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The impact of institutions on economic growth in selected developing countries: An analysis based on Bayesian panel estimation

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ABSTRACT

This paper presents an empirical analysis of the impact of institutions on the economic growth of 27 developing countries during the period 1990-2014. Many creative models of panel data allow variations in slope coefficients both across time and cross-sectional units. All models were established in a Bayesian structure and their performance was tested by using an interesting application of the effect of institution on GDP. Technical details of all these models are given and tools are presented to compare their performance in the Bayesian system. Besides, panel data models and posterior model pools are provided for an insight into the institution's relationship with economic development. The derivation of Bayesian panel data models is included. The previous data has been used in this study and normal gamma prior is used for the models of panel data. 2SLS estimation technique has been used to analyze the classical estimation of panel data models. In the paper, developing countries were viewed as a whole. The study's evaluated results have shown that panel data models are valid Bayesian methodology models. In the Bayesian approach, the results of all independent variables affect the dependent variable significantly and positively. Based on all model standard defects, it is necessary to say that the Fixed Effect Model is the best in Bayesian panel data estimation methods. It was also shown that in comparison to other models, the fixed-effect model has the lowest standard error value.

Keywords

Bayesian, Gamma priors, Fixed effect, Random effect 2SLS.

1. Introduction

In economics, researchers have increased dramatically in the last 30 years to discover the causes of institutional gaps between countries. Understanding main

transmission mechanisms for the performance of an organization on the quality of individual macroeconomic performance. Most researchers' key treatments are to enhance the efficiency of organizations. The findings of different studies have consistently highlighted the positive effect on economic growth and institutional sustainability. The willingness of institutions to respond and implement new strategies in developing countries to the changing economic situation. The advanced countries have experienced unusual growth rates in the past 25 years. Due to the disparity between initial per capita GDP levels between countries, there is no cause for disparities. The main antenna of most research is that institutional quality enhances the impact of institutional reforms on investment, innovation and economic growth. Analysts are particularly interested in feedback on cause-and-effect relations among the quality of institutions and economic growth which can be relevant to the competent modelling of policies on economic and social development. Many studies have brought increasing emphasis to the positive impact of institutional economic growth and development and affirmation that economic development has resulted in qualitative change and broader social progress. The institution's ability, through its institutions and reform policies, to adapt to changing economic situations and develop new rules and practices on transaction shapes the economy's ability to continue to grow. Institutions must therefore not only change over time to create the momentum and regulations necessary to function effectively within an economy in new markets and techniques (Bruinshoofd, 2016; Masuch et al., 2017; Bartelt et al., 2013; Docquier, 2014; Helgason, 2010; Dixit, 2009).

The institutions are also dependent on economic and political growth. Neoclassical assumption describes the fact that growth will occur where benefits are available. The process of growth and development is hindered by violence. It is one of those evils that our societies face today, and it is particularly compounded in developing countries as people promote violence for wealth and other reasons. Institutions contribute to resolving the social and economic dispute. The infrastructure differences are due to the difference between human equity, education, productivity and the difference between countries. As sample countries retain economic growth, the statistically significant and positive impact of institutions and trade on the per capita growth. The increased rate of regional productivity has a positive and strong impact on countries-specific institutions.

For any economy, institutions are crucial. Its institutions play a key role in determining differences in cross-country revenue through multiple indicators affecting development and growth processes. The conflict, however, exists among researchers in economic literature. Some support this view that economic growth depends on institutional quality, whilst researchers who oppose such opinions say that the institution's analysis is at the first stage. More work is therefore needed in this regard. This study focuses on the research that institutions contribute to the development of developing countries through the analysis of panel data. The primary objective of this paper, To estimate the panel data models using the Bayesian technique and choice of the best Bayesian model. This study is therefore structured. Section 2 discusses the study

and connection of past economic growth (GPD) with equity capital, trade opening, and the four institutions (economic institution, financial institution, social institution and political institution). Section 3 provides information sources, processes and model specimens, panel data models and bayesian derivatives. This section also contains data sources. The analysis and interpretation of section 4 are furthermore included in diagnostic plots. During section 5, the conclusion is presented and policies are discussed.

2. Past studies

Josheski, D. et al., (2011), On cross-country results, econometric techniques were applied only to confirm the prior knowledge that the impact of the institution on growth is positive and highly statistically important. All four models confirmed this evidence. For our data, OLS proved to be a better technique than 2SLS, simply because over-identification tests revealed that the tool cannot be measured exogenous, Hausman tests also revealed that OLS is better at 1 per cent and 5 per cent significance levels than 2SLS. The findings of the OLS and 2SLS have just been verified by the G2SLS estimator and Fixed Effects panel estimators. They used rule of law variable as a surrogate variable for institutions, instruments were not only used for revolutions and independence house ranking but also casualties of war. Moreover, trade is negligible in terms of the effect on GDP growth relative to the efficiency of institutions.

Moral-Benito, E., (2012) used panel data for the period 1960 to 2000 for 73 countries. 35 variables data including dependent variable (GDP) is used in this article. They analysed the data models of the Bayesian panel on economic development. Besides, they used previous information for the panel data model. Some cross-sectional simulations used by averaging the Bayesian model to eliminate the problem of the model's uncertainty. To resolve the uncertainty of the models and endogeneity concerns, this study expands the model of panel data approach with a fixed effect. The results and findings indicated that the value of investment products, distance to main cities of the world and political privileges were the most robust growth determinants in the panel environment.

The institutional impact of economic growth calculated by Acemoglu et al., (2010). They used "executive constraints" to replace institutions' property and showed that it had a direct impact on monetary expansion, economic growth in the long-term, investment and macroeconomic stability.

From 1982 to 1997 (taking data from ICRG), panel data is used by Drury et al., (2006) for over 100 Nations. They looked at the relationship between corruption and democracies and non-democracies and found that, in a democratic context, corruption had little to do with economic development, while, in the case of non-democratic context, corruption had a major impact on the economy.

Lee and Kim (2009) examined the link amongst institutions and economic development by control variables such as education and R & D, where panel details of developed and underdeveloped countries were used. For their analysis, a model of fixed-effect and applied GMM used for approximation. They concluded that institutions and R&D had an important role in economic development for developed countries, whereas economic growth had a negative relationship with R & D for under-developed or emerging countries. They also found that primary education, for developed countries, had a meaningful effect on economic development.

Nawaz. S. et al., (2014) used panel data for fifty-six countries over the period from 1981 to 2010 to investigated the impact of various institutions on economic development. PRS (International Country Risk Guide) data was collected and the models of fixed-effect and random effect by using the framework of GMM were calculated. The methodological investigation of the study indicated a positive link between economic development and institutions. In low-yielding countries, the influence of institutional metrics was good against more productive countries. The investment profile impact was less effective for the growth process in developed countries compared to developing countries. The study demonstrated that institutions were critical for long-term economic development. Compared to developing countries, institutions in developed countries played a key role in growth.

Yıldırım, A., & M. F. Gökalp (2016) examined the link between institutions and macroeconomic displays in terms of developed nations. For this reason, 23 institutions and 12 research variables were used in the 2000-2011 years, analyzing the link amongst institutions and macroeconomics in certain nations, while 38 nations used the study of panel data. The results of the investigation showed that the institution's limitation of foreign investment had a beneficial impact on the country's economic development as a trade barrier. On the other hand, according to the findings of the report, variables such as civil liberties, government spending and collective bargaining affected developed countries' macroeconomic conditions.

From 1971 to 2010, Dutta and Williamson (2016) used a panel of 108 nations. The main motivation for the analysis was the influence of the assistance on economic independence, which is restricted to the efficiency of politically aware bodies. By examining the effect of assistance on the provisional value of democratic institutions on economic freedom, they concluded that for democracies, aid could gain economic freedom, while for autocracies, aid could minimize economic independence. Their outcomes were used for decision making. Moreover, they concluded that stable political systems did not help those countries that need assistance from other countries.

