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ANALYSIS OF FINANCIAL PERFORMANCE OF BANKS USING PANEL DATA MODELS – AN EMPIRICAL EVIDENCE OF BRICS

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Abstract
Banks have an important role to play in the economic development of any nation. The financial performance of a bank indicates its profitability which is an important indicator of the efficiency of banks. In this paper an attempt has been made to study the financial performance of banks of Brazil, Russia, India, China and South Africa (BRICS), which are the emerging economies of the world. The financial performance of these banks will have a greater impact on the world economy. Their financial performance is measured using selected financial ratio namely Return on Equity (ROE). The effective and efficient utilisation of equity share capital in particular will pave the way for analysing sound and healthy symptoms of banks in turn leading to economic progress of those countries.

Panel data is also called as longitudinal data or cross-sectional time series data. In panel data , same cross sectional units are collected over time. The study employed panel data regression to analyse the relationship between country-wise banks performance based on ROE.

Objectives of the Study is to study the impact of bank cost to total assets , (BCTTA), bank cost to total income (BCTI), bank credit to bank deposits (BCTBD) and bank overhead to total assets (BOTTA) on ROE of banks of BRICS countries on ROE of banks of BRICS countries and to provide findings/ results based on analysis. Based on objectives, the hypotheses are formed for analysis.

The study is based on secondary panel data covering from 2010-11 to 2013-14.The data has been collected from world Bank. It consist of variables namely bank ratios of Brazil, Russia, India, China and South Africa (BRICS). Various other reports like magazines, journals, published books and other websites are also referred to for the present study.The panel data collected for the study is analysed logically and meaningfully to arrive at meaningful conclusions. R Stat 3.2.1 version is used. It is concluded that random effect model is fit. The variation across countries of BRICS is assumed to be random and uncorrelated with the predictor or independent variables of BCTTA, BCTI, BCTBD and BOTTA. This is also confirmed with the result of Theta as zero. There are unique, time constant attributes of BRICS countries that are the results of random variation and do not correlate with the individual regressors.

Introduction

Banks have an important role to play in the economic development of any nation. The financial performance of a bank indicates its profitability which is an important indicator of the efficiency of banks. The financial performance of banks of Brazil, Russia, India, China and South Africa (BRICS), which are the emerging economies of the world will have a greater impact on the world economy. Their financial performance is measured using selected financial ratio namely Return on Equity (ROE). The effective and efficient utilisation of equity share capital will pave the way for analysing sound and healthy symptoms of banks in turn leading to economic progress of those countries.

The study employed panel data regression to analyse the relationship between country-wise banks performance based on ROE. Behaviour of the entities are observed across time in panel data also called as longitudinal data or cross-sectional time series data. The entities are here, countries. The study employed panel data regression to analyse the relationship among country-wise banks performance based on ROE. Panel data in econometrics is a continuously developing field. Panel data allows for controlling variables, which cannot be observed , measured (like cultural factors or difference in business practices across companies) or changed over time but not across entities (i.e. national policies, federal regulations, international agreements, etc.). This accounts for individual heterogeneity. With panel data, variables at different levels of analysis (i.e. students, schools, districts, states) can be included. It is suitable for multilevel or hierarchical modeling. The study is significant for the fact that it is carried out to find the determinants of financial performance using profitability ratios namely ROE of BRICS banks.

Objectives of the Study

1. 1. To study the impact of bank cost to total assets (BCTTA), bank cost to total income (BCTI), bank credit to bank deposits (BCTBD) and bank overhead to total assets (BOTTA) on ROE of banks of BRICS countries using panel Data models and

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2. To provide findings/ results based on analysis.

Based on objectives, the hypotheses formed for analysis are:

Hypotheses

- H1: Fixed effect model is appropriate (Lagrange Multiplier Test)
- H2: Pooling OLS model is appropriate (pF test)
- H3 random effect model is appropriate (Hausman Test)
- H4: There is no cross-sectional dependence in panels (Pesaran CD test)
- H5: There is no serial correlation (Breusch-Godfrey/Wooldridge test)
- H5: There is no heteroskedasticity (studentized Breusch-Pagan test)

Materials and Methods

The study is based on secondary panel data covering from 2010-11 to 2013-14. It consist of variables namely bank ratios – Return on Equity (ROE), bank cost to total assets , (BCTTA), bank cost to total income (BCTI), bank credit to bank deposits (BCTBD) and bank overhead to total assets (BOTTA) of Brazil, Russia, India, China and South Africa (BRICS). The data has been collected from World Bank. Various other reports like magazines, journals, published books and other websites are also referred to for the present study.

