\rho_\Psi R_\Psi\right)^{-1}, \rho_\Psi\right) \tag{24}$$

$$p\left(\Phi^{-1}\right) \sim W_{L_T}\left(\left(\rho_\Phi R_\Phi\right)^{-1}, \rho_\Phi\right) \tag{25}$$

$$p\left(\sigma_\alpha^2\right) \sim IG\left(\frac{\tau_\alpha}{2}, \frac{\eta_\alpha}{2}\right) \tag{26}$$

$$p\left(\sigma_\xi^2\right) \sim IG\left(\frac{\tau_\xi}{2}, \frac{\eta_\xi}{2}\right) \tag{27}$$

$$p\left(\sigma_\varepsilon^2\right) \sim IG\left(\frac{\tau_\varepsilon}{2}, \frac{\eta_\varepsilon}{2}\right) \tag{28}$$

3. The third stage of the hierarchy postulates the prior distributions of $\left(\overline{\pi}, \overline{\Lambda}, \overline{\Gamma}\right)$:

$$\overline{\pi} \sim MN\left(\overline{\overline{\pi}}, \Omega_{\overline{\pi}}\right) \ , \overline{\Lambda} \sim MN\left(\overline{\overline{\Lambda}}, \Omega_{\overline{\Lambda}}\right) \text{ and } \overline{\Gamma} \sim MN\left(\overline{\overline{\Gamma}}, \Omega_{\overline{\Gamma}}\right) \tag{29}$$

We have supposed that Ψ^{-1} follows a Wishart distribution (a multivariate generalization of the gamma distribution) with scale matrix $(\rho_\Psi R_\Psi)$ and degrees of freedom ρ_Ψ. We have also supposed that σ_α^2, σ_ξ^2 and σ_ε^2 are independent and follow inverse-gamma distributions. The scale hyperparameter $\left(\frac{\eta_\alpha}{2}, \frac{\eta_\xi}{2} \text{ or } \frac{\eta_\varepsilon}{2}\right)$ control the precision of the priors. Small values of $\left(\frac{\eta_\alpha}{2}, \frac{\eta_\xi}{2} \text{ or } \frac{\eta_\varepsilon}{2}\right)$ correspond to precise priors and the view that σ_α^2, σ_ξ^2 or σ_ε^2 are probably constant over individuals, implying nearly homoscedastic disturbances. Large values of $\left(\frac{\eta_\alpha}{2}, \frac{\eta_\xi}{2} \text{ or } \frac{\eta_\varepsilon}{2}\right)$ convey the view that disturbances may be quite variable or heteroscedastic. Generally, in order to implement the Gibbs sampler, we fix values of shape $\left(\frac{\tau_\alpha}{2}, \frac{\tau_\xi}{2} \text{ or } \frac{\tau_\varepsilon}{2}\right)$ and scale $\left(\frac{\eta_\alpha}{2}, \frac{\eta_\xi}{2} \text{ or } \frac{\eta_\varepsilon}{2}\right)$ hyperparameters.

Let $Z^{(i)\prime} = \left(\overline{Z}_1, ..., \overline{Z}_N\right)$, $Z^{(t)\prime} = \left(\overline{Z}_1, ..., \overline{Z}_T\right)$, $Q^{(i)\prime} = (q_1, ..., q_N)$ and $F^{(t)\prime} = (f_1, ..., f_T)$. Combining the priors (21)-(29) with the data $\left(y_{it}, \overline{Z}_i, \overline{Z}_t\right)$, we can obtain the posteriors of $\theta = \left(\pi, \Lambda, \Gamma, \Psi, \Phi, \sigma_\alpha^2, \sigma_\xi^2, \sigma_\varepsilon^2\right)$:

$$
\begin{aligned}
p\left(\theta | y_{it}, \overline{Z}_i, \overline{Z}_t\right) \propto & \prod_{i=1}^{N}\prod_{t=1}^{T}\left(2\pi\sigma_y^2\right)^{-\frac{1}{2}}\left\{\exp\left[-\frac{1}{2\sigma_y^2}\left(y_{it}-X_{it}\beta\right)'\left(y_{it}-X_{it}\beta\right)\right]\right\} \\
& \times|\Psi|^{-\frac{N}{2}}\exp\left[-\frac{1}{2}\mathrm{tr}\Psi^{-1}\left(Z^{(i)}-Q^{(i)}\Lambda'\right)'\left(Z^{(i)}-Q^{(i)}\Lambda'\right)\right] \\
& \times|\Phi|^{-\frac{T}{2}}\exp\left[-\frac{1}{2}\mathrm{tr}\Phi^{-1}\left(Z^{(t)}-F^{(t)}\Gamma'\right)'\left(Z^{(t)}-F^{(t)}\Gamma'\right)\right] \\
& \times|\Omega_\pi|^{-\frac{1}{2}}\exp\left[-\frac{1}{2}\left(\pi-\overline{\pi}\right)'\Omega_\pi^{-1}\left(\pi-\overline{\pi}\right)\right] \\
& \times|\Omega_\Lambda|^{-\frac{1}{2}}\exp\left[-\frac{1}{2}\left(\Lambda-\overline{\Lambda}\right)'\Omega_\Lambda^{-1}\left(\Lambda-\overline{\Lambda}\right)\right] \\
& \times|\Omega_\Gamma|^{-\frac{1}{2}}\exp\left[-\frac{1}{2}\left(\Gamma-\overline{\Gamma}\right)'\Omega_\Gamma^{-1}\left(\Gamma-\overline{\Gamma}\right)\right] \qquad (30) \\
& \times\left(\sigma_\alpha^{-2}\right)^{\frac{\tau_\alpha}{2}+1}\left(\frac{\eta_\alpha}{2}\right)^{\frac{\tau_\alpha}{2}}\exp\left[-\sigma_\alpha^{-2}\frac{\eta_\alpha}{2}\right] \\
& \times\left(\sigma_\xi^{-2}\right)^{\frac{\tau_\xi}{2}+1}\left(\frac{\eta_\xi}{2}\right)^{\frac{\tau_\alpha}{2}}\exp\left[-\sigma_\xi^{-2}\frac{\eta_\xi}{2}\right] \\
& \times\left(\sigma_\varepsilon^{-2}\right)^{\frac{\tau_\varepsilon}{2}+1}\left(\frac{\eta_\varepsilon}{2}\right)^{\frac{\tau_\varepsilon}{2}}\exp\left[-\sigma_\varepsilon^{-2}\frac{\eta_\varepsilon}{2}\right] \\
& \times|\Psi|^{-\frac{1}{2}(\rho_\Psi-L_N-1)}\exp\left[-\frac{1}{2}\mathrm{tr}\left[\left(\rho_\Psi R_\Psi\right)\Psi^{-1}\right]\right] \\
& \times|\Phi|^{-\frac{1}{2}(\rho_\Phi-L_T-1)}\exp\left[-\frac{1}{2}\mathrm{tr}\left[\left(\rho_\Phi R_\Phi\right)\Phi^{-1}\right]\right]
\end{aligned}
$$

Unfortunately, there is no closed form for the posteriors. The posterior distributions of $\theta=\left(\pi,\Lambda,\Gamma,\Psi,\Phi,\sigma_\alpha^2,\sigma_\xi^2,\sigma_\varepsilon^2\right)$, given the observed data, are very complicated and are not amenable to analytical calculation or to direct Monte Carlo sampling. Hence MCMC is used to approximate the desired posterior distributions and we use the statistical package OpenBUGS (the open source variant of WinBUGS, see Spiegelhalter, Thomas and Best (2000)).

In principle, all prior distributions are specified to be as noninformative as possible. A multivariate normal distribution, $N(0_K, 10^2 I_K)$ is chosen for the $(K\times 1)$ vector of hyperparameters $\overline{\pi}$. In order to increase the speed of convergence, we use the one-way FE estimates for hyperparameters of the intercept, capital and labor variables. An inverse-gamma prior $(0.1, 0.1, 0.1)$

is chosen for the variance parameters σ^2_α, σ^2_ξ and σ^2_ε. Selecting a prior for the covariance matrices Ω_Λ and Ω_Γ turned out to be a more interesting and challenging problem. The conjugate prior, inverse Wishart with scale matrix R_Ψ (resp. R_Φ) and degrees of freedom ρ_Ψ (resp. ρ_Φ), is commonly used in practice. The degrees of freedom must satisfy $\rho_\Psi \geq L_N$ (resp. $\rho_\Phi \geq L_T$) to yield a proper prior distribution. The prior scale matrices R_Ψ and R_Φ are set to $10^{-2} I_{L_N}$ and $10^{-2} I_{L_T}$. $\overline{\overline{\pi}}$ is a $(K \times 1)$ zero vector and $\Omega_{\overline{\pi}} = 10^2 I_K$. $\overline{\overline{\Lambda}}$ and $\overline{\overline{\Gamma}}$ are initialized as estimated factor loadings coming from the factor analysis. $\Omega_{\overline{\Lambda}} = 10^{-1} I_{L_N}$ and $\Omega_{\overline{\Gamma}} = 10^{-1} I_{L_T}$. Results from convergence diagnostics indicated that it was sufficient to burn in the first $5,001$ samples and take the subsequent $10,000$ samples.

5 The dataset

The data for the indicators that we use to infer the common factors in the cross section and time series dimensions are taken from the World Development Indicators compiled by the World Bank from officially recognized international sources[2] and the CANA dataset (Castellacci and Natera (2011)). For the productivity equation, we use the GDP (in 1997 constant USD), the capital stock[3] (in 1997 constant USD and base year PPPs), the labor force and the population from 82 countries over a 19-year period (from 1990 to 2008).

In our search for useful indicators we are driven by two criteria: first, we expect the common factors to pertain to innovation, infrastructure and institutions indicators, and second, we retain variables that are available for a great number of countries and for which there are not too many missing observations[4] over time. In the end we choose 21 indicators from 82 countries over a 19-year period (from 1990 to 2008).

[2] See http://data.worldbank.org/data-catalog/world-development-indicators

[3] The capital stock is computed from the gross capital formation data by the permanent inventory formula:

$$\begin{aligned} K_{it} &= (1-\delta) K_{it-1} + I_{it} \ , \ I_{i1} = (\delta + g_y) K_{i0} \\ g_y &= \left(\frac{\Delta Y}{Y} \right)_{90-92} \ , \ \delta = 5\% \end{aligned}$$

[4] Missing values were linearly interpolated instead of using missing imputation methods.