3. Research Methodology

To analyse the effect of the most relevant structural dimensions on the economic development of developing countries for the period 1990-2014, a model was constructed for this paper. Ultimately, the model can show that quality institutions in

developing countries are an important driver. The secondary data collection from a credible data source was used in this analysis, primarily to highlight the relationship amongst several organizations and economic development, thus using panel data for the period 1990 to 2014 (24 years) for the case of 27 developing nations of the International Development Association (IDA). The World Development Indicator (WDI) was used to extract data from 27 countries. The data is gathered from (WDI) for GDP and Gross Capital Development. The data source for the Foreign Country Risk Guide (ICRG) is used to gather data from various types of organizations. Political, technological, social, and financial threats were expected by the ICRG. The ICRG makes data for 27 nations available on a yearly base. The ICRG used data belonging to investors banks, foreign exporters, and importers, etc. The advantage of using the data of ICRG is that the economic, political and risk of financial business and investment can be known.



3.1 Model specification

The following statistical model is used by Hall and Jones (1999) to evaluate the impact of organizations on financial expansion. Control variables i-e., capital stocks, trade's openness, financial's institutions, economic's institutions, social's institutions and political's institutions are used in the model. The model can be written as.

$$y_{it} = \beta_0 + \beta_1 k_{it} + \beta_2 T_{it} + \beta_3 F_{it} + \beta_4 E_{it} + \beta_5 S_{it} + \beta_6 P_{it} + \mu_{it}$$

Where the dependent variable is the GDP and is represented by Y_{it} , whereas the model's intercept is β_0 ,

k_{it}	Capital's stock
T_{it}	Trade's openness
F_{it}	Financial's Institutions
E_{it}	Economic's Institution
S_{it}	Social's institutions
P_{it}	Political's institutions
μ_{it}	The error of the model.

3.2 Panel Data Regression Models

For periods and cross-section units, there are 3 primary types of data. These forms are as follows: time-related data is known as time-series data and is represented by observations varying for the time duration. The period can be one second, one minute, one hour, one day, one week, one year, etc. Relevant variable data obtained from various units at the same time is referred to as cross-sectional data e.g. Institutional Predictor Data for the year 2015 for 27 developing countries. Data of relevant variable obtained for more than one time period from various units is referred to as pool data, i.e. findings vary for some time as well as for cross-sectional units, e.g. Institutional Indicator Data for the period 1990-2014 for 27 developing countries.

$$Y_{it} = F(x_{it}) + \mu_{it}$$

If one parameter of the model at least varies according to either the time-period or w. r. t transverse units then that model is referred to as the fixed-effect model. The LSDV model assigns intercepting values for heterogeneity to all of its candidate entities.

Consider the following model.

$$y_{it} = \beta_{0i} + \beta_1 k_{it} + \beta_2 T_{it} + \beta_3 F_{it} + \beta_4 E_{it} + \beta_5 S_{it} + \beta_6 P_{it} + \mu_{it}$$

In the above equation, the subscript “i” means we can allow intercepts to vary or differ across countries because all countries have their characteristics. These characteristics are, such as capital stock, trade openness and four institutions etc. The overhead model is known as the fixed-effect model in the sense that every country has its intercept value and does not vary over time means time-invariant. If varies concerning time then we can also introduce time dummies in the model for all time-periods. How we can allow fixed effect intercept to differ among the countries? We can handle this simply by using the dummy variable method. Now we can write as follows

$$y_{it} = \beta_1 + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 \dots \dots + \beta_{27} D_{27} + \beta_1 k_{it} + \beta_2 T_{it} + \beta_3 F_{it} + \beta_4 E_{it} + \beta_5 S_{it} + \beta_6 P_{it} + \mu_{it}$$

Where

D2=1 for country 2,

Otherwise 0;

D3=2 for country 3,

Otherwise zero and so on.

We have 27 countries and we can launch 26 dummies. Kaushik at al., (1984) use “this model for the analysis of combining ability for seed oil content in cotton”

Al through the LSDV or fixed-effects model can be expensive concerning the degree of freedom if several cross-sectional units are surveyed. Supporters of the ECM (error component model) or random effect model gave the idea that if dummy variable show

limited information about the model, we can introduce error term in the model to express this limited information.

It is easy to define the REM as if the model parameters should vary randomly with w.r.t units or periods, so that an introduction of the random error term may take into account random parameter variations.

$$y_{it} = \beta_{0i} + \beta_1 k_{it} + \beta_2 T_{it} + \beta_3 F_{it} + \beta_4 E_{it} + \beta_5 S_{it} + \beta_6 P_{it} + \mu_{it}$$

We can assume that β_{0i} is fixed, instead of treating β_{0i} as a random variable through a mean value of β_0 and the intercept value for an individual. This can be said as

$$\beta_{0i} = (\beta_0 + \varepsilon_i)$$

Where

$$i = 1, 2, 3, \dots \dots N$$

Where ε_i is a random error term with a mean value of zero and variance $\sigma^2\varepsilon$

$$y_{it} = \beta_0 + \beta_1 k_{it} + \beta_2 T_{it} + \beta_3 F_{it} + \beta_4 E_{it} + \beta_5 S_{it} + \beta_6 P_{it} + \varepsilon_{it} + \mu_{it}$$

Where

$$w_{it} = \varepsilon_{it} + \mu_{it}$$

The complex error term consists of two components, “the cross-sectional or individual-specific error component and the combined time-series and cross-sectional error component”. The normal assumptions made by ECM are

- The individual error terms are uncorrelated with each other.
- The individual error term, not autocorrelated with both units and time periods.

If we can estimate this model by using OLS and the above assumptions are not taken into account, their resultant estimates will not efficient. The most valid method in this case we can apply is the GLS method. When regressors are correlated with error term then we can apply instrumental variable technique such as 2SLS or GMM. Abrahamson and Youngs (1992) studied “a stable algorithm for regression analyses using the random-effects model”

3.3 Instrumental variables (2SLS)

To evaluate the impact on Y for that part of X which is associated with Z, the econometrician may use an instrumental variable Z. Since Z is uncorrelated to “e” and “e” must also be uncorrelated to any portion of X that is correlated to Z. A contributory variable-assist the econometrician to discover a portion of X that acts as if it were assigned randomly. A productive selection of instrument is just a dissimilar portion of the identical variable if the economist is concerned about measurement error. There may be errors in the new measure, but they are not likely to be associated with errors in the

first measure or some other element (Murray, 2006). Contributory variables are not an explanation of interest. We do not only use contributory variables as explanator substitutes but use IV's technique to tease out the random component of X (or at least unrelated). For a measurement error, let's create a reliable IV estimator.

$$\begin{aligned}
 Y_i &= \beta_0 + \beta_1 X_i + \varepsilon_i & E(\varepsilon_i) &= 0 \\
 \text{Var}(\varepsilon_i) &= \sigma_\varepsilon^2 < \infty & \text{Cov}(\varepsilon_i, \varepsilon_j) &= 0, \quad i \neq j \\
 M_i &= X_i + v_i & E(v_i) &= 0 \\
 \text{var}(v_i) &= \sigma_v^2 & \text{Cov}(v_i, v_j) &= 0, \quad i \neq j \\
 \text{Cov}(v_i, X_i) &= 0 & \text{Cov}(Z_i, X_i) &\neq 0 \\
 \text{Cov}(Z_i, X_i) &= 0
 \end{aligned}$$

3.4 Outline of the Bayesian Approach

We assume, from the Bayesian point of view, that the unknown parameter information should be characterized in the form of density. We then used the Bayes formula to update the previous information and obtain the posterior density after detecting all the data. In these terms, formulas for the prior-to-posterior transformation have a simple explanation for the normal distributions.

After observing the results, all information about the after the parameter is stored in the posterior distribution. The mean of the posterior is a strong one-point description of this data and is an optimal Bayesian estimator for a loss function class like a quadratic loss. Thus, for Bayesian regression parameter estimators, the prior to-posterior modification formulae directly yield formulae. After the prior knowledge is in the form of a normal density, the formula is easiest.