The panel data collected for the study is analysed logically and meaningfully to arrive at meaningful conclusions. **R Stat**

3.2.1 version is used.

Independent Variables are BCTTA, BCTI, BCTBD and BOTTA and dependent variable is ROE.

Statistical Articulation

Descriptive Statistics

Descriptive statistics of all variables ,viz. Independent and dependent variables has been performed indicating the mean, standard deviation, range, coefficient of variation , compound annual growth rata for all variables,

Panel Data Regression

Panel data econometrics is a continuously developing field. The increasing availability of data observed on cross-sections of units (like households, firms, countries etc.) and over time has given rise to a number of estimation approaches exploiting this double dimensionality to cope with some of the typical problems associated with economic data, first of all that of unobserved heterogeneity. Some drawbacks are data collection issues (i.e. sampling design, coverage), non-response in the case of micro panels or cross-country dependency in the case of macro panels (i.e. correlation between countries).

Time-wise observation of data from different observational units has long been common in other fields of statistics (where they are often termed longitudinal data). In the panel data field as well as in others, the econometric approach is nevertheless peculiar with respect to experimental contexts, as it is emphasizing model specification and testing and tackling a number of issues arising from the particular statistical problems associated with economic data. The note “(strongly balanced)” refers to the fact that all countries have data for all years. If, for example, one country does not have data for one year then the data is unbalanced. Ideally you would want to have a balanced dataset but this is not always the case, however you can still run the model.

The result of our work is bundled in the plm add-on package, available from the Comprehensive R Archive Network at http://CRAN.R-project.org/package=plm.

Model estimation

Estimation of the basic models with plm

Several models can be estimated with plm by filling the model argument:

- The Fixed Effects Model (Within),
- The Pooling Model (Pooling),
- The First-Difference Model (Fd),
- The Between Model (Between),
- The error components model (random).

The most common one parameter is homogeneity, which means that $\alpha_{it} = \alpha$ for all i, t and $\beta_{it} = \beta$ for all i, t. The resulting model

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$yit = \alpha + \beta xit + uit$

It is a standard linear model pooling all the data across i and t. To model individual heterogeneity, one often assumes that the error term has two separate components, one of which is specific to the individual and does not change over time. This is called the unobserved effects model:

$yit = \alpha + \beta xit + uit$ (Within-entity error) $+ \varepsilon it$ (Between-entity error)

The appropriate estimation method for this model depends on the properties of the two error components. The idiosyncratic error εit it is usually assumed well-behaved and independent from both the regressors x_{it} and the individual error component μi . The individual component may be in turn either independent from the regressors or correlated.

If it is correlated, the ordinary least squares (OLS) estimator for β would be inconsistent, so it is customary to treat the μi as a further set of n parameters to be estimated, as if in the general model $\alpha it = \alpha i$ for all t. This is called the fixed effects (also known as within or least squares dummy variables) model, usually estimated by OLS on transformed data, and gives consistent estimates for β.

If the individual-specific component μ_i is uncorrelated with the regressors, a situation which is usually termed random effects, the overall error u_{it} also, so the OLS estimator is consistent. Nevertheless, the common error component over individuals induces correlation across the composite error terms, making OLS estimation inefficient, so one has to resort to some form of feasible generalized least squares (GLS) estimators. This is based on the estimation of the variance of the two error components, for which there are a number of different procedures available.

If the individual component is missing altogether, pooled OLS is the most efficient estimator for β. This set of assumptions is usually labelled pooling model, although this actually refers to the errors' properties and the appropriate estimation method rather than the model itself. If one relaxes the usual hypotheses of well-behaved, white noise errors and allows for the idiosyncratic error εit it has to be arbitrarily heteroskedastic and serially correlated over time, a more general kind of fe asible GLS is needed, called the unrestricted or general GLS. This specification can also be augmented with individual-specific error components possibly correlated with the regressors, in which case it is termed fixed effects GLS.