The 5 technological indicators are:

- R&D expenditures (in 1997 USD),
- US patents granted per country of origin
- Royalties and license fees (in 1997 USD),
- Scientific publications,
- Trademark applications

The 7 infrastructure indicators are

- Telecommunication revenue (in 1997 USD),
- Internet users,
- Secure internet servers,
- Mobile and fixed-line subscribers,
- Electricity consumption (in kwh),
- Paved roads as a percentage of the whole roads' length of the country
- Registered carrier departures worldwide

The 9 institution indicators are:

- Index democracy and autocracy, from +20 (democratic) to 0 (autocratic)
- Electoral self-determination, from 0 (no freedom) to 3 (high freedom)
- Political rights, from 1 (low freedom) to 7 (total freedom)
- Civil liberties, from 1 (low freedom) to 7 (total freedom)
- Women's rights, from 0 (low women rights) to 9 (high women rights)
- Physical integrity human rights, from 0 (no Government respect) to 8 (full Government respect)

- Freedom of press, degree of print, broadcast, and internet freedom, from 0 (no freedom) to 100 (high freedom)

- Freedom of speech, from 0 (Government censorship) to 2 (No Government Censorship)

- Freedom of association, from 0 (total restriction) to 2 (no restriction)[5],[6].

6 The results

6.1 The benchmark

We first give results of one-way fixed effects (FE) regressions for productivity equations. We regress the log of the output per capita on 3 variables (log of capital per capita, log of labor per capita and a trend) (see Table 1). The FE model leads to constant returns of scale with elasticities of capital and labor of 0.41 and 0.45. The exogeneous technical progress proxied by a time trend is estimated to be 2.3%. The constant returns to scale assumption cannot be rejected at a 10% level. The estimated coefficient of capital is close to those found by Easterly and Levine (2001). The absence of a correlation between the three inputs and the individual effects is rejected by the Hausman test, and hence also the validity of the random effects model. The variance of these individual effects represents more than 98% of the total residual variance. When we explicity assume constant returns to scale (column 2), the capital elasticity of output is estimated to be 0.408 leading to similar results as without imposing constant returns to scale. One may be surprised to get such a high estimated elasticity of capital (more than 0.4) but this result is quite usual and reminiscent of many problems in estimating production functions on macro data. We generally observe unstable elasticities of

[5] The data for all 21 indicators, except secure internet servers and trademark applications, come from the CANA dataset.

[6] Missing values were replaced by interpolation for each country. The number of interpolated observations are 7 for GDP, labor and population, R&D, patents, royalty, and telecom revenue, 11 for GDP growth, 26 for gross fixed capital formation, 12 for GDP deflator, 159 for trademark applications, and 994 for internet servers. Negative values for some of the variables have been replaced by the lowest positive values in the sample: R&D (100000, 7 cases), royalty (1000, 37 cases), patents (1, 328 cases), publications (0.5, 35 cases), trademark applications (10, 30 cases), internet users (10, 220 cases), internet servers (1000, 466 cases).

capital (or labor) on macro panels. For instance, Martin and Mitra (2002), with a panel of 50 countries and using a Cobb-Douglas production function imposing constant returns to scale, estimate a capital coefficient at 0.69 for manufacturing (resp. 0.12 for agriculture). Under perfect competition, the coefficient of capital in the value-added production function can be assimilated to the physical capital share in aggregate income (*i.e.*, approximately one-third for capital share and two-thirds for labor share). But, considerable variations in the factor shares across countries have been pointed out (see Durlauf *et al.* (2005), Eberhardt and Teal (2011)). For instance, labor shares range from 5% to 80% of the aggregate value-added (United Nations (2004)) and this deviation is attributed to the mismeasurement of labor income in less-developed countries. Furthermore, as emphasized by Eberhardt and Teal (2011), a majority of empirical studies produce capital coefficients far in excess of 0.3.
Adding the 21 indicators Z_{it} (column 3) strongly reduces the elasticity of capital from 0.4 to 0.2, which is compensated by impacts of electricity consumption (0.16), telecom revenue (0.10), and to a lesser extent carrier departures (0.03), patents (0.014), R&D (0.012), ... Institutional indicators do not seem to have significant effects or for some variables surprising signs. Now, the constant returns to scale assumption is strongly rejected. Again, the absence of correlation between the regressors and the individual effects is rejected by the Hausman test. Although the sum of the factor elasticities of labor and capital is way below 1, indicating decreasing returns to scale, the estimated coefficients do not vary tremendously and the signs are basically the same as when we do not impose constant returns to scale (see column 4). As mentioned previously, estimation of such a specification with a large number of predictors (*i.e*, the Z_{it}) on a panel of countries with the usual panel data estimators (FE, RE or LSDV) leads to the curse of dimensionality if we try to include them all at once. As emphasized by Bai and Ng (2008), we need to use a small number of factors, as conditioning variables, to get a parsimonious way to capture the main information instead of using a handful of predictors.

6.2 The individual and time factor scores

All variables are log-transformed. For the 82 countries over the $1990-2009$ period, $L_N = 21$ individual means ($\overline{z}_{i,l}$) of indicators are constructed. For the construction of the time means ($\overline{z}_{t,m}$) we only keep the 14 indicators with

the largest time variabilities.
As usual in factor analysis, the variables are standardized. We use the mean and standard deviation of $(\overline{z}_{i,l})$ for $l = 1, ..., L_N$ and of $(\overline{z}_{t,m})$ for $m = 1, ..., L_T$. It implies that a change of a composite variable over individuals (resp. over time) will reflect changes in each country's position relative to the other countries (resp. changes in the importance of the underlying indicators over time, relative to other indicators).
As we have 3 groups of indicators (technology, infrastructures and institutions), we specify our FAR model as:

$$\begin{cases} y_{it} & = & \begin{array}{c} X_{it}\beta + \delta'_{techno} q_{i,techno} + \delta'_{infra} q_{i,infra} + \delta'_{instit} q_{i,instit} \\ +\mu' f_t + \alpha_i + \xi_t + \varepsilon_{it} \end{array} \\ \overline{Z}_{i,techno} & = & \Lambda_{techno} q_{i,techno} + e_{i,techno} \\ \overline{Z}_{i,infra} & = & \Lambda_{infra} q_{i,infra} + e_{i,infra} \\ \overline{Z}_{i,instit} & = & \Lambda_{instit} q_{i,instit} + e_{i,instit} \\ \overline{Z}_t & = & \Gamma f_t + e_t \end{cases}$$

We could have merged all the 21 indicators. But, we preferred to split them into 3 clusters for two main reasons: first, it seems natural to suppose that indicators belonging to a specific cluster (for instance, the technology cluster) represent a coherent set and are not necessary correlated with other indicators belonging to another cluster (for instance, institutions)[7]. Second, we have tried to estimate the factor scores of the whole 21 indicators. We found only 3 common factors for the individual means, which seems consistent with our expectation, but the ranking of the countries on the basis of the scores lead to a few unrealistic results.
The factor analysis is used to analyze the correlation matrix of the 21 indicators. The factor loadings are computed using the squared multiple correlations as estimates of the communality (the variance shared with other variables).
Since all indicators are normalized, the sum of all eigenvalues of the correlation matrix is the total number of variables. The number of principal components that we should retain depends on how much information (*i.e.*, unaccounted variance) we are willing to sacrifice, which, of course, is a judgemental question. In general and in the case of standardized data, three rules are used:

[7]We would like to thank Jacques Mairesse for this suggestion.

- the Kaiser criterion, which suggests to retain those factors with eigenvalues equal to or greater than 1.

- the scree plot (plot of eigenvalues against each principal component) and its typical elbow form according to which the number of principal components that needs to be retained is given by the elbow.

- the parallel analysis (*i.e.*, a regression equation to estimate the eigenvalues for random data for standardized data inputs (see Allen and Hubbard (1986)) according to which the observed eigenvalues should be higher than the estimated eigenvalues obtained from this regression.

The Kaiser criterion, the scree plot and the parallel analysis suggest to retain only one factor (see Figures 1, 2 and 3) for the technological indicators, the infrastucture indicators and the institution indicators. The factor explains 76.94% (resp. 63.49%, 81.72%) of the total variance for the 5 technological indicators (resp. the 7 infrastructure indicators and 9 institution indicators). Table 2 shows that all the variables have, in general, high positive weights: from 0.80 for publications to 0.95 for R&D among the technological capabilities, from 0.51 for electricity revenue to 0.95 for internet servers among the infrastructure capabilities, and from 0.77 for the political rights to 0.97 for the physical rights among the institutional capabilities. As all factor loadings are of the same sign and roughly of the same order of magnitude, the principal components for our three clusters of variables do indeed capture common factors.
The Bayesian approach gives similar results[8]. Table 3 reports the posterior mean, the standard error and the Monte Carlo standard error of the mean (MC error, see Roberts (1996)) of the factor loadings for the individual means of indicators. One way to assess the accuracy of the posterior estimates is by calculating the Monte Carlo error (MC error) for each parameter. This is an estimate of the difference between the mean of the sampled values (which we are using as our estimate of the posterior mean for each parameter) and the true posterior mean. As a rule of thumb, the simulation should be run until the Monte Carlo error for each parameter of interest is less than about 10% of the sample standard error (see Brooks and Gelman (1998)).

[8]For the Bayesian approach to be comparable to the frequentist approach, we forced the number of common factors for each cluster of indicators to be equal to one, as what we found with the frequentist approach.

On Figure 4, the Kaiser criterion, the scree plot and the parallel analysis also suggest to retain only one time common factor, which explains 90% of the total variance of the time averages of the 14 individual indicators. One could argue that this factor mesures common shocks or "*time trends*". Table 4 shows that all 14 variables have positive weights higher than 88% indicating again the common factor interpretation of the first principal component. The Bayesian approach gives again similar results.
Figures 5, 6 and 7 rank countries according to the estimated factors scores using the frequentist and Bayesian approaches. One can note a few differences between the two methods by and large the two approaches display the same distribution. We shall concentrate on the results from the Bayesian approach for reasons laid out in the next section. The interesting result concerns the relative positions of the countries for the technological, infrastructure and institutional capabilities. In each figure, we have also drawn the $\pm 0.5\sigma$ and $\pm\sigma$ confidence intervals (shortdash dot and dash lines). These confidence intervals include respectively the 38% and the 68% of the distribution around the mean. The $\pm\sigma$ confidence interval allows us to define 4 groups of country:

- $[-2; -\sigma]$: low capabilities
- $]-\sigma; 0]$: medium low capabilities
- $]0; +\sigma]$: medium high capabilities
- $]+\sigma; 2]$: high capabilities.

