Can Weighted Average Least Square Solve Spurious Regression Problem?

M.PHIL THESIS

(ECONOMETRICS)

By

Muhammad Sijawal Gulzar
Registration No: PIDE2015FMPHILETS18

Supervisor
Dr. Atiq Ur Rehman
Assistant Professor
Department of Econometrics and Statistics
PIDE

(February 2018)

Department of Econometrics and Statistics

Pakistan Institute of Development Economics Islamabad, Pakistan

Pakistan Institute of Development Economics

CERTIFICATE

This is to certify that this thesis entitled: **"Can Weighted Average Least Square Solve Spurious Regression Problem?"** submitted by Mr. Muhammad Sijawal Gulzar is accepted in its present form by the Department of Econometrics and Statistics, Pakistan Institute of Development Economics (PIDE), Islamabad as satisfying the requirements for partial fulfillment of the degree in **Master of Philosophy in Econometrics**.

Supervisor:

Dr. Atiq ur Rahman
Assistant Professor
PIDE, Islamabad.

External Examiner:

Dr. Mudassir Khawaja
Incharge Undergraduate Programme
COMSATS, Islamabad.

Head,
Department of Econometrics and Statistics:

Dr. Amena Urooj

ACKNOWLEDGMENT

In the name of ALLAH, who is the Most Beneficial and Merciful, all thanks to ALLAH Almighty, who gave me the opportunity, ability and power to accomplish the task of final thesis of M.PHIL.

At this moment of great achievement, first of all I would like to thanks to my supervisor, **Dr. Atiq Ur Rehman**, without his guidance this extensive study would not have possible. Under his guidance I successfully overcome many difficulties and learn a lot. Without his passionate participation and input, the validation of this research study could not have been successfully conducted.

I would also like to thanks to all my teachers who taught me from the beginning of MPhil journey, especially thankful to Dr. Saud Ahmed khan and Dr. Hafsa Hina as they provided cooperative atmosphere at work and also the useful feedback and insightful comments on my work.

And my special thanks to my family and all my friends who have been supportive and gave me much needed encouragement specially my Parents who prayed a lot for me.

I want to dedicate this thesis to my **Father** and **Mother** because their love, guidance and Prayers were always with me throughout the journey. At the end, it was pleasure to express my thanks to all those who have contributed in many ways to complete this study and made it a remarkable experience for me.

Muhammad Sijawal Gulzar

Table of Contents

List of Tables

Abstract

Regression is termed as spurious regression if the regression outputs shows very significant relationship between two independent series. It occurs due to two major reasons, (i) non-stationarity and (ii) omitted relevant variables. The solution for omitted variable bias is to include all the relevant variables into the model. But sometimes this method becomes quite difficult to handle due to very large number of potential explanatory variables and it becomes very difficult to avoid missing variable bias. The recently introduced Weighted Average Least Square (WALS) technique which is a Bayesian combination of frequentist estimators can handle the case of large number of regressors. But does it really reduce the probability of spurious regression, no answer to the question can be found in literature. Therefore, this study evaluates the performance of WALS estimator to avoid the problem of spurious regression and compare the forecast performance of WALS with the classical estimator.

The size and power for WALS and OLS estimates has been calculated because size depicts the probability of spurious relationship between consumption and GDP of two different countries whereas, the power calculation refers the probability of true relationship between Consumption and GDP of the same countries. Thirty countries belongs to low and lower middle income group have selected for this study. The estimated results suggested that WALS and OLS have same power and forecast performance but other than this, WALS is much better than OLS because it reduces the probability of spurious regression form 99.7% to 20.6% under 5% while 8.4% under 1% nominal size respectively. So, from these it is suggested that WALS can avoid the problem of spurious regression.

Chapter 1

Introduction

Spurious regression is one the most serious problem in econometric analysis. Initially, Yule (1926) observed the problem of spurious regression in time series. Since then, econometricians have put their efforts to understand and in research of how to avoid this problem. The concept of spurious regression is quite simple, it shows a significant association between two or more variables even when there exists no relationship between them. As, Hendry (1980) assessed a regression in which he used a money supply of United Kingdom (UK) as a regressand and a cumulative rainfall in the UK as a regressor. The estimated results of this regression were highly significant, that shows the strong association between money supply and the cumulative rainfall. But in reality, there is no relationship between these variables, so this is a case of spurious regression that misleads us.

There are two major reasons for spurious regression that are Omitted Variable Bias and the Non-Stationarity of the data set. Omitted Variable Bias occurs if we drop out the essential regressors during the construction of the model. The "bias" occurs if model shifts the effect of omitted variables on other explanatory variables of the model by under or overestimating them. Until 1974, omitted variable bias was considered as an only reason of the spurious regression but Granger and Newbold (1974) showed that this phenomenon arises even if we regress two or more independent random walks on each other that is the case of non-stationarity with no third missing variable.

After Granger and Newbold (1974) diagnosis, Most of the economists start considered only non-stationarity as a reason of spurious regression problem. They ignored omitted variable bias as a reason for this problem, but in fact, it still exists. Granger et,al. (1998) stated that spurious regression can occurs even if series are stationary and this occurs due to omitted relevant variables. Therefore, in this study, we focus on spurious regression occurs due to omitted variable bias.

The solution for omitted variable bias that leads to spurious regression is to include all the relevant variables into the model. But this method is not always easy to handle because adding all the relevant variables make the model too large and sometimes the number of predictors becomes greater than the number of observation making the estimation impossible.

Weighted Average Least Square (WALS) is one of the latest model averaging technique developed by Magnus et, al. (2010) that was based on Equivalence theorem and Mean square error term (MSE) discussed in Magnus and Durbin (1999). WALS is a Bayesian combination of frequentist estimators. It can solve the problem of a large number of regressors by distinguishing explanatory variables into two types i.e. Focus variable and the Auxiliary variable. Focus variable is our interest variable or the one in which we are interested. While the auxiliary variables are those which are the determinants of regressors but are not directly part of question that we want to address. They have the status of potential explanatory variables and their absence may create bias. WALS takes large number of subsets of auxiliary variables and run the regression having these subsets with the focus regressors, at the end WALS estimator is calculated as an average of these estimates. In this manner WALS can handle the problem of large numbers.

The aim of this study is to analyse whether or not can WALS solve the problem of spurious regression. However, to evaluate this, we have test WALS for consumption and GDP of two different countries. Consumption of country (*i*) regressed on GDP of country (*j*) and ($i \neq j$), results obtained from this suggested that WALS can avoid the spurious regression problem.

So, WALS can take into account, as many control variable as you want. Therefore one can expect it to remedy that is bias. The example cited in motivational section actually provides evidence for this anticipation.

1.1 Objective of the Study

The purpose of this study is to evaluate the performance of Weighted Average Least Square estimator to avoid the problem of spurious regression and compare the forecast performance of WALS with the classical estimator i.e. OLS.

1.2 Motivation of the Study

Motivation for this study comes from a simple example, it is well known that consumption of one country regressed on GDP of another country gives spurious results as is shown in case of consumption of India and GDP of Pakistan. However, in the same regression if actual determinant of Indian consumption i.e. Indian GDP and Indian lag consumption are used as auxiliary regressors. The coefficient of Pakistani GDP becomes insignificant through the use of WALS, indicating the removal of spurious regression. The dataset of Indian Consumption and Pakistani GDP used without taking first difference because first difference causes loss of long-run information. To avoid the loss of long-run information we would estimate WALS and OLS over the level of variables.

Assume a linear regression model:

$$IND_{const} = \alpha_0 + \alpha_1 PAK_{GDPt} + \varepsilon_t \quad \dots (1)$$

Indian consumption (IND_{const}) regress on Pakistani GDP (PAK_{GDPt}) from 1971-2010. The estimated results of above model through the use of OLS and WALS are as follows:

Table 1.1 OLS AND WALS

	OLS	**WALS**
$\hat{\boldsymbol{\alpha}}_{\mathbf{1}}$	0.82	0.82
t-stat	30.16	1.39

By the use of the OLS t-stat of $\hat{\alpha}_1$ is greater than 2 (30.16) that is highly significant. It indicates that there is strong relationship between Indian Consumption and Pakistani GDP. But on theoretical grounds there is no any relationship exist between them. So, it is a problem of spurious regression that misguide us. This problem could be solved by adding all the relevant variables but this solution is sometimes difficult to perform. Therefore, we used WALS to check whether it deal with spurious regression problem or not.

So, by the use of WALS the t-stat of $\hat{\alpha}_1$ is less than 2 (1.39) that is insignificant. It indicates that there is no relationship between Indian Consumption and Pakistani GDP. From these results it has been depicted that WALS can be deal with the problem of spurious regression.

1.3 Significance of the Study

As the spurious regression is one of the serious problem in Econometrics Analysis. Weighted Average Least Square could be a solution to that problem. This study would be a greatest contribution in the field of econometrics as it helps to avoid the spurious regression, especially in cases where researchers are unable to estimate a general model with all potential regressors.

1.4 Outline of the study

The rest of the study is arranged as follows, Second Chapter presents the concept of Weighted Average Least Square (WALS) in detail and comparison with Ordinary least square, and then Chapter 3 contains literature review related to spurious regression problem. After that, in Chapter 4 we would discuss the methodology and data that used to compare WALS and OLS. Chapter 5 presents the results and discussion. On the basis of estimated results, final chapter would be the conclusion and the recommendation of this study.

Chapter 2

Weighted Average Least Square (WALS)

Weighted Average Least Square (WALS) is one of the latest model averaging technique. It is a Bayesian combination of Frequentist estimator and base on equivalence theorem of mean square error (MSE). This theorem was discussed by Magnus et.al (1999). WALS was discussed by Magnus et.al (2010) while handling the problem of parameter estimation in the presence of model uncertainty. Furthermore, they compared the performance of Weighted Average Least Square with the Bayesian Model Averaging (BMA) technique. Particularly, they contrast BMA with WALS, a technique that was applied for the first time in this context. WALS has theoretical and computational advantages over the other model averaging techniques; Bayesian Model Averaging (BMA) and Frequentist Model averaging (FMA) technique. Theoretical advantage, because it provide clear treatment of ignorance and also has a better risk properties; avoiding unbounded risk. Computational advantage, because its calculation time increase linearly rather then exponentially with the dimension of model selection space.

2.1 Empirical Frame Work

Following Magnus et, al. (2010) the regression is as follows:

$$Y = \alpha + X_1\beta_1 + X_{2(i)}\beta_2 + \varepsilon \; \ldots (2)$$

Where, X_1 is set of focus variable which do not change. While, $X_{2(i)}$ is a subset of the auxiliary variables. With each $X_{2(i)}$, we get different estimates of β_1 and β_2. Let $\widehat{\beta_1}(i)$ denote the estimated coefficients of focus regressor for the subset $X_{2(i)}$. The WALS estimate is the average of $\widehat{\beta_1}(i)$ where, *i*=1,2,3,…..

The computational details are given as under;

Let we have linear regression model:

$$y = X\beta + \varepsilon = X_1\beta_1 + X_2\beta_2 + \varepsilon, \qquad \varepsilon \sim i.i.d\ N(0, \sigma^2)$$

Where,

y is nx1 vector of observations

X_1 (nxk_1), X_2 (nxk_2) are the matrices of explanatory variables

ϵ_t is an error term

Magnus et, al. (2010) assumed that:

$$k_1 \geq 1 \qquad k_2 \geq 1 \qquad k = k_1 + k_2 \leq n\text{-}1$$

Where,

k_1 = Number of focus variables

k_2 = Number of Auxiliary variables

k = Total number of Explanatory variables

X_1 contains a regressor which is focus in the current research and X_2 contains the regressors which may or may not have relation with y, but they are not focus of the current research. Therefore, the regressors of X_2 are known as Auxiliary variables. They have the status of potential explanatory variables and their absence may create bias.

Whereas, the estimator β_2 contains k_2 components of auxiliary variables so different model arises when different subset of β_2's is set equal to zero. If k_2 = 0, no model selection occurs. If k_2 = 1, then two models arises that are restricted and the unrestricted model. If k_2 = 2, then four models arises that are two partially restricted models (where one of the two β_2's is zero), third the restricted model and fourth the unrestricted model. Generally, 2^{k_2} models arises to consider.

2.2 Un-Restricted Least Square

Following Magnus et.al (2010) the un-restricted least square (LS) estimators of β_1 and β_2 are as follows:

$$\hat{\beta}_1 = \hat{\beta}_{1r} - Q\hat{\beta}_2 \qquad\qquad \hat{\beta}_2 = X_2'M_1y$$

Where,

$\hat{\beta}_{1r} := (X_1'X_1)^{-1}X_1'y$ (r denotes restriction, β_2=0)

Q: $= (X_1'X_1)^{-1}X_1'X_2$

$M_1 := In - X_1(X_1'\,X1)^{-1}X_1'$

2.3 Restricted Least Squares

The restricted LS estimators of β_1 and β_2 are as follows:

$$\hat{\beta}_{1i} = \hat{\beta}_{1r} - QW_i\hat{\beta}_2, \qquad\qquad \hat{\beta}_{2i} = W_i\,\hat{\beta}_2$$

Where,

Where $W_i := I_{k2} - S_iS_i'$

Wi be the diagonal matrix with order $k_2 \times k_2$. It contains k_{2i} ones and (k_2-k_{2i}) zeros on its diagonal, such that if ($\beta_{2j} = 0$) then jth diagonal element of this matrix is equals to zero otherwise equals to one. If k_{2i} equals to k_2 then Wi should be equals to I_{k2}.

S_i be a selection matrix of order $k_2 \times (k_2 - k_{2i})$ with full column rank and $0 \leq k_{2i} \leq k_2$, so $S_i' = (I_{k2-k2i}: 0)$. Our interest is in the restricted estimators of β_1 and β_2 so the restriction would be $S_i'\beta_2 = 0$.

The joint distribution of $\hat{\beta}_{1i}$ and $\hat{\beta}_{2i}$ is as follows:

$$\begin{pmatrix}\hat{\beta}_{1i}\\ \hat{\beta}_{2i}\end{pmatrix} \sim \mathrm{N}_k\left(\begin{pmatrix}\beta_1 + QS_iS'_i\beta_2\\ W_i\beta_2\end{pmatrix},\ \sigma^2\begin{pmatrix}(X_1'X_1)^{-1} + QW_iQ' & -QW_i\\ -W_iQ' & W_i\end{pmatrix}\right),$$

The residual term is defined as, $e_i = D_iy$. Where, $D_i = M_1 - M_1X_2W_iX_2'M_1$ is a symmetric idempotent matrix. The distribution of $s^2_i = e_i'e_i/(n - k_1 - k_{2i})$ is:

$$\frac{(n-k_1-k_{2i})s_i^2}{\sigma^2} \sim \chi^2(n-k_1-k_{2i}, \frac{\beta_2{}'S_iS'_i\,\beta_2}{\sigma^2})$$

It follows that if σ^2 is unknown then it is replaced by S^2 that would be defined in coming section.

2.4 The Equivalence Theorem

Following Magnus and Durbin (1999) the Equivalence theorem for WALS estimator of β_1 is defined as:

$$b_1 = \sum_{i=1}^{2^{k_2}} \lambda_i\hat{\beta}_{1i}$$

The sum is taken for all 2^{k_2} different models acquired by setting subset of β_2's = 0. λ_i are the model weights, satisfy the following conditions:

- $0 \leq \lambda_i \leq 1$;
- $\sum_i \lambda_i = 1$;
- $\lambda_i = \lambda_i(M_1y)$.

Weight are assigned by taking Precision of Var-Cov matrix of each model:

$$\lambda_i = \Sigma_i^{-1}(\Sigma_1^{-1} + \Sigma_2^{-1} + \ldots + \Sigma_i^{-1})^{-1}$$

Σ_i^{-1} is Var-Cov matrix of model *i*.

Moreover, to calculate t-stat of WALS estimator "b_1" we need standard error of estimators, for that purpose var (b_1) is defined as:

var(b_1) = $\sigma^2(X_1' X_1)^{-1}$ + Qvar(b_2)Q and var(b_2) = $\sigma^2\, \sigma_\eta{}^2\, P\Lambda^{-1}P'$

Where, $\sigma_\eta{}^2 = 2/C^2$ and C =log 2.

P be an orthogonal and Λ be a diagonal matrix, calculated by diagonalization of $P'X_2'M_1X_2P = \Lambda$. σ^2 is unknown so it is replaced by S^2, which is defined by Magnus et.al (2004) in equivalence theorem as $S^2 = (y\text{-}X_1b_u\text{-}X_2\hat{\beta}_2)'\,(y\text{-}X_1b_u\text{-}X_2\hat{\beta}_2)/(n\text{-}k_1\text{-}k_2)$.

2.5 OLS vs WALS

In this research we used OLS and WALS to check the relationship between two variables that are consumption of country "*i*" and GDP of country "*j*"in two situation; (i=j) and (i≠j). Whereas, the difference is that OLS contain just one explanatory variable that is:

$$y = X_1\beta_1 + \varepsilon \;\dots (3)$$

However, WALS contains additional Auxiliary variables as a regressors, such that:

$$y = X_1\beta_1 + X_2\beta_2 + \;\varepsilon \;\dots (4)$$

Here, X_2 represents the auxiliary variables. These auxiliary variables are explained in coming section of methodology.

Chapter 3

Literature Review

Spurious regression is the serious problem in econometrics analysis and this problem is not new. There is large amount of literature available on spurious regression. Initially this problem was founded by Yule in 1926.

3.1 Spurious Regression and Yule Diagnosis

Yule (1926) expressed that sometime we get very high correlation among the quantities that are varying with the time and also there is no any significant physical relationship between them, although there would be significant correlation under ordinary test. In this way this is "non-sense correlation". He additionally clarified this idea by assessing the coefficients of correlation of marriages in Church of England for yearly data 1866-1911 and mortality rate per thousand for the same period. There was significant relationship among these variables that was equals to +0.9512. Then he anticipated that the fall in the ratio of marriages in Church of England was simply because of spread of scientific thinking and also the drop in mortality rate was obviously due to the "Progress of Science" since 1866; subsequently both variables were highly effected by a mutual variable and consequentially they would by significantly correlated. That is why, Yule stated that correlation is purely non-sense and this type of correlation has no meaning.

Moreover, Simon (1954) tried to clear the assumptions and rational procedure that would test whether the correlation between two variables is spurious or not. The procedure starts by introducing the relationship among the variables in a large variable (three-variable) system and these variables are assumed to be independent of each other. The assumptions that Simon had made are of two types. First one was that, certain variables have no causal effect on other certain variable. This assumption would decrease the number of degree of freedom. Secondly, mostly implicit than explicit, that is the random error terms related to large variable system are not correlated. This assumption would estimate the causal comparison of variables. From these two assumption and procedure he founded that if two certain variables are correlated in large variable system then the correlation between them is not spurious.

Until 1974, economist considered omitted variable bias as a reason of the spurious regression that had founded by Yule (1926). In 1974 Granger and Newbold founded non-stationarity as one more reason of spurious regression.

3.2 Granger and Newbold Experiment and Implication

Granger and Newbold (1974) performed an experiment and showed that the estimated results of two independent non-stationary time series turns to be highly significant. They developed autoregressive series of independent variables such as, X_t and Y_t. Both X_t and Y_t are depend on their own lag values.

$$Y_t = Y_{t-1} + \varepsilon_{yt}$$

$$X_t = X_{t-1} + \varepsilon_{xt}$$

Then they regressed Y_t on X_t and X_t on Y_t. Such as,

$$Y_t = \alpha + \beta_1 X_t + \varepsilon_{yt}$$

$$X_t = \alpha + \beta_1 Y_t + \varepsilon_{xt}$$

The estimated results of these two regression were highly significant even there is no missing variable. Therefore this is a case of spurious regression due to non-stationary variables. This alternate reason of spurious regression become famous in literature and after that econometricians starts ignoring other reasons of spurious regression.