To estimate the parameters in the model, we use the Bayesian estimation method. The Bayesian research has several benefits over the Classical method of estimation, especially in small samples. Berger (1988) defines some of the benefits as:

1. The Bayesian analysis assumes that the measured parameter is random with some prior density, as opposed to the classical estimation. This property makes the Bayesian approximation acceptable for panel data where model parameters are different from each other.
2. Bayesian research offers a natural way to merge prior beliefs (knowledge) with knowledge. Any subjective option of prior information should, in theory, be paired with data information in the first place. The average of individual parameter estimates can be used as before in the panel data models.
3. There are more accurate Bayesian estimates than classical estimates. This implies that the standard error of Bayesian estimates is small, which helps to make the inference more accurate.

4. Reliable results for small samples are given by Bayesian calculations. Bayesian estimates do not depend on one asymptotic outcome, as opposed to classical estimates.

3.5 Bayesian Derivation of the fixed effect model

$$Y_{it} = \beta_0i + \beta_1x_{1it} + \beta_2x_{2it} + \beta_3x_{3it} + \beta_4x_{4it} + \beta_5x_{5it} + \beta_6x_{6it} + \epsilon_{it} \quad (1)$$

The above model in the matrix form can be written in the following form as

$$Y_{it} = [y_1, y_2, \dots \dots y_n], X_{it} = [1, 1 \dots \dots 1, x_{11}, x_{12} \dots \dots x_{1n}, x_k \dots \dots x_{kn}], \beta$$

$$= [\beta_0 \dots \dots \beta_k],$$

$$\epsilon = [\epsilon_1 \dots \dots \epsilon_n]$$

The model 1 is written as follows

$$Y = X\beta + \epsilon$$

Where, $\epsilon \sim NID(0, \delta^2)$

$$f(y) = \frac{1}{\sqrt{2\pi\delta^2}} \exp \frac{-\epsilon^t \epsilon}{2\delta^2}$$

$$L = \prod_{i=1}^n \left[\left(\frac{1}{\sqrt{2\pi\delta^2}} \exp \frac{-\epsilon^t \epsilon}{2\delta^2} \right) \right]$$

$$L = \left(\frac{1}{2\pi\delta^2} \right)^{\frac{n}{2}} \exp \frac{-\epsilon^t \epsilon}{2\delta^2} \quad (2)$$

$$Y = X\beta + \epsilon$$

$$\epsilon = Y - X\beta$$

Put ϵ in 2nd model, get the subsequent equation

$$L = \left(\frac{1}{2\pi\delta^2} \right)^{\frac{n}{2}} \exp \left[-\frac{1}{2\delta^2} (Y - X\beta)^t (Y - X\beta) \right]$$

Now, applying kernel technique of density, the following equation is obtained

$$L \propto \left(\frac{1}{\delta^2} \right)^{\frac{n}{2}} \exp \left[-\frac{1}{2\delta^2} (Y - X\beta)^t (Y - X\beta) \right] \quad (3)$$

From common facts:

$$\delta^2 = \frac{(y - \hat{y})^2}{n-1} \quad \text{as } \hat{y} = x\hat{\beta}$$

$$\delta^2 = \frac{(y - x\hat{\beta})^2}{n-1}$$

When it is written in form of matrix the square term becomes

$$A^2 = A^T A$$

$$\delta^2 = \frac{(y - x\hat{\beta})^T (y - x\hat{\beta})}{n - k}$$

$$(n - k)\delta^2 = (y - x\hat{\beta})^T (y - x\hat{\beta})$$

Since,

$$(\beta - \hat{\beta})^T x^T (y - x\hat{\beta})$$

Where,

$$\hat{\beta} = (x^T x)^{-1} x^T y$$

Put the value of $\hat{\beta}$ in the above equation

Now

$$(\beta - \hat{\beta})^T x^T (y - x\hat{\beta})$$

Similarly,

$$(y - x\hat{\beta})^T x (\beta - \hat{\beta})^T = 0$$

Put the above value in equation (3), the following equation is obtained as

$$\begin{aligned} &= (n - k)\delta^2 - 0 - 0 + (\beta - \hat{\beta})^T x' x (\beta - \hat{\beta}) \\ &= (n - k)\delta^2 + (\beta - \hat{\beta})^T x' x (\beta - \hat{\beta}) \end{aligned}$$

Where, $v = n - k$ put in equation 4

$$L(y) \propto \left(\frac{1}{\delta^2}\right)^{\frac{n}{2}} \exp\left[-\frac{1}{2\delta^2}[v\delta^2 + (\beta - \hat{\beta})^T x' x (\beta - \hat{\beta})]\right] \quad (4)$$

To derive posterior distribution of β and δ^2 we have to specify prior distribution

If β_i follows normal distribution with hyper parameter (β_{0i}, δ_i^2)

$$\beta_i \sim NID(\beta_{0i}, \delta_i^2)$$

i-e

$$\begin{aligned} \beta_0 &\sim N(\beta_0, \delta_0^2) \\ \beta_1 &\sim N(\beta_1, \delta_1^2) \\ \beta_k &\sim N(\beta_k, \delta_k^2) \\ \beta &\sim MN(\beta_0, \varepsilon_0) \end{aligned}$$

$$P(\beta) = (2\pi)^{-\frac{K}{2}} |\varepsilon|^{1/2} \exp\left[-\frac{1}{2}(\beta - \beta_0)\varepsilon_0^{-1}(\beta - \beta_0)\right]$$

Now, if δ^2 follows a Gamma distribution having hyper parameter (a, b)

$$\delta^2 \sim \text{Gamma}(a, b)$$

[v_0 is the prior degree of freedom]

$$p(\delta^2) = \frac{b^a}{\sqrt{a}} (\delta^2)^{a-1} e^{-b/\delta^2}$$

Put “a” and “b” in the above equation

$$p(\delta^2) = \frac{\left(\frac{v_0 \delta_0^2}{2}\right)^{v_0/2}}{\sqrt{v_0/2}} (\delta^2)^{v_0/2-1} e^{-v_0 \delta_0^2 / 2\delta^2}$$

Now

$$p(\beta, \delta^2 / y, x) \propto L(y) \times p(\beta) \times p(\delta^2)$$

$$\begin{aligned} &\propto \left(\frac{1}{\delta^2}\right)^{\frac{n}{2}} \exp\left[-\frac{1}{2\delta^2}[v\delta^2 + (\beta - \hat{\beta})^T x' x (\beta - \hat{\beta})]\right] \times \exp\left[-\frac{1}{2}(\beta - \beta_0)\varepsilon_0^{-1}(\beta - \beta_0)\right] \\ &\quad \times (\delta^2)^{v_0/2-1} e^{-v_0 \delta_0^2 / 2\delta^2} \\ &\propto [(\delta^2)^{\frac{v_0}{2}-1-\frac{n}{2}} \exp\left[-\frac{v_0 \delta_0^2 - v\delta^2}{2\delta^2}\right]] \times \exp\left[-\frac{1}{2}(\beta - \beta_0)\varepsilon_0^{-1}(\beta - \beta_0) + (\beta - \hat{\beta})^T \frac{x' x}{\delta^2} (\beta - \hat{\beta})\right] \end{aligned}$$

$$\propto (\delta^2)^{-\left(\frac{v_0+n}{2}\right)-1} \exp\left[-\frac{v_0\delta_0^2-v\delta^2}{2\delta^2}\right] \times \exp\left[-\frac{1}{2}(\beta-\beta_0)\varepsilon_0^{-1}(\beta-\beta_0)+(\beta-\hat{\beta})^T\frac{x'x}{\delta^2}(\beta-\hat{\beta})\right] \quad (5)$$