Remember that the three factor scores follow a standard normal distribution. The individual factor scores for our 82 countries will hence be distributed according to this standard normal distribution. Regarding the technological common factor, we notice the usual suspects at the upper end of the distribution (with high capabilities): the G-7 countries, but also some countries like Spain, Belgium, Switzerland, Sweden and Australia and two of the BRICS countries, China and Brazil. Most of the other EU countries, the remaining three BRICS countries and the countries of the G-20 group belong to the medium-high group. It is somewhat astonishing that Israël and Finland do not belong to the high group. To a large extent the ranking of the countries in the four categories remains the same for the infrastructure and institutions common factors with a few notable exceptions: the BRICS countries fall into the medium-low category regarding infrastructure and India even in the lowest category. Many of the latest new member states in the

EU belong to the medium-high category possibly thanks to the structural adjustment funds from the EU. It is on the institutional front that there is the highest concentration of countries in the two tails of the distribution. China and Russia now belong to the low-group, South Africa and India to the medium-low and Brazil to the medium-high. Again, the most developed countries belong to the high end of the distribution while many of the African countries are at the lower end of the distribution.
Figure 8 gives the estimated time scores using the frequentist and the Bayesian approach showing a linear time trend over the period 1990-2008. Figures 9, 10, and 11 confirm the positive correlations between the GDP per capita means of countries (in logs) and these estimated factors. The correlation is most pronounced for the pair GDP per capita - infrastucture capabilities (the adjusted R^2 of the regressions are respectively 0.65, 0.89 and 0.54 for technological, infrastructure and institutional capabilities). Lastly, Figure 12 shows the quasi-linear relation between the average GDP over the 82 countries at each time period (in logs) and the estimated time factor scores.

6.3 The factor-augmented productivity equation

These estimated factor scores, both for the individual means and the time means, are used in the productivity equation as generated regressors. Table 5 gives the ML estimation of the general factor-augmented two-way error component model and the Bayesian posterior means, standard errors and the MC errors of this productivity equation. We have supposed that the GDP per capita (in logs) depends on two inputs: the capital stock per capita (in logs) and the labor force per capita (in logs) augmented with the 4 estimated factor scores: 3 in the individual dimension (technology, infrastructures and institutions) and 1 in the time dimension.
If the estimated elasticity of production relative to capital (0.417) seems plausible, the elasticity of production relative to labor appears under-estimated (0.256). Technological capabilities have a positive effect on productivity (0.23). But, infrastructures seem to have the strongest impact (0.43) and, more surprisingly, institutions have a positive effect on productivity (0.20) quite similar to technological capabilities. Finally, the common trends (0.13) cannot be associated to the the time trend in the standard one-way FE Cobb-Douglas function (estimated at 0.023). This ML estimation of the general FAR two-way error component model leads to strong decreasing returns to scale: the 95% confidence interval is $[0.524; 0.823]$ which seems unrealistic. Moreover,

the mean relative error between observed and estimated output per capita is large : -8.58%.
These unrealistic results may come from biased and inconsistent estimations using the two-step frequentist approach. This will be checked later on with a Monte-Carlo study on the properties of the proposed frequentist and Bayesian estimators. The posterior means obtained with the Bayesian method gives more realistic results. The estimated elasticities for capital and labor are respectively (0.287) and (0.557) leading to quasi-constant returns to scale: $[0.741; 0.949]$. Factor scores on technology, infrastructures and institutions all have a positive effect on productivity: the strongest is associated with infrastructure (0.605), followed by technology (0.255) and institutions (0.198). These estimated coefficients may be interpreted as semi-elasticities, *i.e.*, the percentage change in GDP per capita due to a one unit change (*i.e.*, 1σ) in the capabilities. Finally, a one standard deviation in the time common factor increases TFP by 0.14 percent. With the Bayesian approach, the variance of the individual effect σ_α^2 is similar to that of the FAR regression (0.14) but the variance of the time-specific effect is higher: 0.01 against 0.001. There is no significant difference for the residual variance between the two approaches. The log-likelihood of the productivity equation shows the superiority of the Bayesian approach (1213.91) over the multi-step ML estimation (990.92). This better fit is confirmed by the very low mean relative errors between observed and estimated output per capita : 0.61%.
Figure 13 shows the percentage contribution of TFP to output per capita. The part of output not due to use of factors of production is typically larger for the more developed countries. For only 10 countries of our sample is the contribution of TFP to output per capita lower than 50%. For the top third of our countries this contribution is nearer to 60% and this set regroups mostly the OECD countries. Figure 14 shows that the evolution of this share seems to be increasing over time, a result we had already noticed from the slightly convex curve of the time component in figure 12. The contribution of TFP to output per capita has been increasing by about 2 percentage points over the last 15 years.
Fagerberg and Shrolec (2008) estimate 4 factors using 25 indicators. They do not assume separability between the 4 clusters of indicators, but they notice that some indicators are highly correlated with some factors and little with the others. The two factors that come out significant in their GDP per capita regression are the "innovation system" and "governance". The other two, "political system" and "openness" are insignificant. Their "innovation

system" is essentially our factor "technology", part of our factor "infrastructure" and some variables regarding education that we have not included. Our factor "institutions" is closest to their factor "political system". Their "governance" and "openness" factors are not really captured by our indicators. A positive correlation between the global innovation index (which regroups 7 clusters of variables: institutions, human capital and research, infrastructure, market sophistication, business sophistication, knowledge and technology outputs and creative outputs) is also reported in the Global Innovation Index 2014 (see Cornell University, INSEAD, WIPO, 2014). The Global Innovation Index contains more variables, but is not based on a factor analysis (although robustness experiments have been made using the factor analysis methodology). In summary, our result of positive correlations between our three factors and GDP per capita is confirmed in other studies. The leading role of infrastructure over technology and institutions is something that does not come out so clearly from these other studies.

7 Conclusion

To evaluate the importance of technology, infrastructure and institutions in explaining differences in total factor productivity among 82 countries between 1990 and 2008, we have estimated a factor-augmented GDP equation with 21 technology, infrastructure and institutional indicators and unobserved country- and time-specific individual effects. The data are taken from the World Development Indicators database of the World Bank and the CANA dataset. First, we have done a factor analysis, in which we have allowed for two kinds of common factors, those based on individual (country) means and those based on yearly means. Secondly, we have inserted the individual and time common factors in a factor-augmented productivity equation using the frequentist approach. Thirdly, we have proposed a more robust Bayesian approach based on noninformative priors and a Markov Chain Monte Carlo simulation, where all equations are estimated simultaneously. The Bayesian estimator leads to a better fit and somewhat more reasonable input elasticities. The explanation of TFP is, however, quite similar between the two approaches.

A sizeable portion, for many countries more than 50%, of total factor productivity is explained by the 4 common factors we have introduced. Particularly interesting is the country distribution of the technology, infrastructure and

institutions effects, summarized by their common factors. The greatest portion of the variation is explained by infrastructures, followed by technology and finally institutions. Our results confirm the preeminence of TFP over factor accumulation in growth accounting as also emphasized for example by Easterly and Levine (2001). This is not a new result. What we show in addition is that the TFP residual is driven by three clusters of variables: technology, infrastructure and institutions. We have not tested the direction of causality but we think that it is more likely to run from these factors, which take time to build up, than the other way around. Since there are many ways to measure these influences, we have taken a series of measures related to them and estimated common factors for each of them. These common factors are then included in an extended Cobb-Douglas production function to explain TFP. Our results show that infrastructure is the greatest contributor of TFP, followed by technology and finally institutions. Infrastructures are at least twice as important as technology, whereas often it is assumed that TFP captures just technological change. Finally, our analysis reveals the weaknesses of certain countries regarding some of the determinants to TFP. Our results may of course differ if we introduced another set or a larger set of indicators than the 21 that we have used, for which data were readily available. Some of our original data are obtained by interpolation. Increasing the quality of the construction of the data is another area of future research. For many countries unfortunately too many raw data were missing. Extending the analysis to more countries would be another worthy research endeavor.

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Table 1 - Fixed effects productivity equations

log(gdp/pop)	One-way FE			One-way FE			One-way FE with Zit			One-way RE with Zit		
	coef.	s.e	T-stat	coef.	s.e	T-stat	coef.	s.e	T-stat	coef.	s.e	T-stat
log(capital/pop)	0.4105	0.0178	23.1241				0.1940	0.0195	9.9556			
log(labor/pop)	0.4567	0.0848	5.3861				0.2942	0.0673	4.3729			
trend	0.0230	0.0008	29.5332	0.0223	0.0007	34.0014	0.0148	0.0015	9.5924	0.0125	0.0015	8.0913
log(capital/labor)				0.4088	0.0177	23.0559				0.2108	0.0197	10.6779
log(R&D)							0.0123	0.0031	3.9188	0.0114	0.0032	3.5714
log(patents)							0.0147	0.0047	3.1514	0.0174	0.0048	3.6477
log(royalties)							0.0033	0.0019	1.7543	0.0035	0.0019	1.8176
log(publications)							-0.0294	0.0038	-7.7994	-0.0291	0.0038	-7.5627
log(trademark appl.)							-0.0099	0.0036	-2.7300	-0.0040	0.0036	-1.1051
log(telecom rev.)							0.1051	0.0071	14.8482	0.1052	0.0072	14.5779
log(internet users.)							-0.0071	0.0021	-3.4266	-0.0081	0.0021	-3.8617
log(internet servers)							-0.0015	0.0009	-1.6363	-0.0012	0.0009	-1.3023
log(phones)							0.0120	0.0076	1.5896	0.0101	0.0077	1.3094
log(electricity)							0.1601	0.0180	8.9048	0.1363	0.0181	7.5464
log(carriers)							0.0321	0.0058	5.5749	0.0348	0.0059	5.9526
paved roads							-0.0010	0.0003	-3.0585	-0.0010	0.0003	-2.9796
democracy							-0.0009	0.0015	-0.6290	-0.0016	0.0015	-1.0634
elect. self determ.							0.0015	0.0064	0.2384	-0.0023	0.0065	-0.3458
political rights							-0.0087	0.0049	-1.7767	-0.0063	0.0050	-1.2695
civil liberties							0.0040	0.0055	0.7208	0.0048	0.0056	0.8491
women rights							-0.0054	0.0024	-2.2858	-0.0065	0.0024	-2.7293
physical rights							-0.0073	0.0022	-3.3796	-0.0068	0.0022	-3.0922
freedom press							0.0013	0.0004	3.2040	0.0014	0.0004	3.4504
freedom speech							-0.0033	0.0057	-0.5732	-0.0039	0.0059	-0.6721
freedom assoc.							-0.0111	0.0064	-1.7298	-0.0084	0.0065	-1.2806
var (indiv)	0.7657			0.7619			0.7793			0.7310		
var (epsilon)	0.0132			0.0132			0.0075			0.0078		
Hausman test (p-value)	329.7900	0.0000		325.5800	0.0000		497.5300	0.0000		372.7400	0.0000	
c.r.s (p-value)	2.6300	0.1051					11.8300	0.0006				

