COMPARISON OF MODEL SELECTION METHODOLOGIES WITH APPLICATION OF ECONOMIC GROWTH AND BALANCE OF TRADE

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ABSTRACT

The process of selecting an appropriate econometric model represents a historical and enduring challenge within the field. This challenge stems from the inherent complexity of reality, characterized by dynamic social structures and laws that undergo continual change. The multitude of methods and criteria employed by economists and empirical researchers to discern the most fitting model from an array of candidates contributes to a lack of clarity regarding the relative efficacy of these approaches.

Commonly used methods for assessing statistical procedures involve Monte Carlo experiments, where data is generated based on predetermined processes. However, a notable limitation arises from the specific set of assumptions under which the data is generated in these experiments. This raises concerns about the applicability of the findings to real-world data, where the validity of assumptions may be questionable.

In response to these challenges, this study adopts a real data-based comparison approach to assess model selection procedures. The primary metric for evaluating performance is the forecast error, calculated as the difference between actual and predicted values. This method, referred to as real data-based comparison, offers a more practical and applicable means of assessing the performance of econometric procedures. The objective is to discern the most effective procedure for selecting models under real-world conditions.

In instances where a variable of interest is associated with a multitude of theoretical models, each characterized by distinct sets of independent variables, the formulation of a generalized unrestricted model (GUM) becomes progressively impractical and, in certain cases, unattainable. Notably, in the domain of Growth Econometrics, Darlauf's compilation of growth models reveals an aggregate inclusion of over 150 independent variables. Introducing a single lag for all variables amplifies the total count of regressors to 300, rendering the estimation of a GUM unviable, particularly when dealing with annual data.

In light of these challenges, our present study strategically narrows its focus to models that boast a minimum of three substantiated studies within the existing literature. This judicious selection process aims to circumvent the methodological complexities inherent in attempting to accommodate the comprehensive array of models, thereby enhancing the feasibility and rigor of our empirical investigation.

The study evaluates a spectrum of model selection procedures, including those based on information criteria, shrinkage methodologies (such as LASSO, Adaptive LASSO, WALS, and elastic net), coefficient consistency procedures (exemplified by Leamer's and Sala-i-Martin's extreme bound analysis), and automatic model selection procedures (including encompassing and automatrix).

To validate the utility of these procedures, the study employs two real-life problems: selecting a model for the balance of trade and a model for economic growth. Given the paramount importance of these variables in macroeconomics, understanding their determinants is crucial. The plethora of theories leads to a variety of econometric models, necessitating model selection to guide policymakers. Consequently, the study seeks to identify the most suitable models for each variable and determine the best-performing model selection procedure based on forecast performance. In essence, the research aims to offer a comprehensive solution to the dual challenges of model selection in the contexts of both the balance of trade and economic growth.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABBREVIATIONS

BOT	Balance of Trade
EC	Economic Growth
AIC	Akaike Information Criterion
AICc	Akaike Information Criterion Corrected
BIC	Bayesian Information Criterion
BICc	Bayesian Information Criterion Corrected
LR	Likelihood Ratio
EBA	Extreme Bound Analysis
LEBA	Leamer Extreme Bound Analysis
SAI EBA	Sala-i-Martin Extreme Bound Analysis
WALS	Weighted Average Least Squares
GUM	General Unrestricted Model
LASSO	Least Absolute Shrinkage and Selection Operator
E-Net	Elastic Net
ALASSO	Adaptive Least Absolute Shrinkage and Selection Operator
MSP	Model Selection Procedures
G-S	General to Specific
DHSY	Davidson, Hendry, Srba, and Yeo,(DHSY)
TSS	Total Sum of Squares
RSS	Residuals Sum of Squares
ESS	Estimate Sum of Squares
MSE	Mean Square Error
FRMSE	Forecast Root Mean Square Error
SSE	Sum of Squares of Error
HQC	Hannan and Quinn's Criterion
BC	Bridge Criterion
MSPE	Mean Squared Prediction Error
FPE	Finite Prediction Error

CHAPTER 1

INTRODUCTION

In all disciplines, including social sciences, model selection becomes an essential component of empirical research whenever a prior theory does not pre-define a complete and correct specification. Economics is unquestionably an empirical science, owing to the complexity, high dimensionality, and non-stationary economic processes at the aggregate level. Therefore, model selection is a component of empirical economics.

The model selection takes many forms, e.g., includes

1) Choice of appropriate determinants from a list of potential determinants
2) Finding an appropriate dynamic structure gives a specific set of determinants
3) Finding appropriate functional forms

The focus of the current study is to choose appropriate determinants.

Model construction has always been debated due to diversity in selecting variables, lag lengths, structural breaks, or functional forms. Although these issues have frequently been discussed, the issues remained unsolved. The importance of model selection came into the limelight at the start of the 70s, when most prevailing macroeconomic models became unsuccessful in appropriately forecasting and were immensely disparaged. This gave a new impetus to developing model selection procedures, and various techniques and model selection criteria were revised. The selection variables and model specification area is quite vast in its nature and scope. To select the appropriate model, several econometric techniques and approaches are designed. With such a variety of model selection techniques, the issue of selection among the model selection techniques emerges.

Many procedures can be used for model selection. For example, suppose $X_1, X_2, X_3, \ldots X_n$ are the potential determinant of Variable "Y". But it is not possible to make a model with all possible candidates.

Suppose we have a variable Y, and we have three different models for Y

$$M_1\text{: Y = f1 } (X_1, X_2, X_3)$$

$$M_2\text{: Y= f2 } (X_2, X_4)$$

$$M_3\text{: Y= f3 } (X_5, X_6)$$

Three different models are based on the three different theories. The econometric theory says that to have a valid model for Y all of the relevant variables should be present in these models.

One solution for this is to make a model containing all the variables present in these models.

$$\text{Y = f } (X_1, X_2, X_3, \ldots X_6)$$

The three models mentioned above could be drawn by testing restrictions on this most general model. This strategy was recommended by Davidson, Hendry, Sarba, and Yu (1978) in their seminal paper known as DHSY. This process often works successfully, but sometimes, this process cannot be used for making a model. For example, there are dozens of growth models, and the total number of variables used in these models is in the hundreds. One cannot make the most general model with hundreds of variables because of the dimensionality problem. So, we need to adopt a strategy that can save the model from the dimensionality problem and can also save the model from the missing variable bias.

Because of the importance of model selection, many procedures have been designed to choose among such conflicting models. These model selection procedures can be divided into different classes. For example, one class of the model selection procedure is based on information criteria. Several information criteria are available in the literature, and each information criterion leads to a different model selection procedure. We have Akaike Information Criteria, (AIC) Swartz Bayesian Criterion, (SIC) Hannan Quinn Criterion (HQC), etc. Similarly, we have another class of model selection procedures based on shrinkage methodology, including (LASSO, Weighted average least Squares). These classes of model selection procedures also contain many methods.

The number of model selection procedures is very large and can be divided into several classes; within one class of models, the model selection procedures have been compared, but within a different class of procedures, there is a lack of comparison. The practitioner has difficulty choosing which model selection procedures should be used in empirical modeling. For example, consider the case of economic growth. There are hundreds of theories for economic growth consisting of a separate set of determinants. In the presence of many theories and determinants for a variable of interest, a model based on any one theory will be subject to missing variable bias.

Model selection is a set of procedures for selecting the statistical model that best fits the observed measurements from a group of candidate models. Model selection methods can only approximate the true model with observed data because the reality of any economic phenomenon is essentially a complex event. The following are some examples of model selection:

- Model selection using ordinary least square residuals, such as R square (R^2), Adjusted R square, ($\overline{R}^2$) and finite prediction error (FPE), and so on.
- Model selection using information criteria such as Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Akaike Information Criterion corrected (AIC), Bayesian information Criterion corrected (BIC), Mallow's Cp, Likelihood Ratio test (LR), Hannan and Quinn Criterion (HQC), and Bridge Criterion (BC), among others.
- Stepwise Regression-based model selection criteria include Forward Stepwise Regression, Backward Stepwise Regression, and Bi-directional Stepwise Regression.
- Least Absolute Shrinkage and Selection Operator (LASSO), Adoptive least Absolute Shrinkage and Selection Operator (ALASSO), Elastic net, and other shrinkage methodologies are used to select models.
- PcGets and Autometrics; model selection
- Leamer's Extreme Bound Analysis and Sala-i-Martin Extreme Bound Analysis are two model selection methods based on parameter consistency.
- Model Selection using Non- Nested Encompassing

The error in the model's fit was the initial criterion that was used to evaluate the model's overall quality. The quality of the model will increase in proportion to how well it fits the data. This is accomplished through the use of the methodology of ordinary least square, and the natural extension of this became the utilization of R^2 for model selection. The R^2 statistic explains the variation in the dependent variable that can be attributed to the independent variables. R^2 is a function of independent variables that do not get smaller as more variables are added. Therefore, it consistently rises whenever an additional independent variable is added to the regression model. The issue with R^2 is that its value always goes up, regardless of whether or not the additional independent variable is significant. To find a solution to this issue, adjusted R^2 was developed. The adjusted R^2 will only increase if the newly introduced variable is significant; otherwise, it will decrease or even turn negative. FPE is yet another method of model selection that uses residuals. The FPE criterion can provide a measurement of the quality of the model by simulating the scenario in which the model is evaluated using a different data set.

Akaike (1973) introduced the Akaike information criterion (AIC), a model selection criterion based on Kullback-Leibeler information. The Akaike information criteria reduce the disparity between empirical probability and theoretical probability. Subsequently, numerous criteria were introduced along similar lines.

Bayesian information criterion (BIC), was developed by Schwartz in 1978. The information that was modified from Mallow's Cp. Mallow's Cp is a solution to the issue of over-fitting, which occurs when the balance amount of squares, which includes model selection statistics, is always smaller as extra regressors are included in the estimated model. Mallow's Cp addresses this issue. The likelihood ratio (LR) test is an additional extension of the information-based criterion that can be used. Any strongly consistent method must miss efficiency by at least a factor, so in this sense, HQC follows the law of repeated logarithm, which says that any very consistent method must be less efficient by at least a factor. In this way, HQC did very well asymptotically. BIC is a way to control the order of a time series data-fitted autoregressive model. It has the benefits of both the Akaike and Bayesian information criteria, which are well-known ways to choose a model.

Efroymson (1960) proposed an alternative algorithm that recursively selects the explanatory variable for a multiple regression model from a group of candidate variables using a series of automated steps. At each stage of the process, the candidate variables are assessed in terms of the coefficients of the currently considered variables. A forward-selection rule is specific to the general methodology that begins with the smallest number of explanatory variables and then adds variables one at a time until no more significant variables are left. Backward elimination is a rule that goes from general to specific. It begins with all of the possible explanatory variables and then eliminates, one by one, the variables that have the least amount of statistical significance.

Autometrics, which handles both general to specific and encompassing regulations simultaneously using a complex algorithm, was formally developed by Hendry (2004) and is a hybrid of both methods. The Forward Stepwise regression begins with a model that does not contain any X variables, then add additional X Variables before checking to see if any of them are insignificant. This will continue to be the case until no more regressors can be added to the model, and most people will be unable to find a better model (Lovell, 1983; Whittingham et al., 2006). After that, subsequent enhancements were demonstrated in the form of PcGets, which were demonstrated by (Hoover and Perez (1999) and Hendry and Krolzig (2001, 2002).

In contrast to the forward stepwise and backward stepwise, this algorithm begins the selection procedure in which all models are included by including all variables and reducing it by testing down the procedure and removing the insignificant variables. The specific-to-general and general-to-specific methods are collectively called the GETS methods (Hendry & Doornik, 2014). The Autometrics method is a hybrid of these two approaches, and its name comes from the combination of the two terms (Doornik & Hendry, 2007; Doornik, 2009). The autometrics application of the tree search algorithm is outlined in chapter 4.

The model selection procedures comprising the Shrinkage approach are based on mathematical programming techniques. These techniques eliminate the data's high dimensionality and reduce irrelevant variables to zero. Tibshirani introduced the Least Absolute Shrinkage and Selection Operator (LASSO) as a popular estimation method in a linear regression framework (1996). Like ridge regression, the LASSO method sets some coefficients to precisely zero with a substantial bias. The resulting model is straightforward to interpret and has the lowest forecast error. LASSO can estimate the parameters and select one variable at a time. Before LASSO, stepwise selection was the most common method for choosing regressors; in most cases, prediction accuracy was only marginally improved. When there are more variables than observations, LASSO can handle the situation. Zou demonstrated that the LASSO estimator lacks the oracle property and introduced the adaptive LASSO, a straightforward and effective solution.

In contrast, the L1 penalty in LASSO penalizes each coefficient equally. In contrast, each coefficient is assigned a distinct weight in ALSSO. Zou demonstrated that ALSSO can possess the oracle property if the weights are data-dependent and meticulously chosen.

Extreme Bound Analysis (EBA) is a model selection procedure based on the consistency of estimated model coefficients. EBA chooses the relevant variable by employing the method of selecting relevant parameters that are consistent with the relevant variables. The extreme bound analysis is followed by two popular procedures: Leamer extreme bound analysis and Sala-i-Martin extreme bound analysis.

The economic phenomenon is usually based on some assumptions, but the data does not allow these assumptions to be tested. So, in multivariate analysis, we use a small number of variables in a simple functional form and only for ideal distributions. The data sets are not more useful if the assumptions are not met. If the underlying variable's coefficients do not change when doubtful variables are added to the model in different combinations. In extreme bound analysis, different groups of dubious variables are selected, and the coefficients of the core variables are estimated. In response to EBA's purported inflexibility, Sala-i-Martin (1997) proposed a replacement method considering the entire distribution of regression coefficients, not just the extreme bounds. The binary variable robust or fragile is not given to a variable in the Sala-i-Martin EBA, but it does assign a confidence level for robustness to the variable under consideration. Sala-i-Martin uses the weighted mean of the regression to estimate the normal model.

There are a great number of studies that compare these processes on both a theoretical and an empirical level. These studies compare the criteria for model selection used by different procedures that belong to the same family, such as. Lutkepohl (1985) used the Monte Carlo simulation to analyze and compare a variety of criteria for selecting a model, including AIC, BIC, FPE, Shibata, and others. Mills and Prasad (1992) evaluated the relative performance of various models by comparing the selection criteria of various models that were based on information. Wenjiang et al. (1998)

compared the LASSO and Bridge regressions. Using a shrinkage-based methodology, FU (1998) analyzed and contrasted a variety of criteria for model selection. Kuha (2004), Wei, and Zhou (2010) examined the model selection process through the lens of the shrinkage methodology (ridge regression, LASSO, Elastic Net). Meinshausen, (2006) did a comparison of the two different shrinkage methods, LASSO, and RELAXED LASSO, for model selection.

Model selection criteria such as AIC, HQC, BIC, AICc, Vector Corrected Kullback Information Criterion (KICvc), and Weighted-Average Information Criterion (WIC) were compared by Pchen et al. (2008). The consistency properties of the AIC, AICc, BIC, and HQC information criterion for factor models were investigated by Choi and Jeong (2013). Ismail et al. (2015) conducted an analysis in which they compared the predictive abilities of several different model selection algorithms using the Root Mean Square Error (RMSE) and the Geometric Root Mean Square Error to forecast the flow of air passengers (GRMSE).

There have also been a few studies that compared model selection procedures between different classes. For example, Epprecht et al. (2021) compared LASSO, adoptive LASSO, and Auto-metrics.

1.1 Objectives

1. To compare the model selection procedure based on FRMS for
   a. Growth Models
   b. Balance of Trade Model
2. To Test the Robustness of the Model selection procedure
3. To use the optimal model selection procedure for the construction of
   a. Optimal model for Growth in the case of Pakistan
   b. Optimal model for Balance of Trade in the case of Pakistan

1.2 Research Gap

This study makes four contributions to the econometrics literature
Firstly, this study contributes to the refinement of model selection procedures, addressing a notable gap identified in prior research. Preceding studies predominantly relied on pairwise comparisons, limiting their efficacy in guiding the selection of a procedure from a comprehensive array of available options. In contrast, the current investigation systematically compares a multitude of model selection procedures, providing a substantive guideline for choosing among a diverse set of options.

Secondly, unlike existing studies that predominantly employ Monte Carlo experiments to evaluate model selection procedures, this research conducts a comparison grounded in real-world data. Prior studies relying on Monte Carlo experiments are bound by specific data-generating processes and assumptions, which may not align with the complexities inherent in real-world data. This study endeavors to bridge this gap by presenting findings that are more closely aligned with the intricacies of actual data. Notably, the third and fourth contributions of this thesis involve identifying optimal models for Balance of Trade and Economic Growth.

Prior research predominantly focused on comparing model selection procedures within the same family, such as those based on shrinkage or Information criteria. In contrast, this study extends its scope by comparing procedures from distinct and disjoint families, including encompassing, weighted average least squares (BAYESIAN MODEL AVERAGING), and Extreme Bound Analysis. While sharing similarities with Khan's study (2020), this research diverges in critical aspects. For instance:

This study adopts a real data-based analysis rather than relying on Monte Carlo Simulation, differentiating it from Khan's (2020) methodology.
Unlike Khan (2020), which shortlists methods post-Monte Carlo Simulation, this study incorporates those methods, such as LASSO and WALS, in its comprehensive evaluation.
While Khan (2020) exclusively discusses the retention of variables in the final models, our study extends the discourse to include forecast performance and model validity for out-of-sample countries.
The inclusion of the Balance of Trade model enhances the robustness of our findings by addressing the underlying phenomenon.
Furthermore, this study introduces an additional class of test procedures, specifically the encompassing technique, a facet not explored in Khan's (2020) thesis.

1.3 Significance of the Study

The choice of model is the oldest and unresolved issue because reality is complex, simultaneously dynamic, non-synchronous, and high-dimensional. Social structures change from time to time, and social laws also change over time. For any observed phenomenon, there may exist many economic theories based on different logic that look quite reasonable. Therefore, in selecting an appropriate model, the economic theory alone cannot help much to select the suitable model. A model selection method is thus needed to select the most appropriate model. There are many candidates for such a model selection criterion. This study would help choose the appropriate model selection method. This will support researchers to narrow down the best technique by using the available information set.

1.4 Organization of the Study

The organization of the current study is structured as follows: Chapter one introduces and provides background information for the study. In chapter two, the literature review is presented, while chapter three offers an explanation of the study's background. Chapter 4 covers computational details related to model selection criteria and the comparison of various methodologies. Chapters 5 and 6 are dedicated to presenting and discussing the results. Chapter 7 focuses on explaining the optimal models within the context of Pakistan. Chapter 8 concludes the study with a summary, conclusions, recommendations, Finally, Chapter 9 concludes with an exploration of references and bibliography.

CHAPTER 2

LITERATURE REVIEW

Model selection is an important part of any statistical analysis and in fact, is central to the pursuit of science in general. Numerous authors have examined this question extensively, and many tools have been suggested to select the "best model" in the literature, both from frequentist and Bayesian points of view. Selection of an appropriate model for a given phenomenon is not an easy task. There are a lot of theories and a plethora of models which can be applied to theories. The selection of an appropriate model is an issue of great concern and has a very long history, but it is still unresolved. The reason is that the model simplifies reality, which is very complex due to its dynamic nature and high-dimensionality. Social structures and laws change over time, in the existence of these problems and the selection of the most appropriate model for given economic phenomena. The literature review is divided into three parts. Part I summarizes the literature on model selection procedures and their comparison. Part II is to obtain selected literature on the Balance of trade model, and part III is about the Growth Model.

2.1 Information-Based Procedures

The earliest procedure developed for the model selection procedure was based on Akiake's Information Criteria (AIC) introduced by Akiake (1973). Later on, several other measures of information criteria were developed, for example Schwarz (1978),

The model selection procedure based on information theory minimizes the loss of information by choosing a different number of variables or a group of variables. For those variables where the loss of information is minimum, then these model selection procedures declare that these variables are most relevant to the dependent variable.

For model selection using information criteria, all possible models are estimated separately and the method with the smallest information criterion value is selected. Various information criteria exist in literature whose theoretical details are mentioned below.

2.2 Comparison of Information Criteria

Several comparisons of the model selection procedures are based on information criteria.

Lutkepohl (1985) compared different criteria for selecting intervals (AIC, BIC, FPE, Shibata, etc.). According to Schwarz's BIC criterion, a small average square in a sample of normally available size leads to a prediction error, and it automatically chooses the correct order. The study has concluded that AIC and BIC are sensitive to sample size.

Mills and Prasad (1992) compared the selection criteria of models based on information to evaluate their relative performance. They examine the relative performance of criteria in several situations, such as the distribution of errors, collinearity among regressors, and non-stationary data. He predicted samples for quality assessment and the selection of real models. He concluded that the Schwartz Bayesian Information Criteria are consistent beyond the predictive performance of the sample.

Kuha (2004) investigated the quality of behavior in selecting good models and discovered that combining AIC and BIC yields useful information for model selection.

Ng and Perron (2005) explored the performance of information criteria. Compared to the selection of different models, such as the effect of the degree of freedom on the coefficient of variations, the size of the sample, and the suitability of the sample size and performance in many situations. The study has concluded that AIC and BIC are sensitive to sample size.

Reffalovich et al. (2008) compare model selection criteria such as Bayesian information criteria (BIC), Akaike information criteria (AIC), Akaike information criteria (AICc), Adjusted R^2, Mallows CP and stepwise regression to find the best model. Using different sample sizes, the researchers investigated the ability of these selection methods to eliminate irrelevant variables while simultaneously adding important variables. The model's description addressed this issue directly. Using large samples, BIC outperforms other methods in which they have accurately identified the discovery under the integrated R^2, Mallow's CP, AIC, and AICc are significantly inferior and should be avoided when comparing models.

Choi and Kurozumi (2008) compared the model selection criteria like Mallows C_p Criterion, Akaike AIC, Hurvich, and Tsai corrected AIC and the BIC of Akaike and Schwarz. They ran different information procedures and concluded that the BIC appears to be most successful in reducing MSE and C_p in reducing bias.

Wei and Zhou (2010) proposed a modified version of the Akaike information criterion and two modified versions of the Bayesian information criterion. To select the number of principal components and to choose the penalty parameters of penalized splines in a joint model of paired functional data. Numerical results show that compared with an existing procedure using cross-validation, the procedure based on the information criteria is computationally much faster while giving a similar performance.

Choi and Jeong (2013) analyzed the consistency properties of (AIC), corrected AIC, BIC, and the Hannan and Quinn information criterion for factor models. They concluded that it is difficult to determine which criterion performs the best and why.

In a nutshell, despite having many comparisons, there is no clarity about the best information criteria and the performance information criterion depends on several nuisance procedures such as sample size.

2.3 Model Selection Procedures based on Shrinkage Methodology

The idea of the Shrinkage estimator gets motivation from the Bayesian Methodology, which combines the information from prior knowledge with information from data and clubs the information to Shrinkage the variance of the estimators. In Shrinkage methodology, different combinations of regressors are estimated, and information is clubbed in Bayesian Fashion, which Shrinkage the variance of the estimators. There are many kinds of Shrinkage estimation.

The Least Absolute Shrinkage and Selection Operator, or LASSO, was first presented by Tibshirani (1996) and is currently the most well-known approach in this class. The LASSO algorithm provides the capacity to make parameter estimates and choose one variable at a time. LASSO is virtually identical to ridge regression, with a few key distinctions. Before the introduction of the LASSO approach, the stepwise selection was the method that was most commonly used for determining the regressors. However, this strategy only enhanced the accuracy of the prediction in a few circumstances, while in most cases, it made the forecast worse. Ridge regression can recover prediction error by lowering big regression coefficients to reduce the amount of overfitting, but it cannot choose the appropriate variables.

LASSO has the capability of dealing with situations in which there are more variables than observations. Numerous modifications of LASSO have been suggested in an attempt to couple the issues that are associated with LASSO. One such variation, adaptive LASSO (ALSSO), has garnered much interest. Other modifications include elastic net (E-Net) and adaptive LASSO (ALSSO). Among the many modifications of LASSO proposed to address the difficulties of LASSO as Elastic Net, the one that has gotten the most attention is called Adaptive LASSO, abbreviated as ALSSO (E-Net).

Weighted Average Least Square (WALS) is a recently introduced technique that can handle many regressors. Magnus et al. developed WALS in 2010, based on Magnus and Durbin's Equivalence theorem and Mean square error term (MSE) (2009). (1999). WALS combines frequentist and Bayesian estimation methods. Categorizing explanatory variables into Focus and Auxiliary variables can assist numerous regressors.

2.4 Comparison of Shrinkage Criteria

Several comparisons of the model selection procedures are based on Shrinkage criteria.

Fu and Wj (1998) analyzed different models like Bridge, Ridge, and Lasso. Researchers have compared different criteria for model selection based on a compression approach. He performed an empirical exercise and used the prostate cancer data. According to the results, Bridge regression performs better from ridge and LASSO.

Meinshausen (2006) compared the two shrinkage procedures of model selection LASSO and RELAXED LASSO. A two-stage procedure, the relaxed Lasso, was influential in overcoming the conflicting requirements of a proficient computational procedure and fast convergence rates of the 2-loss. Relaxed Lasso solutions for orthogonal designs provide a continuum of solutions that include both soft and hard thresholding of estimators. It is possible to compute all relaxed Lasso solutions at the same time as computing all regular Lasso solutions, and computing all relaxed Lasso solutions is often as expensive as computing all regular Lasso solutions. It has been demonstrated in the study's numerical results that the relaxed Lasso estimator produces lighter models with the same or lower prediction loss than the regular Lasso estimator when dealing with high-dimensional data.

In cross-sectional modeling, Epprecht et al. compare the LASSO and ALSSO estimates with classical techniques (Autometrics) in forecasting and covariate selection. The result indicates that LASSO and ALSSO estimates outperform Autometrics in prediction.

Automatic Model Selection Procedure

Hendry &Doornik (2007) and Doornik (2009) developed an automated algorithm for model selection, which is based on General-to-Specific approach framework and followed the work done by Hoover and Perez (1999) and Hendry &Krolzig (2005). After making the general unrestricted model, it uses an enhanced search method named tree search instead of multiple searches. It takes all sets and systematically discards the irrelevant sets and diagnostic testing. Different sub-models are then re-united to get the final model. It is known as 3rd generation algorithm and named Autometrics and is included in Pc-Give software as a part. The algorithm of Autometrics can be divided into three stages, as described below:

Stage I: Estimation and evaluation of the General Unrestricted Model (GUM)

Stage II: Reduction Process

Stage III: Iterative Search

Sara Muhammadullah et al. (2022) compare regularization techniques with Autometrics in time-series modeling to reduce the dimensionality of parameter space and improve out-of-sample forecasting performance. The study compared weighted lag adaptive LASSO (WLALSSO) to Autometrics, and the findings concluded that WLALSSO is a more robust technique in out-of-sample forecasting and covariate selection than all other considered models.

2.5 Model Selection Procedures based on Parameter Sensitivity

Any variable y may have a large number of potential determinants. Suppose X_i is a variable of interest, taking a set of control variables gives some coefficients of X_j. Changing the control variables will change the coefficients of estimate. There are many possible combinations of control variables, which will lead to different coefficients. The idea behind parameter consistency is that if X_i is having focus variables relation with y, its coefficients should be possible given any combination of control variables.

In the analysis of economic data, model selection processes based on parameter sensitivity depend on assumptions that the data cannot test. So, we only use ideal distributions and a minimal number of variables in multivariate analysis using a basic functional form. The data sets are not more valuable if the assumptions are not fully satisfied. Sometimes, we turn to traditional modeling by ignoring presumptions like the general distribution of linear functions and the presence of few variables. The choice of variables is a common sensitivity analysis step in linear regression. The researcher reports various outcomes based on various subsets of the variables rather than reporting the findings of one regression. Hence a common set of variables is shared by all results.

When the dubious variables are added to the model in various combinations, it may be gratifying that the coefficients of the underlying variable do not change. Have these analysts tried to uncover outlandish forecasts that these numbers are acceptable? For this circumstance, "Extreme bound analysis" provides 37 solutions. In extreme bound analysis, various groups of shaky variables are chosen, and the core variable's coefficient is computed.

If the coefficient of a core variable is outside the extreme constraints, then the final model does not include this variable. The final model may include the coefficient if it continues to fall within the acceptable range. This occurs when the essential and supplementary variables are free to act independently. But, most of the time, when dealing with the most pertinent economics data, these bound analyses might extend to excruciating levels, and we are either compelled to withdraw in terror or find a means to discover a way to lower the limitations. Other models could be modified to permit only add-on options rather than all linear combinations within all constraints. This would be one technique to restrict the range of possible limits. The table of alternate outcomes, generally offered as evidence of unreasonable consistency, has its foundation in these exclusion limitations. Hence, the collection of various estimates serves as an upper bound. In addition, the chance of using the regression coefficient to determine whether or not they are zero depends on the integrated system used to define the effect parameters in the model. Extreme boundaries are certainly produced by setting the parameters to zero within a known coordinate system; hence, the restriction to inclusion or exclusion is meaningless without instruction on defining the coordinate.

The goal of EBA, a type of sensitivity analysis, is to identify the most extreme estimates given a fixed subgroup of permitted coefficients and a changeable set of linear identical limitations. Edward E. Leamer initially created it, and Clive Granger and Harald Uhlig advanced it in 1990. Compared to traditional econometrics, it is a more precise way of quantifying specification uncertainty since it considers prior knowledge and employs a methodical approach to assess the delicate nature of coefficients. It enables researchers to find the upper and lower bounds for any set of potential regressors for the parameter of interest.

2.5.1 Macro Variable and Balance of Trade

The literature on the Balance of Trade is vast and it is extremely large to cover the entire literature. We have selected a few of these studies so that the list of variables used by these studies may cover the variables in the maximum number of existing studies.

Baharumshah (2001) attempted to identify the major economic factors that influence the trade balances of Malaysia and Thailand using the unrestricted VAR model, quarterly frequency data from 1980 to 1996. Results indicated a stable long-run relationship between trade balance and three macro variables of the exchange rate, domestic income, and foreign income. The real effective exchange rate was an important variable in the trade balance equation, and devaluation improved the trade balances of both economies in the long run.

In the case of Malaysia, Duasa (2007) researched the short-run and long-run correlations among the balance of trade, exchange rate, income, and money supply.

To determine the impact of the elasticity of exchange on the balance of trade, a monetary absorption approach was utilized rather than a conventional absorption approach.

Muhammad (2010) investigated the short-term and long-term effects of Pakistan's widening trade deficit on the country's economy. The years 1975 through 2008 were included in the data sample for this study. In this particular analysis, the long-run estimation was performed using the Johnson co-integration method, and the short-run approach was carried out using the VEC estimation method. The list of variables such as foreign income (FI), domestic consumption (DC), real effective exchange rate (RER), and foreign direct investment was included in the research. The findings of this investigation unequivocally demonstrated that there is a positive connection between all variables and the trade deficit. Edward Nienga (2010) used OLS regression to investigate the factors that influence Kenya's trade balance from 1970 to 2010. In 2010, his findings were published. He used variables such as the real exchange rate, government consumption expenditure, foreign income, domestic income, foreign direct investment, and money supply during his research (M3). He concluded that the real exchange rate, government consumption expenditure, domestic income, and money supply (M3) were the most important factors in Kenya, while foreign income was not a significant factor.

Shawa and Shen (2013) used the Ordinary Least Squares Method (OLS) to investigate the determinants of the Tanzanian trade balance from 1980 to 2012. This period's findings revealed significant and positive relationships between FDI, human capital development, natural resource availability, foreign income, and trade liberalization. Household and government expenditures, as well as inflation, were found to have negative coefficients. The real exchange rate coefficient was negative but insignificant.

Osoro (2013) examined the significant determinants of trade balance using annual data from Kenya from 1963 to 2012. Using Johansen's co-integration approach and Error Correction Modeling, this study investigated the long and short-run trade deficit (ECM) determinants. The study revealed that trade balance coefficients significantly and positively correlated with budget deficits, FDI, and real exchange rates.

Tran and Dinh (2014) investigated the effects of FDI inflows on external imbalances in Asian developing and transition economies and discovered that current FDI inflows increase trade deficits, which harms the host country's macroeconomic stability. However, when a lag was introduced to the FDI variable, the estimated coefficient became negative, implying that FDI inflows worsened the trade balance first and then improved it.

Shah's (2015) investigation of the determinants of Pakistan's balance of trade (1975-2010) using multiple regression models for empirical assessment discovered that only the Pakistan Rupee exchange rate significantly impacted the country's balance of trade. Meanwhile, the money supply, foreign direct investment (FDI), GDP, and total domestic consumption remained insignificant.

This paper will explore the core problems of trade balance by adding exchange rate, infrastructure, market size, domestic consumption, and inflation from 1980 to 2020. This will be the paper's main objective. The researcher in this study made it abundantly clear that there is an association between the variables that can be measured over both the short and long run. Because of the negative equilibrium value, it was hypothesized that the economy is moving toward convergence. On the other hand, inflation is at a high stage in the economy, which is a fundamental problem for the country's highest possible production costs. Because the nation strongly emphasizes importing goods, there is a growing demand-supply gap, which in turn contributes to an expanding trade deficit. The smaller gap between imports and exports may be possible thanks to the expanded market size and improved infrastructure.

A vast body of research has been done to investigate and analyze the effects of trade imbalances on macroeconomic variables. According to Fleming (1962) and Mundell (1963), an increase in the budget deficit causes upward pressure on interest rates, which in turn causes capital inflows and an appreciation of the exchange rate, which in turn causes an increase in the current account deficit. Several researchers, including Volcker (1987), Kearney and Monadjemi (1990), and Smyth et al. (1995), have posited that government deficits may be the root cause of trade deficits through a variety of different channels.

2.5.2 Macro variables and Economic Growth

The literature on Economic Growth is extensive and it is enormous to cover the entire literature. We have selected a few of these studies so that the list of variables used by these studies may cover the variables in the maximum number of existing studies.

Baroo (1996) says that the neoclassical growth model shows that a country's savings equal domestic investment. If the saving rate is higher, it may improve domestic investment. Finally, the output level per worker is steady, resulting in a higher growth rate. Although the study discovered a favorable association between domestic investment and GDP, it was not statistically significant. Ibid concludes investment is vital to the growth rate to some extent.

Mallick (2008) used a cointegration procedure in his study of India from 1960 to 2005. the paper concluded that inflation effects negatively to economic growth. Most of the previous studies also suggest that inflation harms economic growth, so the current study also validates the results.

Giuliano (2008) found that remittances boost growth in less developed countries because they provide a means to support domestic investment and reduce liquidity constraints. Remittances from workers also contribute significantly to human capital investment, as the recipient country does not face resource constraints and can finance its projects. Calero (2008) discovered that remittances improve school enrollment and reduce the extent of child labor in terms of education.

Din et al. (2009) conducted a study and analyzed the determinants of economic growth; the findings reveal that inflation has a negative relationship with economic growth. Anyanwu (2104), on the other hand, discovered an adverse relationship between inflation and economic growth. Similarly, in the case of Bangladesh, Shamim and Mortaza (2005) also discovered that inflation harms economic growth. On the other hand, Awan (2010) discovered that inflation is positively related to economic growth in the case of Pakistan.

Several researchers (Gupta et al., 2009; Jongwanich, 2007; Stark and Lucas, 1988) have examined the relationship between foreign remittances and economic growth in developing countries. According to the findings of the study, remittances have a positive impact on economic growth in developing countries. They argue that developing countries, particularly those with weak financial sectors, may be able to benefit from foreign remittances to meet their investment needs. Fayissa and Nsiah (2008) argue that developing countries, particularly those with weak financial sectors, may be able to benefit from foreign capital remittances to meet their investment needs.

Kogid et al. (2010) explain how foreign direct investment is vital for economic growth and how it works. A stable economy has enough room to attract investors to invest. However, it is crucial to note that if foreign direct investment (FDI), which is a primary component of economic growth, is not adequately handled, it can deteriorate the stability of economic growth. According to the study, foreign direct investment is a critical driver of economic growth in developing countries.

Bajona et al. (2010) say evidence exists for the negative relationship between economic growth and trade liberalization. Ibid says when trade policy is relaxed, and you go into the episodes of free trade, your economic growth may slow down. Liberalization works well only when your institutions are strong and well-managed. Effective labor, credit, and product market regulation can also contribute to the success of liberalization.

Anwar and Nguyen (2010) describe how foreign direct investment (FDI) is a critical driver of economic growth in developing countries; there are Huge Multinational Corporations (MNCs) which have a major contribution to FDI. It also positively impacts research and development, the employee's skills, the development of human capital, and the technological advancement of the host country's economy. Higher economic growth results in higher inwards FDI.

Mamo (2012) investigated the relationship between the rate of inflation and the rate of growth in the economy. The study also found no evidence of a link between economic growth and inflation. There are many controversial findings regarding the relationship between inflation and economic growth, and we know that inflation is considered one of the central subjects of macroeconomic research, and policy is one of the most controversial. Various studies (Mamo, 2012) indicated that the relationship between economic growth and inflation could be negative, positive, or neutral.

Ahmad et al. (2012) used co-integration and error correction techniques to investigate the relationship between economic growth and FDI. The study takes the gross domestic product model, which depends on FDI, labor force, and capital formation as explanatory variables. The findings suggest that the country's economic growth and foreign direct investment (FDI) are positively related in both the short and long run.

Biwott et al. (2013) foreign direct investment is a critical driver of economic growth. It plays a crucial role in the transfer of technology. FDI has more contribution than domestic investment in the achievement of economic growth. If a financial system is more developed, it contributes positively to the technological diffusion process connected to FDI.

Uneze (2013) also investigated whether there is a link between economic growth and capital formation in Sub-Saharan African countries and whether this link is significant. Finally, the researchers discovered a bidirectional causality between private capital formation and gross capital formation for both variables. A similar analysis was carried out by Silaghi and Medeşfălean (2014) in Romania, and they discovered that capital formation had a positive impact on economic growth, as had been discovered previously.

Bal et al. (2016) attempted to determine the relationship between India's capital formation and economic growth. The paper examined a long-term relationship between economic growth and capital formation.

Ali and Saif (2017) examined the factors responsible for economic growth in Pakistan. The causality relationship among different variables includes Foreign Direct. Investment (FDI), economic growth (GDP), Agriculture Rate (AGRI), Trade Openness (TO), and Energy Consumption (EC) show that there is a favorable impact of all these variables, including energy consumption, agriculture, FDI, and trade liberalization on GDP. In addition, FDI harms GDP, although AGRI and EC have a favorable impact in the short term. The granger causality runs from GDP, TO, FDI, EC, and AGRI growth rates, according to the block of exogeneity tests. Only the Agriculture Growth Rate (AGRI) and Energy Consumption (EC) are significant.

About the V4 countries (the Czech Republic, the Slovak Republic, Hungary, Poland, and Romania), Mihaela et al, (2017) The Bayesian generalized ridge regression method is used to conduct the empirical analysis, which covers the years 2003-2016. The findings revealed that foreign direct investment (FDI) stimulated economic growth in all countries except the Slovak Republic. Only in the Czech Republic did expenditures on education result in economic growth, whereas expenditures on research and development positively impacted Romania, Hungary, and the Czech Republic, among other countries. Study findings indicated that the V4 economies and Romanian, achieving sustainable growth, must improve their international competitiveness.

Al-Smadi and Malkawi (2020) investigated the relationship between economic growth, domestic investment, labor, economic openness, and foreign direct investment in the case of Jordan. The study employed an autoregressive distributed lag model, considering the data's time series characteristics. The findings of the study found that foreign direct investment, domestic investment, economic openness, and labor are the factors that spur economic growth both in the short and long run. Finally, the study concludes that domestic investment and FDI are needed in the Jordanian economy to improve economic growth.

2.6 Theoretical Literature

Schneider et al. (2013), Sanika et al. (2015), Raja (1994), and Iqbal et al. are the principal authors who have researched the theoretical distinction between market-oriented factors and export-oriented factors of Economic Growth (2018), Hassan and colleagues (2000) and Jackson et al. (1995) used market-related variables such as population and GDP per capita to question the robustness of various other determinants of GDP. Using the data set, Hassan et al. (2011) discovered that the correlation between market size and GDP was no longer as strong as previously thought. According to Mbulawa (2015), financial institutions play a significant role in determining economic growth drivers. There is a correlation between institutional quality and growth.

While questioning the robustness of various other factors that determine GDP, they discovered a change in the robustness of the correlation between market size and GDP in the information set that Hassan et al. (2011) used to investigate the correlation between institutions and economic development. Mbulawa (2015) investigated financial institutions' influence on the factors that propel economic growth. According to the study's findings, the marginal effects of institutional quality matter in the growth process (Guterries, Solimano, 2007). As is well known, a significant contributor to the expansion of a nation's economy is the amount of money saved within that nation. According to the available literature, there is a positive and significant relationship between domestic savings and economic growth. The positive relationship is described and supported by a significant number of hypotheses. There is a theory that suggests that if we raise our level of savings, we will also see an increase in the rate of economic growth brought about by increased investment (Bebczuk. 2000). In addition, the growth models developed by Harrod (1939), Domar (1946), and Solow (1956) traced and supported this approach. Many of the findings from empirical research provided support for the hypothesis that if savings are increased, it will lead to an increase in economic growth (Alguacil, Cuadros, and Orts (2004) Singh et al. (2009).

According to Borda (2015), the variables concerning export orientation are the most significant contributor to GDP attraction. Their variables consisted of human capital, population growth, trade openness, government burden, fiscal deficit, external debts, natural disasters, good governance, and macroeconomic stability. The policy crime rate, and remittances Their findings imply a growing tendency toward a growing complementarity between GDP and trade, which appears to be on the rise. The results of their study lend further support to the tariff-jumping hypothesis.

Every researcher contributing to the available literature imposes a prior zero restriction without explaining the other theory. They did so on the specific factors, even though their model specification was largely irrelevant because a variety of factors related to GDP, both minor and major, were disregarded in the calculation, which led to an inaccurate result. This study will help close the knowledge gap by incorporating the economic variables that are most relevant backward by economic channel. Then, by making use of a variety of models that are founded on a variety of theories. According to econometric theory, it is necessary to include all of the relevant variables in the equation to have an accurate GDP model. Creating a model that incorporates all of the variables featured in these models is one approach to resolving this issue. The final model could then be derived by performing restriction testing on the most general (parsimonious model) model.

2.7 Advanced Artificial Intelligence methods for Model Selection

3sophisticated methods for model selection in various domains. These methods, which encompass cutting-edge techniques like Efficient Neural Architecture Search (ENAS) (Pham, Guan, Zoph, Le, & Dean, 2018), Bayesian Optimization for Hyperparameter Tuning (Snoeyink, Tavakoli, & Sedighian, 2019), and Auto-sklearn (Feurer, Klein, Eggensperger, Springenberg, Blum, & Hutter, 2015), hold great promise in optimizing the choice of machine learning models and their hyperparameters. However, conducting a comprehensive comparative analysis of these evolving techniques goes beyond the scope of the current thesis. These dynamic developments reflect the continual advancements in AI, offering exciting avenues for future research and application.

2.8 Literature Gap

The literature does not compare different classes of the model selection procedures based on real data analysis. This study helps in the choice of appropriate model selection procedures. Before this study, most of the papers make a pairwise comparison of the model selection procedures. These studies don't help in choosing a procedure among all available options. The present study compares many model selection procedures and gives a guideline for choice among a large class of procedures. The existing studies compare the model selection procedures based on Monte Carlo experiments. The Monte Carlo experiments are performed under a specific data-generating process following a specific set of assumptions and for real data, we don't know about the assumption. The current study makes a real data-based comparison of model selection procedures, therefore giving findings closer to reality.

2.9 Conclusion

Monte Carlo simulations and Real Data Based Analysis are two methods for evaluating an econometric procedure. Our research is based on the results of a Real Data Based Analysis. The current study is expected to provide useful insights into the search for an appropriate model selection procedure from a set of procedures. Most studies have compared model selection procedures of the same class, and the comparison has been limited. The existing studies compare the model selection procedures based on Monte Carlo experiments. The Monte Carlo experiments are performed under a specific data-generating process following a specific set of assumptions, and for real data, we don't know about the assumption. This study makes a real data-based comparison of large classes of model selection procedures, therefore giving findings closer to reality. There has never been a study that compares large classes of model selection procedures based on real data analysis.

CHAPTER 3

THE HISTORY OF MODEL SELECTION PROCEDURES

Monte Carlo simulations and Real Data Based Analysis are two methods for evaluating an econometric procedure. Our research is based on the results of a Real Data Based Analysis. The current study is expected to provide useful insights into the search for an appropriate model selection procedure from a set of procedures, which will be useful because many policy formulation and implementation issues rely heavily on model selection. Model selection aims to find an appropriate model that outperforms other models. It is critical that the chosen model is not sensitive to sample size to achieve the previous objectives. If this is the case, selecting a prediction model is fine, but selecting a model for insights and interpretation can be misleading and unreliable.

Economists explain the structure of the economic model to express their philosophical ideas and beliefs. After that, a diagnostic method is used to estimate the parameters, such as maximum likelihood methods, generalized method of moment, Bayesian estimation, and so on. The results are then used for a variety of purposes, including decision-making, forecasting, finding stochastic structures, and so on. The quality of these solutions is generally determined by the variables included in the model and the model's estimation method. The former option necessitates the selection of a model. Economists create empirical models by combining economic theory and statistical models to assess economic performance, which is complicated by the economy's structure, economic theory, and statistical evidence. The economy is multi-dimensional, complex, dynamic, non-linear, and multi-dimensional at the same time. Social systems change over time. Changes in technology also occur.

In most cases, the researcher has many candidate variables that could explain the dependent variable. The model selection procedure chooses a subset of candidates thought to provide the best explanation for the dependent variable. There are numerous procedures for selecting models.

3.1 Analysis of Leamer's Criticism and Extreme Bound

Leamer (1978) criticizes the conventional inferences of the regression model. According to him, the "traditional version" of the rise of the regression model could be easily rejected because it is based on the unreliable assumption of correct specification, which is unacceptable. Leamer designed the Extreme Bounds Analysis (EBA) to overcome the fragility of inference. Suppose Y is our dependent variable and X1 and Xk are potential explanatory variables that determine Y. Likewise, we doubt including the remaining W1,..., Wr. The EBA recommends testing all sets of variables to determine how much the coefficients vary. W is robust if the coefficient of variable W remains constant within the limits regardless of the inclusion of other variables.

Numerous authors have criticized it for being potentially too risky. According to Uhlig and Granger (1990), the EBA necessitates testing all EBA regressions, including those with very low R-squares, and is therefore statistically very treacherous. He suggests modifying the method to test only those stress attempts with an acceptable R-square value. Sala-i-Martin (1997) modified EBA in response to a situation that produced extreme outcomes. Rather than highlighting a variable as relevant or irrelevant on two extremes, a regressor may be significant at the 95% or 90% level. Entitled EBA amendment, "I've just run two million regressions."

3.2 Davidson, Hendry, Sarba & Yeo (DHSY,1978)

The traditional method is based on the idea that it doesn't consider the short-term effects of regression on dependent variables. Davidson Hendry, Sarba, and Yeo (DHSY, 1978) noticed that, even though the published models were similar, they didn't say much about how disposable income and consumer spending in the UK change over short periods. No one agrees on anything. DHSY used dynamic econometric models to estimate consumption performance and show how different the published estimates are. Traditional theories of consumption were changed by DHSY's model, which gave a state-of-the-art way to estimate consumption by considering all past consumption functions.

3.3 Tibshirani's work (1996) and the Shrinkage method

The traditional method assumes that the regression model must have more observations than parameters. What if the number of observations is more than the number of parameters? Then, the old ways of doing things don't work. A shrinkage method is one way to solve the problem. Most shrinkage methods are based on mathematical programming techniques and their tools. The shrinkage methods eliminate high-dimensional data for lower gains, making it easy to get rid of irrelevant candidates. Least Absolute Shrinkage and Selection Operator (LASSO), made by Tibshirani in 1996, was the first popular method of this type. It can shrink some coefficients to zero.

Second, LASSO is a method for estimating the model and choosing the variables simultaneously. LASSO can work when there are more variables than observations, and it gives sparse models (Zhao and Yu, 2006; Meinshausen and Yu, 2009). As Efron et al. (2004) and Friedman et al. (2010) have shown, the LASSO's regularization path can be figured out quickly. Tibshirani has many generalizations and different types of the LASSO procedure that can be used to solve many problems (2011). Particular attention has been paid to Elastic Net (E-Net) and Adaptive LASSO (ALSSO).

3.4 General to specific methodology Hendry (1995)

Hendry (1995) renames Leamar's Axiom the Axiom of Omniscience and discusses it. The rest of the world is unlikely to do so. Almost all regressions are incorrect if assumptions are taken seriously. "A lot of literature has been developed, hidden as difficult science," wrote David Freedman (2009). Scientific theories can never be proven to be true, but they can be proven to be false, according to famous science philosopher Carl Popper. Econometric models are in the same boat; they can't be proven true, but they can be proven false.

Perez and Hoover (2004) We only ran a single regression, as described by Henry and Krolzig (2004). Sala-(1999) Martin's growth regressions were re-analyzed using PcGets' automatic model selection strategy. Using a simulated study, they discover that Sala-method Martin's requires identifying many regressors. PcGets, conversely, has a simpler procedure for selecting the relevant variables more appropriately. This method is not entirely automated; we can select the type 1 error level. It is possible to make a mistake when selecting a variable.

The first charge leveled by a particular point of view against general to specific relationships, such as the mining of individual data, implies that naturally occurring encompassing relationships only apply to a narrow path of simplicity. In the jungle of models that have rotated in the normal model, there is no automatic encompassing relationship between the final models of different researchers who have wandered in different directions. One answer is that any two models can be tested for coverage by looking at non-nested hypothetical concepts or by using the approach to nesting in a joint model described above. As a result, if any of them is involved, this question can always be answered.

However, critics may argue that such playoffs are uncommon and do not consider the full range of terms, from specific to general. Another argument claims that variables may be linked because they have a real relationship or much in common in small samples. As a result, a method that emphasizes selecting a wide range of variables based on their correlation is restricted to variables that only relate to the dependent variable in a specific set of data, even though this relationship has no economic basis. This is Hess et al. (1998)'s objection to finding specific explanations for Baba et al. (1992)'s choice of an overfitting model.

Third, Pagan (1987) and other econometricians criticize the fact that the selection procedure, in general, is based on a simple path in which variables are removed and data are also changed. If this procedure is followed, the chosen model may differ from the investigator's model. Many reduction paths can be considered from the initial general model. Hoover and Perez (1999a) looked at many different paths and the resulting models. When different model choices emerge from searches, a cover test can be used to distinguish between them, allowing surviving models to be chosen. If multiple specifications exist, a new model is created by combining them into one model, and the simplification process begins again. If the union model reappears, information standards determine which model to use. Data-based model selection, pre-testing bias, measurement without any theory, ignoring the effects of selection, lack of identification, data mining, repeated testing, and concerns that have been raised about relying on someone's possible route are all critics of general-to-specific methods. Models that have been chosen.

3.5 Conclusion

There are a variety of strategies for selecting models, and every strategy produces a distinctive model as a result. That we must believe. This issue can be resolved by contrasting the procedures for selecting models utilized by the various methods of model selection when applied to particular circumstances consistent across all of these methods.

Many studies compare and contrast the primary categories of the model selection procedure. Some studies compare model selection procedures within the class; however, with the application of real data analysis, the family of Extreme Bound Analysis and the family of shrinkage methods are not yet compared under current circumstances. Some studies compare model selection procedures within the class. The general-to-specific methodology and the methodology of extreme bound analysis are excluded from this comparison because they cannot be applied to the current terms and conditions.

CHAPTER 4

MODEL SELECTION PROCEDURES

4.1 Introduction

There is a large number of model selection strategies that could be used to select a model out of the range of candidate models. The objective of the study is to compare these model selection strategies. The comparison would be based on the forecast performance of the finally selected model using each model selection strategy. The details of model selection strategies used in this study and how they are compared are introduced in this chapter.

This chapter is organized as follows in 4.2, we provide a list and computational details of model selection procedures. In 4.3, the details about the methodology for comparison are given. The model selection procedures can be classified into various categories, and from each category, we have chosen a few procedures for the comparison. Common model selection procedures are tested as follows.

Residual Based Criteria

R Square
Adjusted R Square
Finite Prediction Error (FPE)

Information Based Procedures

Akaike Information Criterion (AIC)
Bayesian information criterion (BIC)
Hannan and Quinn criterion (HQC)
Bridge criterion (BC)
Mallow's Cp
Likelihood Ratio Test (LRT)

Stepwise Regression

Forward Stepwise Regression
Backward Stepwise Regression
Bidirectional Stepwise Regression

Model selection procedures based on the consistency of Coefficients

Leamer's Extreme Bound Analysis

Sala-i-Martin Extreme Bound Analysis

Automatic Model Selection Procedures

Automatic Model Selection

Autometrics

Model Selection Procedures based on shrinkage methodology

LASSO

Adoptive LASSO

Elastic Net

Weighted Average Least Square

Other Model Selection Procedures

Non-Nested Encompassing Approach

4.2 Criteria based on Residual

4.2.1 R Square

R-squared measures how closely the data matches the fitted regression line. For multiple regression, it is called the correlation coefficient. In n regression, the most frequently used statistics to measure the degree of fit of a model are perhaps the coefficients of determination R^2 which indicates how much variation in the response is elucidated by the model. The higher the R^2, the better the model fits the data. The formula is quite simple, R-squared is the percentage of variation in. the response variable. That a linear model can explain. As the number of repressors increases, it always increases and never lowers. Adding X variables won't make it any smaller.

- R-squared = Explained variation / Total variation

$$R^2 = \frac{ESS}{TSS} \text{ ……………a)}$$

$$R^2 = 1 - \frac{RSS}{TSS} \text{ ………..b)}$$

$$R^2 = 1 - \frac{\Sigma\mu_i^2}{\Sigma y_i^2} \text{………c)}$$

Modified R^2 = (1 – K /n) R^2

- The range of R-squared is always between 0 and 1.
- 0 shows that the model describes none of the variability of the response data around its mean.
- 1 means the model fully defines the response data variability around the model's mean.
- 0.50 means that the model's inputs explain roughly half of the observed variation in the estimated regression model.
- significant property of R^2 is that additions of explanatory variables to a model often increase the value of R^2 even when the additional variables have no explanatory power. Montgomery and Morrison (1973)

The coefficient is known to be a biased estimate of the theoretical value of the coefficient of determination because it grows with adding new variables (Yin and Fan, 2001). Limited sample size and many factors lead to overly optimistic results (Tomassone et al., 1993). Specifically when different values of the dependent. Variable corresponds to the same set of explanatory variables; the number of distinct rows versus the model's essential parameters matters (Draper and Smith, 1998).

4.2.2 Adjusted R Square

It is more appropriate to use adjusted R square than R square as the R square give an over-optimistic figure for regression fit, mostly in case where the number of observation is not too large. to number of regressors"(Theil notes:)

The model selection might be based on hypothesis testing or information criterion selection.

The adjusted R-square increases when the new term improves the model more than expected by chance. When a predictor improves the model by less than expected by chance, it declines.

$$\overline{R}^2 = 1 - \frac{\sum \hat{\mu}_i{}^2/(n-k)}{\sum y_i{}^2/(n-1)}$$

term adjusted means adjusted for the degree of freedom (df) related to the sums of residuals squares has n − k degree of freedom in the estimates model with k number of parameters, with intercept term, and $\sum yi^2$ has n − 1 df.

$$\overline{R}^2 = 1 - \frac{\widehat{\sigma}^2}{{S_r}^2}$$

Where $\sigma^{\wedge}$ is the variance of a residual, unbiased estimator of true σ^2 and s_{y^2} is a sample variance of Y. It is easy to see that $\overline{R^2}$and R^2 are associated because

$$\overline{R}^2 = 1 - (1 - R^2)\frac{n-1}{n-k-1}$$

It is directly apparent for k > 1, $\overline{R^2}$<R^2 which infers that as the number of X variables rises, the adjustedR^{-2} $also$ increases but less than the unadjusted R^2; and R^{-2} can be negative, although R^2 is necessarily nonnegative. In case R^2 becomes negative in an application, its value is taken as zero.

4.3 Information-Based Procedures

The model selection procedure that is based on information theory minimizes the loss of information by choosing a different number of variables or a group of variables. For those variables where the loss of information is minimum then these model selection procedures declare that these variables are most relevant to the dependent variable.

All possible models are estimated separately for model selection using information criteria, and the method with the smallest information criterion value is selected. Various information criteria exist, whose computational details are mentioned below.

4.3.1 Akiake Information Criteria

Akiake (1973) introduced the AIC to measure the model's goodness of fit. In this case, the information lost is relative. A model is used to produce real, and the model with the lowest AIC is considered the best. Many researchers found it helpful in selecting true lag order. Predictive power increases with a small size of n. Kundu & Murali (1995), Hastie et al.(2005) and Acquah (2010), it is given as:

$$ACI = Ln(\sigma^2) + 2\ (K+ 1)/\ T$$

The function of likelihood is as;

Akiake Information Criteria = - 2 (l/T) + 2 (K/T),

Where in the above function σ^2 is error variance, K is the number of estimated parameters using T observations and l be the value of the log-likelihood function value given by

$$l = -T/2\ (\ 1 + \log\ (\ 2\pi\ ) + \log\ (\varepsilon'\ \varepsilon\ /T)$$

4.3.2 Akiake Information Criteria corrected(AICc)

Hurvich and Tsai have developed AICc, a modified version of AIC (1989). Serial order correction was included for small sample sizes because AIC over-fits models in small samples. It was strongly recommended by Burnham and Anderson (2002) to use the AICc in the case of very small values of n or k, respectively. This method was found to be superior by Kletting & Glatting (2009) and Hacker & Hatemi (2008) when it came to lag selection and forecasting for small samples. It is written as:

Akiake Information Criteria Corrected AICc = Ln (σ^2) + (T + K + 1) / (T – K - 3)

Akiake Information Criteria Corrected AICc = -2 (l/T) + 2 (K/T)

In the above function, K is the number of estimated parameters from T observations, and l is the value of the log-likelihood form as:

$$l = -T/2\ (\ 1 + \log\ (\ 2\pi\ ) + \log\ (\varepsilon'\ \varepsilon\ /T))$$

4.3.3 Schwarz/Bayesian information criteria (SIC/BIC)

In the Econometrics procedure for analysis of lag lengths and other econometric selection criteria, the Bayesian information criterion (BIC) is used. Which is formulated by Schwarz (1978); therefore, another model selection criterion that includes the penalty term for the model's parameter count a given r set of models, the model with desire SBC or BIC? Many studies have found this criterion good at choosing small lag lengths for AR and VAR models and also good at large n prediction properties Rust et. (1995); Acquah (2009); Rehman (2010); Hacker & Hatemi (2006, 2009). It is written as:

Schwarz / Bayesian Information Criteria SIC = log(σ^2) + (K+ 1)+ln(T)/T

Schwarz / Bayesian Information Criteria SIC = -2 (l/T) + K log (T) /T

Where in the above function, K is the number of estimated parameters from T observations, and l is the value of the log-likelihood function it is written as;

$$l = - T/2 \, (1 + \log (2\pi) + \log \, (\varepsilon' \, \varepsilon \, /T))$$

4.3.4 Schwarz Information Criteria Corrected

Bayesian corrected information criteria are introduced by Macquarie and Tsai (1998); like AIC, BIC tends to over-parameterize models. They created the small sample correction by adding an extra penalty, as follows:

$$SICc = \log (\sigma^2) + (K + 1) \; \ln (T) \; / (T - K - 3)$$

The log form of likelihood is:

$$SICc = -2 \, (l/T) + \; k \log(T) /T$$

Here, k denotes the number of the parameter to be estimated using T observations, and *l is the* value of the Log-likelihood function, which can be calculated as:

$$l = - T/2 \, (1 + \log \; (2\pi) + \log \; (\varepsilon' \, \varepsilon \, /T))$$

4.3.5 Hannan -Quinn Information Criteria

It follows the law of repeated logarithms that any strongly consistent method must miss efficiency by at least a factor, so in this sense, HQC is asymptotically performed very well. Van der Pas and Grünwald proved that modified Bayesian estimator-based model selection so-called switch distribution behaves asymptotically like HQC, though retaining the advantages of Bayesian methods such as priors, etc.

$$HQC= -2Lmax + 2k \ln(\ln(n))$$

Where Lmax is the log-likelihood function

K is the number of parameters in the model

N is the sample size

4.3.6 Bridge Criterion (BC)

BC is a relatively new criterion that combines the benefits of both AIC and BIC in an asymptotic system. In a nonparametric framework, BC works similarly to AIC, and in a parametric framework, BC works similarly to BIC. BC is a new criterion for controlling the order of a time series autoregressive model. It combines the benefits of two well-known model selection techniques: The Akaike information criterion and the Bayesian information criterion. Unlike traditional criteria, the proposed criterion is either dependent on the original model or achieves consistency. The quality of the proposed order selection is more robust and flexible than the classical approach in practice, where the observation time series is given without prior knowledge of the model specification.