3.3 Cointegration Analysis as remedy of Spurious Regression

It is common to come across when we run regression and doing empirical analyses by using non-stationary time series data cause spurious regression. Therefore, before further analysis we take first difference to make series stationary. But it cause the loss of long run information. Thus, for such analysis cointegration approach uses because cointegration approach retain short run as well as long run information.

Engle and Granger (1987) presented the popular Granger representation theorem which demonstrates the similarity of vector moving average model, vector error correction and vector autoregressive model representation of co-integration, and additionally the strategies for assessing, modelling and testing of non-stationary time series. Cointegration analysis utilized as a remedy of spurious regression in number of studies in several ways.

Phillips (1986) gave an analytical investigation of linear regression including the levels of time series variables. An asymptotic hypothesis was produced for regression that relate general integrated random procedures. This incorporated, the spurious regression of Granger and Newbold (1974), Granger and Engle (1985) cointegrating regressions. An asymptotic concept was established for the coefficients of regression model and for significance tests. In this study it has been showed that test statistics of F-ratio cannot keep limiting distributions in this perspective but it diverge with the increase in sample size "*T*". The behaviour of regression diagnosis was also analysed such as, coefficient of determination, Durbin-Watson statistic and the Box-Pierce statistics.

Phillips and Ouliaris (1990) developed a test that was based on residuals, the null hypothesis for this test was "There is no Cointegration between time series". The asymptotic distribution for this test depends on the number of deterministic trend and the number of variables. However, Engle and Yoo (1991) developed three step process to avoid the Engle Granger (EG) model. Their procedure showed that estimators follow normal distribution. This is useful for single cointegrated vector. If the number of variables increased and become greater than one then single cointegrated vector does not applicable. In this case more than one cointegrated vactor required. Therefore, Johenson and Juselius (JJ) proposed multivariate cointegration test to overcome this problem. In JJ test we can use more than one cointegrated vector so, it is more useful and reliable than EY and EG tests of cointegration. EG and EY tests consist of single equation process so it loss short-run dynamics. But JJ procedure consider both short-run and long-run dynamics as well.

Pesran et.al (1996) and Pesaran (1997) developed a single equation Autoregressive distributed lag model (ARDL) for cointegration. They proposed it as an alternative approach of Engle Granger (EG) and Engle Yool (EY). The advantage for ARDL model cointegration approach was that, it provides clear tests for the existence of one cointegrating vector, instead of taking assumption of uniqueness.

Pesran and Shin (1995) stated that asymptotically valid theory on long run and short run parameters might be made by taking into account the OLS estimations of ARDL models. SO ARDL approach is improved property to grant for existing correlation between the stochastic parts of the DGP (data generating process) involved in estimation.

Moreover Granger (1993), discovered a necessary and the sufficient condition for cointegration to be maintained after the accumulation is that the number of stochastic common trends provide the nonstationary variables equivalent to one. Having an extensive number of common trends leads to spurious regression after accumulation.

Steven cook (2004) extended the research of Leybourne and Newbold (2003). Leybourne and Newbold used cointegration test in order to avoid the problem of spurious regression. They applied it to independent *I(1)* process with respect to breaks in either trend or level. Whereas, Steven cook (2004) used finite sample for test of cointegration that include structural changes. He showed that when independent *I(1)* process applied subject to regime shifts, test of cointegration authorizing structural variations in the relationship of cointegration and reject the null hypothesis of "no cointegration" spuriously and more frequently as compare to tests considered by Leybourne et.al (2003)

Then Young (2005) considered the conditions in which two random walks that were independent of each other and they were also used in several estimation procedure and non-linear tests. They showed by simulation as well as analytically that all the estimation procedure and non-linear tests wrongly indicated that (i) two random walks that are independent of each other have a non-linear significant relationship (ii) Secondly, the non-linear spurious relationship becomes stronger if the size of sample increase and approached towards infinity.

Moreover, Choi and Ogaki (2004) created two estimators to evaluate structural estimators in the presence of spurious regression. Dynamic regression estimator is a first differenced which is corrected through GLS and it is a form of a dynamic OLS regression estimator. The asymptotic hypothesis or theory demonstrated that under some normality conditions the endogeneity correction of the dynamic regression works for the first differenced regression for both cointegrating approach and the spurious regression. This outcome was useful since it was not clear that the endogeneity correction approach works even in regression with stationary first differenced series. They also developed the Hausman-Wu-type cointegration test by comparing the GLS corrected dynamic regression estimators and dynamic OLS regression. For this test, spurious regression obtained under the alternative theory or hypothesis does not need to be structural.

Stewart (2006) revealed that t-ratios on *I(0)* dependent variable and *I(1)* explanatory variable with or without supplementary *I(0)* explanatory variables converge to random variable and not equal to zero. He showed that these t-ratios generally shows spurious correlation through estimated results obtained by simulation method. This depicts that spurious regression is an extensive concept than it was thought earlier. Furthermore, under the null hypothesis of "no cointegration" this spurious correlation leads to spurious cointegration. No other results in this description shows spurious correlation.

In the same year Santaularia and Noriega (2006) analysed asymptotic behaviour of t-test of Engle Granger for cointegration when there is structural breaks in the data set, instead of using *I(1)* process. They found that t-test cannot follow the limiting distribution, in fact it diverge if sample size increased towards infinity. Their methodology was based on asymptotic behaviour of t-test and on Monte Carlo simulation. Results obtained from this depicted that t-test can diverge in any direction, it becomes unreliable as same as cointegration, when the breaks in data set neglected. They presented an empirical evidence of this theoretical results by the use of real data on murders and car sales in the United States (US).

Santaularia (2009) gave an overview of results of spurious regression, collected from different sources, and clarified his implications in his analysis. According to him the spurious regression can occur whenever trending mechanism exists in the data series. Furthermore, he analysed that some spurious regression arises even in case of some stationary-auto correlated processes. Empirical and observational macroeconomists and the financial specialists have consistently incorporated specialized advances, these includes drift less unit roots, the unit roots with drift, trend, long memory and broken trend and trend stationarity. A high risk of obtaining a spurious relationship occurs when using the least square for macro and financial variables. Cointegration approach seems to be better to avoid non-sense statistical association. Out-of-sample forecasting could be a choice. The golden rule in order to avoid the spurious regression problem was pre-testing the series to find out the nature of trend mechanism. Once the DGP is accurately identified, spurious regression is easier to manage.

Furthermore, Olatayo et.al (2012) investigated the idea of cointegration techniques to deal with spurious regression models. The impact of utilizing arbitrary differencing method to distinguish which spurious regression will occurs from a true model with time series economic data was carried out. It was discovered that the idea of co-integration test is a more expressive to determine variables whose spurious will results from truly related variables.

3.4 Other non-standard Method of Avoiding Spurious Regression

Dwindle and Phillips (1998) presented a theory to analyse the problem of spurious regression. The theory was applied to two examples of misleading regression: regression among independent random walks and regression of stochastic trend on time polynomials. It was demonstrated that such regression repeats in some degree and in entire shows the underlying orthonormal representation. Moreover, it was demonstrated that, if the number of regressors permitted to develop with the sample size (n), these empirical regressions prevail in precisely the full representation in the limit as n tends to infinity and that the regression R^2 approached to unity.

In the previous studies most of the researchers focused on just Type-II spurious regression but chiarella and Gao (2002) focused on Type-I spurious regression[1], that refers to rejection of

[1] In some circumstances regression of differenced time series tends to reject the relation among their levels. This phenomena is known as Type-I spurious regression, it refers the rejection of true relation.

genuine relationships. Time series are dynamic process, and the ignored sustem dynamics will turn into the systematic errors in regression equations. Due to the systematic errors differencing does not shows the underlying relationship among the time series in regression analysis. The reason was that the association between the time series caught by regression is not an invariant relationship, yet it relies upon the order of integration of the time series. The situation is worse in the presence of errors that are random.

Whereas, Fukushige and Wago (2002) focused on Durbin Watson proportion and examined whether it is useful to detect spurious regression in empirical analysis or not. When there is a spurious regression the Durbin Watson ratios merges to zero, so for testing the hypothesis of a cointegrating relationship DW test could be used. Monte Carlo simulation used for some non-sense regression and the outcomes obtained from this suggested that, the usual diagnostic checking process: t-values and the DW proportion in the primary regression and t-values in the second regression, recognized non-sense regression when the spurious impact from the non-stochastic part is expelled.

Besides, Yixiao (2006) demonstrated that a spurious regression can arises between two stationary generalized processes, as long as their generalized fractional differencing parameters sum up to a value greater than 0.5 and their densities have poles at a similar location. This theoretical judgement was verified by simulation. Their analysis depicted that the unboundedness at a nonzero frequency can leads towards the spurious regression.

As Seong, *et al.* (2008) thought about spurious regression among two unique kinds of seasonal time series. First, deterministic seasonal component and the other one with a stochastic seasonal component. When one kind of seasonal time series was regressed on the other sort and they were not depend on each other, the concept of spurious regression arises. A Monte Carlo simulation consider was used, as their simulation study demonstrated the presence of the spurious regression and moreover the spurious rejectionof seasonal Cointegration.

Besides, Noriega and Santaularia (2011) presented a modest method that is ensures the convergence of t-statistics to a essential limit distribution, generating the data processes when there is drift in the integrated, in this way permitting asymptotic inference. They demonstrated that this technique can be utilized to recognize true relationship from a spurious one among integrated I(1) and I(2) forms. Simulation tests demonstrated that the test has decent size and the power properties in little samples. They applied the developed technique to several pairs of independent integrated variables which was proposed and applied by Yule, 1926 (including the marriages and mortality data) and find that their technique, rather than standard OLS (ordinary least square), did not discover (Spurious) significant associations between the variables.

Rehman et.al (2014) stated that there is high correlation between two uncorrelated time series variables due to extremely biased coefficient of correlation "R". This concept is known as spurious correlation. They proved in their study that association between stationary time series variables is also spurious correlation. This phenomena means correlation is unreliable to measure the relationship between the time series models. It happened because of most of the time series are associated to each other. Therefore, they have developed Modified R (MR) as a new measure of association for two time series. This measure is robust to strength and type of autocorrelation, type of deterministic part and the type of non-stationarity in data generating process. MR is unformal measure of correlation but it gives the quick idea of strength of correlation between two series. The performance of MR was demonstrated with the use of Monte Carlo Experiments. They recommended for time series variables we should have to use Modified R (MR) rather than conventional R.

Mingua *et al* (2016) inspected three kinds of spurious regression where both the independent and dependent variables contain deterministic trend, breaking trends or stochastic trend. They demonstrated that if the trend functions are including as additional regressors than the problems of spurious regression will disappears. By the using the FGLS (Feasible General Least Square) it can help to eliminate or remove the problem of autocorrelation. In finite samples their theoretical results were clearly reflected. As an illustration, they connected their techniques to revist the fundamental investigation of Yule (1926).

The latest study regarding the solution of spurious regression is, Ghouse et.al (2018) stated that for non-stationary time series there are some limitations in conventional econometrics to handling the spurious regression. They realized from the experiment of Granger et.al (1974) that spurious regression arises due to lack of lag dynamics. Therefore, from this study econometricians considered cointegration analysis and the unit root test as a remedy of spurious regression. According to Ghouse et.al this phenomena is also unreliable because of some decisions like structural breaks, selection of deterministic parts, innovation process distribution and the selection of lag length in auto regressive process. They proposed an alternate remedy for the problem of spurious regression. They exposed that missing lag values is the major reason of that problem. So to avoid this problem, incorporate all the mission lag values into the model that leads to Auto Regressive Distributed Lag (ARDL) model. In this study they focused on Monte Carlo Simulation. And the estimated results suggested that ARDL model can be used to avoid the problem of spurious regression.

3.5 Literature Gap

Now in our study we will use Weighted Average Least Square (WALS) technique to avoid the problem of spurious regression. In whole literature researchers used different econometric techniques and WALS to incorporate uncertainty. The researcher used Weighted Average Least Square (WALS) in growth theories and to compare with other model averaging techniques that are Bayesian Model Averaging (BMA) technique and Frequentist Model Averaging (FMA) technique. But in whole literature no one used WALS to avoid spurious regression, in this study we evaluate the performance of WALS to avoid the problem of spurious regression and Forecasting, that's the contribution of our study.

Chapter 4

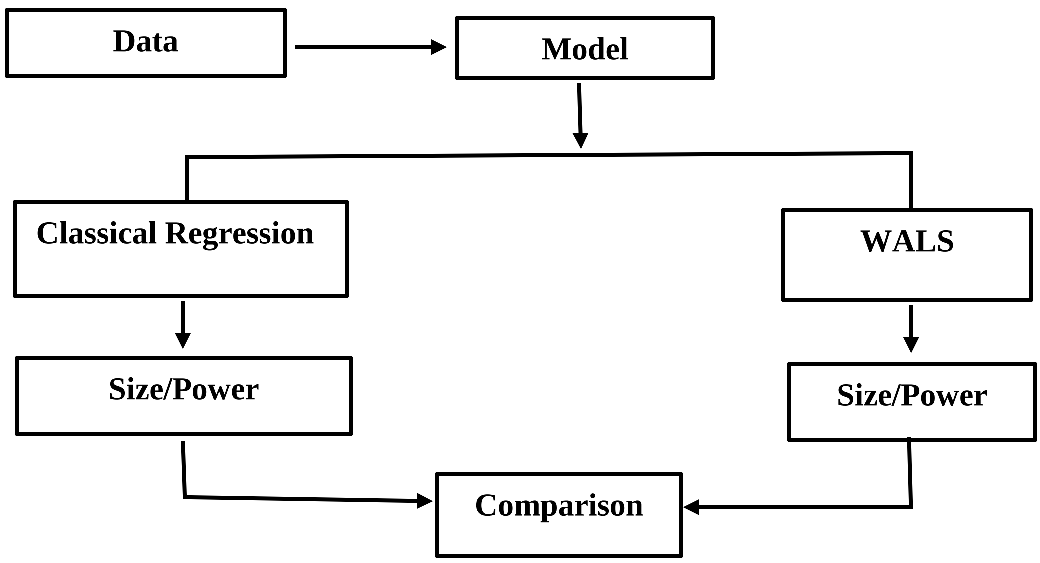
Methodology

Our methodology evaluate the performance of Weighted Average Least Square (WALS) is based on following logic. We have seen that regression of consumption of country "i" on GDP of country "j" ($i \neq j$) give spurious results.

$$CONS(i)_t = \alpha + \beta_1 GDP(j)_t + \epsilon_t \quad \ldots (5)$$

If we estimate above model by using WALS and if β turns out to be insignificant, this would imply that this is not a spurious regression and the WALS has contributed to avoid spurious regression. Based on the mentioned logic methodology is arranged as follows:

Figure 4.1



4.1 Calculating Size and Power

Size and Power can be easily calculated by simulation. For real data Size/Power cannot be calculated because the underlying relationship is unknown. But, in case of Consumption and GDP we can calculate size and power. Suppose we have a linear model:

$$CONS(i)_t = \alpha + \beta_1 GDP(j)_t + \epsilon_t \ \ldots (6)$$

Where, "t" represents time and i, j represents the countries whose data is used. If i = j, that is a case of consumption and GDP of same country, here we are sure that there should be cointegration between that series and the hypothesis (H_0: $\beta_1 = 0$) is not valid. In this case the probability of rejection of null can give us power.

However, if i ≠ j, that is a case of consumption and GDP of different countries, we are sure that there should not be any cointegration between that series and the hypothesis (H_0: $\beta_1 = 0$) is valid. In this case the probability of rejection of null can give us size. And if the actual size is greater than the nominal size, this would indicates the spurious relationship exist.

4.2 Forecasting

Forecasting can be done for the models that contain consumption and GDP of the same countries (*i*=*j*), because there exist true relation between them. Therefore, thirty combination will obtain for the same countries because we have select 30 countries for this study so, 30 times we forecast the WALS and the OLS model. In this process the set of regressors will remain same for both WALS and the OLS regression that would be the GDP of country j. Then estimate the residual sum of square (RSS) of forecasted values that would be forecast errors of the model. Such as,

$$\text{RSS} = \sum_{i=1}^{30}(y_i - (\alpha + \beta x_i))^2 \ldots (7)$$

Where, α is the estimated value of the intercept while, β is the estimated value of the focus variable. The model which has less RSS would be considered the best model. Therefore, the RSS of forecasted values would be compare through the use of five number summary/ Box plot. Whereas, five number summary is the set of Descriptive statistics consist of five sample percentile. i.e.

- Minimum (*Presents the lowest forecast error of WALS and OLS model*)
- Quartile 1 (Q1) (*Presents 25% of the values of forecast error are less than this value*)
- Median/ Quartile 2 (Q2) (*Presents 50% of the values are less than this value*)
- Quartile 3 (Q3) (*Presents 75% of the values are less than this value*)
- Maximum (*Presents the highest forecast error of WALS and OLS model*)

At last we would estimate mean difference, to check whether the difference between the forecast performance of both models is significant or not. For that purpose we would use pooled case of t-test, because here our null hypothesis is "there is no difference between forecasting performances of two models" and also the variance for both are same. The test is as follows:

$$t = \frac{\overline{X}_1 - \overline{X}_2}{\sqrt{\frac{{S_p}^2}{n_1} + \frac{{S_p}^2}{n_2}}} \ldots (8)$$

$$where, {S_p}^2 = \frac{(n_1 - 1){S_1}^2 + (n_2 - 1){S_2}^2}{n_1 + n_1 - 2} \quad with\ D.f = n_1 + n_2 - 2$$

If the absolute value of "t" is greater than the critical value then there would be significant difference exist between them and vice versa.

4.3 Model Specification

The model for our study in order to estimate WALS is as follows:

$$CONS(i)_t = \alpha_0 + \beta_1 GDP(j)_t + \beta_2 GDP(i)_t + \beta_3 GDP(i)_{t-1} + \ \beta_4 CON(i)_{t-1} + \epsilon_t \ldots (9)$$

Where,

$CONS(i)_t$= Consumption of Country *i*

$GDP(j)_t$= Gross Domestic product of Country *j*

$GDP(i)_t$ = Gross Domestic product of Country *i*

$GDP(i)_{t-1}$ = Lag of Gross Domestic product of Country *i*

$CONS(i)_{t-1}$= Lag of Consumption of Country *i*

ϵ_t= Error Term of the model

For the above model we have selected 30 countries to check the spurious relationship by making all the possible combinations between them. The possible combination for size calculation would be 870 and for power calculation is 30. In this model $GDP(j)_t$ is treated as focus variable while rest of the regressors used as an auxiliary variables. So, our interest is in the estimation of β_1 through WALS. If β_1 is insignificant it means that WALS can be used to avoid spurious relationship among the two independent variables.

The purpose of this exercise is to see whether or not WALS can handle the missing variables problems. The missing variables in our case are income, lag income and lag consumption of the country whose consumption is used as dependent variable. These variables are already included in the model. Including the variables arbitrarily makes no sense. However in other cases where number of independent variables could be very large, one can include very large number of Auxiliary variables as well.

4.4 Comparison

We compare WALS with the classical regression model (OLS) on the basis of size, power and the forecast performance of these models. The models are estimated on data of consumption and GDP, in which 85% of the data used for estimation while 15% used for forecasting. The model would be considered the best model that contain better size/power performance and the smaller forecast error values.