Table 2 - Factor loadings - Individual means - Frequentist approach

Variables	Principal component analysis		
	factor 1 q_{1i} technological	factor 2 q_{2i} infrastructures	factor 3 $q3_i$ institutions
log(R&D)	0.9497		
log(patents)	0.8978		
log(royalties)	0.8958		
log(publications)	0.8016		
log(trademark appl.)	0.8330		
log(telecom rev.)		0.6532	
log(internet users.)		0.9244	
log(internet servers)		0.9507	
log(phones)		0.9574	
log(electricity)		0.5080	
log(carriers)		0.8450	
paved roads		0.6088	
democracy			0.9614
elect. self determ.			0.9300
political rights			0.7640
civil liberties			0.7973
women rights			0.9711
physical rights			0.9750
freedom press			0.8791
freedom speech			0.9315
freedom assoc.			0.9013

Table 3 - Factor loadings - Individual means - Bayesian approach (posterior means on 10000 replications)

Variables	Bayesian approach								
	factor 1 q_{1i} technological			factor 2 q_{2i} infrastructures			factor 3 $q3_i$ institutions		
	mean	s.e	MC error	mean	s.e	MC error	mean	s.e	MC error
log(R&D)	0.9543	0.0187	5.76E-04						
log(patents)	0.8729	0.0406	0.001428						
log(royalties)	0.8726	0.03842	7.19E-04						
log(publications)	0.7933	0.0459	0.001049						
log(trademark appl.)	0.8331	0.04059	0.001085						
log(telecom rev.)				0.6402	0.05834	0.001535			
log(internet users.)				0.8835	0.03831	0.001039			
log(internet servers)				0.94	0.02187	5.30E-04			
log(phones)				0.9352	0.02548	7.01E-04			
log(electricity)				0.4236	0.0711	0.001258			
log(carriers)				0.8586	0.03274	8.65E-04			
paved roads				0.5906	0.06026	0.001248			
democracy							0.9477	0.02274	5.23E-04
elect. self determ.							0.925	0.02676	5.37E-04
political rights							0.7542	0.04879	0.001122
civil liberties							0.7524	0.05306	0.001747
women rights							0.9664	0.01591	2.28E-04
physical rights							0.9631	0.01768	3.61E-04
freedom press							0.8703	0.03731	9.03E-04
freedom speech							0.9259	0.02689	6.35E-04
freedom assoc.							0.9036	0.02875	4.32E-04

Table 4 - Factor loadings - Time means - Frequentist and Bayesian approaches

Variables	PCA factor f_t	Bayesian approach factor f_t		
		mean	s.e	MC error
R&D	0.9614	0.9638	0.01501	2.41E-04
Royalty	0.9922	0.9836	0.01123	3.35E-04
Patents	0.9626	0.9549	0.02221	4.65E-04
Publications	0.9570	0.9426	0.02944	6.15E-04
Trademark	0.8852	0.8615	0.03375	9.57E-04
Telecom. Revenue	0.9851	0.9857	0.006729	1.48E-04
Electricity	0.9808	0.9828	0.007893	1.48E-04
Internet users	0.9821	0.9712	0.01714	4.75E-04
Phones	0.9894	0.9888	0.006384	1.92E-04
Internet servers	0.9545	0.9528	0.02042	4.21E-04
carriers	0.9346	0.9363	0.02461	4.35E-04
Paved roads	0.9312	0.9201	0.03149	7.91E-04
Civil liberties	0.8918	0.9044	0.02682	5.82E-04
Democracy	0.9232	0.9055	0.03198	8.80E-04

Table 5 - Factor-augmented productivity equations

log(gdp/pop)	Two-way FAR			Bayesian FAR		
	coef.	s.e	T-stat	post. mean	s.e	MC error
log(capital/pop)	0.4172	0.0167	24.9607	0.2879	0.0522	0.0052
log(labor/pop)	0.2568	0.0790	3.2512	0.5575	0.1292	0.0115
q_{1i} (technological)	0.2304	0.0678	3.3990	0.2553	0.0755	0.0072
q_{2i} (infrastructures)	0.4379	0.0828	5.2856	0.6050	0.0670	0.0061
q_{3i} (institutions)	0.2007	0.0569	3.5275	0.1989	0.0539	0.0050
f_t	0.1300	0.0097	13.4454	0.1407	0.0266	0.0023
intercept	2.5684	0.2609	9.8460	2.5890	0.2191	0.0127
var (indiv)	0.1388			0.1407	0.0317	0.0021
var (time)	0.0015			0.0141	0.0054	0.0001
var (epsilon)	0.0120			0.0127	0.0006	0.0000
log-L (Y_{it})	990.9299			1213.9150		

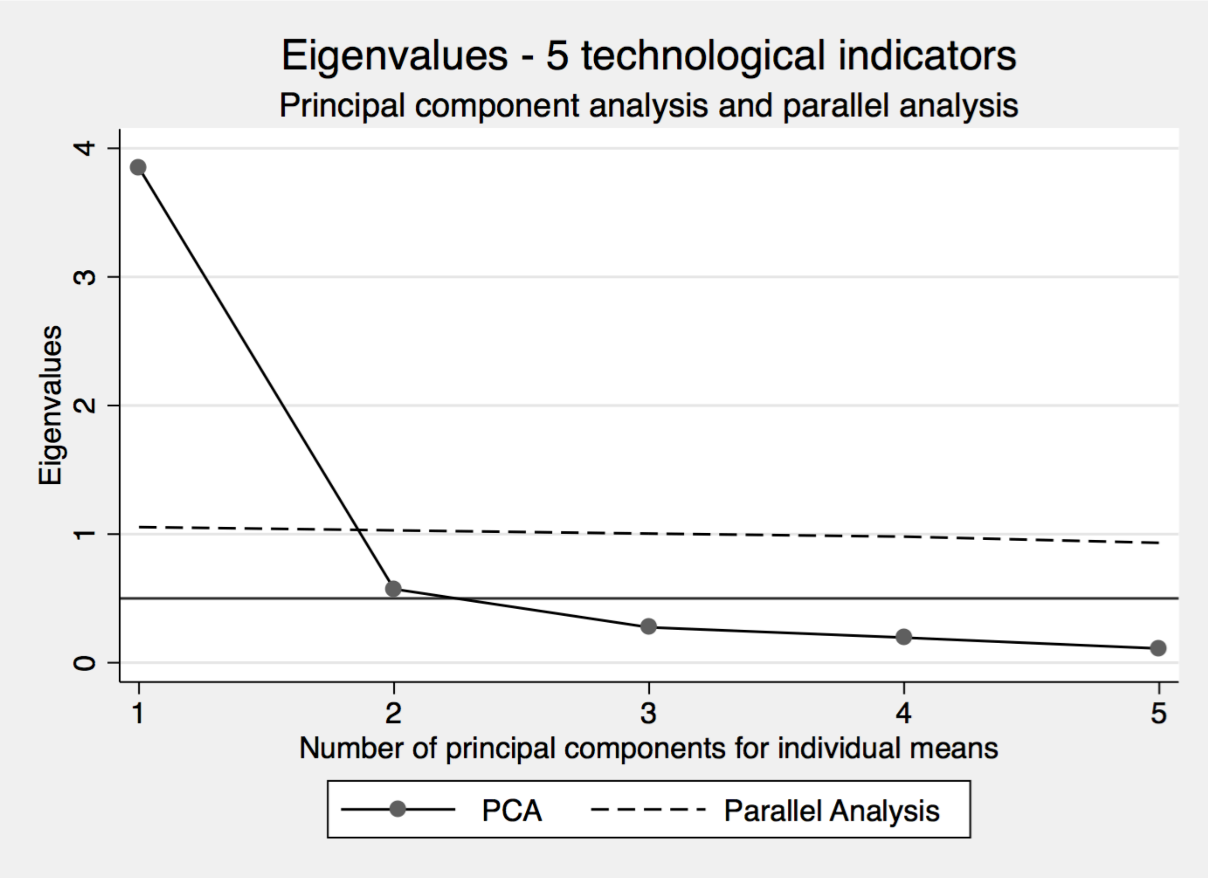


Figure 1.

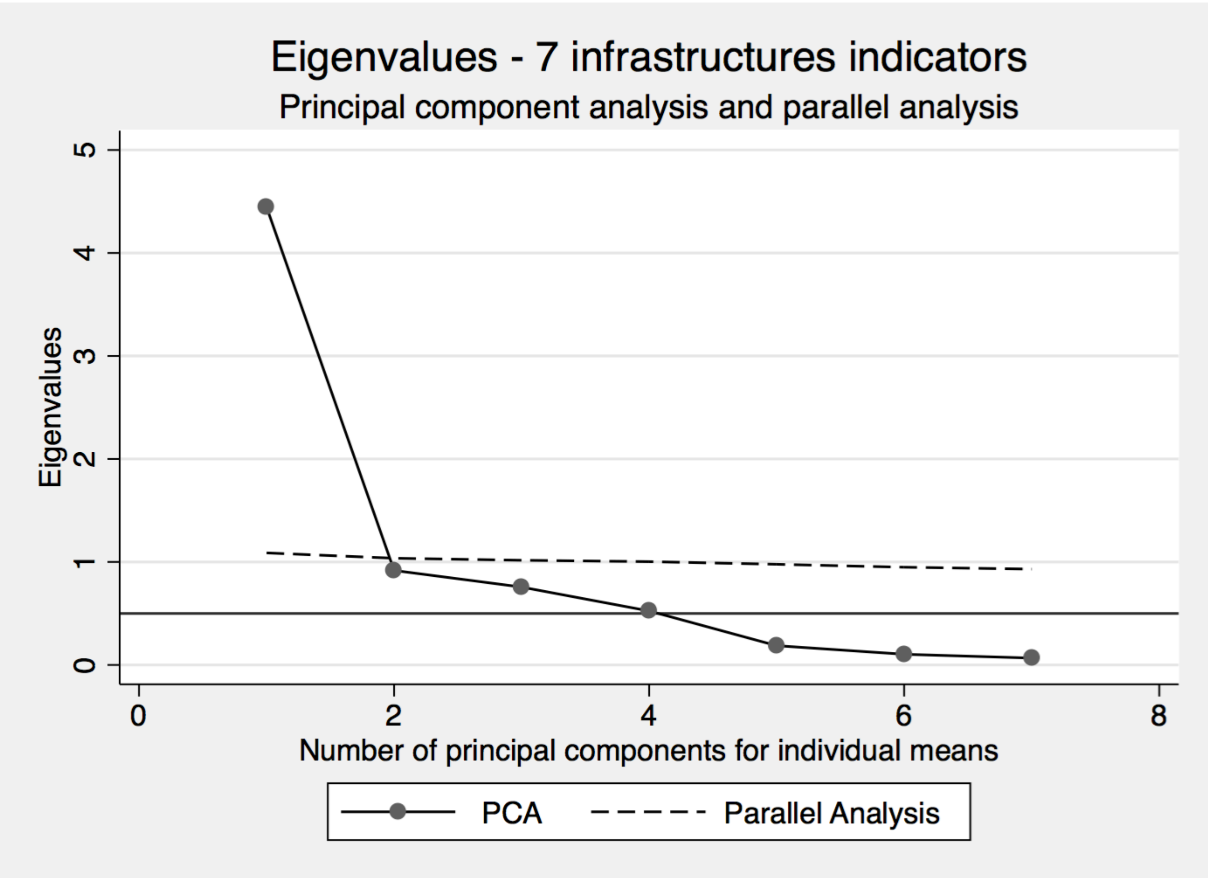


Figure 2.