When these procedures help to reduce the number of variables, it's a win-win situation (selecting the relevant variables). The following are a few concepts that are related to preventing data loss. When it is marginalizing to disaggregate if the provided information gives a bundle of statistics for interested parameters, aggregation of the variables does not result in any loss of information. If the error process derived is relative to the history of random regressors, sequential factorization does not result in information loss.

4.3.7 Mallows's C_p

In the context of model selection, the goal is to identify the best model that includes the fraction of variables possible given the availability of some predictive variables that can be used to predict specific outcomes. Considering its size, the model is reasonably accurate. Mallow's C_p solves the problem of over-fitting, in which the balance amount of squares, such as model selection statistics, always goes down as variables are added to the model. This is a problem that can only be solved by adding more variables. Because of this, if we choose the model that has the lowest RSS, then we will choose this model. Instead Mallow's C_p statistics were constructed based on data sample mean squared prediction error (MSPE).

$$C_P = \frac{RSS_P}{\widehat{\sigma}^2} - (n - 2p)\widehat{\sigma}^2$$

As a rule, C_p statistics are used to prevent various types of step-by-step. Mallows proposes a statistic for choosing a model from a set of alternatives. The expectation is equal to C_p for models that do not have an admirable reduction in fit (bias). On the other hand, this is a term other than P that has a positive bias. C_p < P cannot be resisted in extreme cases; otherwise C_p < 0. In the P, which is for the list of subsets ordered by adding P, it is recommended that a substrate approaching P be chosen in the P. That is $C_p < 2_p$ it.

Using a selection of the model does not prevent it from being more appropriate. This is because the C_p statistics that are based on the sample are an estimation of the MSPE. For instance, it is a possibility that the sample that was chosen was one in which C_p that was especially tolerant of the significant amount of MSPE loss. When compared to the entire model, the predictive ability of the subset model should be evaluated. The best model for forecasting in general; however, if multi-collinearity is present, parameter estimation is useless. As long as there is no discernible "bias" in the values predicted by the entire model, a portion of the overall model that does not contain as many instances of multicollinearity will perform better (i.e., close to the same predictability).

C_p penalizes for the number of variables by comparing the ratio of SSE for a p – 1 variable model to the MSE for the full model:

$$C_p = \frac{SSE_p}{MSE\ (full)} - (n - 2p)$$

SSE_p=Model's sum of squared errors with P repressors

$MSE\ (full)$= denotes the Mean squared errors

N = denotes the sample size.

A model is considered "good" if and only if. Consider the smallest model for which this is true (to reduce intercorrelation). $C_p \leq p$

The benefit of C_p is that it can be used to choose model size, resulting in a good model with as few variables as possible. The researcher can also choose the model with the lowest C_p, but it's more about C_p relative to p and reducing the number of variables in the model while maintaining the same predictive ability.

4.3.8 Likelihood Ratio Test

When two competing statistical models are compared based on the ratio of their likelihoods, the likelihood-ratio test is used to determine the goodness of fit. Explicitly, one model is found by imposing a restriction, and the other model is found by maximization over the entire parameter space; the likelihood ratio test is used to determine the goodness of fit. If the observed data supports the constraint (i.e., the null hypothesis), then the two likelihoods should not differ by more than the sampling error between the two estimates. As a result, the likelihood ratio test determines whether its natural logarithm is significantly different from zero, whether its ratio is significantly different from one, or whether they are equivalent.

For hypothesis testing, there are three traditional methods. The three tests listed above are the Lagrange multiplier test, the Wald test, and the likelihood ratio test, which is the oldest of the three. The Lagrange multiplier and Wald tests are asymptotically similar approximations to the likelihood ratio test. The Neyman–Pearson lemma can be used to justify using the likelihood ratio test when comparing two models with unknown parameters. The lemma proves that the test is the most powerful of all competitors.

$$LR = -2ln\left(\frac{L(\theta)}{L(\hat{\theta})}\right)$$

It rejects the null hypothesis if the statistical value is too small. The test's significance level determines how small is too little. What is the maximum amount of type I error that can be tolerated? “Type I errors are defined as the rejection of a correct null hypothesis”

The numerator corresponds to the likelihood of an observed outcome under the null hypothesis. While the numerator refers to the maximum likelihood of an observed outcome where parameters vary over the parameter space, the denominator refers to the highest probability of an observed outcome. The denominator of this ratio is greater than the numerator, and the likelihood ratio's value ranges from 0 to 1. If the likelihood ratio is low, the observed result is considerably less likely to occur under the null hypothesis than the alternative hypothesis. If the number is high, it means that the observed outcome was almost as likely to happen under the null hypothesis as it was under the alternative hypothesis. As a result, we can't rule out the null hypothesis.

4.4 Stepwise Regression

Stepwise regression is a semi-automated method for constructing a model by eliminating or adding variables based solely on the t-statistics of their estimated coefficients. As a result, it's helpful in looking at many potential independent factors. Using it improperly will give you a false sense of security. As a result, you must engage your brain and carefully read the instructions, or else you may waste your time because this tool is not for beginners, nor is it a substitute for education and experience in the field.

Stepwise regression is a method of fitting regression models in which predictive variables are chosen automatically. Each step considers a variable from the set of explanatory variables that rely on some predetermined criterion for subtraction or addition. This is commonly done with a series of F-tests or t-tests, but other methods are also possible, such as,

Akaike information criterion,

Schwarz /Bayesian information criterion,

Adjusted R^2,

Mallow's Cp.

4.4.1 Forward Selection

In this process, the beginning model starts with no variable; based on information criteria, we can choose a fitted model and then add variables. After including the variables, we can apply test restrictions to check the significance and drop the redundant variables. If the inclusion of variables improves the significance, the process should be repeated until the model achieves a significance level and shows parsimony.

4.4.2 Backward Elimination

With all candidate variables, forward elimination checks the model fit criterion by eliminating the variable, and the loss of the variable yields a statistically significant result. This procedure should be performed as often as necessary until no more variables can be removed without causing a statistically significant loss of fit.

4.4.3 Bidirectional Elimination

Forward elimination and backward elimination are collectively known as Bidirectional Elimination. It looks for variables to exclude or include at each stage. Assume you have a forecasting model and wish to identify the subset of potential independent variables. That can be employed in the model. The stepwise option lets you start with no variables in the model and work your way forward, or you can start with all possible variables and work your way backward. At each step, the program computes the t-statistic. For its estimated coefficient, square it and report it as the "F-to-remove". Statistic: for each variable not in the model, it computes the t-statistic for its estimated coefficient if the next variable was added, squares it, and reports it as the "F-to-e" statistic. The program then automatically enters or removes the variable with the greatest F-to-enter statistic or the variable with the lowest F-to-remove statistic, as indicated by the control parameters. Thus, the essential relationship to recall is F = t-squared.

4.5 Model Selection Procedures Based on Consistency of Parameters

In economic data analysis, assumptions are made, and the data does not allow these assumptions to be tested. So, in multivariate analysis, we use a small number of variables in a simple functional form, and only for ideal distributions. The data sets aren't any more useful if the assumptions aren't met. We occasionally resort to traditional modeling by ignoring assumptions such as linear functions, general distribution, and a small number of variables. The selection of variables is a common application of sensitivity analysis in linear regression. Rather than presenting the results of a single regression, the researcher presents various results based on different subsets of the variables. And all of the outcomes have the same set of variables.

When the doubtful variables are included in the model with different combinations, it may be satisfying that the coefficients of the underlying variable do not change. Have these analysts worked so hard to come up with improbable estimates that these figures are permissible? This problem can be solved using 'extreme bound analysis.' Different groups of doubtful variables are chosen for extreme bound analysis, and the coefficient of the core variable is estimated.

If a core variable's coefficient is outside the extreme bounds, the variable is excluded from the final model. The coefficient will be kept in the final model if it remains within the limits. When the core and doubtful variables are independent, this happens. However, when it comes to the most relevant economic data, these extreme bound analyses can quickly deteriorate to painful levels, forcing us to retreat in fear or find a way to narrow the boundaries. Alternative models that allow only add-on options, rather than all linear combinations within all limits, are one way to limit the range of limits.

The table of alternative outcomes, mostly provided as evidence of irrational consistency, is based on these exclusion restrictions. As a result, the set of alternative estimates serves as an extreme bound. Furthermore, the integrated system for defining the effect parameters in the model is on the probability of applying the regression coefficient to consider them zero. Extreme bounds are certainly constructed by setting the parameters to zero in a defined coordinate system, so the inclusion/exclusion restriction is meaningless without guidance on how to define the coordinate.

EBA is a type of sensitivity analysis that aims to find the most extreme estimates possible for a fixed set of allowed coefficients and a variable set of linear same restrictions. Edward E. Leamer created the concept in 1983, and Clive Granger and Harald Uhlig refined it in 1990. Because it uses a systematic methodology to examine the delicacy of coefficients, it is a more precise method of measuring specification doubt than traditional econometrics. It allows researchers to obtain upper and lower limits for any possible set of regressors for the parameter of interest.

4.6 Computational Details of Extreme Bound Analysis

4.6.1 Extreme Bound Analysis by Leamer (1978)

Leamer (1978) and Chamberlain (1978) proposed and developed extreme bound analysis regarding the uncertainty involved in building econometric models. By excluding or including variables of "doubtful" importance, the researcher can examine the impact of the variable on the regression. A "focus" variable's correlation coefficient concerning the alternative probability of the sample data was used to generate the likelihoods.

Some explanatory variables are to be known in the model, but many more are "doubtful" variables. They are used to control for other variables. The "focus" variables have large standard errors due to all of the uncertain variables in the estimating equation. It's standard practice to change the list of suspect variables, hoping that the focus variable coefficients don't change much. Contrary to popular belief, the list of doubtful variables does not allow for any averaging. It formalizes the search for an econometric specification that corrects both flaws.

Suppose the dependent variable is a function of the explanatory variables W_{it} and model 1 is like this:

$$Y_t = X_t\beta_j + W_{1t}\alpha_1 + W_{2t}\alpha_2 + \varepsilon_t \text{.........................(1)}$$

where β_j, α_1 and α_2 are the estimated regression coefficients and ε_t is a disturbance term. For example, if a researcher wants to estimate the focus variable X_t's coefficient β_j, but the model's exact specification is unknown. Considering the variables W_{1t} and W_{2t} being doubtful helps to handle this uncertainty. In other words, the researcher is unsure about the effects of doubtful variables but refuses to remove them from the equation. Defining a composite variable in this equation

$$Z_t(\theta) = W_{1t} + \theta W_{2t} \text{.....................(2)}$$

$$Y_t = X_t\beta_j + Z_t(\theta)\alpha + \varepsilon_t \text{ ....(3)}$$

By including or excluding the doubtful variables (θ), the regression can be compared to any of the other four regressions. According to Cooley and LeRoy (I981), there is no reason to exclude these four regressions from consideration because the doubtful variables are a subset of a large class to which any value can be assigned to them.

A new set of values for doubtful variables (θ) and thus, we can estimate the focusing coefficient. β_j is a set of all possible values which is defined by α_1 and α_2 varying and (which is defined by varying itself). This analysis computes the focus coefficient's maximum and minimum point estimates over a sequence of likelihood ellipsoids (standard confidence intervals around the estimated coefficient of the focus variable in an OLS model). Consider that a likelihood ellipsoid's upper and lower bounds are larger than an OLS coefficient's sampling standard error. In that case, researchers should know that estimating the focus variable is impossible.

4.6.2 Extreme Bounds Analysis by Sala-i-Martin (SIMEBA)

Sala-i-Martin (1997) proposes an alternative method for analyzing the extreme bounds of regression coefficients, rather than concentrating on the extreme bounds of regression coefficients. Each variable is assigned a confidence level instead of the binary label "robust" or "fragile."

In the regression equation to estimate the normal model, Sala-i-Martin first calculates the weighted mean of the regression coefficients $\boldsymbol{\widehat{\beta}_j}$ and of the variances $\widehat{\sigma}^2{}_j$.

$$\overline{\beta} = \sum_{J=1}^{N} \omega_j \widehat{\beta}_j \text{........................}(4)$$

$$\overline{\sigma}^2 = \sum_{J=1}^{N} \omega_j \widehat{\sigma}^2{}_j \text{..................}(5)$$

where ω_j are the weights used to estimate each coefficient for regression. Sala-i-Martin (1997) recommends that the researcher "give greater emphasis to regression or models which are more likely to be the true model." After estimating the true model, first calculate the weighted means of coefficients and standard errors. Sala-i-Martin calculates the cumulative density function evaluated at zero – CDF (0) – i.e., based on the assumption of normal distribution of regression coefficients by using the following equation.

$$\beta \sim N\ (\overline{\beta}, \widehat{\sigma}^2{}_j) \ldots\ldots\ldots\ldots\ldots\ldots(6)$$

From each regression model separately, A doubtful variable's robustness is assessed by estimating the cumulative density function (CDF). In this process, first, he estimates an individual CDF (0), which is denoted by $\emptyset_j\ (\,0/\,\widehat{\beta}_j\overline{\sigma}^2{}_j\,)$. From each regression model, and all the individual CDF (0) for 0's: computes the weighted average mean is given in this equation as;

$$\emptyset(0\,) = \sum_{J=1}^{M} \omega_J\, \emptyset_j\ (\,0/\,\widehat{\beta}_j\overline{\sigma}^2{}_j)$$

It is necessary to incorporate likelihood into both the normal and generic models. Sala-i-Martin employs proportional weights to favor models that have a better fit to the data:

$$\omega_j = \frac{L_i}{\sum_{i=1}^{M} L_i}$$

The weights may also be based on some other measure of goodness of fit. Using McFadden's likelihood ratio index (McFadden 1974) or applying equal weights to each regression model, Hegre and Sambanis (2006) were able to achieve their results (Sturm and de Haan 2005; Gassebner et al. 2013).

4.7 Discussion on Autometrics

Hendry and Doornik (2007) and Doornik (2009) developed an automated algorithm for the model based on the work of Hoover and Perez (1999) as well as Hendry and Krolzig (2007) selection (2005). Instead of multiple searches, it uses an enhanced search method called tree search, which takes all sets of variables and systematically discards irrelevant sets, along with diagnostic testing F statistics. The final model is made up of various sub-models. It is a 3rd generation algorithm called Autometrics and is part of the Pc-Give software. The Autometrics algorithm is divided into three stages.

Stage 1: Estimation and evaluation of the General Unrestricted Model (GUM)

The formulation, estimation, and evaluation of the general unrestricted model (GUM) and the detection of outliers through dummy saturation and the pre-search for lag length are covered in the first section. Initially, The first part of this stage is to make GUM, which is formulated as follows:

$$Y_t = \beta_o + \beta_o X_1 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots\ldots\ldots \beta_n X_n + \mu_t \ldots\ldots\ldots\ldots\ldots (1)$$

Autometrics also allows you to drop irrelevant variables with low significance levels. A top-down search eliminates insignificant variables, while a bottom-up search retains significant variables using a joint F-test. They used the F test until it failed to determine the lag length to use. To save time, Pre-searches are not used by default in Autometrics. GUM 0 is created after the first stage. It could be similar to the initial GUM, contain any dummy discovered to be significant in dummy saturation detection, or remove variables or lags through pre-search. The next stage starts at GUM 0.

Stage II: Reduction Process

This section searches for terminals in multiple paths. Autometrics attempts to simplify the general model, GUM0, using the enhanced tree search method by deleting repeated paths generated by insignificant variables. The algorithm stops if all of the regressors in the GUM0 (discovered at the end of stage I) are statistically significant if GUM0 contains insignificant variables, Autometrics will begin searching by deleting one or more of them. The terminal is reached when all model variables are significant and the reduced model encompasses the diagnostic test. If reduction fails at any point during the reduction path, Autometrics returns to the previously accepted model before moving on to the alternative reduction path. Finding only one terminal model after searching all paths of insignificant variables will be the final model for subsequent replications. However, because Autometrics searches for terminals in multiple paths, it is possible to come across more than one terminal model following the search. To deal with this situation, Autometrics creates a union of all found terminals and compares each terminal to the union, i.e., Cox comparison (1961). The remaining terminals that are part of the test will serve as the starting point for the next stage of the process.

Stage III: Iterative Search

Autometrics repeats stage II up to union (Iterative multiple searches) and includes the terminal model in this section. The algorithm stops if the stage II unions match stage I unions. Assume the encompassing test against the union finds multiple terminals. In that case, the terminal models will be chosen based on SIC (1978), AIC (1973, 1981), and HQC (1979) information criteria. If the union of two stages (I and II) is not equal, Autometrics will run another search. The algorithm uses a tree search to navigate the model space. But finding all possible models takes too long. Pruning, bunching, and chopping are employed to eliminate unnecessary paths and speed up the process. If someone wants to improve their computational strategies, avoid repeating the same model estimations, delaying diagnostic tests, and having to recollect terminals between iterations.

General to specific modeling Begin with GUM: Then, to reduce complexity, remove statistically insignificant variables and apply a battery of diagnostic tests to validate reductions to ensure final model congruence. Rivals are included in the final Progressive research strategy (PRS) test selection. Recently, there have been significant advancements in both theory and practice of automatic model selection.

Autometrics provides a powerful model-selection procedure that includes the following steps:

a) Impulse saturation
b) Encompassing choices
c) Non-linearity
d) Multi-path searches,

4.7.1 Computational Detail of Autometrics

4.7.1.1 Tree Search

In the initial model, the variables generate a model space. An estimated model can be found at each node of this tree. The model's variables' significance can order the next level's sub-nodes. As shown in Figure 1. Assuming that GUM has four variables WXYZ, the figure shows four distinct models (the order of variables within an irrelevant model). The root GUM is removed, followed by W, WX, etc. The w model's variables can be ordered however you want. Open circles symbolize the redundant models. In the right column, the first open circle is Z; Two unique models are labeled in Figure 1: GUM model WXZ root node in the GUM, W is the least significant variable. Then comes YZ, where X is the least important. But if Z is the least significant in XYZ, it should be removed first. And then re-label the tree graph. An individual t-value determines the regression model's significance.

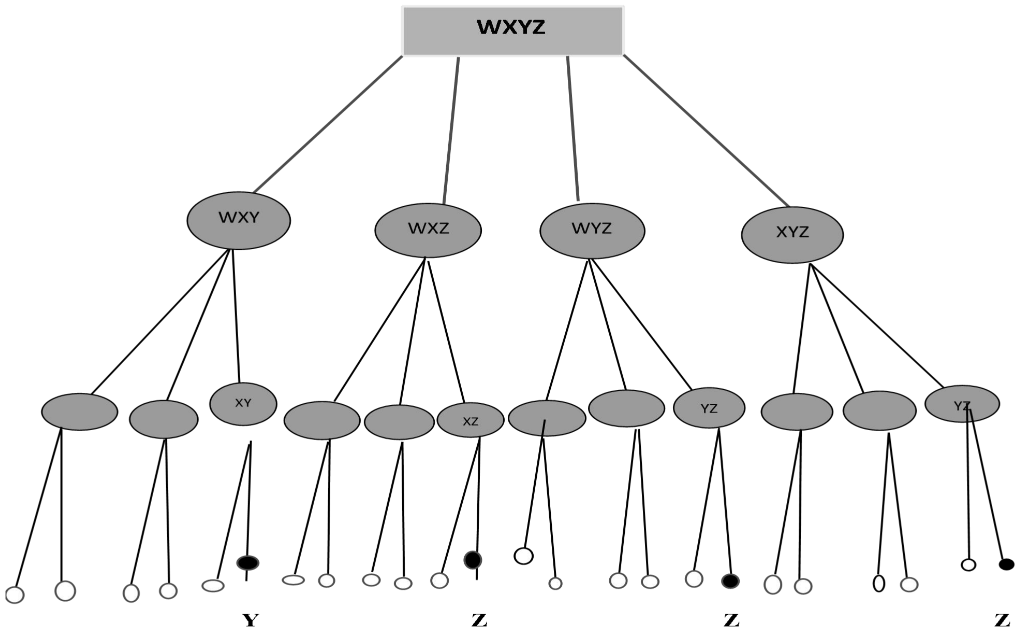

Figure 4.1: General Unrestricted Model (GUM) with variables wxyz leads to all unique models

After finishing the first major branch that started with deleting w, we can move on to the next major branch that starts with deleting variable X. The models in this branch always include variable W: WYZ, WZ, W, WY. The resulting tree in Figure 1 represents the model space uniquely, and moving through it from left to right and top to bottom we will estimate all potential models. Figure 2 depicts the Hendry–Krolzig Hoover–Perez and multiple-path search with constant ordering. The first Autometrics path matches the first Hoover–Perez and Hendry–Krolzig path, but afterward the methodologies diverge.

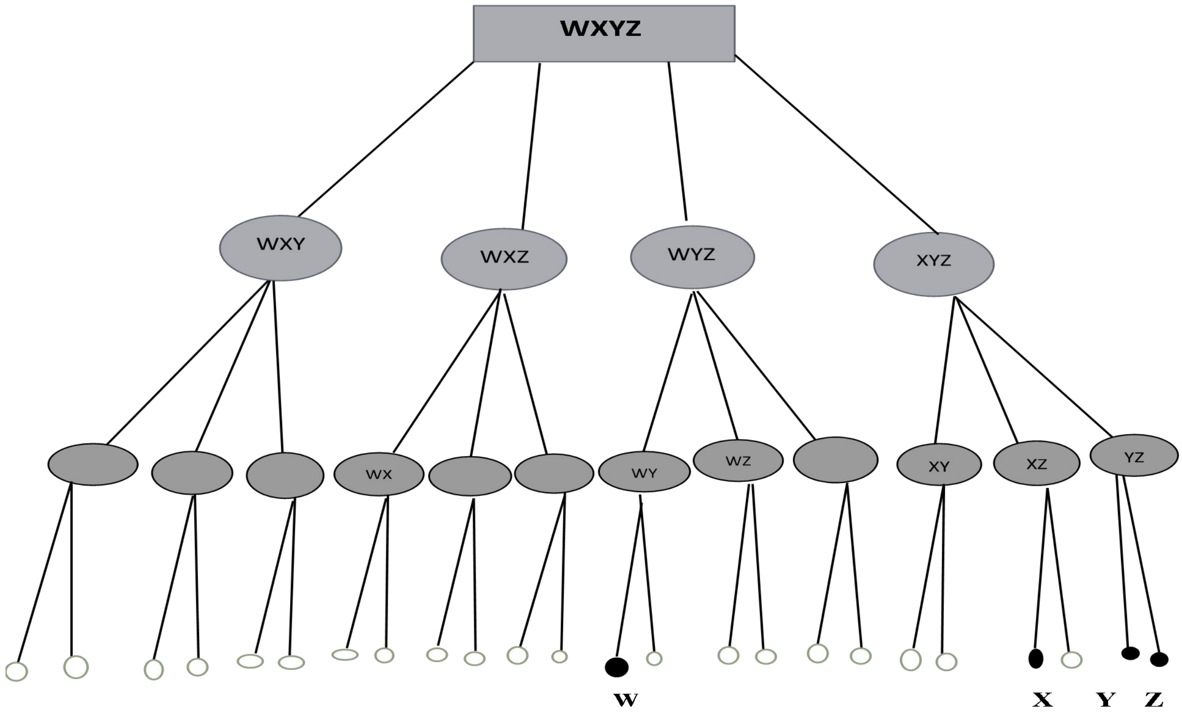

Figure 4.2: General Unrestricted Model (GUM) with variables WXYZ leads to all unique Models

Efficient Search for Trees with 2_k models for k insignificant variables, visiting each node is impractical. Autometrics uses several strategies to move through the tree efficiently. Figure 3 shows the order of node visits. Remember that the least significant variable comes first at each node. The graph doesn't show this unless the letters refer to diverse variables (so, as depicted here, in the model YZ, Y is the highly t insignificant variable).

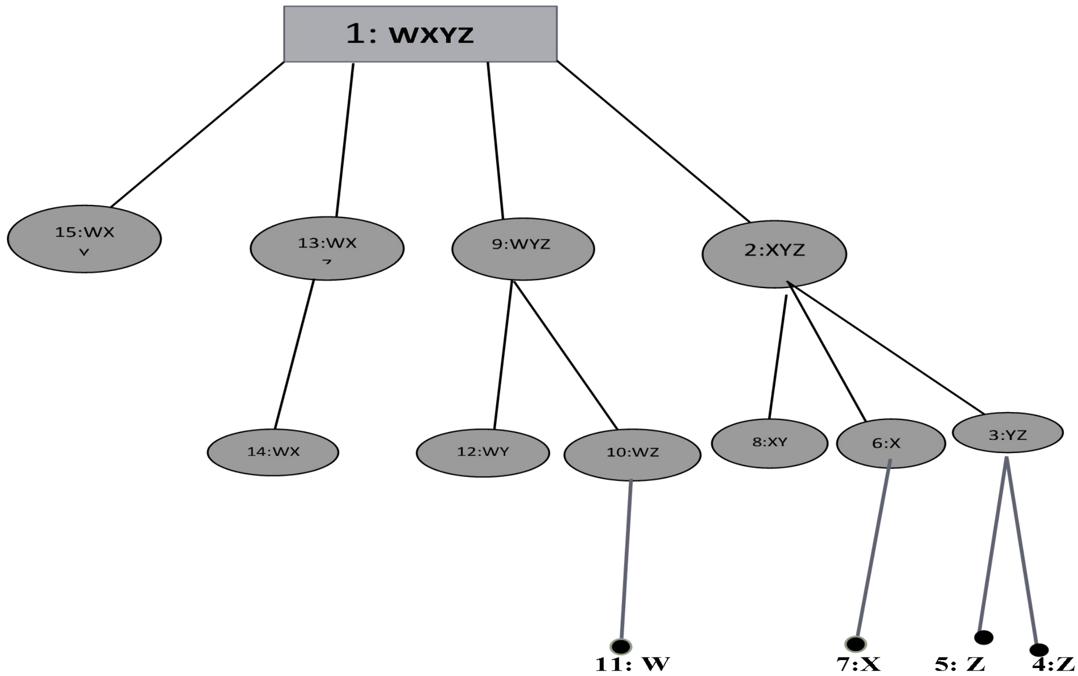

Figure 4.3: Search tree for all unique models starting with GUM WXYZ (Numbered by the search algorithm's performance)

Also, note the reduction path from the GUM: for model 12, WY, this is 1 - 9 -12. The search algorithm can be designed to keep only k models of the path back to the GUM in memory rather than the entire tree.

4.7.2 Autometrics advances tree search by using these principles

4.7.2.1 Pruning

Every reduction removes one variable by default. The first principle is that a node is invalid if a deletion or reduced model fails (backtesting or diagnostic testing). Then, prune the tree's subsequent sub-branches (ignored).

Starting with model XYZ in Figure 3, if variable B cannot be removed, models YZ, Z, and Y are unnecessary. For example, if model YZ fails the GUM backtest, we can skip over sub-nodes of YZ and go to node XZ. The central Autometrics p-value pa governs this pruning and set a cutoff significance level below which a variable can't be deleted. Ideally, pa defines the procedure's empirical behavior: the size of irrelevant variables retained is close to pa.

4.7.2.2 Bunching

Instead of removing one variable at a time, consider groups. That is a clump of branches. Bunching works: variables are grouped along the generated search path if their individual insignificance merits it. Then, deletion is a block. If successful, we can skip several steps and replace them with a single blocked step. If the deletion fails, the algorithm loops backward until a bunch of size one is found. So, in Figure 3, the second node, model XYZ, variables XY are insignificant enough to be bunching candidates. Then, we do an F-test on XY together. If successful, we get node Z directly. If not, we delete Y only (i.e. model YZ).

The amount of bunching is determined by the p-value (pb). A high pb causes excessive and costly backtracking. Despair might be hidden in the midst of minor terms. When it's set too low, bunching is disabled at a cost in terms of computation.

4.7.2.3 Chopping

The task of Chopping is to remove the most insignificant variable from the set of model branches. When a bunch is too small, the whole bunch may be chopped. Chopping saves computation but may miss some variable combinations. We are continuing with node XYZ. If Y is too small to be considered for chopping, we skip over any nested models that contain X. After Y, we reach node WYZ. If XY can be cut from XYZ, we only visit model Z before reaching node WYZ. The p-value pc determines chopping. pc = pb

4.7.2.4 Contrasts

No further reduction of a terminal candidate model is possible using the adopted criteria. Once found, the same model does not need to be found again. This is possible because the tree is uniquely ordered. This can help us move faster through the tree. Say we found model Z as a terminal candidate and the search led us to model 9: WYZ. A is always kept in the WYZ models, significant or not; Y and Z are the 'free' variables. Model WYZ nests Z, which is irrelevant when Z is terminal. An F-test can immediately check this bunch with the help of restricted tests at pa if YZ is removed.

While the underlying principles of pruning, chopping, and bunching are simple, implementing them in software requires some administrative code. Bunching and chopping together is a form of embedded research. But it's part of the search procedure's structure here. One fundamental aspect of tree search differs from multiple-path search. Until further reduction fails due to diagnostic testing or backtesting with respect to the General Unrestricted Model, no insignificant variables remain in the latter. Branches in the tree search keep insignificant variables.

In this example, some branches starting with 13: WXZ contain WX, variables which may be statistically significant. So a semi-terminal candidate with minor variables is referred to as a semi-terminal candidate. A semi-terminal can only be refined into a proper terminal, which cannot be reduced further. The study of distributional robustness is vital because the true error distribution is rarely known in practice. We investigate the impact of non-normality on model selection criteria performance. Collinearity among the set of possible regressors is another deviation from the assumed model.

4.8 Model Selection Procedures based on shrinkage methodology

The model selection procedures that consist of the Shrinkage approach are based on mathematical programming techniques. These techniques remove the high dimensionality of the data and shrink irrelevant variables to zero. The Least Absolute Shrinkage and Selection Operator (LASSO) is a popular estimation method in a linear regression framework introduced by Tibshirani (1996). The LASSO method is like ridge regression; however, it sets some coefficients precisely equal to zero with a substantial bias. The resulting model is easy to interpret and Possesses the least forecast error. LASSO can estimate the parameters and select the variable at a time. Before LASSO, the stepwise selection method was most widely used for choosing regressors in which only prediction accuracy is improved in certain cases, most prediction is worse. When there are more variables than observations, LASSO can handle this. (H. Zou,)

4.8.1 Computational Details of Least Absolute shrinkage and selection operator (LASSO)

It is a method of regression analysis that uses regularization to increase prediction accuracy selection of variables and model interpretability. The most commonly used method before LASSO was the selection of stepwise regression, which only improved the accuracy of the prediction if only a few covariates were strongly related to the result. In some cases, a prediction error may worsen. Ridge regression reduces fitting by reducing large regression coefficients, but does not perform covariate selection and hence does not contribute to the model's interpretability.

By forcing the absolute value of the regression coefficients to be less than a fixed value, LASSO can achieve this goal by effectively choosing a simple model without these coefficients. Although this concept is similar to ridge regression, the squares of the coefficients are forced to sum up below a fixed value in ridge regression.

Where The LASSO coefficients, $\widehat{B}_j^L$, minimize the quantity

$$\sum_{i=0}^{n}\left(y_i - B_0 - \sum_{j=1}^{p} B_j x_{ij}\right)^2 + \lambda \sum_{j=1}^{p} \left|B_j\right| = \mathrm{RSS} + \lambda \sum_{j=1}^{p} \left|B_j\right|$$

The LASSO, like ridge regression, reduces coefficient estimates to zero. However, Because of the L1 penalty, some coefficient estimates must be exactly zero when the tuning parameter is large enough. Bias increases with. Variance rises as it falls.
No parameters are removed when $\lambda = 0$. The estimate is the same as linear regression.

So, like best subset selection, the LASSO selects variables. As a result, LASSO models are easier to interpret than ridge regression models. There are several algorithms of LASSO, such as:

Adaptive LASSO, Elastic Net Relaxed LASSO, etc., are all based on shrinkage methodologies.

4.8.2 Adoptive LASSO

Tibshirani introduced the Least Absolute Shrinkage and Selection Operator (LASSO), a popular estimation method in a linear regression framework (1996). The LASSO method is similar to ridge regression but sets some coefficients precisely equal to zero with a significant bias. The resulting model is simple to understand and has the lowest forecast error. Consider the following linear regression model: where Y = $(y_{1t} , y_{2t} , y_{3t} , y_{4t} \text{.........} y_{nt})$ are the continuous response regressors and $x_{it} = (x_{1t} , x_{1t-1} \text{.........} x_{pt-1})$ are the covariates with their lag and γ_j are the estimated coefficients. The equation is as follows

$\hat{\gamma}^{LASSO} \ = \text{argmin}\hat{\gamma} \ \| y_{it-} \ \| \sum_{i=1}^{p} \gamma_{it} \, x_{it} \ \|^2 \ + \lambda \sum_{i=1}^{p} \ p_{\lambda j} \ (\,|\,\gamma_j|\,) \ldots\ldots 1$

The preceding equation is referred to as the "L1 penalty," and a shrinking specific set of coefficients that are precisely equal to zero along with a certain amount of bias leads to a sparse solution when the parameter is present. the amount of shrinkage is determined by the choice of λ, with a range of 0 to 1. 0 < λ <∞ Oracle does not support LASSO. The asymptotic setup, on the other hand, is somewhat unfair because it forces the coefficients to be penalized equally in the L1 penalty.

Different weights can certainly be assigned to different coefficients. Consider the weighted lasso, which Zou introduced after demonstrating that the LASSO estimator lacks the oracle property and introducing the adaptive LASSO, a simple and effective solution. The coefficients in LASSO, on the other hand, are all penalized equally in the 'L1 penalty. In ALSSO, however, each coefficient is given its weight. Zhou demonstrated that the ALSSO can achieve the best results if the weights are data-dependent and carefully chosen; the ALSSO can then be said to have the oracle property.

$\hat{\gamma}^{adoptive\ LASSO} \ = \text{argmin}\hat{\gamma} \| \ y_{it-} \ \sum_{i=1}^{n} \gamma_J \, x_{it} \ \|^{\,2} + \lambda \sum_{i=1}^{j} \ \hat{w}_j \ |B_j| \ |\gamma|_{\,1}.$ (2)

Where w represents a weights vector that is already known. We demonstrate that the weighted lasso can have the properties of an oracle if the weights are data-dependent and if they are carefully chosen. This new approach is known as the adaptive lasso methodology.

$1/\hat{w}_j = \ 1/\,\hat{\gamma}_j *^{\tau}$, $\tau \ > \ 0, \hat{w}_j *$ is an initial estimate of the parameter. As the number of samples increases, the weights for coefficients with zero values spread out to infinity, while the weights for coefficients with values other than zero converge to a finite constant. To estimate the parameter $\hat{\gamma}_j *$. H. Zou recommended the OLS method. The OLS method, on the other hand, does not work when the number of candidate variables exceeds the number of observations. In this case, a ridge estimate can be used as an initial estimator.

Weighted Lag Adaptive LASSO (WLALSSO).

Konzen and Ziegelmann introduced the Weighted Lag Adaptive LASSO (WLALSSO) based on Park and Sakaori's work. It's a special kind of LASSO estimate designed for time-series modeling with lag structure. The concept is similar to Ada-LASSO and was developed for the time-series ARDL framework, as the more distant lags have a smaller impact on predicting the dependent variable, resulting in greater penalties.

$$\hat{\gamma}^{adoptive\ LASSO} = \text{argmin}\hat{\gamma} \| y_{it-} \ \sum_{i=1}^{n} \gamma_J x_{it} \ \|^2 + \lambda \sum_{i=1}^{j} \ \hat{w}_j \ |B_j| \ |\gamma|_1. \qquad (3)$$

In the above equation $\hat{\gamma}_j*$ is an initial parameter estimate,

where $\hat{w}_j = \ /(\hat{\gamma}_j{}^{bridge} \ / e^{-\alpha l} \ )-^{\tau}$ $\lfloor$ is the lag length, and $\alpha \geq 0$ are tuning parameters. $\tau = 1$ lik in ALSSO is a good example of this. To choose, $\alpha,$ Konzen and Ziegelmann (2016) recommend estimating the model for a given λ using a grid (0; 0; 5; 1; : : : ; 10)

and selecting the one with the lowest BIC and the λ parameter chosen using the same criteria.

4.8.3 Elastic Net

Tibshirani (1996) presented a method that showed promise and was named LASSO. The LASSO algorithm is designed to minimize RSS while constrained by a bound on the L1 norm of the coefficients. As a result of the characteristics of the L1 penalty, the lasso can perform continuous shrinkage in addition to automatic variable selection simultaneously. Therefore, the LASSO model has some of the beneficial characteristics of ridge regression and the best subset selection. Although the lasso has proven to be effective in a wide variety of circumstances, it does have a few drawbacks. Take into consideration the following three possibilities:

1. If the number of predictors p is greater than the number of observations n, the lasso is not well-defined unless the bound on the L1 norm of the coefficients is smaller than a certain value.
2. Furthermore, due to its nature, the convex optimization problem only selects n variables. This appears to be the limiting feature of a regularization method.
3. If a group of variables has extremely high pairwise correlations, the lasso will tend to select only one of them, regardless of which one is chosen.
4. When there are high correlations among predictors in

   typical n > p situations, ridge regression dominates the

   lasso's prediction performance by a large margin.

Scenarios (1) and (2) can make the LASSO unsuitable for variable selection in certain situations. Our primary goal is a model-fitting procedure that works as well as the LASSO. When Scenarios (1) and (2) cause the LASSO to be the method of selecting the irrelevant variable in some cases. Scenario (c) is also a regression problem regarding predictive performance. As a result, it is possible to improve LASSO's predictive power. Regarding forecasting accuracy, simulation, and real-world data show that elastic net frequently outperforms LASSO.

4.8.3.1 Computational Detail of Elastic Net

The limitations of the lasso method in scenario (1) are eliminated through the naive elastic net, an automatic method of selecting variables (2). On the other hand, empirical evidence suggests that the naive elastic net does not perform satisfactorily unless it is very close to ridge regression or LASSO. This is the case regardless of how close it is to these two models. The naive elastic net in regression prediction sequencing, an accurate penalization method, can achieve better forecasting performance by exchanging the difference in bias variance for a higher trading value. There are two steps involved in the process of estimating the naive elastic property. The first step is the calculation of the regression coefficients for each value of λ_2. In the second step, shrinkage coefficients of the LASSO type is calculated. When compared to pure LASSO or ridge regression, it is analogous to double shrinkage. However, unlike pure LASSO or ridge regression, double shrinkage does not minimize the variations but rather increases the additional bias.

Given data (Y *on* X) and penalty parameter (λ_1, λ_2), after introducing artificial data (Y^*, X^*), We work on a lasso problem such as :

$$\widehat{\beta} = arg\min_{\beta} \beta^T\left(\frac{X^TX + \lambda_2 I}{1 + \lambda_2}\right)\beta - 2Y^TX\beta + \lambda_1|\beta|_1$$

The estimates $\hat{\beta}$ based on the elastic net can be defined as follows:

$$\widehat{\beta}(elastic\ net) = \sqrt{1 + \lambda_2}\widehat{\beta}^*$$

That

$$\widehat{\beta}(naive\ elastic\ net) = \frac{1}{\sqrt{1+\lambda_2}}\widehat{\beta}^*$$

Thus

$$\widehat{\beta}(elastic\ net) = (1+\lambda_2)\widehat{\beta}(naive\ elastic\ net)$$

The elastic net coefficients are now rescaled to the naive elastic net coefficients. This modification keeps the nave elastic net's variable selection property and easily shrinks the coefficients.

Another demonstration supporting the selection of $1 + \lambda_2$ the scaling factor. When the variables in question are orthogonal and the solution of a naive elastic net is assumed to be found. LASSO is identified as the minimax optimal solution when the naive elastic net can no longer be considered optimal (Donoho et al., 1995). After scaling by $1 + \lambda_2$, the elastic net will reach the minimax optimality.

The decomposition of the ridge regression operator provides a powerful motivation for the rescaling of the value $1 + \boldsymbol{\lambda_2}$. In consideration of the fact that X is the standard.

After that, proceed with the ridge regression using the parameter

$$\lambda, X^T X \qquad \begin{bmatrix} 1 & \rho_{12} & \cdot & \rho_{1p} \\ & 1 & \cdot & \cdot \\ & & 1 & \rho_{p-1,p} \\ & & & 1 \end{bmatrix}_{P \times P}$$

$$\hat{\beta}(\text{ridge}) = R\,Y,$$

We can rewrite R as

$$R = \frac{1}{1+\lambda_2} R^* = \frac{1}{1+\lambda_2} \begin{bmatrix} 1 & \frac{\rho_{12}}{(1+\lambda_2)} & \cdot & \frac{\rho_{1p}}{(1+\lambda_2)} \\ & 1 & \cdot & \cdot \\ & & 1 & \frac{\rho_{12,p}}{(1+\lambda_2)} \\ & & & 1 \end{bmatrix}^{-1} X^T$$

where R is the ridge operator

$$R = (X^T X + \lambda_2 I)^{-1} X^T$$

Where $\overset{*}{R}$ is identical to the OLS operator, but decorrelation refers to the reduction in correlation caused by the ratio $1/(1+\ \lambda_2)$. The equation that was just shown is the ridge operator after it has been decorrelated using direct scaling shrinkage. This would imply that the decorrelation step affects the grouping effect of the ridge regression. When the grouping effects of the ridge and LASSO are combined, there is no longer a requirement for the direct shrinkage that is performed with $1/(1+\ \lambda_2)$.

LASSO shrinkage is the only variance control method used later to achieve sparsity in the ridge regression model, which requires $1/(1+\ \lambda_2)$.
Assuming That $\widehat{\beta}$as $\widehat{\beta}$(elastic net)
Given X, y and $(1+\ \lambda_2)$ the elastic net estimates are as.

$$\widehat{\beta} = arg \min_{\beta} \beta^T (\frac{X^T X + \lambda_2 I}{1+\lambda_2})\beta - 2Y^T X\beta + \lambda_1 |\beta|_1$$

Or can be written

$$\widehat{\beta}(lasso) = arg\min_{\beta} \beta^T (X^T X) - 2Y^T X\beta + \lambda_1 |\beta|_1$$

The elastic net is distinguished from the lasso by the de-correlation. The lasso is an example of an elastic net with $\lambda_2 = 0$.. Another interesting special case of the elastic net occurs when
$\lambda_2 \rightarrow \infty$.
Therefore when the parameter $\lambda_2 \rightarrow \infty, \widehat{\beta} \rightarrow \widehat{\beta}(\infty)$, then,

$$\widehat{\beta}(\infty) = arg\min_{\beta} \beta^T \beta - 2Y^T X\beta + \lambda_1 |\beta|_1$$

Choosing the tuning parameters
Most of the time, (λ_1, λ_2) is used to describe an elastic net, but this is not always the case. For friction parameters of L_1-norm, the standard parameter in LASSO is (L_1) -norm. $\widehat{\beta}$ and, $\hat{\beta}^*$, (λ_2, s) is used to set the parameters of an elastic net because of the proportional relationship to each other. We use (λ_2, s) because s is always between 0 and 1. A tuning parameter can be chosen in many different ways. If you only have

training data, tenfold cross-validation is mostly used to determine your wrong predictions and compare models. An elastic net has two tuning parameters, so the cross-validation is done on a two-dimensional surface. Most of it is just a small grid of numbers for λ_2. LARS-EN creates the whole solution of the elastic net for each value of λ_2. (λ_2, s). Tenfold cross-validation is also used to choose the best solution.

4.9. Weighted Average Least Square

The Weighted Average Least Square (WALS) technique, which was recently introduced, can handle many regressors. In 2010, Magnus et al. developed WALS, which was based on the Equivalence theorem and Mean square error term (MSE) discussed in Magnus and Durbin (2009; (1999). WALS combines both the frequentist and Bayesian estimators. It can help many regressors by categorizing explanatory variables into Focus and Auxiliary variables. Our focus variable is our interest variable.

Auxiliary variables are determinants of regressors but do not directly address the question. They are explanatory variables and their absence can lead to biasness in the true model. WALS operates a large number of subsets of auxiliary variables.

4.9.1 Computational Detail of Weighted Average Least Square

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

$Y = \alpha + X_1\beta_1 + X_{2(i)}\beta_2 + \varepsilon$ where i = 1,2,3,4………..

Where the set of focus variables that do not change is X_1 is. While a subset of the auxiliary variables is a set of $X_{2(i)}$ and with each $X_{2(i)}$, we get diverse estimates of β_1 and β_2. Let $\widehat{\beta}_{1(i)}$ signify the estimated coefficients of focus variables for the subset $X_{2(i)}$The WALS estimate is the average of $\widehat{\beta}_{1(i)}$ in the regression equation.

Following are the statistical details;

Here we have a linear regression model:

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

Here,

y is the vector of observations for nx1; the matrices of explanatory variables are $X_1(n\text{x}k_1)$, X_2 $(n\text{x}k_2)$ and the error term, which is denoted by ε_t

In (2010), Magnus et al. assumed that:

$K_1 \geq 1$ $K_2 \geq 1$ k = k_1+ k_2 ≤ n-1

Where,

Number of focus variables = k_1

Number of Auxiliary variables = k_2

Total number of Explanatory variables = k

It is possible that some of the regressors in X_1 have some relationship with y, but they are the focus variables of the current research. X_2 contains the regressors that may or may not have a relationship with y, but they are not the focus of the current research. As a result, auxiliary variables are used to refer to the regressors of X_2. Their absence may result in bias because they have the status of potential explanatory variables.

When a different subset of β_2's is set equal to zero, a different model emerges, whilst the estimator β_2's comprises K_2components of auxiliary variables. There is no model selection if K_2 = 0. When K_2 = 1, two models emerge the restricted model and the unrestricted model. When K_2 = 2, there are four models: two partially restricted models (where one of the twoβ_2's is zero), a restricted model, and an unconstrained model. In general, there are two models to examine.

4.9.2 Un-Restricted Least Square

Following Magnus et.al (2010), the un-restricted least square (LS) estimators of β_2 and Un-Restricted Least Square :

$$\widehat{\beta}_1 = \widehat{\beta}_{1r} - Q\widehat{\beta}_2\widehat{\beta}_2 = X_2 M\acute{}_1 y$$

Where

$(X'_1X_1)^{-1}X'_1y = \widehat{\beta}_{1r}$: (r indicates the restriction that β_2=0)

$(X'_1X_1)^{-1}X'_1X_2$ = Q

$ln - X_1(X'_1X_1)^{-1}X'_1 = M_1$:

Restricted Least Squares Model

The restricted LS estimators of β1 and β2 are as follows:

$\widehat{\beta}_{1i} = \widehat{\beta}_{1r}QW_i\widehat{\beta}_2$, $\widehat{\beta}_{2i} = W_i\widehat{\beta}_2$

Where $W_i \coloneqq 1k_2 - S_iS'_i$

The joint distribution of β 1i and β 2i is as follows:

W_i is defined as the diagonal matrix of order $K_2 \times K_2$. A diagonal element of this matrix contains K_{2_i} ones and (K_{2_i}-K_{2_i}) zeros, such that if (β_{2_j} = 0), then the jth diagonal element of this matrix is equal to zero; otherwise, it is equal to one. If K_{2_i} is equal to K_2, then W_i should be equal to IK_2 as well. Assume that Si is a selection matrix of order. In the case of Si′ = (I. 0), the full column rank and zero $0 \leq K_{2_i} \leq K_2$., digits are used, as in so Si′ = (IK_2. $-K_{2_i}$: 0). Because we are interested in the restricted estimators of β_1 and β_2, the restriction would be Si′β_2 = 0.

in this case.

$$\begin{pmatrix}\widehat{\beta}_{1i}\\ \widehat{\beta}_{2i}\end{pmatrix} \sim N_k\begin{pmatrix}\beta_1 + PS_iS'_i\beta_2\\ W_i\beta_2\end{pmatrix}, \sigma^2\begin{pmatrix}(X'_1X_1)^{-1} + PW_iP' - PW_i\\ -W_iP\,W_i\end{pmatrix}$$

The residual term is defined as, $e_i = D_{iy}$. Where, $D_i = M_1 - M_1X_2W_iX'_2M_1$ is a symmetric

idempotent matrix. The distribution of S_{2i} = ei′ei /(n $- K_1 - K_{2_i}$) is:

$$\frac{(n-k_1-k_{2i})S^2{}_i}{\sigma^2} \sim \chi^2(\text{n-}k_1 - k_{2i}, \frac{\beta'_2S_iS'_i\beta_2}{\sigma^2}$$

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

4.9.3 Equivalence Theorem

Following Magnus and Durbin (1999) the Equivalence theorem for the WALS estimator of β1 is

Defined as:

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

λ_i are the model weights, and the sum is taken for all, $2k_2$ various models developed by setting a subset of β_2's = 0. Which fulfill the following conditions:

- $\sum_i \lambda_i = 1;$
- $0 \leq \lambda_i \leq 1;$
- $\lambda_i = \lambda_i(M_1 y),$

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

$$\lambda_i = \sum_i^{-1} (\sum_1^{-1} + \sum_2^{-1} + \ldots + \sum_i^{-1})^{-1}$$

$\sum_i^{-1}$ ' is Var-Cov matrix of model i.

Furthermore, with the help of t-statistics, we can calculate the Weighted Average Least Square estimator "b_1" So, we need standard error of the regression estimators, for that purpose, Var(b_1)is defined as:

Var$(b_1) = \sigma^2(X_1, X_2)^{-1} + Pvar(b_2)P$ $\quad$ $and\ var(b_2) = \sigma^2 \sigma_n^2 T \lambda^{-1} T'$

Where $\sigma_n^2 = 2/c^2$ $\quad$ C = log 2

To be an orthogonal matrix and Λ to be a diagonal matrix, both of which are calculated through diagonalization of T′X_2′M1X_2T = Λ. When the value of σ^2 is unknown, so it is interchanged by S^2, which is defined. al in equivalence theorem as $S^2 = (y - X_1bu - X_2\widehat{\beta}_2)'$(y-$X_1bu - X_2\widehat{\beta}_2)/(n - k_1 - k_2)$.by Magnus et (2004)

4.10 Other Model Selection Procedures

Hendry and Richard (1989) and Lu and Mizon (1996) both focus on variance and parameter encompassing. Cox-type tests of non-nested hypotheses are variance-encompassing tests, according to Mizon and Richard (1986). Hendry and Richard (1989) summarize encompassing literature and discuss encompassing in dynamic models. Wooldridge (1990) compares the Mizon-Richard and Cox tests. A regression-based test is used when no single model considered encompasses all other models. M1 is nested within M2 if and only if M1 ⊆ M2; whenever M1 and M2 do not satisfy the conditions in this definition, they are said to be non-nested. The encompassing model contains predictors that are insignificant for the dependent variables. We'll move from a general to a specific approach to achieve a more compact model. Two tests will be performed to determine whether any parameters are statistically insignificant. Individual parameter significance is checked using the T-test, while the F-test is used to verify the results of the joint hypothesis test. Statistically insignificant variables will be eliminated from the study.

4.10.1 Computational Detail of Non-Nested Encompassing Approach

Nestedness is defined as M1 being contained within M2, and non-nestedness is defined as the absence of any of the conditions in this definition being met by M1 and M2. When M1 and M2 do not satisfy the conditions in this definition, they are said to be non-nested.

M_1: $\boldsymbol{Y} = \boldsymbol{X\beta} + \boldsymbol{\varepsilon}$ …….. M_1 and M_2 (Non-Nested)

M_2: $\boldsymbol{Y} = \boldsymbol{Z\gamma} + \boldsymbol{u}$ ……..

M^* : $\boldsymbol{Y} = \boldsymbol{X\beta} + \boldsymbol{Z\gamma} + \boldsymbol{W\delta} +$ …. Both M_1 and M_2 (Nested)

4.10.1.1 Encompassing and General to specific approach

The encompassing approach connects various models. This section will use a non-nested hypothesis test to encompass. Assume we have 'n' and follow the steps below.

Predict all models and note the error. The best model is the one with the least error. One model must have the least regression prediction error (Hoover et al. 1999). Say M* has the best prediction error.

4.10.1.2 Combine the best model with other models using the hypothesis test below.

$H_{1:}$ Model M^* encompasses (Model)1

$H_{2:}$ Model M^* encompasses (Model) 2

$H_{3:}$ Model M^*encompasses (Model) 3

$H_{4:}$ Model M^* encompasses (Model) 4

$H_{n:}$ Model M^* encompasses (Model)' n'

All of the above hypothesis testing procedure is done using one of the test statistics mentioned below.

- Cox Test
- Ericson Test
- Sargan Test
- joint test statistics

Because it contains the model's properties, the model that encompasses will be ignored in this case. If any of the hypotheses are rejected. It means the model can improve its predictive power. So, we will combine the model with the model. Then, we'll move from a broad to a specific approach.

4.10.1.3 General to Specific Approach

Hendry, LSE, and PcGets are well-known names for the general-to-specific approach. To be consistent with their view of econometrics, the LSE School of Economics proposed empirical modeling. This theory of reduction explains how econometric models are derived from the DGP. Based on reduction theory, the empirical model is developed. The main goal of reduction theory is to study the probability concept used in the empirical model simplification (Hendry, 1995). This process replaces the specific modeling data-generating process (LDGP). When two variables are combined to form a single distribution, this is known as the LDGP (Hendry, 2000b).

$$Y_t = \beta_o + \beta_o X_1 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots\dots\dots\dots\dots\dots \beta_n X_n + \mu_t \dots\dots(1)$$

The encompassing model may contain predictors that are insignificant for the dependent variables. We'll move from a general to a specific approach to achieve a more compact model. Two tests will be performed to determine whether any parameters are statistically insignificant.

T-test statistics:

$$t - test\ statistic = \frac{\bar{S} - \mu}{S/\sqrt{n}}$$

Where **S** is denoted as the slandered deviation, and this test follows the two-tail test and t-distribution test statistics such as given:

For the linear hypothesis (F- Statistics)

$$F - statistic = \frac{(SSE_1 - SSE_2)\ /m}{SSE_2\ /\ (n-K)}$$

There are m restrictions, k parameters in the restricted model, and n observations. Individual parameter significance is checked using T-test, while the F-test is used to verify the results of the joint hypothesis test. Statistically insignificant variables will be eliminated from the study. The unit root test and co-integration analysis will be used to ensure that there is no spurious regression.

The unrestricted model (1) is built from the encompassing results.

The final result should be sparse after estimating the above model and applying joint linear restriction and non-linear restrictions.

4.11 Data Discriptions

Model 1: Balance of Trade (BOT)

1. **Dependent Variable:**

- **Balance of Trade (BOT):** The trade balance, representing the difference between exports and imports.

2. **Independent Variables (Focus):**
    - **Foreign Direct Investment (FDI):** Investment from abroad into the country.
    - **Gross Domestic Product (GDP):** The total economic output of the country.
    - **Exchange Rate (ER):** The value of the country's currency relative to others.

3. **Auxiliary Variables:**
    - Domestic Investment (DI)
    - Money Supply (MS)
    - Exports Value Index (EVI)
    - Imports Value Index (IVI)
    - Inflation (INF)
    - Personal Remittances (REMI)
    - Government Expenditure (GEXP)
    - Budget Deficit (BDEFI)
    - Domestic Consumption (DC)
    - Trade (TR)

Model 2: Economic Growth (LNGDP)

1. **Dependent Variable:**
    - **Economic Growth (LNGDP):** The logarithm of Gross Domestic Product, representing economic growth.

2. **Independent Variables (Focus):**
    - **Gross Fixed Capital Formation (LNGCF):** Total investments in fixed assets.
    - **Total Labor Force (LNTLF):** The overall number of employed and unemployed individuals.
    - **Foreign Direct Investment (FDI):** Investment from abroad into the country.
3. **Auxiliary Variables:**
    - Trade Openness (TOP)
    - Labor Growth (LG)
    - Domestic Interest (DI)
    - Total Debts (TDebts)
    - Inflation (INF)
    - Total Population (LNTOTP)
    - Education Expenditure (EDU)
    - Exports of Goods and Services (LNREXP)
    - Personal Remittances (REMI)
    - Government Expenditure (LNGEXP)

Data Collection:

- **Time Period:** 1980 to 2020.
- **Data Sources:** International Financial Statistics, Political Risk Services (PRS), and World Development Indicators.

This research analyzes the relationships between these variables to understand the determinants of Balance of Trade and Economic Growth in Pakistan and other cross countries.

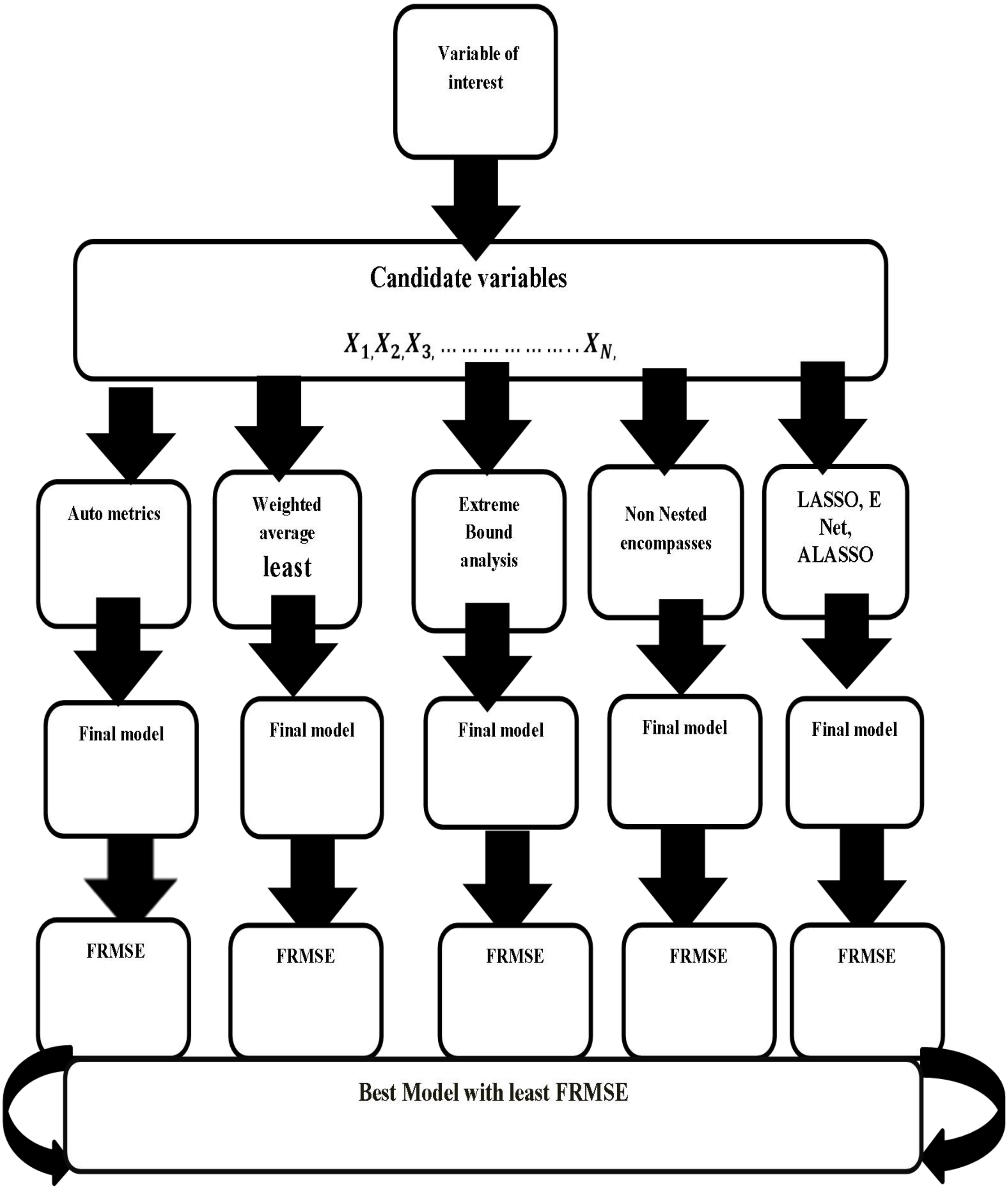

Figure 4: Flow chart of the methodology for comparison

- We compare the model selection procedure using two criteria.
- The first criterion is the model's predicted performance (FRMSE)

- The second is based on the robustness of the model

4.12 Limitations of the Study

It is possible to incorporate the findings from the tests for heteroskedasticity, serial correlation, and outliers, but such an inclusion would inevitably result in a considerable expansion of the study's content, presenting a difficulty in succinctly summarizing it within the scope of the thesis.