Another way of estimating unobserved effects models through removing time-invariant individual components is by **first-differencing the data**: lagging the model and subtracting, the time-invariant components (the intercept and the individual error component) are eliminated, and the model

$\Delta yit = \beta > \Delta x_{it} + \Delta u_{it}$

(where $\Delta yit = yit - yi,t-1$, $\Delta xit = xit - xi,t-1$ and, from (3), $\Delta uit = uit - ui,t-1 = \Delta\ \varepsilon it$ for t = 2, ..., T) can be consistently estimated by pooled OLS. This is called the first-difference, or FD estimator. Its relative efficiency, and so reasons for choosing it against other consistent alternatives, depends on the properties of the error term. The FD estimator is usually preferred if the errors u_{it} are strongly persistent in time, because then the Δuit will tend to be serially uncorrelated.

Lastly**, the between model**, which is computed on time (group) averages of the data, discards all the information due to intra group variability but is consistent in some settings (e.g., non stationarity) where the others are not, and is often preferred to estimate long-run relationships. Variable coefficients models relax the assumption that $\beta_{it} = \beta$ for all i, t. Fixed coefficients models allow the coefficients to vary along one dimension, like $\beta_{it} = \beta_i$ for all t. Random coefficients models instead assume that coefficients vary randomly around a common average, as $\beta_{it} = \beta + \eta i$ for all t, where ηi is a group- (time-) specific effect with mean zero.

The hypotheses on parameters and error terms (and hence the choice of the most appropriate estimator) are usually tested by means of pooling tests to check poolability, i.e., the hypothesis that the same coefficients apply across all individuals,

- if the homogeneity assumption over the coefficients is established, the next step is to establish the presence of unobserved effects, comparing the null of spherical residuals with the alternative of group (time) specific effects in the error term,
- The choice between fixed and random effects specifications is based on Hausman-type tests, comparing the two estimators under the null of no significant difference: if this is not rejected, the more efficient random effects estimator is chosen,
- Even after this step, departures of the error structure from sphericity can further affect inference, so that either screening tests or robust diagnostics are needed.

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Tests of Poolability

Hausman test phtest computes the Hausman test which is based on the comparison of two sets of estimates (see Hausman 1978). A classical application of the Hausman test for panel data is to compare the fixed and the random effects models: In order to choose between the fixed effect estimates which are consistent if the individual effects are correlated with the individual variables and the random effect estimates, which are consistent and efficient if the individual effects are correlated with the independent variables but inconsistent otherwise. Hausman Test (1978) is used. If the null hypothesis is that if the individual effects are uncorrelated with the other regressors is rejected A fixed effect model is favoured over its random counterpart otherwise random effect model is preffered. The hausman Test shows that "the covariance of an efficient estimator with its difference from an in efficient estimator is zero" (Greene(2008).

Testing for Serial Correlation: Serial correlation in panel data model biases the standard error and causes the result to be less efficient. it covers when error terms for different independent variables are correlated. Wooldridge (2002) devised a test to detect the presence of serial correlation in panel data called as Wooldridge serial correlation test.

Wooldridge's method uses the residuals from a regression in first differences. First differencing the data in the panel data regression model removes the individual level effect, the term based on the time-invariant covariates and the constant.

Results and Discussion:

Table-1: Descriptive Statistics of BRICS Banks

	BCTBD	BCTI	BCTTA	BOTTA	ROE
Mean	131.120	56.476	8.474	6.392	15.250
Median	113.900	54.982	7.700	2.881	15.545
Maximum	299.789	98.871	13.300	83.314	28.034
Minimum	59.312	33.597	4.400	0.749	3.332
Std. Dev.	65.788	16.283	2.413	13.146	5.730
Skewness	1.234	1.057	0.511	4.682	0.072
Kurtosis	3.203	3.695	2.029	26.104	2.984
Jarque-Bera	12.768	10.310	4.136	1294.785	0.044
Probability	0.002	0.006	0.126	0.000	0.978
Sum	6555.981	2823.793	423.700	319.623	762.511
Sum Sq. Dev.	212072.900	12992.430	285.296	8467.899	1608.753
Observations	50.000	50.000	50.000	50.000	50.000
C.V	0.502	0.288	0.285	2.056	0.376
CAGR	-0.988	-0.985	-0.979	-0.961	-0.987
	0.012	0.015	0.021	0.039	0.013

Source: Output from E-views 7.1 version

Table -1 depicts that average annual mean of ROE of BRICS is 15.20%. There is compound annual decline rate is 1.3% during the study period with consistency of 0.376 ranging from 28.034% to 3.332%.