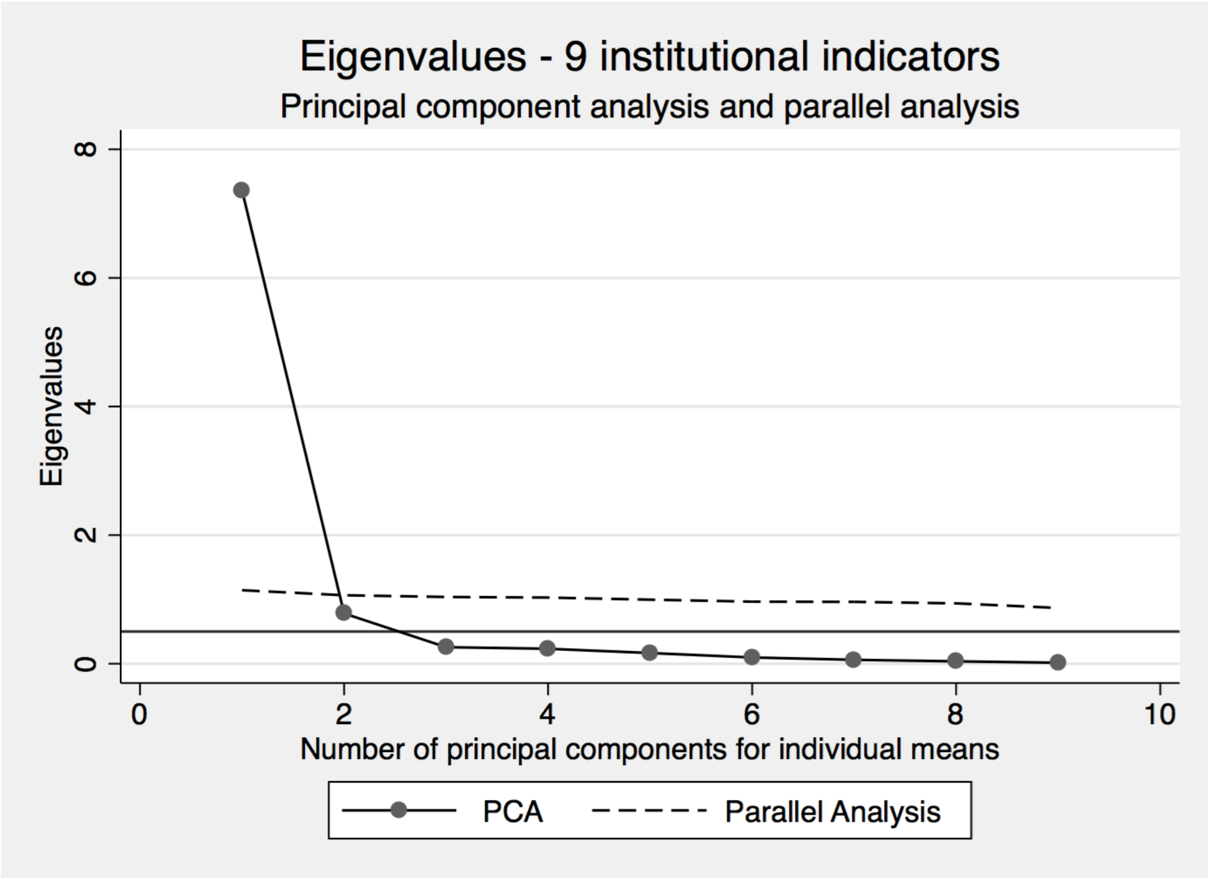


Figure 3.

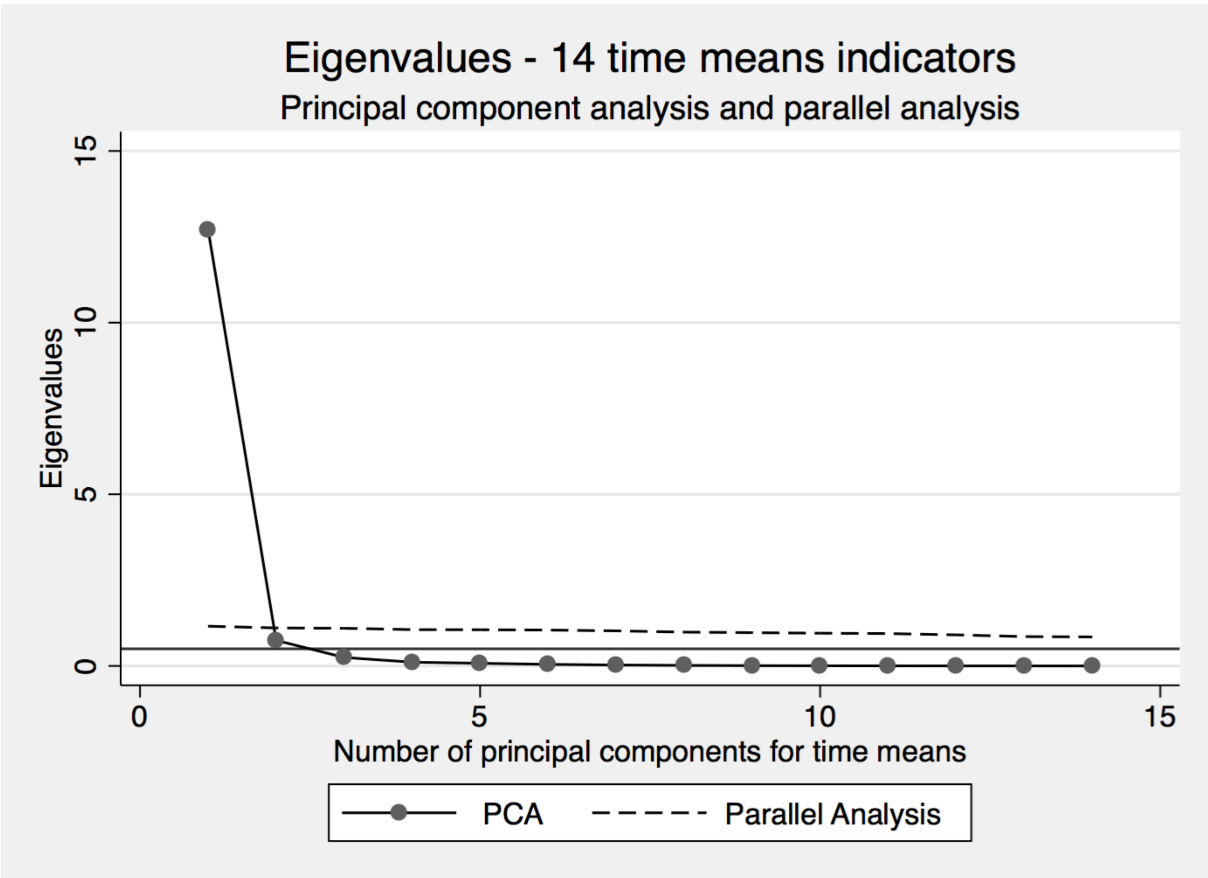


Figure 4.