Let $a^* = \frac{v_0+n}{2}$, $b^* = \frac{v_0\delta_0^2+v\delta^2}{2}$

$$M^* = \left(\varepsilon_0^{-1}\beta_0 + \frac{x'x\hat{\beta}}{\delta^2}\right)$$

$$V^* = \left(\varepsilon_0^{-1} + \frac{x'x}{\delta^2}\right)^{-1} \left(\varepsilon_0^{-1}\beta_0 + \frac{x'x\hat{\beta}}{\delta^2}\right)$$

Put in equation (5) we will get

$$p(\beta, \delta^2/y, x) \propto MN \sim G(M^*, V^*, a^*, b^*)$$

3.6 Bayesian Derivation of the random effect model

$$y_{it} = \beta_0 + \beta_1x_{1it} + \beta_2x_{3it} + \beta_3x_{3it} + \beta_4x_{4it} + \beta_5x_{5it} + \beta_6x_{6it} + \varepsilon_{it}$$

$$y_{it} = \beta_0 + \mu_{it} + \beta_1x_{1it} + \beta_2x_{3it} + \beta_3x_{3it} + \beta_4x_{4it} + \beta_5x_{5it} + \beta_6x_{6it} + \varepsilon_{it} \quad (6)$$

Where $\mu = \beta_0 + \mu_{it}$

Model 1 written as follows

$$y_{it} = \beta_0 + \sum \beta_j x_{jit} + \varepsilon_{it} + \mu_{it}$$

$$y_{it} = \beta_0 + \sum \beta_j x_{jit} + w_{it} \quad (7)$$

Where, $w_{it} = \mu_{it} + \varepsilon_{it}$

$w_{it} \sim N(0, \delta^2 w)$

$\delta^2 w = (\delta^2 \varepsilon + \delta^2 u)$

The model is written as follows

$$y = x\beta + w$$

Where,

$X = [e, x]$, $e = [1, 1, \dots, 1]^T$ has length NT , $Y = [Y_{11}, Y_{1T}, \dots, Y_{21}, \dots, Y_{NT}]^T$ Has NT , $X = [x_1, x_2, \dots, x_n]^T$ is $NT \times K$ design matrix,

$\beta = [\beta_0, \beta_1, \dots, \beta_k]^T$ has length $k + 1$, and

$w = [w_{11}, w_{12}, \dots, w_{NT}]^T$ has length NT . from model 3 we have

$$y \sim N(x\beta, \Psi)$$

$$\Psi = E(w'w) = I_N \times (\delta^2 \varepsilon I_t + \delta^2 u e e')$$

$$\delta^2 \varepsilon (I_N \times I_t) + \delta^2 u (I_N \times e e')$$

Replace I_t by $(E_t + J_t)$ and $e e'$ by T_{JT} , where $J_t = \frac{1}{T} e e'$ and $E_t = I_t + J_t$, then

$$\Psi = \delta^2 \varepsilon [(I_N \times (E_t + J_t))] + \delta^2 u (I_N \times T_{JT})$$

$$= \delta^2 \varepsilon (I_N \times I_t) + \delta^2 \varepsilon (I_N \times J_t) + T \delta^2 u (I_N \times J_t) \quad (8)$$

Where

$$Q = (I_N \times E_t)$$

$$\delta^2_1 = (\delta^2 \varepsilon + T \delta^2 u)$$

$$P = (I_N \times J_t)$$

Replace this in equation 5

$$= \delta^2 \epsilon Q + \delta^2_1 P$$

$$\Psi^{-1} = \left(\frac{Q}{\delta^2 \epsilon} + \frac{P}{\delta^2_1} \right)$$

$$|\Psi| = (\delta^2 \epsilon)^{N(T-1)} (\delta^2_1)^N$$

Now likelihood function is the joint density of the y`s that is

$$\begin{aligned} L(y; \mathbb{Q}, \Psi) &= \prod_{i=1}^{NT} t = 1 (2\pi)^{-\frac{1}{2}} |\Psi|^{1/2} \exp\left\{-\frac{1}{2(y-x\beta)^T \Psi (y-x\beta)}\right\} \\ &= (2\pi)^{-\frac{NT}{2}} (\delta^2 \epsilon)^{-\frac{N(T-1)}{2}} (\delta^2_1)^{\frac{N}{2}} \exp\left\{-\frac{1}{2}(y-x\beta)^T \left[\frac{Q}{\delta^2 \epsilon} + \frac{P}{\delta^2_1}\right] (y-x\beta)\right\} \end{aligned} \tag{9}$$

The prior information:

For a Bayesian model, a prior distribution on $(\beta, \delta^2 \epsilon, \delta^2_1)$ is needed. The uniform distribution $u(0, 1)$ of the vector parameters β is required, also assume that the prior distribution on $\delta^2 \epsilon$ and δ^2_1 are invers gamma having parameters $\alpha_\epsilon, \beta_\epsilon, \alpha_1$ and β_1 respectively.

$$P(\delta^2 \epsilon) = \frac{\beta_\epsilon^{\alpha_\epsilon}}{\sqrt{\alpha_\epsilon}} (\delta^2 \epsilon)^{-(\alpha_\epsilon+1)} \exp\left(\frac{-\beta_\epsilon}{\delta^2 \epsilon}\right)$$

And

$$P(\delta^2_1) = \frac{\beta_1^{\alpha_1}}{\sqrt{\alpha_1}} (\delta^2_1)^{-(\alpha_1+1)} \exp\left(\frac{-\beta_1}{\delta^2_1}\right)$$

$$L(y/\mathbb{Q}, \delta^2 \epsilon, \delta^2_1) = \prod_{i=1}^{NT} t = 1 (2\pi)^{-\frac{1}{2}} |\Psi|^{1/2} \exp\left\{-\frac{1}{2(y-x\beta)^T \Psi (y-x\beta)}\right\}$$

Where $\hat{y} = x\hat{\beta}$

$$[(y-x\beta)^T \Psi^{-1} (y-x\beta)]$$

Adding and subtracting $x\hat{\beta}$

$$[(y-x\hat{\beta} + x\hat{\beta} - x\beta)^T \Psi^{-1} (y-x\hat{\beta} + x\hat{\beta} - x\beta)]$$

$$= [(y-x\hat{\beta}) - x(\beta - \hat{\beta})]^T \Psi^{-1} [(y-x\hat{\beta}) - x(\beta - \hat{\beta})]$$

$$= [(y-x\hat{\beta})'(y-x\hat{\beta}) - (y-x\hat{\beta})^t x(\beta - \hat{\beta}) - (\beta - \hat{\beta})x'(y-x\hat{\beta}) + (\beta - \hat{\beta})x'x(\beta - \hat{\beta})] \dots\dots\dots(10)$$

Now the joint posterior density of the coefficient β and variance $\delta^2 \epsilon$ and δ^2_1 given by the expression.

$$\begin{aligned} \pi_1\left(\beta, \delta^2 \epsilon, \frac{\delta^2_1}{y}\right) &\propto L\left(\frac{y}{\beta}, \delta^2 \epsilon, \delta^2_1\right) \pi_0(\beta, \delta^2 \epsilon, \delta^2_1) \propto \\ &(2\pi)^{-\frac{NT}{2}} (\delta^2 \epsilon)^{-\frac{N(T-1)}{2}} (\delta^2_1)^{\frac{N}{2}} \exp\left\{-\frac{1}{2}(y-x\hat{\beta})^T \left[\frac{Q}{\delta^2 \epsilon} + \frac{P}{\delta^2_1}\right] (y-x\hat{\beta})\right\} \exp^{-1/2(\beta-\hat{\beta})^T X^T \Psi^{-1} X(\beta-\hat{\beta})} \times \frac{\beta_\epsilon^{\alpha_\epsilon}}{\sqrt{\alpha_\epsilon}} \\ &(\delta^2 \epsilon)^{-(\alpha_\epsilon+1)} \exp\left(\frac{-\beta_\epsilon}{\delta^2 \epsilon}\right) \frac{\beta_1^{\alpha_1}}{\sqrt{\alpha_1}} (\delta^2_1)^{-(\alpha_1+1)} \exp\left(\frac{-\beta_1}{\delta^2_1}\right) \\ &\propto (\delta^2 \epsilon)^{-\left(\alpha_\epsilon + \frac{N(T-1)}{2} + 1\right)} \exp\left\{-\frac{1(y-x\hat{\beta})^T Q(y-x\hat{\beta}) + \beta_\epsilon}{2\delta^2 \epsilon}\right\} \\ &\times \delta^2_1^{-\left(\alpha_1 + \frac{N}{2} + 1\right)} \exp\left\{-\frac{1/2(y-x\hat{\beta})^T P(y-x\hat{\beta}) + \beta_1}{\delta^2_1}\right\} \exp\{1/2(\beta-\hat{\beta})^T X^T \Psi^{-1} X(\beta-\hat{\beta})\} \end{aligned}$$