2.Comparing Estimators for Panel Data Models

ROE	Pooling	Between	Within	First Difference	Random
BCTTA	0.300	-10.578	0.077	-0.183	0.300
	(0.515)		(0.845)	(0.600)	(0.515)
BCTI	**-0.172**	**-0.269**	**-0.100**	**-0.117**	**-0.172**
	(0.0414 *)		(0.184)	(0.07679)	(0.0414 *)
BCTBD	-0.004	-0.513	0.004	0.009	-0.004
	(0.769)		(0.716)	(0.319)	(0.769)
BOTTA	**-0.052**	**-0.616**	**-0.072**	**-0.038**	**-0.052**
	(0.533)		(0.361)	(0.585)	(0.533)
Constant	23.292	0.069		0.271	23.292
	(6.884e-05 ***)			(0.763)	(6.884e-05 ***)
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					
R2 Within	**0.246**				

R2between	1.000				
R2 overall	**0.234**				
R2 first difference	**0.399**				
R2 random	**0.234**				
Sigma					
Sigma					
Rho					
Theta					0.000
idiosyncratic			19.680	4.437	1.000
individual			0.000	0.000	0.000

1. Output from *R version 3.3.2* (2016-10-31) .
2. Figures in parenthesis are prob. values of t statistics.

- Results of OLS model with respect to regressors is the same as results of Random effect model.
- Results show that higher values of Bank cost to Total Income (BCTI) are negatively and significantly associated with higher values of ROE for all estimators; similarly, lower values of Bank Overhead to Total Deposits (BOTTA) with lower values of ROE.
- Bank cost to Total Assets (BCTTA) is related negatively, considerably and significantly with ROE for OLS, between and random estimators but not with rest of the estimators.
- Bank Credit To Total Deposits is correlated negatively and significantly with ROE for between and first difference estimators but not with rest of the estimators.
- **OLS across BRICS (countries) and overtime**: Average ROE is considerably increased by 0.3% with the change in one year of BCTTA across BRICS countries. Average ROE is decreased by 0.172%, with the change in one year of BCTI across BRICS countries. There is negligible change in ROE as result of change in BCTBD with completion of a year and across BRICS.
- **Between BRICS Countries:** Average ROE is considerably decreased by 10.578 %, 0.269%, 0.513% and 0.616% among BRICS countries as a result of variation in BCTTA, BCTI, BCTBD and BOTTA respectively.
- **Within the country of BRICS:** Average ROE is increased and reduced negligibly with the changes in BCTTA& BCTBD and BCTI & BOTTA respectively in each additional year within the countries of BRICS
- **First Difference from one year to next country:** There is average decline in ROE by 0.183%, 0.117% and 0.038% in consequent to change in BCTTA, BCTI and BOTTA respectively from one year to next year. There is negligible increase in ROE.
- **Random:** ROE is increased randomly on an average by 0.3%, due to change in BCTTAI with one year passage of time and decreased in ROE randomly on an average by 0.172%, due to change in BCTI with one year passage of time. Other variables namely BCTTA, and BOTTA are negligible influence.
- Between estimators do not provide t statistics
- The positive change in ROE by 26.6% is because of only change in BCTTA across BRICs and overtime.
- R^2 between estimators depicts 1% followed by 0.399% of first difference estimators, 0.246% of within estimators, and 0.234% of overall and random estimators respectively.
- Zero Theta causes no variation from countries

3. plm test (pooling) Lagrange Multiplier Test - for balanced panels (Random effect v/s OLS)			
Model with independent variable	Normal	Degree of Freedom	P-value
ROE	3.7356,		9E-05

Output from *R version 3.3.2* (2016-10-31)

On testing of plm test, there is strong evidence that there is a significant effect. Hence, random effect OLS model is appropriate and better than pooling OLS model since prob. values of F Statistics is 0.00009.