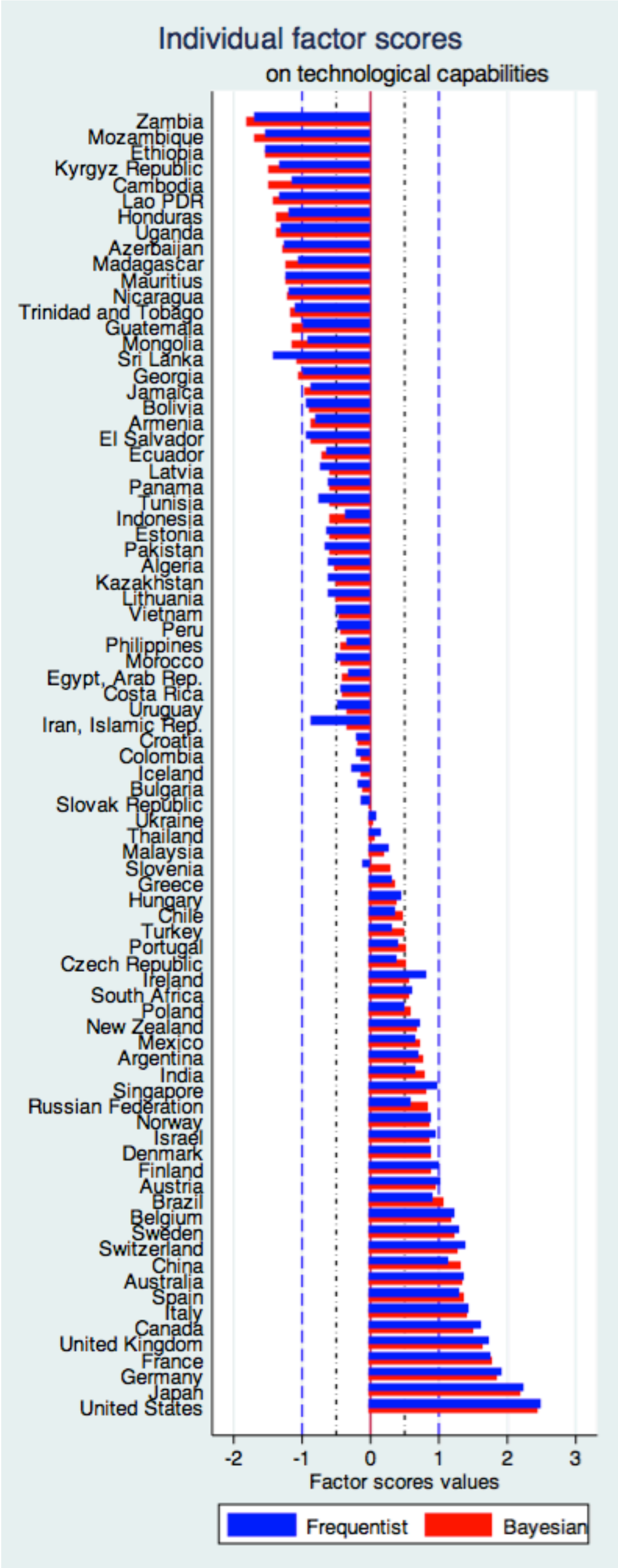
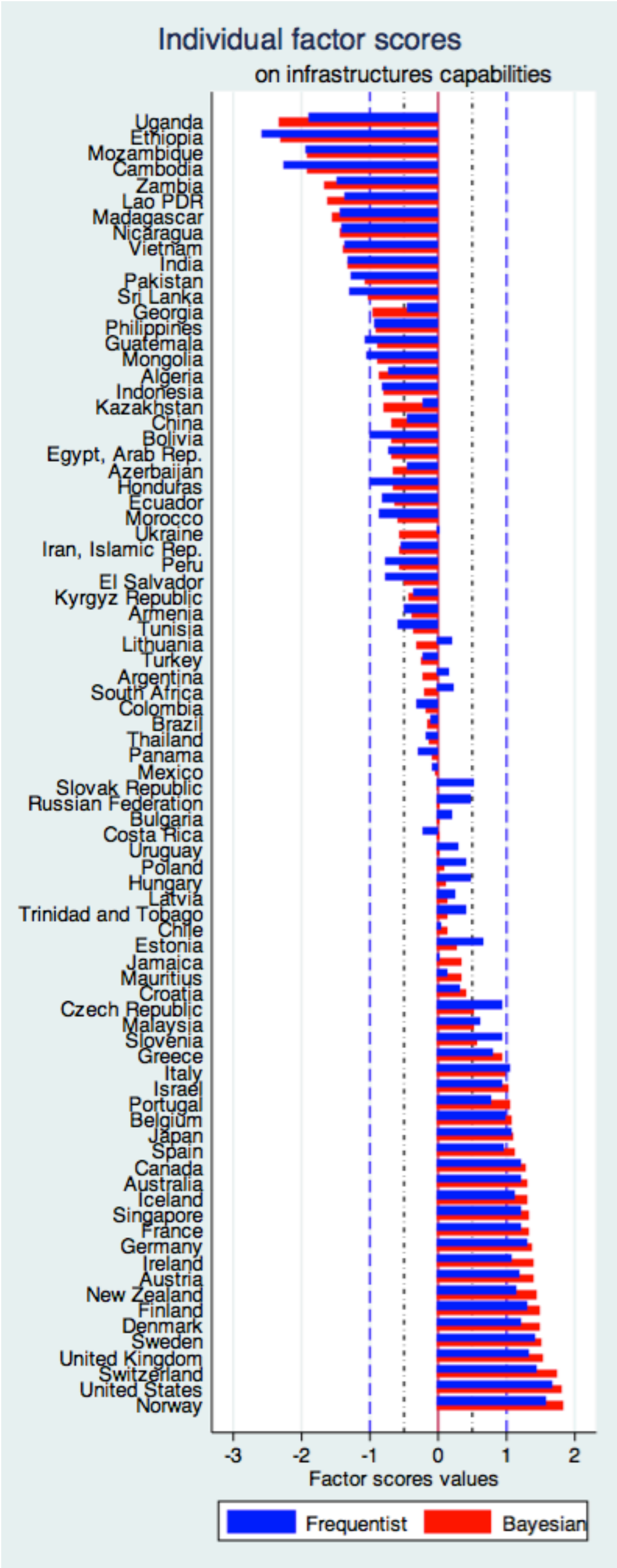
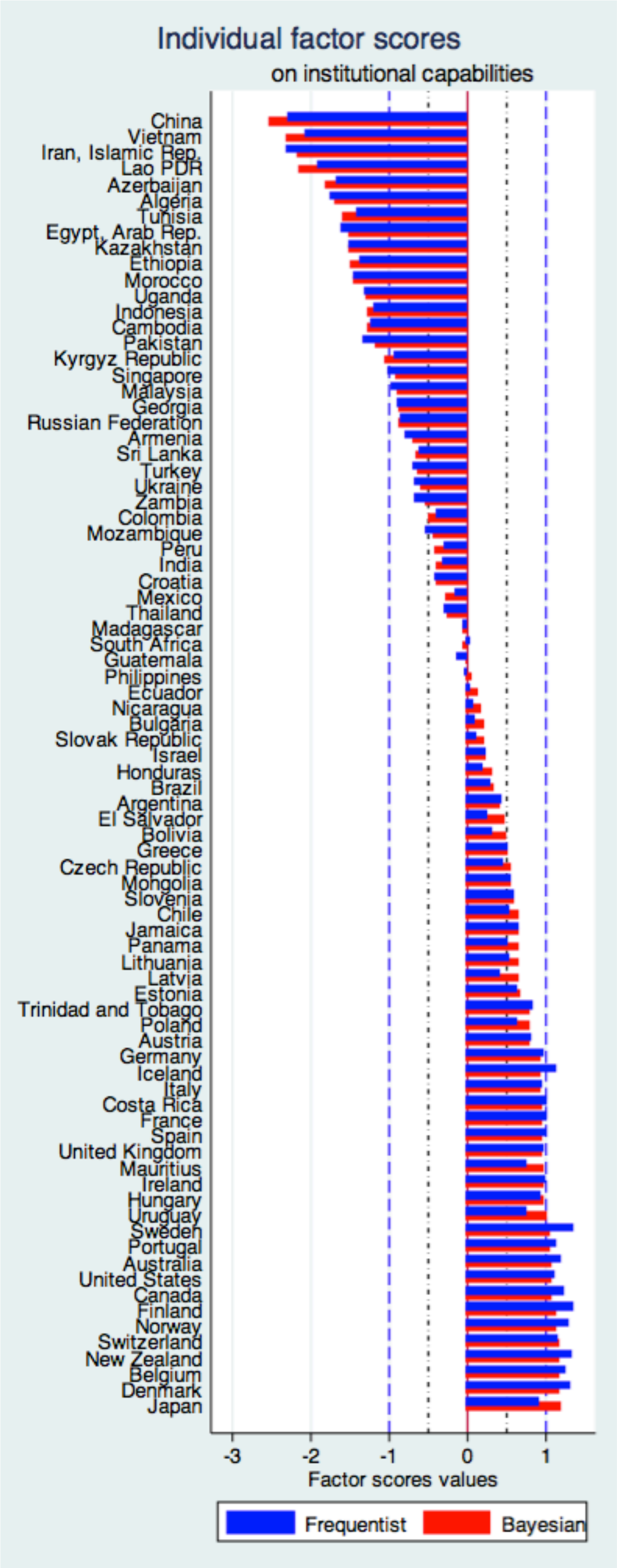

Individual factor scores
on technological capabilities
Zambia
Mozambique
Ethiopia
Kyrgyz Republic
Cambodia
Lao PDR
Honduras
Uganda
Azerbaijan
Madagascar
Mauritius
Nicaragua
Trinidad and Tobago
Guatemala
Mongolia
Sri Lanka
Georgia
Jamaica
Bolivia
Armenia
El Salvador
Ecuador
Latvia
Panama
Tunisia
Indonesia
Estonia
Pakistan
Algeria
Kazakhstan
Lithuania
Vietnam
Peru
Philippines
Morocco
Egypt, Arab Rep.
Costa Rica
Uruguay
Iran, Islamic Rep.
Croatia
Colombia
Iceland
Bulgaria
Slovak Republic
Ukraine
Thailand
Malaysia
Slovenia
Greece
Hungary
Chile
Turkey
Portugal
Czech Republic
Ireland
South Africa
Poland
New Zealand
Mexico
Argentina
India
Singapore
Russian Federation
Norway
Israel
Denmark
Finland
Austria
Brazil
Belgium
Sweden
Switzerland
China
Australia
Spain
Italy
Canada
United Kingdom
France
Germany
Japan
United States
-2
-1
0
1
2
3
Factor scores values
Frequentist
Bayesian

Figure 5.



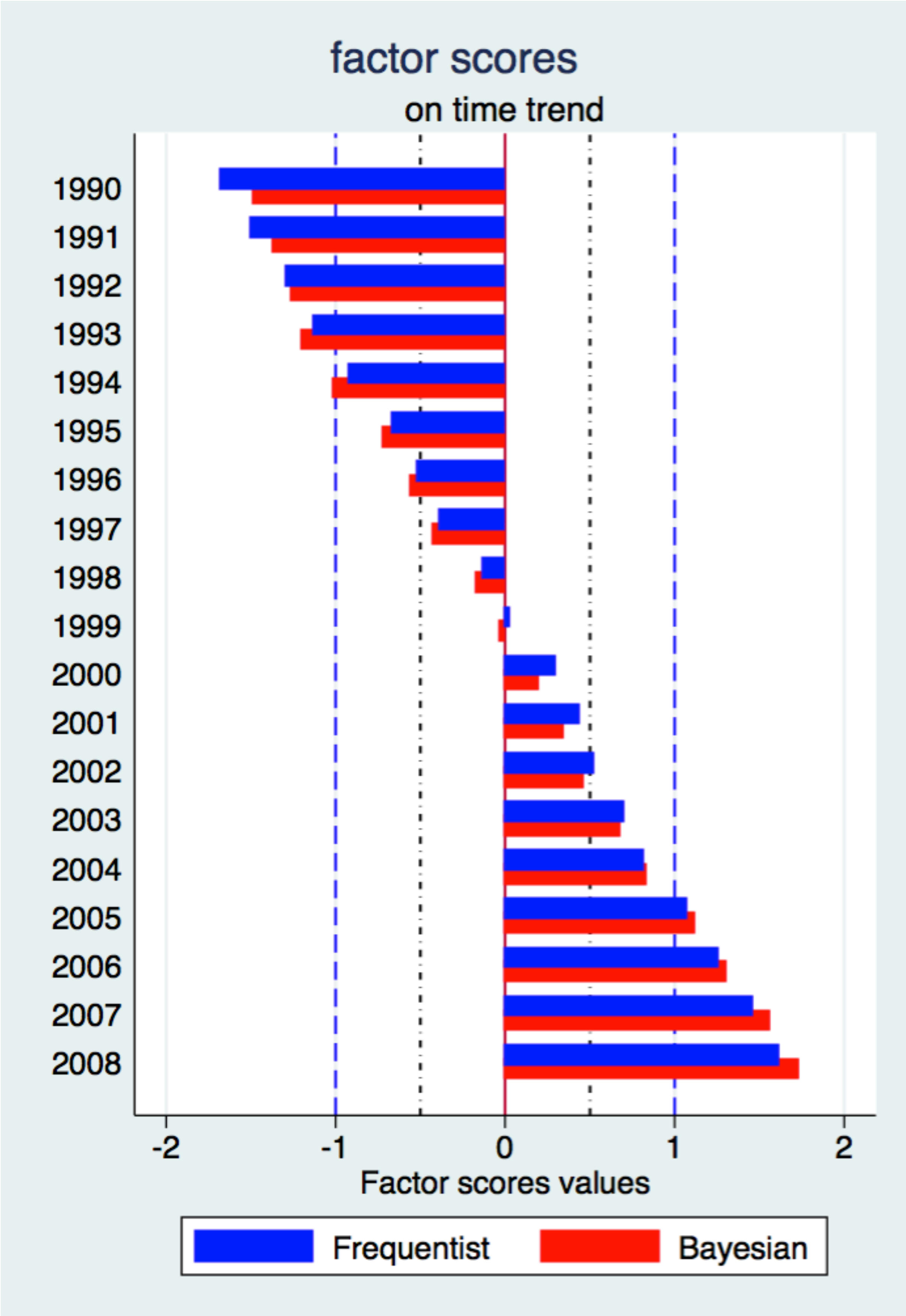
Individual factor scores
on infrastructures capabilities
Uganda
Ethiopia
Mozambique
Cambodia
Zambia
Lao PDR
Madagascar
Nicaragua
Vietnam
India
Pakistan
Sri Lanka
Georgia
Philippines
Guatemala
Mongolia
Algeria
Indonesia
Kazakhstan
China
Bolivia
Egypt, Arab Rep.
Azerbaijan
Honduras
Ecuador
Morocco
Ukraine
Iran, Islamic Rep.
Peru
El Salvador
Kyrgyz Republic
Armenia
Tunisia
Lithuania
Turkey
Argentina
South Africa
Colombia
Brazil
Thailand
Panama
Mexico
Slovak Republic
Russian Federation
Bulgaria
Costa Rica
Uruguay
Poland
Hungary
Latvia
Trinidad and Tobago
Chile
Estonia
Jamaica
Mauritius
Croatia
Czech Republic
Malaysia
Slovenia
Greece
Italy
Israel
Portugal
Belgium
Japan
Spain
Canada
Australia
Iceland
Singapore
France
Germany
Ireland
Austria
New Zealand
Finland
Denmark
Sweden
United Kingdom
Switzerland
United States
Norway
-3
-2
-1
0
1
2
Factor scores values
Frequentist
Bayesian