4.5 Variables and Selected Countries

As Pakistan belongs to low middle income group therefore, we selected thirty countries belongs to low and lower middle income groups. Two variable used in this study that are Final consumption expenditure (current US$) and GDP (current US$). The selected countries for this study are Rwanda (RWA), Benin (BEN), Senegal (SEN), Burkina Faso (BFA), Sierra Leone (SLE), Burundi (BDI), Central African Republic (CAF), Malawi (MWI), Togo (TGO), Mali (MLI), Zimbabwe (ZWE), Gambia,The (GMB), Niger (NER), Indonesia (IDN), Philippine (PHL), Kenya (KEN), Sri Lanka (LKA), Bolivia (BOL), Sudan (SDN), Swaziland (SWZ), Cameroon (CMR), Congo, Rep. (COG), Mauritania (MRT), Egypt, Arab Rep. (EGY), El Salvador (SLV), Ghana (GHA), Guatemala (GTM), Honduras (HND), Pakistan (PAK), India (IND) from 1971-2015.

4.6 Source of the Data

Data set for these variables collected from the site of World Development Indicators (WDI).

Chapter 5

Results and Discussion

As mentioned in previous section that the performance of Weighted Average Least Square compare with the OLS in order to avoid the problem of spurious relationship is on the basis of Size, Power and the forecast performance.

For that purpose we have selected 30 countries and making all the possible combination between them. In order to calculate size of the models we make combinations between two different countries such as a consumption of country "*i*" depends on GDP of a country "*j*" (*i* ≠j). For this exercise 870 combinations have been obtained. Whereas, in order to calculate power of the models, combination between the same countries have been made in which the consumption of country "*i*" depends on a GDP of country "*j*" (*i*=*j*). Therefor, 30 combinations have been calculated for power estimation.

5.1 Size Calculation

In order to calculate size of the WALS and the OLS our proposed model is:

$$CONS(i)_t = \alpha + \beta 1 GDP(j)_t + \epsilon_t \; \ldots (10) \qquad (i \neq j)$$

The null and the alternative hypothesis is:

H_O: $\beta_1 = 0$ (No Relationship Exists)

H_1: $\beta_1 \neq 0$ (Relationship Exists)

The model shall be considered the best model in order to avoid spurious relationship that has lowest probability of rejecting the true null hypothesis through WALS or OLS. The estimated results are as follow:

Table 5. 1 Nominal Size and Actual Size

	Nominal Size	Number of Models	Actual Size
OLS	5%	870	99.7%
OLS	1%	870	99.7%
WALS	5%	870	20.6%
WALS	1%	870	8.4%

This table shows that 99.7% out of 870 models, OLS reject the true null hypothesis under both 5% and 1% nominal size. Whereas, through the use of WALS out of 870 models 20.6% of the WALS models reject the true null hypothesis under 5% nominal size while just 8.4% of the WALS models reject the true null hypothesis under 1% nominal size.

So the probability of spurious relationship through OLS under 5% and 1% nominal size are 94.7% (99.7% - 5%) and 98.7% (99.7% - 1%) respectively. Whereas, by the use of WALS the probability under 5% and 1% nominal size are 15.6% (20.6% - 5%) and 7.4% (8.4% - 1%) respectively. Therefore, use of WALS has reduced the probability of spurious regression by 79.1% (94.7% - 15.6%) and 91.3% (98.7% - 7.4%) under 5% and 1% nominal size respectively. So it has been concluded that WALS can be used in order to avoid spurious regression, because it reduced the probability of spurious regression problem significantly.

5.2 Power Calculation

In order to calculate Power of the WALS and OLS model our proposed model is:

$$CONS(i)_t = \alpha + \beta 1GDP(j)_t + \epsilon_t \; \ldots (11) \quad (i = j)$$

While the null and the alternative hypothesis is:

H_O: $\beta_1 = 0$ (No Relationship Exists)

H_1: $\beta_1 \neq 0$ (Relationship Exists)

In this case the model shall be considered the best model that has highest probability of rejecting the false null hypothesis through WALS or OLS. The estimated results are as follow:

Table 5. 2 Power of OLS and WALS

	Number of Models	**Power**
OLS	30	100%
WALS	30	100%

This table shows that, both OLS and WALS have same power of rejecting the false null hypothesis that is 100% out of 30 models. Both of them have shown significant relationship between consumption of country "*i*" and GDP 0f country "*j*" (*i* = *j*). So, it has been concluded that the power performance of both WALS and OLS is same.

5.3 Forecasting

Forecast performance of WALS and OLS would be compared through five number summary. For that purpose we have calculated residual sum of square (RSS) of forecast errors for both OLS and WALS models, then calculate five number summary of estimated results of RSS of both models to compare their forecast performance. Five number summary has been presented through Box whisker plot.

Figure: 5.3.1

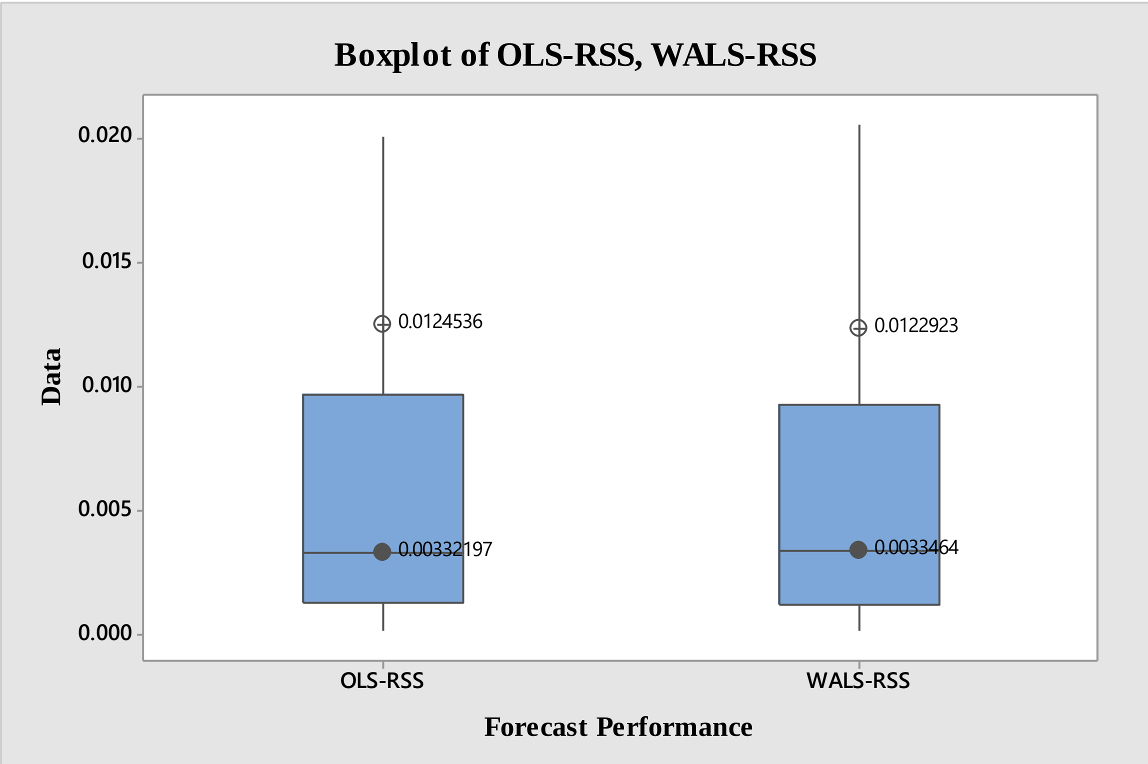


Table 5. 3 Five number Summary

Variable	Minimum	Q1	Median	Q3	Maximum
OLS-RSS	0.00016	0.00127	0.00332	0.00967	0.12922
WALS-RSS	0.00016	0.00120	0.00335	0.00927	0.12740

The five number summary of forecast error of WALS and OLS shown that both have same forecast performance because the minimum and the maximum value of forecast error are approximately same. While the values of Q1, median and Q3 are also about to same which means forecast error of WALS and OLS have same variations. These variations are clearly shown in box plot by box region. And if we look at the skewness then both of them are positively skewed, it means most of the data of forecast error lie above average. We confirm that both are performing same or not through mean difference calculation. The estimated result of mean difference is:

$$t_{cal} = 0.022 \qquad and\ t_{Critical} = 2.0017$$

As, calculated value of "t" is less than above critical value so, it means there is no difference exist between WALS and OLS forecast performance. Therefore, it has been concluded that WALS is performing as same as the OLS performed in forecasting.

5.4 Discussion

Above estimated results suggested that WALS and OLS performing about to same in power and forecast performance. In power, when we regressed consumption and GDP of same countries both WALS and OLS rejecting the null hypothesis ($\beta_1 = 0$) and shown a power of 100%. While, in forecasting average of RSS (median) and overall range from minimum to maximum through box plot is also same. There is no difference between the RSS of WALS and OLS in box range. However, both of them are positively skewed and also the value of mean difference suggested that no difference exist between there forecast performance. So, it has been suggested that OLS and WALS have same forecast performance.

Whereas, in order to calculate size we regressed consumption and GDP of two different countries WALS performed much better than OLS. By the use of WALS the probability of rejecting the true null hypothesis ($\beta_1 = 0$) was 20.6% and 8.4% under 5% and 1% nominal size respectively. While, the probability through the use of OLS was 99.7% and both 5% and 1% nominal size. As, we know if actual size is greater than the nominal size then it is a case of spurious regression. So, from above results we can say that WALS has reduced the probability of spurious relationship by 79.1% (99.7 - 20.6) under 5% nominal size while, 91.3% (99.7 – 8.4) under 1% nominal size.

Therefore, from all these discussion it has been depicted that other than Power and forecast performance WALS can be used to avoid the problem of spurious regression and it is performing much better than OLS whenever there is a chance of spurious relationship between two independent variables. Actually both OLS and WALS presents exactly (almost) same estimates, but WALS provide higher corresponding SEs which makes insignificant (smaller) t-stats (see the estimates and corresponding SEs in appendix)

Chapter 6

Summary, Conclusion and Recommendations

6.1 Summary

Spurious regression shows significant relationship between two or more independent variables. If we regress consumption of country "*i*" on GDP of country "*j*" ($i \neq j$) through the use of OLS, there results turns to be highly significant that is a case of spurious regression. There are two major reasons of spurious regression that are omitted variable bias and the non-stationarity of the data set. This study focused on omitted variable bias that lead to spurious regression. The solution for that problem is to include all the relevant variables but this method is not easy to handle because sometime time it makes the model too large and also sometime the number of predictors become greater than the number of observation making estimation impossible. Therefore, in this paper one of the latest model averaging technique that is Weighted Average Least Square (WALS) used in order to avoid the problem of spurious regression, as it handles the problem of large number of explanatory variables by making the subsets of auxiliary variables with focus variable. WALS is the Bayesian combination of frequentist estimator, earlier it was used to incorporate model uncertainty. Whereas, this study compared the performance of WALS with OLS to avoid the problem of spurious regression on the basis of Size/Power and the forecast performance. For that, data set of consumption expenditure and GDP of thirty countries belongs to low and lower middle income groups from 1971-2015 has selected. The size has calculated for consumption and GDP of different countries, where the relationship between them is not valid so the null hypothesis (β_1=0) is valid hence the probability of rejection of true null hypothesis gives us size. If the actual size greater than the nominal size then this would be the case of spurious regression. However, if consumption and

GDP of same countries regressed on each other, then the relationship between them is valid and the null hypothesis (β_1=0) is not valid. Here the probability of rejection of null hypothesis gives us the power of the models. Whereas, forecast performance can be compared through boxplot/five number summary and mean difference calculation. In this way we compared the performance of WALS with OLS to avoid the spurious regression problem.

6.2 Conclusion

It has been concluded from this study that weighted Average Least Square (WALS) can avoid the problem of spurious regression. As, the estimated results suggested that both WALS and OLS have same power and forecast performance. But other than this WALS is much better than OLS because the probability of rejecting the true null hypothesis by the use of WALS is smaller than the probability by the use of OLS. Such as, WALS gives the probability 20.6% under 5% and 8.4% under 1% nominal size. However, OLS gives the probability 99.7% under both nominal sizes. So, this indicated that WALS has reduced the probability of spurious regression by 79.1% and 91.3% under 5% and 1% nominal size respectively. Hence, this study concludes that WALS perform superior than OLS and shows significant results to avoid the major problem of econometrics analysis that is the problem of spurious regression.

6.3 Recommendations

Weighted average least square (WALS) is the remedy for spurious regression problem. In this practice we use only three Auxiliary variables in WALS model even then it shows significant results to avoid the problem of spurious regression. So, the recommendation is that measure the performance of WALS by increasing the number of auxiliary variables in the model to check how it perform in order to avoid the spurious regression problem. Secondly, other model averaging techniques that are Bayesian Model Averaging (BMA) technique and the Frequentist Model Averaging (FMA) technique can also be used to check how they perform to avoid the spurious regression problem and also compare their performance with WALS in avoiding this problem.

References

Chiarella, C., & Gao, S. (2002). Type I spurious regression in econometrics.

Choi, C. Y., Hu, L., & Ogaki, M. (2004). Structural Spurious Regressions and A Hausman-type Cointegration Test. *Rochester Center for Economic Research Working Paper*, (517).

Cook, S. (2004). Spurious rejection by cointegration tests incorporating structural change in the cointegrating relationship. *Applied Economics Letters*, *11*(14), 879-884.

Deng, A. (2015). A Primer on Spurious Statistical Significance in Time Series Regressions.

Engle, R. F., & Granger, C. W. J. (1987). Co-Integration and Error Correction: Representation, Estimation, and Testing. *Econometrica*, *55*(2), 251-276.

Engle, R. and Yoo Sam (1991). Forecasting and Testing in Co-integrated Systems, In Engle and Granger (eds.), Long Run Economic Relationships. Readings in Cointegration, *Oxford University Press*, *New York*, 237-67.

Fukushige, M., & Wago, H. (2002). Using the Durbin-Watson Ratio to Detect a Spurious Regressions: Can We Make a Rule of Thumb?

Ghouse, G., Khan, S. A., & Rehman, A. U. (2018). ARDL model as a remedy for spurious regression: problems, performance and prospectus.

Granger, C. W., & Newbold, P. (1974). Spurious regressions in econometrics. *Journal of econometrics*, *2*(2), 111-120.

Granger, C.W.J. and R.F. Engle, 1985, Dynamic model specification with equilibrium constraints: Cointegration and error correction, Discussion paper no. 85-18 (University of California at SanDiego, CA).

Granger, C. W. J. (1993). Implications of seeing economic variables through an aggregation window. *Ricerche Economiche*, *47*(3), 269-279.

Granger, C.W.J., N. Hyung, and Y. Jeon (1998), "Spurious Regressions with Stationary Series", Mimeo.

Juselius, K. (1992). Testing structural hypotheses in a multivariate cointegration analysis of the PPP and the UIP for UK. *Journal of econometrics, 53(1-3),* 211-244.

Hendry, D. F. (1980). Econometrics-alchemy or science? *Economica*, 387-406.

Kim, T. H., Lee, Y. S., & Newbold, P. (2004). Spurious regressions with stationary processes around linear trends. *Economics Letters*, *83*(2), 257-262.

Leybourne, S. J., & Newbold, P. (2003). Spurious rejections by cointegration tests induced by structural breaks. *Applied Economics*, *35*(9), 1117-1121.

Lee, Y. S., Kim, T. H., & Newbold, P. (2005). Spurious nonlinear regressions in econometrics. *Economics Letters*, *87*(3), 301-306.

Magnus, J. R., & Durbin, J. (1999). Estimation of regression coefficients of interest when other regression coefficients are of no interest. *Econometrica*, *67*(3), 639-643.

Magnus, J. R., Powell, O., & Prüfer, P. (2010). A comparison of two model averaging techniques with an application to growth empirics. *Journal of econometrics*, *154*(2), 139-153.

Magnus, J. R., & De Luca, G. (2016). Weighted-Average Least Squares (WALS): A Survey. *Journal of Economic Surveys*, *30*(1), 117-148.

Magnus, J. R., Wang, W., & Zhang, X. (2016). Weighted-average least squares prediction. *Econometric Reviews*, *35*(6), 1040-1074.

McCallum, B. T. (2010). Is the spurious regression problem spurious?. *Economics Letters*, *107*(3), 321-323.

Moghadam, S. A. (2012). *Model Uncertainty & Model Averaging Techniques* (Doctoral dissertation).

Noriega, A., & Ventosa-Santaularia, D. (2006). Spurious cointegration: the Engle-Granger test in the presence of structural breaks. *Banco de México, Documentos de investigación*, (2006-12).

Noriega, A. E., & Ventosa-Santaularia, D. (2011). *A Simple Test for Spurious Regressions* (No. 2011-05).

Olatayo, T. O., Adeogun, A. W., & Lawal, G. O. (2012). Cointegration approach to the spurious regression model.

Pesaran, M. H., Shin, Y., & Smith, R. J. (1996). Testing for the' Existence of a Long-run Relationship' (No. 9622). *Faculty of Economics, University of Cambridge.*

Pesaran, M. H. (1997). The role of economic theory in modelling the long run. *The Economic Journal, 107(440),* 178-191.

Pesaran, M. H., & Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of econometrics, 68(1*), 79-113.

Phillips, P. C. (1986). Understanding spurious regressions in econometrics. *Journal of econometrics*, *33*(3), 311-340.

Phillips, P. C. (1998). New tools for understanding spurious regressions. *Econometrica,* 1299- 1325.

Phillips, P. C., & Ouliaris, S. (1990). Asymptotic properties of residual based tests for cointegration. *Econometrica: Journal of the Econometric Society*, 165-193.

Rehman, A. U., & Malik, M. I. (2014). The modified R a robust measure of association for time series. *Electronic Journal of Applied Statistical Analysis*, *7*(1), 1-13.

Simon, H. A. (1954). Spurious correlation: A causal interpretation. *Journal of the American statistical Association*, *49*(267), 467-479.

Stewart, C. (2006). Spurious correlation of I (0) regressors in models with an I(1) dependent variable. *Economics Letters*, *91*(2), 184-189.

Seong, B., Ahn, S. K., & Jeon, Y. (2008). A note on spurious regression in seasonal time series. *Journal of Statistical Computation and Simulation*, *78*(9), 843-851.

Sun, Y. (2006). Spurious regressions between stationary generalized long memory processes. *Economics Letters*, *90*(3), 446-454.

Trapani, L., & Urga, G. (2004). Cointegration versus Spurious Regression in Heterogeneous Panels. *Econometric Society*.

Ventosa-Santaulària, D. (2009). Spurious regression. *Journal of Probability and Statistics*, *2009*.

Ventosa-Santaulària, D. (2012). Unbalanced regressions and spurious inference. *Open Journal of Statistics*, *2*(03), 297.

Wu, M., You, P., & Zou, N. (2016). On spurious regressions with trending variables. *arXiv preprint arXiv:1606.05049*.

Yule, G. U. (1926). Why do we sometimes get nonsense-correlations between Time-Series?a study in sampling and the nature of time-series. *Journal of the royal statistical society*, *89*(1), 1-63.