4. PF test for individual effects (fixed effect v/s OLS)			
Model with independent variable	F Statistics	Degree of Freedom	P-value
ROE	5.4122,	df1 = 4, df2 = 41	0.001358

Output from *R version 3.3.2* (2016-10-31)

The statistics of PF test shows that fixed effect model is preferred to OLS model There is significant effect for its prob. value is lesser than 0.05.

5. Hausman Test (fixed v/s Random effect)			
Model with independent variable	Chi-Square Statistics	Degree of Freedom	P-value
ROE	5.2725	4	0.2605

Output from *R version 3.3.2* (2016-10-31)

Random effect model is better than fixed effect model since there is no significant effect.Its prob. value is 0.2605.

6 Pesaran CD test for cross-sectional dependence in panels			
Model with independent variable	Chi-Square Statistics	Degree of Freedom	P-value
ROE	1.6626		0.09639

Output from *R version 3.3.2* (2016-10-31)

The statistics of pesaran CD test for cross-sectional dependence in panels is accepted. Hence, there is acceptance of null hypothesis whose prob. value is more than 0.05.

7. Breusch-Godfrey/Wooldridge test for serial correlation in panel models			
Model with independent variable	Chi-Square Statistics	Degree of Freedom	P-value
ROE	12.878,	df = 10	0.2306

Output from *R version 3.3.2* (2016-10-31)

It is revealed from the statistics of Breusch-Godfrey/Wooldridge test that there is serial correlation.

8. student zed Breusch-Pagan test			
Model with independent variable	BP	Degree of Freedom	P-value
ROE	2.5447	df = 4	0.6366

Output from *R version 3.3.2* (2016-10-31)

There is existence of heteroskedasticity since prob. value is 0.6366. Hence alternative hypothesis is accepted.

Conclusions

In a nut shell, it is revealed that results of OLS model is the same as that of Random model. The variation across countries of BRICS is assumed to be random and uncorrelated with the predictor or independent variables of BCTTA, BCTI, BCTBD and BOTTA. This is also confirmed with the result of Theta as zero. There are unique, time constant attributes of BRICS countries that are the results of random variation and do not correlate with the individual regressors.

References

1. Yves Crossant and Giovanni Mills (2008), " Panel data econometrics in R –the plm package:, Journal of statistical software, vol.27, issue 2, Pp-1-41.
2. Eric Biora and Terje p. Hagen and Tor Iversen and Jon Magnessen (2008 posted 5, Apr.2008), " The effect of Activity Based Financing on Hospital Efficiency: A Panel Data Analysis of DEA Efficiency Scores 1992-2000", MPRA paper No. 8099
3. Aburime, U. (2005) Determinants of Bank Profitability: Company-Level Evidence from Nigeria. Nigeria: University of Nigeria, Enugu Campus.
4. Baltagi, B.H. (2005) Econometric Analysis of Panel Data, England: John Wiley & Sons Ltd., The Atrium, Southern Gate, Chichester, West Sussex PO19 8SQ
5. Arellano M, Bond S (1991). "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations." Review of Economic Studies, 58, 277–297.
6. Bates D (2004). "Least Squares Calculations in R." R News, 4(1), 17–20. URL http: //CRAN.R-project.org/doc/Rnews/.
7. Bhargava A, Franzini L, Narendranathan W (1982). "Serial Correlation and the Fixed Effects Model." Review of Economic Studies, 49, 533–554.
8. Bivand R (2008). spdep: Spatial Dependence: Weighting Schemes, Statistics and Models. R package version 0.4-17, URL http://CRAN.R-project.org/package=spdep.
9. Breusch TS, Pagan AR (1980). "The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics." Review of Economic Studies, 47, 239–253.
10. Hausman JA, Taylor WE (1981). "Panel Data and Unobservable Individual Effects." Econometrica, 49, 1377–1398. 42 Panel Data Econometrics in R: The plm Package Holtz-11'.akin D, Newey W, Rosen HS (1988). "Estimating Vector Autoregressions with Panel Data." Econometrica, 56, 1371–1395.
11. Laird NM, Ware JH (1982). "Random-Effects Models for Longitudinal Data." Biometrics, 38, 963–974.
12. undlak Y (1978). "On the Pooling of Time Series and Cross Section Data." Econometrica, 46(1), 69–85.
13. www.data.worldbank.org .