Figure 6.



Individual factor scores
on institutional capabilities
China
Vietnam
Iran, Islamic Rep.
Lao PDR
Azerbaijan
Algeria
Tunisia
Egypt, Arab Rep.
Kazakhstan
Ethiopia
Morocco
Uganda
Indonesia
Cambodia
Pakistan
Kyrgyz Republic
Singapore
Malaysia
Georgia
Russian Federation
Armenia
Sri Lanka
Turkey
Ukraine
Zambia
Colombia
Mozambique
Peru
India
Croatia
Mexico
Thailand
Madagascar
South Africa
Guatemala
Philippines
Ecuador
Nicaragua
Bulgaria
Slovak Republic
Israel
Honduras
Brazil
Argentina
El Salvador
Bolivia
Greece
Czech Republic
Mongolia
Slovenia
Chile
Jamaica
Panama
Lithuania
Latvia
Estonia
Trinidad and Tobago
Poland
Austria
Germany
Iceland
Italy
Costa Rica
France
Spain
United Kingdom
Mauritius
Ireland
Hungary
Uruguay
Sweden
Portugal
Australia
United States
Canada
Finland
Norway
Switzerland
New Zealand
Belgium
Denmark
Japan
-3
-2
-1
0
1
Factor scores values
Frequentist
Bayesian

Figure 7.



factor scores
on time trend
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
-2
-1
0
1
2
Factor scores values
Frequentist
Bayesian

Figure 8.

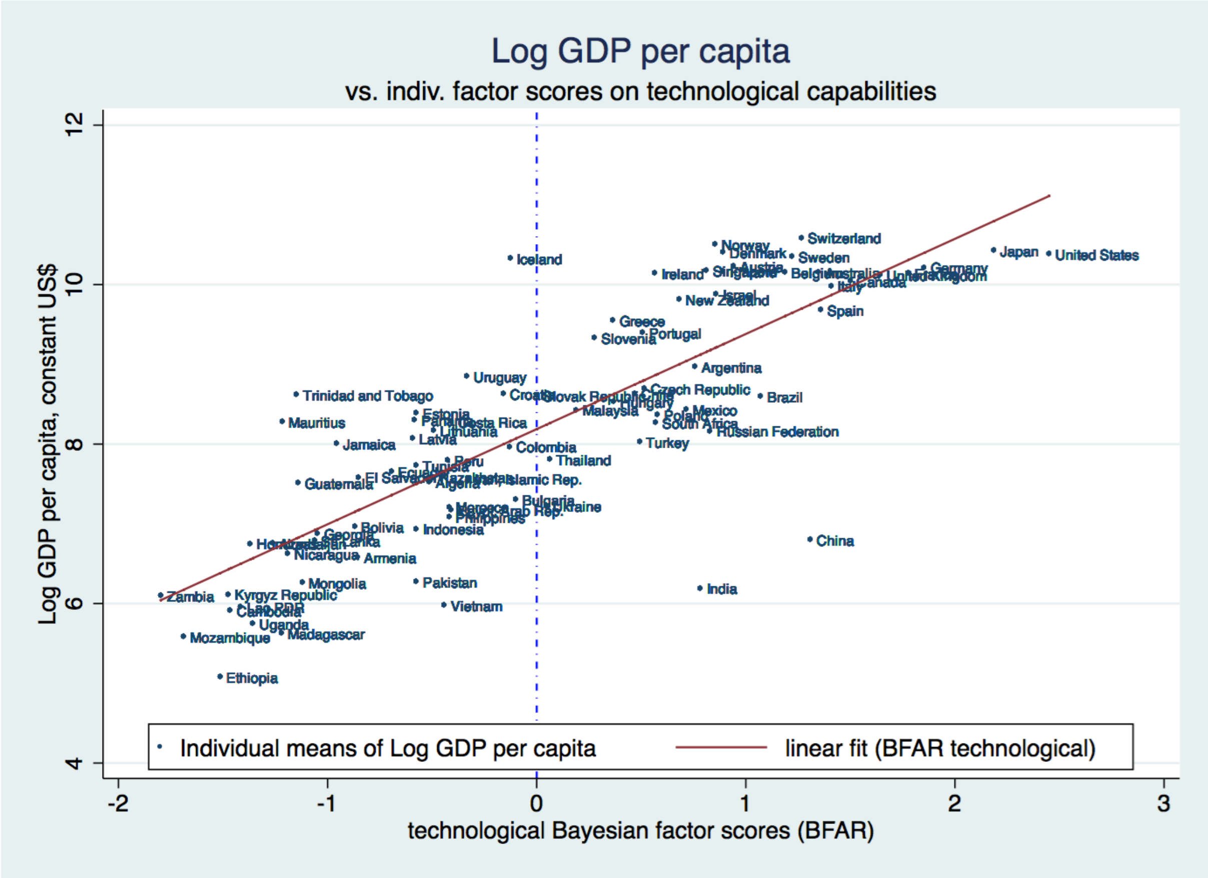


Figure 9.

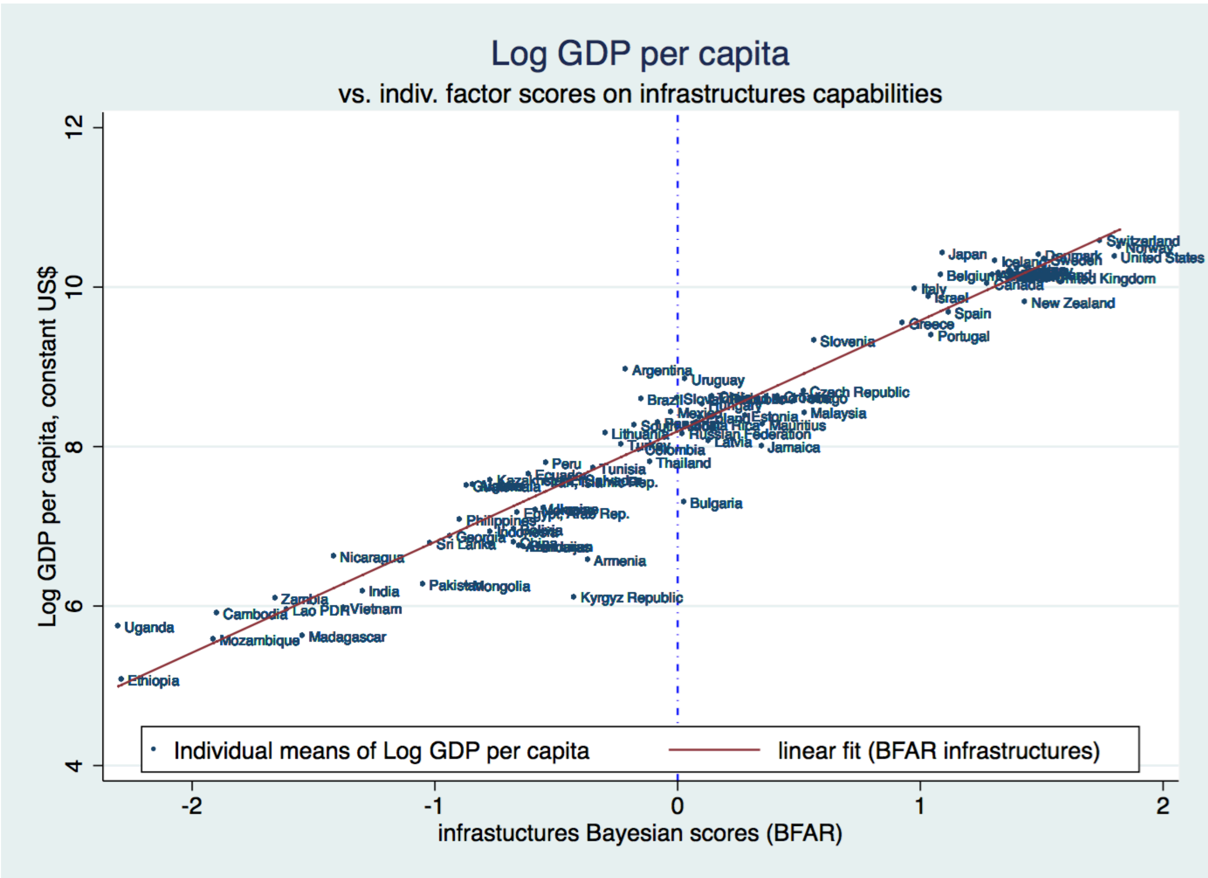


Figure 10.