Appendix A

Estimation of coefficients and t-stat of WALS and OLS

Sr#	Country i	Country J	WALS α	WALS t-stat	WALS β11	WALS t-stat	OLS α	OLS t-stat	OLS β11	OLS t-stat
1	RWA	RWA	0.08	0.712	0.99	4.93	0.08	0.506	0.99	56.73
2	RWA	BEN	0.99	0.490	0.88	0.66	1.00	1.596	0.88	13.02
3	RWA	SEN	-2.16	-1.211	1.17	1.36	-2.17	-3.311	1.18	17.30
4	RWA	BFA	-0.39	-0.589	1.02	1.39	-0.40	-0.712	1.02	17.13
5	RWA	CAF	-2.43	-2.228	1.29	2.42	-2.42	-5.413	1.30	25.87
6	RWA	MWI	0.28	0.228	0.96	0.82	0.28	0.429	0.97	13.77
7	RWA	TGO	-2.31	-1.091	1.26	1.22	-2.32	-3.399	1.27	16.84
8	RWA	MLI	1.15	0.725	0.85	0.86	1.15	2.066	0.86	14.35
9	RWA	GMB	2.84	0.361	0.74	0.25	2.85	4.083	0.74	9.02
10	RWA	NER	-4.22	-0.711	1.43	0.75	-4.24	-4.373	1.44	13.83
11	RWA	IDN	1.42	0.754	0.70	0.78	1.43	2.590	0.70	13.98
12	RWA	PHL	0.22	0.096	0.83	0.62	0.22	0.326	0.84	13.13
13	RWA	KEN	-0.03	-0.020	0.92	0.73	-0.03	-0.043	0.92	13.65
14	RWA	LKA	1.69	0.276	0.75	0.33	1.70	2.087	0.75	9.16
15	RWA	BOL	-1.33	-0.716	1.07	1.03	-1.34	-1.943	1.08	15.24
16	RWA	SDN	-0.31	-0.187	0.93	0.64	-0.31	-0.405	0.94	12.49
17	RWA	SWZ	2.95	0.440	0.69	0.36	2.97	4.908	0.69	10.26
18	RWA	CMR	-0.91	-1.498	1.01	1.92	-0.90	-2.829	1.01	31.65
19	RWA	COG	1.23	1.511	0.84	1.66	1.24	2.796	0.85	17.92
20	RWA	MRT	0.18	0.116	0.99	0.77	0.18	0.273	1.00	13.52
21	RWA	SLE	-1.42	-0.097	1.18	0.20	-1.42	-0.823	1.18	6.12
22	RWA	BDI	-4.48	-2.791	1.52	2.01	-4.48	-6.901	1.53	21.02
23	RWA	EGY	0.97	0.407	0.76	0.56	0.98	1.499	0.77	12.45
24	RWA	SLV	1.86	0.303	0.74	0.32	1.87	2.413	0.75	9.42
25	RWA	ZWE	-7.80	-0.192	1.73	0.24	-7.81	-3.188	1.73	6.93
26	RWA	GHA	-0.35	-0.111	0.97	0.42	-0.35	-0.370	0.97	10.05
27	RWA	GTM	0.55	0.209	0.85	0.53	0.56	0.764	0.86	11.83
28	RWA	HND	0.71	0.607	0.88	0.95	0.72	1.239	0.88	14.60
29	RWA	PAK	0.62	0.370	0.80	0.72	0.63	1.005	0.80	13.55
30	RWA	IND	-0.56	-0.254	0.84	0.69	-0.57	-0.758	0.85	13.01
31	BEN	RWA	1.21	0.289	0.86	0.62	1.23	2.001	0.87	13.07
32	BEN	BEN	0.50	1.310	0.94	3.38	0.50	5.219	0.94	90.63
33	BEN	SEN	-2.19	-2.040	1.18	2.18	-2.19	-5.859	1.19	30.54
34	BEN	BFA	-0.51	-0.901	1.04	1.61	-0.51	-2.290	1.04	43.37
35	BEN	CAF	-1.25	-0.484	1.16	0.74	-1.27	-1.626	1.17	13.49
36	BEN	MWI	0.02	0.026	1.00	1.93	0.02	0.056	1.00	28.12
37	BEN	TGO	-2.23	-2.274	1.26	2.85	-2.24	-4.669	1.26	23.92

38	BEN	MLI	0.83	1.265	0.90	1.43	0.83	5.771	0.90	58.19
39	BEN	GMB	2.69	0.547	0.75	0.65	2.73	4.759	0.76	11.35
40	BEN	NER	-4.06	-1.207	1.42	1.04	-4.09	-5.098	1.43	16.60
41	BEN	IDN	1.36	1.527	0.71	2.02	1.36	3.744	0.71	21.73
42	BEN	PHL	-0.07	-0.049	0.87	1.22	-0.07	-0.178	0.87	25.25
43	BEN	KEN	-0.33	-0.363	0.96	1.75	-0.33	-1.024	0.96	29.46
44	BEN	LKA	0.99	0.958	0.82	2.04	1.00	2.154	0.83	17.78
45	BEN	BOL	-1.20	-1.425	1.07	2.90	-1.20	-2.176	1.07	18.90
46	BEN	SDN	-0.16	-0.069	0.92	0.87	-0.16	-0.245	0.93	14.28
47	BEN	SWZ	2.49	2.212	0.75	1.41	2.49	8.045	0.75	21.76
48	BEN	CMR	-0.07	-0.059	0.93	1.47	-0.07	-0.130	0.94	16.51
49	BEN	COG	1.41	1.509	0.84	2.32	1.41	3.996	0.84	22.25
50	BEN	MRT	-0.09	-0.086	1.03	1.41	-0.09	-0.274	1.03	27.14
51	BEN	SLE	-2.40	-0.217	1.29	0.30	-2.41	-1.699	1.30	8.22
52	BEN	BDI	-2.10	-0.235	1.26	0.28	-2.12	-1.672	1.27	8.96
53	BEN	EGY	0.81	0.978	0.79	2.39	0.81	1.855	0.79	19.28
54	BEN	SLV	1.16	1.115	0.82	1.66	1.17	2.869	0.82	19.83
55	BEN	ZWE	-3.29	-0.065	1.28	0.12	-3.29	-1.120	1.28	4.26
56	BEN	GHA	-0.83	-0.423	1.02	1.46	-0.84	-1.319	1.03	15.79
57	BEN	GTM	0.15	0.133	0.90	1.61	0.15	0.384	0.90	22.90
58	BEN	HND	0.58	0.740	0.90	1.93	0.58	1.775	0.90	26.35
59	BEN	PAK	0.42	0.408	0.83	1.39	0.42	1.185	0.83	24.74
60	BEN	IND	-1.00	-0.586	0.89	1.22	-1.00	-3.059	0.89	31.24
61	SEN	RWA	2.32	2.174	0.79	3.12	2.33	5.641	0.79	17.63
62	SEN	BEN	2.23	0.992	0.80	1.59	2.23	7.167	0.80	23.70
63	SEN	SEN	-0.52	-1.240	1.05	4.08	-0.52	-4.536	1.05	88.37
64	SEN	BFA	1.16	0.722	0.90	1.37	1.16	4.800	0.90	34.86
65	SEN	CAF	-0.15	-0.118	1.09	2.00	-0.15	-0.371	1.09	24.67
66	SEN	MWI	1.72	1.136	0.86	2.03	1.72	4.609	0.86	21.15
67	SEN	TGO	-0.54	-0.593	1.12	1.44	-0.55	-1.834	1.12	34.06
68	SEN	MLI	2.39	0.804	0.77	1.19	2.39	10.224	0.77	30.83
69	SEN	GMB	3.93	1.108	0.65	1.43	3.98	7.789	0.66	11.00
70	SEN	NER	-2.08	-1.919	1.25	3.07	-2.09	-3.175	1.26	17.77
71	SEN	IDN	2.83	1.690	0.61	2.23	2.84	7.752	0.61	18.43
72	SEN	PHL	1.73	1.283	0.74	2.31	1.74	3.888	0.74	17.58
73	SEN	KEN	1.55	1.209	0.81	2.57	1.55	3.477	0.81	18.05
74	SEN	LKA	2.72	1.297	0.69	2.16	2.73	5.229	0.69	13.15
75	SEN	BOL	0.79	0.872	0.90	3.40	0.81	1.337	0.90	14.46
76	SEN	SDN	1.44	0.771	0.80	1.97	1.45	2.489	0.81	14.02
77	SEN	SWZ	3.89	2.052	0.64	2.70	3.90	11.107	0.64	16.24
78	SEN	CMR	1.20	1.009	0.85	1.50	1.22	3.555	0.85	24.53
79	SEN	COG	2.80	1.723	0.73	2.30	2.81	8.854	0.73	21.44
80	SEN	MRT	1.52	0.712	0.89	1.25	1.52	4.652	0.89	24.64
81	SEN	SLE	0.12	0.012	1.04	0.42	0.12	0.091	1.05	6.95

82	SEN	BDI	-0.99	-0.150	1.18	0.89	-0.98	-1.072	1.18	11.57
83	SEN	EGY	2.50	1.962	0.67	3.22	2.51	5.161	0.67	14.55
84	SEN	SLV	2.96	1.227	0.67	1.99	2.98	5.748	0.68	12.78
85	SEN	ZWE	-2.47	-0.042	1.23	0.19	-2.48	-1.027	1.23	5.01
86	SEN	GHA	0.93	0.641	0.88	2.21	0.93	1.563	0.89	14.61
87	SEN	GTM	2.08	1.641	0.74	3.05	2.10	3.951	0.75	14.13
88	SEN	HND	2.35	1.865	0.75	3.15	2.36	5.374	0.76	16.53
89	SEN	PAK	2.10	1.456	0.71	2.34	2.11	5.167	0.71	18.37
90	SEN	IND	0.97	0.790	0.75	2.22	0.97	2.119	0.75	18.92
91	BFA	RWA	1.36	2.330	0.87	2.58	1.37	3.004	0.87	17.48
92	BFA	BEN	1.16	1.251	0.88	1.35	1.16	4.239	0.88	29.97
93	BFA	SEN	-1.60	-1.181	1.13	1.17	-1.60	-4.924	1.13	33.59
94	BFA	BFA	-0.04	-0.296	1.00	3.46	-0.04	-0.365	1.00	90.69
95	BFA	CAF	-1.02	-1.742	1.15	2.68	-1.02	-1.678	1.16	17.02
96	BFA	MWI	0.61	1.290	0.95	1.63	0.61	1.698	0.95	24.10
97	BFA	TGO	-1.69	-1.477	1.21	1.48	-1.69	-4.159	1.21	27.15
98	BFA	MLI	1.40	1.031	0.85	1.09	1.40	6.158	0.85	34.98
99	BFA	GMB	3.31	0.650	0.68	0.53	3.38	5.481	0.70	9.63
100	BFA	NER	-3.73	-2.466	1.40	2.58	-3.73	-6.339	1.40	22.19
101	BFA	IDN	1.96	2.519	0.67	2.42	1.97	4.670	0.67	17.49
102	BFA	PHL	0.68	1.930	0.81	2.20	0.69	1.442	0.81	18.14
103	BFA	KEN	0.27	0.835	0.91	1.76	0.27	0.756	0.91	25.77
104	BFA	LKA	1.79	1.363	0.75	1.20	1.80	3.152	0.76	13.21
105	BFA	BOL	-0.50	-1.331	1.01	2.83	-0.49	-0.839	1.01	16.73
106	BFA	SDN	0.20	0.368	0.90	1.70	0.20	0.360	0.90	16.31
107	BFA	SWZ	3.12	2.287	0.69	2.02	3.13	7.730	0.69	15.29
108	BFA	CMR	0.27	0.739	0.91	2.43	0.28	0.615	0.91	19.94
109	BFA	COG	1.81	1.522	0.80	1.45	1.81	5.990	0.80	24.85
110	BFA	MRT	0.58	1.176	0.97	0.96	0.58	1.389	0.97	20.87
111	BFA	SLE	-1.74	-0.267	1.23	0.41	-1.75	-1.295	1.23	8.18
112	BFA	BDI	-2.05	-0.420	1.25	0.72	-2.09	-1.983	1.28	10.84
113	BFA	EGY	1.49	2.252	0.73	2.41	1.50	2.954	0.74	15.46
114	BFA	SLV	1.95	1.455	0.75	1.48	1.96	3.718	0.75	14.01
115	BFA	ZWE	-3.42	-0.078	1.30	0.17	-3.42	-1.266	1.30	4.71
116	BFA	GHA	-0.20	-0.440	0.97	1.56	-0.20	-0.321	0.97	14.95
117	BFA	GTM	0.92	2.227	0.84	2.66	0.92	1.822	0.84	16.57
118	BFA	HND	1.16	2.133	0.85	2.37	1.17	3.175	0.85	22.23
119	BFA	PAK	1.07	2.064	0.78	2.21	1.08	2.530	0.78	19.37
120	BFA	IND	-0.28	-0.840	0.84	1.70	-0.28	-0.664	0.84	22.94
121	CAF	RWA	2.16	1.991	0.74	1.94	2.16	7.575	0.74	23.69
122	CAF	BEN	2.76	1.448	0.66	1.64	2.77	5.452	0.67	12.14
123	CAF	SEN	0.17	0.406	0.91	2.25	0.16	0.360	0.91	19.22
124	CAF	BFA	1.67	1.976	0.77	2.54	1.67	3.692	0.78	16.02
125	CAF	CAF	-0.16	-0.828	1.02	3.79	-0.16	-1.394	1.02	79.51

126	CAF	MWI	2.25	1.562	0.72	1.87	2.26	4.194	0.72	12.37
127	CAF	TGO	0.05	0.124	0.98	2.39	0.05	0.098	0.98	18.63
128	CAF	MLI	2.83	1.909	0.65	2.15	2.84	6.425	0.65	13.78
129	CAF	GMB	4.03	1.116	0.57	0.95	4.06	7.728	0.57	9.25
130	CAF	NER	-1.32	-1.020	1.10	1.71	-1.32	-1.787	1.10	13.83
131	CAF	IDN	3.07	2.290	0.53	2.42	3.09	6.857	0.53	12.95
132	CAF	PHL	2.24	1.644	0.62	1.83	2.26	3.915	0.63	11.57
133	CAF	KEN	2.16	1.040	0.68	1.31	2.16	3.590	0.68	11.22
134	CAF	LKA	3.41	0.631	0.54	0.62	3.45	5.103	0.55	8.11
135	CAF	BOL	1.25	1.036	0.78	1.74	1.27	1.928	0.79	11.65
136	CAF	SDN	1.89	0.762	0.69	1.01	1.90	2.938	0.70	10.86
137	CAF	SWZ	4.20	1.155	0.52	1.11	4.23	8.938	0.52	9.95
138	CAF	CMR	1.24	1.150	0.77	1.22	1.25	4.831	0.77	29.75
139	CAF	COG	3.03	2.209	0.63	2.41	3.04	7.379	0.63	14.31
140	CAF	MRT	2.11	1.888	0.75	2.20	2.12	3.997	0.75	12.84
141	CAF	SLE	1.22	0.097	0.85	0.33	1.22	0.885	0.86	5.57
142	CAF	BDI	-1.38	-1.160	1.15	1.92	-1.36	-2.389	1.15	18.03
143	CAF	EGY	2.95	1.135	0.56	1.16	2.97	5.027	0.56	10.08
144	CAF	SLV	3.49	0.723	0.55	0.73	3.52	5.558	0.55	8.55
145	CAF	ZWE	-3.85	-0.250	1.29	0.46	-3.92	-2.062	1.31	6.76
146	CAF	GHA	1.83	0.563	0.72	0.78	1.84	2.380	0.72	9.18
147	CAF	GTM	2.62	0.954	0.62	1.10	2.64	4.120	0.63	9.84
148	CAF	HND	2.75	1.275	0.64	1.46	2.76	5.088	0.64	11.36
149	CAF	PAK	2.58	1.663	0.59	1.79	2.60	4.754	0.60	11.58
150	CAF	IND	1.75	1.038	0.62	1.31	1.76	2.671	0.62	10.90
151	MWI	RWA	1.15	0.379	0.87	0.78	1.15	1.684	0.87	11.70
152	MWI	BEN	0.39	0.456	0.95	1.35	0.40	1.359	0.95	30.00
153	MWI	SEN	-2.28	-1.866	1.19	1.84	-2.28	-4.204	1.19	21.11
154	MWI	BFA	-0.58	-0.764	1.04	1.44	-0.58	-1.407	1.04	23.63
155	MWI	CAF	-1.36	-0.663	1.17	0.98	-1.37	-1.579	1.18	12.16
156	MWI	MWI	-0.45	-1.188	1.04	4.26	-0.45	-3.223	1.04	69.36
157	MWI	TGO	-2.35	-2.140	1.27	2.03	-2.36	-3.876	1.27	18.94
158	MWI	MLI	0.71	0.692	0.90	1.46	0.72	0.295	0.90	28.60
159	MWI	GMB	2.41	0.592	0.78	0.79	2.45	4.313	0.79	11.80
160	MWI	NER	-3.96	-1.130	1.41	0.94	-3.98	-3.958	1.41	13.06
161	MWI	IDN	1.09	1.054	0.73	1.87	1.10	3.014	0.73	22.19
162	MWI	PHL	-0.30	-0.325	0.89	1.71	-0.29	-0.689	0.89	22.78
163	MWI	KEN	-0.41	-0.521	0.96	1.84	-0.40	-0.860	0.96	20.38
164	MWI	LKA	0.72	0.724	0.85	2.01	0.74	1.564	0.85	17.76
165	MWI	BOL	-1.38	-1.702	1.08	2.26	-1.36	-2.145	1.08	16.60
166	MWI	SDN	0.01	0.003	0.90	0.77	0.01	0.010	0.91	11.13
167	MWI	SWZ	2.26	1.931	0.77	1.59	2.28	7.037	0.77	21.21
168	MWI	CMR	-0.22	-0.249	0.94	1.95	-0.20	-0.315	0.94	0.06
169	MWI	COG	1.27	1.056	0.84	1.90	1.28	3.016	0.84	18.61