4.13 Forecast-Based Comparison

Suppose Y is a variable of interest and $X_1, X_3,.X_n$ are the candidate variables, and f_1 be the model of selection procedure applied to select the model of and $X_1, X_2, X_2,.X_n$, let and $X_{f1}, X_{f2}, X_{f3},.X_{fk}$ be the variable selected by the procedure f_1, Let there are t observation estimate $Y_i\, f\ (X_{11}, X_{12}, X_{13}, ..X_{1k})$ for $T - S$ observation leaving "S" observation for forecasting purposes. Use the estimate observation $\widehat{Y}_{t-s+1}$, and calculate$\widehat{Y}_{t-s+2}, \widehat{Y}_{t-s+3}.\widehat{Y}_t$

$$FRMSE_1 = \sum (\widehat{Y}_{t-S+i} - \widehat{Y}_{t-S+i})^2$$

Let there be a procedure f_2 and forecast $FRMSE_2$ be the Forecast root mean square error (FRMSE). Which forecasting the model selected by f_2 in this way, one can find FRMSE for all models through different model selection procedures. A comparison of FRMSE for different models will give us an idea of the best model selection procedure, so therefore, the final model with the least forecast RMSE will consider the best model.

4.14 Robustness

We have tested the performance of the model selection procedures for some countries and the research has identified the best procedure. A natural question arises: if we change the sample countries, would it change the same procedure that will be performed best? To test this, we have divided the sample countries into two groups. Group I countries 43 countries and these countries would be used to find out the model selection procedures that perform best. Group II contains 6 countries for the Growth model and 9 countries for the Balance of trade model. The models would be restricted for group II to know whether the models applying best in sample I maintain their performance for group II.

4.15 Retention of Variables

In his Ph.D. thesis, Khan (2020) compared model selection procedures using Monte Carlo experiments. The study of Khan was based on the Monte Carlo experiment; therefore, he was able to find the probability of retention of the true variables. Our study is based on real data therefore, we are unable to find the true variables because true variables are not known. We are trying to select a model out of many candidate models. These candidates' models gain a long list of explanatory variables. We can find the retention frequency of these variables to make the study compared with the study of Khan.

4.16 Software Used in the Estimation Process

OX-Metrics was employed for both Automatrics and Non-Nested Encompassing procedures, while the WALS technique was executed using Stata 17. In contrast, R served as the software of choice for conducting the shrinkage procedures, including LASSO, Adaptive LASSO, and Elastic Net, as well as for assessing the consistency of coefficients through Extreme Bound Analysis.

CHAPTER 5

MODEL SELECTION FOR BALANCE OF TRADE

5.1 The Generalized Unrestricted Model (GUM) for Balance of Trade

The Generalized Unrestricted Model (GUM) is a model that consists of variables of various theoretical models. These theoretical models can be drawn as a special case of the Generalized Unrestricted Model (GUM) for Balance of Trade was constructed as follows.

There are many models for the Balance of Trade and it is impossible to cover the entire range of candidate variables. For the selection of variable use in this study, we surveyed the literature published after 2010. Among these studies, the models were selected to cover various determinants. The models having variables used only in one or two papers were dropped. After adopting this procedure, we are left with the following models.

Balance Of Trade	*Theory Base Model*
Model 1	Kakar (2010) BOT =f (DI , MS , ER,EVI, IVI)
Model 2	Sharif (2016) BOT =f (FDI , ER, Inf)
Model 3	Murangzed, et al. (2014) BOT =f (LnGDP , FDI , ER , P(remi))
Model 4	Nienga (2010) BOT =f (ER , G exp , DI , MS ,)
Model 5	Osro(2013) BOT =f (FDI , ER , Bdefi ,)
Model 6	Shah (2015) BOT =f (TR , FDI , MS , LnGDP , DC)

5.2 The Econometric Model takes the following form

BOT =f (DI , MS , ER , EVI , IVI , FDI, INF , REMI , LnGDP , LnGEXP , $BDEFI$, DC , TR)

$$\mathrm{BOT}_t = \beta_o + \ + \beta_1 \mathrm{DI}_t + \beta_2 \mathrm{MS}_{\ t} + \beta_3 \mathrm{ER}_{\ t} + \beta_4 \mathrm{EVI}_{\ t} + \beta_5 \mathrm{IVI}_t + \beta_6 \mathrm{FDI}_t + \beta_7 \mathrm{INF}_t + \beta_8 \mathrm{REMI}_t + \beta_9 \mathrm{LnGDP}_t + \beta_{10} \mathrm{LnGEXP}_{\ t} + \beta_{11} BDEFI_{\ t} + \beta_{12} DC_{\ t} + \beta_{13} \mathrm{TR}_t + \mu_t$$

The list mentions only 6 models; the variables in the generalized unrestricted model (GUM) variables cover the variables found in 95% of the existing studies on the balance of trade.

5.3 Details of Econometric Models and Variables

This section is based on details of econometric models and variables. The objective of this study is to expand computational proficiency and provide a way to work when the numbers of variables are more than observations. It makes it more general because of these problems; different econometrics techniques are applied to handle large data sets and also to make comparisons among all these methodologies based on robustness and forecasting (root mean square error). In this study, we present the results using methodologies: Least Absolute Shrinkage and Selection Operator (LASSO), Adoptive Least Absolute Shrinkage and Selection Operator (ALASSO), Elastic Net, Non-Nested Encompassing, Autometrics, Weighted Average Least Square, and Extreme Bound analysis. These procedures are used to show which methodology is best to be used in variable selection and model selection. The robustness is based on the most repeatedly significant variables in all models. The robustness analysis refers to a model with the most significant variables, and after employing all the techniques, we choose the most repeated model in each methodology and re-estimate the most repeated model for a few countries and show the robustness of the model.

In the same way, we employed all the techniques and estimated forecasts for each country model and found root mean square error. The model with the least root mean square error is the best model and the most repeated model in re-estimation is the most robust model. We also estimate the total significance for each model to show the more repeatedly significant variable in each modeling for all the countries.

5.3.1 Description of Variables

Table 1 shows the results of Absolute Shrinkage and Selection Operator (LASSO). The results in Table 1 are based on the modeling of the balance of trade modeling. In this model, the balance of trade (BOT) is the dependent variable and foreign direct investment (FDI), gross domestic product (GDP), the exchange rate(ER), domestic investment (DI), money supply (MS), exports value index (EVI), imports value index (IVI), inflation (INF), personal remittances (REMI), government expenditure (GEXP), the budget deficit (BDEFI), domestic consumption (DC), and trade (TR). The FDI, LNGDP, and ER are our focus variables in this modeling, while the DI, MS, EVI, IVI, INF, REMI, GEXP, BDEFI, DC, and TR are the auxiliary variables.

Some of the model selection procedures require dividing independent variables into focus and auxiliary variables. The focus variables are ones in which the researcher might be interested, whereas auxiliary variables are those used as control variables. We used the most commonly found determinants as focus variables and others as auxiliary variables for the Balance of Trade Model (BOT) are as under.

Dependent Variables

Balance of Trade (BOT)

Focus Variables

Foreign direct investment (FDI),

Gross domestic product (GDP),

Exchange rate(ER),

Auxiliary variables
Domestic investment (DI)
Money supply (MS)
Exports value index (EVI)
Imports value index (IVI)
Inflation (INF)
Personal remittances (REMI)
Government expenditure (GEXP)
Budget Deficit (BDEFI), domestic consumption (DC)
Trade (TR)

5.4 Model Selection Procedures Based on Shrinkage Methodology

The idea of the Shrinkage estimator gets motivation from the Bayesian Methodology which combines the information from prior knowledge with information from the data and clubs the information to Shrinkage the variance of the estimators. In Shrinkage methodology, different combinations of regressors are estimated and information is clubbed in Bayesian Fashion which Shrinkage the variance of the estimators. There are many kinds of Shrinkage estimation.

5.4.1 Results of LASSO Regression

Table 5.1 presents the outcomes of the estimation conducted using the LASSO methodology. This table offers valuable insights into the regression coefficients of variables, showcasing differences in signs across various countries. These differences in coefficient signs reflect the presence of country-specific heterogeneity, a crucial aspect of our analysis.

Each country is examined individually within this table, allowing us to unveil the heterogeneity inherent in the model across different nations. The final column in the table presents root mean square errors (RMSE) for each estimated model, aiding in assessing their predictive performance.

Variables that have been excluded from the model by LASSO are denoted by ellipses (…), highlighting the specific variables that the LASSO procedure deemed insignificant. For instance, in the case of Argentina (Row 1), the LASSO procedure excluded the variables LNGEXP and BDEFI from the model due to their lack of significance.

Similarly, when considering Australia, the LASSO procedure identified the variables INF, BDEFI, DC, and TR as insignificant and consequently removed them during the estimation process.

The bottom row of the table provides valuable information regarding the frequency with which each variable is retained across all the countries. This data indicates that out of the 43 countries studied, the variable INF was found to be significant in 35 cases. This table serves as a comprehensive tool for understanding the heterogeneity and significance of variables within the econometric models we've employed.

Table 5.2: The Results of Least Absolute Shrinkage and Selection Operator for Balance of Trade Modeling

Country Name	CONS	FDI	LNGDP	ER	DI	MS	EVI	IVI	INF	REMI	LNGEXP	BDEFI	DC	TR	RMSE
Argentina	293.2	0.3	-9.3	-2.1	-0.1	-0.2	0.2	-0.4	-0.1	-107.5	..	..	-0.1	0.3	18.8
Australia	902.9	1.5	-22.9	17.1	-0.8	-0.1	-0.1	0.1	..	48.1	-10.7	..	..	..	10.5
Austria	-3.2	8.8	-4.7	-3.4	-1.7	7.7	-7.2	-1.7	-2.3	-2	1.9	4.9	-2.1	-4.1	3.3
Bangladesh	-1.6	-1.5	..	3	..	..	..	-4.7	..	..	9.3	-6.2	..	-3.3	6.1
Belgium	-3.4	..	-9.5	-1.7	..	2.2	-1.5	-4.2	-1.3	1.1	1.4	-1.7		-8.3	1.8
Bhutan	49.3	..	..	..	..	..	..	..	..	..	..	..	..	..	12.5
Bulgaria	6.8	..	3.1	..	..	..	..	4.1	..	..	..	1.4	..		0.6
Brazil	-11.5	-1.5	-16.5	-5.8	3.2	0.2	..	-0.1	3.2	-2	21.6	0.1	-0.2	..	4.7
Canada	1.2	1.3	-2.9	2.5	-6.8	1.9	-2.1	-1.8	1.2	..	2.9	4.5	-3.1	-5.4	0.7
China	474.6	-1.8	-16.7	4.7	0.9	0.3	..	-0.1	-0.1	15.2	..	..	-0.2	-0.1	12
Chile	167.3	..	-37.2	..	3.2	3.2	3.2	0	3.2	-35.8	36.5	..	3.2	-0.6	1.2
Denmark	70.9	-0.1	-21.6	0.2	-0.4	0.1	-0.1	3.2	0.1	-1.4	23.1	..	-0.1	-0.3	1.7
France	94.7	0.2	-1.7	-0.2	..	..	-0.5	-0.7	-0.2	-0.1	..	-0.2	3.2	-0.7	0.6
Germany	117.1	0.2	-26.8	-0.7	..	0.1	0.1	-0.1	-0.1	-1.5	26.1	-0.1	-0.7	-0.6	0.5
Ghana	118.3	0.6	-3	11.2	..	..	..	3.2	0	-5.7	..	-0.7	-0.5	-0.1	27.6
Hungary	-53.4	-0.1	-0.1	..	-0.7	-0.1	..	-0.1	0.2	1.3	4.4	..	..	..	4.4
India	210.9	-1.2	-11.2	-0.7	22	0.1	..	3.2	-0.1	-1	4.8	..	..	3.2	2.6
Indonesia	1.4	-8.2	..	4.5	..	..	6.5	..	..	-2.5	-3.8	8.1	4	..	6.3
Iran	-2.6	-2.4	-1.1	2.2	9.8	..	-9.7	-2.3	1.5	-1.1	2.6	2.6	..	-3.7	58
Japan	3.9	..	8.5	..	..	2.2	..	..	-1.2	-3.3	-2.2	..	..	4.3	4.9
Luxembourg	45.9	3.2		0.1	..	..	3.2	..	0.4	-0.7	-0.2	..	3.2	..	4.1
Malaysia	25.3	-0.3	-43.3	0.2	-0.3	0.2	0.3	3.2	-0.1	0.7	38.4	3.2	0.1	-0.3	2.5

Country Name	CONS	FDI	LNGDP	ER	DI	MS	EVI	IVI	INF	REMI	LNGEXP	BDEFI	DC	TR	RMSE
Maldives	-75.9	0.3	-7.2	-1.8	3.2	-0.1	0.1	0.1	0.2	-1.3	15.4	..	..	0.2	28.4
Mexico	47.3	..	..	..	..	0.3	..	..	0.1	..	..	..	-2.1	..	2.4
Morocco	13.9	0.1	-26.5	-0.6	0.1	..	1.1	-2.1	-0.2	0.4	25.8	0.1	..	-0.5	1.5
Nepal	23		-11.6	..	..	..	-2.1	3.2	0.1	-0.1	14	..	..	-0.2	13.8
Netherland	24.2	3.2	..	1.1	0.1	..	0.1	0.3	-0.1	9.6	0.9	-0.1	1.1	..	1.5
New Zealand	41.1	..	..	9.6	0.2	3.2	..	0.2	-0.2	6.6	..	-0.1	-2.1	3.2	2.2
Norway	81.1	0.5	-48.6	-0.3	-2.1	0.3	-2.1	0.4	1.1	8.1	43.9	0.1	0	-0.6	9.6
Pakistan	-12.9	-0.8	-6	0.3	-0.6	1.1		0.3	1.1	1.1	15.1	..	-0.1	-0.2	4
Peru	45.2	..	..	..	..	..	..	..	..	..	..	..	..	0.2	2.4
Paraguay	3.5	-0.3	-4.1	1.1	0.3	-0.2	0.1	9.6	0.3	-1.9	6.6	-0.1	0.1	9.6	2.1
Philippines	42.3	..	..	..	..	..	..	..	..	..	..	..	..	..	5.2
Portugal	1.4	2.4	-3.9	..	-1.6	-7.1	1.8	2.3	2.1	2.8	3.9	4	7.4	-6.5	8.4
Qatar	28.5	..	0.1	..	..	..	..	..	..	1	-8.1	2.1	..	..	31
South Africa	15.5	-0.2	-39.3	..	..	0.3	1.1	1.1	0.3	..	41.2	3.2	0.3	0.9	1.4
Sri Lanka	-1.1	1.7	1.3	8.8	2.1	-2.7	-1.5	9.6	3.2	5.7	2.3	-1.4	9.5	2.6	8.9
Switzerland	-1.2	8.6	-1.6	5	5.6	2.4	3.4	2.5	-3.5	1.2	2.4	-4.5	-8.4	-3	1
Sweden	32.7	3.2	..	0.3	0.1	-0.1	0.1	1.1	-0.1	..	1	..	..	..	1.6
Turkey	70	0.5	-23.6	2.2	3.2	0.1	0.3	3.2	1.1	0.4	25.3	-0.1	-2.1	-0.7	2.3
United States	-67.5	-0.3	-31.1	..	0.2	0.1	1.1	..	-0.2	-14.6	39.6	0.3	0.3	-1.6	1.6
United Kingdom	18.9	-2.1	2.6	5.3	0.3	-2.1	9.6	0.3	3.2	0.8	-0.1	-2.1	-2.1	0.3	0.2
Uruguay	9.2	-7.8	-2.5	-1.7	9.1	6.8	2.1	3.5	2.4	-7.8	2.6	-6.8	4.9	-3.1	3.3
Retention Frequency		**31**	**32**	**29**	**27**	**29**	**26**	**31**	**35**	**33**	**33**	**25**	**28**	**31**	

Figure 5.1: Graph of the Retention Variables in LASSO for Balance of Trade Modeling

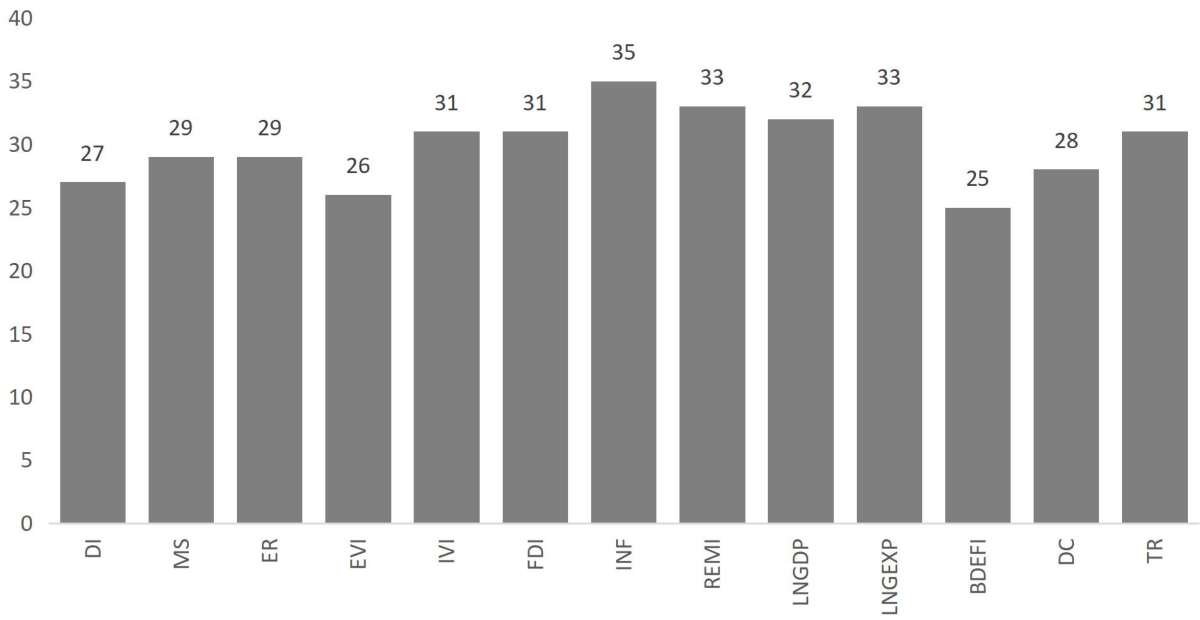

Figure 5.1 summarizes the retention frequency of variables in the BOT model using LASSO. The results show that inflation is most likely significant, with a retention frequency of 35 out of 43. The next most common variables are REMI and LNGNXP, with a retention frequency of 33/43.

5.4.2 Results of Adoptive LASSO Regression

Table 5.2 presents the outcomes of estimation through the application of the Adaptive LASSO method. Within this table, you can observe the regression coefficients associated with various variables, and it's noteworthy that these coefficients display differing signs across distinct countries. This variance in the signs of variable coefficients signifies the presence of country-specific heterogeneity in our analysis. We conducted the analysis separately for each country, which allows us to uncover the unique heterogeneity patterns within the model.

The final column of the table displays the root mean square errors for each model estimated. Notably, cells marked with "(...)" denote the variables that have been excluded from the model by the Adaptive LASSO procedure. For instance, in the first row, we find that for Australia, the variables "INF" and "TR" were eliminated by the LASSO.

Similarly, in the case of Austria, the variables "LNGDP," "REMI," "BDEFI," and "TR" were found to be statistically insignificant and were consequently removed during the estimation process. In the last row, you can observe the frequency at which each variable was retained across all the countries. Remarkably, out of the 43 countries considered, the variable "FDI" exhibited statistical significance in 39 instances.

Table 5.2: The Results of Adaptive Least Absolute Shrinkage and Selection Operator for Balance of Trade Modeling

Country Name	CONS	FDI	LNGDP	ER	DI	MS	EVI	IVI	INF	REMI	LNGEXP	BDEFI	DC	TR	RMSE
Argentina	291.4	0.3	-9.2	-2	-0.1	-0.2	0.2	-0.4	-0.1	-106.1	..	..	2.1	0.3	20.5
Australia	177.2	..	-4.9	..	..	..	..	..	1	21.6	..	..	..	..	13.4
Austria	-4.1	3.3	..	-1.3	-1.8	1.7	-1.6	-9.1	-2.6	..	1.8	..	-3.1	..	3
Bangladesh	-1.6	-1.5	..	3.3	..	..	..	-4.7	-9	..	9.4	9.1	..	-4.1	3.5
Belgium	1.7	-1.1	-1.3	-2.3		3.3	-9.1	-4.1	-1.1	1.9	1.4	-5.3	-1.8	-7.9	1.3
Bhutan	49.3	..	..	..	..	..	..	..	..	..	..	..	..	..	12.5
Bulgaria	..	..	2.5	..	..	..	..	..	..	..	..	..	..	..	3.2
Brazil	3.1	-1.7	-9.8	-1.4		7.2	1.3	-1.3	3.6	-2.5	..	1.7	..	..	3.8
Canada	1.2	1.3	2.7	2	-5.5	2.1	-3.7	-1.9	9.8		2.7	3.3	-3.3	-4.9	2.3
China	50	..	..	0.6	0.1	..	..	..	..	10.1	..	,,	-0.1		2.7
Chile	16.4	-36.8	..	..	0	-0.6	2.1	-1.1	-0.6	-36.2	36.1	..	-0.6	-0.6	0.7
Denmark	-4.1	3.3	..	-1.3	-1.8	1.7	-1.6	-9.1	-2.6	..	1.8	..	-3.1	..	3
France	15.7	0.2	-30.9	2.1	0.2	0.1	-1.1	0	0.1	-0.4	28	-0.2	-0.6	-0.8	1
Germany	11.1	0.2	-26	-0.7	..	0.1	0.1	-1.1	-0.1	-1.5	25.3	-0.1	0	-0.6	0.5
Ghana	96.9	0.5	-2.1	8.3	..	..	..	2.5	2.1	-4.3	..	..	-0.4	-0.6	16.9
Hungary	-5.4	-5.5	-1.1	..	3.9	-7.6	-3.7	1.8	2.1	1.3	5.4	..	..	..	4.6
India	196.5	-1.2	-19.9	..	8.3	0.3		2.1	-0.6	-1.5	15.6	..	-1.1	-0.4	2.4
Indonesia	1.4	-8.2	..	4.5	..	..	6.5	..	..	-2.5	-3.8	8.1	4	..	6.1
Iran	-23.7	-2.7	-11.6	-0.6	..	..	-0.1	-1.1	-1.1	-1.2	26.6	-0.3	..	0.4	80.9
Japan	3.9	1.1	8.2	-2	4.9	3.3	1.3	-5.6	-6.3	1.8	-2.2	-2	..	6.4	5.4
Luxembourg	45.5	-0.6	..	0.1	..	..	-0.6	..	0.4	-0.6	-0.2	..	-0.6	-0.6	3.7
Malaysia	237.1	-0.3	-46.4	-0.6	-0.2	-0.6	0.1	-0.2	-0.1	0.7	41.2	-0.2	0.1	-0.3	3

Country Name	CONS	FDI	LNGDP	ER	DI	MS	EVI	IVI	INF	REMI	LNGEXP	BDEFI	DC	TR	RMSE
Maldives	-74.5	0.3	-7.7	-1.8	0.1	-0.1	0.1	-0.1	0.2	-1.3	15.9	..	..	-0.6	28.6
Mexico	134.5	-0.8	-17	-0.1	0.1	0.3	..	..	0.1	0.5	14.8	-0.2	..	-0.2	3.6
Morocco	167.1	-0.6	-30.6	-0.7	0.1	-0.6	0.1	-0.6	-0.2	0.4	29	0.1	-0.2	-0.6	2.4
Nepal	31	0.3	-12.5	..	..	..	0	-0.2	0.1	-0.1	14.6	..	..	-0.3	16.3
Netherland	22.8	0.1	0.1	1.1	0.1	..	0.1	0.1	..	-0.6	1	-0.1	-0.6		1.2
New Zealand	39.6	-0.6	..	0.3	0.2	0.1	..	-0.6	-0.2	8.9	..	-0.1	0.1	0.1	2.2
Norway	281.1	0.1	-48.6	-0.3	-2.1	-0.6	-0.6	0.1	0	8.1	43.9	0.1	-0.2	-0.6	10.4
Pakistan	31.1	-0.3	-7.5	0.2	0.2	-0.1	0.1	0.1	-0.1	-1.9	9	0.7	0.3	-0.1	2
Peru	-2.2	-1.1	..	..	-7.5	..	..	-3.7	-2	..	1.2	-2.2	-8.5	-1	4.6
Paraguay	45.2	..	..	..		..	..	..	..	..	..	..	..	0.2	11.4
Philippines	31.1	-0.3	-7.5	2.9	0.2	-0.1	0.1	0.5	-0.1	-1.9	9	2.9	3.1	-0.1	2
Portugal	81.3	0.1	-6.9	0.1	-0.1		0		0.1	-0.8	1.4	1.8	-1.3	..	4
Qatar	1.3	3.9	-3.8	6.8	-4.1	-5.6	1.7	1.8	2.4	-1.3	3.8	3.2	8.9	-6.5	9.9
South Africa	1.4	2.4	-3.9	..	-1.6	-7.1	1.8	2.3	2.1	2.8	3.9	4	7.4	-6.5	9.9
Sri Lanka	28.5	..	0.1	..	..	..	..	..	..	1	-8.1	..	..	..	32.3
Switzerland	10.7	-0.2	-39.7	..	..	1.2	0.1	2.9	0.3	..	41.6	0.2	0.3	-0.9	0.8
Sweden	-1.1	1.7	-1.3	8.8	2.1	-2.7	-1.5	-9.6	3.2	5.7	2.3	-1.4	9.5	-2.6	9
Turkey	-1.1	1.3	-1.8	4.9	5.3	2.4	3.1	2.4	-4.3	1	2.6	-5	-8	-3.3	0.9
United States	33.8	0.7	-0.1	0.3	0.1	-0.1	0.8	1.1	..	..	0.9	..	..	..	1.6
United Kingdom	70.6	0.5	-24.3	2.2	0.1	0.1	0.3	2.9	0.4	0.5	26.2	-0.1	2.9	-0.7	2.7
Uruguay	9.2	-7.8	-2.6	-1.8	..	6.3	2	-3.5	8.3	-6.1	2.6	-7.2	5.1	-3.2	3.2
Retention Frequency		**39**	**32**	**31**	**27**	**30**	**32**	**34**	**36**	**34**	**36**	**28**	**30**	**31**	

Figure 5.2: Graph of the Retention Variables in Adoptive LASSO for Balance of Trade Modeling

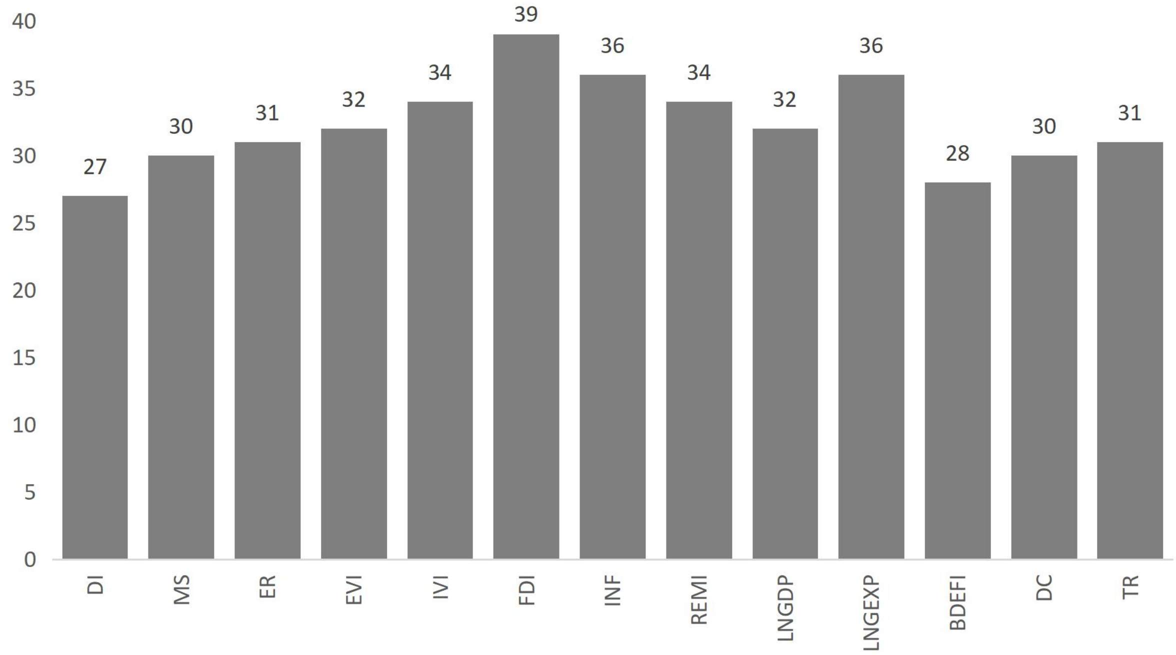

Figure 5.2 summarizes the retention frequency of variables in the BOT model using Adoptive LASSO. The results show that focus variable foreign direct investment (FDI) is most likely significant, with a 39 out of 43 retention frequency. The next most common variables are INF and LNGNXP, with a retention frequency of 36/43. Similarly, other variables Import Value Index (IVI) and personal Remittances (REMI) were significant with a retention frequency of 34/43.

5.4.3 Results of Elastic Net Regression

In Table 5.3, you can observe the outcomes of our estimation using the Elastic Net method. This table presents the regression coefficients of various variables, which display different signs for different countries. The variability in the signs of these coefficients serves as an indicator of country-specific heterogeneity within our analysis. We have approached this analysis by examining each country individually, allowing us to uncover the distinctive patterns of heterogeneity present within the model.

Cells marked with "(...)" in the table indicate the variables that were excluded from the model by the Elastic Net procedure. For instance, in Row 2, we find that for

Australia, both the "Inflation" (INF) and "Trade" (TR) variables were excluded by the Elastic Net method due to their lack of significance.

Similarly, in the case of Austria, the variables "LLNGDP," "REMI," "BDEFI," and "TR" were identified as statistically insignificant and were consequently eliminated during the estimation process. In the last row of the table, you can observe the frequency with which each variable was retained across all the countries. Remarkably, among the 43 countries considered, the variable "FDI" displayed statistical significance in 39 instances.

Table 5.3: The Results of Elastic Net for Balance of Trade Modeling

Country Name	CONS	FDI	LNGDP	ER	DI	MS	EVI	IVI	INF	REMI	LNGEXP	BDEFI	DC	TR	FRMSE
Argentina	3.2	2.5	-1	-2.6	-1.3	-2.5	2	-3.9	-1.4	-1.2	3.4	-3.7	-7.4	3.2	2.192
Australia	624.5	1.5	-11.5	19.3	-0.5	-0.2	-1.4	0.1	..	40.8	-11	-1.4	-0.1	..	1.508
Austria	-4.1	2.6	..	-1.8	-2	8.4	-6	-8.1	-3.4	..	1.8	..	-4.4	..	4.039
Bangladesh	-149.6	-1.9	..	0.2	-3.7	8.1		-3.7	-0.1	-0.1	8.6	8.1	-3.7	-0.1	1.07
Belgium	1.1	-1.1	-1.2	-2.2	..	2.9	-1	4.2	-1.1	1.9	1.4	-6.7	-6.2	-8.1	2.13
Bhutan	49.3	..	..	..	..	..	..	..	..	..	..	..	..	..	1.273
Bulgaria	4.7	..	..	..	..	..	..	..	..	..	..	..	..	..	0.616
Brazil	1	-1.6	-1.3	-4.9	-1.9	1.8	5.7	-4.9	9.9	-2.2	1.2	5.9	-1.3	1.3	0.41
Canada	80.9	0.1	-1.2	2.4	..	8.1	-1.9	..	-6.3	0.1	..	-0.1	..	..	2.565
China	4.8	3.5	..	2.5	..	..	3.8	1.2	..	6.5	..	..	..	1.7	1.612
Chile	197.7	-3.7	40	-0.2	-0.2	-0.1	-0.2	-1.9	-3.7	-50.1	38.8		2.9	-0.7	2.173
Denmark	190.4	0.2	-26.2	-0.1	0.1	0.1	-3.7	-0.2	-0.2	-0.4	23	-0.2	-3.7	-0.6	0.314
France	195.7	0.2	-30.9	-6.3	0.2	0.1	-6.3	-1.4	0.1	-0.4	28	-0.2	-6.3	-0.8	3.173
Germany	141	0.2	-26.3	-0.9	-1.2	-3.7	0.1	-6.3	-0.1	-1.3	25.1	-0.1	0.5	-0.6	0.628
Ghana	65.3	..	-0.8	-6.3	..	..	..	..	..	-0.7	..	..	-0.2	-1.4	61.43 1
Hungary	-5.2	-5.5	-7.2	-10	3.8	-9.2	-6.3	1.7	2.1	1.3	5	..	..	..	1.13
India	208.5	-1.2	-15.6	-3.7	15.5	0.2	..	-1.9	8.1	-1.4	10.1	..	-3.7	-0.2	0.391
Indonesia	1.4	-8.2	..	4.5	..	..	6.5	..	..	-2.5	-3.8	8.1	4	..	0.191
Iran	-252.4	-4.5	-12.2	-0.2	-0.1	-0.2	-0.1	-1.4	-0.2	-1.4	27.3	-0.3	-0.1	-0.4	4.576
Japan	3.9	1.1	8.2	-2	4.9	3.3	1.3	-5.6	-6.3	1.8	-2.2	-2	..	6.4	3.175
Luxembourg	44.9	3.3	..	..	..	..	0.9	0.1	0.4	3.3	-0.1	..	0.9	3.3	1.146
Malaysia	224.2	-0.3	-41.5	0.3	-0.4	0.3	0.1	0.3	-0.1	0.7	36.6	0.3	0.1	-0.3	1.06

Country Name	CONS	FDI	LNGDP	ER	DI	MS	EVI	IVI	INF	REMI	LNGEXP	BDEFI	DC	TR	FRMSE
Maldives	-72.5	0.3	-7.4	-1.8	..	-0.1	0;4	-0.1	0.2	-1.4	15.4	-0.9	-0.9	0.3	2.287
Mexico	104.7	-0.5	-27.2	-0.7	0.1	0.2	-0.1	0.2	-6.3	-0.4	27.8	-0.1	0	-0.3	2.693
Morocco	161	0.5	-29.6	-0.7	0.1	0.1	0.1	0.11	-0.2	0.4	28.2	0.1	0.3	-0.5	1.293
Nepal	-56.6	1.7	-10.4	-0.1	2.2	..	0.2	0	0.1	-0.2	16.8	0.1	0.1	-0.3	2.168
Netherland	3	5	3.4	9.6	6.9	..	2.2	3.9	-1	..	3.7	-1.1	-2.1	..	0.184
New Zealand	40.7	0.3	..	0.1	0.2	-0.1	..	01	-0.2	7.2	..	-0.1	0.3	-0.9	4.263
Norway	283.6	-0.1	-47.6	-0.4	-2.3	0.5	0.1	0,5	0.5	8.5	42.6	0.1	0.7	-0.6	2.161
Pakistan	-46.4	-0.7	-12.7	0.1	-0.6	0.1	0.1	0.2	0.5	-0.1	18.3	0.3	-0.1	-0.4	1.186
Peru	-229.1	-0.1	-8.9	-0.6	0.1	0.8	0.5	-0.1	-6.3	0.3	22.2	-0.1	-0.8	-0.1	2.365
Paraguay	29.7	-0.3	-7.1	0.3	0.2	-0.2	0.1	0.4	-0.1	-1.9	8.6	0.5	0.1	-0.1	5.716
Philippines	64	..	-0.9	..	..	..	..	..	0.7	..	..	..	6.3	..	1.359
Portugal	1.3	3.9	-3.8	6.8	-4.1	-5.6	1.7	1.8	2.4	-1.3	3.8	3.2	8.9	-6.5	0.17
Qatar	3.1	1.7	1.2	..	..	1.3	2.9	8.4	-5.7	2.6	-9.8	1.1	..	..	0.082
South Africa	91.6	-0.2	-40.1	-0.1	-0.9	..	0.1	-0.9	0.3	0.6	42.6	0.1	-0.9	-0.9	1.216
Sri Lanka	-1	2.2	-1.4	2.5	9	-2.9	-3.5	-9	3.1	9.3	2.3	-1.3	1	-2.6	1.636
Switzerland	-1.3	6.7	1.4	5.3	5.9	2.5	3.7	2.7	-3	1.2	2.2	-3.9	-9	-2.8	0.411
Sweden	45.6	0.3	-0.1	0.2	0.1	0.1	0.1	5.	..	..	0.5	..	..	..	0.954
Turkey	95.3	0.5	-22.6	1	0.1	-0.1	6.3	-0.9	-0.9	0.3	23.1	-0.1	0.9	-0.6	1.786
United States	-67.5	-0.3	-31.1	..	0.2	0.1	5.	..	-0.2	-14.6	39.6	6.3	0.5	-1.6	0.177
United Kingdom	19.6	0.1	2.5	5.2	0.1	-0.1	0.1	6.3	0.2	0.8	-0.9	0.5	0.2	-0.9	0.058
Uruguay	9.2	-7.8	-2.6	-1.8	..	6.3	2	-3.5	8.3	-6.1	2.6	-7.2	5.1	-3.2	1.247
Retentionfrequency		39	35	38	31	33	36	37	36	37	35	32	35	33	0.058

Figure 5.3: Graph of the Retention Variables in Elastic Net for Balance of Trade Modeling

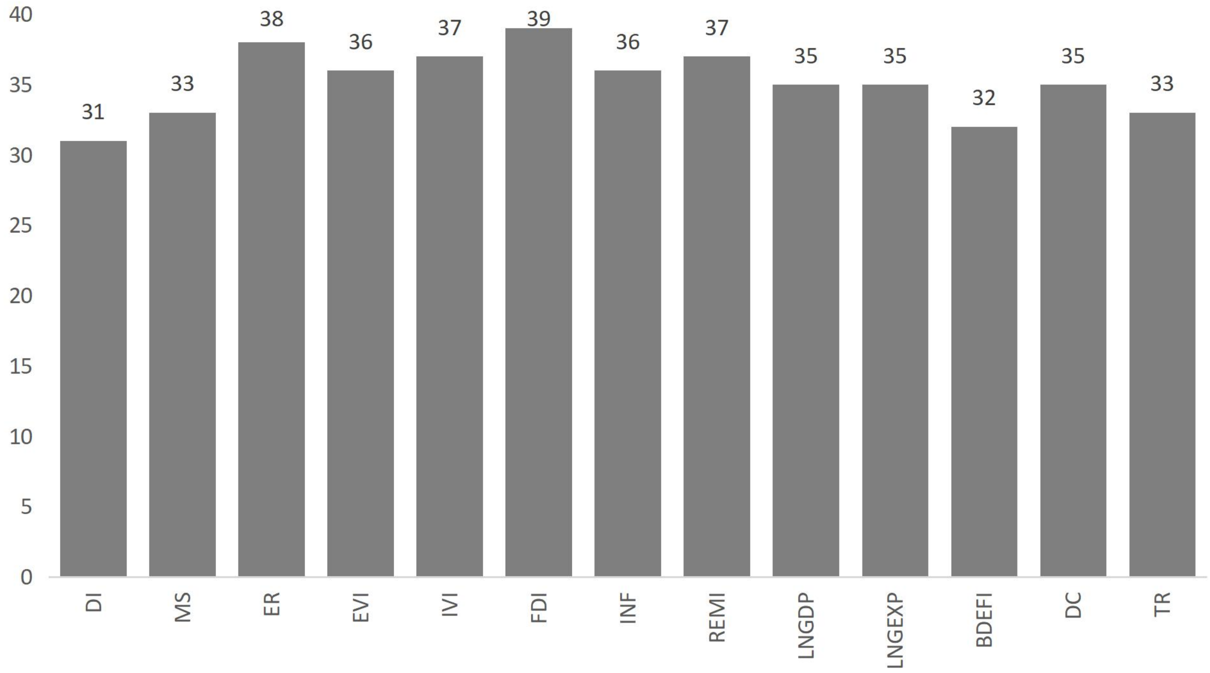

Figure 5,3 summarizes the retention frequency of variables in the BOT model using Elastic Net. The results show that focus variable foreign direct investment (FDI) is most likely significant, with a 39 out of 43 retention frequency. The next most common variables are Exchange rate (ER), Import value index (IVI), and personal Remittances (REMI) with retention frequencies of 38/43 and 37/43, respectively.

5.4.4 Results of Weighted Average Least Square

The Weighted Average Least Square Regression (WALS) method has been utilized to assess the significance of variables, aiding us in the process of model selection and specification. Table5.4 displays the estimation outcomes obtained through the WALS procedure. Within this table, you can observe the regression coefficients of various variables, which exhibit different signs across different countries. This variation in the signs of variable coefficients serves as an indicator of country-specific heterogeneity within our analysis. Our approach involves examining each country individually, revealing the diverse patterns of heterogeneity present within the model.

In the table, cells marked with "(...)" indicate the variables that have been excluded from the model by the Weighted Average Least Square procedure. For instance, in Row 1, we find that for Argentina, the variables "Foreign Direct Investment" (FDI), "Money Supply" (MS), "IVI," "Inflation" (INF), "LNGEXP," "BDEFI," "DC," and "Trade" (TR) were excluded by the WALS procedure due to their lack of significance.

Similarly, for Australia, the variables "FDI," "MS," "Exchange Rate" (ER), "EVI," "INF," "LNGEXP," "BDEFI," "DC," and "TR" were identified as statistically insignificant and, as a result, were omitted during the estimation process. In the last row of the table, you can observe the frequency with which each variable was retained across all the countries. Notably, among the 43 countries considered, the variable "LNGEXP" was significant in 37 cases, making it the most common significant variable, while the next most frequently significant variable, "TR" (Trade), was found to be significant in 29 cases.

Table 5.4: The Trade Modeling Results of Weighted Average Least Square Analysis

Country	Consta	FDI	LNGDP	ER	DI	MS	EVI	IVI	INF	REMI	LNGEXP	BDEFI	DC	TR	FRM
Argentina	53 .451	..	-26.307	1.635	-.215	..	.321	..	..	-	..	..	..	..	**2.192**
Australia	11 .991	..	-32.552	..	-1.358	..	..	.126	..	56.036	..	..	..	..	**1.508**
Austria	-34.573	.0746	..	-.486	..	..	-.015	-.023	-.495	..	17.272	.487	-.028	..	**4.039**
Bangladesh	..	..	-10.517	.178	.366	..	..	-.029	..	..	15.709	..	..	-.256	**1.07**
Belgium	..	..	-14.777	-.275	..	..	..	-.002	..	.028	13.820	..	..	-.069	**2.13**
Bhutan	..	..	3.458	..	..	..	.028	-.027	..	..	.768	..	..	..	**1.273**
Bulgaria	86.281	-.222	..	..	..	..	.038	..	.005	..	..	.071	..	..	**0.616**
Brazil	..	-1.696	-16.075	-3.342	..	.151	..	..	..	-1.890	19.563	..	..	..	**0.41**
Canada	12.0221	..	34.629	..	..	..	..	..	.214	..	34.864	.123 2	..	-.631	**2.565**
China	..	..	..	1.861	..	..	..	..	..	11.937	..	..	-.238		**1.612**
Chile	169.204	..	-36.448	..	-.037	-.043	..		.	-26.40	(35.480	..	-.012	-.604	**2.173**
Denmark	..	..	-22.035	..	-.232	.078	-.062	.006	.	..	25.991	..	-.028	-.313	**0.314**
France	18.0558	.173	-18.721	..	..	.139	..	..	..	..	14.947	..	..	-.402	**3.173**
Germany	..	..	-18.937	-1.898	..	..	...	.	-.283	..	17.392	-.198	..	-.314	**0.628**
Ghana	10.504	..	-15.866	4.281	..	-.431	..	..	..	..	12.845	..	..	..	**61.43**
Hungary	..	..	..	..	..	..	..	..	..	1.068	4.712	.130	..	..	**1.13**
India	21.295	-1.043	-16.820	..	..	.161	..	..	..	..	11.539	..	..	-.303	**0.391**
Indonesia	20.971	-1.316	..	..	..	..	...	-.020	..	..	-3.700	..	..	.168	**0.191**
Iran	-27.354	2.156	..	..	.367	..	..	..	..	..	19.349	-.286	..	-.194	**4.576**
Japan	..	..	..	..	1.241	..		..	-1.02	..	-17.813	..	..	..	**3.175**
Luxembour	..	..	13.227	.481	..	..	-.029	..	..	-.058	..	..	..	.0454	**1.146**
Malaysia	14.095	-.267	-41.072	. ..	..	..	..	..	..	1.280	39.466	..	.054	-.258	**1.06**
Maldives	7.115	..	-13.623	..	..	-.204	-.020	..	..	..	10.696	.006	..	-.046	**2.287**
Mexico	..	..	-24.829	-2.829	..	..	..	..	.062	..	22.338	..	..	..	**2.693**
Morocco	17.166	..	-20.294	..	..	-.067	.040	..	-.193	..	20.024	..	..	-.334	**1.293**
Nepal	..	..	-13.778	.154	..	..	..	..	..	..	13.325	..	..	-.319	**2.168**
Netherland	..	..	..	..	.134	..	..	.004	..	..	6.891	-.083 1	..	-.064	**0.184**
New Zealand	50.070	..	..	..	.230	..	..	..	-.293	..	2.229	-.128	.018	.	**4.263**

Norway	120.252	-.188	-29.875	..	..	-.298	-.019	..	..	..	31.042	.217	..	-.442	**2.161**
Pakistan	..	..	-11.225	.045	..	..	..	-.039	..	..	18.372	..	..	-.244	**1.186**
Peru	..	..	-17.526	..	..	..	0.436	-.020	-.022	-.266	19.067	-.089	-.365	-.140	**2.365**
Paraguay	..	..	-10.888	.008	.214	..	.055	-.009	-.049	-1.191	9.659	-.029	-.079	-.099	**5.716**
Philippines	174.011	..	-15.297	..	-.199	.083	.069	-.033	.0642	-1.067	11.065	.034	.050 5	-.171	**1.359**
Portugal	..	..	-34.217	..	.570	-.095	.002	.003	-.050	.002	32.307	.020	-.003	-.413	**0.17**
Qatar	..	-.812	..	..	-.786	.061	.003	-.004	-.069	-14.368	24.028	3.636	.082	.108	**0.082**
South Africa	118.134	-.2321	-41.368	-.2051	.057	-.063	.0478	-.008	.22458	5.179	42.934	.062	.030	-.873	**1.216**
Sri Lanka	..	...	-11.476	..	-.037	-.009	-.040	-.052	-.023	-.639	17.232	-.011	.044	-.198	**1.636**
Switzerland	-5.899	.003 (0.23)	-12.345	4.723	.039	.030	.001	.002	.047	.823	19.799	-.073	-.053 7	-.258	**0.411**
Sweden	59.152	.065	-18.462	.418	.084	-.029	-.004	-.001	-.0702	-.608	20.072	.022	.0144	-.331	**0.954**
Turkey	3.52	.1390	-23.318	3.627	.0352	-.0316	.005	-.012	.032	.582	23.666	-.068	-.003	-.602	**1.786**
United States	-30.526	-.089	-31.276	.0452	.1463	.101	-.009	.008	-.160	-25.337	38.522	-.115	-.034	-1.830	**0.177**
United Kingdom	25.990	-.002	2.347	4.401	.022	-.007	.003	.001	-.0241	.575	-.031	.001	.006	.003	**0.058**
Uruguay	19.017	-.474	-21.215	-.3971	.0198	.0904	-.0018	-.043	-.0179	2.613	24.608	-.1352	.0539	-.226	**1.247**
Retention Frequency		13	33	19	11	12	13	11	10	11	37	10	11	29	

Figure 5.4: Graph of Retention Variables in Weighted Average Least Square for Balance of Trade Modeling

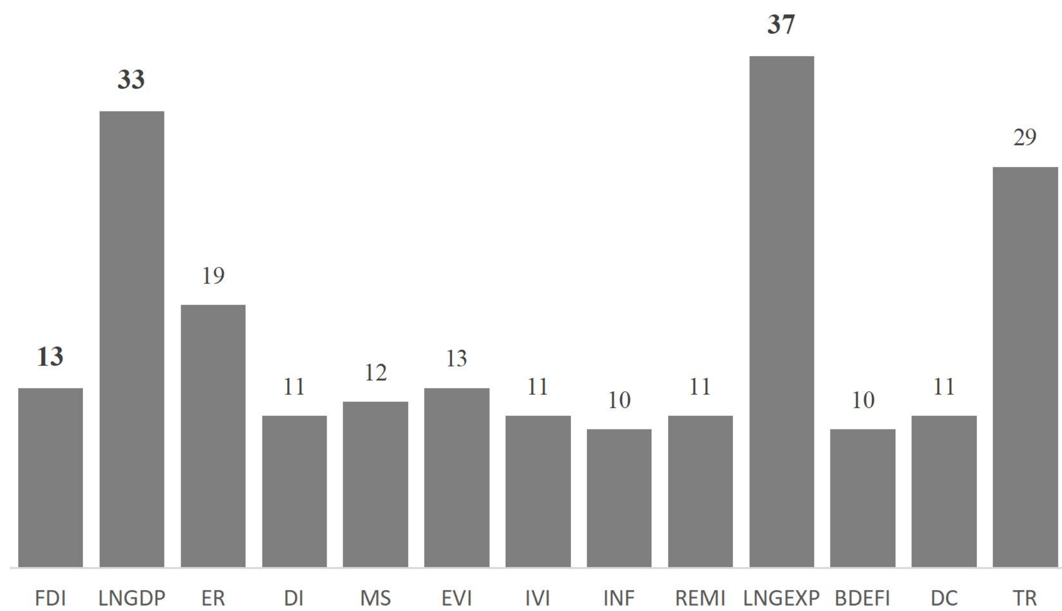

Figure 5.4 summarizes the retention frequency of variables in the BOT model using weighted average least squares (WALS). The results show that variable Government Expenditures (LNGEXP) are most likely significant, with 37 out of 43 retention frequencies. The next most common variables are government expenditures (LNGEXP) and gross domestic product (LNGDP) with retention frequencies 37/43 and 33/43, respectively.

5.4.5 Results of Encompassing Procedure

The process of model selection through encompassing involves multiple steps. In the final step, each model is presented separately, and the model with the lowest Root Mean Square Error (RMSE) is chosen. Subsequently, in the next step, we assess whether the model with the smallest RMSE encompasses the other models. In the third step, we construct the revised General Unrestricted Model (GUM) by combining the model with the smallest RMSE and the models that are not encompassed by it. We then simplify the General Unrestricted Model (GUM) using the General-to-Specific (GLS) methodology. The summarized results of this encompassing process can be found in Table 5.5.

Table 5.5 displays the outcomes of the estimation conducted through the encompassing procedure. This table provides the regression coefficients of various variables, which exhibit different signs across different countries. These differences in the signs of variable coefficients indicate the presence of country-specific heterogeneity, and the analysis considers each country individually to reveal this heterogeneity.

In the table, cells marked with "(...)" indicate the variables that have been excluded from the model by the Non-Nested encompassing procedure. For example, in Column 1, it is shown that for Argentina, the variables "Inflation" (INF), "Domestic Investment" (DI), "Personal Remittances" (REMI), and "Trade" (TR) with both current and lag values were excluded by the encompassing procedure due to their lack of significance.

Similarly, for Australia, the variables "INF," "LNGDP," "LNDEXP," "BDEFI," and "TR" were identified as statistically insignificant and were therefore removed during the estimation process. In the last column of the table, you can observe the frequency with which each variable was retained across all the countries. Remarkably, among the 43 countries considered, the lag value dependent on the variable "BOT_1" was found to be significant in 37 cases, making it the most commonly significant variable. The next most frequently significant variable was the "Export Value Index" (EVI), which was significant in 19 cases.

Table 5.5: The Results of Final Model (Non-Nested Encompassing) for Balance of Trade Modeling

County	Argentina	Australia	Austria	Bangladesh	Belgium	Bhutan	Bulgaria	Brazil	Canada	China	Chile	Retention Frequency
Variables												
Constant	..	..	..	..	..	34.391	2.010	..	..	4.667	33.940	**..**
BOT_1	0.387	0.613	0.729	0.730	0.753	0.287	..	0.973	..	0.384	..	**37**
DI	..	..	..	..	-0.496	..	0.309	..	..	-1.322	..	**13**
DI_1	..	..	..	0.320	..	..	..	..	0.588	1.726	..	**13**
BM	-0.766	0.685	..	-0.240	..	..	..	..	..	..	..	**16**
BM_1	..	..	..	..	..	0.021	-0.064	0.042	0.224	..	..	**15**
ER	0.765	..	..	0.345	0.229	..	..	-1.315	-0.016	-0.016	-0.016	**17**
ER_1	..	16.2134	..	..	..	..	-1.776	-3.372	5.449	..		**13**
EVI	0.122	..	..	0.049	..	0.017	0.060	0.265	..	..	0.243	**19**
EVI_1	..	..	..	-0.028	..	..	..	-0.218	..	..	..	**09**
IVI	-0.072	..	..	-0.028	..	-0.021	-0.015	-0.045	..	..	..	**12**
IVI_1	..	..	..	..	..	..	-0.007	0.041	..	..	..	**10**
FDI	..	..	..	..	..	..	-0.171	..	..	..	..	**08**
FDI_1	..	..	..	..	..	..	..	0.806	0.241	1.177	..	**07**
INF	..	..	..	..	..	..	..	-0.001		..	..	**04**
INF_1	..	..	..	..	..	..	0.008	..	..	..	..	**04**
P(remi)	..	52.181	..	..	..	..	..	..	..	12.517		**07**
P(remi)_1	..	-47.434	..	..	..	..	..	..	..	..	-11.360	**08**
LnGDP	-9.510	..	..	..	..	..	..	..	1.119	..		**17**
LnGDP_1	10.073	..	..	..	..	..	..	..	..	-8.455	-11.768	**15**
LnGexp	2.374	..	-0.523	..	..	..	..	..	..	..	..	**11**
LnGexp_1	..	..		..	..	..	..	..	..	..	..	**05**
Bdefi	-2.229	..	..	..	..	..	..	-0.087	-0.231	0.626	..	**05**
Bdefi_1	..	..	..	..	..	..	..	..	..	..	..	**0**
DC	-0.305	-2.000	..	..	..	..	..	..	..	..	..	**06**
DC_1	0.916	1.465	..	..	..	..	..	..	..	..	..	**08**
TR	..	..	..	..	..	..	..	..	0.282	..	..	**09**

County	**Argentina**	**Australia**	**Austria**	**Bangladesh**	**Belgium**	**Bhutan**	**Bulgaria**	**Brazil**	**Canada**	**China**	**Chile**	**Retention**
TR_1	..	..	..	..	..	..	..	..	-0.210	..	..	**05**
RMSE	**0.092**	**0.052**	**0.093**	**0.011**	**0.107**	**0.053**	**0.148**	**0.035**	**0.009**	**0.065**	**0.024**	**Minimum**

Country **Variables**	**Denmark**	**France**	**Germany**	**Ghana**	**Hungary**	**India**	**Indonesia**	**Iran**	**Japan**	**Luxembourg**	**Malaysia**	**Retention Frequency**
Constant	..	89.028	..	27.272	17.746	..	..	..	10.120	2.810	..	**..**
BOT_1	0.727	0.209	0.663	0.408	0.658	0.408	..	0.511	0.795	0.584	0.952	**37**
DI	..	..	..	..	..	35.352	..	..		9.841	..	**13**
DI_1	..	..	0.372	..	-0.106	-35.186	..	..	..	..	0.745	**13**
BM	..	..	..	-0.230	..	0.526	..	-0.276	..	..	..	**16**
BM_1	..	..	..	..	..	-0.343	-0.186	..	..	10.168	..	**15**
ER	..	..	..	1.998	..	..	..	..	..	0.171	..	**17**
ER_1	..	..	1.559	..	..	..	..	0.007	..	..	..	**13**
EVI	..	..	..	..	..	0.032	0.165	..	..	-0.009	0.017	**19**
EVI_1	..	..	..	..	..	..	-0.157	..	..	..	..	**09**
IVI	..	-0.011	..	..	..	-0.014	..	..	..	..	..	**12**
IVI_1	..	..	..	..	..	..	..	..	..	..	..	**10**
FDI	..	..	-0.158	..	..	..	-2.222	..	..	0.026	-0.354	**08**
FDI_1	..	0.281	..	..	..	..	..	..	..	..	..	**07**
INF	..	-0.246	..	..	..	..	..	..	..	..	..	**04**
INF_1	..	..	..	0.065	..	0.175	..	..	..	..	04	**04**
P(remi)	..	..	..	..	..	-1.860	..	..	..	..	-0.758	**07**
P(remi)_1	..	..	-5.440	..	..	..	-1.571	..	..	..	..	**08**
LnGDP	-2.422	-1.712	0.663	..	..	0.982	6.910	..	..	..	..	**17**
LnGDP_1	3.054	..	..	..	..	..	-4.935	1.556	..	..	..	**15**
LnGexp	..	..	..	..	..	-0.257	..	..	..	0.344	-0.126	**11**
LnGexp_1	..	0.353	..	..	..	..	..	..	..	..	..	**05**
Bdefi	..	..	..	..	..	..	..	..	..	..	..	**05**

Country / Variables	Denmark	France	Germany	Ghana	Hungary	India	Indonesia	Iran	Japan	Luxembourg	Malaysia	Retention Frequency
Bdefi_1	..	..	..	..	..	..	..	..	..	..	..	**0**
DC	..	-0.010	..	..	..	-0.730	..	..	..	..	..	**06**
DC_1	..	..	..	..	..	0.305	0.088	..	..	..	..	**08**
TR	-0.104	..	..	..	..	0.164	0.150	..	..	..	..	**09**
TR_1	0.084	..	..	..	..	..	..	..	..	..	..	**05**
RMSE	**0.021**	**0.019**	**0.003**	**0.124**	**0.01**	**0.037**	**0.024**	**0.012**	**0.099**	**0.014**	**0.017**	**Minimum value 0.003**

Country Name / Variables	Maldives	Mexico	Morocco	Nepal	Netherland	New Zealand	Norway	Pakistan	Peru	Paraguay	Philippines	Retention Frequency
Constant	18.209		..	54.098	..	30.359	..	..	15.046	..	..	**..**
BOT_1	0.382	0.688	0.748	0.476	0.577	0.485	0.766	..	0.704	0.501	0.434	**37**
DI	..	..	1.066	-34.773	0.061	0.126	..	..	-0.004	..	..	**13**
DI_1	..	..	..	34.282	..	..	-0.682	..	-0.003	..	..	**13**
BM	..	0.543	..	-0.375	-0.298	..	..	..	0.104	..	-0.334	**16**
BM_1	..	..	..	0.298	..	0.207	..	..	-0.169	0.290	0.290	**15**
ER	1.285	-1.435	..	..	1.594	-1.085	6.367	-0.228	..	0.004	..	**17**
ER_1	..	..	..	..	-0.804	..	-6.381	-0.216	..	-0.003	..	**13**
EVI	-0.020	-0.183	0.106	-0.002	-0.006	..	..	0.086	..	..	0.111	**19**
EVI_1	..	..	-0.082	..	..	-0.009	..	..	..	..	-0.095	**09**
IVI	..	..	-0.007	0.003	..		..	-0.039	..	..	-0.078	**12**
IVI_1	..	-0.007	..	0.035	..	..	..	0.002	..	..	0.052	**10**
FDI	..	..	..	..	..	..	..	-2.361	..	..	..	**08**
FDI_1	..	..	..	6.743	..	..	..	..	..	..	..	**07**
INF	..	..	..	..	..	..	..	..	..	..	..	**04**

Country Name / Variables	Maldives	Mexico	Morocco	Nepal	Netherland	New Zealand	Norway	Pakistan	Peru	Paraguay	Philippines	Retention Frequency
INF_1	0.159	..	..	..	..	..	..	..	..	..	..	**04**
P(remi)	..	..	..	..	..	..	..	..	..	..	..	**07**
P(remi)_1	..	..	..	..	..	..	..	-1.496	..	..	..	**08**
LnGDP	..	-8.531	..	-24.749	1.022	..	39.493	..	..	-8.594	-10.575	**17**
LnGDP_1	-8.481	8.724	..	..	..	..	-39.579	1.892	..	7.098	11.684	**15**
LnGexp	..	-0.594	..	..	-0.107	..	0.464	..	-0.245	15.787	..	**11**
LnGexp_1	..	..	..	..	..	..	..	..	-0.411	-12.991	..	**05**
Bdefi	..	..	..	..	..	..	..	..	..	-0.060	..	**05**
Bdefi_1	..	..	..	..	..	..	..	..	..	..	..	**0**
DC	..	..	..	0.341	..	..	..	..	..	..	..	**06**
DC_1	..	-0.071	..	..	..	..	..	..	..	..	..	**08**
TR	..	0.623	..	-0.228	-0.027	..	..	..	..	-0.219	..	**09**
TR_1	..	..	..	..	..	..	..	..	..	0.222	..	**05**
RMSE	**0.036**	**0.031**	**0.013**	**0.054**	**0.059**	**0.009**	**0.028**	**0.053**	**0.109**	**0.036**	**0.039**	**Minimum value 0.009**

Country Name / variables	Portugal	Qatar	South Africa	Sri Lanka	Switzerland	Sweden	Turkey	United States	United Kingdom	Uruguay	Retention Frequency
Constant	..	..	169.915	19.461	-41.588	19.096	134.600	..	2.143	..	**..**
BOT_1	0.970	0.953	0.354	0.518	0.329	..	0.503	1.044	0.97	0.876	**37**
DI	89.787	..	..	..	..	..	0.184	..	..	..	**13**
DI_1	-90.274	..	..	..	..	..	-0.172	..	..	-0.083	**13**
BM	9.630	..	..	..	..	0.112	0.236	..	0.003	0.293	**16**
BM_1	-9.508	..	0.277	..	0.023	-0.261	..	..	..	..	**15**
ER	0.047	..	0.413	..	..	..	4.196	..	..	..	**17**

ER_1	..	..	..	..	..	0.654	..	..	..	-0.629	**13**
EVI	0.037	..	..	..	..	..	-0.037	..	..	..	**19**
EVI_1	..	..	..	0.072	..	..	..	-0.131	..	-0.159	**09**
IVI	..	..	..	-0.048	..	..	..	..	..	..	**12**
IVI_1	0.008	..	..	0.006	..	..	0.031	0.091	..	0.039	**10**
FDI	0.004	..	..	..	..	..	-1.685	..	..	..	**08**
FDI_1	-0.010	..	..	..	..	..	..	0.686	..	..	**07**
INF	0.736	..	..	..	..	..	..	..	0.041	..	**04**
INF_1	..	..	..	..	..	..	..	..	..	..	**04**
P(remi)	-0.013	-44.734	..	..	..	5.761	..	..	..	..	**07**
P(remi)_1	..	52.280	..	..	..	..	-1.605	..	..	13.755	**08**
LnGDP	-3.837	..	-5.518	..	..	..	-4.856	..	0.018	..	**17**
LnGDP_1	..	..	..	..	3.042	1.482	..	..	..	0.543	**15**
LnGexp	..	..	..	..	..	..	..	..	..	3.878	**11**
LnGexp_1	..	..	..	..	..	-0.312	..	..	..	-4.105	**05**
Bdefi	..	..	..	..	..	..	..	..	..	..	**05**
Bdefi_1	..	..	..	..	..	..	..	..	..	..	**0**
DC	..	..	..	..	..	..	..	..	0.007	..	**06**
DC_1	0.045	..	..	..	..	..	0.035	..	0.003	..	**08**
TR	-0.144	..	..	..	..	..	..	..	..	..	**09**
TR_1	0.095	..	-0.286	..	..	..	..	..	..	..	**05**
RMSE	**0.057**	**0.004**	**0.032**	**0.041**	**0.041**	**0.012**	**0.036**	**0.005**	**0.005**	**0.017**	**Minimum value 0.004**

Figure 5.5: Graph of Retention of Variables in Encompassing Procedure for Balance of Trade Modeling

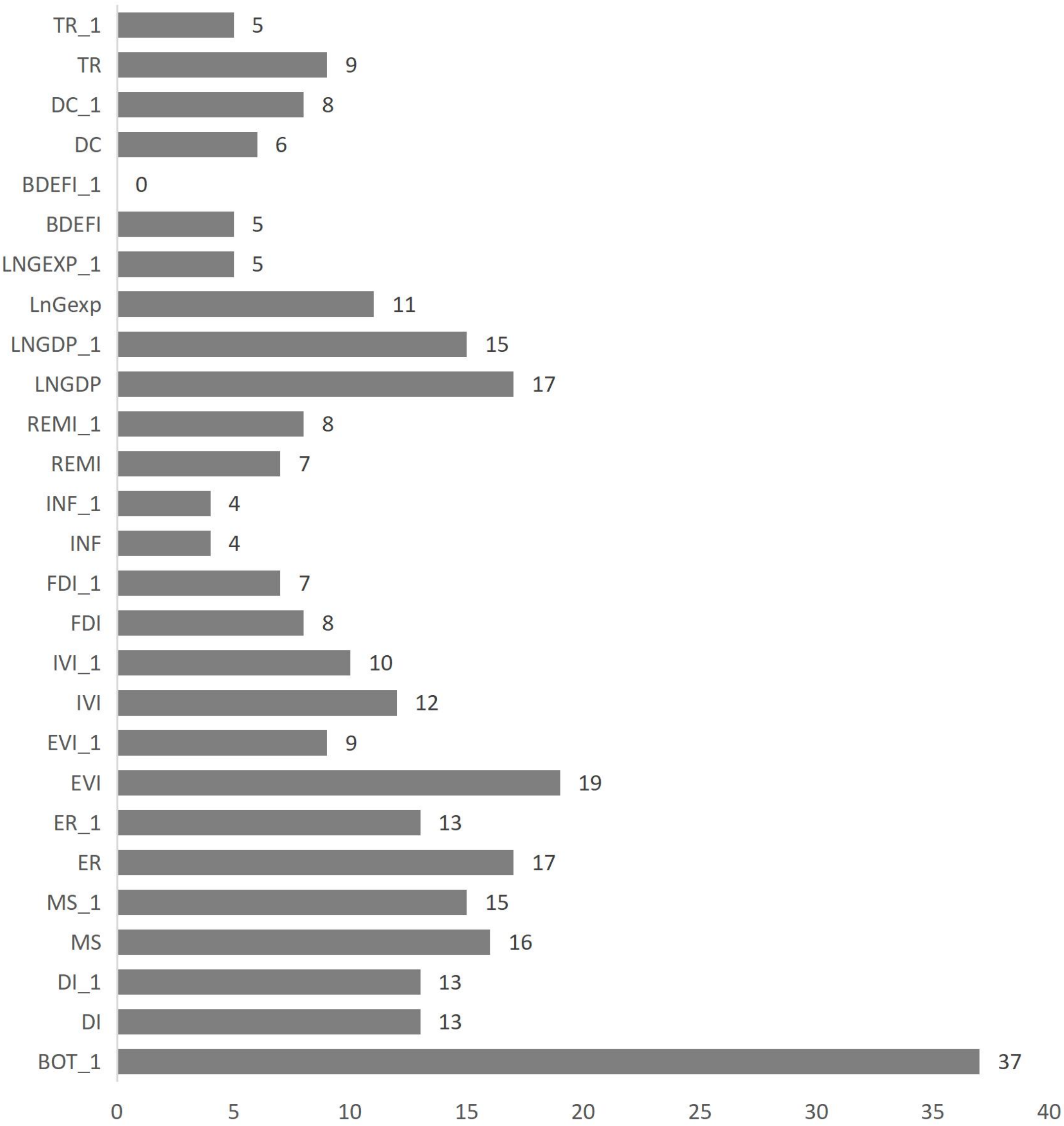

Figure 5.5 provides a summary of the frequency at which variables are retained in the Balance of Trade (BOT) model using the Non-Nested Encompassing procedure. The findings reveal that the variable "BOT_1" is consistently significant, appearing in 37 out of the 43 regressions. Following closely are the variables "Export Value Index" (EVI), "Exchange Rate" (ER), and "Personal Remittances" (REMI), which show retention frequencies of 19 out of 43 and 17 out of 43, respectively.