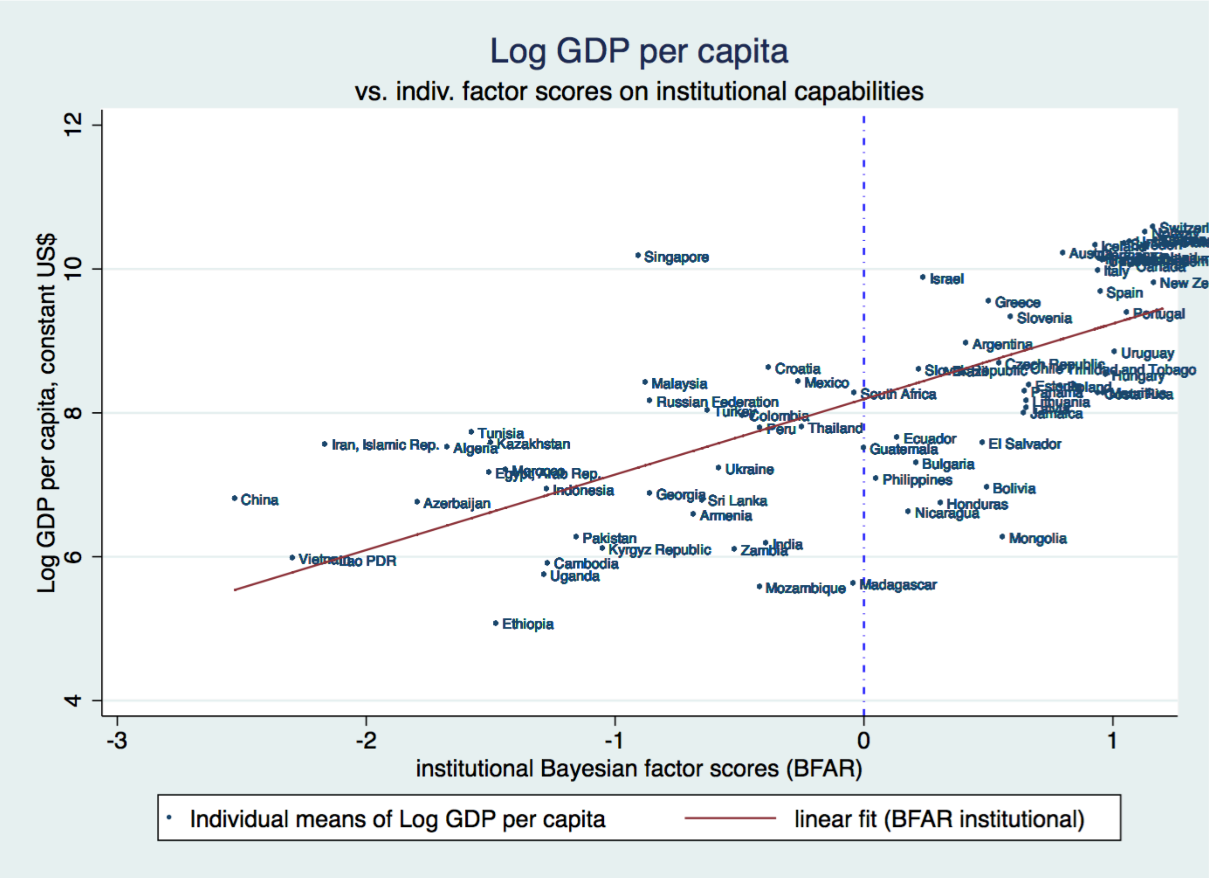


Figure 11.

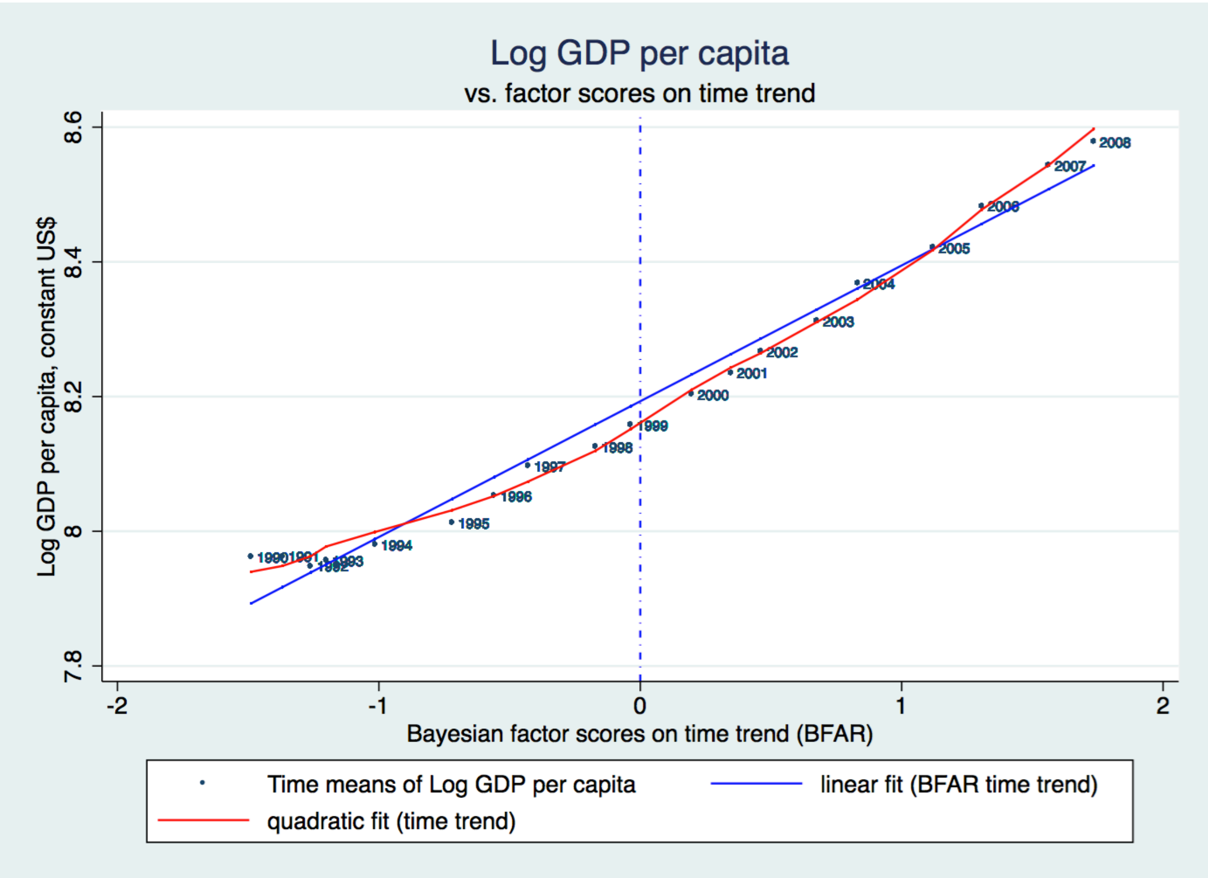
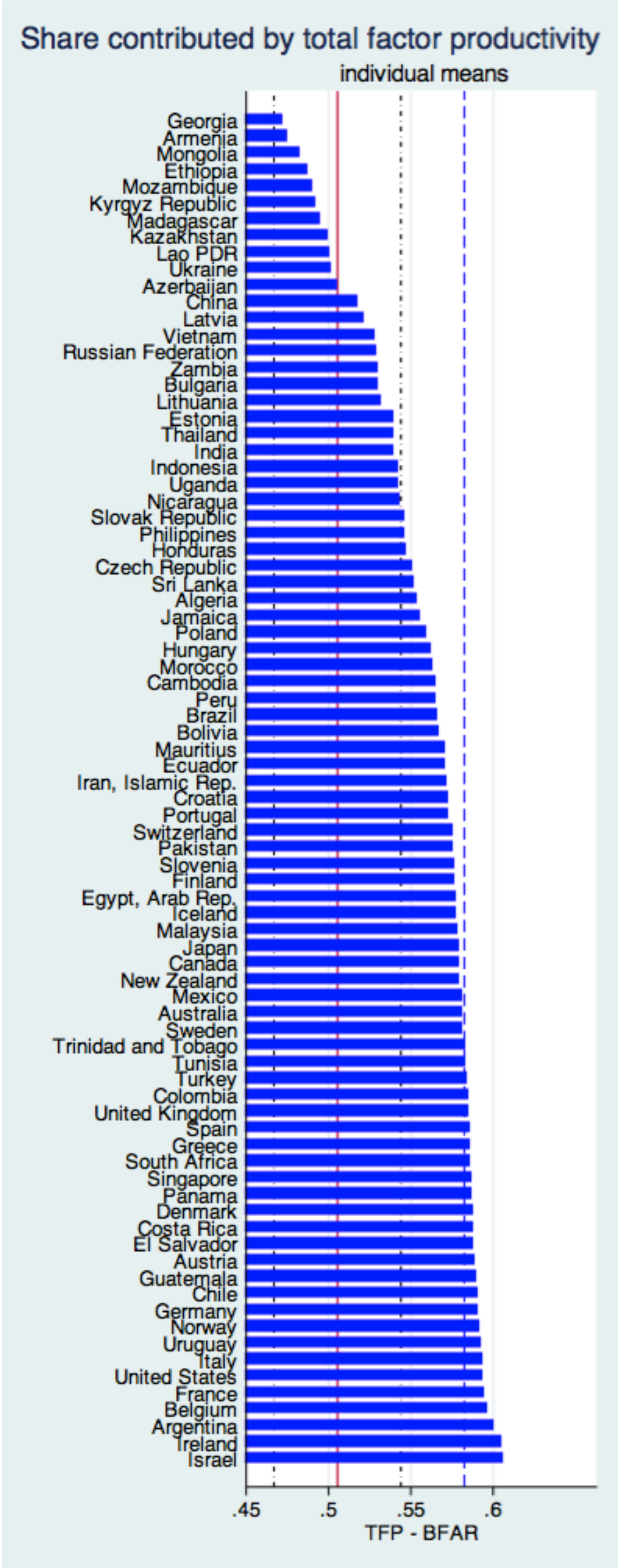


Figure 12.



Share contributed by total factor productivity
individual means
Georgia
Armenia
Mongolia
Ethiopia
Mozambique
Kyrgyz Republic
Madagascar
Kazakhstan
Lao PDR
Ukraine
Azerbaijan
China
Latvia
Vietnam
Russian Federation
Zambia
Bulgaria
Lithuania
Estonia
Thailand
India
Indonesia
Uganda
Nicaragua
Slovak Republic
Philippines
Honduras
Czech Republic
Sri Lanka
Algeria
Jamaica
Poland
Hungary
Morocco
Cambodia
Peru
Brazil
Bolivia
Mauritius
Ecuador
Iran, Islamic Rep.
Croatia
Portugal
Switzerland
Pakistan
Slovenia
Finland
Egypt, Arab Rep.
Iceland
Malaysia
Japan
Canada
New Zealand
Mexico
Australia
Sweden
Trinidad and Tobago
Tunisia
Turkey
Colombia
United Kingdom
Spain
Greece
South Africa
Singapore
Panama
Denmark
Costa Rica
El Salvador
Austria
Guatemala
Chile
Germany
Norway
Uruguay
Italy
United States
France
Belgium
Argentina
Ireland
Israel
.45
.5
.55
.6
TFP - BFAR

Figure 13.

Share contributed by total factor productivity
time means
TFP (total factor productivity) - BFAR
.555
.56
.565
.57
1990
1995
2000
2005
2010
Year

Figure 14.

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