From this expression, the following conditional and marginal posterior distribution is obtained as

$$\begin{aligned} \pi_i(\beta/\delta^2\varepsilon, \delta^2_1, Y) &\propto \exp\left\{\frac{1}{2(\beta-\hat{\beta})^T X^T \Psi^{-1}(\beta-\hat{\beta})}\right\} \\ \pi_i(\delta^2\varepsilon/\beta, \delta^2_1, Y) &\propto (\delta^2\varepsilon)^{-\left(\alpha_\varepsilon + \frac{N(T-1)}{2} + 1\right)} \exp\left\{-\frac{1(y-x\hat{\beta})^T Q(y-x\hat{\beta}) + \beta_\varepsilon}{2\delta^2\varepsilon}\right\} \pi_i(\delta^2_1/\beta, \delta^2\varepsilon, Y) \\ &\propto \delta^2_1^{-\left(\alpha_1 + \frac{N}{2} + 1\right)} \exp\left\{-\frac{1/2(y-x\hat{\beta})^T P(Y-x\hat{\beta}) + \beta_1}{\delta^2_1}\right\} \end{aligned}$$

Therefore, it follows that

$$\begin{aligned} (\beta/\delta^2\varepsilon, \delta^2_1, Y) &\sim N(\mathbb{Q}, X^T \Psi^{-1} X)^{-1} \\ (\delta^2\varepsilon/\beta, \delta^2_1, Y) &\sim IG\left(\alpha_\varepsilon + \frac{N(T-1)}{2}, \frac{1}{2}(y-x\hat{\beta})^T Q(y-x\hat{\beta}) + \beta_\varepsilon\right) \\ (\delta^2_1/\beta, \delta^2\varepsilon, Y) &\sim IG\left(\alpha_1 + \frac{N}{2}, \frac{1}{2}(y-x\hat{\beta})^T P(Y-x\hat{\beta}) + \beta_1\right) \end{aligned}$$

4. Results and discussion

4.1 2SLS Results

Table 1: Results of Classical estimation of panel data models

Models	Fixed effect model	Random effect model
Coefficients	Mean	Mean
	[Std. Error]	[Std. Error]
	P-Value	P-value
Intercept	2.3462	2.3483
	0.0146	0.0151
	0.000	0.000
Capital stock	0.0074	0.0034
	0.0035	0.0035
	0.039	0.323
Trade openness	0.0063	0.0063
	0.0013	0.0001
	0.000	0.000
Financial Institutions	0.00141	0.0034
	0.00709	0.0060
	0.984	0.578
Economic Institutions	0.00741	0.0121
	0.0094	0.0063
	2.11	0.055
Social Institutions	0.00789	0.00844
	0.005789	0.0056
	0.884	0.870
Political Institutions	0.007077	0.1259
	0.00641	0.0056
	0.270	0.027
R-Squared	0.81	0.80

Hausman= 0.0019, VIF= 1.45.

A unit increase in gross capital stock induces an increase in GDP value by 0.0074 units with a standard error of 0.0035 effects significantly on the dependent variable, whereas a unit increase in trade's openness induces an increase in GDP value by 0.0063 units with a standard error of 0.0013 effects significantly on the dependent variable. A unit increase in economic's institutes induces an increase in GDP value added by 0.0074 units with a standard error of 0.0094 showing an insignificant dependent variable effect. Besides, a unit change in social institutions induces an increase in GDP value by 0.00789 units with a standard error of 0.0094 suggests effects insignificantly the variable that is dependent and a unit increase in political's institutions induces an increase in GDP value by 0.00789 units with a standard error of 0.0057 suggests an insignificant effect of the dependent variable. The R-squared value indicates that independent variables have an 81% effect on the dependent variable. Moreover, the value of the Hausman test is less than 0.05, which mean the fixed effect model is an appropriate and good model.

4.2 Bayesian Estimation Results.

Table 2 Bayesian estimation

Models	Fixed effect model	Random effect model
Coefficients	Mean [Std. Error] C.D.I[2.5-97.5%]	Mean [Std. Error] C.D.I[2.5-97.5%]
Intercept	140.8 0.000862 126.1-156.7	1474.406 0.01811 1474.5-1474.4
Capital stock	0.00802 0.01102 0.02948-0.01342	473.2 0.09453 473.3-473.2
Trade openness	0.06127 0.02053 0.02122-0.1016	8.42 3.098 4.714-15.51
Financial Institutions	0.02744 0.003989 0.01961-0.0352	105.2 0.05849 105.1-105.3
Economic Institutions	0.02156 0.004303 0.01308-0.03004	74.66 0.05442 74.55-74.76
Social Institutions	0.00196 0.003613 0.0051-0.00918	0.4144 0.06936 0.2818-0.5469
Political Institutions	0.00439 0.003967 0.00322-0.0122	50.01 0.06228 49.89-50.13

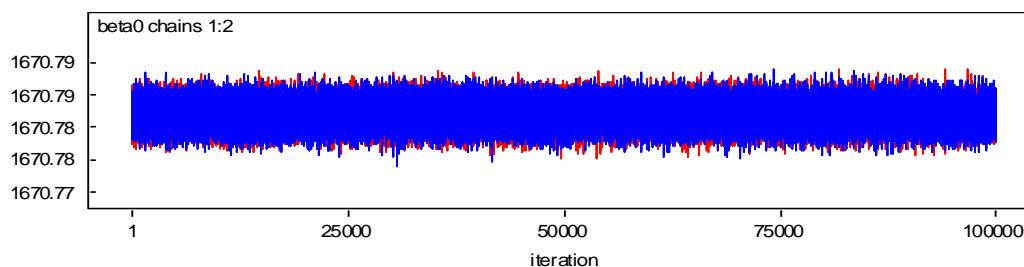
The estimation of variables is important based on a 95% accurate interval coefficient since the interval does not contain 0.0. The results in the table above show that the best model from all model is the fixed effect model. Based on standard error, Bayesian approach is considered as the best model in the model of fixed effect nature. The Fixed effect model shows better outcomes relative to other models, that is why in this research only the fixed effect model is considered.

A unit increase in gross capital stock induces an increase in GDP value by 0.000862 units with a standard error of 0.01102 effects significantly on the dependent variable, whereas a unit increase in trade's openness induces an increase in GDP value by 0.06127 units with a standard error of 0.2053 effects significantly on the dependent variable. A unit increase in economic's institutes induces an increase in GDP value by 0.02156 units with a standard error of 0.004303 showing a significant dependent variable effect. Besides, a unit change in social institutions induces an increase in GDP value by 0.00196 units with a standard error of 0.003613 effects significantly on the variable that is dependent and a unit increase in political's institutions induces an increase in GDP value by 0.00439 units with a standard error of 0.003967 effects significantly on the dependent variable. Based on an approximation of 95% of the interval for all variables, the dependent variable is significantly influenced.