Automatic Model Selection Procedure

The Automatic Model Selection Procedure is an algorithmic approach for model selection within the General-to-Specific framework. It operates by first creating a general unrestricted model and then employs an advanced search technique known as "tree search" instead of multiple exhaustive searches. This tree search method systematically eliminates irrelevant sets of variables through diagnostic testing. Subsequently, the algorithm reunites different sub-models to arrive at the final selected model. This approach is often referred to as a 3rd generation algorithm and is named "Autometrics." Autometrics is integrated into the Pc-Give software suite as one of its components.

5.4.6 Results of Autometrics Procedure

Table 5.6 displays the results obtained from the estimation process conducted using the Autometrics procedure.The table displays regression coefficients for various variables, and these coefficients exhibit different signs across different countries. This variance in the signs of variable coefficients serves as an indication of country-specific heterogeneity, highlighting that we have examined each country individually to uncover this diversity within the model. Additionally, the final row of the table presents the Root Mean Square Errors (RMSE) for each estimated model.

Cells marked with "(...)" in the table indicate the variables that have been excluded from the model by the Autometrics procedure. For instance, in Column 1, it is indicated that, for Argentina, the Autometrics procedure excluded the variables "DI," "MS," "ER," "FDI," "INF," "REMI," "LNGDP," and values of "BDEFI" along with both its current and lag values due to their insignificance.

Similarly, for Australia, both the current and lag values of the variables "MS," "ER," "IVI," and "INF" were identified as statistically insignificant and, as a result, were omitted during the estimation process. In the last column of the table, you can observe the frequency with which each variable was retained across all the countries. Remarkably, among the 43 countries considered, the variable "LNGEXP" was found to be significant in 41 cases, making it the most frequently significant variable in the analysis.

Table 5.6: The Results of Autometrics for Balance of Trade Modeling

Country / Variables	Argentina	Australia	Austria	Bangladesh	Belgium	Bhutan	Bulgaria	Brazil	Canada	China	Chile	Retention Frequency
Constant	237.238	1621.29	-162.173	..	..	82.896	..	..	49.385	512.046	195.873	
BOT_1	0.732	..	0.722	..	0.045		..	..	..	0.410	..	**19**
DI	..	-4.962	..	..	4.398	..	0.076	0.076	..	-1.840	..	**18**
DI_1	..	..	..	..	..	..	..	..	0.398	2.972	..	**14**
MS	..	..	..	..	2.421	..	0.085	0.085	0.011	0.164	..	**13**
MS_1	..	..	..	..	..	..	..	..	..	-0.111	..	**6**
ER	..	..	..	0.172	-9.48	..	-4.975	-4.975	2.899	..	..	**20**
ER_1	..	..	..	..	..	..	2.829	2.829	..	..	..	**13**
EVI	0.203	0.140	-0.009	0.043	..	..	..	..	..	0.1070	..	**14**
EVI_1	..	0.235		..	..	..	..	..	..	-0.047	0.085	**5**
IVI	-0.131	..	..	-0.038	..	-0.044	-0.014	-0.014	-0.042	..	-0.010	**20**
IVI_1	0.163	..	..	..	..	..	0.013	0.013	0.039	..	..	**14**
FDI	..	3.997	..	-2.357	..	..	-0.251	-0.251	..	..	..	**15**
FDI_1	..		..	..	..	..	..	..	-0.103	0.951	..	**9**
INF	..	..	-0.457	..	..	-0.102	0.009	0.009	..	..	0.130	**13**
INF_1	..	..	..	..	..	-0.218	0.010	0.010	..	0.234	..	**15**
P(remi)	..	140.104	..	..	0.022	1.326	-0.709	-0.709	-3.123	..	..	**09**
P(remi)_1	..	..	..	..	..	..	..	..	3.128	..	..	**09**
LnGDP	..	..	-4.526	-15.154	-18.511	..	..	..	-28.348	-18.499	-39.217	**29**
LnGDP_1	..	-49.870	5.208	..	..	..	..	..	..	..	8.564	**14**
LnGexp	11.553	-33.820	16.605	18.919	14.076	..	2.359	2.359	35.762	-2.389	39.857	**41**
LnGexp_1	-22.178	20.017	-10.218	..	..	-1.456	..	..	-4.965	1.967	-12.404	**19**
Bdefi	0.206	..	..	-0.417	..	..	..	..	..	2.972	0.062	**16**
Bdefi_1	..	1.539	..	..	..	..	..	..	..	..	-0.050	**6**

Country Variables	Argentina	Australia	Austria	Bangladesh	Belgium	Bhutan	Bulgaria	Brazil	Canada	China	Chile	Retention Frequency
DC	..	..	..	..	..	..	-0.166	-0.166	..	..	-0.064	**16**
DC_1	0.342	2.053	..	..	..	..	..	..	..	-2.972	0.0397	**14**
TR	0.459	3.088	-0.142	-0.369	-0.090	0.093	0.093	0.093	-0.465	..	-0.517	**31**
TR_1	-0.335	..	0.097	..	..	..	-0.093	-0.093	..	0.167	0.136	**14**
RMSE	**3.096**	**9.508**	**3.039**	**2.070**	**2.140**	**1.173**	**0.856**	**0.5101**	**0.565**	**1.712**	**2.373**	**Minimum 0.510**

Country Variables	Denmark	France	Germany	Ghana	Hungary	India	Indonesia	Iran	Japan	Luxembourg	Malaysia	Retention Frequency
Constant	..	259.733	75.1782	69.495	..	2.283	9.090	-17.713	..	-10.349	..	
BOT_1	..	..	0.745	0.798	..	..	..	0.489	..	0.883	0.786	**19**
DI	..	0.314	..	..	..	29.421	..	..	..	68.524	..	**18**
DI_1	..	..	..	..	..	-40.4379	..	..	..	-19.676	0.422	**14**
MS	0.113	0.282	..	..	..	0.542	-0.303	0.267	..	..	..	**13**
MS_1	..	..	..	..	..	-0.183	-0.127	-0.325	..	4.2862	..	**6**
ER	..	-0.381	-4.959	..	-0.027		-0.001	..	0.220	0.021	..	**20**
ER_1	..	..	2.853	..	..	0.277	-0.001	..	-0.118	..	..	**13**
EVI	-0.104	0.025	..	0.037	..	..	..	..	..	-0.012	..	**14**
EVI_1	..	..	..	..	..		..	..	..	0.086	..	**5**
IVI	0.006	..	..	-0.052	-0.021	..	0.041	..	..	0.001	..	**20**
IVI_1	..	..	..	0.050	0.017	..	-0.023	..	..	..	..	**14**
FDI	..	..	-0.193	..	..	..	-0.741	..	..	0.008	-0.207	**15**
FDI_1	..	..	..	0.555	..	..	..	..	..	-0.019	..	**9**
INF	..	..	..	..	..	-0.105	-4.460	..	-1.279	0.286	..	**13**
INF_1	..	..	..		0.148	..	6.962	..	0.730	..	..	**15**

Country Variables	Denmark	France	Germany	Ghana	Hungary	India	Indonesia	Iran	Japan	Luxembourg	Malaysia	Retention Frequency
P(remi)	..	..	..	..	..	-3.594	..	..	..	..	..	**09**
P(remi)_1	..	..	..	..	1.417	..	..	2.713	..	..	..	**09**
LnGDP	-19.536	-33.711	-27.528	..	..	-14.677	-38.362	..	53.743	..	-36.540	**29**
LnGDP_1	..	..	28.152	..	-2.952	..	5.307	..	-34.334	-6.356	30.012	**14**
LnGexp	23.806	28.161	23.890	15.340	5.365	8.407	29.576	21.060	-19.853	-3.019	37.343	**41**
LnGexp_1	..	..	-27.018	..	..	..	..	-12.486	..	3.009	-30.043	**19**
Bdefi		..	-0.157	..	..	-0.161	..	..	-0.389	0.154	..	**16**
Bdefi_1	..	..	..	..	0.22	..	..	..	..	0.102	..	**6**
DC	-0.051	..	..	..	..	-0.671	..	..	..	-0.064	..	**16**
DC_1	..	..	..	..	..	0.389 7	-0.050	..	..	0.018	..	**14**
TR	-0.200	-0.753	-0.33	..	..	..	-0.455	..	0.805	..	-0.234	**31**
TR_1	..	..	0.486	..	..	..	0.176	..	-0.267	-0.044	0.192	**14**
RMSE	**0.6446**	**0.573**	**0.688**	**1.439**	**1.180**	**0.791**	**0.991**	**5.576**	**3.775**	**1.186**	**1.030**	**Minimum 0.573**

Country Variables	Maldives	Mexico	Morocco	Nepal	Netherland	New Zealand	Norway	Pakistan	Peru	Paraguay	Philippines	Retention Frequency
Constant	..	3.746	155.586	..	..	30.886	5.017	-9.639	..	..	7.791	
BOT_1	0.879	0.295	..	..	0.386	0.417	..	..	0.536	..	0.452	**19**
DI	..	-0.067	..	6.325	0.106	0.141	..	..	..	0.368	..	**18**
DI_1	..	-0.384	..	..	..	..	-0.389	..	-0.002	-0.202	..	**14**
MS	..	..	-0.097	..	..	..	-0.196	..	..	..	0.424	**13**
MS_1	..	..	..	..	..	..	..	..	..	..	..	**6**
ER	1.513	-0.860	-0.344	0.224	0.823	-0.741	..	..	..	..	-0.218	**20**
ER_1	-1.669	..	..	..	..	..	..	-0.062	-2.662	0.001	..	**13**
EVI	..	..	0.049	..	-0.011	..	-0.017	..	..	..	..	**14**

Country	Maldives	Mexico	Morocco	Nepal	Netherland	New	Norway	Pakistan	Peru	Paraguay	Philippines	Retention
EVI_1	..	..	..	..	..	..	..	..	..	..	..	**5**
IVI	-0.065	0.0037	..	..	..	..	..	-0.050	-0.065	-0.019	..	**20**
IVI_1	0.078	-0.004	..	..	..	..	..	..	0.046	..	..	**14**
FDI	-0.529	-0.814	..	..	..		-0.242	-1.371	..	..	-0.994	**15**
FDI_1	..	..	..	..	..	..	-0.307	1.314	..	..	-1.013	**9**
INF	..	0.135	-0.200	..	..	..	..	-0.112	..	..	..	**13**
INF_1	..	0.110	-0.146	..	..	..	..	-0.138	..	..	..	**15**
P(remi)	..	..	..	..	0.048	..	..	..	..	..	..	**09**
P(remi)_1	1.164	..	0.661	..	..	..	..	-0.469	-0.490	..	..	**09**
LnGDP	-8.486	-30.348	-23.283	-13.625	..	..	-37.526	..	-9.897	..	-24.332	**29**
LnGDP_1	9.036	..	..	..	..	..	38.737	-7.225	..	..	..	**14**
LnGexp	19.303	27.140	21.224	16.713	1.290	..	..	19.972	30.157	14.024	21.657	**41**
LnGexp_1	-19.670	..	..	..	..	..	..	-5.738	-18.389	-10.387	..	**19**
Bdefi	0.314	-0.137	..	..	-0.071	..	0.274	..	-0.302	..	0.113	**16**
Bdefi_1	-0.206	..	..	..	..	..	..	..	-0.271	..	..	**6**
DC	..	0.023	0.131	..	..	0.141	..	-0.195	0.204	..	-0.410	**16**
DC_1		0.094	-0.122	..	..	..	..	..	..	..	0.308	**14**
TR	..	-0.433	-0.403	-0.340	-0.026	..	-0.487	..	..	-0.153	-0.273	**31**
TR_1	..	..	..	..	..	..	..	..	..	..	..	**14**
RMSE	**2.487**	**2.993**	**1.191**	**2.468**	**0.284**	**0.263**	**1.611**	**1.486**	**2.465**	**1.716**	**1.459**	**Minimum 0.26**

Country Name	Portugal	Qatar	South Africa	Sri Lanka	Switzerland	Sweden	Turkey	United States	United Kingdom	Uruguay	Retention Frequency
Variables											
Constant	10.241	..	14.520	-114.210	-1.252	22.339	81.954	..	1.2697	..	
BOT_1	0.229	-0.210	..	..	..	..	0.257	..	0.981.	0.354	**19**
DI	..	-0.697	0.125	..	..	..	0.120	0.659	-0.001	0.028	**18**

Country Name **Variables**	**Portugal**	**Qatar**	**South Africa**	**Sri Lanka**	**Switzerland**	**Sweden**	**Turkey**	**United States**	**United Kingdom**	**Uruguay**	**Retention Frequency**
DI_1	34.489	-0.387	-0.179	..	..	..	-0.115	-0.391	..	0.073	**14**
MS	-19.358	-0.032	..	..	..	..	..	..	0.002	-0.140	**13**
MS_1	..	-0.089	..	..	0.038	-0.086	..	0.065	..	..	**6**
ER	..	-33.690	..	..	6.236		5.518	..	..	-0.373	**20**
ER_1	..	62.077	..	..	..	0.592	-4.293	-27.971	-0.068	..	**13**
EVI	..	0.004	..	-0.031	..	..	..	..	-0.001	-0.018	**14**
EVI_1	..	0.028	..	..	..	..	..	0.046	..	..	**5**
IVI	..	0.006	..	-0.066	..	..	-0.018	-0.031	..	-0.058	**20**
IVI_1	2.003	-0.0002	..	..	0.003	..		..	..	0.042	**14**
FDI	..	0.388	..	..	..	..	-1.334	..	-0.001	-0.417	**15**
FDI_1	..	-0.139	..	..	..	..	..	..	-0.001	-0.196	**9**
INF	..	-0.072	0.262	..	..	..	..	..	0.043	..	**13**
INF_1	0.104	-0.075	..	..	..	0.097	..	0.180	..	-0.082	**15**
P(remi)	..	-14.313	..	-0.473	..	..	..	-56.794	..	..	**09**
P(remi)_1	..	-14.863	7.324	..	..	..	..	..	..	17.212	**09**
LnGDP	-26.840	-3.844	-40.023	-14.572	-13.094	-22.609	-20.713	-31.196	..	-15.993	**29**
LnGDP_1	..	-3.349	..	7.399	..		..	33.856	..	4.543	**14**
LnGexp	26.023	31.559	42.874	22.243	22.384	20.774	21.107	29.413	0.022	25.7757	**41**
LnGexp_1	..	-3.313	-2.585	-6.486	..	..	..	21.315	..	-11.664	**19**
Bdefi	..	15.227	..	-0.032	-0.150	..	..	..	..	..	**16**
Bdefi_1	..	11.661	..	..	..	..	..	..	..	-0.189	**6**
DC	-0.083	0.096	0.028	..	..	..	..	..	-0.006	0.165	**16**
DC_1	0.084	0.040	..	..	-0.082	..	0.014	-0.021	..	..	**14**
TR	-0.402	0.081	-0.919	-0.155	-0.281	-0.301	-0.501	1.008	..	-0.282	**31**
TR_1	0.067	0.068	..	..	-0.052	..	..	0.745	..	..	**14**
RMSE	**0.670**	**0.082**	**1.616**	**1.616**	**0.842**	**0.540**	**1.527**	**0.317**	**0.055**	**1.824**	**Minimum 0.055**

Figure 5.6: Graph of Retention of Variables in Autometrics Procedure for Balance of Trade Modeling

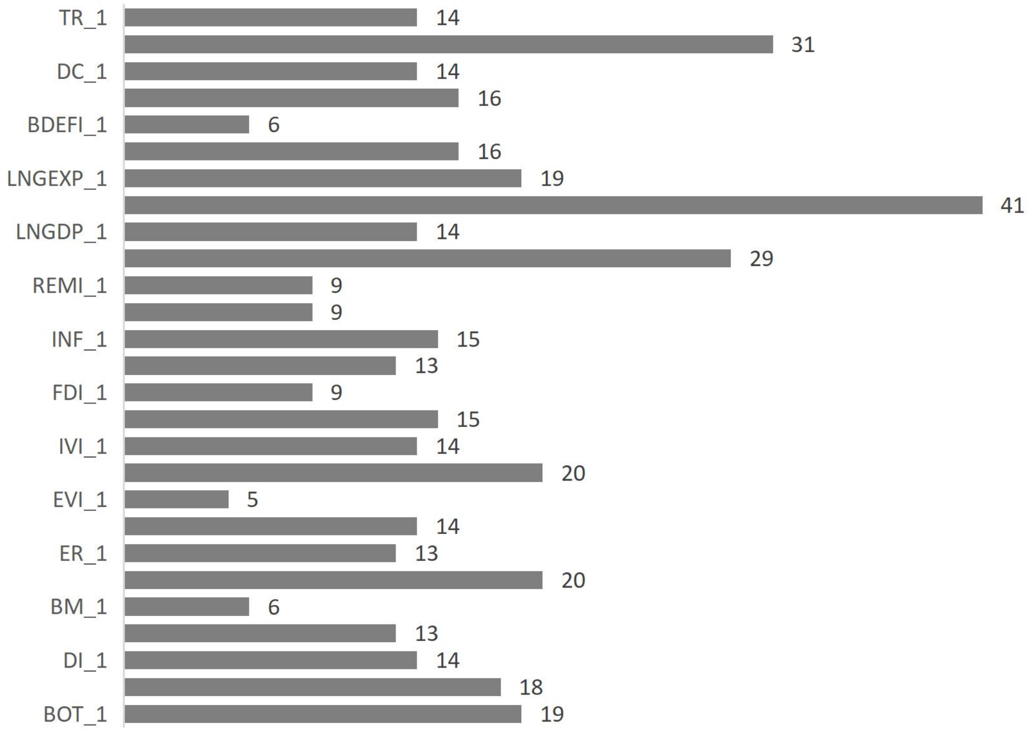

Figure 5.6 summarizes the frequency of retention variables in the BOT model using the Autometrics Procedure. The results show that LNGEXP is most likely significant, with a retention frequency of 41 out of 43. The next most common variables are TR and LNGDP, with retention frequencies of 31 and 29 out of 43.

Model Selection Procedures based on Parameter Sensitivity

Any variable y may have a large number of potential determinants. Suppose X_i is a variable of interest, taking a set of control variables gives some coefficients of X_i. Changing the control variables will change the coefficients of estimate. There are many possible combinations of control variables, which will lead to different coefficients. The idea behind parameter consistency is that if X_i is having focus variables relation with y, its coefficients should be possible given any combination of control variables.

5.4.7 Results of Extreme Bound Analysis

The Extreme Bound Analysis procedure relies on two estimators to identify variables for model selection. This analysis aids in determining the frequency of retained variables, which is crucial in our model selection process. The following results of the Extreme Bound Analysis are presented in Tables 5.7 and 5.8.

Table 5.7 provides the outcomes of the estimation process using the Extreme Bound Analysis. This table offers regression coefficients for various variables, and these coefficients exhibit different signs across different countries. This variability in the signs of variable coefficients indicates the presence of country-specific heterogeneity, and we have taken the approach of examining each country individually to uncover this heterogeneity within the model.

For Leamer’s Extreme Bound Analysis, the criterion for variable selection is that if the lower and upper bounds have the same sign, the variable is considered for inclusion. Conversely, Sala-i-Martin's Extreme Bound Analysis argues that if a substantial part of a variable's distribution lies to the right side of zero, it signifies the variable's significance and usability in modeling.

For instance, in Column 1, it is indicated that, for Argentina, Leamer’s Extreme Bound Analysis excluded the variables "Inflation" (INF), "Domestic Investment" (DI), "Personal Remittances" (REMI), and "Trade" (TR) in the balance of trade model due to differing signs in the bounds. Similarly, Sala-i-Martin's Extreme Bound Analysis for the balance of trade model excluded the variables "INF," "LNGDP," "LNDEXP," "BDEFI," and "TR" for Argentina due to insignificance based on their distribution.

In the last row of the table, you can observe the frequency with which each variable was retained in the estimated model. Interestingly, among the 43 countries considered, the variable "Import Value Index" (IVI) was deemed significant in 26 cases by Leamer’s Extreme Bound Analysis and in 25 cases by Sala-i-Martin's Extreme Bound Analysis.

Table 5.8 displays the forecasted Root Mean Square Error (RMSE) for each country after selecting the final model using the Extreme Bound Analysis. This provides an assessment of model performance in terms of prediction accuracy for each country.

Table 5.7: The Results of Leamer's and Sala-i-Martin Extreme Bound Analysis for Trade Modeling

			DI	MS	EVI	IVI	INF	REM	GEXP	DC	BDEFI	TRAD	FDI	LNGDP	ER
			free	free	free	free	free	free	free	free	Free	Free	focus	focus	focus
Argentina	LEBA	LEB	-0.6	-1.1	0.0	-0.2	-1.3	-215.7	-0.7	-2.3	-1.1	-1.0	-2.9	-34.4	0.0
		UEB	0.0	1.6	0.7	0.0	1.3	37.9	2.2	0.8	0.8	1.0	1.4	-10.6	3.2
	SIMEBA	CDF(beta>0)	0.2	73.1	99.5	5.9	35.5	4.4	82.7	16.6	29.2	43.0	18.8	0.0	99.1
Australia	LEBA	LEB	-3.3	-0.7	-0.1	0.0	-3.6	32.5	-4.1	-5.5	-0.9	-1.4	-1.6	-76.0	-23.8
		UEB	0.1	0.6	0.2	0.3	3.6	126.7	7.0	3.1	0.7	3.8	3.3	0.9	42.8
	SIMEBA	CDF(beta>0)	1.5	40.5	84.3	99.9	49.1	100.0	72.2	28.6	31.1	88.6	79.4	2.1	73.8
Austria	LEBA	LEB	-9.7	0.3	-0.1	-0.2	-2.0	-1.7	-4.7	-3.5	-0.2	-1.1	-0.6	-42.0	-4.0
		UEB	3.8	2.1	0.1	0.1	2.1	2.8	3.9	3.2	0.1	0.1	0.1	14.8	0.0
	SIMEBA	CDF(beta>0)	25.6	100.0	42.7	23.8	47.8	68.8	44.5	40.6	38.1	4.8	6.2	33.1	0.6
Belgium	LEBA	LEB	-6.9	-0.3	0.0	-0.1	-2.2	-0.3	-5.8	-1.4	-0.2	-0.8	-0.1	7.2	-0.4
		UEB	14.2	1.4	0.0	0.0	3.0	0.3	1.7	4.7	0.8	0.7	0.1	59.9	1.7
	SIMEBA	CDF(beta>0)	65.6	91.0	6.4	11.4	59.6	41.4	8.3	92.5	88.0	37.3	27.9	99.9	90.5
Bhutan	LEBA	LEB	-1.2	-1.5	0.0	-0.1	-0.2	-0.5	-0.6	-0.4	-0.1	0.0	-0.2	-0.5	-0.3
		UEB	0.6	1.1	0.0	0.0	0.1	2.6	0.4	0.6	0.1	0.2	0.2	11.4	0.2
	SIMEBA	CDF(beta>0)	18.0	45.2	86.9	0.0	22.5	92.5	26.2	71.8	60.8	96.4	53.9	96.1	45.7
Brazil	LEBA	LEB	0.0	-0.7	0.0	-0.1	0.0	-4.3	-0.2	-0.3	0.0	-1.6	-3.7	-23.6	-9.3
		UEB	0.0	1.1	0.3	0.0	0.0	-0.4	0.4	0.3	0.1	1.5	-0.1	0.9	1.8
	SIMEBA	CDF(beta>0)	53.0	53.6	99.5	25.6	57.0	0.1	79.8	46.9	86.7	58.9	0.8	1.8	5.1
Bulgaria	LEBA	LEB	0.0	0.2	0.0	0.0	0.0	-1.0	-0.4	-0.2	0.0	-0.1	-0.3	-5.4	-2.6

		UEB	0.5	0	0.1	0.0	0.0	0.2	0.3	0.4	0.1	0.1	-0.1	-0.3	0.5
	SIMEBA	CDF(beta>0)	99.8	0	100.0	1.6	99.3	4.4	56.7	66.1	58.6	82.6	0.1	1.0	8.7
Canada	LEBA	LEB	-0.4	-0.6	0.0	0.0	-0.5	-1.1	-0.5	-0.6	-0.1	-0.2	-0.6	-10.2	-11.3
		UEB	0.6	-4.9	0.0	0.0	0.6	0.4	0.6	0.4	0.1	0.3	0.5	-2.0	5.4
	SIMEBA	CDF(beta>0)	62.4	-2	0.9	6.7	46.8	10.5	55.0	32.2	37.0	68.4	51.6	0.0	18.5
Chile	LEBA	LEB	-0.4	-1.1	0.0	-0.1	-0.3	-254.8	-2.1	-0.5	0.0	-0.2	-1.0	-19.7	-0.1
		UEB	0.2	-0.4	0.3	0.1	0.6	21.0	0.8	1.9	0.0	0.6	0.5	0.2	0.0
	SIMEBA	CDF(beta>0)	18.9	0	97.4	34.2	73.7	1.6	14.6	92.5	27.4	94.2	23.7	1.5	0.5

			DI free	**MS free**	**EVI free**	**IVI free**	**INF free**	**REM Free**	**GEXP free**	**DC free**	**BDEFI free**	**TRAD free**	**FDI focus**	**LNGDP focus**	**ER focus**
China	LEBA	LEB	-0.8	0.7	0.0	0.0	-0.5	1.3	-3.9	-0.2	-0.5	-0.3	-2.1	-25.4	-1.0
		UEB	1.4	0.2	0.1	0.0	0.3	30.4	1.1	0.9	0.0	0.2	1.4	2.7	3.7
	SIMEBA	CDF(beta>0)	72.9	0	83.7	14.4	22.3	99.2	13.9	89.0	2.5	22.8	40.4	4.6	86.5
Denmark	LEBA	LEB	-0.5	0	-0.1	0.0	-0.6	-2.4	-0.8	0.1	-0.1	-0.2	-0.1	-3.0	-0.8
		UEB	0.1	3.8	0.0	0.0	0.4	9.6	0.0	0.7	0.0	0.0	0.1	12.2	1.5
	SIMEBA	CDF(beta>0)	5.5	1	14.4	99.7	10.1	88.7	1.5	99.5	21.9	1.8	81.8	94.7	39.1

France	LEBA	LEB	-0.6	1.8	0.0	0.0	-0.6	-0.9	-0.4	-0.4	0.0	-0.2	0.0	-3.7	-0.9
		UEB	0.8	0.1	0.1	0.0	0.0	0.5	0.4	0.1	0.0	0.1	0.5	-0.2	0.5
	SIMEBA	CDF(beta>0)	56.6	0.1	98.4	0.3	1.3	35.9	45.6	4.4	5.4	23.9	97.4	0.3	21.4
Germany	LEBA	LEB	-1.7	1.6	-0.1	0.0	-0.9	-9.3	-2.3	0.2	0.0	-0.1	-0.5	-6.7	-4.8
		UEB	1.0	4	0.1	0.0	-0.3	2.8	-0.4	2.2	0.0	0.1	0.2	3.5	0.6
	SIMEBA	CDF(beta>0)	40.4	0	55.1	95.5	0.0	15.9	0.1	99.6	21.8	53.1	19.0	59.8	3.0
Ghana	LEBA	LEB	-0.5	-2.1	0.0	-0.1	-0.1	-1.2	-1.8	-0.6	-2.2	-0.2	-0.6	-14.5	0.3
		UEB	0.3	0	0.0	0.1	0.0	2.4	0.6	1.8	0.3	0.3	1.5	7.0	7.4
	SIMEBA	CDF(beta>0)	33.8	0	83.0	34.6	13.3	79.9	15.6	85.6	3.0	69.5	78.8	37.0	99.3
Hungary	LEBA	LEB	-0.2	-0.9	0.0	0.0	-0.1	1.0	-1.0	0.2	0.0	-0.1	0.0	-5.4	0.0
		UEB	0.4	0	0.0	0.0	0.4	2.4	0.0	1.0	0.3	0.1	0.0	2.2	0.0
	SIMEBA	CDF(beta>0)	76.2	-1.1	41.2	99.9	86.9	100.0	1.1	99.9	99.2	49.6	33.1	19.1	85.1
India	LEBA	LEB	-0.9	-2.3	-0.1	0.0	-0.3	-3.5	-1.7	-0.7	-0.4	-0.2	-1.8	-20.4	-0.4
		UEB	75.1	-0.1	0.1	0.0	0.2	0.4	0.6	1.4	0.2	0.2	1.9	-4.3	0.3
	SIMEBA	CDF(beta>0)	99.2	-0.1	58.6	8.0	32.9	3.6	14.1	75.0	33.4	71.3	45.9	0.1	40.5
Indonesia	LEBA	LEB	-0.3	0	-0.1	-0.1	-1.9	-3.1	-1.3	-0.4	-0.1	-0.1	-2.8	-12.4	0.0
		UEB	0.2	-17.6	0.2	0.0	2.4	1.6	0.6	1.4	0.1	0.3	0.3	8.9	0.0

	SIMEBA	CDF(beta>0)	33.8	0.1	73.7	8.4	54.5	14.1	21.5	87.6	49.9	88.5	5.8	36.8	48.1
Iran	LEBA	LEB	-0.3	0.4	0.0	-0.1	-0.1	-12.7	-3.4	-1.9	-0.4	-0.2	-0.6	-13.6	0.0
		UEB	1.1	0.3	0.2	0.1	0.3	3.8	2.0	3.3	0.7	0.4	7.4	10.8	0.0
	SIMEBA	CDF(beta>0)	86.5	0	98.1	54.8	82.0	15.0	35.2	68.0	85.5	73.5	96.3	41.4	72.8
Japan	LEBA	LEB	0.6	0.3	-0.1	-0.2	-5.0	-44.8	-1.0	-1.5	-0.5	-1.0	-6.5	-63.4	-0.6
		UEB	7.5	-0.1	0.0	0.0	1.5	32.1	4.3	0.4	0.1	1.9	18.8	25.6	0.2
	SIMEBA	CDF(beta>0)	99.8	0.6	4.5	4.7	15.1	27.2	92.6	10.5	8.5	72.1	86.6	53.2	8.8

			DI	MS	EVI	IVI	INF	REM	GEXP	DC	BDEFI	TRAD	FDI	LNGDP	ER
			free	free	free	free	free	Free	free	free	free	Free	focus	focus	focus
Luxembourg	LEBA	LEB	-9.7	26.5	-0.1	-0.1	-0.2	-0.1	-1.0	-1.3	0.0	0.0	0.0	-5.5	-0.1
		UEB	66.4	64.3	0.0	0.0	1.3	0.0	1.8	1.0	0.0	0.1	0.1	24.9	0.8
	SIMEBA	CDF(beta>0)	94.1	68.1	2.9	55.0	96.9	2.8	77.5	36.8	19.9	99.7	98.3	77.6	90.6
Maldives	LEBA	LEB	-1.7	3.6	-0.1	0.0	-0.2	-3.9	-0.8	-1.5	-0.1	-0.1	-0.6	-18.0	-2.1
		UEB	0.5	83.4	0.0	0.0	0.5	1.5	1.6	0.7	0.1	0.0	0.7	-2.4	4.2
	SIMEBA	CDF(beta>0)	14.0	79.4	22.8	42.4	88.1	11.2	76.6	16.3	76.0	2.1	56.2	0.0	63.9
Malaysia	LEBA	LEB	-14.6	11.1	-0.3	0.0	-3.6	0.0	-4.5	0.0	0.9	-0.1	0.0	0.1	0.0
		UEB	-9.8	58.4	1.0	0.0	0.3	0.0	0.3	0.0	1.3	0.0	0.0	0.3	0.1

	SIMEBA	CDF(beta>0)	0.0	1.1	87.3	73.6	2.3	74.1	1.5	98.5	100.0	18.6	56.3	100.0	99.0
Mexico	LEBA	LEB	-0.1	0	-0.2	0.0	-0.1	-6.7	-1.6	-3.9	-0.1	-0.9	-4.1	-17.1	-0.7
		UEB	0.5	0	0.2	0.0	0.2	3.7	4.1	1.4	0.0	0.5	1.8	10.5	4.4
	SIMEBA	CDF(beta>0)	95.7	0.3	60.7	33.5	78.6	27.9	82.5	14.9	3.2	36.5	21.0	35.5	92.6
Morocco	LEBA	LEB	1.1	0	0.0	0.0	-0.4	-0.9	-1.3	0.2	-0.3	-0.3	-0.4	-10.0	-1.3
		UEB	2.6	2.6	0.1	0.0	0.3	0.7	-0.2	1.3	0.2	0.1	0.8	4.4	0.9
	SIMEBA	CDF(beta>0)	100.0	0.8	99.9	63.6	34.5	39.1	0.1	99.9	29.4	22.4	77.3	24.6	39.2
Netherlands	LEBA	LEB	0.0	0.2	0.0	0.0	-0.3	-0.1	-0.5	0.0	0.0	-0.1	0.0	-0.1	-0.4
		UEB	0.3	0.5	0.0	0.0	0.1	0.1	-0.1	0.4	0.0	0.0	0.0	3.5	2.3
	SIMEBA	CDF(beta>0)	99.6	0	59.4	98.0	6.7	61.2	0.1	97.5	22.7	27.6	95.7	98.8	93.3
Nepal	LEBA	LEB	-18.9	8.3	0.0	0.0	-0.4	-1.4	-0.8	-0.1	-0.3	-0.6	-16.6	-33.0	-0.2
		UEB	7.7	0.2	0.0	0.0	0.5	0.0	0.2	0.8	0.4	0.0	0.9	-6.2	0.4
	SIMEBA	CDF(beta>0)	20.4	-0.7	1.1	17.5	71.2	0.9	14.1	93.8	61.0	0.7	2.7	0.0	71.5
New Zealand	LEBA	LEB	0.0	0	0.0	0.0	-0.4	-3.5	-0.5	-0.1	0.0	0.0	0.0	0.0	-1.2
		UEB	0.4	-0.1	0.0	0.0	0.2	11.3	0.0	0.5	0.0	0.0	0.0	2.2	1.6
	SIMEBA	CDF(beta>0)	99.7	-0.1	30.5	95.4	11.1	87.6	0.5	88.7	95.8	49.6	64.4	97.7	52.3
Norway	LEBA	LEB	-1.6	-3.1	-0.1	0.0	-1.6	-56.1	-0.9	-1.2	-0.2	0.0	-0.9	-4.4	-2.3

		UEB	0.3	-1.2	0.0	0.0	0.0	147.8	1.8	0.7	0.0	0.7	0.1	5.3	-0.1
	SIMEBA	CDF(beta>0)	8.1	-0.5	0.0	86.9	0.5	84.3	73.2	30.2	0.5	98.9	5.9	64.0	0.7
Pakistan	LEBA	LEB	-0.8	-0.2	0.0	-0.1	-0.3	-1.5	-3.4	-20.9	-0.9	-0.3	-3.0	-28.8	-0.3
		UEB	0.7	-0.2	0.1	0.0	0.4	0.4	20.9	3.4	0.2	0.5	0.7	17.8	0.0
	SIMEBA	CDF(beta>0)	42.6	-1.2	99.3	0.0	66.6	8.8	93.7	6.2	5.7	74.0	5.8	39.0	0.2

			DI	MS	EVI	IVI	INF	REM	GEXP	DC	BDEFI	TRAD	FDI	LNGDP	ER
			free	free	free	free	free	free	free	free	free	free	focus	focus	focus
Paraguay	LEBA	LEB	0.2	-2.3	0.0	0.0	-0.6	-4.9	-2.0	-1.1	-0.4	0.0	-2.0	-19.8	0.0
		UEB	0.7	-0.1	0.2	0.0	0.0	3.8	1.0	1.8	0.1	0.1	1.6	4.0	0.0
	SIMEBA	CDF(beta>0)	100.0	-0.1	100.0	33.8	2.0	24.3	30.1	62.8	7.0	98.7	59.0	10.4	100.0
Peru	LEBA	LEB	0.0	0	0.0	0.0	-0.1	0.0	-1.5	-1.7	-0.6	0.1	-1.0	-14.7	-2.8
		UEB	0.2	-17.6	0.2	0.0	0.0	1.0	1.5	1.6	0.0	0.9	0.7	9.8	4.3
	SIMEBA	CDF(beta>0)	96.7	0.1	99.7	18.5	3.9	98.0	50.4	44.7	4.0	99.5	35.0	34.3	60.3
Philippines	LEBA	LEB	-0.7	0.3	0.0	-0.1	-0.1	-3.1	-1.2	-0.5	-0.2	-0.2	-1.2	-7.8	-0.1
		UEB	0.4	0	0.3	0.0	0.3	-0.1	0.6	1.2	0.3	0.2	1.7	3.6	0.7
	SIMEBA	CDF(beta>0)	33.4	2.6	97.0	0.6	84.8	0.5	15.5	87.2	66.2	69.3	65.8	20.7	96.8
Portugal	LEBA	LEB	-2.1	0.8	0.0	0.0	-0.9	0.0	-1.1	-2.3	-0.1	-0.1	0.0	-17.6	0.1

		UEB	1.1	0.2	0.0	0.0	0.3	0.0	2.6	0.8	0.2	0.5	0.0	8.3	0.2
	SIMEBA	CDF(beta>0)	26.5	0.5	64.3	68.1	3.6	83.4	79.4	11.1	58.4	78.8	64.0	37.1	100.0
Qatar	LEBA	LEB	-3.6	0	-0.1	0.0	-0.7	-78.4	-42.1	-83.2	-0.3	-0.1	-2.7	-16.1	-809.2
		UEB	0.1	8.3	0.1	0.0	0.4	-9.8	37.6	118.4	0.1	0.3	-0.2	9.6	412.8
	SIMEBA	CDF(beta>0)	2.1	0.2	75.6	41.6	20.9	0.1	44.5	63.8	9.9	85.2	0.7	30.1	27.1
Sri Lanka	LEBA	LEB	-0.3	-1.2	-0.1	-0.1	-0.1	-2.0	-1.2	-0.1	0.0	-0.2	-0.8	0.7	-0.2
		UEB	0.2	-0.5	0.2	-0.1	0.2	0.9	0.0	1.2	0.3	0.1	2.1	13.0	0.1
	SIMEBA	CDF(beta>0)	23.2	-0.2	76.3	0.0	62.4	18.3	2.1	97.1	99.1	23.6	81.7	98.7	34.5
South Africa	LEBA	LEB	-0.5	-0.2	-0.2	0.0	0.0	-28.1	-0.5	-1.0	-0.1	-0.5	-1.1	-13.3	-0.6
		UEB	0.6	-1.2	0.3	0.0	0.9	22.3	1.3	0.6	0.1	0.0	0.7	4.4	1.1
	SIMEBA	CDF(beta>0)	54.0	-7.8	75.7	36.4	97.5	42.0	83.6	28.3	41.1	2.0	32.4	15.0	74.3
Sweden	LEBA	LEB	-0.1	-0.1	-0.1	0.0	-0.3	-5.0	-0.4	-0.4	-0.1	-0.1	0.0	-2.9	-0.6
		UEB	0.5	0.6	0.0	0.0	0.1	4.1	0.3	0.2	0.0	0.1	0.2	1.7	0.4
	SIMEBA	CDF(beta>0)	88.6	1.2	0.1	43.1	32.2	48.8	39.4	25.5	2.8	59.4	87.7	31.8	34.6
Switzerland	LEBA	LEB	-0.1	0.3	0.0	0.0	-0.3	-16.1	-2.3	-1.0	-0.1	0.0	-0.1	-0.4	-2.3
		UEB	0.1	0.2	0.0	0.0	0.3	19.4	0.9	1.9	0.1	0.1	0.0	12.9	8.8
	SIMEBA	CDF(beta>0)	52.0	1.7	24.3	45.8	47.4	61.7	15.2	75.4	80.4	90.9	42.1	97.3	63.0

Turkey	LEBA	LEB	0.0	3.6	0.0	-0.1	-0.1	-4.2	-1.4	-0.2	-0.1	0.0	-0.6	-6.3	-1.8
		UEB	0.2	0.7	0.0	0.0	0.0	1.8	0.1	1.2	0.0	0.4	2.3	4.8	7.4
	SIMEBA	CDF(beta>0)	99.9	0.9	72.7	1.8	0.4	17.0	2.3	95.0	1.4	99.3	87.5	38.2	89.8

			DI	MS	EVI	IVI	INF	REMI	LNGE XP	DC	BDEFI	TR	FDI	LNGDP	ER
			free	free	free	free	free	free	free	free	free	Free	focus	focus	focus
United Kingdom	LEBA	LEB	0.0	-1.1	0.0	0.0	-0.3	-2.9	-0.1	-0.1	0.0	0.0	0.0	1.0	-0.7
		UEB	0.1	-2.3	0.0	0.0	0.0	3.7	0.1	0.3	0.0	0.2	0.1	2.5	4.9
	SIMEBA	CDF(beta>0)	93.5	-0.1	99.8	58.0	0.3	71.2	66.7	73.6	97.5	67.3	52.2	100.0	97.9
United States of America	LEBA	LEB	-1.2	-0.1	-0.2	-0.4	-0.1	-240.8	-1.5	-1.0	-0.1	0.3	-1.9	-20.2	-26.5
		UEB	0.5	0	0.6	-0.1	0.8	5.8	1.3	1.1	0.0	1.8	0.6	15.6	17.5
	SIMEBA	CDF(beta>0)	16.9	-17.6	87.5	0.0	95.0	2.3	43.3	54.0	2.6	99.7	16.2	39.2	34.1
Uruguay	LEBA	LEB	0.0	0.1	0.0	0.0	-0.3	-11.0	-1.5	-1.6	-0.2	-0.5	-1.1	-20.6	-1.2
		UEB	0.4	0.2	0.1	0.1	0.1	29.4	1.5	1.2	0.3	0.5	0.2	5.4	0.2
	SIMEBA	CDF(beta>0)	99.8	1.7	91.9	53.8	7.4	79.7	47.2	39.1	67.4	72.5	9.1	10.8	6.5
Retention Frequency	LEBA		**19**	**15**	**25**	**26**	**5**	**7**	**1**	**5**	**11**	**10**	**9**	**10**	**8**
	SIMEBA		**19**	**11**	**26**	**10**	**15**	**17**	**11**	**13**	**12**	**21**	**19**	**11**	**23**

Table: 5.8 Forecast Root Mean Square Error of Trade Modeling

Country	LEBA	SIMEBA	Country	LEBA	SIMEBA
Argentina	2.875	1.874	Malaysia	5.664	1.820
Australia	8.814	6.971	Mexico	3.144	2.285
Austria	4.700	4.838	Morocco	2.627	5.498
Bangladesh	1.855	1.845	Netherlands	4.656	3.068
Belgium	6.398	7.057	Nepal	3.985	1.051
Bhutan	3.111	1.886	New Zealand	3.734	3.082
Brazil	4.264	3.248	Norway	3.985	1.146
Bulgaria	2.264	2.260	Pakistan	4.560	4.015
Canada	1.320	1.066	Paraguay	1.132	3.390
Chile	2.997	2.828	Peru	2.258	3.335
China	4.525	4.871	Philippines	1.573	3.620
Denmark	2.585	1.480	Portugal	4.885	2.299
France	1.952	1.835	Qatar	1.593	5.401
Germany	1.790	5.051	Sri Lanka	4.135	1.943
Ghana	1.511	3.002	South Africa	5.716	5.095
Hungary	2.539	2.384	Sweden	2.752	4.022
India	1.091	4.831	Switzerland	1.802	5.526
Indonesia	4.128	3.764	Turkey	2.910	1.803
Iran	2.003	4.715	UK	4.976	3.859
Japan	2.700	4.885	USA	3.829	1.722
Luxembourg	1.313	3.534	Uruguay	3.442	3.344
Maldives	2.719	2.684			

Figure 5.7: Graph of Retention Variables in Leamer's Extreme Bound Analysis for Balance of Trade Modeling

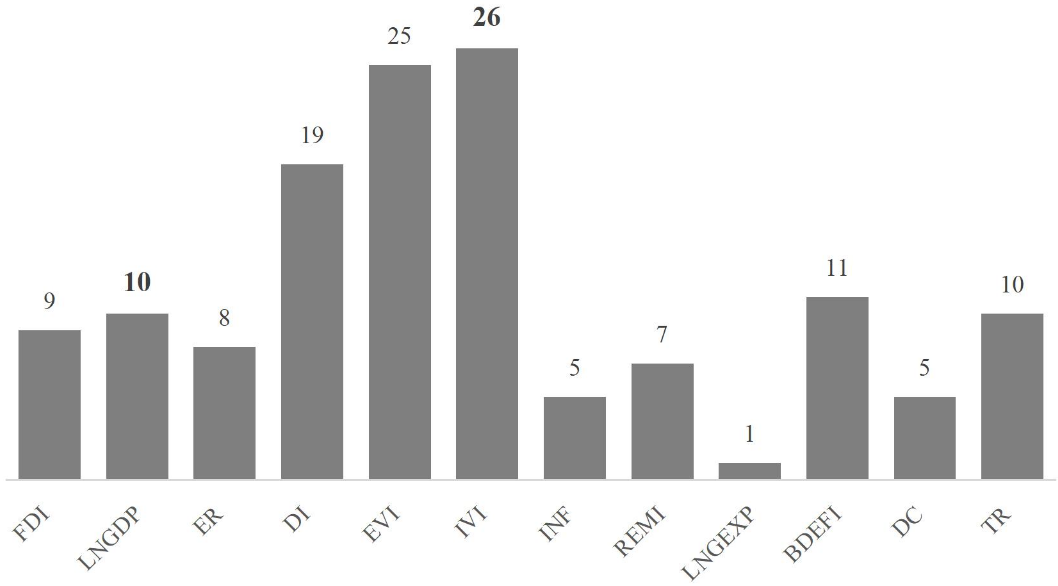

Figure 5.7 provides an overview of the frequency at which variables are retained in the Balance of Trade (BOT) model across all countries using Leamer's Extreme Bound Analysis. The findings indicate that the auxiliary variable, the "Imports Value Index" (IVI), appears to be highly significant, being retained in the model 26 times out of 43.

Following closely behind are the "Import Value Index" (IVI) and "Domestic Investment" (DI) variables, which show retention frequencies of 25 out of 43 and 19 out of 43, respectively.

This analysis helps us understand which variables consistently demonstrate significance across various countries in the context of the BOT model, assisting in our model selection and specification processes.

Figure 5.8: Graph of Retention Variables in Sala-i-Martin Extreme Bound Analysis for Balance of Trade Modeling

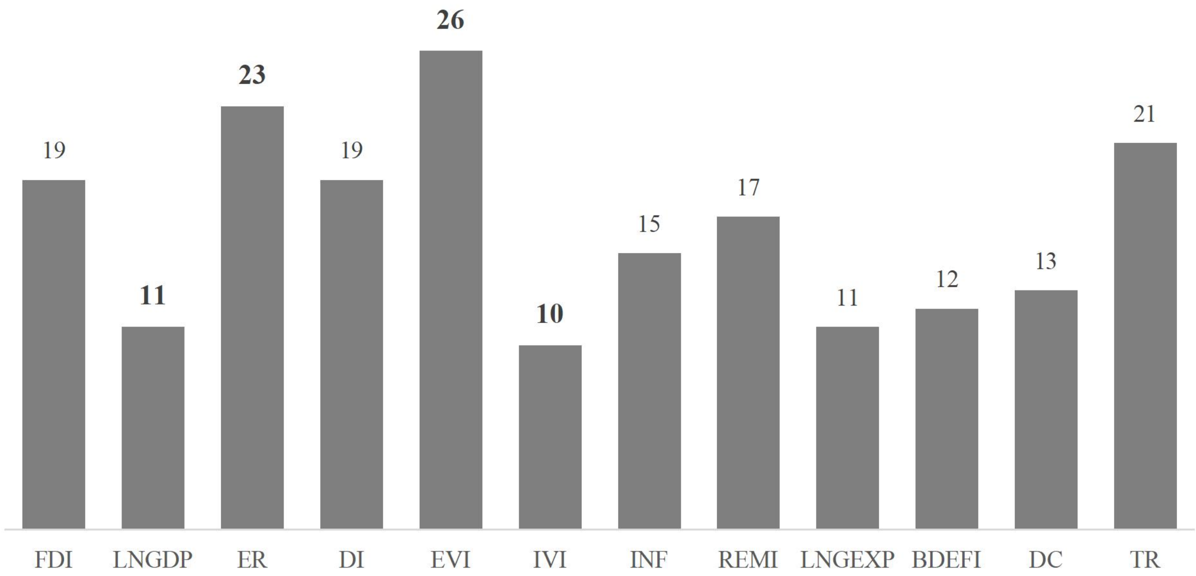

Figure 5.8 summarizes the retention frequency of variables in the BOT model using Sala-i-Martin Extreme Bound for all countries. The results show that the auxiliary variable, the export value index (EVI), is most likely significant, with a retention frequency of 26 out of 43. The next most common variables are exchange rate (ER) and trade (TR) with retention frequency, 23/43 and 21/43, respectively.

Forecast Based Comparison

As stated earlier, we are using two criteria for comparing the model selection procedures. The first criterion is the forecast performance of the finally selected model and the other is the robustness of the model. Suppose Y is a variable of interest and $X_1, X_2, X_2, .X_n$ are the candidate variables, suppose f_1 be the model of selection procedure applied to select the model out of $X_1, X_2, X_2, \ .. \ X_n$, Let $X_{f1}, X_{f2}, X_{f3}, \ .. X_{fk}$ be the variable selected by the procedure f_1 , f_2 f_3 ……f_k Let there are t observations Estimates $Y_i f$ $(X_{11}, X_{12}, X_{13}, ..X_{1k})$ for $T - S$ observation leaving "S" observation for forecasting purposes. Use the estimated model $\widehat{Y}_{t-s+1}$, $\widehat{Y}_{t-s+2}$, $\widehat{Y}_{t-s+3}..\widehat{Y}_t$ and calculate

$$\boldsymbol{FRMSE_1} = \sum (\boldsymbol{\widehat{y}_{t-s+i}} - \boldsymbol{y_{t-s+i}})^{\boldsymbol{2}}$$

Let there be a procedure f_2 and forecast $FRMSE_2$ be the forecast root mean square error (FRMSE) which forecasts the model selected by f_2 in this way, one can find FRMSE for all model selection procedures. A comparison of FRMSE for different models will give us an idea of the best model selection procedure.

Table: 5.9: Least Forecast Values of RMSE for Balance of Trade Model (Group I)

Country Name	Autometrics	Non –Nested Encompassing	WALS	LASSO	Adoptive LASSO	Elastic Net	LEBA	SIMEBA	Minimum Values RMSR	Best Method for selection least RMSE
Argentina	3.096	3.092	2.192	18.773	20.478	20.478	2.875	1.874	1.874	**SIMEBA**
Australia	9.508	0.052	1.508	10.462	13.416	13.416	8.814	6.971	0.052	**Non –Nested encompassing**
Austria	3.039	1.093	4.039	3.280	2.960	2.960	4.7	4.838	1.093	**Non –Nested encompassing**
Bangladesh	2.070	0.011	1.070	6.066	3.541	3.541	1.855	1.845	0.011	**Non –Nested encompassing**
Belgium	2.140	0.107	2.130	1.841	1.301	1.301	6.398	7.057	0.107	**Non –Nested encompassing**
Bhutan	1.173	0.053	1.273	12.478	12.478	12.478	3.111	1.886	0.053	**Non –Nested encompassing**
Bulgaria	0.856	0.148	0.616	0.643	1.341	1.341	4.264	3.248	0.148	**Non –Nested encompassing**
Brazil	0.510	1.035	0.410	4.709	3.801	3.801	2.264	2.26	0.41	**WALS**
Canada	0.565	1.009	2.565	0.711	2.262	2.262	1.32	1.066	0.565	**Autometrics**
China	1.712	4.065	1.612	11.972	2.672	2.672	2.997	2.828	1.612	**WALS**
Chili	2.373	2.024	2.173	1.221	0.720	0.720	4.525	4.871	0.72	**LASSO**
Denmark	0.644	0.021	0.314	1.746	1.018	1.018	2.585	1.480	0.021	**Non –Nested encompassing**
France	0.573	0.019	3.173	0.552	1.018	1.018	1.952	1.835	0.019	**Non –Nested encompassing**
Germany	0.688	0.843	0.628	0.546	0.540	0.540	1.79	5.051	0.540	**ALASSO E-Net**
Ghana	1.439	0.100	61.43 1	27.581	16.873	16.873	1.511	3.002	0.1	**Non –Nested encompassing**

Country Name	Autometrics	Non –Nested Encompassing	WALS	LASSO	Adoptive LASSO	Elastic Net	LEBA	SIMEBA	Minimum Values RMSR	Best Method for selection least RMSE
Hungary	1.180	30.010	1.130	4.423	4.614	4.614	2.539	2.384	1.13	**WALS**
India	0.791	0.037	0.391	2.610	2.363	2.363	1.091	4.831	0.037	**Non –Nested encompassing**
Indonesia	0.991	30.024	0.191	6.284	6.090	6.090	4.128	3.764	0.191	**WALS**
Iran	5.576	0.012	4.576	58.029	6.090	6.090	2.003	4.715	0.012	**Non –Nested encompassing**
Japan	3.775	2.099	3.175	4.939	80.949	80.949	2.7	4.885	2.099	**Non –Nested encompassing**
Luxembourg	1.186	0.014	1.146	4.104	3.730	3.730	1.313	3.534	0.014	**Non –Nested encompassing**
Malaysia	1.030	1.017	1.060	2.504	2.986	2.986	2.719	2.684	1.017	**Non –Nested encompassing**
Maldives	2.487	0.336	2.287	28.367	28.649	28.649	5.664	1.820	0.336	**Non –Nested encompassing**
Mexico	2.993	0.031	2.693	2.418	3.603	3.603	3.144	2.285	0.031	**Non –Nested encompassing**
Morocco	1.193	0.013	1.293	1.546	2.417	2.417	2.627	5.498	0.013	**Non –Nested encompassing**
Nepal	2.468	0.054	2.168	13.811	16.331	16.331	4.656	3.068	0.054	**Non –Nested encompassing**
Netherland	0.284	0.059	0.184	1.456	1.193	1.193	3.985	1.051	0.059	**Non –Nested encompassing**
New Zealand	0.263	8.109	4.263	2.156	2.181	2.181	3.734	3.082	0.263	**Autometrics**
Norway	1.611	3.028	2.161	9.625	10.400	10.400	3.985	1.146	1.146	**SIMEBA**
Pakistan	1.486	0.053	1.186	4.022	4.619	4.619	4.56	4.015	0.053	**Non –Nested encompassing**

Country Name	Autometrics	Non –Nested Encompassing	WALS	LASSO	Adoptive LASSO	Elastic Net	LEBA	SIMEBA	Minimum Values RMSR	Best Method for selection least RMSE
Peru	1.109	2.465	2.365	2.375	11.419	11.419	1.132	3.39	1.109	**Autometrics**
Paraguay	1.716	0.036	5.716	2.077	1.984	1.984	2.258	3.335	0.036	**Non –Nested encompassing**
Philippines	1.459	0.039	1.359	5.203	3.980	3.980	1.573	3.62	0.039	**Non –Nested encompassing**
Portugal	0.670	0.057	0.170	8.365	9.934	9.934	4.885	2.299	0.057	**Non –Nested encompassing**
Qatar	0.008	0.004	0.082	31.002	32.276	32.276	1.593	5.401	0.004	**Non –Nested encompassing**
South Africa	1.616	6.032	1.216	1.408	0.809	0.809	4.135	1.943	0.809	**ALASSO E-Net**
Sri Lanka	1.616	0.041	1.636	8.946	8.966	8.966	5.716	5.095	0.041	**Non –Nested encompassing**
Switzerland	0.842	5.041	0.411	0.951	0.935	0.935	2.752	4.022	0.411	**WALS**
Sweden	0.540	0.012	0.954	1.552	1.567	1.567	1.802	5.526	0.012	**Non –Nested encompassing**
Turkey	1.527	1.036	1.786	2.348	2.746	2.746	2.91	1.803	1.036	**Non –Nested encompassing**
United States	0.317	7.005	0.177	1.602	1.647	1.647	4.976	3.859	0.177	**WALS**
United Kingdom	0.005	1.005	0.058	0.159	0.156	0.156	3.829	1.722	0.005	**WALS**
Uruguay	1.82476	5.017	1.247	3.273	3.162	3.162	3.442	3.344	1.247	**WALS**
Minimum Value RMSE	0.005	0.003	0.058	0.159	0.156	0.156	1.091	1.051	0.003	**Non –Nested encompassing**
Total	3	25	7	0	3	3	0	2		

Table 5.9 provides a summary of the Forecast Root Mean Square Errors (FRMSE) for the final models selected by various model selection procedures. These FRMSE values offer insights into the forecast accuracy of the chosen models.