170	MWI	MRT	-0.29	-0.339	1.05	1.51	-0.28	-0.677	1.05	22.82
171	MWI	SLE	-2.49	-0.268	1.29	0.31	-2.50	-1.668	1.30	7.78
172	MWI	BDI	-2.19	-0.345	1.26	0.38	-2.20	-1.633	1.27	8.42
173	MWI	EGY	0.59	0.662	0.80	2.20	0.62	1.288	0.80	17.77
174	MWI	SLV	0.95	0.980	0.84	1.98	0.97	2.184	0.84	18.45
175	MWI	ZWE	-3.97	-0.126	1.34	0.17	-3.97	-1.339	1.34	4.43
176	MWI	GHA	-0.99	-0.711	1.03	1.46	-0.99	-1.391	1.04	14.27
177	MWI	GTM	-0.07	-0.081	0.92	1.88	-0.05	-0.106	0.92	20.51
178	MWI	HND	0.50	0.595	0.90	2.12	0.51	1.134	0.90	19.27
179	MWI	PAK	0.16	0.175	0.85	1.61	0.18	0.466	0.85	23.63
180	MWI	IND	-1.18	-0.953	0.90	1.54	-1.17	-2.702	0.90	23.90
181	TGO	RWA	1.55	0.843	0.81	2.31	1.53	3.269	0.82	15.93
182	TGO	BEN	1.37	0.672	0.83	1.61	1.37	4.036	0.83	22.59
183	TGO	SEN	-1.34	-1.129	1.07	1.15	-1.35	-4.142	1.08	31.77
184	TGO	BFA	0.36	0.193	0.92	1.27	0.35	1.020	0.93	25.11
185	TGO	CAF	-0.96	-0.697	1.11	1.94	-0.97	-1.935	1.12	19.86
186	TGO	MWI	0.87	0.473	0.88	1.74	0.86	2.072	0.89	19.61
187	TGO	TGO	-1.52	-1.322	1.16	2.79	-1.53	-4.670	1.16	32.23
188	TGO	MLI	1.55	0.688	0.80	1.49	1.55	5.694	0.80	27.48
189	TGO	GMB	2.95	1.311	0.71	2.02	2.97	6.291	0.71	12.78
190	TGO	NER	-2.63	-1.691	1.25	1.59	-2.70	-3.124	1.26	13.53
191	TGO	IDN	2.03	0.960	0.63	1.82	2.04	4.986	0.63	17.06
192	TGO	PHL	0.75	0.421	0.77	1.57	0.76	1.764	0.77	19.06
193	TGO	KEN	0.64	0.388	0.84	1.88	0.62	1.357	0.84	18.40
194	TGO	LKA	1.79	0.822	0.72	2.01	1.79	3.462	0.73	14.00
195	TGO	BOL	-0.14	-0.096	0.94	2.01	-0.14	-0.225	0.94	14.55
196	TGO	SDN	0.88	0.245	0.80	1.20	0.86	1.201	0.81	11.40
197	TGO	SWZ	3.00	1.320	0.67	1.93	3.01	8.992	0.67	17.92
198	TGO	CMR	0.40	0.245	0.87	1.71	0.41	0.964	0.87	19.98
199	TGO	COG	2.11	1.047	0.74	2.02	2.11	5.125	0.74	16.82
200	TGO	MRT	0.71	0.359	0.92	1.38	0.70	1.768	0.92	20.88
201	TGO	SLE	-0.10	-0.008	1.01	0.35	-0.10	-0.063	1.01	5.89
202	TGO	BDI	-1.66	-0.431	1.19	1.13	-1.69	-1.620	1.20	10.27
203	TGO	EGY	1.46	0.939	0.71	2.36	1.48	3.352	0.71	17.08
204	TGO	SLV	1.94	1.059	0.72	2.28	1.95	4.087	0.72	14.81
205	TGO	ZWE	-4.24	-0.170	1.35	0.31	-4.27	-1.770	1.36	5.51
206	TGO	GHA	0.35	0.125	0.88	1.35	0.31	0.429	0.89	11.91
207	TGO	GTM	1.11	0.693	0.79	2.30	1.11	2.153	0.79	15.26
208	TGO	HND	1.45	0.902	0.79	2.32	1.46	3.239	0.79	16.73
209	TGO	PAK	1.17	0.722	0.74	1.98	1.19	2.886	0.74	18.97
210	TGO	IND	0.05	0.033	0.78	2.03	0.05	0.102	0.78	18.46
211	MLI	RWA	0.83	0.415	0.92	0.73	0.84	1.497	0.93	15.24
212	MLI	BEN	0.36	0.571	0.97	1.11	0.37	1.731	0.97	42.42
213	MLI	SEN	-2.59	-1.497	1.24	1.72	-2.59	-8.346	1.24	38.48

214	MLI	BFA	-0.77	-0.948	1.08	1.70	-0.77	-3.483	1.08	45.66
215	MLI	CAF	-1.84	-0.983	1.25	1.08	-1.86	-2.737	1.25	16.46
216	MLI	MWI	-0.21	-0.319	1.04	2.02	-0.21	-0.633	1.04	28.37
217	MLI	TGO	-2.66	-2.154	1.32	2.64	-2.66	-6.251	1.32	28.24
218	MLI	MLI	0.64	1.498	0.93	2.33	0.64	4.121	0.93	56.15
219	MLI	GMB	2.51	0.620	0.79	0.68	2.53	4.417	0.80	11.90
220	MLI	NER	-4.59	-1.334	1.49	1.44	-4.61	-6.024	1.50	18.22
221	MLI	IDN	1.11	1.811	0.75	2.03	1.11	3.335	0.75	24.83
222	MLI	PHL	-0.30	-0.371	0.90	1.74	-0.30	-0.785	0.90	25.36
223	MLI	KEN	-0.52	-0.705	0.99	2.21	-0.52	-1.392	0.99	26.34
224	MLI	LKA	0.89	0.880	0.84	1.81	0.90	1.724	0.85	16.17
225	MLI	BOL	-1.55	-2.049	1.11	2.66	-1.56	-2.953	1.12	20.64
226	MLI	SDN	-0.40	-0.202	0.96	0.88	-0.41	-0.605	0.97	14.40
227	MLI	SWZ	2.39	3.358	0.77	2.58	2.40	6.962	0.78	20.17
228	MLI	CMR	-0.48	-0.939	0.99	1.80	-0.49	-0.987	0.99	19.81
229	MLI	COG	1.16	2.108	0.87	2.71	1.15	3.643	0.88	25.90
230	MLI	MRT	-0.38	-0.434	1.08	1.47	-0.38	-1.227	1.08	31.13
231	MLI	SLE	-2.64	-0.172	1.33	0.29	-2.65	-1.781	1.33	8.07
232	MLI	BDI	-2.97	-0.213	1.37	0.25	-2.99	-2.556	1.38	10.55
233	MLI	EGY	0.65	1.300	0.81	3.02	0.65	1.380	0.82	18.36
234	MLI	SLV	1.09	1.513	0.84	2.32	1.10	2.296	0.84	17.28
235	MLI	ZWE	-4.52	-0.049	1.42	0.08	-4.51	-1.533	1.42	4.71
236	MLI	GHA	-1.13	-0.478	1.07	1.21	-1.13	-1.736	1.07	16.11
237	MLI	GTM	-0.02	-0.044	0.93	2.81	-0.03	-0.059	0.93	21.43
238	MLI	HND	0.43	0.919	0.93	2.49	0.43	1.143	0.93	23.75
239	MLI	PAK	0.22	0.321	0.86	1.74	0.22	0.577	0.86	24.46
240	MLI	IND	-1.21	-0.862	0.92	1.62	-1.20	-3.092	0.92	27.11
241	GMB	RWA	0.69	0.068	0.85	0.17	0.69	0.638	0.85	7.26
242	GMB	BEN	-0.46	-0.177	0.95	0.47	-0.47	-0.619	0.97	11.75
243	GMB	SEN	-3.07	-0.279	1.20	0.32	-3.09	-2.747	1.21	10.32
244	GMB	BFA	-1.07	-0.169	1.02	0.28	-1.08	-1.072	1.03	9.54
245	GMB	CAF	-2.65	-0.191	1.25	0.24	-2.66	-2.225	1.25	9.34
246	GMB	MWI	-0.85	-0.164	1.01	0.33	-0.85	-0.927	1.02	10.21
247	GMB	TGO	-3.43	-0.312	1.31	0.34	-3.48	-3.191	1.32	11.01
248	GMB	MLI	-0.09	-0.037	0.91	0.42	-0.10	-0.127	0.92	11.36
249	GMB	GMB	-0.06	-0.666	1.00	4.92	-0.08	-1.115	1.01	114.28
250	GMB	NER	-3.55	-0.135	1.30	0.17	-3.55	-1.946	1.30	6.62
251	GMB	IDN	-0.08	-0.050	0.77	0.66	-0.08	-0.127	0.78	13.15
252	GMB	PHL	-1.90	-1.236	0.97	1.47	-1.90	-3.052	0.98	16.72
253	GMB	KEN	-1.11	-0.203	0.96	0.35	-1.11	-1.146	0.97	9.92
254	GMB	LKA	-0.42	-0.150	0.88	0.49	-0.42	-0.552	0.90	11.66
255	GMB	BOL	-2.69	-0.413	1.13	0.50	-2.75	-2.858	1.16	11.71
256	GMB	SDN	0.25	0.020	0.82	0.15	0.25	0.184	0.82	5.97
257	GMB	SWZ	0.89	0.946	0.85	1.21	0.90	1.955	16.67	0.19

258	GMB	CMR	-1.23	-0.165	0.98	0.29	-1.23	-1.237	0.98	9.78
259	GMB	COG	0.89	0.147	0.81	0.24	0.89	0.994	0.82	8.49
260	GMB	MRT	-1.47	-0.448	1.09	0.54	-1.51	-1.949	1.11	12.97
261	GMB	SLE	-0.81	-0.029	1.04	0.11	-0.81	-0.355	1.04	4.08
262	GMB	BDI	-3.24	-0.118	1.32	0.16	-3.25	-1.848	1.32	6.70
263	GMB	EGY	-0.85	-0.447	0.87	0.87	-0.86	-1.269	0.88	13.87
264	GMB	SLV	-0.59	-0.512	0.93	1.16	-0.58	-0.980	0.93	15.39
265	GMB	ZWE	-7.72	-0.094	1.66	0.12	-7.73	-2.413	1.66	5.08
266	GMB	GHA	-1.21	-0.125	0.99	0.21	-1.22	-0.945	1.00	7.57
267	GMB	GTM	-1.36	-0.494	0.97	0.74	-1.39	-1.867	0.99	13.34
268	GMB	HND	-0.19	-0.037	0.90	0.34	-0.19	-0.209	0.91	9.72
269	GMB	PAK	-1.04	-0.432	0.89	0.70	-1.05	-1.472	0.90	13.39
270	GMB	IND	-1.93	-0.299	0.91	0.40	-1.95	-1.975	0.91	10.61
271	NER	RWA	4.17	1.795	0.56	1.83	4.18	12.089	0.56	14.75
272	NER	BEN	4.22	2.395	0.54	2.57	4.22	12.529	0.55	14.98
273	NER	SEN	2.36	1.476	0.72	1.75	2.36	6.436	0.72	18.84
274	NER	BFA	3.34	1.485	0.63	1.58	3.34	12.866	0.63	22.83
275	NER	CAF	2.73	2.258	0.73	2.64	2.73	5.590	0.73	13.40
276	NER	MWI	3.79	1.952	0.60	2.01	3.79	10.938	0.60	15.84
277	NER	TGO	2.27	1.644	0.77	1.95	2.27	5.896	0.77	18.15
278	NER	MLI	4.34	2.063	0.53	2.03	4.35	14.302	0.53	16.21
279	NER	GMB	5.74	1.140	0.41	1.15	5.78	11.775	0.41	7.10
280	NER	NER	0.44	1.224	0.95	4.36	0.47	3.214	0.95	60.70
281	NER	IDN	4.66	2.616	0.42	2.70	4.67	13.025	0.42	12.86
282	NER	PHL	3.96	3.184	0.50	3.47	3.97	8.917	0.50	11.93
283	NER	KEN	3.56	2.193	0.57	2.35	3.56	10.269	0.57	16.46
284	NER	LKA	4.69	1.827	0.45	2.02	4.73	9.754	0.46	9.38
285	NER	BOL	3.09	2.473	0.63	2.65	3.10	6.449	0.63	12.86
286	NER	SDN	3.36	2.575	0.59	2.93	3.36	8.602	0.59	15.14
287	NER	SWZ	5.47	3.044	0.42	3.26	5.50	15.358	0.42	10.54
288	NER	CMR	3.57	1.938	0.57	2.04	3.58	9.019	0.57	14.36
289	NER	COG	4.42	1.316	0.52	1.39	4.42	18.746	0.52	20.61
290	NER	MRT	3.74	1.946	0.61	2.04	3.75	10.246	0.61	15.11
291	NER	SLE	1.53	1.183	0.86	2.02	1.53	1.990	0.86	10.05
292	NER	BDI	1.68	2.470	0.85	1.26	1.69	2.576	0.85	11.51
293	NER	EGY	4.59	2.439	0.44	2.67	4.61	9.615	0.44	9.70
294	NER	SLV	4.90	1.727	0.44	1.90	4.94	10.137	0.44	8.88
295	NER	ZWE	0.94	0.110	0.84	0.49	0.95	0.536	0.85	4.70
296	NER	GHA	3.03	2.347	0.64	2.70	3.03	7.278	0.64	14.97
297	NER	GTM	4.14	3.319	0.51	3.63	4.15	8.942	0.51	11.04
298	NER	HND	4.27	3.021	0.52	3.26	4.28	10.974	0.52	12.82
299	NER	PAK	4.26	3.228	0.47	3.49	4.27	9.907	0.47	11.62
300	NER	IND	3.32	2.588	0.52	2.98	3.32	7.755	0.52	13.88
301	IDN	RWA	0.92	0.091	1.08	0.33	0.92	1.019	1.09	11.08

302	IDN	BEN	-0.01	-0.012	1.18	1.70	-0.01	-0.027	1.18	23.20
303	IDN	SEN	-3.22	-0.586	1.46	0.85	-3.23	-3.878	1.47	16.95
304	IDN	BFA	-1.13	-0.491	1.28	1.04	-1.14	-1.721	1.28	18.24
305	IDN	CAF	-2.29	-0.118	1.47	0.30	-2.30	-2.063	1.48	11.81
306	IDN	MWI	-0.79	-0.574	1.27	1.40	-0.79	-1.447	1.27	21.32
307	IDN	TGO	-3.30	-0.453	1.56	0.69	-3.32	-3.659	1.57	15.65
308	IDN	MLI	0.45	0.378	1.11	1.41	0.45	0.894	1.12	20.82
309	IDN	GMB	2.25	0.373	1.00	0.46	2.26	3.419	1.01	13.03
310	IDN	NER	-5.32	-0.291	1.74	0.34	-5.34	-3.862	1.74	11.74
311	IDN	IDN	0.36	1.082	0.95	3.65	0.30	2.331	0.96	81.99
312	IDN	PHL	-1.26	-1.098	1.14	1.53	-1.26	-3.558	1.14	34.41
313	IDN	KEN	-1.12	-0.841	1.21	1.28	-1.13	-1.843	1.21	19.61
314	IDN	LKA	0.35	0.139	1.05	0.72	0.35	0.549	1.06	16.73
315	IDN	BOL	-2.86	-1.741	1.41	2.01	-2.86	-5.251	1.41	25.27
316	IDN	SDN	-0.90	-0.133	1.17	0.37	-0.90	-0.936	1.17	12.27
317	IDN	SWZ	2.23	1.234	0.96	1.44	2.23	5.356	0.97	20.79
318	IDN	CMR	-0.93	-0.167	1.18	0.64	-0.93	-1.170	1.19	14.82
319	IDN	COG	0.96	0.522	1.06	1.03	0.96	1.782	1.06	18.36
320	IDN	MRT	-1.08	-1.068	1.32	1.96	-1.08	-2.250	1.33	24.93
321	IDN	SLE	-4.12	-0.130	1.67	0.15	-4.12	-2.256	1.67	8.22
322	IDN	BDI	-4.03	-0.118	1.67	0.23	-4.04	-2.585	1.67	9.56
323	IDN	EGY	0.08	0.064	1.01	1.39	0.08	0.140	1.02	18.37
324	IDN	SLV	0.51	0.376	1.06	1.20	0.51	0.953	1.06	19.49
325	IDN	ZWE	-7.10	-0.036	1.84	0.07	-7.10	-1.994	1.84	5.05
326	IDN	GHA	-1.70	-0.239	1.28	0.38	-1.70	-1.755	1.29	12.97
327	IDN	GTM	-0.96	-1.437	1.18	1.83	-0.96	-2.295	1.18	28.39
328	IDN	HND	-0.04	-0.046	1.14	1.43	-0.04	-0.078	1.14	19.75
329	IDN	PAK	-0.42	-0.622	1.06	2.02	-0.42	-0.847	1.07	22.98
330	IDN	IND	-2.06	-1.420	1.13	1.62	-2.06	-3.511	1.13	22.05
331	PHL	RWA	1.46	0.081	0.98	0.38	1.48	1.757	0.99	10.81
332	PHL	BEN	0.49	0.493	1.09	3.59	0.48	1.294	1.09	27.44
333	PHL	SEN	-2.43	-0.609	1.34	1.31	-2.45	-3.364	1.35	17.85
334	PHL	BFA	-0.45	-0.159	1.17	1.59	-0.47	-0.791	1.18	18.48
335	PHL	CAF	-1.57	-0.118	1.33	0.53	-1.59	-1.587	1.36	12.11
336	PHL	MWI	-0.05	-0.027	1.15	2.24	-0.07	-0.132	1.16	19.64
337	PHL	TGO	-2.63	-0.672	1.45	1.25	-2.66	-3.570	1.46	17.75
338	PHL	MLI	0.92	0.830	1.03	3.80	0.90	2.220	1.03	23.76
339	PHL	GMB	2.21	0.762	0.97	1.65	2.23	5.177	0.98	19.35
340	PHL	NER	-3.95	-0.260	1.54	0.29	-4.00	-2.941	1.57	10.71
341	PHL	IDN	1.09	0.666	0.86	2.29	1.08	3.517	0.86	31.02
342	PHL	PHL	-0.73	-1.276	1.06	3.15	-0.78	-8.457	1.06	123.51
343	PHL	KEN	-0.53	-0.459	1.11	3.18	-0.56	-1.097	1.12	21.98
344	PHL	LKA	0.66	0.378	0.99	2.56	0.66	1.440	0.99	21.59
345	PHL	BOL	-1.96	-1.758	1.28	1.43	-1.98	-3.723	1.29	23.56

346	PHL	SDN	0.14	0.007	1.02	0.33	0.14	0.146	1.03	10.47
347	PHL	SWZ	2.43	2.255	0.91	2.68	2.43	9.712	0.91	32.50
348	PHL	CMR	-0.25	-0.038	1.08	0.89	-0.25	-0.341	1.09	14.62
349	PHL	COG	1.60	0.273	0.95	1.03	1.60	2.876	0.96	16.12
350	PHL	MRT	-0.44	-0.531	1.22	3.85	-0.46	-1.135	1.22	27.25
351	PHL	SLE	-2.00	-0.055	1.40	0.10	-2.01	-1.055	1.40	6.61
352	PHL	BDI	-2.74	-0.113	1.49	0.25	-2.75	-1.810	1.49	8.76
353	PHL	EGY	0.30	0.188	0.97	1.76	0.31	0.953	0.97	31.38
354	PHL	SLV	0.77	0.642	1.00	2.57	0.77	2.485	1.00	31.79
355	PHL	ZWE	-5.82	-0.067	1.67	0.12	-5.83	-1.780	1.68	5.00
356	PHL	GHA	-0.89	-0.068	1.15	0.45	-0.89	-0.970	1.17	12.47
357	PHL	GTM	-0.38	-0.232	1.09	1.46	-0.38	-1.215	1.09	35.02
358	PHL	HND	0.49	0.470	1.05	4.12	0.49	1.020	1.05	21.14
359	PHL	PAK	0.00	0.003	0.99	2.03	0.01	0.022	0.99	33.97
360	PHL	IND	-1.42	-1.501	1.04	3.91	-1.44	-3.132	1.05	26.19
361	KEN	RWA	1.31	0.206	0.92	0.64	1.33	1.799	0.93	11.54
362	KEN	BEN	0.51	0.336	1.01	1.59	0.52	1.578	1.01	28.46
363	KEN	SEN	-2.17	-1.969	1.25	2.67	-2.18	-3.245	1.25	17.92
364	KEN	BFA	-0.56	-0.395	1.11	1.61	-0.56	-1.308	1.11	24.22
365	KEN	CAF	-0.97	-0.134	1.19	0.45	-0.98	-0.934	1.21	10.36
366	KEN	MWI	-0.04	-0.028	1.08	2.32	-0.03	-0.058	1.08	21.00
367	KEN	TGO	-2.41	-2.133	1.35	2.64	-2.43	-3.670	1.36	18.60
368	KEN	MLI	0.89	0.534	0.96	1.74	0.89	2.540	0.96	25.65
369	KEN	GMB	2.87	0.236	0.80	0.54	2.92	4.339	0.81	10.35
370	KEN	NER	-4.43	-1.435	1.53	1.12	-4.47	-4.582	1.54	14.71
371	KEN	IDN	1.43	0.838	0.76	2.52	1.43	2.955	0.77	17.47
372	KEN	PHL	-0.27	-0.206	0.95	2.02	-0.26	-0.618	0.95	23.84
373	KEN	KEN	-0.77	-1.259	1.07	3.15	-0.78	-8.457	1.06	123.51
374	KEN	LKA	0.81	0.483	0.91	2.35	0.82	1.691	0.91	18.67
375	KEN	BOL	-1.60	-1.409	1.18	2.28	-1.60	-2.772	1.18	19.92
376	KEN	SDN	-0.32	-0.074	1.01	0.85	-0.33	-0.444	1.01	13.68
377	KEN	SWZ	2.63	1.239	0.80	2.26	2.65	6.402	0.81	17.49
378	KEN	CMR	0.17	0.038	0.97	0.77	0.18	0.223	0.98	12.18
379	KEN	COG	1.44	0.921	0.90	2.51	1.44	3.175	0.90	18.57
380	KEN	MRT	-0.18	-0.141	1.11	2.00	-0.18	-0.393	1.11	21.50
381	KEN	SLE	-2.85	-0.146	1.41	0.31	-2.86	-1.844	1.42	8.21
382	KEN	BDI	-2.11	-0.191	1.33	0.20	-2.12	-1.436	1.34	8.11
383	KEN	EGY	0.58	0.475	0.87	2.68	0.59	1.338	0.87	21.13
384	KEN	SLV	1.03	0.730	0.90	2.62	2.37	0.436	0.90	20.26
385	KEN	ZWE	-3.27	-0.052	1.34	0.10	-3.28	-1.003	1.34	4.02
386	KEN	GHA	-1.18	-0.503	1.13	1.39	-1.20	-1.769	1.13	16.36
387	KEN	GTM	-0.10	-0.079	0.99	2.01	-0.10	-0.240	0.99	24.35
388	KEN	HND	0.42	0.275	0.99	1.70	0.43	1.155	0.99	25.54
389	KEN	PAK	0.32	0.258	0.90	2.56	0.33	0.733	0.90	21.51