5. Graphical representation:

5.1 Plots of trace series

The following figure 1, showed the plots of the trace of samples vs the amount of simulation running in two numerous chains, each one representing a unique shade. This shows that the convergence has been attained as both chains seem to be merged. The trace represents the transformation of the chain to the stationary distribution after a long period of burns. Stationary's feature is quite similar to trace plot i-e., it has a comparatively constant average and variance. Figure 1 below, displays a plot of the perfect trace. Since the middle of the chain seems close to the constant average values having minor variations. This specifies that the target would be achieved by the chain i-e., (right, stationary) distribution. It is concluded that mixing is better for every parameter.



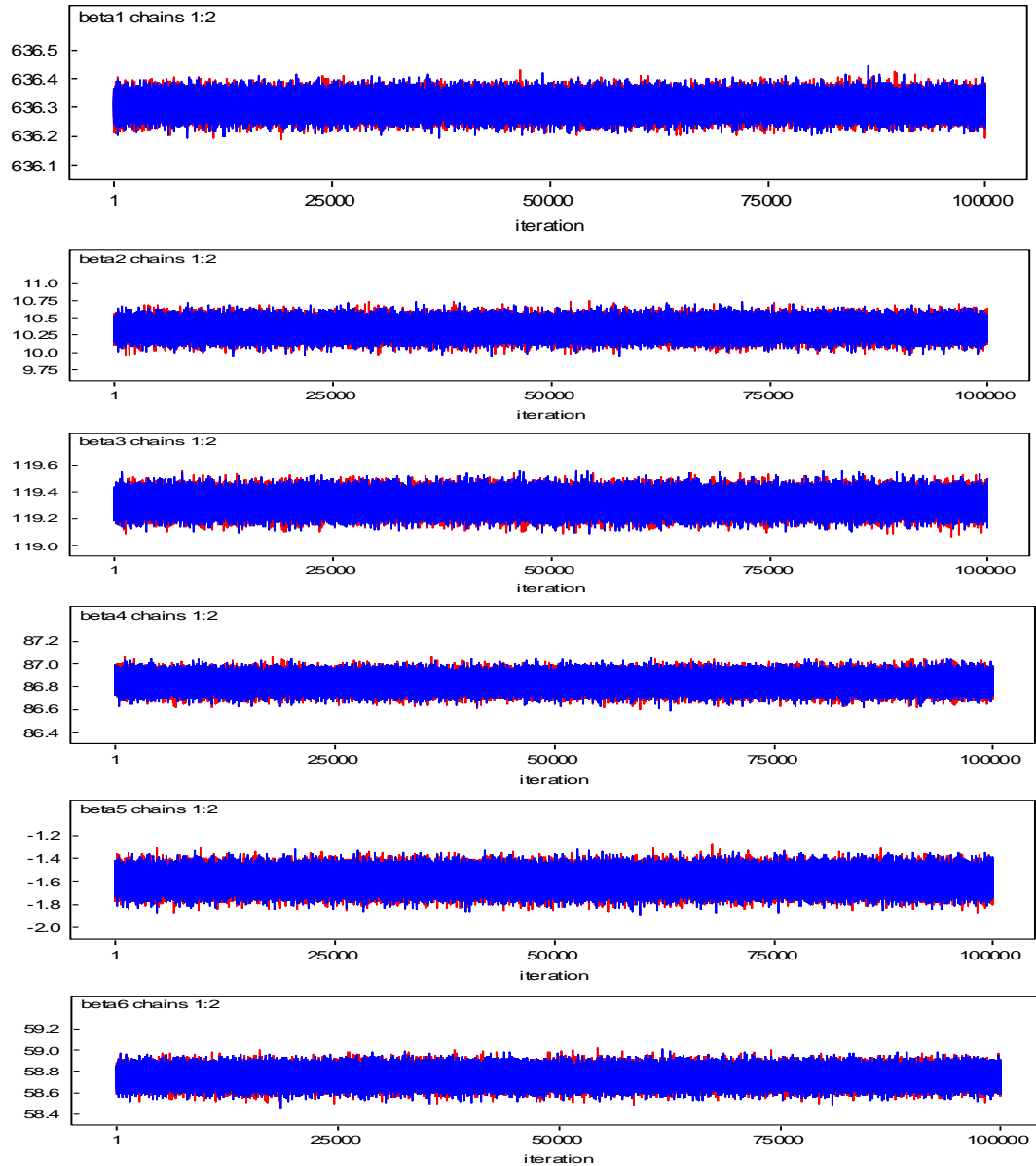


Figure 1: Plot of the trace series

4.2 Kernel density plots

The following Fig 2, displayed the plots of kernel density which is a different visualization of the parameters of the marginal posterior simulated distribution. The posterior marginal distribution of $\beta_0, \beta_1, \dots, \beta_6$ is normal in terms of a prior non-informative distribution. The plot of kernel density specifies the estimate of the Bayesian point of the posterior average or median and the range amongst 2.5th and 95.5th

percentile signify 95% Bayesian confidence interval also named as the credible interval. The numerical values of the variables provide a graphical representation that gives the same outcomes. Hence the density of the posterior kernel aimed to stabilize and it converges for every parameter.

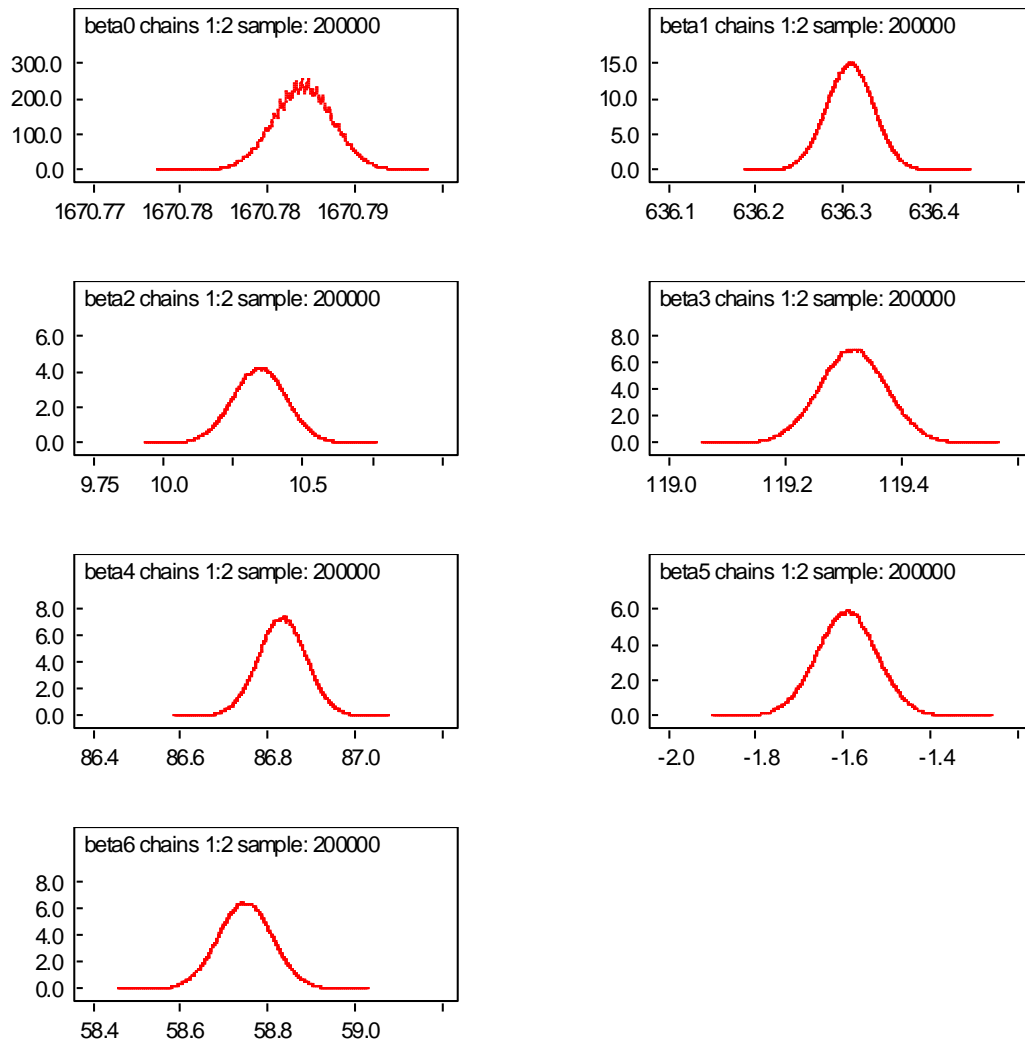


Figure 2: Kernel density plots

4.3 Plots of the Autocorrelation function

Following is the plot of the autocorrelation function in Fig 3 below, which specifies the chain for each dimension and the parameter of the posterior distribution. Mixing is

frequently related to a small posterior correlation amongst parameters. The plots designate that all the parameters are properly mixing with autocorrelation, fading before five intervals in every case.