For instance, the FRMSE for the final model selected by the Autometrics procedure is reported as 3.096. Similarly, the Non-Nested Encompassing procedure resulted in an FRMSE of 3.092 for its final model, while the Weighted Average Least Squares (WALS) procedure yielded an FRMSE of 2.192 for its selected model.

This table provides a comprehensive overview of FRMSE values obtained for models selected through different procedures. Notably, Argentina achieved its lowest FRMSE for the model selected by the SIM-EBA procedure. The FRMSE values for all other countries are also documented in Table 5.9.

These FRMSE values are crucial for assessing the forecasting performance of the models generated by various selection procedures, assisting in the identification of the most effective approach for model selection in each specific context.

Figure 5.9: The Comparison of Balance of Trade Models based on Least Forecast RMSE

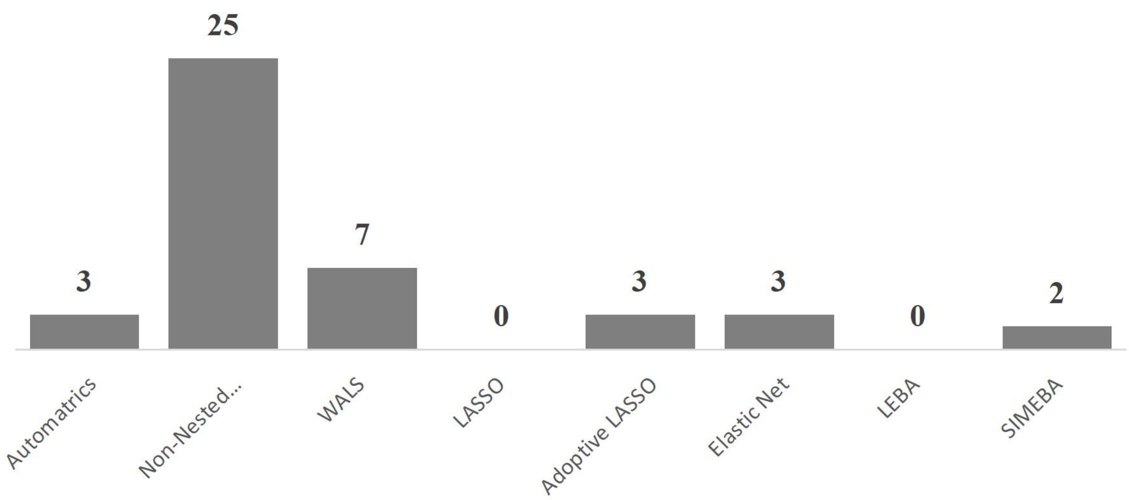

Figure 5.9 builds upon the data from Table 5.9, focusing on the minimum Forecasted Root Mean Square Errors (FRMSE) achieved by various model selection procedures. The findings are as follows:

The Non-Nested Encompassing procedure consistently outperformed others, securing the lowest FRMSE in 58% of the total cases (25 out of 43). This procedure is a dependable choice for achieving superior forecast accuracy in the majority of scenarios.

Weighted Average Least Squares (WALS) delivered the lowest FRMSE in 14% of the total cases (7 out of 43).

Automatrics, Adoptive LASSO, and Elastic Net collectively obtained the lowest FRMSE in 7% of the total cases (3 out of 43). While not as consistent as Non-Nested Encompassing, they demonstrated effectiveness in specific instances.

SIM-EBA achieved the lowest FRMSE in 7% of the total cases, on par with the previous group.

LASSO and Leamer's Extreme Bound Analysis (LEBA) did not achieve the lowest FRMSE in any of the 43 cases, indicating their relative ineffectiveness in minimizing forecast errors.

In summary, the Non-Nested Encompassing procedure consistently stood out as the most reliable choice for achieving the highest forecast accuracy across the majority of cases. Conversely, LASSO and LEBA performed poorly in minimizing FRMSE in any of the cases. This analysis helps in identifying the model selection procedures that are more likely to result in accurate forecasts based on the minimum FRMSE.

Retention of Variables for Restricted Model (Group I)

In his Ph.D. thesis, Khan (2020) compared model selection procedures using Monte Carlo experiments. The study of Khan was based on the Monte Carlo experiment; therefore, he was able to find the probability of retention of the true variables. Our study is based on real data; therefore, we cannot find the true variables because true variables are not known. We are trying to select a model out of many candidate models. These candidates' models gain a long list of explanatory variables. We can find the retention frequency of these variables to make the study compared with the study of Khan.

The results of Table 10 summarize the frequency of retention of the true variables among different classes of model selection Procedures in the model of Balance of trade.

The results show that the model selection procedure based on the shrinkage family provides the best results for the maximum number of cases to find potential determinants of the Balance of Trade model therefore, the model selected by Elastic Net performs the best in most cases to find the maximum frequency of retention variables for each estimated model. Finally, the results of the current study support the existing study of Khan (2020).

Table 5.10: Frequency of Retention variables for General Unrestricted Model (Balance of Trade Model)

Variables	**Autometrics**	**Encompassing**	**WALS**	**LASSO**	**ALASSO**	**EN**	**LEBA**	**SIM-EBA**	**Max Value**	**Best Model with Frequency Retention**
DI	18	13	11	27	27	31	19	19	31	**E lastic Net**
MS	13	16	12	29	30	33	15	13	33	**E lastic Net**
ER	20	17	19	29	31	38	8	23	38	**E lastic Net**
EVI	14	19	13	26	32	36	25	26	36	**E lastic Net**
IVI	20	12	11	31	34	37	26	10	37	**E lastic Net**
FDI	15	8	13	31	39	39	9	19	39	**EN,ALASSO**
INF	13	4	10	35	36	36	5	15	36	**EN,ALASSO**
REMI	9	7	11	33	34	37	7	17	37	**E lastic Net**
LnGDP	29	17	33	32	32	35	10	11	35	**E lastic Net**
LnGexp	41	11	17	33	36	35	1	11	41	**Autometrics**
Bdefi	16	5	10	25	28	32	11	12	32	**E lastic Net**
DC	16	6	11	28	30	35	5	13	35	**E lastic Net**
TR	31	9	29	31	31	33	10	21	33	**E lastic Net**

5.4.8 The Comparison of Econometric Models Based on Robustness

5.4.8.1 Robust Analysis for Balance of Trade Model

We have tested the performance of the model selection procedures for many countries and the research has identified the best procedure. A natural question arises: if we change the sample countries, would it change the same procedure that will be performed best? To test this, we have divided the sample countries into two groups. Group I countries 43 countries and these countries would be used to find out the model selection procedures that perform best. Group II contains countries for the Balance of trade model. The models would be restricted for group II to know whether the models applying best in sample I maintain their performance for group II.

5.4.8.2 Description of Variables

The underlying concept here is to identify the most frequently chosen model from the earlier modeling stages and apply these models to samples from nine different countries to assess their validity and significance. In this evaluation, we estimate both the Forecast Root Mean Square Error (FRMSE) and the Retention of Variables.

In these models, the dependent variable of interest is the Balance of Trade (BOT). We consider various independent variables, including Foreign Direct Investment (FDI), Gross Domestic Product (GDP), Exchange Rate (ER), Domestic Investment (DI), Money Supply (MS), Exports Value Index (EVI), Imports Value Index (IVI), Inflation (INF), Personal Remittances (REMI), Government Expenditure (GEXP), Budget Deficit (BDEFI), Domestic Consumption (DC), and Trade (TR).

For this modeling effort, we specifically focus on the variables FDI, LNGDP, and ER. These variables are of particular interest to our research. Meanwhile, the remaining variables, namely DI, MS, EVI, IVI, INF, REMI, GEXP, BDEFI, DC, and TR, serve as auxiliary variables.

It's important to note that certain model selection procedures necessitate the classification of independent variables into two categories: focus and auxiliary variables. Focus variables are those that hold particular research interest, while auxiliary variables are used as control variables to account for potential influences. In our Balance of Trade Model (BOT), the frequently encountered determinants are designated as focus variables, while the others are considered auxiliary variables.

Frequency of Retention Variables for Restricted Model (Group II)

The results of Table 11 summarize the frequency of retention of true variables among different classes of model selection Procedures using restricted models of Economic Growth. Table results show that the model selection procedure based on the shrinkage family and other model selection procedures encompassing provides the best results for the maximum number of cases to determine potential determinants for the model Balance of trade. Therefore, selection criteria based on the frequency of retention variables validate the final result of both groups (general unrestricted model (group I) and robust restricted model (group II)

.

Table 5.11: Results of Retention variables for Balance of Trade Modeling with Final Model Specification

Variables	LASSO	ALASSO	EN	ENCOM	AUT	LEBA	SIMEBA	WALS	Max value	Best Model Based on Retention variables
FDI	3	3	7	..	..	..	4	2	**7**	**E-Net**
LNGEXP	5	5	5	7	6	..	5	8	**8**	**WALS**
LNGEXP_1	..	..	..	6	4	..	..	..	**6**	**ENCOM**
INF	3	3	3	..	..	..	..	..	**3**	**LASSO ,ALASSO ,EN**
IVI	2	4	4	3	4	4	4	..	**4**	**ALASSO, EN.AUT,LEBA,SIM-EBA**
IVI_1	..	..	..	3	1		..	..	**3**	**ENCOM**
REMI	2	3	5	..	..	3	6	..	**6**	**SIM-EBA**
LNGDP	7	4	5	1	3	5	7	4	**7**	**LASSO SIM-EBA**
LNGDP_1	..	..	..	4	2	..	..	..	**4**	**ENCOM**
EVI	2	..	5	2	..	3	4	4	**5**	**ENCOM**
EVI_1	..	..	..	4	..	..	..	..	**4**	**ENCOM**
TR	4	4	..	..	2	..	3	2	**4**	**LASSO ,ALASSO ,EN**
TR_1	..	..	..	..	1	..	..	..	**1**	**AUT**
ER	5	..	5	4	3	..	6	3	**6**	**SIM-EBA**
ER_1	..	..	..	4	2	..	..	..	**4**	**ENCOM**
DC	..	..	5	..	..	..	..	..	**5**	**EN,AUT**
DC_1	..	..	..	..	2	..	..	..	**2**	**AUT**
BOT_1	..	..	..	7	8	..	..	..	**8**	**AUT**
BM	..	..	..	4	..	..	..	..	**4**	**ENCOM**
BM_1	..	..	..	5	..	..	..	..	**5**	**ENCOM**
DI	..	..	..	3	4	2	..	..	**4**	**AUT**
DI_1	..	..	..	4	..	..	..	..	**4**	**ENCOM**

Figure 5.10: Graph of Retention Variables for Balance of Trade Modeling (Group II)

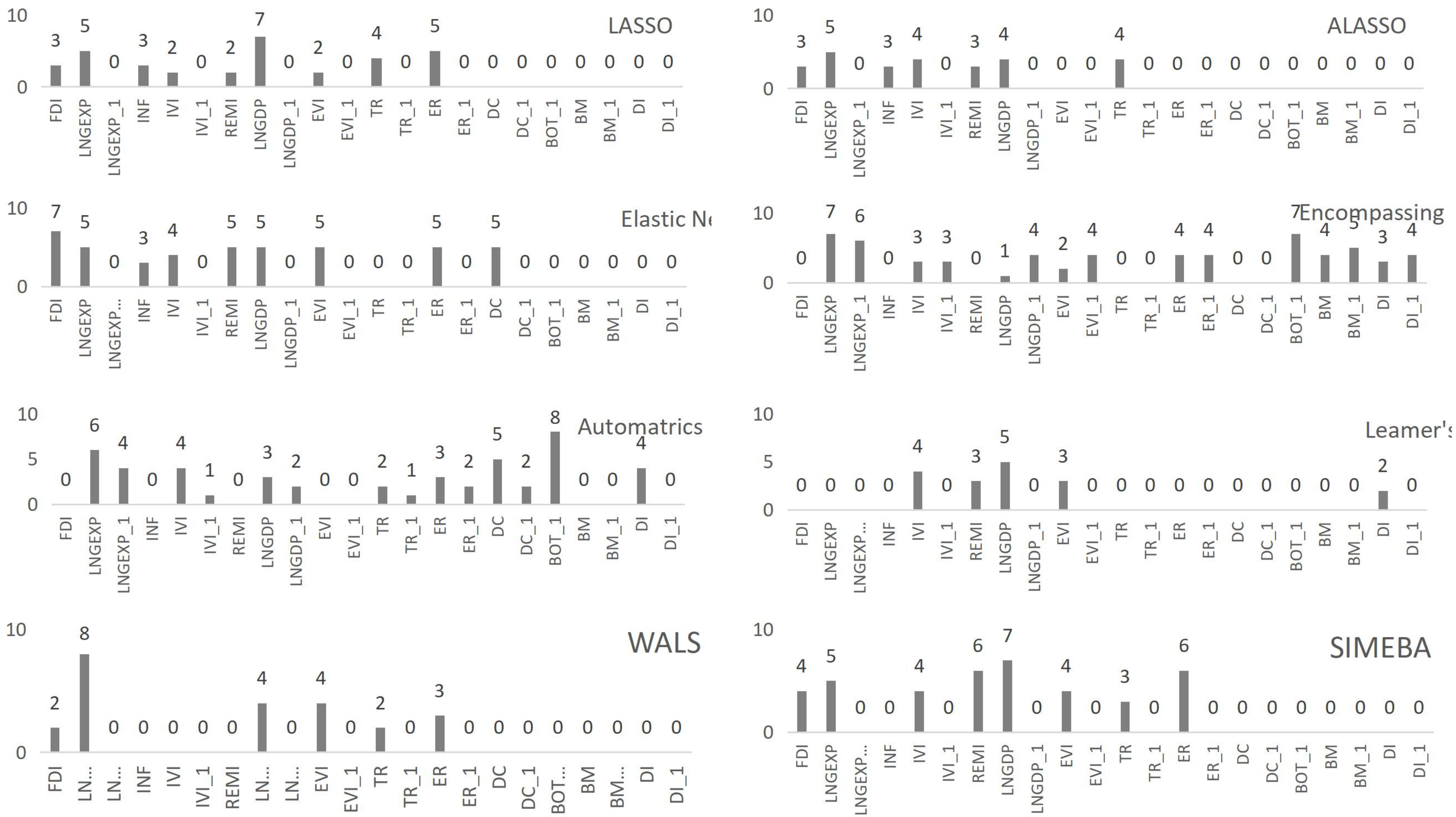

Figure 5.10, given above, is the graph of Table 5.11 statistics. Regarding focus variables in LASSO modeling, the FDI got significance only 3 times out of 9 regressions. In ALASSO it found significant 3 times out of 9 regressions. In Elastic Net, the FDI got significance 7 out of 9 regressions. In Sala-i-Martin EBA the FDI was found significant 4 times and in WALS 2 times out of 9 regressions. While the Encompassing, Autometrics, and Leamer's EBA did not take this variable in the final selection.

Similarly, the results of Table 15 and Figure 14 above show that the second focus variable LNGDP in LASSO modeling got significance only 7 out of 9 regressions. In ALASSO it came out significant 4 times out of 9 regressions. In Elastic Net, they got significance 5 times out of 9 regressions. In Leamer's and Sala-i-Martin EBA, the LNGDP was found significant 5, and 7 times respectively. In WALS, 4 times out of 9 regressions. While Encompassing, the current and lag value of LNGDP got significant 1 and 4 times out of 9 regressions, respectively. The results of Autometrics indicate that lag and current values of LNGDP were found significant 3 and 2 times, respectively.

Third focus variables ER in LASSO modeling got significance 5 times out of 9 regressions. In Elastic Net, they got significance 5 times out of 9 regressions. In Sala-i-Martin EBA the LNGDP was found significant 6 times. In WALS, it was found significant 3 times out of 9 regressions. While Encompassing, ER current and lag values got significant 4 and 3 times out of 9 regressions, respectively. The results of Autometrics indicate that lag and current values ER were found to be significant 3 and 2 times, respectively. The final model of ALASSO and Leamer's EBA came out insignificant.

In the case of auxiliary variables in Table 13 and Figure 10, the BM is only significant in the case of encompassing, and in all other procedures, this variable is not a part of the final model. The lag value of the dependent variable BOT is only significant in encompassing and Autometrics. In auxiliary variables, the LNGEXP got high significance in all the models. The least significant variable is BM.

Figure 5.11: Graph of Least Forecast RMSE for Balance of Trade Modeling (Group II)

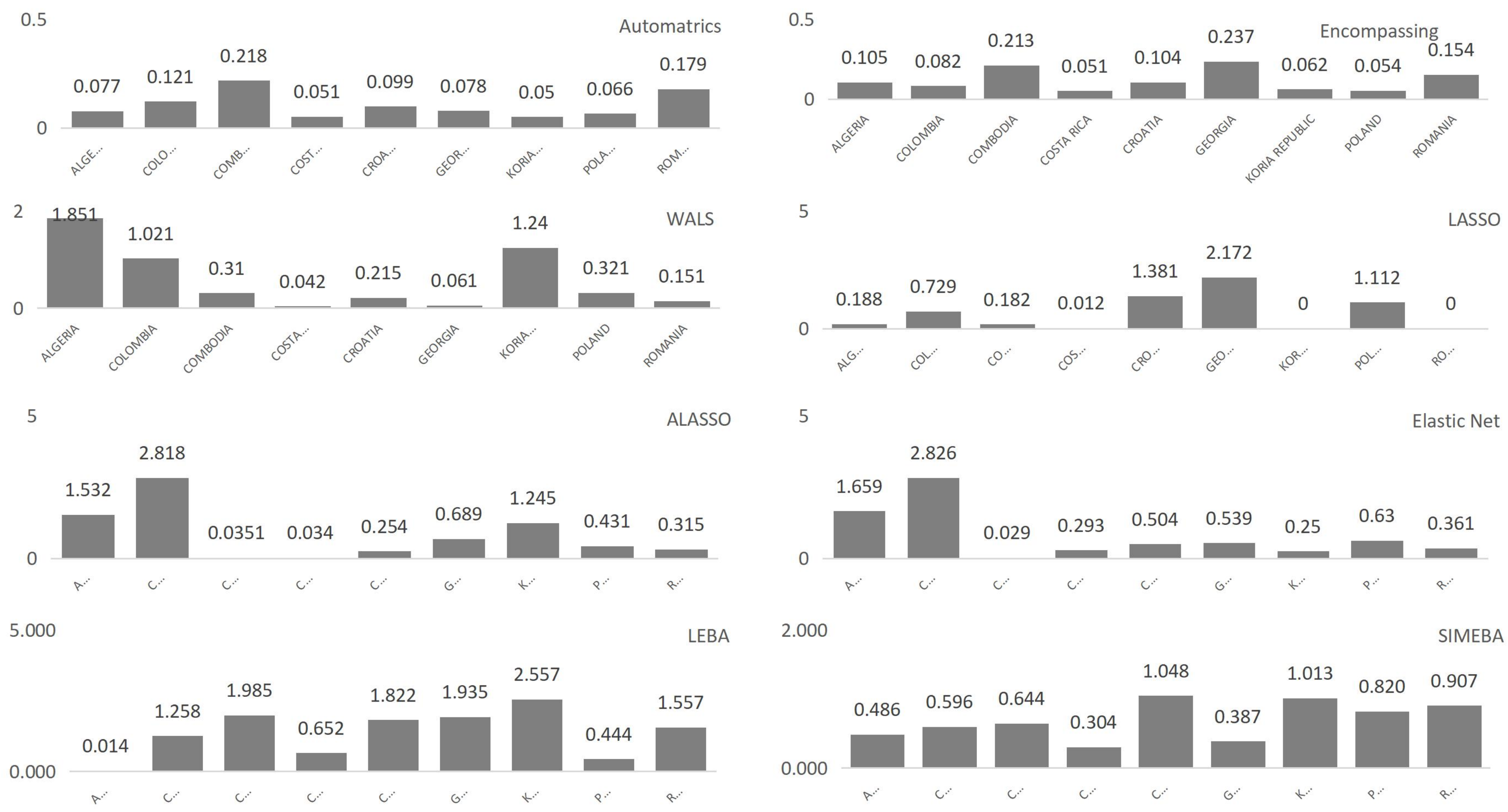

Figure 5.11 provides a summary of the outcomes regarding the least forecasted Root Mean Square Error (RMSE) achieved through various procedure classes. Let's examine the results:

- In the realm of LASSO regression, the Georgia model demonstrated the lowest RMSE, which stood at 0.072.
- Shifting to ALASSO regression, the Costa Rica model emerged with the least RMSE of 0.246.
- In contrast, Elastic Net regression, when applied to the Algeria model, yielded the lowest RMSE at 0.138.
- When employing WALS and LEBA models, the Romania model secured RMSE values of 0.031 and 0.391, respectively.
- Sala-i-Martin EBA (SAI-EBA) delivered the best results with the Georgia model, achieving a minimum RMSE of 0.219.
- Encompassing and Autometrics procedures showcased noteworthy performance by Cambodia, with the former resulting in a minimum FRMSE of 0.422 and the latter achieving an impressively low RMSE of 0.022.

These findings underscore the effectiveness of various regression procedures across different models and highlight the models that performed exceptionally well in terms of minimizing RMSE for their respective procedures.

Table: 5.12: Least Forecast Values of RMSE for Balance of Trade Model

Country	**Autometrics**	**Encompassing**	**WALS**	**LASSO**	**ALASSO**	**Elastic Net**	**LEBA**	**SIMEBA**	**Minimum Value**	**Best Model Based on least forecast value**
Algeria	0.077	0.105	1.851	0.188	1.532	1.659	0.014	0.486	0.014	LEBA
Colombia	0.121	0.082	1.021	0.729	2.818	2.826	1.258	0.596	0.082	ENCOM
Cambodia	0.218	0.213	0.31	0.182	0.0351	0.029	1.985	0.644	0.029	EN
Costa Rica	0.051	0.051	0.042	0.012	0.034	0.293	0.652	0.304	0.012	LASSO

Croatia	0.099	0.104	0.215	1.381	0.254	0.504	1.822	1.048	0.099	AUT
Georgia	0.078	0.061	0.237	2.172	0.689	0.539	1.935	0.387	0.061	ENCOM
Korea Republic	0.06	0.05	1.24	0.672	1.245	0.25	2.557	1.013	0.05	ENCOM
Poland	0.066	0.054	0.321	1.112	0.431	0.63	0.444	0.82	0.054	ENCOM
Romania	0.179	0.151	0.154	4.091	0.315	0.361	1.557	0.907	0.151	ENCOM

Table 5.12 summarizes the forecast root mean square errors (FRMSE) of the final robust models retained by the model selection procedures. The table indicates that the least value of FRMSE for the final model selected by oxmatrix is 0.077 for Non-Nested Encompassing, it was 0.105, for Weighted Average Least Squares (WALS) it was 1.851 and in this way, the forecast root mean square errors (FRMSE) for another model selection procedures are summarized. The results reveal that Algeria's smallest forecast root means square error (FRMSE) was obtained for the model selected by Leamer's Extreme Bound Analysis (LEBA). The results for all other countries are also visible in Table 5.12.

Figure 5.12: The Comparison of Restricted Models based on Least Forecast RMSE for Balance of Trade Modeling

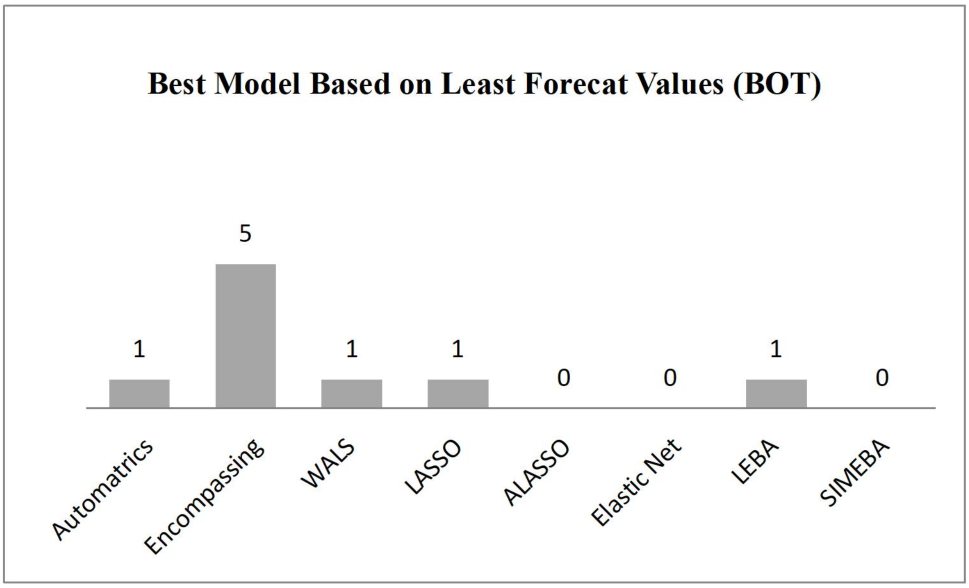

Figure 5.12 is based on the results reported in Table 5.12. The last column gives the minimum FRMSE for each estimated model. The results of the figure summarize the maximum number of cases based on the minimum forecasted root mean square errors

(FRMSE). The model selected by Non-Nested Encompassing provides minimum FRMSE for the maximum number of cases. In 5 out of 9 cases, the model selected by the Non-Nested Encompassing yielded the lowest forecast root mean square errors (FRMSE), which is 56% of the total cases.

Weighted average least square (WALS), Automatrics, LASSO, and Leamer's Extreme Bound Analysis (LEBA), these four different procedures came up with a minimum FRMSE of 1 out of 9 cases, 11% of the total cases. The model selected by Adoptive LASSO, Elastic Net and SIM-EBA with minimum FRMSE is 0 out of 9 cases. It means the probability of getting minimum values of FRMSE of these models is 0% on the given sample's basis.

The final results indicate that Non-Nested Encompassing performs best and Encompassing, Adoptive LASSO, Elastic Net and SIM-EBA are considered the worst models among all other model selection procedures based on minimum FRMSE

CHAPTER 6

MODELING ECONOMIC GROWTH

6.1 The Generalized Unrestricted Model (GUM) for Economic Growth

There are huge numbers of models for Economic Growth and it is impossible to cover the entire range of candidate variables. For the selection of variable use in this study, we surveyed the literature published after 2010. Among these studies, the models were selected to cover various determinants. The models having variables used only in one or two papers were dropped. After adopting this procedure, we are left with the following models.

Theory-Based Models for Economic Growth

Model 1	Akram, et al. (2011). LnGDP =f (FDI(inf) , T Debts, DI , Inf)
Model 2	Mihaela, et al. (2017). LnGDP =f (Inf, LnTLF, TOTP, FDI (inf), GExp)
Model 3	Sami, et al. (2014). LnGDP =f (Edu, RExp, P(remi), FDI)
Model 4	Ajmair, et al. (2015). LnGDP =f (Inf, LnGCF , Rexp, P(remi)
Model 5	Al-Smadi, (2020). LnGDP = f (FDI ,TOP, LG, DI , LnGCF ,)
Model 6	. Udeaja, et al. (2015). LnGDP =f (DI, FDI, Edu, TOP)

6.2 The Econometric Model takes the following form.

LnGDP =f (FDI, TOP, LG, DI, LnGCF, TDebts, INF , LnTLF, LnTOTP EDU, LnREXP , LnGEXP , REMI)

$$\begin{aligned} LNGDP_t = \beta_o + &+ \beta_1 \text{FDI(inf)}_t + \beta_2 \text{TOP}\ _t\, \beta_3 \text{LG}_t + \beta_4 \text{DI}\ _t + \beta_5 \text{LnGCF}_t \\ &+ \beta_6 \text{TDebtS}_t + \beta_7 \text{Inf}_t + \beta_8 \text{LnTLF}_t + \beta_9 \text{LnTOTP}_t + \beta_{10} \text{Edu}_t \\ &+ \beta_{11} \text{LnRExp}\ _t + \beta_{12} LnGExp\ _t + \beta_{13} P(remi)\ _t + \mu_t \end{aligned}$$

6.3 Details of Econometric Models and Variables

his section is centered around the description of econometric models and the variables utilized in the analysis. The primary objective here is to present the results achieved through various methodological approaches, including Least Absolute Shrinkage and Selection Operator (LASSO), Adoptive Least Absolute Shrinkage and Selection Operator (ALASSO), Elastic Net, Encompassing, Autometrics, Weighted Average Least Square, and Extreme Bound analysis.

The key elements of this section include:

1. **Variable and Model Selection**:
   - Utilizing a range of econometric methodologies, the aim is to identify the most appropriate techniques for variable selection and model selection.
   - Robustness analysis focuses on determining the variables that consistently appear as significant across multiple models. Robustness is evaluated by selecting models with the most significant variables.
   - The process involves employing various techniques and choosing the most frequently occurring model within each methodology. This selected model is then re-estimated for specific countries to demonstrate its robustness.
2. **Model Evaluation**:
   - The analysis includes estimating forecasts for each country's model and calculating the Root Mean Square Error (RMSE) for each model.
   - The model with the lowest RMSE is considered the best-performing model in terms of predictive accuracy.
3. **Total Significance**:
   - To showcase the most frequently significant variable in each modeling approach across all countries, total significance is calculated.
4. **Application to Growth Modeling**:

- These methodologies, including LASSO, ALASSO, Elastic Net, Encompassing, Autometrics, Weighted Average Least Square, and Extreme Bound Analysis, are applied to growth modeling to evaluate their effectiveness and performance in selecting variables and models.

In summary, this section explores various econometric methodologies to determine their suitability for variable and model selection. The focus is on robustness, predictive accuracy, and the identification of consistently significant variables across different modeling approaches, particularly in the context of growth modeling.

6.3.1 Selecting Models for Economic Growth

In Table 20, the Least Absolute Shrinkage and Selection Operator (LASSO) results are based on economic growth modeling. In this model, economic growth (LNGDP) is the dependent variable and Gross fixed capital formation (LNGCF), total Labor force (LNTLF), foreign direct investment (FDI) and independent variables are trade openness (TOP), labor growth (LG), domestic interest (DI), total debts (TDebts), inflation (INF), total population (LNTOTP), education expenditure (EDU), exports of goods and services (LNEXP), personal remittances (REMI), and government expenditure (LNGEXP). In this modeling, the FDI, LNGCF, and LNTLF are our focus variables, while the LNGEXP, REMI, LNREXP, EDU, LNTOTP, INF, TDebts, DI, LG, and TOP are the auxiliary variables.

Some of the model selection procedures require dividing independent variables into focus and auxiliary variables. The focus variables are ones in which the researcher might be interested, whereas auxiliary variables are those used as control variables. We used the most commonly found determinants as focus variables and others as auxiliary variables, Economic Growth (LNGDP) as under.

Dependent Variables
Economic Growth (LNGDP)
Focus Variables
Foreign Direct Investment (FDI)
Gross fixed capital formation (LNGCF)
Total Labor Force (LNTLF)

Auxiliary variables

Trade Openness (TOP)

Domestic Investment(DI)

Labor Growth (LG

Total Debts (TDebts)

Inflation (INF)

Total Population (LNTOTP)

Education Expenditure (EDU)

Exports of Goods and Services (LNEXP)

Personal Remittances (REMI)

Government Expenditure (LNGEXP)

6.3.2 Model Selection Procedures Based on Shrinkage Methodology

The concept of the Shrinkage estimator is inspired by Bayesian Methodology, where prior knowledge is integrated with information from current data to reduce the variance of estimators. This approach combines different combinations of regressors and leverages Bayesian principles to assess the variance of these estimators. It's important to note that there are various types of Shrinkage estimation techniques employed in statistical modeling and analysis.

6.3.3 Results of LASSO Regression

Table 6.1 presents the results obtained through the LASSO estimation method. This table provides detailed insights into the regression coefficients for various variables, highlighting differences in coefficient signs across different countries. These variations in signs signify the presence of country-specific heterogeneity, and the analysis was conducted separately for each country to reveal this heterogeneity within the model.

Here are the main points from Table 6.1:

- The last column of the table contains Root Mean Square Error (RMSE) values, which measure the predictive accuracy of each estimated model.
- Variables that were excluded from the model by the LASSO method are marked with (…). For example, in the case of Argentina (Row 1), focus variables like FDI and LNGC, as well as auxiliary variables DI, INF, and EDU, were deemed insignificant and removed from the model.
- The table also highlights instances where specific variables were considered insignificant and subsequently eliminated from the models for various countries. For instance, in Austria, focus variable FDI and auxiliary variables LG, TDebts, LNTOTP, EDU, and REMI were all found to be insignificant according to the LASSO procedure.
- In the last row of the table, the frequency of retention for each variable is provided. This frequency indicates how often each variable remained significant across the models estimated for all 43 countries. Notably, the

variable LNEXP was found to be significant in 31 out of the 43 cases, underlining its importance in the analysis.

Table 6.1 serves as a valuable resource for gaining insights into the variability in model outcomes, the influence of different variables, and the predictive accuracy of the models across diverse countries.

Table 6.1: The Results of Least Absolute Shrinkage and Selection Operator for Growth Modeling

Variables	Constant	LnGCF	LnTLF	FDI	TOP	LG	DI	TDebts	INF	LnTOTP	Edu	LnRexp	REMI	LnGexp	RMSE
Country Name															
Argentina	16.224	..	-0.016	..	-11.983	2.015	..	-0.003	..	0.533	..	0.427	-0.388	0.002	**0.01**
Australia	-1.381	..	-4.394	..	..	-8.438	-8.145	..	-6.903	1.881	-3.194	6.463	1.429	8.825	**0.114**
Austria	27.256	0.095	-0.011	..	-11.378	..	-0.005	..	-0.0002	..	..	0.391	..	0.001	**0.024**
Bangladesh	0.781	0.134	..	..	..	..	..	..	..	0.646	..	0.1006	..	..	**0.404**
Belgium	-3.623	9.406	-5.4	..	..	..	..	..	-3.18	2.253	..	..	7.96	..	**0.157**
Bhutan	-2.727	..	..	..	..	-6.874	..	..	-8.246	3.64	..	3.6414	-5.858	..	**0.441**
Bulgaria	1.873	3.143	..	..	..		..	..		0.775	..	0.625	..	..	**0.981**
Brazil	-2.641	0.679	0.045	..	..	0.432	..	-0.036	..	..	..	..	-0.118	..	**0.145**
Canada	21.498	0.194	..	..	..	..	..	-0.025	..	..	..	..	-0.015	..	**0.163**
China	-99.42	0.707	..	0.015	1.1069	..	..	..	..	5.156	..	..	..	..	**0.416**
Chili	6.997	..	-0.002	..	..	0.357	-0.002	..	-0.002	..	..	0.0018	..	0.049	**0.181**
Denmark	51.781	-0.105	..	0.001	..	-1.262	..	..	0.001	-3.183	0.011	0.136	..	0.916	**0.089**
France	7.562	..	..	..	..	..	..	..	..	..	..	..	..	0.766	**0.039**
Germany	-291.952	0.788	-1.154	-0.003	-288.285	-4.205	..	-0.179	-0.029	16.481	0.152	-0.665	1.192	0.763	**0.201**
Ghana	20.68	-0.099	..	0.075	..	..	..	..	..	..	..	0.121	..	0.049	**0.921**
Hungary	13.898	..	0.079	..	..	..	..	..	..	..	-0.042	0.032	..	0.387	**0.151**
India	14.089	..	..	..	..	0.155	0.298	-0.016	..	..	..	..	..	0.042	**0.41**
Indonesia	7.992	..	..	..	..	..	..	..	0.003	..	..	..	..	..	**0.605**
Iran	22.423	..	..	..	..	..	0.021	-0.021	..	..	..	..	..	0.138	**0.621**

Variables	Constant	LnGCF	LnTLF	FDI	TOP	LG	DI	TDebts	INF	LnTOTP	Edu	LnRexp	REMI	LnGexp	RMSE
Japan	4.456	6.014	4.026	-2.431	-1.906	4.305	-8.508	-1.993	-3.044	-2.334	-1.623	-1.633	-3.977	4.336	**0.707**
Luxembourg	-11.82	0.439	-0.05	..	..	-0.356	-0.172	-0.731	..	1.911	0.1296	..	0.001	..	**0.195**
Malaysia	1.042	0.514	-0.044	-0.0253	..	-0.247	0.043	-3.946	..	..	-0.045	-0.122	-0.011	0.237	**0.296**
Maldives	-3.913	..	-5.82	1.246	..	9.244	1.027	2.781	..	4.697	1.831	..	-3.806	1.572	**0.774**
Mexico	7.799	0.283	0.04	..	..	..	..	..	-0.0006	0.089	..	..	..	0.285	**0.136**
Morocco	2.095	3.938	-1.679	..	-1.036	..	-1.989	..	-2.805	..	..	5.052	..	..	**0.034**
Nepal	20.904	..	-0.009	0.013	-8.409	-2.017	-0.0773	..	..	..	..	0.3501	0.004	0.009	**0.081**
Netherland	9.926	..	-0.152	..	-0.365	..	..	..	-0.007	..	..	0.101	..	0.001	**0.082**
New Zealand	21.659	..	..	..	-9.833	..	..	..	-0.002	..	..	0.811	..	..	**0.069**
Norway	17.235	..	..	..	..	..	-0.033	..	..	..	..	0.42	..	..	**0.159**
Pakistan	8.261	..	..	..	-7.531		0.001	-0.008	..	0.714	-0.016	0.007	..	..	**0.063**
Peru	1.637	3.304	-7.044	4.494	-8.903	-5.039	..	..	-1.696	2.5202	..	2.687	-6.965	1.354	**0.072**
Paraguay	1.747	8.064	..	..	-1.048	-1.367	..	-3.083	-4.048	1.834	3.026	3.898	..	1.814	**0.024**
Philippines	15.372	0.081	..	-0.003	-10.259	-0.004	-0.003	-0.0114	..	0.441	..	0.071	..	0.301	**0.025**
Portugal	6.362	..	-0.029	..	..	..	..	..	-0.007	..	..	0.287	..	..	**0.067**
Qatar	46.382	..	0.012	..	-10.877	..	-0.01	..	..	0.007	..	..	..	..	**0.178**
South Africa	2.305	..	1.063	..	-1.151	..	..	..	..	..	4.65	5.083	..	-3.964	**0.011**
Sri Lanka	2.84	0.144			-9.459			-0.001		0.986	-0.009	0.189		0.156	**0.032**
Switzerland	23.217	..	-0.066	..	-10.896	..	..	..	-0.002	..	0.009	0.314	..	0.002	**0.023**
Sweden	2.583	..	-1.455	..	-1.189	-2.365	7.653	2.882	..	..	..	9.517	..	..	**0.017**
Turkey	9.972	..	..	3.337	-9.95	..	-3.336	..	-8.731	7.193	-6.375	2.153	1.154	1.886	**0.06**
United States	19.446	0.1	0.063	..	..	1.099		..	-0.014	..	-0.603	..	0.793	..	**3.57**

Variables	Constant	LnGCF	LnTLF	FDI	TOP	LG	DI	TDebts	INF	LnTOTP	Edu	LnRexp	REMI	LnGexp	RMSE
United Kingdom	20.773	..	-0.003	..	-10.541		..	..	..	..	..	0.475	..	0.007	**0.018**
Uruguay	-2.989	0.174	-0.002	..	-8.77	..	..	..	..	1.36	0.003	0.367	-0.165	0.007	**0.073**
Retention Frequency		**21**	**25**	**11**	**21**	**18**	**17**	**15**	**19**	**21**	**16**	**30**	**16**	**26**	

Figure 6.1: Graph of the Retention Variables in LASSO for Growth Modeling

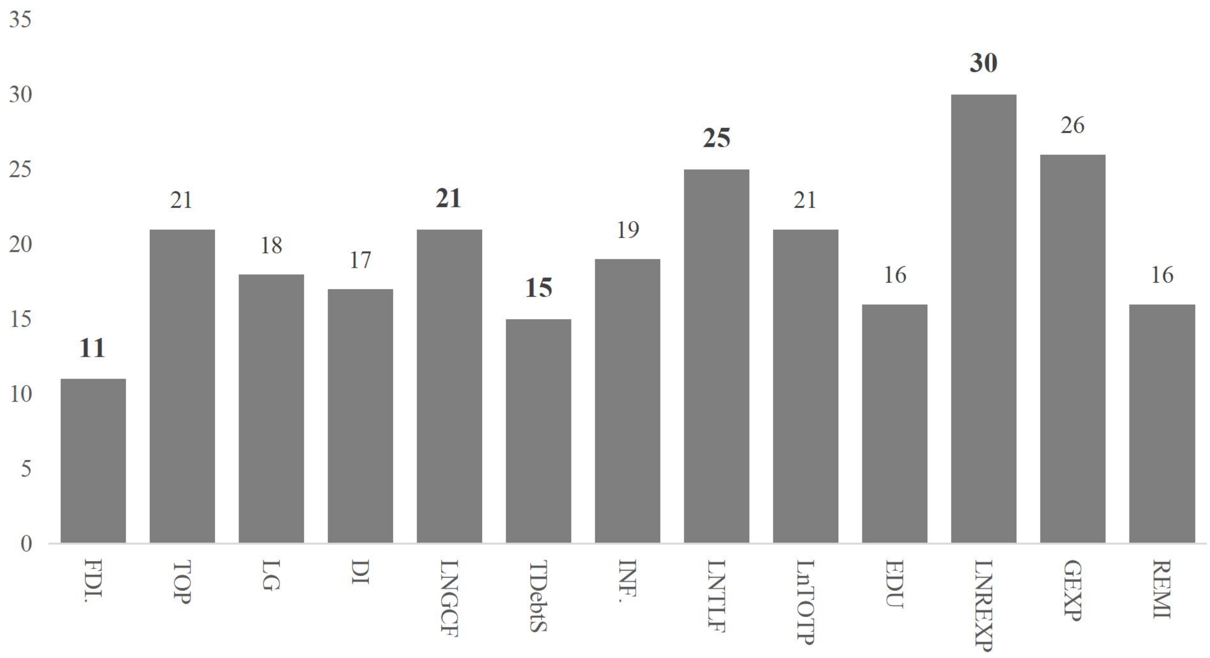

Figure 6.1 summarizes the variables' retention frequency in the Economic Growth model using LASSO. The results show that Variable real export (LNRexp) is most likely to be significant with a retention frequency of retention 30 out of 43. The next most common variables are LNGNXP and REMI with retention frequencies of 26/43 and 25/43,s respectively.

6.3.1.1 Results of Adoptive LASSO Regression

Table 6.2 shows the results of estimation using Adoptive LASSO. The table provides regression coefficients of the variables with different signs for different countries; the difference in the signs of coefficients of variables is an indication of country-specific heterogeneity, We have taken the countries individually, which reveals the heterogeneity in the model.The last column gives root mean square errors for each estimated model. The cells marked with (…) indicate the variables excluded from the model by Adoptive LASSO. Row 1 indicates that for Australia, the focus variable FDI, LNGCF and other auxiliary variables like DI, INF and EDU were excluded by LASSO.

Similarly, for Australia, the variable FDI, LNGCF, DI, and TDebts were considered insignificant and dropped by estimation procedures. In the last row, the frequency of retention of each variable is provided. The table shows that out of 43 countries, the variable LNGEXP was significant in 35 cases.

Table 6.2: The Results of Adaptive Least Absolute Shrinkage and Selection Operator for Growth Modeling

Country Name	Constant	LnGCF	LnTLF	FDI	TOP	LG	DI	TDebts	INF	LnTOTP	Edu	LnRexp	P(remi)	LnGexp	RMSE
Argentina	16.224	..	0.016	..	11.983	2.015	..	0.003	..	0.533	..	0.427	0.388	0.002	0.03
Australia	-17.935	..	-0.352	..	..	-6.907	..	..	-0.004	2.177	-0.034	0.558	0.046	0.007	0.191
Austria	27.256	0.095	-0.011	..	11.378	..	-0.005	..	-0.002	0.364	..	0.391	..	0.001	0.064
Bangladesh	-0.632	0.093	-0.011	..	..	0.078	0.009	..	-0.008	0.698	..	0.093 9	..	0.007	0.379
Belgium	-46.472	0.952	-0.037	..	..	0.186	..	..	-0.034	2.767	-0.004	..	0.002	0.211	0.332
Bhutan	-2.727	..	..	..	..	..	-6.874	..	-8.246	..	..	-3.641	-5.858	-2.695	0.515
Bulgaria	9.061	0.036	..	..	-56.536	..	..	..	..	..	..	0.491	..	0.142	.0.535
Brazil	-2.622	0.68	0.045	..	..	0.4	..	-0.035	..	..	..	..	-0.115	0.146	0.735
Canada	22.42	0.151	..	..	..	..	..	-0.025	..	..	..	..	-0.009	0.1288	0.535
China	8.489	7.232	..	2.163	-2.494	..	..	..	..	4.431	..	8.285	..	3.262	0.402
Chili	6.95	..	-0.001	..	..	0.311	-0.002	..	-0.002	..	..	0.001	..	0.043	0.263
Denmark	48.441	-0.103	..	0.001	..	-1.256	..	..	0.001	-2.953	0.009	0.123	..	0.918	0.131
France	7.758	..	..	..	..	..	..	..	..	..	..	..	..	0.762	0.081
Germany	-50.916	0.394	0.372	..	..	..	..	..	..	2.699	..	..	..	0.476	0.174
Ghana	21.352	-0.11	..	0.077	..	..	..	..	-0.001	..	0.005	0.0383	0.004	0.133	0.891
Hungary	17.911	..	..	..	..	..	..	..	..	..	..	..	..	0.294	0.154
India	13.892	..	..	..	..	0.106	0.236	-0.009	..	..	..	..	..	0.043	0.513
Indonesia	8.175	..	..	..	..	..	..	..	0.002	..	..	..	..	0.662	0.662
Iran	24.768	..	..	..	..	..	0.018	..	..	..	..	..	..	0.039	0.712
Japan	9.246	0.563	0.321	-0.377	-565.92	3.83	-0.057	-0.85	..	..	..	..	..	-0.045	0.139

Country Name	Constant	LnGCF	LnTLF	FDI	TOP	LG	DI	TDebts	INF	LnTOTP	Edu	LnRexp	P(remi)	LnGexp	RMSE
Luxembourg	-11.75	0.426	-0.052	..	..	-0.451	-0.182	-0.732	..	1.929	0.137	..	0.001	..	0.149
Malaysia	0.011	..	..	..	..	..	..	-0.977	..	..	..	..	..	0.467	0.469
Maldives	-3.95	..	..	6.857	..	6.472	9.385	2.707	..	4.735	1.719	..	-3.664	9.892	1.47
Mexico	2.265	0.455	0.048	0.047	..	..	..	..	-0.001	0.227	..	..	..	0.31	0.122
Morocco	-2.513	..	..	..	..	..	..	..	..	0.716	..	0.474	..	..	0.053
Nepal	20.904	..	-0.009	0.013	-8.409	-2.017	-0.077	..	..	..	..	0.35	0.004	0.001	0.078
Netherland	2.238	..	-4.38	..	-1.032	..	2.89	..	-2.929	..	..	2.565	..	6.08	0.018
New Zealand	21.659	..	..	..	-9.833	..	..	..	-0.002	..	..	0.811	..	..	0.049
Norway	17.235	..	..	..	-8.405	..	-0.033	..	..	0.068	..	0.42	..	..	0.083
Pakistan	8.261	..	..	..	-7.531	..	0.001	-0.008	..	0.007	-0.016	0.007	..	0.248	0.105
Peru	1.637	3.304	-7.044	4.494	-8.903	5.039	..	..	-1.696	2.52	..	2.687	-6.965	1.354	0.075
Paraguay	1.747	8.064	..	..	-1.048	-1.367	..	-3.083	-4.048	1.834	3.026	3.898	..	1.814	0.043
Philippines	7.153	0.141	..	-0.007	-7.497	..	-0.005	-0.021	..	0.821	..	0.063	..	0.162	0.017
Portugal	6.353	..	-0.027	..	..	..	..	..	-0.006	..	..	0.287	..	..	0.132
Qatar	46.382	..	0.012	..	-10.877	..	-0.01	..	..	0.006	..	..	..	..	0.188
South Africa															0.535
Sri Lanka	2.84	0.144	..	..	-9.459	..	..	-0.001	..	0.986	-0.009	0.189	..	0.156	0.052
Switzerland	23.217	..	-0.066	..	-10.896	..	..	..	-0.001	..	0.009	0.314	..	0.002	0.01
Sweden	2.583	..	-1.455	..	-1.189	-2.365	7.653	..	..	..	..	9.517	..	2.882	0.017
Turkey	9.972	..	..	3.337	-9.95	..	-3.336	..	-8.731	7.193	-6.375	2.153	-1.154	1.886	0.081
United States	19.446fr	0.1	0.063	..		1.099	..	..	-0.014	..	-0.603	..	..	..	1.66

Country Name	Constant	LnGCF	LnTLF	FDI	TOP	LG	DI	TDebts	INF	LnTOTP	Edu	LnRexp	P(remi)	LnGexp	RMSE
United Kingdom	20.773	..	0.003	..	-10.541	..	..	..	..	..	..	0.475	0.793	0.007	0.051
Uruguay	-2.989	0.174	-0.001	..	-8.772	..	..	..	..	1.36	0.002	0.367	-0.165	0.007	0.048
Retention Frequency		19	21	10	20	16	17	12	18	21	13	26	14	35	

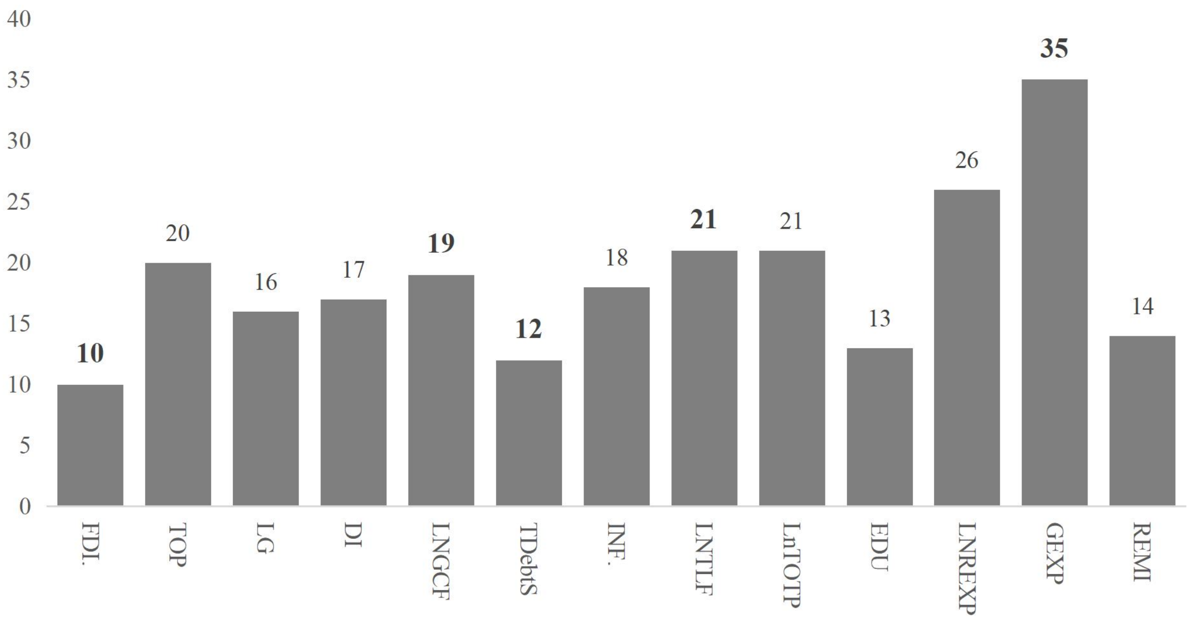

Figure 6.2: Graph of Retention Variables in Adoptive LASSO for Growth Modeling

Figure 6.3 summarizes the retention frequency of variables in the model of Economic Growth using Adoptive LASSO. The results show that Variable real export (LNGEXP) is most likely to be significant with a retention frequency of retention 35 out of 43. The next most common variables are LNREXP, LNTOTP and LNTLF with retention frequencies of 26/43 and 21/43, respectively.

6.3.1.2: Results of Elastic Net Regression

Table 6.3 presents the outcomes obtained through the Elastic Net estimation technique. This table offers an extensive examination of the regression coefficients for various variables, providing insight into differences in the signs of these coefficients across different countries. These variations in coefficient signs indicate the presence of country-specific heterogeneity, and the analysis was carried out separately for each country to uncover and understand this heterogeneity within the model.

Here is a detailed breakdown of the information in Table 6.3:

- The last column of the table displays Root Mean Square Error (RMSE) values, which serve as a metric to gauge the predictive accuracy of each estimated model.

- Variables that were excluded from the model by the Elastic Net method are marked with (…). For instance, in the case of Argentina (Row 1), the focus variable, foreign direct investment (FDI), and auxiliary variables such as domestic investment (DI), inflation (INF), and education (EDU) were deemed insignificant and were therefore removed from the model.
- The table also highlights instances where specific variables were considered insignificant and subsequently eliminated from the models for various countries. For example, in Austria, only one auxiliary variable, labor growth (LG), was found to be insignificant and was consequently omitted from the estimation procedures.
- In the last row of the table, the frequency of retention for each variable is provided. This frequency indicates how often each variable remained statistically significant across the models estimated for all 43 countries. Notably, the variable government expenditure (LNGEXP) was identified as significant in 37 out of the 43 cases, emphasizing its significance in the overall analysis.

Table 6.3 serves as a comprehensive resource for gaining a deeper understanding of the variability in model outcomes, the influence of different variables, and the predictive accuracy of the models across a diverse set of countries.

Table 6.3: The Results of Elastic Net for Growth Modeling

Country Name	Constant	LnGCF	LnTLF	FDI(inf)	TOP	LG	DI	TDebts	INF	LnTOTP	Edu	LnRexp	P(remi)	LnG exp	RMSE
Argentina	8.344	0.175	-0.208	..	-11.283	3.254	..	0.004	..	0.998	..	0.232	-0.701	0.204	**0.03**
Australia	-7.472	..	-0.036	..	..	..	..	0.01	-0.002	1.562	-0.014	0.146	..	0.143	**0.191**
Austria	9.462	0.164	-0.018	-0.0002	-10.315	..	-0.005	0.001	-0.008	0.807	0.024	0.18	0.004	0.147	**0.064**
Bangladesh	6.521	0.138	0.014	0.002	-2.952	0.359	0.003	..	0.002	..	..	0.091	..	0.086	**0.379**
Belgium	-5.078	8.329	5.251	2.447	1.890 -	..	..	..	-3.525	3.2432	-3.583	..	..	..	**0.211**
Bhutan	-7.681	..	..	..	..	..	..	..	-0.006	2.202			-0.079	-0.014	**0.515**
Bulgaria	..	..	..	..	-6.1577	..	-0.007	..	..	..	-0.003	-0.013	..	..	**..**
Brazil	-4.578	0.779	0.05	..	..	0.408	..	-0.034	..	..	..	0.04	-0.106	0.023	**0.146**
Canada	-6.28	0.268	..	..	..	..	..	-0.008	..	1.211	..	..	-0.011	0.085	**0.129**
China	-48.233	0.68	0.02	0.012	-6.303	..	..	..	..	2.655	0.134	0.024	..	0.025	**0.402**
Chili	8.525	1.378	-8.213	..	-2.449	4.705	-4.634	..	-1.201	..	..	1.057	..	1.009	**0.263**
Denmark	63.054	-0.134	0.006	0.002	6.117	-1.355	..	..	0.004	-3.945	0.024	0.248	..	0.845	**0.131**
France	0.725	..	0.039	..	..	..	..	0.01	..	0.576	..	0.16	..	0.283	**0.081**
Germany	-1.38	4.942	1.19	..	..	1.462	..	..	5.58	7.573	..	..	6.279	4.727	**0.174**
Ghana	20.274	-0.097	-0.001	0.069	-0.762	..	..	..	..	..	..	0.088	..	0.082	**0.891**
Hungary	12.396	..	0.116	..	2.46	..	..	..	0.001	..	-0.044	0.17	-0.007	0.286	**0.154**
India	13.531	0.132	..	..	..	..	0.076	..	..	..	..	0.108	..	0.106	**0.513**
Indonesia	8.65	..	..	0.026	-3.752	..	..	..	0.011	0.199	..	0.203	..	..	**0.662**
Iran	23.275	..	..	..	-7.482	..	0.014	-0.018	..	..	..	..	..	0.106	**0.712**
Japan	1.131	4.931	2.736	-2.905	-8.087	2.724	-5.112	-5.518	..	..	-9.824	..	..	..	**0.139**
Luxembourg	-3.713	3.529	-4.563	..	-9.247	-1.94	-4.234	-6.816	..	1.434	1.246	..	9.786	..	**0.149**

Country Name	**Constant**	**LnGCF**	**LnTLF**	**FDI(inf)**	**TOP**	**LG**	**DI**	**TDebts**	**INF**	**LnTOTP**	**Edu**	**LnRexp**	**P(remi)**	**LnG exp**	**RMSE**
Malaysia	7.075	0.058	..	..	-16.126	..	..	-0.8	..	0.412	..	0.077	..	0.175	**0.469**
Maldives	6.37	..	..	..	..	..	..	..	..	0.597	..	0.108	..	0.112	**1.472**
Mexico	5.945	3.166	2.934	3.674	-2.947	..	-1.455	..	-1.395	5.708	..	9.168	..	1.388	**0.122**
Morocco	2.069	1.017	-1.699	..	-1.074	..	-3.845	..	-1.016	..	..	3.195	-2.693	2.595	**0.053**
Nepal	2.136	6.19	-7.618	2.547	-8.09	-1.764	-1.069	1.863	-3.005	..	9.249	1.98	5.101	1.319	**0.078**
Netherland	21.191	0.035	-0.046	..	-10.577	..	..	..	-0.001	0.095	..	0.323	..	0.266	**0.018**
New Zealand	20.635	..	..	..	-10.05	..	..	-0.097	-0.002	0.138	..	0.311	..	0.277	**0.049**
Norway	10.711	..	..	..	-8.016	..	-0.026	-0.115	..	0.545	..	0.221	-0.254	0.188	**0.083**
Pakistan	9.827	0.059	..	0.001	-7.538	..	0.008	-0.012	..	0.6	-0.018	0.182	..	0.163	**0.105**
Peru	1.363	1.597	-4.157	3.438	-8.226	-7.246	..	-1.551	-9.118	3.361	..	2.497	-7.565	1.897	**0.075**
Paraguay	1.633	1.416	-1.704	..	-1.021	-2.35	-1.278	-9.036	-6.911	1.985	1.109	2.548	..	1.873	**0.043**
Philippines	1.412	1.121	..	-3.321	-1.007	-9.452	-3.62	-1.39	1.463	4.953	-2.523	2.236	6.36	1.757	**0.017**
Portugal	10.65	0.004	-0.05	..	..		0.006	-0.055	-0.008	..	..	0.174	..	0.163	**0.132**
Qatar	4.365	..	2.156	1.987	-1.027	4.021	-1.364	..	1.111	1.085	..	..	..	..	**0.188**
South Africa	22.389	0.047	0.015	..	-11.494	..	..	..	-0.001		0.006	0.301	..	0.265	**0.01**
Sri Lanka	2.027	0.225	-0.016	..	-9.548	..	..	-0.009	..	1.05	-0.009	0.213	..	0.193	**0.052**
Switzerland	20.851	0.168	-0.046	..	-11.101	..	..	..	-0.001	..	0.002	0.299	-0.067	0.261	**0.01**
Sweden	1.857	5.714	..	-1.278	-1.219	-3.654	1.684	..	..	3.344	-4.12	2.995	..	2.501	**0.017**
Turkey	3.556	..	0.054	0.009	-9.531	0.113	-0.001	-0.015	..	1.128	-0.002	0.219	..	0.159	**0.081**
United States	19.985	0.131	0.059	-0.002	-1.955	1.115	-0.004	0.003	-0.012		-0.283	**0.042**	0.664	0.024	**1.66**
United Kingdom	13.602	0.113	-0.001	..	-12.655	..	..	0.002	..	0.585	..	0.333	0.04	0.299	**0.051**
Uruguay	-10.188	0.393	-0.006	..	-6.726	..	..	0.007	..	1.516	0.012	0.178	-0.341	0.159	**0.048**

Country Name	**Constant**	**LnGCF**	**LnTLF**	**FDI(inf)**	**TOP**	**LG**	**DI**	**TDebts**	**INF**	**LnTOTP**	**Edu**	**LnRexp**	**P(remi)**	**LnG exp**	**RMSE**
Retention Frequency		**31**	**30**	**17**	**34**	**16**	**20**	**23**	**23**	**28**	**20**	**35**	**17**	**37**	

Figure 6.4: Graph of the Retention Variables in Elastic Net for Growth Modeling

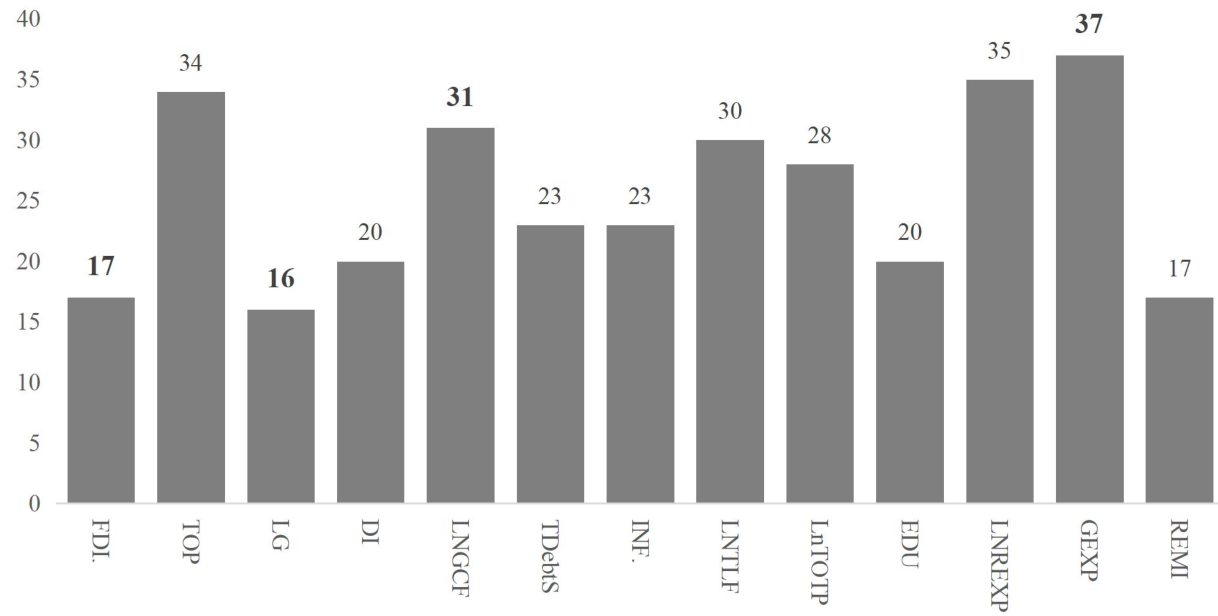

Figure 6.4 summarizes variables' retention frequency in the Economic Growth model using Elastic Net. The results show that auxiliary variable government expenditure (LNGEXP) is most likely significant, with 37 out of 43 retention frequencies. The next most common variables are real export (LNRexp) and trade openness(TOP), with retention frequencies of 35/43 and 34/43, respectively.