390	KEN	IND	-1.33	-0.904	0.98	1.54	-1.33	-3.781	0.98	31.85
391	LKA	RWA	1.92	0.192	0.87	0.23	1.92	1.946	0.87	8.07
392	LKA	BEN	0.41	1.334	1.02	3.23	0.41	0.870	1.02	20.30
393	LKA	SEN	-2.22	-0.741	1.25	0.90	-2.24	-2.646	1.26	14.34
394	LKA	BFA	-0.37	-0.248	1.09	0.94	-0.37	-0.524	1.09	14.49
395	LKA	CAF	-0.67	-0.062	1.18	0.25	-0.67	-0.537	1.18	8.45
396	LKA	MWI	-0.06	-0.056	1.07	1.19	-0.06	-0.095	1.08	15.75
397	LKA	TGO	-2.02	-0.485	1.23	0.62	-2.19	-2.312	1.33	12.75
398	LKA	MLI	0.81	1.589	0.96	2.45	0.81	1.656	0.97	18.59
399	LKA	GMB	2.41	0.499	0.85	0.44	2.47	3.899	0.87	11.70
400	LKA	NER	-3.25	-0.216	1.41	0.30	-3.25	-2.161	1.41	8.72
401	LKA	IDN	1.26	0.926	0.78	0.96	1.27	2.290	0.78	15.59
402	LKA	PHL	-0.45	-0.965	0.96	2.04	-0.45	-0.862	0.97	19.65
403	LKA	KEN	-0.54	-0.823	1.04	1.84	-0.55	-0.926	1.05	17.52
404	LKA	LKA	0.02	0.322	0.99	6.77	0.00	0.032	0.99	260.60
405	LKA	BOL	-1.27	-0.257	1.10	0.49	-1.32	-1.522	1.15	12.89
406	LKA	SDN	-0.11	-0.024	0.98	0.43	-0.11	-0.115	0.99	10.52
407	LKA	SWZ	2.24	3.529	0.85	3.58	2.24	6.529	0.85	22.27
408	LKA	CMR	0.40	0.059	0.95	0.30	0.40	0.411	0.96	9.67
409	LKA	COG	1.50	0.507	0.87	0.60	1.55	2.461	0.89	13.23
410	LKA	MRT	-0.50	-1.353	1.15	3.09	-0.51	-1.029	1.15	21.08
411	LKA	SLE	-1.79	-0.076	1.30	0.18	-1.79	-0.950	1.30	6.19
412	LKA	BDI	-1.12	-0.028	1.23	0.13	-1.12	-0.624	1.23	6.14
413	LKA	EGY	0.20	0.844	0.91	2.02	0.20	0.486	0.91	23.62
414	LKA	SLV	0.66	2.257	0.94	3.03	0.66	1.617	0.94	22.63
415	LKA	ZWE	-1.63	-0.012	1.18	0.06	-1.63	-0.456	1.18	3.21
416	LKA	GHA	-1.41	-0.556	1.15	0.89	-1.42	-1.873	1.16	14.87
417	LKA	GTM	-0.20	-0.401	1.00	1.91	-0.21	-0.378	1.00	18.36
418	LKA	HND	0.45	0.662	0.98	1.46	0.45	0.797	0.98	16.69
419	LKA	PAK	0.01	0.057	0.93	3.23	0.01	0.016	0.93	21.39
420	LKA	IND	-1.61	-2.438	1.00	2.70	-1.62	-3.728	1.00	26.50
421	BOL	RWA	2.51	2.045	0.77	2.00	2.54	4.853	0.78	13.65
422	BOL	BEN	2.36	3.591	0.79	3.65	2.37	5.721	0.79	17.69
423	BOL	SEN	0.21	0.389	0.97	1.86	0.21	0.310	0.98	14.31
424	BOL	BFA	1.55	2.716	0.86	2.70	1.55	3.044	0.87	15.95
425	BOL	CAF	0.52	0.422	1.02	1.27	0.53	0.722	1.02	12.39
426	BOL	MWI	1.86	2.939	0.84	3.05	1.87	3.906	0.85	16.34
427	BOL	TGO	-0.02	-0.036	1.06	1.89	-0.02	-0.034	1.07	15.03
428	BOL	MLI	2.66	3.403	0.75	3.45	2.66	6.357	0.75	16.75
429	BOL	GMB	3.66	1.352	0.70	1.11	3.69	8.585	0.70	13.96
430	BOL	NER	-1.33	-0.522	1.18	0.80	-1.34	-1.361	1.18	11.19
431	BOL	IDN	2.65	2.409	0.64	2.00	2.65	9.261	0.64	24.55
432	BOL	PHL	1.40	2.068	0.78	2.04	1.40	4.807	0.78	28.41
433	BOL	KEN	1.46	3.277	0.82	3.32	1.46	3.339	0.83	18.78

434	BOL	LKA	2.69	1.319	0.70	1.35	2.70	5.061	0.70	13.07
435	BOL	BOL	0.00	0.030	0.99	2.77	0.01	0.035	0.99	62.14
436	BOL	SDN	1.82	0.787	0.77	0.75	1.83	2.496	0.78	10.72
437	BOL	SWZ	3.89	2.021	0.64	1.93	3.92	10.556	0.64	15.54
438	BOL	CMR	1.44	3.336	0.83	3.59	1.46	2.884	0.83	16.27
439	BOL	COG	2.94	3.495	0.72	3.38	2.95	7.189	0.72	16.40
440	BOL	MRT	1.68	3.082	0.88	3.23	1.68	3.738	0.89	17.79
441	BOL	SLE	-0.04	-0.004	1.07	0.23	-0.05	-0.035	1.08	7.10
442	BOL	BDI	-1.04	-0.489	1.19	1.08	-1.04	-1.104	1.20	11.38
443	BOL	EGY	2.21	3.713	0.70	3.47	2.22	5.772	0.70	19.39
444	BOL	SLV	2.63	3.397	0.72	3.29	2.64	6.453	0.72	17.19
445	BOL	ZWE	-3.89	-0.143	1.39	0.26	-3.90	-1.723	1.39	5.99
446	BOL	GHA	1.42	0.652	0.84	0.61	1.43	1.819	0.84	10.45
447	BOL	GTM	1.54	1.724	0.81	1.72	1.54	5.474	0.81	28.97
448	BOL	HND	2.15	2.786	0.78	2.69	2.15	5.825	0.79	20.35
449	BOL	PAK	1.98	3.378	0.72	3.35	1.98	5.298	0.73	20.61
450	BOL	IND	0.99	3.166	0.75	3.76	0.99	1.954	0.76	17.18
451	SDN	RWA	2.54	1.584	0.81	1.69	2.57	4.547	0.81	13.23
452	SDN	BEN	2.75	1.233	0.78	1.25	2.76	4.650	0.79	12.27
453	SDN	SEN	0.13	0.140	1.02	2.39	0.13	0.175	1.03	13.85
454	SDN	BFA	1.49	1.978	0.91	2.30	1.48	2.777	0.91	15.99
455	SDN	CAF	0.63	0.368	1.04	1.03	0.64	0.759	1.05	11.10
456	SDN	MWI	2.25	0.996	0.84	1.20	2.25	3.416	0.85	11.81
457	SDN	TGO	0.21	0.142	1.07	1.58	0.22	0.269	1.08	12.05
458	SDN	MLI	2.91	1.926	0.76	1.73	2.91	5.392	0.76	13.18
459	SDN	GMB	5.19	0.269	0.56	0.27	5.20	6.529	0.57	6.07
460	SDN	NER	-2.15	-1.698	1.31	2.70	-2.16	-2.589	1.31	14.63
461	SDN	IDN	3.22	1.106	0.61	1.22	3.23	5.801	0.62	12.20
462	SDN	PHL	2.30	0.651	0.72	0.86	2.32	3.210	0.72	10.69
463	SDN	KEN	1.65	1.885	0.84	2.01	1.64	2.887	0.84	14.73
464	SDN	LKA	3.14	0.510	0.68	0.55	3.18	4.518	0.69	9.74
465	SDN	BOL	0.95	0.455	0.93	1.13	0.95	1.255	0.93	11.99
466	SDN	SDN	0.54	1.512	0.94	4.73	0.59	4.578	0.94	73.04
467	SDN	SWZ	4.67	0.531	0.59	0.50	4.70	7.722	0.60	8.75
468	SDN	CMR	1.73	1.060	0.83	1.43	1.74	2.627	0.84	12.53
469	SDN	COG	3.01	2.636	0.75	2.61	3.01	6.660	0.75	15.57
470	SDN	MRT	2.02	1.257	0.88	1.54	2.02	3.215	0.89	12.79
471	SDN	SLE	-1.16	-0.114	1.24	0.47	-1.17	-0.945	1.25	9.07
472	SDN	BDI	-1.11	-0.431	1.24	0.61	-1.12	-1.090	1.25	10.87
473	SDN	EGY	2.97	0.622	0.65	0.73	3.00	4.329	0.66	10.13
474	SDN	SLV	3.58	0.431	0.65	0.48	3.61	4.912	0.66	8.76
475	SDN	ZWE	-1.07	-0.024	1.13	0.11	-1.05	-0.375	1.13	3.97
476	SDN	GHA	0.85	0.578	0.93	1.62	0.84	1.268	0.94	13.81
477	SDN	GTM	2.42	0.595	0.75	0.81	2.44	3.457	0.76	10.78

478	SDN	HND	2.46	1.592	0.79	1.79	2.46	4.575	0.79	14.08
479	SDN	PAK	2.61	0.853	0.69	0.99	2.63	3.981	0.70	11.23
480	SDN	IND	1.17	0.922	0.77	1.78	1.16	1.817	0.77	13.86
481	SWZ	RWA	-2.09	-0.080	1.20	0.24	-2.10	-1.969	1.20	10.30
482	SWZ	BEN	-3.29	-2.029	1.32	1.80	-3.38	-6.623	1.33	24.08
483	SWZ	SEN	-6.94	-0.712	1.64	0.67	-6.99	-7.560	1.65	17.19
484	SWZ	BFA	-4.47	-0.663	1.42	0.68	-4.51	-5.728	1.43	17.04
485	SWZ	CAF	-5.97	-0.213	1.66	0.30	-5.99	-4.865	1.67	12.09
486	SWZ	MWI	-4.00	-0.886	1.40	0.91	-4.04	-5.681	1.41	18.20
487	SWZ	TGO	-7.11	-0.637	1.76	0.60	-7.16	-7.287	1.77	16.35
488	SWZ	MLI	-2.80	-1.313	1.25	1.31	-2.87	-5.270	1.26	21.64
489	SWZ	GMB	-1.34	-0.668	1.19	1.41	-1.33	-2.572	1.20	19.75
490	SWZ	NER	-8.73	-0.210	1.89	0.23	-8.77	-5.110	1.90	10.30
491	SWZ	IDN	-2.56	-1.758	1.04	2.04	-2.58	-5.364	1.04	23.87
492	SWZ	PHL	-4.75	-1.586	1.28	1.48	-4.75	-12.11	1.28	34.83
493	SWZ	KEN	-4.34	-0.801	1.33	0.82	-4.39	-5.541	1.34	16.79
494	SWZ	LKA	-2.96	-1.540	1.19	1.26	-3.05	-4.600	1.20	18.05
495	SWZ	BOL	-6.16	-0.874	1.54	0.97	-6.17	-7.487	1.55	18.30
496	SWZ	SDN	-3.35	-0.138	1.21	0.21	-3.37	-2.501	1.22	9.10
497	SWZ	SWZ	-1.12	-1.568	1.12	2.79	-1.13	-4.408	1.12	39.39
498	SWZ	CMR	-4.30	-0.270	1.33	0.42	-4.32	-4.680	1.33	14.33
499	SWZ	COG	-1.98	-0.291	1.16	0.57	-1.99	-2.752	1.17	15.08
500	SWZ	MRT	-4.41	-2.387	1.47	2.03	-4.49	-7.819	1.48	23.31
501	SWZ	SLE	-5.95	-0.107	1.65	0.12	-5.98	-2.467	1.66	6.14
502	SWZ	BDI	-7.26	-0.089	1.81	0.15	-7.27	-3.838	1.81	8.53
503	SWZ	EGY	-3.42	-1.767	1.16	2.04	-3.42	-6.041	1.16	21.76
504	SWZ	SLV	-2.89	-2.344	1.20	2.03	-2.94	-5.925	1.21	23.84
505	SWZ	ZWE	-11.38	-0.051	2.07	0.08	-11.4	-2.861	2.08	5.09
506	SWZ	GHA	-4.83	-0.305	1.40	0.31	-4.86	-4.005	1.41	11.34
507	SWZ	GTM	-4.30	-2.229	1.31	2.28	-4.29	-7.755	1.31	23.86
508	SWZ	HND	-3.14	-0.601	1.25	0.82	-3.17	-4.363	1.26	16.64
509	SWZ	PAK	-3.96	-2.052	1.21	2.03	-3.95	-8.753	1.21	28.46
510	SWZ	IND	-5.47	-1.609	1.25	1.52	-5.55	-7.770	1.26	20.23
511	CMR	RWA	1.32	1.961	0.93	2.02	1.31	3.261	0.93	21.11
512	CMR	BEN	1.59	0.896	0.89	0.91	1.59	3.267	0.89	16.90
513	CMR	SEN	-1.49	-1.827	1.17	2.04	-1.50	-3.234	1.17	24.49
514	CMR	BFA	0.38	0.724	1.01	1.63	0.37	0.820	1.01	20.71
515	CMR	CAF	-1.50	-1.830	1.27	1.94	-1.50	-3.959	1.27	29.93
516	CMR	MWI	0.98	0.688	0.96	0.93	0.98	1.819	0.96	16.40
517	CMR	TGO	-1.49	-1.330	1.24	1.61	-1.50	-2.608	1.25	19.70
518	CMR	MLI	1.80	1.153	0.85	1.18	1.80	4.138	0.86	18.42
519	CMR	GMB	3.31	0.593	0.75	0.56	3.36	5.704	0.76	10.96
520	CMR	NER	-3.12	-0.663	1.39	0.68	-3.15	-3.304	1.39	13.62
521	CMR	IDN	2.07	1.895	0.70	1.95	2.09	4.744	0.70	17.59

522	CMR	PHL	0.87	0.842	0.84	1.38	0.88	1.576	0.84	15.95
523	CMR	KEN	0.85	0.460	0.90	0.81	0.85	1.340	0.90	14.18
524	CMR	LKA	2.19	0.412	0.75	0.38	2.22	3.192	0.76	10.96
525	CMR	BOL	-0.34	-0.305	1.04	1.38	-0.34	-0.504	1.04	14.99
526	CMR	SDN	0.64	0.260	0.90	0.63	0.64	0.870	0.91	12.44
527	CMR	SWZ	3.42	0.797	0.71	0.67	3.45	7.271	0.71	13.47
528	CMR	CMR	-0.10	-0.466	1.00	2.67	-0.19	-1.447	1.01	76.92
529	CMR	COG	2.07	2.031	0.83	2.32	2.08	5.169	0.83	19.29
530	CMR	MRT	0.79	0.863	1.00	1.28	0.80	1.537	1.00	17.30
531	CMR	SLE	-0.56	-0.043	1.15	0.20	-0.56	-0.339	1.16	6.26
532	CMR	BDI	-2.95	-1.180	1.42	1.57	-2.97	-3.536	1.43	15.25
533	CMR	EGY	1.70	0.841	0.76	0.99	1.71	2.972	0.76	14.09
534	CMR	SLV	2.35	0.480	0.75	0.50	2.39	3.650	0.76	11.36
535	CMR	ZWE	-5.84	-0.132	1.60	0.21	-5.85	-2.329	1.60	6.24
536	CMR	GHA	0.40	0.089	0.95	0.38	0.41	0.469	0.96	10.85
537	CMR	GTM	1.26	0.595	0.85	0.88	1.26	1.984	0.85	13.45
538	CMR	HND	1.49	1.103	0.87	1.43	1.49	2.948	0.87	16.45
539	CMR	PAK	1.26	1.331	0.80	1.68	1.28	2.535	0.80	16.94
540	CMR	IND	0.11	0.082	0.84	1.04	0.11	0.178	0.85	15.56
541	COG	RWA	1.48	1.110	0.83	1.42	1.45	3.387	0.84	17.99
542	COG	BEN	1.76	0.901	0.80	1.26	1.80	3.387	0.79	13.79
543	COG	SEN	-1.02	-0.517	1.05	1.51	-1.02	-1.872	1.05	18.61
544	COG	BFA	0.49	0.328	0.92	1.33	0.52	1.169	0.92	19.55
545	COG	CAF	-0.54	-0.251	1.08	1.24	-0.61	-0.894	1.09	14.39
546	COG	MWI	1.10	0.672	0.87	1.49	1.13	2.109	0.87	14.93
547	COG	TGO	-0.94	-0.453	1.11	1.45	-0.98	-1.500	1.11	15.55
548	COG	MLI	1.90	1.238	0.77	1.48	1.92	4.160	0.77	15.59
549	COG	GMB	3.99	0.258	0.60	0.28	3.99	5.539	0.60	7.15
550	COG	NER	-3.27	-1.020	1.33	1.28	-3.31	-5.179	1.34	19.49
551	COG	IDN	2.25	1.402	0.62	1.43	2.29	4.551	0.62	13.62
552	COG	PHL	1.31	0.472	0.73	1.07	1.33	2.031	0.73	11.92
553	COG	KEN	0.71	0.421	0.85	1.44	0.75	1.446	0.84	16.27
554	COG	LKA	2.25	0.398	0.69	0.60	2.26	3.403	0.69	10.36
555	COG	BOL	-0.02	-0.008	0.94	1.36	0.01	0.009	0.94	13.19
556	COG	SDN	0.15	0.106	0.89	1.75	0.13	0.293	0.89	20.88
557	COG	SWZ	3.67	0.658	0.61	0.56	3.68	6.653	0.61	9.85
558	COG	CMR	0.65	0.431	0.85	1.47	0.64	1.190	0.86	15.79
559	COG	COG	1.88	3.031	0.78	3.15	1.94	5.918	0.77	22.08
560	COG	MRT	0.90	0.567	0.91	1.49	0.93	1.836	0.91	16.12
561	COG	SLE	-1.84	-0.101	1.22	0.32	-1.85	-1.503	1.22	8.91
562	COG	BDI	-2.24	-0.528	1.27	0.92	-2.32	-2.679	1.28	13.21
563	COG	EGY	2.07	0.546	0.66	0.80	2.08	3.193	0.66	10.85
564	COG	SLV	2.75	0.302	0.65	0.40	2.76	3.853	0.65	8.92
565	COG	ZWE	-2.78	-0.055	1.22	0.14	-2.82	-1.066	1.22	4.52