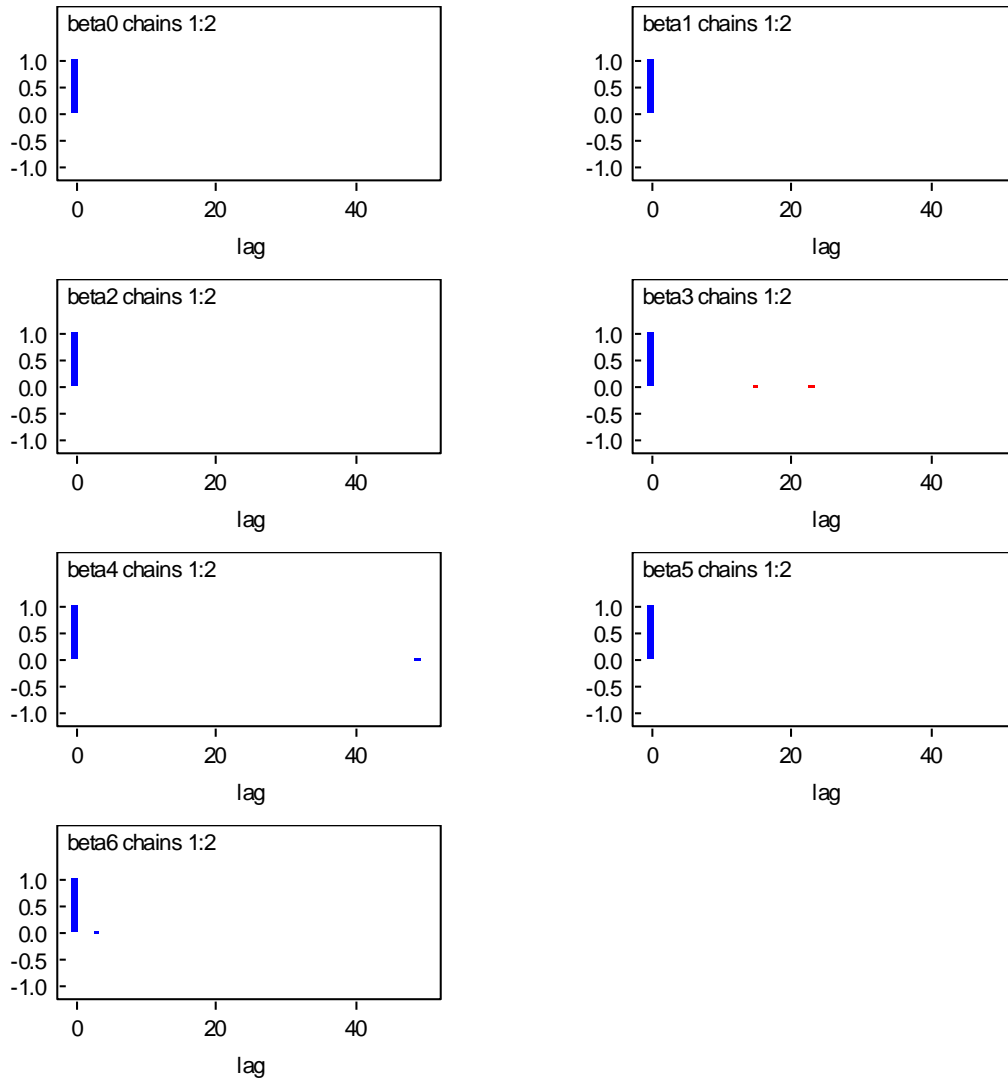
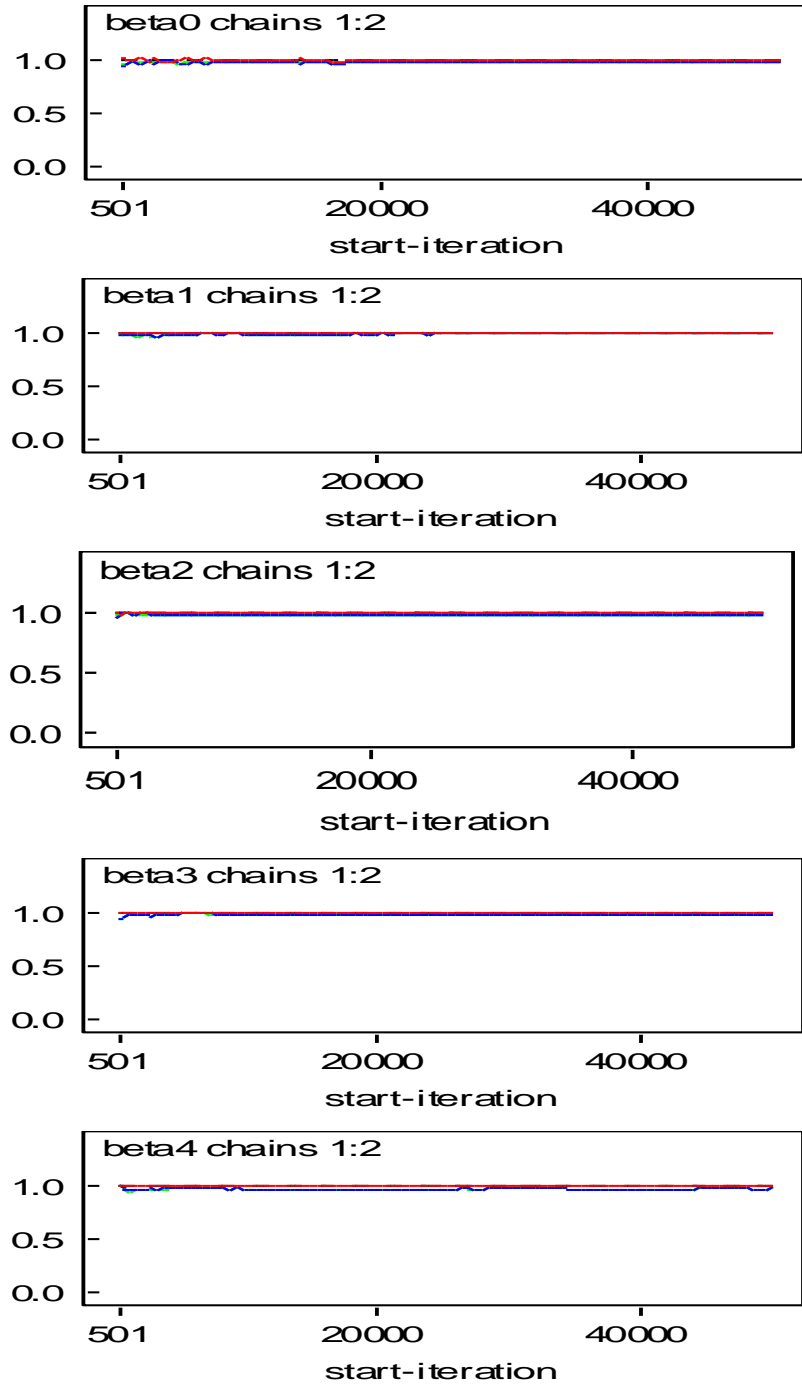


Figure 3: Plots of the Auto correlation function

4.4 Plots of BGR statistic

From the following Figure 4, the plots of BGR specifies the diagnostic plot produced for β 's 2500000 values tested from coins and removing the 1st 90,000. Blue colour lines symbolize the normal width of 80% credible interval calculated from 3 distinct chains.