6.3.4 Results of Weighted Average Least Square

The weighted average least square regression is used to determine the significance of variables, which helps us in the model selection or specifications. Table 16 shows the estimation results using the weighted average least square (WALS) procedure. The table provides regression coefficients of the variables with different signs for different countries; the difference in the signs of coefficients of variables is an indication of country-specific heterogeneity, We have taken the countries individually, which reveals the heterogeneity in the model. The last row gives each estimated model's root mean square errors (MSE). The cells marked with (…) indicate the variables excluded from the model by the weighted average least square procedure. Column 1 indicates that for

Argentina, focus variables gross capital formation (LNGCF), the total labor force (LNTLF) and other auxiliary variables like trade openness (TOP), inflation (INF), total population (LNTOTP), real export (LNRexp), and personal remittances (REMI) were excluded by weighted average least square (WALS) procedure.

Similarly, for Australia's focus variable total labor force (LNTLF) and other auxiliary variable labor growth (LG), real export (LNRexp) and personal remittances (REMI) were traced out be insignificant and therefore dropped by estimation procedures. In the last row, the frequency of retention of each variable is provided. The table shows that out of 43 countries, the variables' real exports (LNRexp) and trade openness (TOP)` were significant in 43 cases.

Table 6.4: The Results of Weighted Average Least Square for Growth Modeling

Country	Constant	LnGCF	LnTLF	FDI	TOP	LG	DI	TDebts	INF	LnTOTP	Edu	LnRexp	P(remi)	GEXP	FRMSE
Argentina		.851	-1.019	..	-9.792	..			-.009	1.874	.	.506	-.991	-.003	1.236
Australia			-.531			-10.047						.763	.263		5.833
Austria	48.235		.082	-.001	-11.822				.029 8			.529	.017 3.77		3.585
Bangladesh	36.821	.497			-9.333	1.382				-1.265		.752		. .	0.751
Belgium	61.143	.308			-4.279		-.017		.008	1.861		.373			2.248
Bhutan		.308	-.621		-4.279		-.017		.008	1.861		.373			1.62
Bulgaria		.040	-.038	.003	-12.164 -			-.004	-.002	1.173		1.059	.011 7	-.003	1.628
Brazil	26.646	.925	.069		-12.798					-1.188		.832			2.149
Canada		.357			-14.057						.018	.812			0.543
China					-8.259		.011 0.98					.611		-.037	2.418
Chili	76.484	.599			-15.893	-.260				-3.258		.738			3.625
Denmark		.122	.0414		-10.506					1.815		1.083		.002	0.156
France					-15.016		.012			1.923	-.038	1.048			0.485
Germany	48.833		.270	.003	-14.945				.008		.050	.991			0.586
Ghana	18.972		-.0439	-.001	-8.430	-.440	-.003	-.001	.002	.450	.011	.710	-.003	-.008	3.067
Hungary		.132	-.098		-12.752		-.006					.903		-.002	2.12
India	21.291	.359	-.036		-11.810				.003			.872		.003	0.312
Indonesia	65.351	.049		.042	-10.634				.051			.924			1.716
Iran	36.794	.010	-.109	-.097	-13.037			-.034			-.031	.636			3.104
Japan					-10.063		-.048					1.023		.024	4.351
Luxembourg	29.652				-9.988					-.761	-.025	.873 5	.0002	-.006	1.476
Malaysia	36.309	.206			-12.300							.939			0.315
Maldives		-.092	-.051		-7.750 -7.75							.539 5.95		.010 2.70	5.005
Mexico		.617	.063		-8.165							.503 7			1.051
Morocco	29.020	.471	-.091		-11.308					-.778	.072	.883			0.392

Country	Constant	LnGCF	LnTLF	FDI	TOP	LG	DI	TDebts	INF	LnTOTP	Edu	LnRexp	P(remi)	GEXP	FRMSE
										-2.59	3.45				
Nepal		.081			-6.854		-.338					.313			2.137
Netherland		.139		-.0002	-13.123							.969			1.358
New Zealand	31.801	.118		-.0002	-12.308				.006 4.02			.908			0.527
Norway		.575	-.132		-15.730										2.213
Pakistan	22.894	.501			-13.228			-.036 -3.05				.892 5.88	.032 4.66		2.601
Peru	8.661	.514			-9.076					.544		.563			3.64
Paraguay	21.712	.373			-12.150		-.005			-.302		.933			4.136
Philippines	19.595	.258	.099		-10.876		-.006	-.014				.695		.002 .	2.261
Portugal		.381		-.0001	-10.761					3.499		.828	.003		0.171
Qatar	34.434				-10.637							.377			0.039
South Africa	20.989	.408	.066		-12.545							.863			1.53
Sri Lanka	27.367	.581	-.199		-10.803							.677			2.748
Switzerland	24.234	.346			-13.180							.960			0.683
Sweden		.154			-13.892							.991			4.667
Turkey	26.885		.189		-12.511		-.002	-.018				.953			1.157
United States	46.083	.456		-.011	-9.607						-.0189	.530			1.792
United Kingdom	35.481				-15.305		.006					1.04	.202		0.074
Uruguay		.438			-8.713							.644	-.269		2.465
Retention Frequency		**33**	**19**	**09**	**43**	**03**	**11**	**07**	**09**	**15**	**08**	**43**	**10**	**09**	

Figure 6.5: Graph of Retention Variables in Weighted Average Least Square for Growth Modeling.

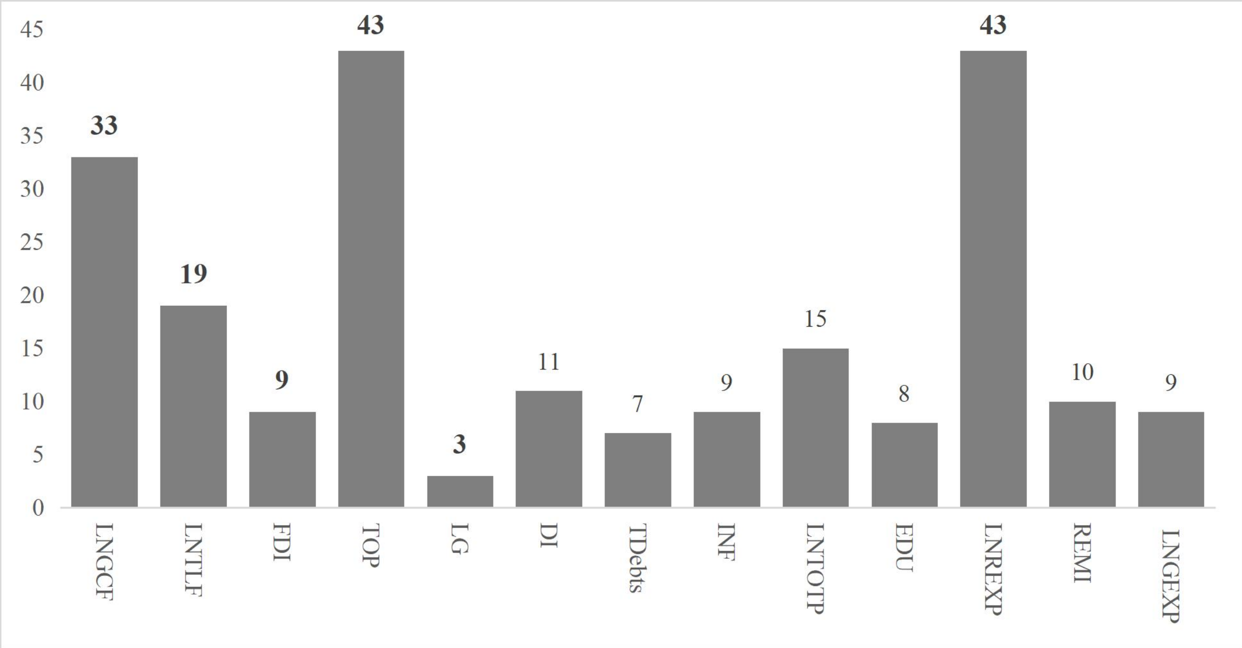

Figure 6.5 summarizes variables' retention frequency in the Economic Growth model using weighted average least squares (WALS). The results show that variable variables real exports (LNRexp) and trade openness (TOP) are most likely significant, with a retention frequency of 43 out of 43. The next most common variables are gross capital formation (LNGCF)) with a retention frequencies of 33 out of 43.

6.3.4.1 Results of Encompassing Procedure

The model selection by encompassing is based on multiple procedures having many steps. In the last step, each model is stated separately and the model with minimum root mean square error (RMSE) is selected. In the next step, whether the model with the smallest root mean square error (RMSE) encompasses the other model or not is tested. In the third step, the revised general unrestricted model (GUM) is constructed by combining the model with the smallest root mean square error (RMSE) and the models not encompassed by this model. The general unrestricted model (GUM) is then simplified using general to specific (GLS) methodology. The final results of encompassing are summarized in Table 6.5

Table 6.5 shows the results of the estimation using the encompassing procedure. The table provides regression coefficients of the variables with different signs for different countries; the difference in the signs of coefficients of variables is an indication of country-specific heterogeneity, We have taken the countries individually, which reveals the heterogeneity in the model. The last row gives each estimated model's root mean square errors (MSE). The cells marked with (…) indicate the variables excluded from the model by a Non-Nested encompassing procedure. Column 1 indicates that for Argentina, the variable foreign direct investment (FDI) current and lag value of the variables education (EDU_1) and government expenditure (LNGEXP_1) and other variables Inflation (INF), Domestic Investment (DI), total debts (TDebts), the total labor force (LNTLF), total population (TOTP) real export(LNRexp) and Personal remittances (REMI) with current and its lag values were excluded by encompassing procedure. Similarly, for Australia the lag values of DI_1, TOTP_1, EDU_1and other variables foreign direct investment (FDI), labor Growth (LG)), gross capital formation(LNGCF), total debts (TDebts), total labor force (LNTLF) government expenditure (LNGEXP) and Personal remittances (REMI) with current and its lag values were traced out be insignificant and therefore dropped by estimation procedures. In the last column, the frequency of retention of each variable is provided. The table shows that out of 43 countries, the lag value of the dependent variable LNGDP_1 was significant in 40 cases.

Table 6.5: The Results of the Final Model (Non-Nested Encompassing) for Growth Modeling

Country Name	**Argentina**	**Australia**	**Austria**	**Bangladesh**	**Belgium**	**Bhutan**	**Bulgaria**	**Brazil**	**Canada**	**China**	**Chili**	**Retention frequency**
Variables												
Constant	-4.692	-15.647	..	38.729	..	..	..	..	5.731	-1.645	-41.445	**..**
LNGDP_1	0.927	0.614	0.437	0.135	0.909	0.960	0.245	0.933	0.821	0.871	0.646	**40**
FDI(inf)	..		..	..	..	0.0152	..	..	..	..	..	**07**
FDI(inf)_1	0.021	..	..	-0.041	..	..	..	..	..	0.040	..	**08**
TOP	-9.127	1.918	-3.650	-9.949	..	-0.107	..	-14.964	-13.495	..	..	**28**
TOP_1	9.557	2.447	..	..	..	..	..	13.371	10.163	..	..	**18**
LG	..	..	..	0.729	..	..	..	..	..	..	..	**04**
LG_1	-23.419	..	..	..	..	..	..	..	..	..	..	**05**
DI	..	0.034	0.039	..	..	..	..	2.114	..	0.011	..	**11**
DI_1	..	..	..	..	..	0.019	..	..	..	..	-0.002	**10**
LnGCF	1.090	..	0.882	0.761	0.756	0.051	..	0.703	0.301	..	0.305	**31**
LnGCF_1	-0.847	..	..	-0.288	-0.661	..	..	-0.599	-0.276	..	..	**19**
TDebtS	..	..	..	..	..	..	-0.014	..	..	..	8.103	**11**
TDebtS_1	..	..	..	..	..	..	0.013	..	..	..	-8.290	**09**
Inf	..	-0.035	..	0.004	..	..	..	..	..	..	..	**14**
Inf_1	..	-0.018	..	0.045	..	-0.008	..	..	..	..	0.011	**11**
LnTLF	..	..	..	..	..	..	-0.110	..	..	..	..	**10**
LnTLF_1	..		..	..	..	..	..	..	..	..	..	**04**
LnTOTP	..	0.773	..	-13.474	..	..	..	..	..	..	22.894	**14**
LnTOTP_1	..	..	..	12.117	..	..	0.318	..	..	..	-20.667	**11**
Edu	-0.047	-0.135	..	..	..	..	-0.037	-0.041	..	..	..	**12**
Edu_1	..	..	..	..	..	..	..	0.034	..	..	..	**06**
LnRExp	..	0.538	..	0.683	..	..	0.645	0.927	0.760	..	0.579	**35**
LnRExp _1	..	-0.312	..	..	..	..	..	-0.848	-0.575	..	-0.349	**22**
GEXP	-0.022	..	..	..	..	0.002	0.004	..	..	..	..	**12**
GEXP_1	..	..	..	-0.002	..	..	..	..	..	..	..	**08**
P(remi)	..	..	..	0.0089	..	..	..	..	..	..	..	**12**

Country Name / **Variables**	**Argentina**	**Australia**	**Austria**	**Bangladesh**	**Belgium**	**Bhutan**	**Bulgaria**	**Brazil**	**Canada**	**China**	**Chili**	**Retention frequency**
P(remi)_1	..	..	..	..	..	..	..	0.023	..	..	3.136	**12**
RMSE	**1.323**	**11.833**	**4.585**	**1.751**	**7.248**	**1.72**	**1.318**	**2.059**	**0.843**	**2.518**	**3.715**	**Minimum**

Country Name / **Variables**	**Denmark**	**France**	**Germany**	**Ghana**	**Hungary**	**India**	**Indonesia**	**Iran**	**Japan**	**Luxembou**	**Malaysia**	**Retention frequency**
Constant	9.538	..	28.1776	..	20.004	30.276	18.454	42.044	5.882	..	9.658	**..**
LNGDP_1	0.434	0.528	0.041	0.601	0.132	0.3034	0.221	..	0.838	0.743	0.607	**40**
FDI(inf)	..	-0.002	0.006	..		..	0.027	-0.022	..	-0.003	..	**07**
FDI(inf)_1	..	..	0.004	..		..	..		..	..	..	**08**
TOP	..	-17.715	-13.087	-8.006	-11.704	..	-10.919	-12.290	..	-9.846	-11.295	**28**
TOP_1	..	9.553	..	4.710	0.733	..	..	-1.528	..	7.406	6.144	**18**
LG	..	-0.262	..	..		..	..	-1.213	..	..	..	**04**
LG_1	..	..	-3.551	..		..	-1.458		..	..	0.171	**05**
DI	-0.788	..	..	..		..	-0.007	-0.009	..	..	..	**11**
DI_1	0.902	0.011	-1.368	..		..	0.004	..	..	..	..	**10**
LnGCF	-0.179	0.332	-0.160	-0.077	0.231	0.699	-0.004	..	..	..	0.196	**31**
LnGCF_1	0.201	-0.329	0.084	..	-0.110	..	0.059	0.010	..	0.076	-0.137	**19**
TDebtS	-4.962	72.803	-1.345	..	..	..	..	-0.025	..	..	..	**11**
TDebtS_1	4.962	-72.805	..	..	..	..	..	..	..	..	..	**09**
Inf	-0.035	0.013	..	..	-0.001	..	..	..	..	-0.004	..	**14**
Inf_1	..	-0.010	..	..	..	..	..	..	-0.031	..	..	**11**
LnTLF	0.080	..	0.394	..	..	-0.032	..	-0.150	..	..	..	**10**
LnTLF_1	..	..	..	..	..	..	..	-0.102	..	..	..	**04**
LnTOTP	..	..	..	1.040	..	-65.038	..	11.038	0.254	..	..	**14**
LnTOTP_1	..	..	1.405	..	..	63.691	..	-11.248	..	..	..	**11**
Edu	..	-0.039	..	..	..	..	-0.011	..	..	..	..	**12**
Edu_1	..	..	..	..	..	..	..	..	..	..	-0.008	**06**

Country Name / Variables	Denmark	France	Germany	Ghana	Hungary	India	Indonesia	Iran	Japan	Luxembou	Malaysia	Retention frequency
LnRExp	0.970	0.981	1.038	..	0.830	..	0.848	0.573	..	0.874	0.881	**35**
LnRExp _1	-0.417	-0.412	..	..	..	..	..	0.1400	..	-0.659	-0.521	**22**
GEXP	..	-0.007	..	0.002	-0.002	..	..	..	0.052	-0.128	0.002	**12**
GEXP_1	..	..	..	..	-0.002	..	..	..	-0.047	..	0.001	**08**
P(remi)	..	..	..	..	-0.018	..	..	-0.049	..	..	..	**12**
P(remi)_1	..	-0.010	0.381	..	..	..	0.063	..	..	..	..	**12**
RMSE	**0.756**	**0.595**	**0.786**	**3.077**	**2.11**	**0.832**	**1.396**	**6.104**	**2.351**	**2.276**	**0.915**	**Minimum 0.595**

Country Name / Variables	Maldives	Mexico	Morocco	Nepal	Netherland	New Zealand	Norway	Pakistan	Peru	Paraguay	Philippines	Retention frequency
Constant	..	..	14.167	..	7.786	21.466	..	..	..	24.461	..	**..**
LNGDP_1	0.901	0.619	0.357	0.905	0.4608	0.054	0.894	0.8438	0.138	0.159	0.962	**40**
FDI(inf)	..	..	-0.023	..	..	..	..	..	..	..	..	**07**
FDI(inf)_1	-0.011	..	-0.014	..	..	..	..	..	..	..	0.024	**08**
TOP	-8.817	-10.838	-11.544	-5.895	..	-11.662	-16.215	..	-7.802	-10.812	..	**28**
TOP_1	8.190	9.335	1.818	6.743	..	..	15.512	..	2.708	..	..	**18**
LG	..	-1.548	..	..	..	..	..	..	..	..	..	**04**
LG_1	..	..	..	..	..	..	..	..	..	..	..	**05**
DI	..	..	..	..	..	..	..	..	..	-0.0075	..	**11**
DI_1	..	..	..	..	..	..	..	..	..	..	..	**10**
LnGCF	..	0.367	0.388	..	..	..	0.518	0.312	0.414	0.255	0.260	**31**
LnGCF_1	..	..	-0.291	..	..	..	-0.407	-0.331	..	..	-0.260	**19**
TDebtS	..	..	0.011	..	..	..	..	..	..	..	..	**11**
TDebtS_1	..	..	..	..	..	..	..	..	..	..	..	**09**
Inf	..	-0.004	..	..	-0.027	..	..	..	4.173	0.003	..	**14**
Inf_1	..	0.003	..	..	..	..	..	..	..	..	..	**11**

Country Name	Maldives	Mexico	Morocco	Nepal	Netherland	New	Norway	Pakistan	Peru	Paraguay	Philippines	Retention
LnTLF	..	..	-0.035	..	-0.171	..	..	..	..	..	..	**10**
LnTLF_1	..	..	..	..	..	..	..	..	..	..	..	**04**
LnTOTP		..	..	..	..	5.531	..	..	0.685	-0.619	..	**14**
LnTOTP_1	..	..	..	..	..	-5.321	..	..	..	..	..	**11**
Edu	-0.014	..	0.059	..	..	..	..	0.047	..	..	-0.036	**12**
Edu_1	0.022	..	0.051	..	..	..	..	..	0.033	..	..	**06**
LnRExp	0.636	0.753	0.765	0.347	0.652	0.920	0.773	0.196	0.508	0.880	0.807	**35**
LnRExp _1	-0.460	-0.609	..	-0.318	-0.288	-0.040	-0.712	..	..	..	-0.776	**22**
GEXP	..	..	..	..	..	..	..	..	0.002	..	..	**12**
GEXP_1	..	-0.015	..	..	0.010	..	..	..	..	..	..	**08**
P(remi)	..	..	0.027	..	..	-0.088	..	-0.035	..	0.064	..	**12**
P(remi)_1	..	..	..	0.010	..	..	-1.239	0.041	-0.019	..	..	**12**
RMSE	**2.005**	**1.032**	**0.492**	**2.337**	**0.358**	**0.427**	**2.202**	**2.101**	**3.84**	**2.126**	**1.261**	**Minimum 0.358**

Country Name	Portugal	Qatar	South Africa	Sri Lanka	Switzerland	Sweden	Turkey	United States	United Kingdom	Uruguay	Retention frequency
Variables											
Constant	-4.869	46.623	24.411			21.841	25.403	..	78.833	..	**..**
LNGDP_1	0.696	-0.295	..	0.903	0.838	..	0.161	0.856	0.288	0.319	**40**
FDI(inf)	..	..	..	..	..	..	..	..	..	..	**7**
FDI(inf)_1	..	..	..	..	..	..	..	..	-0.005	..	**8**
TOP	..	-9.881	-11.803	..	..	-12.308	-13.824	..	..	-10.873	**28**
TOP_1	..	-2.472	..	..	..	-1.037	..	..	..	..	**18**
LG	..		..	..	..	..	..	..	..	..	**4**
LG_1	..	-336.927	..	..	..	..	..	..	..	..	**5**
DI	..		..	-0.004	..	..	-0.002	..	..	-0.037	**11**
DI_1	..		..	0.010	..	..	0.002	..	0.018	-0.034	**10**

Country Name	Portugal	Qatar	South	Sri	Switzerland	Sweden	Turkey	United	United	Uruguay	Retention
LnGCF	0.2578	-0.163	0.255	..	0.643	..	0.086	0.206	0.601	31	**31**
LnGCF_1	..	0.167	..	..	-0.530	-0.064	-0.108	-0.099	..	-0.301	**19**
TDebtS	..	..	..	-0.011	..	..	-0.020	..	0.018	71.638	**11**
TDebtS_1	..	..	..	-0.013	..	..	..	..	..	-72.200	**9**
Inf	-0.016	..	-0.008	0.004	..	..	..	..	..	0.0053	**14**
Inf_1	0.015	..	..	-0.004	..	0.003	..	..	0.012	..	**11**
LnTLF	..	26.890	0.090	..	..	..	..	..	..	-0.031	**10**
LnTLF_1	..	- 26.8992	..	-0.050	..	0.510	..	..	..	..	**4**
LnTOTP	..	..	-0.4982	9.954	9.480	4.812	..	..	..	..	**14**
LnTOTP_1	..	..	..	-9.919	-9.514	-5.029	..	..	-5.105	..	**11**
Edu	..	-0.047	..	-0.044	..	..	..	..	..	..	**12**
Edu_1	..	-0.034	..	..	..	..	..	..	..	..	**6**
LnRExp	0.677	0.425	0.944	0.133	0.598	1.008	1.051	0.098	0.571	0.842	**35**
LnRExp _1	-0.415	..	0.073	..	-0.525	0.069	-0.102	-0.052	..	..	**22**
GEXP	..	..	..	..	..	..	..	..	-0.011	-0.202	**12**
GEXP_1	..	..	..	0.001	..	0.005	..	..	..	..	**8**
P(remi)	0.001	-0.319	..	-0.036	..	-0.087	..	-0.427	..	..	**12**
P(remi)_1		-0.198	-0.424	..	..	0.077	..	..	..	..	**12**
RMSE	**0.671**	**0.029**	**1.93**	**1.848**	**0.883**	**0.667**	**1.557**	**1.292**	**0.084**	**2.365**	**Minimum 0.029**

Figure 6.6: Graph of Retention Variables in Encompassing Procedure for Growth Modeling

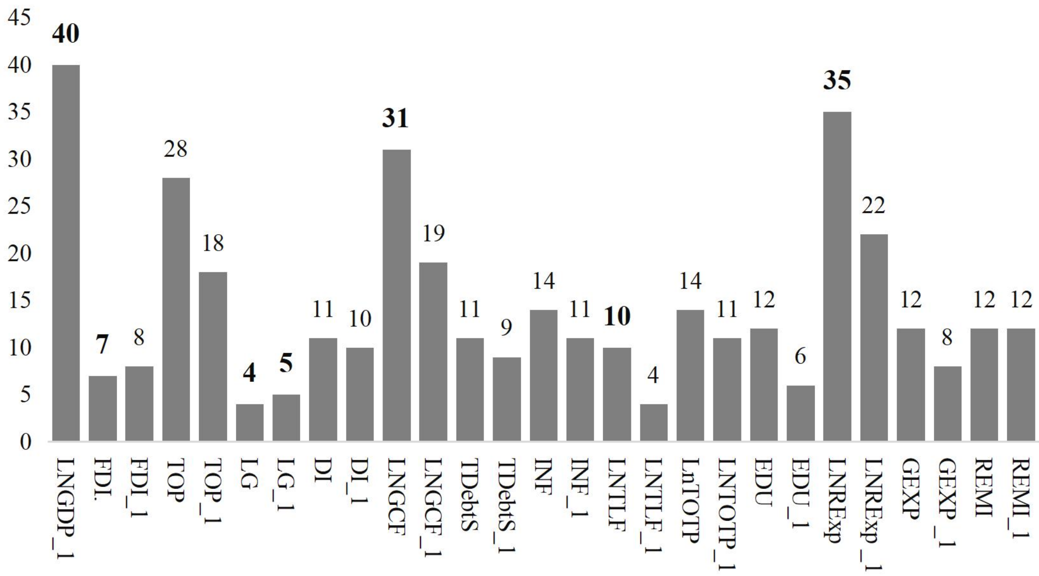

Figure 6.6 summarizes the frequency of retention variables in the model of Economic Growth using the Non-Nested Encompassing procedure. The results show that variable LNGDP_1 is most likely significant, with a retention frequency of 40 out of the 43 regressions. The next most common variables are Real Export (LNRexp) and gross capital formation (LNGCF), with retention frequencies 35/43 and 31/43, respectively.

Automatic Model Selection Procedure

An automated algorithm for the model selection procedure is based on a general-to-specific framework, after making the general unrestricted model, it uses an enhanced search method named tree search in place of multiple searches, which take all sets and then systematically discards the irrelevant sets along with diagnostic testing. Different sub-models are then re-united to get the final model. It is known as 3rd generation algorithm and named Autometrics and is included in Pc-Give software as a part.

6.3.4.2 Results of Autometrics Procedure

Table 6.5 offers an extensive analysis of the Autometrics procedure's results. This table delves into the regression coefficients for various variables, shedding light on the disparities in coefficient signs observed across different countries. These differences in coefficient signs are indicative of country-specific heterogeneity, and the analysis was conducted separately for each country to uncover and understand this heterogeneity within the model.

Here's a detailed breakdown of the information within Table 6.5:

- The last row of the table provides Root Mean Square Error (RMSE) values, which serve as metrics for evaluating the predictive accuracy of each estimated model.
- Variables excluded from the model by the Autometrics method are denoted with (…). For instance, in the case of Argentina (Column 1), variables such as FDI, LNTOTP along with its current value, TOP_1, and EDU_1 along with its lag value were excluded from the model through the Autometrics procedure.
- The table also highlights cases where specific variables were considered insignificant and subsequently removed from models in various countries. For Australia, for instance, both the current and lag values of the FDI variable, along with LG, LNGCF, TOTP, and REMI, were identified as insignificant and therefore removed during the estimation process.
- In the last column of the table, the frequency of retention for each variable is provided. This frequency indicates how often each variable remained statistically significant across the models estimated for all 43 countries. Remarkably, the variable "trade opens" (TOP) was found to be significant in 42 out of the 43 cases, underscoring its substantial importance in the overall analysis.

Table 6.5: The Results of Autometrics for Growth Modeling

Country Name / Variables	Argentina	Australia	Austria	Bangladesh	Belgium	Bhutan	Bulgaria	Brazil	Canada	China	Chili	Retention Frequency
Constant	7.60155	..	14.879	20.560	44.623	4.541	..	..	-23.670	..		
LNGDP_1	0.065	0.451	0.504	0.299	0.726	0.753	..	1.185	0.740	0.297	0.199	**31**
FDI(inf)	..	..	..	..	..	0.009	..	..	..	..	..	**08**
FDI(inf)_1	0.013	..	..	-0.040	..	0.007	0.003	..	..	-0.021	..	**9**
TOP	-12.712	2.790	-13.734	-8.684	-16.766	-5.522	-12.542	-14.287	-11.912	-8.754	-10.919	**42**
TOP_1	..	2.398	7.539	2.849	11.300	4.218	..	15.646	7.584	-1.324	..	**14**
LG	..	..	..	0.540	..	..	..	1.162	..	-0.602	..	**13**
LG_1	..	..	..	..	-573.302	-201.459	..	2.54521	..	-0.702	..	**11**
DI	0.001	0.051	..	..	..	0.001	-0.002	-4.302	..	..	..	**21**
DI_1	..	..	..	..	..	0.002	..	-9.3900	..	..	-0.001	**14**
LnGCF	0.833	..	..	..	..	0.145	0.075	0.468	0.348	..	0.383	**29**
LnGCF_1	..	..	..	..	-0.192	-0.063	..	-0.699	-0.231 1	0.173	..	**14**
TDebtS	..	..	..	..	..	-0.001	..	..	..	-0.039	4.324	**20**
TDebtS_1	..	0.011	..	0.050	0.011	..	..	..	0.009	-0.003	-4.443	**13**
Inf	..	-0.035	0.018	0.003	0.026	0.005	-0.002	..	..	0.008	..	**21**
Inf_1	..	-0.021	..	..	..	-0.002	-0.002	0.003	..	0.006	0.004	**13**
LnTLF	-0.749	..	..	..	37.755	16.079	..	..	..	..	..	**17**
LnTLF_1	-0.454		..	-0.078	-37.750	-16.237	..	..	..	..	..	**11**
LnTOTP	..	..	-3.185	-22.554	..	0.132	..		1.836	-42.016	16.603	**11**
LnTOTP_1	1.366	..	3.467	22.253	-1.812	-0.012	1.388	..	..	43.021	-15.736	**17**
Edu	-0.021	-0.122	..	..	..	..	0.012	..		-0.040	..	**09**
Edu_1	..	..	..	-0.096	..	-0.007	..	..	-0.014	..	..	**09**
LnRExp	0.538	0.371	0.655	0.670	0.834	0.504	1.056	1.041	0.681	0.539	0.710	**42**
LnRExp _1	0.118	..	-0.431	..	-0.569	-0.408	..	-1.102	-0.503	..	..	**15**
GEXP	..	-0.022	..	..	..	2.251	-0.002	0.002	..	0.616	-0.003	**12**
GEXP _1	..	..	-0.008	..	..	0.004	-0.002	0.002	..	-0.608	..	**13**

Country Name	Argentina	Australia	Austria	Bangladesh	Belgium	Bhutan	Bulgaria	Brazil	Canada	China	Chili	Retention Frequency
P(remi)	..	..	..	-0.018	..	..	..	..	..	..	..	**10**
P(remi)_1	..	..	0.006	..	..	0.019	0.013	0.032	..	-0.100	1.814	**14**
RMSE	**0.0323**	**0.051**	**0.0254**	**0.018**	**0.0541**	**0.012**	**0.111**	**0.031**	**0.007**	**0.038**	**0.023**	

Country Name	Denmark	France	Germany	Ghana	Hungary	India	Indonesia	Iran	Japan	Luxem bourg	Malay sia	Retention Frequency
Variables												
Constant	..	..	..	24.840	..	18.090	..	42.593	12.594	..	54.808	
LNGDP_1	-0.060	0.064	0.052	..	..	0.135	0.133	..	0.298	0.855	0.139	**31**
FDI(inf)	..	-0.005	0.005	..	..	..	0.025	..	..	..	0.010	**08**
FDI(inf)_1	..	..	0.004	..	..	..	..	..	..	..	..	**9**
TOP	-10.779	-14.510	-13.284	..	-13.312	-11.030	-10.763	-13.108	-9.002	-9.852	-10.507	**42**
TOP_1	..	..	..	-9.494	..	..	..	-1.4789	..	..	..	**14**
LG	..	..	..	..	..	-0.250	-1.289	-1.408	-1.195	..	0.256	**13**
LG_1	..	..	3.606	..	..	-0.423	..	1.740	..	..	..	**11**
DI	..	0.014	0.875	..	..	-1.031	-0.0059	..	-0.040	..	-0.009	**21**
DI_1	..	..	-0.835	-0.006	..	0.685	..	..	0.015	0.079	..	**14**
LnGCF	0.089	..	-0.096	-0.037	0.121	0.153	..	..	..	0.079	0.137	**29**
LnGCF_1	..	..	..	-0.040	-0.061	..	0.081	..	..	0.064	..	**14**
TDebtS	..	-0.031	..	-0.013	..	..	..	-0.025	..	..	-1.703	**20**
TDebtS_1	..	..	..	0.010	0.297	..	..	..	..	..	..	**13**
Inf	..	..	..	-0.001	-0.001	..	..	..	..	..	..	**21**
Inf_1	..	..	..	-0.001	-0.002	..	..	..	..	..	..	**13**
LnTLF	0.060	..	0.411	..	..	..	-0.142	-0.279	..	..	0.028	**17**
LnTLF_1	..	..	..	..	-0.081	-0.030	..	..	..	..	..	**11**
LnTOTP	1.095	1.515	..	-29.732	1.665	..	45.947	16.449	..	..	-2.616	**11**
LnTOTP_1	..	..	1.110	30.003	..	..	-44.783	-16.640	..	..	..	**17**
Edu		-0.056	..	..	..	..	..	..	..	..	0.015	**09/06**
Edu_1		..	..	0.039	..	0.011	..	..	..	..	..	**09**
LnRExp	1.099	1.035	1.016	0.665	0.934	0.902	0.825	0.617	0.905	0.883	0.974	**42**

Country Name **Variables**	**Denmark**	**France**	**Germany**	**Ghana**	**Hungary**	**India**	**Indonesia**	**Iran**	**Japan**	**Luxembourg**	**Malaysia**	**Retention Frequency**
LnRExp _1	..	..	..	..	..	..	..	0.133	..	-0.787	..	**15**
GEXP	..	-0.004	..	..	..	0.002	..	..	0.014	-0.004	..	**12**
GEXP _1	..	..	..	-0.001	-0.003	0.003	..	..	..	..	..	**13**
P(remi)	..	..	..	..	-0.021	..	..	..	..	..	..	**10**
P(remi)_1	..	..	0.330	..	..	..	0.082	..	-0.269	..	..	**14**
RMSE	**0.006**	**0.007**	**0.008**	**0.036**	**0.009**	**0.017**	**0.022**	**0.051**	**0.030**	**0.061**	**0.010**	

Country Name **Variables**	**Maldives**	**Mexico**	**Morocco**	**Nepal**	**Netherland**	**New Zealand**	**Norway**	**Pakistan**	**Peru**	**Paraguay**	**Philippines**	**Retention Frequency**
Constant	..	-5.846	16.508	..	28.496	24.497	..	16.264	11.741	23.789	41.198	
LNGDP_1	0.901	1.065	0.324	0.453	..	..	0.894	0.370	0.101	0.158	..	**31**
FDI(inf)	..	..	..	..	..	-0.0001	..	..	..	..	..	**08**
FDI(inf)_1	-0.011	..	..	..	..	..	..	..	..	..	..	**9**
TOP	-8.8177	-11.203	-13.024	-5.992	-13.686	-12.339	-16.215	-9.603	-9.570	-10.802	-14.242	**42**
TOP_1	8.1907	15.414	..	..	..	..	15.512	..	..	..	..	**14**
LG	..	-1.651	..	..	..	..	..	..	..	..	1.189	**13**
LG_1	..	..	..	..	..	..	..	..	..	..	..	**11**
DI	..	0.003	..	-0.112	..	-0.003	..	..	0.001	-0.007	-0.006	**21**
DI_1	..	..	0.015	..	..	..	..	..	..	..	..	**14**
LnGCF	..	0.482	0.286	0.053	0.068	0.080	0.518	0.419	0.4309	0.258	0.149	**29**
LnGCF_1	..	-0.450	..	..	..	..	-0.407	-0.281	..	..	..	**14**
TdebtS	..	-0.007	..	-0.157	..	..	..	-0.018	..	-0.003	..	**20**
TDebtS_1	..	..	..	..	..	..	..	..	..	..	0.019	**13**
Inf	..	-0.004	0.008	..	..	0.003	..	-0.007	-0.003	0.002	..	**21**
Inf_1	..	0.004	0.007	..	..	..	..	..	..	..	..	**13**
LnTLF	..	..	..	..	..	..	..	..	-0.076	..	0.129	**17**

Country Name	**Maldives**	**Mexico**	**Morocco**	**Nepal**	**Netherland**	**New Zealand**	**Norway**	**Pakistan**	**Peru**	**Paraguay**	**Philippines**	**Retention Frequency**
Variables												
LnTLF_1	..	..	..	..	..	..	..	..	..	..	..	**11**
LnTOTP	..	..	..	1.009	4.902	..	..	..	0.358	-0.566	-50.480	**11**
LnTOTP_1	..	..	..	..	-5.086	..	..	..	..	..	49.510	**17**
Edu	-0.014	..	..	..	..	..	..	..	..	..	..	**09**
Edu_1	0.022	..	0.082	..	..	..	..	..	..	..	0.038	**09**
LnRExp	0.636	0.669	0.750	0.259	1.002	..	0.925	0.606	0.578	0.872	1.00	**42**
LnRExp _1	-0.460	-0.851	..	..	..	..	-0.712	..	..	..	..	**15**
GEXP	..	..	..	..	..	..	..	..	..	..	..	**12**
GEXP _1	..	-0.003	..	..	..	..	..	..	..	..	..	**13**
P(remi)	..	..	0.012	..	..	-0.102	..	..	..	0.060	..	**10**
P(remi)_1	..	..	..		..	..	-1.239	0.022	..	..	-0.023	**14**
RMSE	**0.045**	**0.031**	**0.020**	**0.062**	**0.007**	**0.006**	**0.030**	**0.024**	**0.031**	**0.017**	**0.050**	

Country Name	**Portugal**	**Qatar**	**South Africa**	**Sri Lanka**	**Switzerland**	**Sweden**	**Turkey**	**United States**	**United Kingdom**	**Uruguay**	**Retention Frequency**
Variables											
Constant	-36.317	10.501	24.441	13.712	19.311	20.180	26.095	-16.903	..	73.907	
LNGDP_1	0.208	-0.505	..	0.345	..	..	..	0.577	..	0.291	31
FDI(inf)	..	0.007	..	..	..	-0.002	..	..	..	..	08
FDI(inf)_1	..	0.002	..	..	..	..	..	-0.006	..	..	9
TOP	-13.426	-10.410	-11.161	-7.787	-13.030	-12.842	-14.001	3.439	-16.661	-11.188	42
TOP_1	..	-4.952	..	..	..	..	..	..	..	..	14
LG	0.590	0.043	0.635	..	..	..	..	..	..	..	13
LG_1	..	-402.844	..	..	..	..	..	-14.601	0.437	-0.352	11
DI	9.298	..	..	..	..	..	-0.002	0.068	..	-0.003	21
DI_1	-7.564	0.011	..	..	..	..	0.01	..	0.006	-0.003	14

Country Name	Portugal	Qatar	South	Sri	Switzerland	Sweden	Turkey	United	United	Uruguay	Retention
LnGCF	0.211	..	0.316	0.309	0.293	..	..	0.133	..	0.231	29
LnGCF_1	..	..	..	..	..	-0.088	..	..	..	-0.281	14
TDebtS	12.357	13.419	..	-0.010	-0.012	..	-0.025	1.437	38.208	-0.564	20
TDebtS_1	3.672	-34.200	..	..	..	..	..	-1.319	-38.203	..	13
Inf	0.007	-0.002	-0.007	0.002	-0.003	..	..	..	..	0.005	21
Inf_1	..	-0.002	..	..	..	..	..	0.0041	-0.007	..	13
LnTLF	0.037	32.166	0.095	-0.072	..	0.807	0.108	78.187	..	..	17
LnTLF_1	..	-32.149	..	..	..	..	..	-78.225	0.044	-0.036	11
LnTOTP	..	-1.040	-0.575	..	..	5.086	..	1.248	7.057	..	11
LnTOTP_1	..	0.953	..	..	..	-5.552	..	..	-7.589	..	17
Edu	..	..	0.013	..	..	-0.012	..	..	..	..	09
Edu_1	..	-0.056	..	..	..	..	..	..	..	..	09
LnRExp	0.928	0.457	0.953	0.477	0.979	1.003	1.015	0.276	1.057	0.869	42
LnRExp _1	..	0.079	..	..	..	0.108	..	-0.109	0.049	..	15
GEXP	..	0.500	..	..	..	..	..	..	..	-0.203	12
GEXP _1	0.001	0.104	..	..	..	0.008	..	..	-0.004	..	13
P(remi)	..	-0.404	-0.292	..	..	-0.100	..	0.699	0.095	..	10
P(remi)_1	..	-0.215	..	..	..	..	..	..	0.131	..	14
RMSE	**0.007**	**0.007**	**0.027**	**0.033**	**0.006**	**0.010**	**0 .023**	**0.0036**	**0.005**	**0.019**	

Figure 6.7: Graph of Retention of Variables in Autometrics Procedure for Growth Modeling

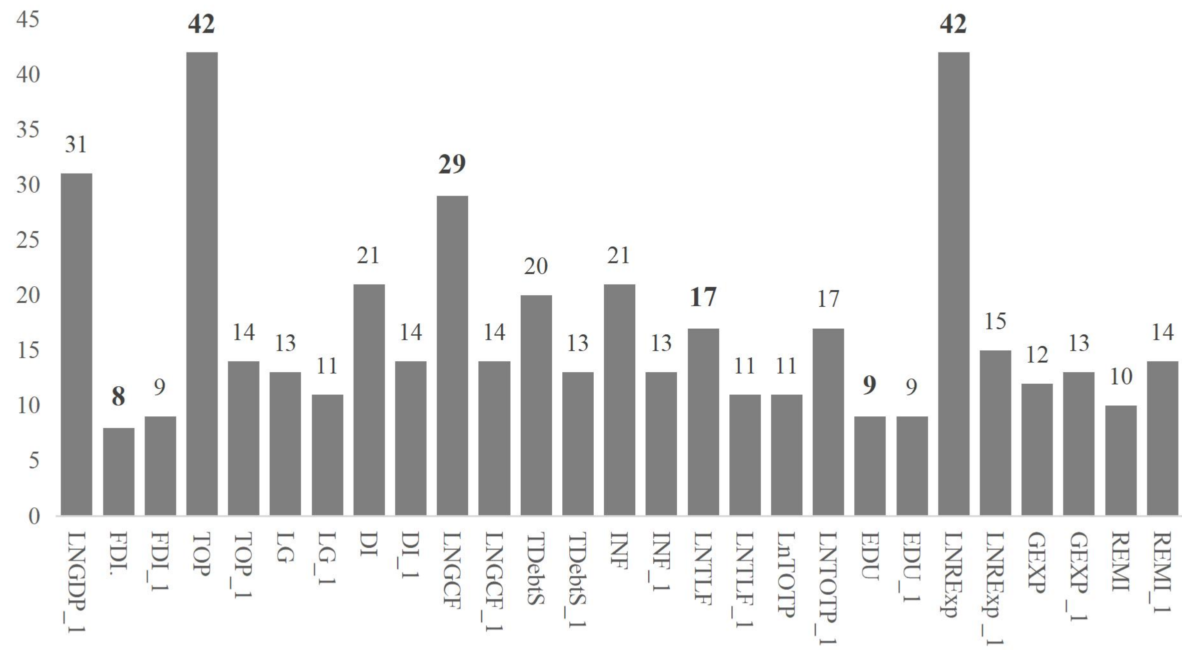

Figure 6.7 summarizes the frequency of retention variables in the model of Economic Growth using the Autometrics Procedure. The results show that variables trade openness (TOP) and real exports (LNRexp) are most likely significant, with a retention frequency of 42 out of the 43 regressions. The next most common variables are lag value of the dependent variable (LNGDP_1) and gross capital formation (LNGCF) with retention frequencies 31 and 29 out of 43 cases, respectively.

Model Selection Procedures based on Parameter Sensitivity

Any variable y may have a large number of potential determinants. Suppose X_i is a variable of interest, taking a set of control variables gives some coefficients of X_i. Changing the control variables will change the coefficients of estimate. There are many possible combinations of control variables, which will lead to different coefficients. The idea behind parameter consistency is that if X_i is having focus variables relation with y, its coefficients should be possible given any combination of control variables.

6.3.5 Results of Extreme Bound Analysis

The Extreme Bound Analysis procedure is based on two estimators and finds the frequency of retention variables, which helps us select the model. The results of the extreme bound analysis are given below in table . We use Leamer's and Sala-i-Martin estimators for extreme bound analysis. The criteria of Leamer's extreme bound analysis of variable selection is that if the sign of the lower and upper bound are the same, then we can use this variable. But Sala-i-Martin, for extreme bound analysis, argues that if the more part of the distribution of a variable is on the right side of zero value, it shows that the variable is significant and can be used in modeling. The last row of Table 19 shows the retention variables of each country. Table 6.7 shows the forecasted RMSE for each country after selecting the final model using extreme bound analysis.

Table 6.6 shows the results of the estimation using extreme bound analysis. The table provides regression coefficients of the variables with different signs for different countries; the difference in the signs of coefficients of variables is an indication of country-specific heterogeneity, We have taken the countries individually, which reveals `is provided for the estimated model. Column 1 indicates that for Argentina, the variable Inflation (INF), Domestic Investment (DI), Personal remittances (REMI) and Trade (TR) were excluded by Leamer's extreme bound analysis for the balance of trade model. Similarly, for Argentina, the variables INF, LNGDP, LNDEXP, BDEFI, and TR were traced out to be insignificant by the Sala-i-Martin extreme bound analysis for the Growth Model and, therefore, dropped by estimation procedures. In the last row, part (b), each variable's retention frequency is provided. The table shows that out of 43 countries, the variable trade openness (TOP) was significant in 26 cases by Leamer's extreme bound analysis and 23 cases by Sala-i-Martin extreme bond analysis.

Table 6.6: The Growth Modeling Results of Leamer's and Sala-i-Martin Extreme Bound Analysis

			TOP	LG	DI	TDETS	INFL	LTOTP	EDU	LREXP	REMI	GEXP	LGCF	LTLF	FDI
			Free	**Free**	**Free**	**Free**	**Free**	**Free**	**Free**	**Free**	**Free**	**Free**	**Focus**	**Focus**	**Focus**
Argentina	LEBA	LEB	-13.0	-5.1	0.0	0.0	0.0	-0.2	-0.1	0.4	-5.3	0.0	0.4	-1.5	-0.1
		UEB	2.0	47.6	0.0	0.0	0.0	3.0	0.0	1.1	-0.1	0.0	1.0	1.0	0.0
	SIMEBA	CDF(beta>0)	3.5	90.3	92.7	26.1	9.0	98.9	26.9	100.0	0.5	39.9	100.0	28.3	52.4
Austria	LEBA	LEB	-14.0	-1.1	-2.9	-0.5	0.0	-3.4	-0.1	0.4	0.0	0.0	-0.5	0.0	0.0
		UEB	-10.2	1.6	2.9	0.5	0.0	2.0	0.1	0.7	0.0	0.0	0.3	0.2	0.0
	SIMEBA	CDF(beta>0)	0.0	73.1	50.1	51.5	99.9	24.1	48.2	100.0	99.7	54.6	27.0	100.0	1.3
Australia	LEBA	LEB	-4.3	-15.9	0.0	-0.1	-0.1	-5.4	-0.3	0.5	-0.3	-0.1	-0.1	-0.8	0.0
		UEB	1.4	-0.7	0.0	0.1	0.0	9.9	0.1	1.0	0.6	0.0	0.0	-0.3	0.0
	SIMEBA	CDF(beta>0)	20.2	0.5	16.3	56.1	8.4	59.1	26.5	100.0	88.8	5.6	34.3	0.0	67.6
Bulgaria	LEBA	LEB	-14.5	-0.7	0.0	0.0	0.0	-0.6	0.0	1.0	0.0	0.0	0.0	-0.1	0.0
		UEB	-10.2	0.6	0.0	0.0	0.0	2.9	0.0	1.2	0.0	0.0	0.1	0.0	0.0
	SIMEBA	CDF(beta>0)	0.0	40.5	77.8	10.3	0.4	86.8	25.2	100.0	96.7	0.8	98.7	0.1	100.0
Belgium	LEBA	LEB	-18.8	-0.6	-0.2	0.0	0.0	-3.3	0.0	0.8	0.0	0.0	-0.3	0.0	0.0
		UEB	-15.1	0.4	0.8	0.1	0.0	0.8	0.0	0.9	0.0	0.0	0.2	0.0	0.0
	SIMEBA	CDF(beta>0)	0.0	40.0	93.7	97.4	99.8	6.3	100.0	100.0	0.4	89.7	25.0	53.5	94.2
Bangladesh	LEBA	LEB	-15.5	0.3	0.0	0.0	0.0	-2.5	-0.3	0.7	0.0	0.0	0.2	-0.1	-0.1
		UEB	-7.9	2.1	0.0	0.0	0.0	0.5	0.1	1.2	0.0	0.0	0.7	0.1	0.1
	SIMEBA	CDF(beta>0)	0.0	100.0	45.3	95.2	87.4	12.1	5.5	100.0	56.2	66.8	100.0	36.0	39.7
Bhutan	LEBA	LEB	-8.8	-0.3	0.0	0.0	0.0	-0.2	0.0	0.1	0.0	0.0	0.0	-0.8	0.0
		UEB	-1.7	1.4	0.0	0.0	0.0	4.5	0.1	0.8	0.1	0.0	0.4	0.2	0.0
	SIMEBA	CDF(beta>0)	0.0	91.0	4.1	87.9	97.6	98.6	57.3	99.9	96.4	45.5	100.0	48.1	53.1
Brazil	LEBA	LEB	-23.7	-1.5	0.0	0.0	0.0	-2.7	-0.1	0.6	0.0	0.0	0.4	0.0	0.0
		UEB	-11.2	1.1	0.0	0.0	0.0	0.8	0.0	1.6	0.1	0.0	1.1	0.1	0.1
	SIMEBA	CDF(beta>0)	0.0	45.2	73.3	57.0	21.9	18.7	19.7	100.0	83.7	17.4	100.0	97.4	97.2
Canada	LEBA	LEB	-16.6	-0.7	0.0	0.0	0.0	-5.2	0.0	0.7	0.0	0.0	0.2	-0.1	0.0
		UEB	-13.3	1.1	0.0	0.0	0.0	5.6	0.0	1.1	0.0	0.0	0.5	0.1	0.0
	SIMEBA	CDF(beta>0)	0.0	53.6	75.3	63.4	10.8	67.9	89.0	100.0	48.0	52.6	100.0	79.8	42.3
Chile	LEBA	LEB	-24.9	-0.9	0.0	-0.4	0.0	-6.6	0.0	0.7	-1.3	0.0	0.5	-0.1	0.0
		UEB	-14.5	0.4	0.0	0.4	0.0	5.9	0.0	1.3	4.8	0.0	0.7	0.0	0.0

	SIMEBA	CDF(beta>0)	0.0	14.4	43.2	69.9	56.1	25.8	26.9	100.0	58.6	23.6	100.0	7.3	82.2

			TOP	LG	DI	TDETS	INFL	LTOTP	EDU	LREXP	REMI	GEXP	LGCF	LTLF	FDI
			Free	Free	Free	Free	Free	Free	Free	Free	Free	Free	Focus	Focus	Focus
China	LEBA	LEB	-13.3	-1.6	0.0	0.0	0.0	-6.0	-0.1	0.3	-0.5	-0.1	-0.4	-0.1	0.0
		UEB	-4.5	1.5	0.0	0.0	0.0	3.5	0.0	1.0	0.1	0.0	0.5	0.0	0.1
	SIMEBA	CDF(beta>0)	0.0	40.6	75.3	16.7	12.7	42.7	18.8	100.0	10.3	0.6	69.4	0.9	94.6
Denmark	LEBA	LEB	-11.8	-1.0	-0.4	-1.8	0.0	0.1	0.0	1.0	-0.2	0.0	0.1	0.0	0.0
		UEB	-7.4	0.8	0.2	0.7	0.0	5.5	0.0	1.2	0.1	0.0	0.2	0.1	0.0
	SIMEBA	CDF(beta>0)	0.0	61.9	25.9	19.4	16.2	99.3	75.7	100.0	19.9	95.0	100.0	100.0	32.2
France	LEBA	LEB	-17.2	-0.4	0.0	-0.1	0.0	0.5	-0.1	1.0	0.0	0.0	-0.1	0.0	0.0
		UEB	-13.4	0.3	0.0	0.0	0.0	4.8	0.0	1.1	0.0	0.0	0.2	0.0	0.0
	SIMEBA	CDF(beta>0)	0.0	35.2	94.6	2.2	96.6	99.6	0.0	100.0	33.4	7.7	63.1	31.6	5.8
Germany	LEBA	LEB	-17.4	-4.1	-4.3	-4.1	0.0	-1.6	0.0	1.0	-0.2	0.0	0.0	0.1	0.0
		UEB	-13.8	4.3	0.6	0.6	0.0	1.2	0.1	1.1	0.1	0.0	0.3	0.4	0.0
	SIMEBA	CDF(beta>0)	0.0	51.4	5.8	5.8	99.9	36.3	96.8	100.0	18.3	98.9	96.6	99.9	94.8
Ghana	LEBA	LEB	-11.7	-2.1	0.0	0.0	0.0	0.1	0.0	0.6	0.0	0.0	-0.1	-0.1	0.0
		UEB	-7.7	1.1	0.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0
	SIMEBA	CDF(beta>0)	0.0	33.2	7.0	27.6	66.3	99.7	97.0	100.0	27.2	12.5	0.0	11.7	66.5
Hungary	LEBA	LEB	-14.3	-0.9	0.0	-0.4	0.0	-6.4	0.0	0.8	0.0	0.0	0.0	-0.3	0.0
		UEB	-11.0	2.1	0.0	0.7	0.0	9.0	0.0	1.0	0.0	0.0	0.2	0.0	0.0
	SIMEBA	CDF(beta>0)	0.0	81.3	4.3	75.8	63.9	64.4	75.4	100.0	5.6	0.7	100.0	0.8	47.4
India	LEBA	LEB	-19.0	-0.4	-0.9	0.0	0.0	-1.4	0.0	0.8	0.0	0.0	0.0	0.0	0.0
		UEB	-10.5	0.4	0.5	0.0	0.0	0.6	0.0	1.4	0.1	0.0	0.5	0.0	0.0
	SIMEBA	CDF(beta>0)	0.0	45.8	24.7	2.3	89.9	16.7	84.5	100.0	88.9	99.9	98.5	0.1	57.5
Indonesia	LEBA	LEB	-16.0	-2.1	0.0	0.0	0.0	-6.9	0.0	0.8	-0.1	0.0	0.0	-0.2	0.0
		UEB	-9.5	2.3	0.0	0.0	0.1	0.5	0.0	1.4	0.1	0.0	0.1	0.2	0.1
	SIMEBA	CDF(beta>0)	0.0	45.7	35.6	22.7	99.1	1.2	12.9	100.0	38.7	10.0	97.6	40.6	100.0
Iran	LEBA	LEB	-15.9	-1.6	0.0	-0.1	0.0	-0.7	-0.1	0.5	-0.1	0.0	0.0	-0.2	-0.2
		UEB	-12.0	1.3	0.0	0.0	0.0	0.7	0.0	0.8	0.1	0.0	0.0	-0.1	0.0
	SIMEBA	CDF(beta>0)	0.0	31.9	28.0	1.3	70.9	34.5	17.0	100.0	73.0	85.7	62.6	0.0	1.0
Japan	LEBA	LEB	-12.5	-2.6	-0.1	-0.3	0.0	-3.7	0.0	0.9	-0.4	0.0	-0.2	-0.1	-0.2
		UEB	-9.4	2.6	0.0	0.1	0.1	5.7	0.1	1.3	0.2	0.1	0.4	0.3	0.0

	SIMEBA	CDF(beta>0)	0.0	46.3	0.0	21.6	98.8	72.5	62.9	100.0	20.3	99.9	85.0	92.8	7.6