566	COG	GHA	-0.15	-0.068	0.95	1.32	-0.16	-0.291	0.95	16.49
567	COG	GTM	1.52	0.378	0.76	0.80	1.55	2.317	0.76	11.34
568	COG	HND	1.60	0.881	0.78	1.32	1.66	3.138	0.78	14.13
569	COG	PAK	1.58	0.716	0.71	1.22	1.62	2.769	0.71	12.82
570	COG	IND	0.24	0.107	0.77	1.38	0.29	0.491	0.77	14.81
571	MRT	RWA	1.72	1.526	0.79	1.34	1.73	3.234	0.79	13.54
572	MRT	BEN	1.32	2.010	0.83	1.51	1.32	4.474	0.83	25.95
573	MRT	SEN	-1.17	-1.124	1.05	1.61	-1.17	-2.719	1.05	23.64
574	MRT	BFA	0.42	1.675	0.91	1.73	0.42	1.138	0.91	23.09
575	MRT	CAF	-0.49	-0.587	1.06	1.57	-0.50	-0.720	1.06	13.75
576	MRT	MWI	0.77	2.328	0.89	1.91	0.77	2.210	0.89	23.67
577	MRT	TGO	-1.36	-1.545	1.14	2.01	-1.36	-3.249	1.14	24.68
578	MRT	MLI	1.60	1.784	0.79	1.34	1.61	5.397	0.79	24.81
579	MRT	GMB	2.97	2.016	0.70	1.57	2.98	6.350	0.70	12.78
580	MRT	NER	-2.75	-1.013	1.26	1.23	-2.76	-3.354	1.26	14.27
581	MRT	IDN	1.81	1.574	0.65	1.20	1.81	6.591	0.65	26.08
582	MRT	PHL	0.61	1.692	0.79	1.05	0.61	1.859	0.79	25.61
583	MRT	KEN	0.50	1.849	0.85	1.75	0.50	1.328	0.85	22.40
584	MRT	LKA	1.69	2.904	0.73	1.74	1.70	3.594	0.73	15.38
585	MRT	BOL	-0.55	-0.583	0.98	1.35	-0.55	-1.290	0.98	22.54
586	MRT	SDN	0.77	0.953	0.81	1.04	0.77	1.141	0.81	12.14
587	MRT	SWZ	2.96	1.927	0.67	1.58	2.96	9.774	0.67	19.89
588	MRT	CMR	0.65	1.947	0.84	2.03	0.65	1.237	0.84	15.86
589	MRT	COG	2.01	2.439	0.75	2.00	2.01	5.644	0.75	19.57
590	MRT	MRT	0.54	1.900	0.94	2.08	0.88	3.500	0.90	32.21
591	MRT	SLE	-1.21	-0.179	1.13	0.36	-1.22	-0.912	1.14	7.65
592	MRT	BDI	-1.48	-0.337	1.17	0.62	-1.49	-1.386	1.17	9.73
593	MRT	EGY	1.56	3.022	0.70	1.92	1.56	3.351	0.70	15.95
594	MRT	SLV	1.84	2.849	0.73	2.23	1.84	4.357	0.73	16.90
595	MRT	ZWE	-3.49	-0.096	1.27	0.19	-3.49	-1.399	1.28	5.00
596	MRT	GHA	0.06	0.073	0.91	1.27	0.09	0.135	0.91	13.89
597	MRT	GTM	0.84	2.157	0.81	1.54	0.84	2.242	0.81	21.67
598	MRT	HND	1.43	2.788	0.79	2.02	1.43	3.361	0.79	17.75
599	MRT	PAK	1.24	2.339	0.73	1.35	1.24	2.924	0.73	18.27
600	MRT	IND	0.02	0.042	0.78	1.41	0.03	0.059	0.78	19.59
601	SLE	RWA	4.43	0.992	0.49	1.28	4.47	6.803	0.49	6.82
602	SLE	BEN	3.89	1.462	0.54	1.81	3.92	7.515	0.54	9.64
603	SLE	SEN	2.67	0.813	0.65	1.54	2.69	3.381	0.65	7.87
604	SLE	BFA	3.30	1.428	0.60	2.03	3.33	5.583	0.60	9.45
605	SLE	CAF	3.55	0.536	0.60	0.88	3.58	3.830	0.60	5.75
606	SLE	MWI	3.43	1.642	0.60	2.03	3.46	6.353	0.60	10.09
607	SLE	TGO	2.73	0.694	0.68	1.34	2.75	3.268	0.68	7.38
608	SLE	MLI	4.16	1.407	0.51	1.76	4.19	7.959	0.51	9.06
609	SLE	GMB	5.61	0.478	0.38	0.57	5.67	9.102	0.38	5.28

610	SLE	NER	0.65	0.447	0.89	2.02	0.66	0.805	0.89	10.17
611	SLE	IDN	4.21	1.671	0.43	1.94	4.24	8.706	0.43	9.67
612	SLE	PHL	3.53	1.152	0.50	1.52	3.57	5.948	0.50	8.97
613	SLE	KEN	3.21	1.564	0.58	2.04	3.23	5.809	0.58	10.27
614	SLE	LKA	4.31	0.902	0.46	1.09	4.35	7.118	0.46	7.54
615	SLE	BOL	2.44	1.297	0.67	2.03	2.49	4.055	0.66	10.55
616	SLE	SDN	3.16	1.439	0.57	2.02	3.18	4.990	0.57	9.08
617	SLE	SWZ	5.19	0.997	0.41	1.11	5.23	10.748	0.42	7.66
618	SLE	CMR	3.85	0.826	0.51	1.19	3.88	5.318	0.51	6.95
619	SLE	COG	4.16	1.850	0.51	2.02	4.18	9.127	0.51	10.40
620	SLE	MRT	3.57	1.267	0.59	1.79	3.60	5.940	0.59	8.83
621	SLE	SLE	-0.75	-0.793	1.08	3.22	-0.76	-2.234	1.08	28.68
622	SLE	BDI	2.35	0.525	0.73	1.04	2.39	2.188	0.73	6.01
623	SLE	EGY	4.31	0.800	0.43	0.90	4.36	6.867	0.43	7.25
624	SLE	SLV	4.36	0.865	0.46	0.95	4.39	7.676	0.47	7.96
625	SLE	ZWE	2.60	0.144	0.64	0.37	2.62	1.186	0.65	2.87
626	SLE	GHA	2.85	1.377	0.62	2.01	2.87	4.233	0.62	8.96
627	SLE	GTM	3.41	1.494	0.55	1.70	3.45	6.433	0.55	10.24
628	SLE	HND	3.80	1.521	0.53	1.67	3.83	7.274	0.53	9.71
629	SLE	PAK	3.87	1.141	0.47	1.40	3.91	6.689	0.47	8.62
630	SLE	IND	2.96	1.262	0.52	1.81	3.00	4.735	0.52	9.39
631	BDI	RWA	3.24	1.799	0.62	1.95	3.24	11.085	0.62	19.54
632	BDI	BEN	3.95	1.256	0.53	1.05	3.98	7.619	0.54	9.49
633	BDI	SEN	1.94	1.648	0.72	2.04	1.96	3.312	0.72	11.80
634	BDI	BFA	3.05	1.968	0.62	1.91	3.07	6.050	0.63	11.59
635	BDI	CAF	1.51	1.711	0.83	2.03	1.52	3.912	0.83	19.17
636	BDI	MWI	3.48	1.454	0.59	1.34	3.51	6.482	0.59	10.03
637	BDI	TGO	1.87	1.501	0.77	2.01	1.89	3.072	0.78	11.49
638	BDI	MLI	4.03	1.512	0.52	1.25	4.07	8.443	0.52	10.13
639	BDI	GMB	4.91	1.100	0.46	0.82	4.96	10.102	0.47	8.12
640	BDI	NER	0.47	0.390	0.90	1.76	0.47	0.641	0.91	11.52
641	BDI	IDN	3.99	2.628	0.44	1.96	4.01	9.837	0.45	12.08
642	BDI	PHL	3.35	1.662	0.52	1.40	3.38	6.309	0.52	10.39
643	BDI	KEN	3.31	1.281	0.56	1.28	3.34	5.887	0.56	9.89
644	BDI	LKA	4.41	0.702	0.44	0.53	4.46	7.188	0.45	7.21
645	BDI	BOL	2.31	2.318	0.68	2.61	2.32	4.277	0.68	12.20
646	BDI	SDN	3.01	1.255	0.58	1.25	3.03	5.204	0.59	10.15
647	BDI	SWZ	5.09	1.039	0.42	0.70	5.13	11.253	0.43	8.36
648	BDI	CMR	2.50	1.840	0.65	1.75	2.50	8.110	0.65	20.86
649	BDI	COG	3.90	3.260	0.54	2.02	3.91	10.949	0.54	14.07
650	BDI	MRT	3.30	1.713	0.62	1.32	3.33	6.404	0.62	10.81
651	BDI	SLE	2.15	0.260	0.74	0.42	2.19	1.890	0.75	5.81
652	BDI	BDI	-0.30	-0.967	1.03	2.35	-0.30	-1.718	1.03	52.32
653	BDI	EGY	3.92	1.414	0.47	1.20	3.96	7.401	0.47	9.33

654	BDI	SLV	4.52	0.756	0.44	0.62	4.57	7.671	0.45	7.33
655	BDI	ZWE	-2.88	-0.930	1.20	1.39	-2.90	-1.987	1.21	8.11
656	BDI	GHA	3.03	0.747	0.60	0.80	3.06	4.347	0.60	8.37
657	BDI	GTM	3.60	1.233	0.53	1.12	3.63	6.412	0.53	9.39
658	BDI	HND	3.73	1.771	0.54	1.68	3.76	7.641	0.54	10.53
659	BDI	PAK	3.63	1.773	0.49	1.50	3.67	7.206	0.50	10.37
660	BDI	IND	2.97	1.166	0.52	1.14	2.99	4.874	0.52	9.69
661	EGY	RWA	1.57	0.160	0.98	0.25	1.58	1.784	0.98	10.13
662	EGY	BEN	0.61	1.222	1.07	2.27	0.62	1.263	1.07	20.40
663	EGY	SEN	-2.11	-0.366	1.30	0.62	-2.14	-2.399	1.32	14.24
664	EGY	BFA	-0.27	-0.105	1.15	0.77	-0.27	-0.382	1.16	15.20
665	EGY	CAF	-1.18	-0.066	1.31	0.24	-1.18	-1.030	1.31	10.24
666	EGY	MWI	0.15	0.078	1.12	0.86	0.15	0.227	1.13	15.51
667	EGY	TGO	-2.16	-0.323	1.37	0.55	-2.23	-2.345	1.41	13.46
668	EGY	MLI	1.02	1.192	1.01	1.48	1.03	2.034	1.02	18.76
669	EGY	GMB	2.46	0.682	0.93	0.70	2.49	4.406	0.94	14.25
670	EGY	NER	-3.38	-0.129	1.50	0.23	-3.38	-2.196	1.50	9.05
671	EGY	IDN	1.40	0.990	0.82	0.97	1.40	2.654	0.83	17.29
672	EGY	PHL	-0.50	-1.290	1.04	3.31	-0.50	-1.195	1.04	26.29
673	EGY	KEN	-0.51	-0.537	1.11	1.60	-0.51	-0.910	1.11	19.68
674	EGY	LKA	0.50	2.267	1.01	4.04	0.50	1.273	1.01	25.59
675	EGY	BOL	-1.66	-0.460	1.25	0.84	-1.67	-2.291	1.25	16.77
676	EGY	SDN	0.16	0.018	1.03	0.30	0.16	0.160	1.03	10.20
677	EGY	SWZ	2.60	2.097	0.88	2.03	2.62	6.539	0.89	19.85
678	EGY	CMR	0.04	0.005	1.03	0.35	0.03	0.039	1.06	12.20
679	EGY	COG	1.70	0.542	0.93	0.58	1.72	2.753	0.95	14.14
680	EGY	MRT	-0.18	-0.138	1.18	1.16	-0.18	-0.305	1.19	18.00
681	EGY	SLE	-1.10	-0.027	1.30	0.13	-1.10	-0.534	1.30	5.64
682	EGY	BDI	-2.27	-0.050	1.43	0.14	-2.27	-1.384	1.44	7.81
683	EGY	EGY	0.07	0.714	0.99	3.99	0.04	0.637	0.99	170.30
684	EGY	SLV	0.80	2.964	1.00	3.93	0.80	2.143	1.00	26.14
685	EGY	ZWE	-4.71	-0.048	1.56	0.10	-4.71	-1.370	1.56	4.44
686	EGY	GHA	-0.80	-0.114	1.15	0.37	-0.80	-0.828	1.16	11.72
687	EGY	GTM	-0.24	-0.654	1.07	3.26	-0.24	-0.515	1.08	23.45
688	EGY	HND	0.37	1.464	1.06	3.81	0.37	0.836	1.06	23.17
689	EGY	PAK	0.03	0.097	0.99	2.55	0.04	0.094	0.99	27.81
690	EGY	IND	-1.51	-2.912	1.05	3.71	-1.51	-3.367	1.05	26.88
691	SLV	RWA	0.75	0.019	0.98	0.23	0.75	0.722	0.98	8.64
692	SLV	BEN	-0.86	-1.558	1.14	7.12	-0.86	-2.040	1.15	25.15
693	SLV	SEN	-3.51	-0.281	1.34	0.65	-3.61	-3.856	1.39	14.27
694	SLV	BFA	-1.64	-0.222	1.20	0.85	-1.66	-2.236	1.22	15.37
695	SLV	CAF	-2.28	-0.061	1.34	0.27	-2.29	-1.782	1.35	9.37
696	SLV	MWI	-1.29	-0.241	1.19	1.10	-1.30	-1.968	1.20	16.72
697	SLV	TGO	-3.64	-0.302	1.44	0.62	-3.74	-3.800	1.49	13.70

698	SLV	MLI	-0.36	-0.227	1.06	2.66	-0.37	-0.756	1.08	20.91
699	SLV	GMB	1.11	0.163	0.99	0.82	1.13	2.090	1.01	15.93
700	SLV	NER	-4.85	-0.125	1.57	0.25	-4.87	-2.977	1.57	8.94
701	SLV	IDN	0.04	0.012	0.87	1.64	0.03	0.066	0.88	18.87
702	SLV	PHL	-1.98	-1.798	1.10	3.35	-1.98	-5.333	1.10	31.61
703	SLV	KEN	-1.83	-0.800	1.15	2.04	-1.87	-3.071	1.17	19.13
704	SLV	LKA	-0.82	-0.935	1.06	5.01	-0.82	-1.931	1.06	25.00
705	SLV	BOL	-3.08	-0.640	1.31	1.17	-3.11	-4.056	1.32	16.76
706	SLV	SDN	-0.94	-0.030	1.06	0.29	-0.94	-0.830	1.06	9.42
707	SLV	SWZ	1.20	2.416	0.95	6.87	1.19	4.056	0.96	29.09
708	SLV	CMR	-1.09	-0.046	1.09	0.36	-1.10	-1.126	1.09	11.12
709	SLV	COG	0.56	0.039	0.95	0.47	0.60	0.843	0.98	12.92
710	SLV	MRT	-1.60	-0.431	1.25	1.55	-1.62	-2.730	1.26	19.17
711	SLV	SLE	-3.08	-0.046	1.43	0.15	-3.09	-1.481	1.43	6.15
712	SLV	BDI	-2.88	-0.035	1.41	0.16	-2.89	-1.523	1.41	6.67
713	SLV	EGY	-1.08	-0.796	1.02	2.70	-1.07	-2.969	1.02	30.13
714	SLV	SLV	-0.78	-1.384	1.08	2.79	-0.81	-9.314	1.08	121.64
715	SLV	ZWE	-4.65	-0.028	1.47	0.09	-4.66	-1.226	1.47	3.79
716	SLV	GHA	-2.07	-0.088	1.20	0.38	-2.08	-1.966	1.21	11.19
717	SLV	GTM	-1.79	-1.417	1.15	2.03	-1.79	-5.074	1.15	32.74
718	SLV	HND	-0.90	-0.713	1.10	3.25	-0.90	-1.770	1.11	21.05
719	SLV	PAK	-1.34	-1.292	1.04	4.06	-1.33	-3.397	1.04	28.34
720	SLV	IND	-2.88	-3.196	1.10	6.23	-2.88	-5.558	1.10	24.39
721	ZWE	RWA	6.00	2.455	0.40	1.75	6.03	16.249	0.40	9.97
722	ZWE	BEN	6.51	1.598	0.34	1.03	6.55	13.946	0.34	6.77
723	ZWE	SEN	5.32	1.624	0.45	1.30	5.36	8.927	0.45	7.28
724	ZWE	BFA	5.94	1.770	0.40	1.17	5.98	12.049	0.40	7.54
725	ZWE	CAF	4.93	2.257	0.53	2.03	4.95	9.989	0.53	9.64
726	ZWE	MWI	6.09	1.849	0.39	1.12	6.13	12.933	0.39	7.59
727	ZWE	TGO	5.07	1.908	0.51	1.68	5.09	8.914	0.51	8.10
728	ZWE	MLI	6.63	1.604	0.33	1.04	6.66	14.663	0.33	6.73
729	ZWE	GMB	6.97	2.202	0.32	2.03	6.99	17.953	0.32	7.00
730	ZWE	NER	4.27	1.104	0.58	0.97	4.31	6.032	0.58	7.59
731	ZWE	IDN	6.41	2.403	0.30	1.74	6.44	17.092	0.30	8.70
732	ZWE	PHL	5.99	2.124	0.35	1.62	6.02	12.830	0.35	7.90
733	ZWE	KEN	6.11	1.535	0.36	1.02	6.15	11.836	0.36	6.88
734	ZWE	LKA	6.94	1.177	0.28	0.84	6.97	13.104	0.28	5.16
735	ZWE	BOL	5.25	2.333	0.46	1.54	5.29	10.631	0.45	8.90
736	ZWE	SDN	6.24	1.139	0.34	0.84	6.27	10.590	0.34	5.83
737	ZWE	SWZ	7.16	1.815	0.28	1.32	7.19	19.020	0.28	6.69
738	ZWE	CMR	5.50	2.372	0.42	1.75	5.53	13.667	0.42	10.35
739	ZWE	COG	6.51	2.178	0.34	1.24	6.54	16.746	0.34	8.13
740	ZWE	MRT	6.15	1.746	0.39	1.22	6.19	12.332	0.39	7.04
741	ZWE	SLE	5.38	0.500	0.48	0.42	5.41	5.854	0.48	4.67