Green colour lines are calculated from the joint data and red colour lines are the ratio of the two values. Figure 4 specifies that the ratio is 1 and the 3 chains transformed to their preferred distribution.



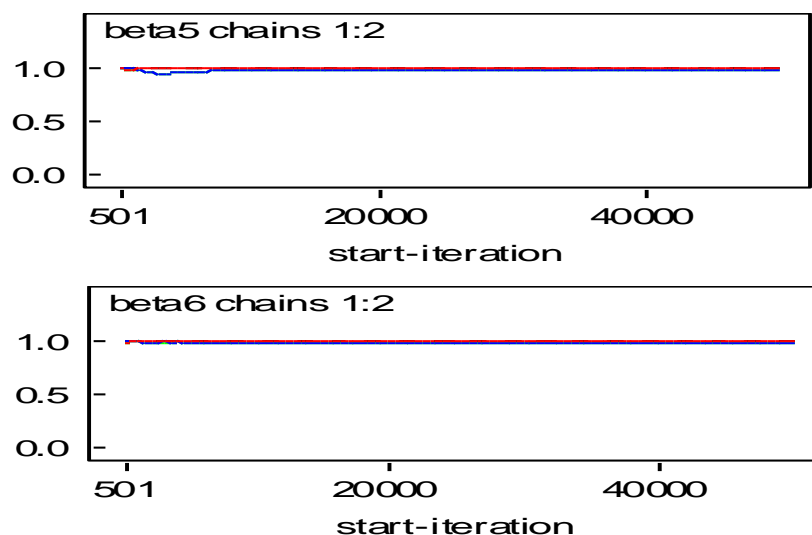


Figure 4: BGR plots statistic

6. Discussion:

For discrete, dependent and control variables the study requires linear regression of random and fixed effect panel data, taking all the above evidence into account. The results are shown in Table 1. In a Hausman test, the relationship between fixed or random effects is determined where the null hypothesis is that the selected model reflects random effects compared with alternative fixed effects (Greenland.S et al., 1985). This checks whether the particular U_{it} errors are connected to the regressors, and the null assumption is that they are not. The Hausman test carried out resulted in a likelihood of almost 100 per cent, suggesting the rejection of his null hypothesis about the adequacy of a random effect multiple regression model. We concluded that the fixed effect model is the best because the p-value of the Hausman test is less than 0.05. Statistical analysis of the dependencies obtained in this research data (the dependencies analyzed between the groups of variables observed are given in Table 1 using panel data model correlations represented by coefficients) with a maximum overall correlation coefficient of $R^2 = 0.80$. This means that approximately 80 per cent of the observations from 1990-2014 in developing countries are accurate. (while variables that are not protected by this model affect the remaining GDP pc variations). The findings provided in Table 1 also indicate that all other institutional development measures are significant statistical determinants of economic growth in developing countries over the period from 1990 to 2014, except for institutions. This is possible when the degree realized is less than 0.05 the significance of likelihood of t-test statistic. The control variables are determined by whether these countries have achieved candidate status for developing country membership, is in a similar situation. In this study, 2SLS estimations techniques have been used for classical estimation to addressed the problem of endogeneity.

Whereas, table 2 indicates the results for Bayesian estimations. Bayesian results are more precise and accurate results as compare to classical estimation. In the Bayesian estimation, all the variables shown positive and significant results on the dependent variable means that Bayesian results are more precise. Moreover, informative prior has been used for Bayesian estimation. Gamma prior and inverse gamma prior have been used as informative prior. Due to the low standard error of the variables, the fixed-effect model is the best in the Bayesian approach. The fixed model has a low standard error as compared to the random-effect model.

7. Conclusion:

Institutions, i.e. constraints created by man to form human intercourse, are rules and procedures in a particular population. Due to synergistic effects, any positive or negative structural change can bring about significant economic and social change. Institutions are aimed at reducing transaction costs, creating a framework for growth in productivity and improving competitiveness and creating an economic growth environment. The study shows that the economic development of selected developed countries during the 1990-14 period is significantly affected by institutions. Which creates assumptions that are critical for their economic growth at future rates. It follows that the introduction of policies for structural reform in these delayed transition countries can have a positive impact on long-term economic development. Institutions promoting government performance and regulatory consistency are of greatest importance to developing countries economic development.

The classical and Bayesian techniques of panel data models discussed in this study. This study explored the fact that, for several reasons, classical models are not reliable models. The Bayesian approach showed that institutions had a positive impact on GDP. Based on standard error, the model of fixed-effect nature is the best model of Bayesian panel data approximation. This is because there is a low standard error in the fixed-effect model relative to other models. Finally, better findings were shown by Bayesian fixed-effect models as opposed to the classical approximation of panel data models. Finally, the best and most suitable models determined were the Bayesian panel models.

References:

- Abrahamson, N. A., & Youngs, R. R. (1992). A stable algorithm for regression analyses using the random effects model. *Bulletin of the Seismological Society of America*, 82(1), 505-510.
- Acemoglu, D., & Robinson, J. (2010). *The role of institutions in growth and development* (p. 135). World Bank Publications.
- Alesina, A., Özler, S., Roubini, N., & Swagel, P. (1996). Political instability and economic growth. *Journal of Economic growth*, 1(2), 189-211.
- Berger, T., & Everaert, G. (2008). Unemployment persistence and the nairu: A bayesian approach. *Scottish Journal of Political Economy*, 55(3), 281-299.

- Dixit, A. (2009). Governance institutions and economic activity. *American economic review*, 99(1), 5-24.
- Drury, A. C., Kriekhaus, J., & Lusztig, M. (2006). Corruption, democracy, and economic growth. *International Political Science Review*, 27(2), 121-136.
- Dutta, N., & Williamson, C. R. (2016). Aiding economic freedom: Exploring the role of political institutions. *European Journal of Political Economy*, 45, 24-38.
- Greenland, S., & Robins, J. M. (1985). Estimation of a common effect parameter from sparse follow-up data. *Biometrics*, 55-68.
- Hall, R. E., & Jones, C. I. (1999). Why do some countries produce so much more output per worker than others?. *The quarterly journal of economics*, 114(1), 83-116.
- Josheski, D., Fotov, R., Lazarov, D., & Koteski, C. (2011). Institutions and growth revisited: OLS, 2SLS, G2SLS random effects IV regression and panel fixed (within) IV regression with cross-country data. *G2SLS Random Effects IV Regression and Panel Fixed (within) IV Regression with Cross-Country Data*.
- Kaushik, S. J., & Luquet, P. (1984). Relationship between protein intake and voluntary energy intake as affected by body weight with an estimation of maintenance needs in rainbow trout. *Zeitschrift für Tierphysiologie Tierernährung und Futtermittelkunde*, 51(1-5), 57-69.
- Lee, K., & Kim, B. Y. (2009). Both institutions and policies matter but differently for different income groups of countries: determinants of long-run economic growth revisited. *World Development*, 37(3), 533-549.
- Moral-Benito, E. (2012). Determinants of economic growth: a Bayesian panel data approach. *Review of Economics and Statistics*, 94(2), 566-579.
- Murray, P., Michael (2006), *Econometrics A modern introduction*, Pearson, Addison (Wesley)
- Nawaz, S., Iqbal, N., & Khan, M. A. (2014). The impact of institutional quality on economic growth: Panel evidence. *The Pakistan Development Review*, 15-31.
- Yıldırım, A., & Gökalp, M. F. (2016). Institutions and economic performance: A review on the developing countries. *Procedia economics and finance*, 38, 347-359.