			TOP	LG	DI	TDETS	INFL	LTOTP	EDU	LREXP	REMI	GEXP	LGCF	LTLF	FDI
			Free	**Free**	**Free**	**Free**	**Free**	**Free**	**Free**	**Free**	**Free**	**Free**	**Focus**	**Focus**	**Focus**
Luxembourg	LEBA	LEB	-11.5	-0.2	-6.5	-20.5	0.0	-1.2	-0.1	0.8	0.0	0.0	-0.1	0.0	0.0
		UEB	-9.4	0.1	12.4	9.6	0.0	-0.2	0.0	1.0	0.0	0.0	0.1	0.0	0.0
	SIMEBA	CDF(beta>0)	0.0	46.9	72.8	23.8	58.8	0.3	2.7	100.0	98.9	0.7	29.8	53.3	5.5
Maldives	LEBA	LEB	-11.4	-0.6	0.0	0.0	0.0	-0.7	0.0	0.4	0.0	0.0	-0.2	-0.1	0.0
		UEB	-6.3	0.4	0.0	0.0	0.0	2.9	0.0	0.9	0.1	0.0	0.1	0.0	0.0
	SIMEBA	CDF(beta>0)	0.0	39.0	94.5	22.2	85.0	95.2	19.9	100.0	64.5	99.1	13.9	5.5	59.8
Malaysia	LEBA	LEB	-14.6	-0.3	0.0	-3.6	0.0	-4.5	0.0	0.9	-0.1	0.0	0.1	0.0	0.0
		UEB	-9.8	1.0	0.0	0.3	0.0	0.3	0.0	1.3	0.0	0.0	0.3	0.1	0.0
	SIMEBA	CDF(beta>0)	0.0	87.3	73.6	2.3	74.1	1.5	98.5	100.0	18.6	56.3	100.0	99.0	98.2
Mexico	LEBA	LEB	-12.8	-1.1	0.0	0.0	0.0	-0.1	0.0	0.4	-0.1	0.0	0.1	0.0	0.0
		UEB	-5.0	1.4	0.0	0.0	0.0	2.1	0.1	0.7	0.0	0.0	0.7	0.1	0.1
	SIMEBA	CDF(beta>0)	0.0	42.0	2.0	2.3	14.5	99.0	74.8	100.0	10.7	27.0	99.9	88.9	84.2
Morocco	LEBA	LEB	-18.8	-2.1	0.0	0.0	0.0	-1.4	0.0	0.8	0.0	0.0	0.2	-0.1	0.0
		UEB	-9.8	0.9	0.0	0.0	0.0	1.0	0.2	1.3	0.0	0.0	0.6	0.0	0.0
	SIMEBA	CDF(beta>0)	0.0	20.0	45.4	55.7	79.1	30.3	100.0	100.0	73.9	81.1	100.0	0.2	33.3
Netherlands	LEBA	LEB	-15.3	-0.6	0.0	-0.3	0.0	-1.7	0.0	1.0	0.0	0.0	0.0	0.0	0.0
		UEB	-12.5	0.5	0.0	0.6	0.0	2.7	0.0	1.0	0.0	0.0	0.2	0.0	0.0
	SIMEBA	CDF(beta>0)	0.0	51.5	17.3	77.7	94.5	76.3	55.5	100.0	64.1	85.5	100.0	39.9	6.6
Nepal	LEBA	LEB	-4.4	-12.9	-34.1	-0.8	-0.5	0.0	-3.4	-0.1	0.0	0.0	0.0	0.0	-1.3
		UEB	74.1	-0.8	20.5	-0.2	0.2	0.0	2.2	0.0	0.7	0.0	0.0	0.1	1.5
	SIMEBA	CDF(beta>0)	0.3	29.7	0.0	6.6	56.8	37.5	0.8	99.0	75.4	74.1	99.9	55.5	92.7
New Zealand	LEBA	LEB	-13.2	-1.3	0.0	-0.4	0.0	-2.0	0.0	0.9	-0.2	0.0	0.0	-0.1	0.0
		UEB	-11.5	1.4	0.0	0.2	0.0	1.0	0.0	1.0	0.1	0.0	0.2	0.1	0.0
	SIMEBA	CDF(beta>0)	0.0	62.2	6.2	19.5	99.6	19.8	41.0	100.0	8.9	94.7	99.8	28.0	5.4
Norway	LEBA	LEB	-25.0	-2.5	0.0	-1.1	0.0	-2.2	0.0	0.7	-2.3	0.0	0.2	-0.2	0.0
		UEB	-6.2	1.5	0.0	2.0	0.0	5.1	0.1	0.9	0.8	0.0	0.8	0.2	0.0
	SIMEBA	CDF(beta>0)	0.0	28.7	42.0	69.2	54.5	84.4	85.3	100.0	15.0	59.0	100.0	33.1	75.2
Pakistan	LEBA	LEB	-22.1	-1.0	0.0	-0.1	0.0	-1.2	0.0	0.7	0.0	0.0	0.1	-0.1	0.0
		UEB	-9.5	1.2	0.0	0.0	0.0	0.8	0.2	1.4	0.1	0.0	0.6	0.1	0.0

			TOP	LG	DI	TDETS	INFL	LTOTP	EDU	LREXP	REMI	GEXP	LGCF	LTLF	FDI
	SIMEBA	CDF(beta>0)	0.0	54.1	48.4	0.1	87.8	28.7	99.7	100.0	100.0	28.0	99.6	59.5	51.0
			Free	Free	Free	Free	Free	Free	Free	Free	Free	Free	Focus	Focus	Focus
Paraguay	LEBA	LEB	-16.2	-0.6	0.0	0.0	0.0	-1.0	0.0	0.9	0.0	0.0	0.1	-0.1	0.0
		UEB	-11.3	3.2	0.0	0.0	0.0	-0.1	0.0	1.3	0.1	0.0	0.4	0.2	0.0
	SIMEBA	CDF(beta>0)	0.0	90.4	6.8	14.1	64.7	0.1	35.8	100.0	82.4	33.7	100.0	78.5	84.7
Peru	LEBA	LEB	-18.8	-2.6	0.0	0.0	0.0	-0.8	0.0	0.5	-0.1	0.0	0.4	-0.2	0.0
		UEB	-2.9	6.5	0.0	0.0	0.0	1.5	0.1	1.2	0.0	0.0	0.5	0.7	0.1
	SIMEBA	CDF(beta>0)	0.0	65.9	86.9	10.6	12.0	91.7	81.2	100.0	12.2	24.8	100.0	55.0	78.9
Philippines	LEBA	LEB	-21.7	-1.8	0.0	0.0	0.0	-1.5	-0.1	0.4	0.0	0.0	0.2	0.0	0.0
		UEB	-6.3	2.5	0.0	0.0	0.0	1.1	0.1	1.5	0.0	0.0	0.3	0.2	0.1
	SIMEBA	CDF(beta>0)	0.0	62.3	31.3	21.7	58.7	57.8	57.9	100.0	73.9	92.3	100.0	99.7	53.7
Portugal	LEBA	LEB	-23.3	-1.7	-0.3	-2.8	0.0	-4.0	-0.1	0.7	0.0	0.0	0.3	-0.2	0.0
		UEB	-7.7	1.5	0.1	1.3	0.0	5.4	0.2	1.3	0.0	0.0	0.5	0.1	0.0
	SIMEBA	CDF(beta>0)	0.0	53.9	35.1	32.8	57.3	82.8	73.8	100.0	78.4	44.8	100.0	33.8	5.1
Qatar	LEBA	LEB	-12.1	-0.4	0.0	-1.4	0.0	0.0	0.0	0.2	-0.2	-1.4	0.0	0.0	0.0
		UEB	-10.2	0.6	0.0	1.5	0.0	0.4	0.1	0.5	0.8	1.6	0.1	0.0	0.0
	SIMEBA	CDF(beta>0)	0.0	67.1	88.9	57.5	86.9	98.5	62.9	100.0	92.2	54.1	86.5	67.4	95.6
Sri Lanka	LEBA	LEB	-21.0	-3.5	0.0	0.0	0.0	-4.6	-0.1	0.5	0.0	0.0	0.3	-0.3	0.0
		UEB	-8.5	2.4	0.0	0.0	0.0	1.9	0.1	1.6	0.1	0.0	0.6	0.2	0.1
	SIMEBA	CDF(beta>0)	0.0	28.6	40.3	58.5	84.1	29.5	48.9	100.0	70.7	57.2	100.0	21.1	89.2
South Africa	LEBA	LEB	-18.2	-1.0	0.0	0.0	0.0	-1.0	0.0	0.8	-0.6	0.0	0.2	0.0	0.0
		UEB	-7.9	2.3	0.0	0.0	0.0	0.1	0.0	1.3	0.8	0.0	0.5	0.2	0.0
	SIMEBA	CDF(beta>0)	0.0	72.4	29.7	77.4	20.7	3.6	63.1	100.0	45.5	33.7	100.0	99.5	76.9
Sweden	LEBA	LEB	-16.0	-8.4	0.0	0.0	0.0	-0.6	0.0	1.0	0.0	0.0	0.0	-0.4	0.0
		UEB	-13.2	9.6	0.0	0.0	0.0	2.2	0.0	1.1	0.2	0.0	0.2	0.9	0.0
	SIMEBA	CDF(beta>0)	0.0	59.3	45.3	7.1	57.2	90.5	34.3	100.0	95.4	84.6	98.4	85.1	19.8
Switzerland	LEBA	LEB	-15.6	-0.8	0.0	0.0	0.0	-2.1	0.0	0.9	-0.3	0.0	0.2	-0.1	0.0
		UEB	-12.6	1.0	0.0	0.0	0.0	0.2	0.0	1.0	0.1	0.0	0.4	0.0	0.0
	SIMEBA	CDF(beta>0)	0.0	70.9	5.2	54.5	12.3	4.3	33.3	100.0	12.4	61.7	100.0	46.2	58.7
Turkey	LEBA	LEB	-17.0	-1.7	0.0	0.0	0.0	-1.1	0.0	0.9	-0.1	0.0	-0.1	0.1	0.0
		UEB	-11.5	2.6	0.0	0.0	0.0	1.2	0.0	1.2	0.0	0.0	0.1	0.2	0.0

	SIMEBA	CDF(beta>0)	0.0	69.2	3.5	0.1	87.2	53.3	89.5	100.0	41.1	78.9	62.2	99.9	53.6

			TOP	LG	DI	TDETS	INFL	LTOTP	EDU	LREXP	REMI	GEXP	LGCF	LNTLF	FDI
			Free	Free	Free	Free	Free	Free	Free	Free	Free	Free	Focus	Focus	Focus
United Kingdom	LEBA	LEB	-17.6	-0.9	0.0	0.0	0.0	-2.6	0.0	1.0	0.0	0.0	0.0	0.0	0.0
		UEB	-12.8	0.4	0.0	0.0	0.0	2.0	0.1	1.2	0.4	0.0	0.3	0.1	0.0
	SIMEBA	CDF(beta>0)	0.0	28.8	99.9	65.7	4.0	30.9	72.7	100.0	99.3	20.4	95.3	99.8	60.8
United States of America	LEBA	LEB	-21.7	-1.0	-0.1	-0.1	0.0	-3.3	0.0	-0.2	-1.0	0.0	0.3	-0.1	0.0
		UEB	7.6	2.4	0.0	0.1	0.0	4.8	0.0	0.9	5.4	0.0	0.5	0.1	0.0
	SIMEBA	CDF(beta>0)	4.1	56.6	62.7	79.7	31.2	30.4	1.8	96.9	83.0	54.9	100.0	53.3	42.5
Uruguay	LEBA	LEB	-17.6	-0.8	0.0	-0.8	0.0	-3.2	-0.1	0.5	-0.5	-0.3	0.1	-0.1	0.0
		UEB	-6.5	0.6	0.0	0.0	0.0	7.5	0.0	1.3	0.3	0.0	0.6	0.0	0.0
	SIMEBA	CDF(beta>0)	0.0	54.0	2.0	0.6	81.6	90.2	34.7	100.0	19.0	0.6	99.8	11.1	94.5
Retention Frequency		**LEBA**	**17**	**11**	**09**	**10**	**17**	**9**	**11**	**18**	**13**	**16**	**8**	**21**	**10**
		SIMEBA	**23**	**16**	**10**	**9**	**19**	**15**	**13**	**21**	**18**	**19**	**17**	**21**	**11**

Table 6.7: Forecast Root Mean Square Error of Growth Modeling

Countries	LEBA	SIMEBA
Argentina	0.168	0.121
Austria	0.248	0.130
Australia	0.096	0.121
Bulgaria	0.137	0.139
Belgium	0.043	0.022
Bangladesh	0.067	0.104
Bhutan	0.307	0.095
Brazil	0.107	0.127
Canada	0.029	0.094
Chile	0.051	0.115
China	0.087	0.126
Denmark	0.025	0.040
France	0.032	0.063
Germany	0.027	0.078
Ghana	0.084	0.150
Hungary	0.042	0.168
India	0.062	0.065
Indonesia	0.082	0.101
Iran	0.090	0.022
Japan	0.050	0.123
Luxembourg	0.035	0.135
Maldives	0.110	0.176
Malaysia	0.028	0.085
Mexico	0.128	0.091
Morocco	0.053	0.086
Netherlands	0.012	0.061
Nepal	0.143	0.129
New Zealand	0.013	0.079
Norway	0.056	0.070
Pakistan	0.120	0.081
Paraguay	0.064	0.167
Peru	0.066	0.088
Philippines	0.048	0.143
Portugal	0.053	0.072
Qatar	0.044	0.282
Sri Lanka	0.045	0.106
South Africa	0.043	0.073
Sweden	0.027	0.101
Switzerland	0.014	0.062
Turkey	0.059	0.132
United Kingdom	0.029	0.057
United States of America	0.034	0.026
Uruguay	0.097	0.043

Figure 6.8: Graph of Retention Variables in Leamer's Extreme Bound Analysis for Growth Modeling

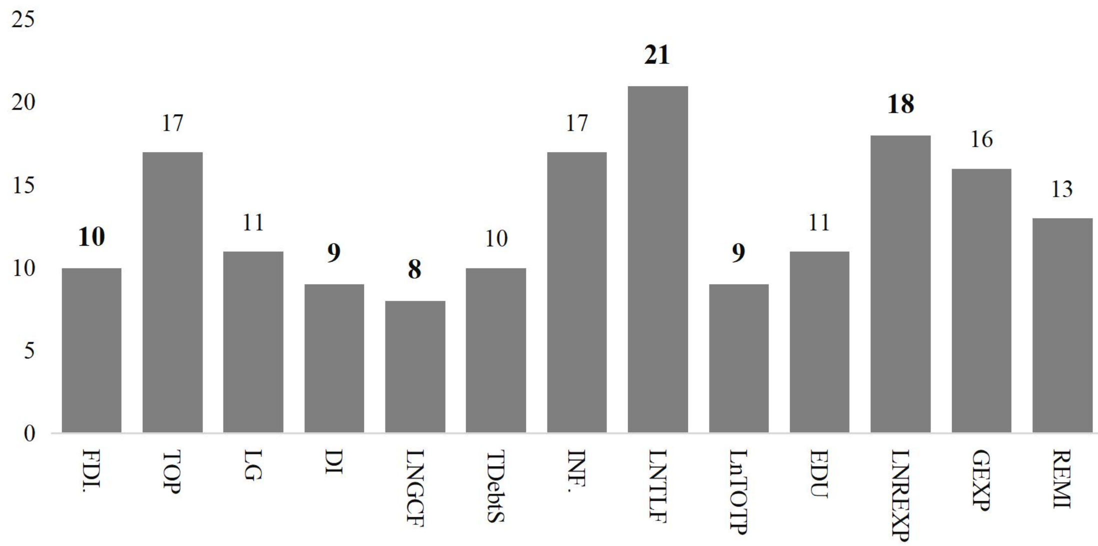

Figure 6.8 summarizes the variables' retention frequency in the Economic Growth model using Leamer's extreme bound analysis for all countries. The results show that the focus variable, the total labor force (LNTLF), is most likely significant, with a retention frequency of 21 out of 43. The next most common variables are real exports (LNRexp), inflation (INF) and trade openness (TOP), with retention frequencies of 18/43 and 17/43, respectively.

Figure 6.9: Graph of Retention Variables in Sala-i-Martin Extreme Bound Analysis for Growth Modeling

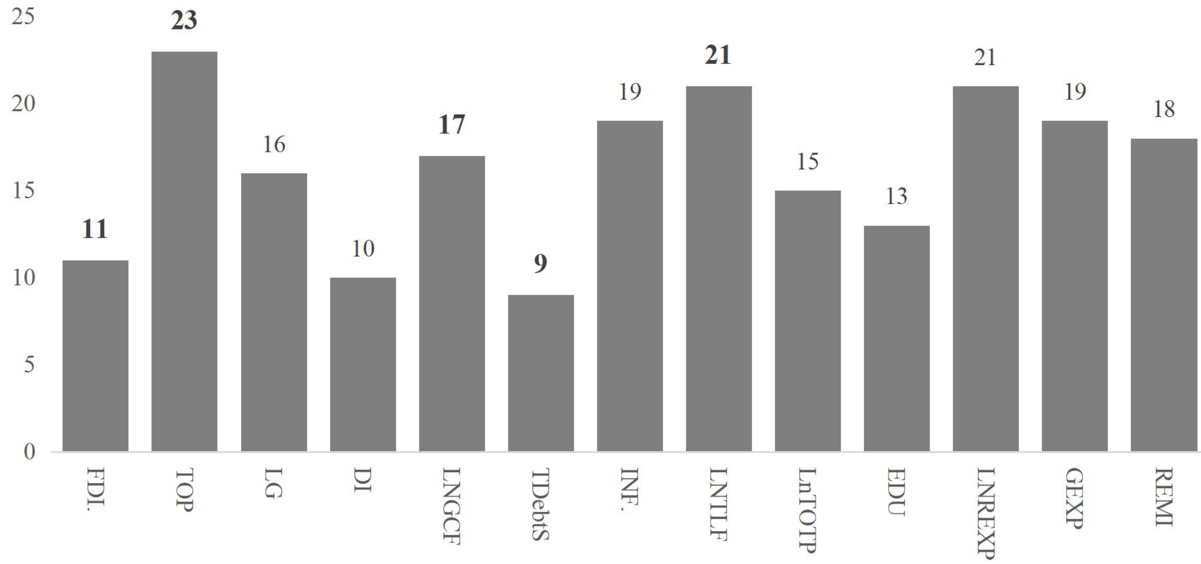

Figure 6.9 summarizes the variables' retention frequency in the Economic Growth model using the Sala-i-Martin Extreme Bound analysis for all countries. The results show that the auxiliary variable, Trade Openness (TOP), is most likely significant, with a retention frequency of 23 out of 43. The next most common variables are real exports (LNRexp) and total labor force (LNTLF) with retention frequency 21/43.

Forecast Based Comparison

As stated earlier, we are using two criteria for comparing the model selection procedures. The first criterion is the forecast performance of the finally selected model and the other is the robustness of the model. Suppose Y is a variable of interest and $X_1, X_2, X_2, .X_n$ are the candidate variables, suppose f_1 be the model of selection procedure applied to select the model out of $X_1, X_2, X_2, ..X_n$, Let $X_{f1}, X_{f2}, X_{f3}, ..X_{fk}$ be the variable selected by the procedure f_1, f_2 f_3 …… f_k Let there are t observations Estimates $Y_i\, f$ $(X_{11}, X_{12}, X_{13}, ..X_{1k})$ for $T - S$ observation leaving "S" observation, for forecasting purposes. Use the estimated model $\widehat{Y}_{t-s+1}$, $\widehat{Y}_{t-s+2}$, $\widehat{Y}_{t-s+3}..\widehat{Y}_t$ and calculate

$$FRMSE_1 = \sum (\hat{y}_{t-S+i} - y_{t-S+i})^2$$

Let there be a procedure f_2 and forecast $FRMSE_2$ be the Forecast root mean square error (FRMSE) which forecasts the model selected by f_2 in this way, one can find FRMSE for all model selection procedures. A comparison of FRMSE for different models will give us an idea of the best model selection procedure.

Table 6.8 summarizes the forecast root mean square errors (FRMSE) of the final models retained by the model selection procedures. The table indicates that FRMSE for the final model selected by oxmatrix 0.032 for Non- Nested Encompassing, it was 1.323 for Weighted average least square (WALS) it was 1.236, and in this way, the forecast root mean square errors(FRMSE) for another model selection procedures are summarized. The results reveal that for Argentina, the smallest forecast root mean square error (FRMSE) was obtained for the model selected by LASSO. The results for all other countries are also visible in Table 6.8.

Table 6.8: Least Forecast Values of RMSE for Unrestricted model (Growth Modeling)

Country Name	Autometrics	Non –Nested Encompassing	WALS	LASSO	Adoptive LASSO	Elastic Net	LEBA	SIMEBA	Minimum Values RMSR	Best Method for selection least RMSE
Argentina	0.032	1.323	1.236	0.010	0.030	0.030	0.168	0.121	0.01	**LASSO**
Australia	0.051	11.833	5.833	0.114	0.191	0.191	0.248	0.130	0.051	**Autometrics**
Austria	0.025	4.585	3.585	0.024	0.064	0.064	0.096	0.121 8	0.024	**LASSO**
Bangladesh	0.018	1.751	0.751	0.404	0.379	0.379	0.137	0.139	0.018	**Autometrics**
Belgium	0.054	7.248	2.248	0.157	0.211	0.211	0.043	0.022	0.022	**SIMEBA**
Bhutan	0.012	1.720	1.620	0.441	0.515	0.515	0.067	0.104	0.012	**Autometrics**
Bulgaria	0.111	1.318	1.628	0.981	0.143	0.143	0.307	0.095	0.095	**SIMEBA**
Brazil	0.031	2.059	2.149	0.145	0.146	0.146	0.107	0.127	0.031	**Autometrics**
Canada	0.007	0.843	0.543	0.163	0.129	0.129	0.02962	0.094	0.007	**Autometrics**
China	0.038	2.518	2.418	0.416	0.402	0.402	0.051	0.1158	0.038	**Autometrics**
Chili	0.023	3.715	3.625	0.181	0.263	0.263	0.087	0.126	0.023	**Autometrics**
Denmark	0.006	0.756	0.156	0.089	0.131	0.131	0.025	0.040	0.006	**Autometrics**
France	0.007	0.595	0.485	0.039	0.081	0.081	0.032	0.063 1	0.007	**Autometrics**
Germany	0.008	0.786	0.586	0.201	0.174	0.174	0.02744	0.078	0.008	**Autometrics**
Ghana	0.036	3.077	3.067	0.921	0.891	0.891	0.084	0.15012	0.036	**Autometrics**
Hungary	0.009	2.110	2.120	0.151	0.154	0.154	0.042	0.168	0.009	**Autometrics**
India	0.017	0.832	0.312	0.410	0.513	0.513	0.062	0.065	0.017	**Autometrics**
Indonesia	0.022	1.396	1.716	0.605	0.662	0.662	0.082	0.101	0.022	**Autometrics**
Iran	0.051	6.104	3.104	0.621	0.712	0.712	0.090	0.022	0.022	**SIMEBA**
Japan	0.030	2.351	4.351	0.707	0.139	0.139	0.050	0.123	0.03	**Autometrics**
Luxembourg	0.061	2.276	1.476	0.195	0.149	0.149	0.035	0.135	0.035	**SIMEBA**
Malaysia	0.010	0.915	0.315	0.296	0.469	0.469	0.110	0.176	0.01	**Autometrics**
Maldives	0.045	2.005	5.005	0.774	1.47	1.472	0.028	0.085	0.028	**SIMEBA**
Mexico	0.031	1.032	1.051	0.136	0.122	0.122	0.128	0.091	0.031	**Autometrics**
Morocco	0.021	0.492	0.392	0.0341	0.053	0.053	0.053	0.086	0.021	**Autometrics**

Country Name	Autometrics	Non –Nested Encompassing	WALS	LASSO	Adoptive LASSO	Elastic Net	LEBA	SIMEBA	Minimum Values RMSR	Best Method for selection least RMSE
Nepal	0.062	2.337	2.137	0.081	0.078	0.078	0.012	0.061	0.012	**SIMEBA**
Netherland	0.007	0.358	1.358	0.082	0.018	0.018	0.143	0.129	0.007	**Autometrics**
New Zealand	0.006	0.427	0.527	0.069	0.049	0.049	0.013	0.079	0.006	**Autometrics**
Norway	0.030	2.202	2.213	0.159	0.083	0.083	0.056	0.070	0.03	**Autometrics**
Pakistan	0.024	2.101	2.601	0.063	0.105	0.105	0.120	0.081	0.024	**Autometrics**
Peru	0.031	3.840	3.640	0.072	0.075	0.075	0.064	0.167	0.031	**Autometrics**
Paraguay	0.017	2.126	4.136	0.024	0.043	0.043	0.066	0.088	0.017	**Autometrics**
Philippines	0.050	1.261	2.261	0.025	0.017	0.017	0.048	0.143	0.017	**Adoptive LASSO**
Portugal	0.0073	0.671	0.171	0.067	0.132	0.132	0.053	0.072	0.0073	**Autometrics**
Qatar	0.007	0.029	0.039	0.178	0.188	0.188	0.044	0.282	0.007	**Autometrics**
South Africa	0.027	1.930	1.530	0.011	0.010	0.010	0.045	0.106 4	0.01	**LASSO, A LASSO, E NET**
Sri Lanka	0.033	1.848	2.748	0.032	0.052	0.052	0.043	0.073	0.032	**Autometrics**
Switzerland	0.006	0.883	0.683	0.023	0.010	0.010	0.027	0.101	0.006	**Autometrics A LASSO, E NET**
Sweden	0.0103	0.667	4.667	0.017	0.017	0.017	0.014	0.062	0.0103	**Autometrics**
Turkey	0 .023	1.557	1.157	0.060	0.081	0.081	0.059	0.132	0.059	**SIMEBA**
United States	0.003	1.292	1.792	3.570	1.660	1.660	0.029	0.057	0.003	**Autometrics**
United Kingdom	0.005	0.084	0.074	0.018	0.051	0.051	0.034	0.026	0.005	**Autometrics**
Uruguay	0.019	2.365	2.465	0.073	0.048	0.048	0.097	0.043	0.019	**Autometrics**
Total	**30**	**0**	**0**	**3**	**1**	**2**	**4**	**3**		

Figure 6.10: The Comparison of General Unrestricted Models Based on Least Forecast RMSE for Growth Modeling.

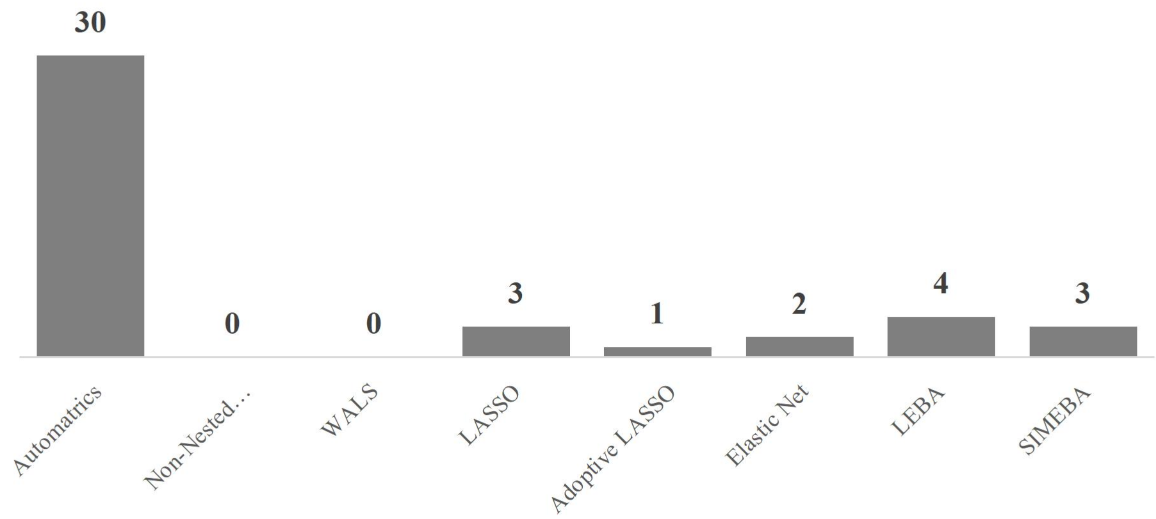

Figure 6.10 is based on the results reported in Table 6.9 above. The last column gives the minimum FRMSE for each estimated model. The results of the figure summarize the maximum number of cases based on the minimum forecasted root mean square errors (FRMSE). The model selected by Automatrics provides minimum FRMSE for the maximum number of cases. In 30 out of 43 cases, the model selected by the Automatrics yielded the lowest forecast root mean square errors (FRMSE), which are 70% of the total cases.

Leamer's extreme bound analysis (LEBA) came up with a minimum FRMSE of 4 out of 43 cases, 9% of the total cases. LASSO and Sala-i-Martin(SIM-EBA) Extreme Bound came up with minimum forecasted root mean square errors (FRMSE) for the maximum number of cases. In 3 out of 43 cases, both models selected by LASSO and Sala-i-Martin(SIM-EBA) Extreme Bound analysis yield the lowest forecast root mean square errors (FRMSE), which is 7% of the total cases. Adoptive LASSO and Elastic Net procedure came 2 and 1 times out of 43 cases with minimum forecast root mean square errors (FRMSE) of 5% and 3% of the total cases. The model selected by Adoptive Non _Nested Encompassing and Weighted average least square (WALS) came up 0 times out of the 43 cases, which means the probability of getting the least FRMSE of both models is 0% based on the given sample.

The final results indicate that Automatrics procedure provides the best results based on the minimum forecasted root mean square errors (FRMSE) for the maximum number of cases. On the other hand, Non-Nested Encompassing and Weighted average least square (WALS) are considered the worst methodologies among all other model selection procedures based on minimum FRMSE.

Retention of Variables for Restricted Model (Group I)

Khan (2020) has compared model selection procedures using Monte Carlo experiments in his PhD thesis. The study of Khan was based on the Monte Carlo experiment; therefore, he was able to find the probability of retention of the true variables. Our study is based on real data; therefore, we cannot find the true variables because true variables are not known. We are trying to select a model out of many candidate models. These candidates' models gain a long list of explanatory variables. We can find the retention frequency of these variables to make the study comparable with the study of Khan.

The results of Table 6.9 summarize the frequency of retention of the true variables in the model of Economic Growth using different classes of model selection Procedures. The results show that the model selection procedure based on the shrinkage family provides the best results for the maximum number of cases to find out potential determinants for the growth model. Therefore, the model selected by Elastic Net performs the best results in most cases to find the maximum frequency of retention variables for each estimated model. Finally, the results of the current study support the existing study of Khan(2020).

Table 6.9: Frequency of Retention Variables for General Unrestricted Model (Economic Growth)

Variables Name	Autometsrics	Encompassing	WALS	LASSO	ALASSO	Elastic Net	LEBA	SIMEBA	Maximum Value	Best Model with Retention Frequency
FDI	8	7	9	11	10	17	10	11	17	**Elastic Net**
TOP	42	28	43	21	20	34	17	23	43	**WALS**
LG	13	4	3	18	16	16	11	16	18	**LASSO**
DI	21	11	11	17	17	20	9	10	21	**Autometrics**
LnGCF	29	31	33	21	19	31	8	17	33	**WALS**
TDebtS	20	11	7	15	12	23	10	9	23	**Elastic Net**
Inf	21	14	9	19	18	23	17	19	23	**Elastic Net**
LnTLF	17	10	19	25	21	30	21	21	30	**Elastic Net**
LnTOTP	11	14	15	21	21	28	9	15	28	**Elastic Net**
Edu	9	12	8	16	13	20	11	13	20	**Elastic Net**
LnRExp	42	35	43	30	26	35	18	21	43	**WALS**
GEXP	12	12	9	26	35	37	16	19	37	**Elastic Net**
REMI	10	12	10	16	14	17	14	18	18	**SIMEBA**

6.4. The Comparison of Econometric Models based on Robustness

6.4.1 Robust Analysis for Growth Modeling

We have tested the performance of the model selection procedures for several countries and the research has identified the best procedure. A natural question arises: if we change the sample countries, would it change the same procedure that will be performed best? To test this, we have divided the sample countries into two groups. Group I countries 43 countries and these countries would be used to find out the model selection procedures that perform best. Group II contains 6 countries for the Growth model. The models would be restricted for group II to know whether the models applying best in sample I maintain their performance for group II.

The idea behind this is to select the most repeated model in the above-given modeling and use these models for 6 countries' samples to test the validity and significance of models. After that, we also estimate the forecast root mean error square (FRMSE) and frequency retention of potential determinant variables for the growth model. In this model, the economic growth (LNGDP) is a dependent variable and Gross fixed capital formation (LNGCF), total Labor force (LNTLF), foreign direct investment (FDI) and independent variables are trade openness (TOP), labor growth (LG), domestic interest (DI), total debts (TDebts), inflation (INF), total population (LNTOTP), education expenditure (EDU), exports of goods and services (LNREXP), personal remittances (REMI), and government expenditure (LNGEXP). In this modeling, the FDI, LNGCF, and LNTLF are our focus variables, while the LNGEXP, REMI, LNREXP, EDU, LNTOTP, INF, TDebts, DI, LG, and TOP are the auxiliary variables.

Some model selection procedures require dividing independent variables into focus and auxiliary variables. The focus variables are ones in which the researcher might be interested, whereas auxiliary variables are those used as control variables. We used the most commonly found determinants as focus variables and others as auxiliary Economic Growth (LNGDP) variables.

Frequency of Retention Variables for Restricted Model (Group II)

The results of Table 22 summarize the frequency of retention of true variables among different classes of model selection Procedures using restricted models of Economic

Growth. Table results show that the model selection procedure based on the shrinkage family provides the best results for the maximum number of cases to find out potential determinants of economic growth. Therefore, selection criteria based on the frequency of retention variables validate the final result of both groups (general unrestricted model (group I) and robust restricted model (group II).

Table 6.10: Results Retention Variables for Growth Modeling with Final Model Specification

Models	**AUT**	**ENCOM**	**WALS**	**LASSO**	**ALASSO**	**EN**	**LEBA**	**SIMEBA**	**Max values**	**Best model-based Retention Frequency**
Variables										
DI	4	..	..	..	..	..	3	4	4	**Automatrics, SIMEBA**
DI_1	1	..	..	..	..	..	..	..	1	**Automatrics**
TDebtS	1	..	..	..	..	2	4	4	4	**LEBA,SIMEBA**
TDebtS_1	0	..	..	..	..	..	..	..	0	**-**
LnTOTP	..	2	4	3	4	2	..	..	4	**ALSSO,WALS**
LnTOTP_1	..	4		..	..	..	..	..	4	**ENCOM**
LnTLF	..	..	2	5	3	2	..	..	5	**LASSO**
LnTLF_1	..	..	..	..	..	..	..	..	0	**-**
LnGexp	..	..	..	5	2	4	..	..	5	**LASSO**
LnGexp_1	..	..	..	..	..	..	..	..	0	**-**
FDI)	..	..	..	..	..	..	4	..	4	**LEBA**
LG	..	..	..	..	..	..	..	5	5	**SIMEBA**
REMI	..	..	..	..	..	..	..	..	0	**-**

Figure 6.11: Graph Frequency of Retention Variables for Growth Modeling (Group II)

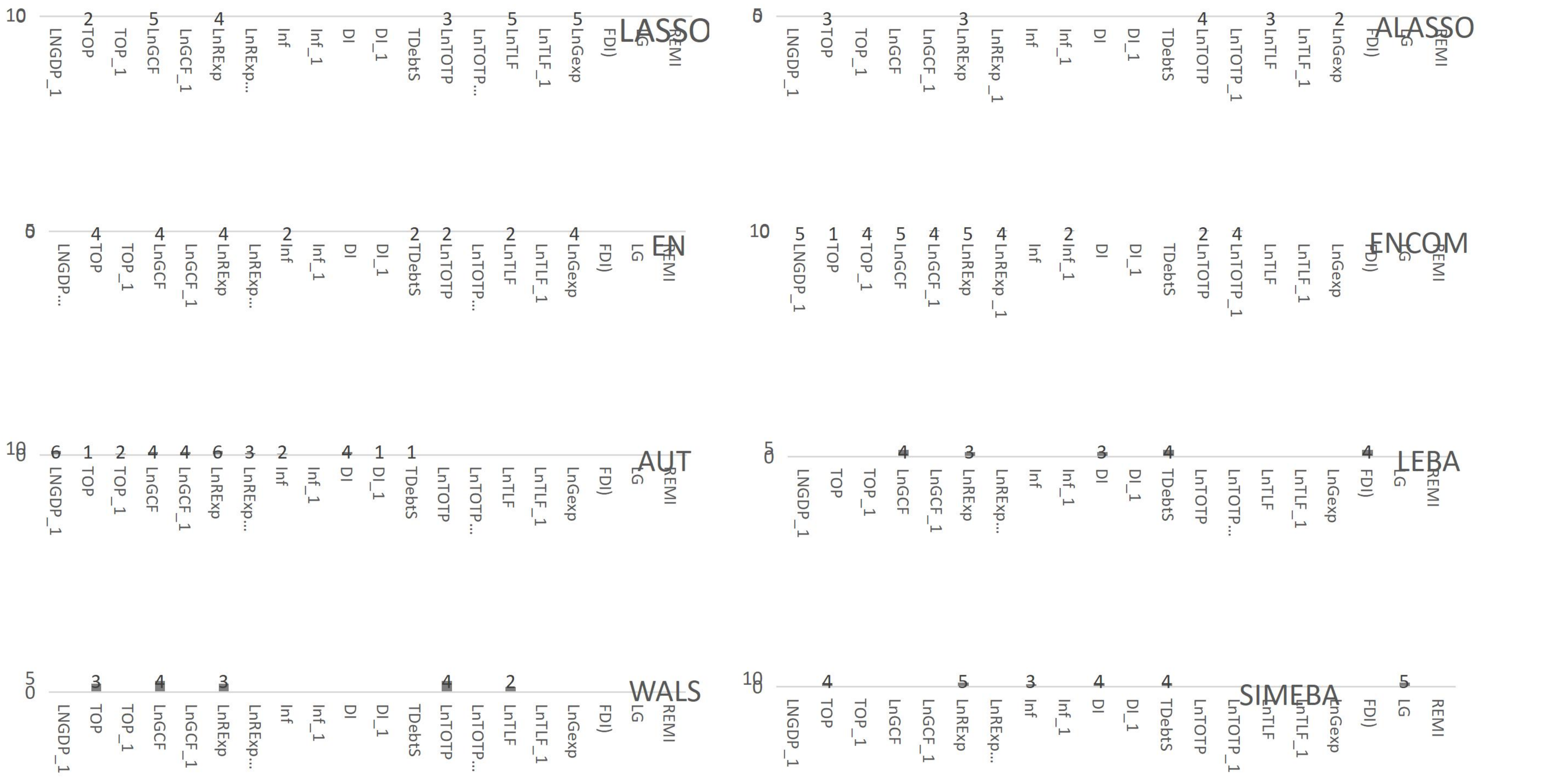

Figure 6.11 summarizes the frequency of retention variables in the economic growth model using different classes of the model selection criteria. Focus variables FDI by Leamer's extreme bound analysis EBA retained this variable in the final equation and came out 4 times out of 6 regressions. While in all other regressions, it does not appear in the final equations. Similarly, the next most common focus variable, LNGCF, came out significantly 4 times in Autometrics, WALS, elastic net and Leamer's EBA. In encompassing and LASSO regression, it came out significantly 5 times out of 6 regressions. The ALSSO and SIM-EBA did not retain this variable in the final equations. The lag value of LNGCF came out significant 4 times in Autometrics and encompassing out of 9 equations. The third focus variable is LNTLF, found significant 5 times in LASSO, 3 times in ALASSO, and 2 times in elastic net and WALS models out of 6 regressions. While in all other procedures, they did not include it in the final equations.

Figure 6.12: Graph of Least Forecast RMSE for Growth Modeling (Group II)

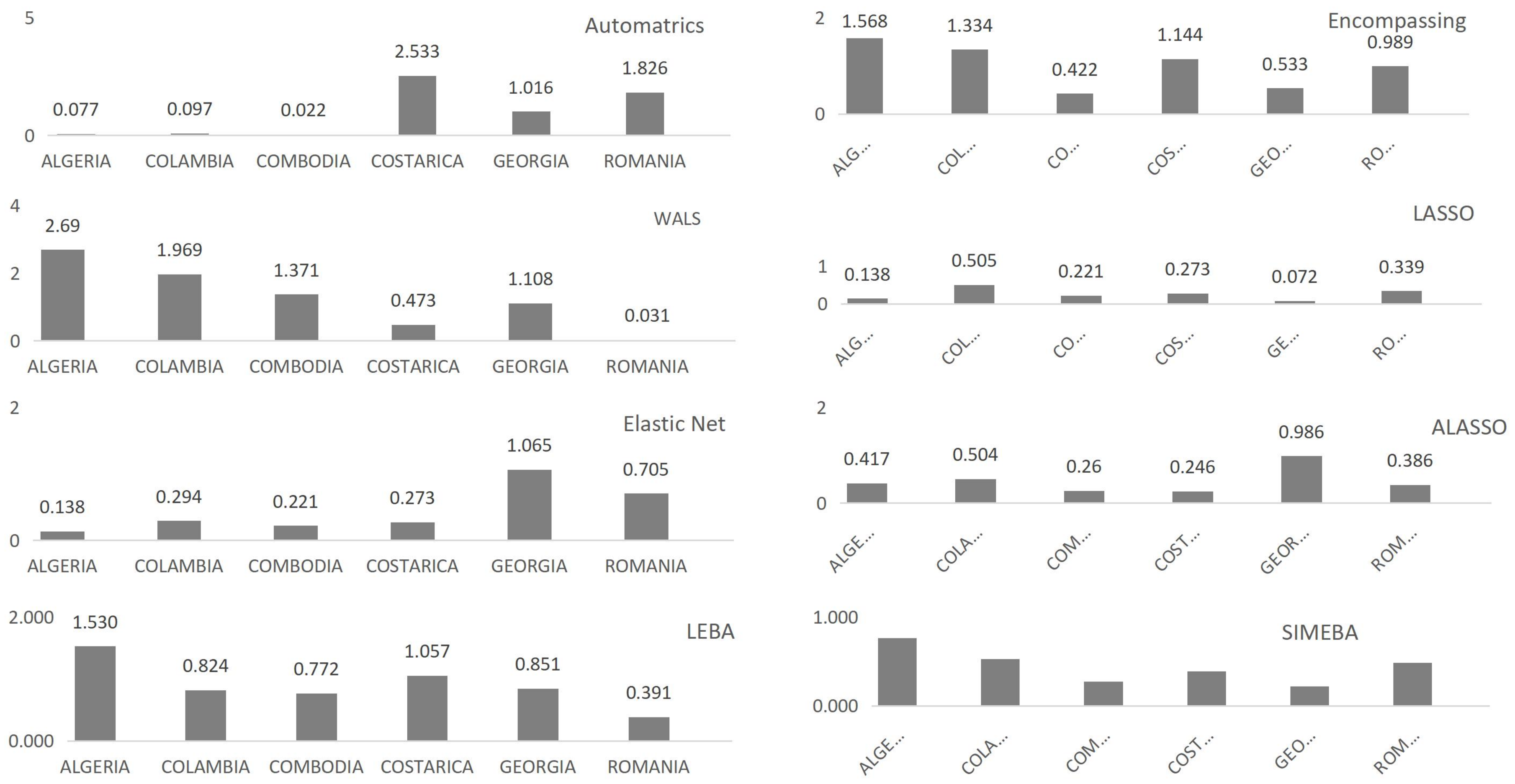

Figure 6.12 Summarizes the results of the least forecasted RMSE using different classes of procedures. In the case of LASSO regression, the Georgia model came up with a minimum RMSE 0.072. In ALASSO regression, the Costa Rica model came up with the least RMSE 0.246. On the other hand, Elastic Net regression with the Algeria model got the lowest RMSE 0.138. The Romania model got the least RMSE 0.031 and 0.391 using WALS and LEBA models. Georgia model got the least RMSE with 0.219 by using SAI-EBA. Cambodia performs best using encompassing and Autometrics procedures with minimum FRMSE 0.422 and 0.022, respectively.

Table 6.11: Least Forecast Values of RMSE for Restricted Robust Model

Country	Automatrics	Encompassing	WALS	LASSO	ALASSO	Elastic Net	LEBA	SIMEBA	minimum value	The best model based on the last FRMSE
Algeria	0.077	1.568	2.69	0.138	0.417	0.138	1.53	0.763	0.077	**Automatrics**
Colambia	0.097	1.334	1.969	0.505	0.504	0.294	0.824	0.525	0.097	**Automatrics**
Combodia	0.022	0.422	1.371	0.221	0.26	0.221	0.772	0.272	0.022	**Automatrics**
Costarica	2.533	1.144	0.473	0.273	0.246	0.273	1.057	0.391	0.246	**ALASSO**
Georgia	1.016	0.533	1.108	0.072	0.986	1.065	0.851	0.219	0.072	**LASSO**
Romania	1.826	0.989	0.031	0.339	0.386	0.705	0.391	0.486	0.031	**WALS**

Table 6.11 summarizes forecast root mean square errors (FRMSE) of the final Roubst models retained by the model selection procedures. The table indicates that FRMSE for the final model selected by Automatrics 0.077 for Non- Nested Encompassing, it was 1.568 for Weighted average least square (WALS) was 2.69, and in this way, the forecast root mean square errors (FRMSE) for another model selection procedures are summarized. The results reveal that the smallest forecast root mean square error (FRMSE) for Algeria was obtained for the model selected by Automatrics. The results for all other countries are also visible in Table 6.12.

Figure 6.13: The Comparison of Restricted Models based on Least Forecast RMSE for Growth Modeling

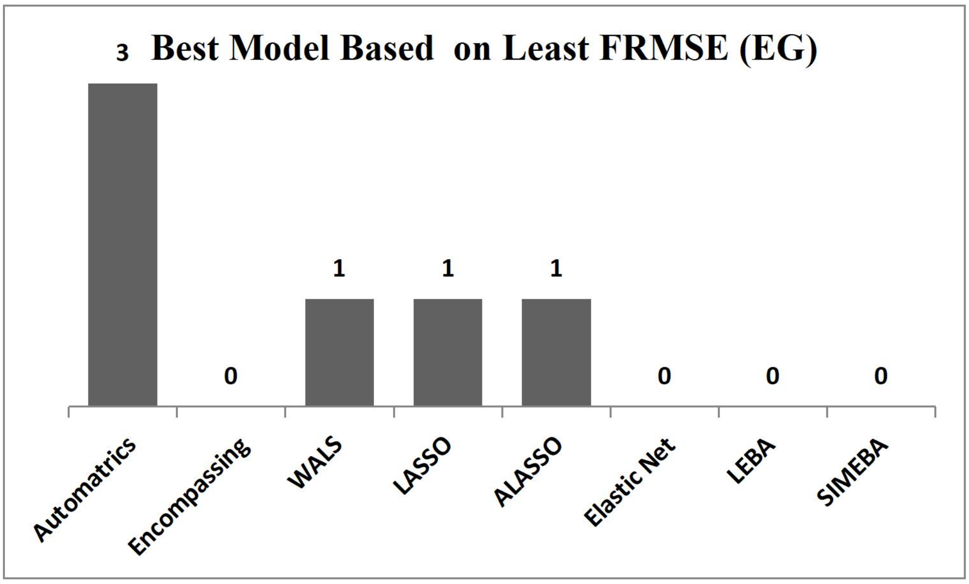

Figure 6.13 is based on the results reported in Table 6.12 above. The last column gives the minimum FRMSE for each estimated model. The results of the figure summarize the maximum number of cases based on the minimum forecasted root mean square errors (FRMSE). The model selected by Automatrics provides minimum FRMSE for the maximum number of cases. In 3 out of 6 cases, the model selected by the Automatrics procedure yields the lowest forecast root mean square errors (FRMSE), which is 50% of the total cases.

Weighted Average least Squares (WALS), LASSO, and Adoptive LASSO; these three different procedures came up with a minimum FRMSE of 1 out of 6 cases, which is 14% of the total cases. The model selected by Encompassing, Elastic Net, LEBA, and

SIM-EBA with minimum FRMSE is 0 out of 6 cases. It means the probability of getting the least FRMSE of these models is 0% on the given sample's basis.

The final results indicate that Autometrics performs best and Encompassing, Elastic Net, LEBA, and SIM-EBA are considered the worst models among all other model selection procedures based on minimum FRMSE.

CHAPTER 7

OPTIMAL MODEL FOR BALANCE OF TRADE MODELING IN THE CASE OF PAKISTAN

The analysis in Chapter 5 concludes that two of the best-performing model selection procedures are non-nested encompassing and the Oxmetrix. Our next objective is to make a model for two important phenomena using these optimal procedures.

Table 7.1: Results of Encompassing and Autometrics Procedure

Model Selected by Encompassing		Model Selected by Oxmetrix	
Country Name	**Pakistan**	**Country Name**	**Pakistan**
Variables	**Non-Nested Encompassing**	**Variables**	**Autometrics**
Constant	..	Constant	-9.639
BOT_1	..	BOT_1	..
DI	..	DI	..
DI_1	..	DI_1	..
BM	..	MS	..
BM_1	..	MS_1	..
ER	-0.228	ER	..
ER_1	-0.216	ER_1	-0.062
EVI	0.086	EVI	..
EVI_1	..	EVI_1	..
IVI	-0.039	IVI	-0.05
IVI_1	0.002	IVI_1	..
FDI	-2.361	FDI	-1.371
FDI_1	..	FDI_1	1.314
INF	..	INF	-0.112
INF_1	..	INF_1	-0.138
P(remi)	..	P(remi)	..
P(remi)_1	-1.496	P(remi)_1	-0.469
LnGDP	..	LnGDP	..
LnGDP_1	1.892	LnGDP_1	-7.225
LnGexp	..	LnGexp	19.972
LnGexp_1	..	LnGexp_1	-5.738
Bdefi	..	Bdefi	..
Bdefi_1	..	Bdefi_1	..
DC	..	DC	-0.195
DC_1	..	DC_1	..
TR	..	TR	..
TR_1	..	TR_1	..

There are many points of agreement in the results of the two procedures. The variables of domestic investment, Broad Money Growth, and their lags are not retained by either model selection procedure. The variable Total Revenue and its lag are also dropped. The variable exchange rate is significant and carries a positive sign in the results of the two procedures. The coefficient of foreign direct investment (FDI) and import value index (IVI) carries a negative in the results of encompassing and carries a negative sign in Oxmetrix. The lag value of the variable gross domestic product LNGDP_1 is significant and carries a positive sign in the results produced by encompassing and carries a negative sign in the results of Oxmetrix. The coefficient of ER carries a negative in the results of encompassing and carries a negative sign in the results of Oxmetrix. It can be concluded that the immediate effect of exchange rate depreciation is negative.

There are some points of disagreement as well. The variable 'DC' appears insignificant in the encompassing, but it is significant, carrying a negative sign in the results produced by Oxmetrix. The lag value of the variable foreign direct investment (FDI) carries a significant negative sign in the results produced by encompassing but appears insignificant in Oxmetrix procedure. Lag value of the variable government expenditure LnGexp_1 was found to be significant in carrying a negative sign in the results produced by Oxmetrix, but it traced out to be insignificant in the encompassing. The coefficient of foreign direct investment (FDI_1) is positive in the Oxmetrix results and appears insignificant in the encompassing.

7.1 OPTIMAL MODEL FOR GROWTH MODELING IN THE CASE OF PAKISTAN

The analysis in Chapter 6 concludes that two of the best-performing model selection procedures are non-nested encompassing and the Oxmetrix. Our next objective is to make a model for two important phenomena using these optimal procedures.

Table 7.2: Results of Encompassing and Autometrics Procedure

Model Selected by Encompassing		**Model Selected by Oxmetrix**	
Country Name	**Pakistan**	**Country Name**	**Pakistan**

Variables	Non-Nested Encompassing	Variables	Automatrics
Constant	..	Constant	16.264
LNGDP_1	0.8438	LNGDP_1	0.37
FDI(inf)	..	FDI(inf)	..
FDI(inf)_1	..	FDI(inf)_1	..
TOP	..	TOP	-9.603
TOP_1	..	TOP_1	..
LG	..	LG	..
LG_1	..	LG_1	..
DI	..	DI	..
DI_1	..	DI_1	..
LnGCF	0.312	LnGCF	0.419
LnGCF_1	-0.331	LnGCF_1	-0.281
TDebtS	..	TdebtS	-0.018
TDebtS_1	..	TDebtS_1	..
Inf	..	Inf	-0.007
Inf_1	..	Inf_1	..
LnTLF	..	LnTLF	..
LnTLF_1	..	LnTLF_1	..
LnTOTP	..	LnTOTP	..
LnTOTP_1	..	LnTOTP_1	..
Edu	0.047	Edu	..
Edu_1	..	Edu_1	..
LnRExp	0.196	LnRExp	0.606
LnRExp _1	..	LnRExp _1	..
GEXP	..	GEXP	..
GEXP_1	..	GEXP _1	..
P(remi)	-0.035	P(remi)	..
P(remi)_1	0.041	P(remi)_1	0.022

There are many points of agreement in the results of the two procedures. The variables of Foreign Direct Investment, Trade Openness, Labour Growth, and their lags are not retained by either model selection procedure. Similarly, the next most common variables, Domestic Investment, Total Labor Force, and Government Expenditures with their lag values, were considered insignificant and dropped from both model selection procedures. The variable lag GDP of the dependent variable in both models is found to be significant and positive. As a result, Pakistan's growth is determined by its LNGDP_1. Lack of convergence or economies scale could be the cause. The variable Gross Capital Formation is significant and has a positive sign in the results of the two procedures. The lag value of the variables Personal Remittances (REMI_1) and Gross Capital Formation (LNGCF_1) carries a negative in the results of encompassing and carries a negative sign in the results of Oxmetrix. The coefficient of Real Exports (LNRexp) is significant and carries a positive in the results of encompassing and carries positive sign in the results of Oxmetrix. It can be concluded that for Pakistan's economy, Real Exports is a significant driver to boost Economic Growth.

There are some points of disagreement as well. The coefficient of personal Remittances (REMI) appears significant and carries a negative sign in the results of encompassing but insignificant in the results of Oxmetrix. The variables Trade Openness (TOP) and Inflation (INF) appear insignificant in the encompassing but carry a significant a negative sign in the results produced by Oxmetrix. The variable Education (EDU) carries a significant positive sign in the results produced by encompassing but appears insignificant in Oxmetrix procedure.

CHAPTER 8

SUMMARY, CONCLUSION AND RECOMMENDATION

8.1 Summary

The main goal of this study was to compare the performance of different methodologies for model selection. These methodologies included Least Absolute Shrinkage and Selection Operator (LASSO), Adoptive Least Absolute Shrinkage and Selection Operator (ALASSO), Elastic Net, Encompassing, Autometrics, Weighted Average Least Square, and Extreme Bound analysis. A comparison was made between forecast RMSE and robustness. In addition, we also compare the frequency of retention of variables. Finally, this study estimates the optimal model for Growth and the Balance of Trade Model as the optimal model.

For FRMSE, we leave some observations from available data and estimate the model. The estimated model is then used to forecast the remaining value and the FRMSE is calculated.

However, selecting an appropriate model for a given phenomenon is not easy. There are many theories and a plethora of models that can be applied for theories, but selecting the most appropriate model is trick The selection of an appropriate model is of great concern and has a long history but is still unresolved. The reason is that model simplifies the reality, which is very complex, dynamic, and high-dimensional.

The final results of model selection procedures based on least FRMSE for the Balance of Trade model indicate that in both groups, the general unrestricted model for 43 countries and the restricted model for 9 countries. The non-Nested Encompassing procedure provides the best results based on the minimum forecast root mean square errors (FRMSE) for the maximum number of cases. In 25 out of 43 cases, the model selected by the Non-Nested Encompassing yielded the lowest forecast root mean square errors (FRMSE). On the other hand, the model selected by Non-Nested Encompassing provides minimum FRMSE for a maximum number of cases. In 5 out of 9 cases, the model selected by the Non-Nested Encompassing yielded the lowest forecast root mean square errors (FRMSE), which is 56% of the total cases. Finally, the results of the current study validate that Non-Nested Encompassing performs best for both groups. In comparison, the shrinkage family and family based on consistencyof coefficients are considered the worst methodologies among all other model selection procedures on the basis of least FRMSE.

The final results of model selection procedures based on the least FRMSE for the Growth model indicate that in both groups, the Autometrics procedure provides the best results based on the minimum forecasted root mean square errors (FRMSE) for the maximum number of cases. In 30 out of 43 cases, the model selected by Autometrics yields the lowest forecast root mean square error (FRMSE), which is 70% of the total cases. On the other hand, the Model selected by Autometrics provides minimum FRMSE for the maximum cases. In 3 out of 6 cases, the model selected by Autometrics yields the lowest forecast root mean square error (FRMSE),, which is 50% of the total cases. Finally, the results of the current study validate that autometrics performs best for both groups. While the shrinkage family and family based on consistency of coefficient are considered as the worst methodologies among all other model selection procedures on the basis of least FRMSE.

The results are based on th the frequency of retention of true variables among different classes of model selection Procedure for the group general unrestricted model for 43 countries and robust restricted model for 6 countries using the model Balance of Trade and Economic Growth. The modelodel selection procedure based on the shrinkage family provides the best results the for the maximum number of cases to potential determinants of the Balance of Trade and economic growth. So, therefore the the model selected by Elastic Net performss best in most ofvthe cases to find the maximum frequency of retention variables for each estimated model. Selection criteria based on the frequency of retention variables validate the final result of both groups (general unrestricted model (group I) and robust restricted model (group II). Finally, the results of the current study support the existing study of Khan (2020).

The optimal model selection procedures are then applied to estimate the models for the Balance of Trade and Growth for Pakistan. The results indicate that the significant determinants for Balance of Trade are ER, EVI, IVI, FDI, INF, LNGEXP, DC, REMI, and LNGDP and for Growth, the significant determinants are LNGDP_1, LNGCF, TDebts, INF, EDU, LNRexp, REMI, and TOP.

8.2 Conclusion

For estimating the both models, same set of variables have been used initially in the regressions, therefore, if we consider some omitted variables, it would be omitted for all countries. But we are starting with a sufficiently general model; the omitted variables bias is less probable. Yet, there are the variables with different signs for different countries. The difference in the signs of coefficients of variables is an indication of country specific heterogeneity. Taking a panel suppresses the heterogeneity but we have taken the countries individually which reveals the heterogeneity. The difference in the signs of a variable has led to the concept of extreme bound analysis, as explained in the thesis.

1. **Economic Growth**:
    - For the study of economic growth, various model selection procedures were employed to identify the most suitable models.
    - The first approach involved selecting models based on the Frequency of Retention of Variables. In this method, both restricted and unrestricted models were considered. The frequency of retention indicates how often specific variables were retained in the models across different analyses. This helps identify the most consistently relevant variables for explaining economic growth.
    - The second approach focused on selecting models based on the Forecasted Least Root Mean Square Error (RMSE). This method aims to find models, both restricted and unrestricted, that provide the smallest forecasted RMSE, indicating their predictive accuracy in explaining economic growth.
2. **Balance of Trade**:
    - In the context of analyzing the balance of trade, different model selection procedures were applied to determine the most appropriate models.

- One of the methods employed shrinkage methodology known as Elastic-Net. This technique is used to select variables and estimate models that best explain variations in the balance of trade.
- Additionally, other Model Selection Procedures, specifically Non-Nested Encompassing, were utilized to identify models that capture the dynamics of the balance of trade.

These model selection procedures serve as crucial tools in econometrics and statistical modeling. They help researchers and analysts choose the models that provide the most accurate and meaningful insights into economic growth and the balance of trade. The methods take into account variable retention frequencies and forecasted RMSE, which are essential criteria for evaluating the performance and robustness of different models in explaining these economic phenomena.

Table 8.2.1: Final Results

Economic phenomena	**Model Selection Procedure Based on the Frequency of Retention of Variables (Restricted and Unrestricted Models)**	**Model Selection Procedure Based on the Forecasted Least RMSE (Restricted and Unrestricted Models)**
Economic Growth	Model selection procedures based on shrinkage methodology Elastic-Net	Automatic Model Selection Procedures (Autometrics)
Balance of Trade	Model selection procedures based on shrinkage methodology Elastic-Net	Other Model Selection Procedures (Non-Nested Encompassing)

The thesis narrows down the options available for model selection. Out of the eight procedures compared in this thesis, five procedures could not perform well on any of the three criteria (FRMSE, robust and retention) used to compare the model selection procedures.

The three procedures that were found better are Oxmetrix, Non-nested encompassing and Elastic net. The first two outperform with respect to FRMSE and the third with respect to retention of variables. Therefore, this study reduces the number of available options to only three procedures.

Furthermore, it was seen that the models selected by Oxmetrics and non-nested encompassing have considerable similarity, which means it doesn't make a big difference if the two model selection procedures are used alternatively.

The estimation also shows that the E-net retains the maximum number of variables, similar to the finding of Khan (2020); however, the E-net doesn't perform well in terms of forecasting.

The study also finds the determinants of the Balance of Trade and Growth for Pakistan, which are mentioned in Chapter Seven.