742	ZWE	BDI	3.63	1.830	0.68	1.70	3.65	7.545	0.68	12.53
743	ZWE	EGY	6.49	1.806	0.30	1.42	6.52	13.712	0.30	6.74
744	ZWE	SLV	6.85	1.432	0.29	1.06	6.89	14.019	0.29	5.76
745	ZWE	ZWE	-0.56	-0.763	1.05	2.09	-0.57	-1.071	1.05	19.30
746	ZWE	GHA	6.39	0.843	0.34	0.53	6.42	9.518	0.34	4.89
747	ZWE	GTM	6.22	1.829	0.35	1.19	6.26	12.630	0.34	6.98
748	ZWE	HND	6.42	1.761	0.34	1.11	6.46	13.746	0.34	6.94
749	ZWE	PAK	6.37	1.797	0.31	1.20	6.40	13.254	0.31	6.86
750	ZWE	IND	5.97	1.422	0.32	0.99	6.01	10.501	0.32	6.49
751	GHA	RWA	2.70	0.655	0.74	0.75	2.77	4.199	0.76	10.59
752	GHA	BEN	2.30	2.181	0.80	2.55	2.29	4.945	0.81	16.07
753	GHA	SEN	-0.21	-0.272	1.03	2.65	-0.22	-0.371	1.03	16.63
754	GHA	BFA	1.27	1.603	0.90	2.70	1.26	2.643	0.91	17.83
755	GHA	CAF	0.80	0.159	0.96	0.68	0.83	0.915	1.00	9.80
756	GHA	MWI	1.73	1.725	0.87	2.70	1.72	3.418	0.87	15.96
757	GHA	TGO	-0.15	-0.134	1.09	2.02	-0.17	-0.240	1.09	14.20
758	GHA	MLI	2.49	2.327	0.77	2.84	2.48	5.963	0.78	17.47
759	GHA	GMB	4.42	0.438	0.61	0.52	4.46	6.545	0.62	7.78
760	GHA	NER	-2.25	-1.144	1.28	2.02	-2.27	-2.866	1.29	15.18
761	GHA	IDN	2.98	1.481	0.61	1.89	2.99	5.796	0.61	13.11
762	GHA	PHL	1.84	1.305	0.74	2.02	1.83	3.062	0.74	13.21
763	GHA	KEN	1.28	1.543	0.85	2.69	1.27	2.831	0.85	18.83
764	GHA	LKA	2.44	1.948	0.73	2.70	2.43	4.810	0.73	14.47
765	GHA	BOL	0.80	0.477	0.91	1.53	0.80	1.096	0.92	12.27
766	GHA	SDN	1.10	1.031	0.85	2.03	1.09	1.925	0.86	15.26
767	GHA	SWZ	4.03	1.263	0.63	1.52	4.05	8.629	0.64	12.16
768	GHA	CMR	1.87	0.482	0.78	0.77	1.91	2.587	0.79	10.62
769	GHA	COG	2.80	2.568	0.74	2.64	2.80	6.724	0.74	16.73
770	GHA	MRT	1.42	1.445	0.92	2.03	1.41	3.375	0.92	19.95
771	GHA	SLE	-1.07	-0.118	1.19	0.52	-1.09	-0.871	1.21	8.70
772	GHA	BDI	-0.23	-0.020	1.11	0.41	-0.23	-0.188	1.12	8.06
773	GHA	EGY	2.56	1.251	0.67	1.68	2.57	4.301	0.68	12.01
774	GHA	SLV	3.02	0.793	0.68	1.09	3.04	4.940	0.69	10.91
775	GHA	ZWE	0.90	0.019	0.90	0.14	0.91	0.311	0.90	3.02
776	GHA	GHA	-0.10	-0.426	1.01	5.70	-0.09	-1.061	1.01	111.53
777	GHA	GTM	2.04	1.056	0.76	1.63	2.04	3.337	0.77	12.61
778	GHA	HND	2.39	1.407	0.76	1.80	2.39	4.333	0.77	13.34
779	GHA	PAK	2.14	1.873	0.71	2.55	2.14	4.025	0.72	14.33
780	GHA	IND	0.75	1.007	0.78	2.65	0.73	1.480	0.79	18.19
781	GTM	RWA	1.43	0.082	0.92	0.47	1.45	1.799	0.93	10.59
782	GTM	BEN	0.49	0.439	1.03	3.73	0.49	1.332	1.03	26.00
783	GTM	SEN	-2.03	-0.282	1.24	1.07	-2.05	-2.551	1.25	15.01
784	GTM	BFA	-0.38	-0.122	1.10	1.92	-0.38	-0.652	1.11	17.64
785	GTM	CAF	-1.03	-0.050	1.22	0.44	-1.04	-0.963	1.23	10.21

786	GTM	MWI	-0.05	-0.023	1.08	2.45	-0.05	-0.103	1.09	19.58
787	GTM	TGO	-2.15	-0.281	1.33	0.96	-2.17	-2.563	1.34	14.39
788	GTM	MLI	0.92	0.772	0.97	4.10	0.93	2.201	0.97	21.57
789	GTM	GMB	2.43	0.246	0.87	0.77	2.46	4.460	0.88	13.65
790	GTM	NER	-3.75	-0.194	1.46	0.48	-3.81	-2.994	1.48	10.85
791	GTM	IDN	1.11	1.034	0.80	4.00	1.11	3.175	0.80	25.39
792	GTM	PHL	-0.57	-0.381	0.99	1.87	-0.57	-2.165	0.99	40.16
793	GTM	KEN	-0.59	-0.528	1.06	3.93	-0.59	-1.383	1.06	24.70
794	GTM	LKA	0.69	0.274	0.93	2.02	0.70	1.494	0.93	19.88
795	GTM	BOL	-2.00	-1.428	1.23	2.03	-2.01	-4.981	1.23	29.79
796	GTM	SDN	-0.04	-0.002	0.97	0.51	-0.02	-0.027	0.99	11.24
797	GTM	SWZ	2.46	1.619	0.84	3.12	2.46	7.167	0.84	21.91
798	GTM	CMR	-0.05	-0.006	1.00	0.80	-0.05	-0.064	1.01	13.15
799	GTM	COG	1.45	0.396	0.90	1.61	1.47	2.930	0.91	17.05
800	GTM	MRT	-0.27	-0.169	1.13	3.11	-0.28	-0.586	1.14	21.67
801	GTM	SLE	-2.72	-0.056	1.41	0.23	-2.72	-1.660	1.42	7.75
802	GTM	BDI	-2.40	-0.072	1.38	0.30	-2.41	-1.633	1.39	8.41
803	GTM	EGY	0.37	0.217	0.91	2.02	0.38	1.043	0.90	26.32
804	GTM	SLV	0.73	0.535	0.95	2.00	0.73	2.539	0.95	32.14
805	GTM	ZWE	-4.12	-0.041	1.44	0.13	-4.13	-1.266	1.44	4.33
806	GTM	GHA	-0.83	-0.056	1.07	0.57	-0.84	-0.974	1.11	12.54
807	GTM	GTM	-0.50	-1.39	1.05	5.65	-0.53	-11.21	1.05	221.73
808	GTM	HND	0.29	0.170	1.01	1.95	0.29	0.874	1.01	28.86
809	GTM	PAK	0.06	0.033	0.94	2.01	0.06	0.195	0.94	29.84
810	GTM	IND	-1.37	-0.661	0.99	2.04	-1.37	-3.273	0.99	27.21
811	HND	RWA	0.52	0.183	0.97	0.78	0.53	0.747	0.98	12.66
812	HND	BEN	0.02	0.051	1.02	2.68	0.01	0.028	1.03	21.73
813	HND	SEN	-2.70	-1.648	1.26	1.74	-2.73	-3.512	1.27	15.73
814	HND	BFA	-1.10	-2.526	1.13	2.62	-1.11	-2.094	1.13	20.06
815	HND	CAF	-1.70	-0.320	1.23	0.47	-1.74	-1.641	1.26	10.58
816	HND	MWI	-0.54	-0.968	1.09	2.70	-0.55	-0.970	1.09	17.81
817	HND	TGO	-2.63	-0.948	1.33	0.92	-2.65	-2.947	1.34	13.51
818	HND	MLI	0.39	0.906	0.97	2.42	0.39	0.864	0.97	20.44
819	HND	GMB	2.69	0.171	0.79	0.16	2.71	3.445	0.80	8.63
820	HND	NER	-4.85	-0.633	1.53	0.72	-4.91	-4.324	1.55	12.69
821	HND	IDN	0.86	0.832	0.78	1.84	0.86	1.634	0.78	16.51
822	HND	PHL	-0.67	-1.887	0.95	1.90	-0.69	-1.192	0.96	17.68
823	HND	KEN	-1.17	-2.836	1.07	2.66	-1.18	-2.670	1.07	24.25
824	HND	LKA	0.34	0.272	0.91	1.45	0.33	0.583	0.92	15.99
825	HND	BOL	-2.19	-2.488	1.19	2.03	-2.22	-3.447	1.20	18.21
826	HND	SDN	-1.25	-0.444	1.06	1.09	-1.25	-1.837	1.07	15.83
827	HND	SWZ	2.29	0.587	0.80	0.81	2.30	4.368	0.80	13.65
828	HND	CMR	-0.74	-0.563	1.02	1.16	-0.75	-1.028	1.03	14.03
829	HND	COG	0.68	1.460	0.94	3.56	0.68	1.710	0.94	22.16

830	HND	MRT	-0.58	-0.763	1.11	1.78	-0.60	-0.973	1.12	16.47
831	HND	SLE	-3.65	-0.137	1.46	0.26	-3.66	-2.303	1.47	8.28
832	HND	BDI	-3.29	-0.272	1.42	0.35	-3.31	-2.324	1.43	9.00
833	HND	EGY	-0.01	-0.017	0.89	2.68	-0.02	-0.036	0.90	19.84
834	HND	SLV	0.59	0.454	0.90	1.19	0.59	1.083	0.91	16.41
835	HND	ZWE	-3.82	-0.044	1.36	0.08	-3.83	-1.127	1.36	3.92
836	HND	GHA	-1.50	-0.313	1.11	0.64	-1.51	-1.785	1.13	12.99
837	HND	GTM	-0.69	-2.352	1.01	1.93	-0.70	-1.497	1.02	21.82
838	HND	HND	-0.47	-1.443	1.04	2.50	-0.52	-3.530	1.05	67.79
839	HND	PAK	-0.32	-0.870	0.92	2.40	-0.33	-0.702	0.93	21.17
840	HND	IND	-1.99	-1.882	1.00	1.69	-2.00	-4.992	1.00	28.74
841	PAK	RWA	1.55	0.238	0.97	0.40	1.56	2.124	0.98	12.26
842	PAK	BEN	0.84	1.607	1.05	3.01	0.85	2.385	1.05	27.43
843	PAK	SEN	-2.06	-1.181	1.31	1.54	-2.07	-3.148	1.31	19.21
844	PAK	BFA	-0.20	-0.279	1.15	1.99	-0.21	-0.409	1.15	21.40
845	PAK	CAF	-1.19	-0.248	1.30	0.52	-1.21	-1.285	1.32	12.46
846	PAK	MWI	0.25	0.343	1.12	2.04	0.25	0.510	1.12	21.34
847	PAK	TGO	-2.03	-0.598	1.38	0.89	-2.04	-2.608	1.39	16.14
848	PAK	MLI	1.20	1.991	1.00	3.05	1.20	3.397	1.00	26.60
849	PAK	GMB	2.90	0.566	0.88	0.57	2.95	5.042	0.89	13.05
850	PAK	NER	-3.73	-0.365	1.53	0.36	-3.75	-3.062	1.54	11.69
851	PAK	IDN	1.54	1.916	0.82	2.70	1.54	4.067	0.82	23.79
852	PAK	PHL	-0.12	-0.213	1.00	2.02	-0.12	-0.360	1.00	31.09
853	PAK	KEN	-0.19	-0.397	1.08	2.64	-0.20	-0.433	1.08	23.53
854	PAK	LKA	1.03	1.695	0.95	3.05	1.03	2.309	0.96	21.32
855	PAK	BOL	-1.42	-1.260	1.23	1.61	-1.43	-2.513	1.23	21.09
856	PAK	SDN	0.11	0.027	1.03	0.35	0.11	0.130	1.04	12.55
857	PAK	SWZ	2.88	2.983	0.86	2.04	2.89	8.228	0.86	21.88
858	PAK	CMR	0.04	0.018	1.05	0.88	0.04	0.058	1.06	15.69
859	PAK	COG	1.71	1.010	0.94	1.53	1.71	3.950	0.95	20.42
860	PAK	MRT	-0.01	-0.028	1.17	3.11	-0.01	-0.033	1.17	25.26
861	PAK	SLE	-2.01	-0.108	1.40	0.17	-2.02	-1.153	1.40	7.19
862	PAK	BDI	-2.51	-0.230	1.46	0.24	-2.51	-1.791	1.46	9.32
863	PAK	EGY	0.72	0.960	0.93	1.58	0.72	2.113	0.93	28.95
864	PAK	SLV	1.28	2.056	0.95	2.03	1.29	3.137	0.95	22.61
865	PAK	ZWE	-3.93	-0.084	1.48	0.12	-3.93	-1.185	1.48	4.37
866	PAK	GHA	-0.78	-0.317	1.14	0.69	-0.80	-1.035	1.16	14.76
867	PAK	GTM	0.11	0.234	1.04	2.65	0.11	0.300	1.04	27.79
868	PAK	HND	0.69	1.243	1.03	2.70	0.69	1.949	1.03	28.00
869	PAK	PAK	0.24	1.051	0.97	3.96	0.25	3.186	0.97	132.64
870	PAK	IND	-1.12	-1.532	1.02	1.99	-1.12	-3.282	1.02	34.15
871	IND	RWA	3.58	0.169	0.83	0.55	3.63	5.738	0.84	12.26
872	IND	BEN	2.96	1.057	0.91	1.68	2.95	11.324	0.91	32.27
873	IND	SEN	0.47	0.313	1.13	4.98	0.44	0.828	1.13	20.44

874	IND	BFA	1.99	0.865	1.00	2.70	1.98	5.585	1.00	26.50
875	IND	CAF	1.37	0.076	1.10	0.62	1.37	1.605	1.12	11.67
876	IND	MWI	2.48	1.380	0.97	3.85	2.46	6.212	0.97	22.49
877	IND	TGO	0.46	0.142	1.19	2.70	0.43	0.686	1.21	17.47
878	IND	MLI	3.28	1.214	0.86	1.98	3.28	11.756	0.86	29.01
879	IND	GMB	5.03	0.220	0.73	0.49	5.09	8.671	0.74	10.71
880	IND	NER	-1.29	-0.103	1.35	0.82	-1.32	-1.421	1.36	13.67
881	IND	IDN	3.68	2.273	0.69	4.89	3.67	10.119	0.70	21.22
882	IND	PHL	2.26	0.945	0.85	2.00	2.25	6.432	0.86	26.10
883	IND	KEN	1.95	0.828	0.95	2.02	1.94	7.289	0.95	35.39
884	IND	LKA	3.10	1.180	0.83	1.93	3.10	9.100	0.83	24.32
885	IND	BOL	1.17	0.524	1.04	3.64	1.15	2.131	1.05	19.03
886	IND	SDN	2.07	0.237	0.92	1.16	2.06	3.427	0.92	15.48
887	IND	SWZ	4.81	3.053	0.73	3.98	4.81	14.796	0.73	20.20
888	IND	CMR	2.41	0.273	0.90	1.10	2.40	3.932	0.90	14.71
889	IND	COG	3.69	1.603	0.82	3.59	3.68	11.226	0.82	23.49
890	IND	MRT	2.28	0.893	1.01	2.01	2.27	6.325	1.01	25.38
891	IND	SLE	0.14	0.002	1.25	0.27	0.13	0.093	1.25	7.90
892	IND	BDI	0.26	0.006	1.24	0.28	0.26	0.207	1.24	8.96
893	IND	EGY	2.92	1.065	0.80	2.02	2.91	9.651	0.80	28.02
894	IND	SLV	3.45	2.097	0.81	4.10	3.45	8.928	0.81	20.51
895	IND	ZWE	-0.80	-0.007	1.24	0.09	-0.81	-0.280	1.25	4.22
896	IND	GHA	1.40	0.283	1.01	1.86	1.40	2.418	1.02	17.30
897	IND	GTM	2.44	1.204	0.89	2.02	2.43	6.756	0.89	24.82
898	IND	HND	2.80	0.796	0.90	1.69	2.79	12.066	0.90	37.14
899	IND	PAK	2.67	0.891	0.82	1.40	2.66	9.203	0.82	30.16
900	IND	IND	1.16	1.316	0.89	2.96	1.19	16.645	0.89	142.97

Appendix B

Countries List

Country	Code	Country	Code
Rwanda	RWA	Kenya	KEN
Benin	BEN	Sri Lanka	LKA
Senegal	SEN	Bolivia	BOL
Burkina Faso	BFA	Sudan	SDN
Sierra Leone	SLE	Swaziland	SWZ
Burundi	BDI	Cameroon	CMR
Central African Republic	CAF	Congo, Rep.	COG
Malawi	MWI	Mauritania	MRT
Togo	TGO	Egypt, Arab Rep.	EGY
Mali	MLI	El Salvador	SLV
Zimbabwe	ZWE	Ghana	GHA
Gambia, The	GMB	Guatemala	GTM
Niger	NER	Honduras	HND
Indonesia	IDN	Pakistan	PAK
Philippine	PHL	India	IND

Residual Sum of Square of Forecast error

Sr#No	Country *i*	Country *j*	OLS-RSS	WALS-RSS
1	RWA	RWA	0.0013	0.0011
2	BEN	BEN	0.0003	0.0003
3	SEN	SEN	0.0022	0.0021
4	BFA	BFA	0.0057	0.0057
5	CAF	CAF	0.0070	0.0070
6	MWI	MWI	0.0016	0.0016
7	TGO	TGO	0.0151	0.0146
8	MLI	MLI	0.0046	0.0046
9	GMB	GMB	0.0028	0.0028
10	NER	NER	0.0027	0.0026
11	IDN	IDN	0.0003	0.0002
12	PHL	PHL	0.0028	0.0027
13	KEN	KEN	0.0013	0.0012
14	LKA	LKA	0.0041	0.0041
15	BOL	BOL	0.0112	0.0110
16	SDN	SDN	0.0002	0.0002
17	SWZ	SWZ	0.0106	0.0091
18	CMR	CMR	0.0092	0.0092
19	COG	COG	0.1292	0.1274
20	MRT	MRT	0.1002	0.0999
21	SLE	SLE	0.0010	0.0009
22	BDI	BDI	0.0029	0.0022
23	EGY	EGY	0.0094	0.0094
24	SLV	SLV	0.0002	0.0002
25	ZWE	ZWE	0.0200	0.0205
26	GHA	GHA	0.0144	0.0143
27	GTM	GTM	0.0002	0.0002
28	HND	HND	0.0034	0.0034
29	PAK	PAK	0.0067	0.0066
30	IND	IND	0.0033	0.0033