8.3 Model Selection and Artificial Intelligence Nexus

Artificial Intelligence (AI) methods leverage advanced econometric procedures, applying them iteratively to sample data for the unveiling of optimal patterns and accurate forecasting. This symbiotic relationship between econometrics and AI is particularly potent. As we pinpoint improved econometric procedures for modeling, this knowledge becomes a catalyst for enhancing AI algorithms. The synergy lies in the capacity to infuse AI systems with refined econometric insights, thereby accelerating the forecasting process.

In this dynamic interplay, the iterative application of econometric methods not only refines predictive models but also cultivates a continuous learning loop within AI frameworks. By identifying and incorporating superior econometric techniques, the AI algorithms gain a sharper acumen for pattern recognition and trend analysis. This, in turn, translates into heightened efficiency in forecasting tasks. The seamless integration of econometric advancements into AI not only expedites the predictive analytics process but also contributes to the adaptability and robustness of the algorithms, ensuring they remain agile in the face of evolving data landscapes.

Considering the promising implications of this integration, a compelling avenue for future research emerges. Investigating the tangible impact of incorporating these refined econometric findings into AI algorithms could provide valuable insights. A research project aimed at quantifying the extent of improvement achievable through this fusion of methodologies would contribute significantly to the advancement of predictive analytics, laying the groundwork for more effective and efficient decision-making processes in various domains.

Harnessing AI can elevate the conclusions of this study by augmenting the analysis of econometric patterns. AI, with its capacity for complex pattern recognition and iterative learning, can refine and optimize econometric procedures identified in the study. It can explore vast datasets, uncover hidden correlations, and fine-tune forecasting models, enhancing the precision of predictions. Additionally, AI's adaptability enables it to dynamically incorporate new insights over time, ensuring continuous improvement. By integrating AI into the study's framework, researchers can unlock unprecedented potential for uncovering nuanced relationships within economic data, amplifying the impact and relevance of their findings in the realm of econometrics.

8.4 Recommendations

We recommend the Oxmetrix and non-nested encompassing in practical problems for the practitioners. It doesn’t matter if any of the two is used.

We have sorted out the determinants of Growth and Balance of Trade for the policymakers.

For future research on the econometric researcher, we recommend adding further scenarios such as structural breaks to get the performance of model selection procedures in the presence of structural breaks.

CHAPTER 9

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APPENDEX

Table: 1 Results of RMSE from Non- Nested Encompassing Procedure (Balance of Trade Model)

Country Name	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Best Model
Argentina	2.923	5.096	4.601	4.042	4.564	**3.096**	**Model 1**
Australia	12.103	11.568	11.181	11.862	12.045	11.211	**Model 3**
Austria	3.837	3.439	3.118	1.066	3.355	**3.289**	**Model 4**
Bangladesh	1.62106	1.992	2.057	1.56064	1.976	**2.024**	**Model 4**
Belgium	5.055	5.445	5.4	1.2552	5.484	**3.508**	**Model 4**
Bhutan	2.352	2.981	2.765	2.532	2.942	**2.727**	**Model 1**
Bulgaria	2.04	1.745	2.185	2.287	1.909	**2.174**	**Model 2**
Brazil	2.363	3.15	2.695	3.152	3.448	2.712	**Model 1**
Canada	0.932	1.024	1.0188	0.668	1.097	0.939	**Model 1**
China	2.76924	3.16605	3.04504	2.9959	3.01092	3.03156	**Model 1**
Chile	3.544	3.792	3.268	2.742	3.791	3.59	**Model 4**
Denmark	0.952	0.872	0.83	0.867	0.924	0.763	**Model 6**
France	0.654	0.623	0.71	0.711	0.682	0.551	**Model 6**
Germany	0.88	0.853	0.76	0.926	0.873 9	0.926	**Model 3**
Ghana	3.308	3.226	3.714	3.045	3.675	3.507	**Model 4**
Hungary	1.883	2.163	1.987	1.408	2.1638	1.948	**Model 4**
India	1.368	1.503	1.43	1.408	1.452	1.394	**Model 1**
Indonesia	2.36	2.503	2.15219	2.537	2.535	2.261	**Model 3**
Iran	5.111	5.213	5.208	2.888	5.343	4.767	**Model 4**
Japan	3.974	4.25	4.034	2.208	4.255	4.17	**Model 4**
Luxembourg	2.12	2.134	1.709	1.238	2.082	2.245	**Model 4**
Malaysia	1.483	1.576	1.592	1.519	1.526	1.636	**Model 1**
Maldives	2.86	2.746	2.688	2.058	2.736	2.513	**Model 4**

Country Name	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Best Model
Mexico	3.214	3.776	3.577	3.121	4.158	3.5	**Model 4**
Morocco	1.675	2.078	2.119	1.77	2.054	2.257	**Model 4**
Nepal	2.614	3.565	3.373	2.083	3.355	3.437	**Model 1**
Netherland	0.416	0.481	0.449	0.406	0.463	0.442	**Model 4**
New Zealand	0.369	0.441	0.445	0.442	0.447	0.449	**Model 1**
Norway	2.349	2.881	2.234	1.544	2.873	2.467	**Model 4**
Pakistan	2.109	2.321	2.05	2.157	2.345	2.3	**Model 3**
Peru	4.12	4.055	4.023	3.222	3.458	4.189	**Model 4**
Paraguay	2.062	2.603	2.643	1.843	2.58	2.42	**Model 4**
Philippines	1.949	1.983	1.99	2.184	2.116	2.079	**Model 1**
Portugal	1.246	1.812	1.957	1.156	2.121	1.825	**Model 4**
Qatar	5.015	5.742	4.223	5.59	5.423	4.364	**Model 3**
South Africa	2.251	2.36	2.354	2.624	2.562	1.968	**Model 6**
Sri Lanka	1.784	2.331	2.335	2.289	2.157	2.343	**Model 1**
Switzerland	0.902 3	0.925	0.915	0.915	0.934	0.825	**Model 6**
Sweden	0.682	0.908	0.872	0.756	0.91	0.703	**Model 6**
Turkey	1.711	2.205	2.202	1.923	2.765	2.166	**Model 1**
United States	1.186	1.315	1.31	1.344	1.335	1.189	**Model 1**
United Kingdom	0.047	0.014	0.057	0.047	0.057	0.05	**Model 2**
Uruguay	2.329	3.026	2.434	2.367	3.348	2.673	**Model 1**

Table: 2 Results of Testing Hypothesis from Non-Nested Encompassing Procedure (Balance of Trade Model)

Testing Hypothesis	..	**Model 1 ⊃ Model 2**	**Model 1 ⊃ Model 3**	**Model 1 ⊃ Model 4**	**Model 1 ⊃ Model 5**	**Model 1 ⊃ Model 6**
Argentina	..	-0.4752 [0.6346]	-1.680 [0.0930]	-5.411 [0.0000]**	-2.170 [0.0300]*	-4.144 [0.0000]**
Testing Hypothesis	Model 3 ⊃ Model 1	Model 3 ⊃ Model 2	..	Model 3 ⊃ Model 4	Model 3 ⊃ Model 5	Model 5 ⊃ Model 6
Australia	-0.6049 [0.5452]	-0.1380 [0.8902]	..	-1.452 [0.1465]	-2.603 [0.0092]**	-4.869 [0.0000]**
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Austria	-0.2416 [0.8091]	-1.657 [0.0975]	-0.7894 [0.4299]		-1.625 [0.1041]	-0.8878 [0.3747]
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Bangladesh	-4.790 [0.0000]**	0.2157 [0.8292]	0.2916 [0.7706]	..	0.9262 [0.3543]	0.3647 [0.7153]
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Belgium	-0.4977 [0.6187]	-1.597 [0.1103]	1.635 [0.1020]	..	-0.2056 [0.8371]	-1.212 [0.2255]
Testing Hypothesis	..	Model 1 ⊃ Model 2	Model 1 ⊃ Model 3	Model 1 ⊃ Model 4	Model 1 ⊃ Model 5	Model 1 ⊃ Model 6
Bhutan		-0.4839 [0.6285]	0.8156 [0.4147]	-9.141 [0.0000]**	-0.008214 [0.9934]	0.3832 [0.7016]
Testing Hypothesis	Model 2 ⊃ Model 1	..	Model 2 ⊃ Model 3	Model 2 ⊃ Model 4	Model 2 ⊃ Model 5	Model 2 ⊃ Model 6
Bulgaria	-7.760 [0.0000]**	..	-0.4163 [0.6772]	-2.274 [0.0230]*	-1.300 [0.1936]	-0.1253 [0.9003]
Testing Hypothesis	..	Model 1 ⊃ Model 2	Model 1 ⊃ Model 3	Model 1 ⊃ Model 4	Model 1 ⊃ Model 5	Model 1 ⊃ Model 6
Brazil	..	-3.964 [0.0001]**	-1.922 [0.0546]	-1.300 [0.1937]	-6.110 [0.0000]**	-1.803 [0.0714]
Testing Hypothesis	..	Model 1 ⊃ Model 2	Model 1 ⊃ Model 3	Model 1 ⊃ Model 4	Model 1 ⊃ Model 5	Model 1 ⊃ Model 6
Canada	..	-1.434 [0.1515]	-0.9282 [0.3533]	-18.08 [0.0000]**	-2.921 [0.0035]**	-2.900 [0.0037]**
Testing Hypothesis	..	Model 1 ⊃ Model 2	Model 1 ⊃ Model 3	Model 1 ⊃ Model 4	Model 1 ⊃ Model 5	Model 1 ⊃ Model 6

Testing Hypothesis	..	**Model 1 ⊃ Model 2**	**Model 1 ⊃ Model 3**	**Model 1 ⊃ Model 4**	**Model 1 ⊃ Model 5**	**Model 1 ⊃ Model 6**
China	..	-0.4581 [0.6469]	-4.767 [0.0000]**	0.6358 [0.5249]	-2.272 [0.0231]*	-5.116 [0.0000]**
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Chili	-2.270 [0.0232]*	0.02156 [0.9828]	-7.318 [0.0000]**	..	-0.2370 [0.8126]	-0.7223 [0.4701]
Testing Hypothesis	Model 6 ⊃ Model 1	Model 6 ⊃ Model 2	Model 6 ⊃ Model 3	Model 6 ⊃ Model 4	Model 6 ⊃ Model 5	..
Denmark	0.01046 [0.9917]	-1.869 [0.0617]	-0.6495 [0.5160]	1.146 [0.2518]	-0.8360 [0.4032]	..
Testing Hypothesis	Model 6 ⊃ Model 1	Model 6 ⊃ Model 2	Model 6 ⊃ Model 3	Model 6 ⊃ Model 4	Model 6 ⊃ Model 5	..
France	-3.295 [0.0010]**	-3.921 [0.0001]**	0.08913 [0.9290]	-3.292 [0.0010]**	1.050 [0.2937]	..
Testing Hypothesis	Model 3 ⊃ Model 1	Model 3 ⊃ Model 2	..	Model 3 ⊃ Model 4	Model 3 ⊃ Model 5	Model 3 ⊃ Model 6
Germany	-1.767 [0.0000]**	-0.4621 [0.6440]	..	-4.237 [0.0004]**	-1.618 [0.1056]	-3.673 [0.0001]**
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Ghana	-1.224 [0.2210]	-2.502 [0.0123]*	0.2161 [0.8289]		0.9641 [0.3350]	-1.110 [0.2671]
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Hungary	-1.522 [0.1281]	1.457 [0.1451]	-1.235 [0.2167]	..	-0.1556 [0.8764]	1.520 [0.1284]
Testing Hypothesis	..	Model 1 ⊃ Model 2	Model 1 ⊃ Model 3	Model 1 ⊃ Model 4	Model 1 ⊃ Model 5	Model 1 ⊃ Model 6
India	..	-4.869 [0.0000]**	-4.328 [0.0000]**	-2.874 [0.0041]**	-5.318 [0.0000]**	-6.798 [0.0000]**
Testing Hypothesis	Model 3 ⊃ Model 1	Model 3 ⊃ Model 2	..	Model 3 ⊃ Model 4	Model 3 ⊃ Model 5	Model 3 ⊃ Model 6
Indonesia	-2.343 [0.0191]*	-0.4713 [0.6374]	..	0.1205 [0.9040]	-0.1877 [0.8511]	-3.514 [0.0004]**
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Iran	-0.2391 [0.8110]	-0.6336 [0.5264]	-2.587 [0.0097]**	..	0.3305 [0.7410]	-1.212 [0.2257]
Testing	Model 4 ⊃	Model 4 ⊃	Model 4 ⊃	..	Model 4 ⊃	Model 4 ⊃

Testing Hypothesis	..	**Model 1 ⊃ Model 2**	**Model 1 ⊃ Model 3**	**Model 1 ⊃ Model 4**	**Model 1 ⊃ Model 5**	**Model 1 ⊃ Model 6**
Hypothesis	Model 1	Model 2	Model 3		Model 5	Model 6
Japan	0.7201 [0.4715]	0.6512 [0.5149]	-1.597 [0.1103]	..	0.7452 [0.4562]	0.8069 [0.4197]
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Luxembourg	-2.192 [0.0284]*	-0.6756 [0.4993]	-1.009 [0.3129]	..	-0.4338 [0.6644]	1.985 [0.0471]*
Testing Hypothesis	..	Model 1 ⊃ Model 2	Model 1 ⊃ Model 3	Model 1 ⊃ Model 4	Model 1 ⊃ Model 5	Model 1 ⊃ Model 6
Malaysia	..	-1.981 [0.0476]*	-2.006 [0.0448]*	-3.097 [0.0020]**	-2.256 [0.0241]*	-0.2181 [0.8273]
Testing Hypothesis	Model 2 ⊃ Model 1	..	Model 2 ⊃ Model 3	Model 2 ⊃ Model 4	Model 2 ⊃ Model 5	Model 2 ⊃ Model 6
Maldives	-4.456 [0.0000]**	..	-6.784 [0.0000]**	-40.89 [0.0000]**	-1.016 [0.3095]	-6.152 [0.0000]**
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Mexico	-4.205 [0.0000]**	-0.8196 [0.4124]	-5.515 [0.0000]**		-1.435 [0.1513]	-3.721 [0.0002]**
Testing Hypothesis	..	Model 1 ⊃ Model 2	Model 1 ⊃ Model 3	Model 1 ⊃ Model 4	Model 1 ⊃ Model 5	Model 1 ⊃ Model 6
Morocco		-0.6950 [0.4871]	-0.3657 [0.7146]	-3.180 [0.0015]**	-1.147 [0.2514]	-0.2458 [0.8059]
Testing Hypothesis	..	Model 1 ⊃ Model 2	Model 1 ⊃ Model 3	Model 1 ⊃ Model 4	Model 1 ⊃ Model 5	Model 1 ⊃ Model 6
Nepal	..	0.2189 [0.8267]	-0.7744 [0.4387]	-10.68 [0.0000]**	-1.448 [0.1476]	-2.614 [0.0089]**
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Netherland	-4.045 [0.0001]**	0.5353 [0.5924]	-1.570 [0.1163]	..	-0.3733 [0.7089]	-3.127 [0.0018]**
Testing Hypothesis	..	Model 1 ⊃ Model 2	Model 1 ⊃ Model 3	Model 1 ⊃ Model 4	Model 1 ⊃ Model 5	Model 1 ⊃ Model 6
New eland	..	0.04253 [0.8730]	-1.063 [0.3119]	-0.3457 [0.5059	0.1189 [0.7367]	0.6120 [0.2515]
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
2	-1.549 [0.1214]	1.357 [0.1747]	2.732 [0.0063]**	..	1.906 [0.0567]	2.410 [0.0160]*

Testing Hypothesis	..	**Model 1 ⊃ Model 2**	**Model 1 ⊃ Model 3**	**Model 1 ⊃ Model 4**	**Model 1 ⊃ Model 5**	**Model 1 ⊃ Model 6**
Testing Hypothesis	Model 3 ⊃ Model 1	Model 3 ⊃ Model 2	..	Model 3 ⊃ Model 4	Model 3 ⊃ Model 5	Model 3 ⊃ Model 6
Pakistan	-4.181 [0.0000]**	0.03255 [0.9740]	..	-3.594 [0.0003]**	-0.4186 [0.6755]	-1.426 [0.1540]
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Peru	-1.054 [0.2919]	0.2948 [0.7682]	-0.3391 [0.7345]	..	-0.05392 [0.9570]	-1.367 [0.1715]
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Paraguay	-1.608 [0.1079]	0.1001 [0.9202]	-0.4212 [0.6736]	..	-4.282 [0.0000]**	-2.545 [0.0109]*
Testing Hypothesis	..	Model 1 ⊃ Model 2	Model 1 ⊃ Model 3	Model 1 ⊃ Model 4	Model 1 ⊃ Model 5	Model 1 ⊃ Model 6
Philippines	..	-4.469 [0.0000]**	-3.651 [0.0003]**	0.2105 [0.8333]	-1.670 [0.0949]	-3.444 [0.0006]**
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Portugal	-3.630 [0.0003]**	-2.470 [0.0135]*	-2.628 [0.0086]**	..	-3.083 [0.0020]**	-2.327 [0.0200]*
Testing Hypothesis	Model 3 ⊃ Model 1	Model 3 ⊃ Model 2	..	Model 3 ⊃ Model 4	Model 3 ⊃ Model 5	Model 3 ⊃ Model 6
Qatar	0.06192 [0.9506]	2.179 [0.0293]*	..	1.2974 [0.2993]	-0.4778 [0.6328]	1.8649 [0.1494]
Testing Hypothesis	Model 6 ⊃ Model 1	Model 6 ⊃ Model 2	Model 6 ⊃ Model 3	Model 6 ⊃ Model 4	Model 6 ⊃ Model 5	..
South Africa	-0.07423 [0.9408]	-2.755 [0.0059]**	-4.344 [0.0000]**	-0.07686 [0.9387]	0.5637 [0.5729]	..
Testing Hypothesis	..	Model 1 ⊃ Model 2	Model 1 ⊃ Model 3	Model 1 ⊃ Model 4	Model 1 ⊃ Model 5	Model 1 ⊃ Model 6
Sri Lanka	..	0.008205 [0.9935]	0.7258 [0.4680]	-0.7232 [0.4695]	-1.980 [0.0477]*	1.395 [0.1631]
Testing Hypothesis	Model 6 ⊃ Model 1	Model 6 ⊃ Model 2	Model 6 ⊃ Model 3	Model 6 ⊃ Model 4	Model 6 ⊃ Model 5	..
Switzerland	-0.3945 [0.6932]	1.136 [0.2561]	0.2266 [0.8208]	0.2266 [0.8208]	0.7545 [0.4506]	..
Testing Hypothesis	Model 6 ⊃ Model 1	Model 6 ⊃ Model 2	Model 6 ⊃ Model 3	Model 6 ⊃ Model 4	Model 6 ⊃ Model 5	..
Sweden	-4.701	-0.4666	-2.705	-5.222	-0.8559	..

Testing Hypothesis	..	**Model 1 ⊃ Model 2**	**Model 1 ⊃ Model 3**	**Model 1 ⊃ Model 4**	**Model 1 ⊃ Model 5**	**Model 1 ⊃ Model 6**
	[0.0000]**	[0.6408]	[0.0068]**	[0.0000]**	[0.3921]	
Testing Hypothesis	..	Model 1 ⊃ Model 2	Model 1 ⊃ Model 3	Model 1 ⊃ Model 4	Model 1 ⊃ Model 5	Model 1 ⊃ Model 6
Turkey	..	-0.3144 [0.7532]	-3.077 [0.0021]**	-0.7420 [0.4581]	-0.7420 [0.4581]	-3.317 [0.0009]**
Testing Hypothesis	..	Model 1 ⊃ Model 2	Model 1 ⊃ Model 3	Model 1 ⊃ Model 4	Model 1 ⊃ Model 5	Model 1 ⊃ Model 6
United States	..	-0.1559 [0.2980	-1.705 [0.0038]**	0.7541 [0.4701]	-0.2316 [0.7408]	-3.260 [0.1529]
Testing Hypothesis	Model2 ⊃ Model 1	..	Model 2 ⊃ Model 3	Model 2 ⊃ Model 4	Model 2 ⊃ Model 5	Model 2 ⊃ Model 6
United Kingdom	-0.9575 [0.3383]	..	-4.840 [0.0000]**	-1.860 [0.0629]	-3.235 [0.0012]**	-3.544 [0.0004]**
Testing Hypothesis	..	Model 1 ⊃ Model 2	Model 1 ⊃ Model 3	Model 1 ⊃ Model 4	Model 1 ⊃ Model 5	Model 1 ⊃ Model 6
Uruguay		-0.2559 [0.7980]	-2.161 [0.0307]*	-4.372 [0.0000]**	-0.4839 [0.6285]	0.3319 [0.7400]

Table: 3 Results of Retained Model (Encompassing Testing) for Balance of Trade Modeling

Country Name Variables	Argentina	Australia	Austria	Bangladesh	Belgium	Bhutan	Bulgaria	Brazil	Canada	Chile
Constant	107.635 (0.1776)	207.477 (0.6360)	-58.300 (0.9644)	5.599 (0.3127)	376.332 (0.9441)	33.059 (0.0122)	45.972 (0.0000)	7.225 (0.5126)	64.554 (0.4431)	326.300 (0.0982)
BOT_1	0.405 (0.0023)	0.659 (0.0191)	0.729 (0.0000)	0.684 (0.0001)	0.758 (0.0000)	0.179 (0.3986)	-0.124 (0.5437)	0.858 (0.0002)	0.129 (0.5075)	-0.103 (0.7577)
DI	0.070 (0.3741)	..	18.560 (0.9271)	-0.374 (0.2869)	21.59 (0.8500)	-0.162 (0.6358)	0.184 (0.4020)	0.001 (0.9121)	-0.165 (0.2997)	0.012 (0.9084)
DI_1	-0.013 (0.8424)	..	-4.476 (0.9880)	0.4207 (0.1344)	-35.749 (0.7596)	0.777 (0.2726)	0.139 (0.5785)	0.001 (0.1717)	0.563 (0.0009)	0.130 (0.2280)
BM	-0.796 (0.0008)	0.401 (0.5909)	0.984 (0.8450)	-0.283 (0.0792)	9.831 (0.7242)	0.088 (0.2886)	-0.014 (0.6891)	0.003 (0.9109)	0.002 (0.8781)	0.052 (0.7436)
BM_1	-0.169 (0.5870)	0.139 (0.8914)	-0.507 (0.9172)	0.108 (0.5004)	-14.335 (0.8112)	0.009 (0.7911)	0.028 (0.4499)	-0.115 0.4272	0.013 (0.3571)	-0.018 (0.8977)
ER	3.068 (0.2191)	-29.297 (0.3333)	-0.323 (0.5440)	0.365 (0.0473)	0.279 (0.3437)	-0.216 (0.3838)	-0.399 (0.8239)	3.371 (0.3051)	-25.798 (0.1419)	-0.067 (0.0904)
ER_1	-2.658 (0.2641)	41.454 (0.1566)	-0.153 (0.7763)	-0.088 (0.6068)	-0.090 (0.7484)	0.171 (0.4639)	0.917 (0.6903)	-6.465 (0.0515)	23.356 (0.1064)	0.057 (0.1575)
EVI	0.199 (0.0110)	..	..	0.071 (0.0214)	..	0.025 (0.1042)	0.037 (0.2850)	0.301 (0.0004)	-0.003 (0.1562)	0.067 (0.7276)
EVI_1	-0.042 (0.6451)	..	-0.069 (0.0440)	..	-0.001 (0.9403)	0.030 (0.4614)	-0.223 (0.0063)	-0.002 (0.6091)	0.146 (0.4765)	
IVI	-2.658 (0.2641)	..	..	-0.046 (0.0138)	..	-0.024 (0.0506)	-0.014 (0.0428)	-0.035 (0.0104)	0.001 (0.6381)	0.033 (0.3347)
IVI_1	-0.075 (0.0060)	..	..	0.034 (0.0980)	..	-0.007 (0.9628)	-0.009 (0.3023)	0.029 (0.0655)	0.002 (0.2153)	-0.033 (0.3630)
FDI	0.186 (0.6308)	1.071 (0.4984)	..	..	..	..	-0.147 (0.0635)	-1.158 (0.0995)	-0.042 (0.8055)	-0.119 (0.7362)
FDI_1	0.393 (0.3682)	-0.457 (0.7641)	..	..	..	..	-0.054 3 (0.5235)	1.126 (0.1065)	0.088 (0.5490)	0.060 (0.8545)
INF	..	..	..	..	..	..	0.001 (0.7813)	0.001 (0.6542)	..	..

Country Name Variables	Argentina	Australia	Austria	Bangladesh	Belgium	Bhutan	Bulgaria	Brazil	Canada	Chile
INF_1	..		..	..	..	..	0.007 (0.0153)	-0.005 (0.1148)	..	..
P(remi)	..	..	..	..	..	..	..	..	..	-16.989 (0.9134)
P(remi)_1	..	..	..	..	..	..	..	..	..	-142.928 (0.2828)
LnGDP	-6.024 (0.1832)	-32.940 (0.3814)	..	..	..	..	..	..	-18.878 (0.2111)	-15.969 (0.2007)
LnGDP_1	2.471 (0.4960)	27.823 (0.4195)	..	..	..	..	..	..	17.482 (0.1983)	4.704 (0.7059)
LnGexp	2.495 (0.0001)	..	-0.523 (0.4480)	0.027 (0.6982)	1.400 (0.1831)	-0.020 (0.5365)	-0.009 (0.8542)	..	0.013 (0.9521)	0.327 (0.2840)
LnGexp_1	0.025 (0.9598)	..	-0.115 (0.8684)	-0.058 (0.5031)	0.758 (0.4603)	0.001 (0.9549)	-0.023 (0.6068)	..	-0.018 (0.9410)	0.440 (0.2806)
Bdefi	-2.449 (0.0001)	-0.773 (0.6063)	..	..	..	..	..	-0.052 (0.4236)	0.176 (0.4244)	..
Bdefi_1	-0.251 (0.6569)	1.104 (0.4539)	..	..	..	..	..	-0.006 (0.8865)	-0.191 (0.2916)	..
DC	-0.245 (0.1262)	-1.806 (0.0506)	..	..	..	..	..	..	..	..
DC_1	0.673 (0.0010)	1.563 (0.1785)	..	..	..	..	..	..	..	..
TR	0.076 (0.7267)	-0.035 (0.9845)	..	..	..	..	..	..	0.443 (0.0159)	..
TR_1	-0.257 (0.3061)	-1.789 (0.3128)	..	..	..	..	..	..	0.443 (0.0159)	..

Country Name / Variables	China	Denmark	France	Germany	Ghana	Hungary	India	Indonesian	Iran	Japan	Luxembourg	Malaysia
Constant	69.082 (0.0083)	-7.803 (0.5581)	147.743 (0.009)3	-1.748 (0.7534)	36.434 (0.0048)	0.619 (0.0001)	84.664 (0.6719)	-77.615 (0.3442)	-4.642 (0.9737)	22.221 (0.1751)	-12.234 (0.1880)	11.338 (0.8785)
BOT_1	0.354 (0.0859)	0.629 (0.0000)	0.208 (0.4026)	0.377 (0.0829)	0.277 (0.2063)	23.916 (0.0029)	0.146 (0.4930)	-0.122 (0.3546)	0.398 (0.0933)	0.700 (0.0000)	0.511 (0.1466)	0.514 (0.0271)
DI	-1.052 (0.0803)	-0.009 (0.4782)	-0.569 (0.0897)	29.233 (0.6458)	-0.006 (0.9966)	0.108 (0.2906)	28.272 (0.1533)	-0.170 (0.2530)	0.209 (0.7726)	1.566 (0.1865)	15.371 (0.0771)	-0.375 (0.4051)
DI_1	1.639 (0.0189)	0.016 (0.2514)	0.918 (0.0171)	-74.641 (0.2205)	0.056 (0.7293)	-0.268 (0.0114)	-33.083 (0.0442)	-0.028 (0.8262)	0.066 (0.8849)	-0.358 (0.7385)	-10.190 (0.6940)	0.317 (0.4590)
BM	0.159 (0.4721)	-0.013 (0.7194)	0.164 (0.8666)	9.320 (0.7533)	-0.353 0.1461)(	0.129 (0.3474)	0.313 (0.0641)	0.374 (0.1167)	-0.349 (0.1922)	0.012 (0.8950)	-6.229 (0.6099)	0.024 (0.3032)
BM_1	0.335 (0.3194)	0.027 (0.4412)	-0.054 (0.9575)	-0.320 (0.7533)	-0.075 (0.7415)	-0.205 (0.1561)	-0.380 (0.1457)	-0.355 (0.1573)	0.098 (0.6991)	-0.046 (0.6448)	18.4862 (0.2205)	-0.009 (0.7480)
ER	-0.462 (0.8396)	..	-0.814 (0.0712)	-7.5147 (0.0049)	4.306 (0.2434)	0.018 (0.3584)	-0.075 (0.7666)	-0.002 (0.8268)	-0.001 (0.8018)	-0.076 (0.2451)	0.468 (0.1367)	-1.252 (0.7793)
ER_1	1.222 (0.2876)	..	0.111 (0.8174)	2.641 (0.1604)	-1.993 (0.6105)	-0.019 (0.3372)	0.476 (0.0961)	0.007 (0.5726)	0.008 (0.2062)	0.0702 (0.2489)	-0.282 (0.2766)	1.503 0.7148)
EVI	0.029 (0.6461)	..	0.028 (0.1579)	0.026 (0.6319)	..	..	-0.022 (0.5100)	0.143 (0.1543)	..	..	-0.019 (0.3424)	-0.03 (0.6520)
EVI_1	0.011 (0.7728)	..	0.016 (0.7564)	0.039 (0.5783)	..	..	-0.007 (0.7945)	-0.241 (0.0511)	..	..	0.050 (0.4142)	00.028 (0.6728)
IVI	0.021 (0.2628)	..	-0.005 (0.3360)	0.005 (0.9310)	..	..	-0.005 (0.5503)	-0.018 (0.3261)	..	..	0.003 (0.7803)	-0.031 (0.3564)
IVI_1	-0.011 (0.4941)	..	0.002 (0.6228)	-0.004 (0.9563)	..	..	0.003 (0.6608)	0.006 (0.7453)	..	..	-0.001 (0.9205)	0.011 (0.7164)
FDI	-1.782 (0.0814)	0.054 (0.3420)	0.107 (0.0780)	-0.400 (0.0741)	-0.801 (0.2131)	..	0.216 (0.7998)	-2.503 (0.0074)	2.991 (0.2744)	..	0.036 (0.0913)	-0.140 (0.6318)
FDI_1	1.585 (0.2556)	0.024 (0.4816)	0.18 (0.1474)	-0.191 (0.4342)	0.766 (0.1487)	..	0.559 (0.4475)	-0.108 (0.8577)	-1.054 (0.8185	..	-0.001 (0.9707)	0.133 (0.6093)

Country Name	China	Denmark	France	Germany	Ghana	Hungary	India	Indonesian	Iran	Japan	Luxembourg	Malaysia
INF	..	..	-0.225 (0.3253)	..	-0.024 (0.4056)	..	0.063 (0.5296)	..	…	..	..	0.295 (0.2813)
INF_1	..	..	-0.002 (0.9863)	..	0.059 (0.0241)	..	0.153 (0.0966)	..	..	..	..	-0.328 (0.1160)
P(remi)	14.073 (0.0261)	..	..	7.199 (0.2003)	..	..	-1.787 (0.1502)	0.962 (0.2467)	-5.964 (0.2685)	..	..	-0.443 (0.5400)
P(remi)_1	4.203 (0.5233)	..	..	-13.576 (0.0481)	..	..	-1.038 (0.3094)	-2.194 (0.0123)	6.994 (0.1228)	..		0.503 (0.5386)
LnGDP	-24.745 (0.0536)	..	-3.695 (0.0928)	-8.740 (0.0219)	..	..	-4.661 (0.4991)	10.139 (0.1684)	-5.213 (0.5676)	..	10.290 (0.3181)	1.696 (0.8475)
LnGDP_1	-1.401 (0.9144)	..	-0.655 (0.7434)	-1.467 (0.7169)	..	..	2.689 (0.6187)	-5.038 (0.4794)	7.091 (0.3584)	..	-10.684 (0.2844)	-0.857 (0.9200)
LnGexp	..	3.777 (0.0127)	0.104 (0.3268)	-0.271 (0.0602)	0.060 (0.1900)	-0.07 (0.2421)	2.68 (0.6187)	..	..	..	0.4794 (0.0404)	-0.263 (0.1036)
LnGexp_1	..	2.573 (0.0751)	0.313 (0.1225)	0.171 6 (0.2157)	0.030 (0.5012)	0.046 (0.4793)	-0.104 (0.8373)	..	0.046 (0.8020)	0.669 (0.4273)	0.003 (0.9901)	-0.185 (0.2695)
Bdefi	0.520 (0.2352)	..	..	..	..	..	0.367 (0.5710)	..	-0.015 (0.9413)	0.048 (0.9623)	..	0.094 (0.5120)
Bdefi_1	0.014 (0.9669)	..	..	..	..	..	-0.019 (0.9675)	..	..	..	..	0.096 (0.5163)
DC	0.070 (0.7226)	..	-0.028 0.3859	-0.001 (0.9385)	..	..	-0.271 (0.4168)	0.014 (0.7220)	..	..	-0.028 (0.4680)	..
DC_1	-0.257 (0.2759)	..	-0.008 0.3034	0.009 (0.9523)	..	..	0.579 (0.0625)	0.048 (0.2119)	..	..	0.015 (0.4069)	..
TR	-0.110 (0.6632)	-0.134 (0.0006)	0.148 0.0527	0.059 (0.5793)	..	..	0.250 (0.2307)	0.289 (0.0322)	..	..	0.013 (0.6446)	..
TR_1	0.218 (0.3853)	0.072 (0.0401)	-0.074 0.3862	-0.004 (0.9677)	..	..	-0.166 (0.4700)	-0.024 (0.8066)	..	..	-0.007 (0.8573)	..

County Name / Variables	Maldives	Mexico	Morocco	Nepal	Netherland	New Zealand	Norway	Pakistan	Peru	Paraguay	Philippines
Constant	175.144 (0.0423)	42.226 (0.8703)	2.933 (0.6064)	76.389 (0.0098)	-30.127 (0.2495)	5.098 (0.9087)	33.616 (0.4418)	-10.558 (0.9331)	19.782 (0.0066)	-55.840 (0.4368)	7.025 (0.9345)
BOT_1	0.436 (0.0309)	0.685 (0.0004)	0.619 0.0008	0.291 (0.1770	0.390 (0.1549)	0.411 (0.0011)	0.683 (0.0007)	0.235 (0.4043)	0.624 (0.0000)	0.099 (0.7278)	0.744 (0.0419)
DI	0.011 (0.9804)	0.069 (0.4905)	1.536 0.0351	-30.163 (0.0027)	0.091 (0.0464)	0.164 (0.0120)	-0.243 (0.5501)	0.078 (0.9040)	-0.004 (0.0446)	0.337 (0.0226)	-0.1760 (0.5993)
DI_1	0.031 (0.9460)	-0.147 (0.2490)	-0.555 (0.4170)	283.768 (0.0049)	-0.040 (0.4611)	-0.06 (0.4478)	-0.489 (0.3457)	0.011 (0.9811)	-0.003 (0.1023)	-0.089 (0.5319)	-0.002 (0.9945)
BM	-0.016 (0.9512)	0.405 (0.2736)	0.349 0.6221	-0.466 (0.0447)	-0.290 (0.1618)	-6.25 (0.9087)	-0.186 (0.3655)	0.019 (0.9197)	-0.121 (0.6135)	-0.079 (0.7094)	-0.137 (0.6129)
BM_1	0.161 (0.5848)	0.132 (0.6357)	-0.136 (0.8392)	-0.251 (0.4328)	0.282 (0.1816)	2.501 (0.8097)	0.260 (0.2253)	0.066 (0.7415)	0.163 (.5045)	-0.555 (0.1512)	0.268 (0.1969)
ER	1.117 (0.5418)	-0.749 (0.6350)	0.117 0.0055	0.161 (0.4683)	2.286 (0.0108)	-0.621 0.1918	7.154 0.0104	-0.254 0.1289	-3.515 0.3377	0.001 0.2826	-0.020 0.9649
ER_1	0.184 (0.9285)	-0.851 (0.6627)	-0.093 0.0472	-0.092 (0.6837)	-0.817 (0.3592)	-0.602 (0.1671)	-7.268 (0.0167)	0.248 (0.1911)	4.347 (0.2340)	-0.002 (0.9171)	-0.406 (0.5104)
EVI	-0.018 (0.2978)	-0.035 (0.8486)	-0.006 0.6681	-0.014 (0.0586)	-0.003 (0.5118)	-0.003 (0.5211)	..	0.109 (0.0416)	..	..	0.117 (0.0942)
EVI_1	-0.009 (0.7860)	-0.035 (0.8486)	0.004 0.7440	0.005 (0.5219)	-0.010 (0.4017)	-0.008 (0.0890)	..	-0.048 (0.5095)	..	..	-0.151 (0.0855)
IVI	0.014 (0.5850)	0.002 (0.4792)	..	-0.032 (0.1022)	2. 005 (0.9403)	0.001 (0.3648)	..	-0.045 (0.0217)	..	..	-0.041 (0.4154)
IVI_1	-0.016 (0.4599)	-0.007 (0.0230)	..	0.028 (0.1063)	0.003 (0.2142)	0.005 (0.5928)	..	0.013 (0.5334)	..	..	0.061 (0.1761)
FDI	0.158 (0.6661)	-0.719 (0.6266)	..	0.082 (0.9799)	0.003 (0.4547)	..	-0.157 (0.5441)	-2.465 (0.0611)	..	-0.657 (0.4290)	0.480 (0.5533)
FDI_1	0.157 (0.7758)	0.511 (0.7106)	..	5.374 (0.1777)	-0.002 (0.6464)	..	0.107 (0.7205)	0.572 (0.6344)	..	-0.502 (0.5373)	-1.188 (0.2046)
INF	-0.044 (0.8937)	..	0.048 (0.7860)	..	..	..	..	..	..	..	0.131 (0.2272)

County Name / Variables	Maldives	Mexico	Morocco	Nepal	Netherland	New Zealand	Norway	Pakistan	Peru	Paraguay	Philippines
INF_1	0.224 (0.1249)	..	0.091 (0.5905)	..	..	..	..	..	..	..	0.031 (0.6833)
P(remi)	0.291 (0.8362)	-4.195 (0.3879)	..	..	..	..	17.049 (0.6049)	-0.483 (0.4518)	..	..	0.580 (0.5878)
P(remi)_1	0.649 (0.8015)	4.799 (0.3305)	..	..		..	-10.525 (0.7948)	-0.748 (0.1911)	..	..	0.868 (0.2885)
LnGDP	1.234 (0.9219)	-10.850 (0.2631)	..	-24.659 (0.0060)	2.939 (0.0504)	..	45.526 (0.0091)	-2.729 (0.7721)	..	1.470 (0.7792)	-14.734 (0.4275)
LnGDP_1	-9.684 (0.4633)	9.636 (0.1976)	..	-9.354 (0.4141)	-0.453 (0.7461)	..	-45.833 (0.0094)	4.510 (0.5921)	..	2.569 (0.6135)	14.964 (0.4615)
LnGexp	-0.125 (0.499)	-0.771 (0.1231)	-0.033 (0.5932)	0.072 (0.4527)	-0.109 (0.0318)	..	0.625 (0.1173)	-0.003 (0.9459)	-0.274 (0.0192)	-0.061 (0.9273)	..
LnGexp_1	0.155 ()0.4778)	-0.354 (0.3862)	0.050 (0.4455)	0.061 (0.4751)	-0.044 (0.3335)	..	0.001 (0.9968)	-0.051 (0.9914)	-0.396 (0.0005)	0.381 (0.5091)	..
Bdefi	..	..	..	..	..	..	..	..	..	-0.005 (0.9939)	..
Bdefi_1	..	..	..	..	..	..	..	..	..	-0.443 (0.4445)	..
DC	0.012 (0.7267)	-0.023 (0.5677)	..	0.499 (0.1339)	0.009 (0.4234)	..	0.110 (0.0706)	..	..	0.022 (0.9258)	-0.145 (0.5631)
DC_1	0.035 (0.4255)	-0.055 (0.2081)	..	0.151 (0.6220)	0.009 (0.8539)	..	-0.083 (0.2099)	..	..	0.224 (0.3692)	-0.184 (0.3937)
TR	0.035 (0.6006)	0.462 (0.2211)	..	-0.320 (0.0485)	-0.029 (0.1019)	..	-0.152 (0.6065)	..	..	0.063 (0.3357)	0.014 (0.9081)
TR_1	-0.107 (0.0918)	0.084 (0.8297)	..	-0.157 (0.3020)	0.010 (0.5318)	..	-0.120 (0.6917)	..	..	0.044 (0.4733)	0.104 (0.4030)

County Name / Variables Name	Portugal	Qatar	South Africa	Sri Lanka	Switzerland	Sweden	Turkey	United States	United Kingdom	Uruguay
Constant	43.641 (0.3856)	1.376 (0.9211)	23.297 (0.0001)	33.732 (0.0009)	-40.294 (0.0684)	53.740 (0.0141)	69.135 (0.0742)	..	2.260 (0.0001)	26.323 (0.8147)
BOT_1	0.377 (0.0792)	0.380 (0.0288)	0.281 (0.0939)	0.221 (0.2936)	0.314 (0.0712)	-0.310 (0.0474)	3621 (0.0410)	0.978 (0.0000)	0.951 (0.0000)	0.791 (0.0084)
DI	28.849 (0.4939)	..	..	-0.112 (0.4005)	..	0.070 (0.4348)	0.109 (0.0951)	1.512 (0.0796)	..	0.039 (0.2959)
DI_1	-2.591 (0.9710)	..	..	-0.121 (0.3771)	..	-0.162 (0.1160)	-0.163 (0.0059)	-1.334 (0.0493)	..	-0.052 (0.2453)
BM	-6.530 (0.8063)	..	0.088 (0.5430)	-0.063 (0.6561)	0.023 (0.3949)	0.089 (0.1582)	0.248 (0.0937)	0.024 (0.8506)	7.345 (0.7856)	0.213 (0.0632)
BM_1	-8.929 (0.3665)	..	0.303 (0.1359)	0.019 (0.8963)	0.012 (0.6628)	-0.176 (0.0093)	-0.039 (0.8030)	0.081 (0.3197)	-0.002 (0.3130)	-0.127 (0.4484)
ER	0.051 (0.2540)	-3.782 (0.9211)	1.062 (0.1256)	0.085 (0.5388)	..	-0.883 (0.2984)	2.268 (0.5480)	-31.260 (0.3877)	0.113 (0.4566)	0.324 (0.5250)
ER_1	0.073 (0.2416)	20.363 (0.7102)	-0.632 (0.3586)	0.054 (0.7292)	..	1.249 (0.1348)	2.846 (0.5387)	..	-0.019 (0.9020)	-0.590 (0.2513)
EVI	0.018 (0.2247)	..	..	0.006 (0.9941)	..	0.002 (0.9458)	-0.003 (0.9272)	0.218 (0.1439)	..	-0.010 (0.7253)
EVI_1	-0.002 (0.6489)	..	..	-0.017 (0.8353)	..	-0.061 (0.2561)	-0.039 (0.2565)	-0.308 (0.0413)	..	-0.098 (0.2459)
IVI	-0.003 (0.3596)	..	..	-0.047 (0.0199)	..	0.002 (0.4721)	-0.019 (0.2594)	-0.144 (0.0515)	..	0.005 (0.9809)
IVI_1	0.003 (0.3414)	..	..	-0.009 (0.7082)	..	-0.003 (0.4153)	0.029 (0.1360)	0.167 (0.0193)	..	0.041 (0.0735)
FDI	0.001 (0.9510)	-0.437 (0.5461)	-0.009 (0.9802)	-0.406 (0.6506)	-0.007 (0.7369)	0.051 (0.3771)	-1.868 (0.0639)	-0.647 (0.2502)	-0.008 (0.3313)	-0.311 (0.3005)
FDI_1	-0.008 (0.7943)	-0.932 (0.2109)	-0.236 (0.5565)	0.345 (0.6586)	0.007 (0.7553)	-0.027 (0.6196)	0.916 (0.1776)	0.704 (0.2138)	-0.001 (0.1605)	-0.333 (0.2575)
INF	..	-0.045 (0.8833)	0.096 (0.6375)	..	..	..	0.056 (0.2235)	..	0.041 (0.0000)	..
INF_1	..	-0.308 (0.3365)	0.212 (0.3544)	..	..	..	-0.039 (0.1992)	..	0.009 (0.6722)	..

County Name / Variables Name	Portugal	Qatar	South Africa	Sri Lanka	Switzerland	Sweden	Turkey	United States	United Kingdom	Uruguay
P(remi)	0.004 (0.5824)	-40.241 (0.0046)	-9.492 (0.6108)	..	..	8.204 (0.0225)	..	-28.437 (0.6754)	0.064 (0.1404)	-10.459 (0.4770)
P(remi)_1	-0.009 (0.2788)	32.218 (0.0521)	2.488 (0.8898)	..	..	-3.202 (0.0949)	..	16.792 (0.7762)	0.007 (0.8622)	26.708 (0.0695)
LnGDP	-2.345 (0.5135)	8.503 (0.2750)	-0.539 (0.9194)	..	0.556 (0.7551)	-6.469 (0.2735)	-4.556 (0.4613)	20.290 (0.4696)	0.021 (0.7968)	-6.224 (0.3852)
LnGDP_1	0.274 (0.9520)	-3.747 (0.6405)	-7.726 (0.1732)	..	..	7.605 (0.2231)	2.404 (0.7083)	-9.619 (0.6460)	0.061 (0.4917)	5.887 (0.2659)
LnGexp	0.239 (0.5635)	..	..	..	..	-0.072 (0.5722)	..	..	..	3.848 (0.1320)
LnGexp_1	-0.934 (0.0405)	..	..	..	..	-0.472 (0.0172)	..	..	..	-4.005 (0.1238)
Bdefi	-0.549 (0.1365)	..	..	0.001 (0.9692)	..	..	..	..	0.009 (0.5916)	..
Bdefi_1	0.780 (0.0588)	..	..	0.047 (0.2471)	..	..	..	..	0.001 (0.5699)	..
DC	-0.106 (0.1457)	..	0.022 (0.6770)	..	-0.075 (0.1333)	-0.077 (0.0338)	0.001 (0.8969)	..	0.003 (0.1516)	..
DC_1	0.104 (0.1080)	..	0.022 (0.7193)	..	0.019 (0.6766)	-0.002 (0.8899)	0.024 (0.1049)	..	0.001 (0.2776)	..
TR	-0.133 0.2013)	..	-0.158 (0.1923)	..	0.018 (0.5824)	-0.018 (0.7488)	-0.004 (0.9694)	..	0.007 (0.4978)	..
TR_1	0.247 (0.0354)	..	-0.210 (0.0930)	..	-0.033 (0.3144)	0.044 (0.6513)	0.138 (0.3507)	..	0.005 (0.5533)	..

Table 4: Results of LASSO for Balance of Trade Modeling with Final Model Specification

Country	Constant	FDI	LNGEXP	INF	IVI	REMI	LNGDP	EVI	TR	ER	RMSE
ALGERIA	..	0.125	..	..	..	..	4.278 1	..	..	-0.047	1.609
COLAMBIA	9.834	0.088	-2.628	..	0.033	..	-0.02	0.624	0.034	-0.08	2.818
COMBODIA	1.761	..	0.363	..	..	..	1.801	..	..	..	0.0351
COSTARICA	..	..	0.941	..	..	..	3.452	..	3.937		0.034
CROATIA	5.841	3.189	..	1.398	0.796	..	..	1.254	..	-0.015	0.254
GEORGIA	5.511	..	4. 382	..	..	1. 934	1.451	..	..	..	0.689
KORIA REPUBLIC	2.136	..	..	0.168	..	..	-0.263	..	0.032	-0.002	1.245
POLAND	3.824		1. 716	0. 878	..	..	..	..	..	-0.252	0.431
Retention Frequency		3	5	3	2	2	7	2	4	5	Minimum 0.034

Table 5: Results of ALASSO for Balance of Trade Modeling with Final Model Specification

Country Name	Constant	INF	LNGEXP	REMI	LNGDP	FDI	TR	IVI	FRMSE
ALGERIA	-0.027	..	..	-0.013	-0.341	..	0.241		**0.188**
COLAMBIA	**0.209**	0.092	..	0.035	..	..	..	0.841	**0.729**
COMBODIA	..	..	-0.292	..	..	..	0.882	..	**0.182**
COSTARICA	**2.078**		-1.035		-2.054	..	..	..	**0.012**
CROATIA	**3.262**	0.8729	-0.013	..	..	0.2416	..	0.87	**1.381**
GEORGIA	-0.021	..	..	..	0.899	..	.002	- 1.181	**2.172**
KORIA REPUBLIC	**6.031**		0.911	..	..	1.803	..	..	**0.6 72**
POLAND	..		.004	..	1.781	..	2.8729	..	**1.112**
ROMANIA	**1.061**	1.229	..	3.19	..	-0.197	..	.015	**4. 091**
Retention frequency		**03**	**05**	**03**	**04**	**03**	**04**	**04**	**Minimum 0.012**

Table 6: Results of Elastic Net for Balance of Trade Modeling with Final Model Specification

Country	Constant	FDI	ER	IVI	REMI	EVI	INF	DC	LNGEXP	LNGDP	FRMSE
ALGERIA	1.66	0.111	-0.044	..	..	..	..		..	3.848	**1.659**
COLAMBIA	-0.991	0.073	0.0001	-0.019	0.402	0.033	..	0.019	0.329	-3.287	**2.826**
COMBODIA	..	..	..	..	..	..	..	0.013	..	1.792	**0.029**
COSTARICA	0482	..	0.134	..	..	1.925	..	..	..	..	**0.293**
CROATIA	9.743	2.013	0.001	0.808	-0.001	0.0001	..	2.193	0.2184	..	**0.504**
GEORGIA	107	0.009	..	..	..	..	..	..	..	0.970	**0.539**
KORIA REPUBLIC	-1,472	-0.222	-0.001	0.045	1.361	..	-0.035	-7.597	5.735	..	**0.250**
POLAND	..	-0.12	..	0.230	3.791	0.0005	0.369	1.641	0.054	..	**0.630**
ROMANIA	1.319	-0.014	..	..	0.31751	0.0001	-0.0005	..	-0.81331	0.839	**0.361**
Retention frequency		**07**	**05**	**04**	**05**	**05**	**03**	**05**	**05**	**05**	**Minimum 0.029**

Table 7: Results of Weighted Average Least Square for Balance of Trade Modeling with Final Model Specification

Country Name	Constant	FDI	LnGDP	ER	LnGexp	EVI	TR	FRMSE
ALGERIA	-28.579	..	..	-.012	-.001	0.241	.011	**1.851**
COLAMBIA	..	..	..	..	..	..		**1.021**
COMBODIA	..	..	. ..	..	.045 2	..	.004	**0.31**
COSTARICA	..	..	3.330	-.001	-.004	0.121	..	**0.042**
CROATIA	..	.006	..	..	.001	..	..	**0.215**
GEORGIA	3.041	.040	-.448	..	-.035	0.541	..	**0.237**
KORIA REPUBLIC	-6.775	-.011	1.379	..	.014	..	..	**1.24**
POLAND	-25.269	..	..	..	-.003	..	..	**0.321**
ROMANIA	-56.272	.082	0.127	.108	-.002	2.424	..	**0154**
Retention Frequency	**5**	**4**	**4**	**4**	**8**	**4**	**2**	**COSTARICA 0.042**

Table8: Results of Encompassing for Balance of Trade Modeling with Final Model Specification

Country Name	Constant	BOT_1	EVI	EVI_1	ER	ER_1	BM	BM_1	LnGDP	LnGDP_1	DI	DI_1	IVI	IVI_1	LnGexp	LnGexp_1	FRMSE
ALGERIA	..	0.984	..	..	..	..	0.899	-0.885	..	..	0.003	-0.004	..	..	..	..	**0.105**
COLAMBIA	..	0.789	..	..	..	..	..	..	..	0.164	..	-0.009	..	0.0432	1.040	-0.957	**0.082**
COMBODIA	..	0.588	..	..	..	9.323	..	..	..	..	..	..	..	..	0.987	-0.448	**0.213**
COSTARICA	..	0.729	..	..	-0.06	..	..	0.14	..	0.163	..	..	-0.001	..	..	..	**0.051**
CROATIA	..	0.754	..	..	..	..	..	0.164	0.411	..	-0.007	0.005	-0.009	..	0.787	-1.092	**0.104**
GEORGIA	7.620	0.823	..	..	-0.017	..	..	..	..	-0.171	..	..	..	..	0.550	-0.490	**0.061**
KORIA REPUBLIC	..	..	..	0.003	-0.001	-0.004	0.946	-0.827	..	1.616	-0.011	0.013	..	-0.003	-1.721	1.060	**0.050**
POLAND	..	0.775	0.001	..	..	-0.113	-0.084	0.141	..	..	..	..	-0.0029	..	2.425	-2.193	**0.054**
ROMANIA	..	..	..	0.001	-0.197	0.109	0.209	..	2.075	..	..	..	..	-0.013	-1.218	..	**0.151**
Retention frequency		**7**	**1**	**2**	**4**	**4**	**4**	**5**	**1**	**4**	**3**	**4**	**3**	**3**	**7**	**6**	**KORIA REPUBLICA 0.050**

Table 9: Results of Autometrics for Balance of Trade Modeling with Final Model Specification

Country Name	Constant	BOT_1	DI	DI_1	ER	ER_1	IVI	IVI_1	LNGDP	LNGDP_1	LNGEXP	LNGEXP_1	DC	DC_1	TR	TR_1	FRM SE
									-0.0166								
ALGERIA	15.292	1.052	0.003	..	..	..	0.088	..	0.629	..	1.296	..	-2.569	..	..	..	**0.07**
COLAMBIA	16.987	0.790	..	..	..	..	0.080		3.520	..	0.886	..	-4.803	..	-0.004	..	**0.12**
COMBODIA	..	0.482	..	..	8.830	..	..	..	..	..	1.114	-0.670	0.615	-0.407	..	..	**0.21**
COSTARICA	..	1.029	-0.006	..	..	..	-0.007	..	..	..	..	..	..	..	..	..	**0.05**
CROATIA	..	0.754	..	..	..	..	..	..	..	..	0.831	..	..	-0.499	..	..	**0.09**
GEORGIA	5.039	1.072	..	..	-0.031	..	..	..	..	-0.113	0.746	-0.303	-0.589	..	..	..	**0.07**
KORIA REPUBLIC	-15.573	..	..	..	..	-0.0364	..	-0.002	..	..	..	0.597	..	..	..	0.007	**0.06**
POLAND	..	0.680	0.006	..	..	..	-0.006	..	0.330	..	2.353	..	-1.542	..	0.004	..	**0.06**
ROMANIA	..	0.956	0.007	..	-0.124	0.1903	..	..	..	-0.666	..	0.757	..	..	..	..	**0.17**
Retention Frequency		**8**	**4**		**3**	**2**	**4**	**1**	**3**	**2**	**6**	**4**	**5**	**2**	**2**	**1**	**0.05**

Table 10: Results of Extreme Bound Analysis for Balance of Trade Modeling with Final Model Specification

			DI	EVI	IVI	INF	REMI	GEXP	DC	BDEFI	TRAD	FDI	LNGDP	ER
			free	free	free	free	free	free	free	free	free	focus	focus	focus
ALGERIA	LEBA	LEB	0.2	0.0	0.0	-0.6	-4.9	-2.0	-1.1	-0.4	0.0	-2.0	-19.8	0.0
		UEB	0.7	0.2	0.0	0.0	3.8	1.0	1.8	0.1	0.1	1.6	4.0	0.0
	SIMEBA	CDF(beta>0)	100.0	100.0	33.8	2.0	64.3	30.1	62.8	7.0	98.7	59.0	10.4	100.0
COLAMBIA	LEBA	LEB	0.0	0.0	0.0	-0.1	0.0	-1.5	-1.7	-0.6	0.1	-1.0	-14.7	-2.8
		UEB	0.2	0.2	0.0	0.0	1.0	1.5	1.6	0.0	0.9	0.7	9.8	4.3
	SIMEBA	CDF(beta>0)	96.7	99.7	18.5	3.9	98.0	50.4	44.7	4.0	99.5	35.0	34.3	60.3
COMBODIA	LEBA	LEB	-0.7	0.0	-0.1	-0.1	-3.1	-1.2	-0.5	-0.2	-0.2	-1.2	-7.8	-0.1
		UEB	0.4	0.3	0.0	0.3	-0.1	0.6	1.2	0.3	0.2	1.7	3.6	0.7
	SIMEBA	CDF(beta>0)	33.4	97.0	0.6	84.8	0.5	15.5	87.2	66.2	69.3	65.8	20.7	96.8
COSTARICA	LEBA	LEB	-2.1	0.0	0.0	-0.9	0.0	-1.1	-2.3	-0.1	-0.1	0.0	-17.6	0.1
		UEB	1.1	0.0	0.0	0.3	0.0	2.6	0.8	0.2	0.5	0.0	8.3	0.2
	SIMEBA	CDF(beta>0)	26.5	64.3	68.1	3.6	83.4	79.4	11.1	58.4	78.8	64.0	37.1	100.0
CROATIA	LEBA	LEB	-3.6	-0.1	0.0	-0.7	-78.4	-42.1	-83.2	-0.3	-0.1	-2.7	-16.1	-809.2
		UEB	0.1	0.1	0.0	0.4	-9.8	37.6	118.4	0.1	0.3	-0.2	9.6	412.8
	SIMEBA	CDF(beta>0)	2.1	75.6	41.6	20.9	90.1	44.5	63.8	9.9	85.2	0.7	30.1	27.1
GEORGIA	LEBA	LEB	-0.3	-0.1	-0.1	-0.1	-2.0	-1.2	-0.1	0.0	-0.2	-0.8	0.7	-0.2
		UEB	0.2	0.2	-0.1	0.2	0.9	0.0	1.2	0.3	0.1	2.1	13.0	0.1
	SIMEBA	CDF(beta>0)	23.2	76.3	0.0	62.4	18.3	2.1	97.1	99.1	23.6	81.7	98.7	34.5
KORIA REPUBLIC	LEBA	LEB	-0.5	-0.2	0.0	0.0	-28.1	-0.5	-1.0	-0.1	-0.5	-1.1	-13.3	-0.6
		UEB	0.6	0.3	0.0	0.9	22.3	1.3	0.6	0.1	0.0	0.7	4.4	1.1
	SIMEBA	CDF(beta>0)	54.0	75.7	36.4	97.5	82.0	83.6	28.3	41.1	2.0	32.4	15.0	74.3
POLAND	LEBA	LEB	-0.1	-0.1	0.0	-0.3	5.0	-0.4	-0.4	-0.1	-0.1	0.0	-2.9	-0.6
		UEB	0.5	0.0	0.0	0.1	4.1	0.3	0.2	0.0	0.1	0.2	1.7	0.4
	SIMEBA	CDF(beta>0)	88.6	0.1	43.1	32.2	48.8	39.4	25.5	2.8	59.4	87.7	31.8	34.6
ROMANIA	LEBA	LEB	-0.1	0.0	0.0	-0.3	-16.1	-2.3	-1.0	-0.1	0.0	-0.1	-0.4	-2.3
		UEB	0.1	0.0	0.0	0.3	19.4	0.9	1.9	0.1	0.1	0.0	12.9	8.8
	SIMEBA	CDF(beta>0)	52.0	24.3	45.8	47.4	61.7	15.2	75.4	80.4	90.9	42.1	97.3	63.0

Table11: The Results of RMSE from Non-Nested Encompassing (Growth Modeling)

Country Name	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Best Model
Argentina	5.045	4.995	5.008	2.355	1.986	4.652	Model 5
Australia	0.102	0.076	0.072	0.073	0.09	0.091	Model 3
Austria	0.105	0.101	0.11	0.101	0.0827	0.096	Model 5
Bangladesh	6.646	1.077	1.027	0.994	9.813	9.167	Model 4
Belgium	1.723	1.788	1.993	1.3204	0.968	1.887	Model 5
Bhutan	0.089	0.056	0.091	0.082	0.056	0.081	Model 2
Bulgaria	0.191	0.129	0.13	0.132	0.193	0.187	Model 2
Brazil	0.171	0.143	0.147	0.112	0.126	0.118	Model 4
Canada	0.066	0.073	0.064	0.045	0.054	0.065	Model 4
China	0.055	0.059	0.065	0.065	0.054	0.065	Model 5
Chile	0.127	0.069	0.071	0.044	0.079	0.084	Model 4
Denmark	0.092	0.032	0.061	0.042	0.083	0.081	Model 2
France	1.256	1.114	1.314	1.23	1.244	1.256	Model 2
Germany	1.885	1.546	1.775	1.758	1.837	1.972	Model 2
Ghana	0.153	0.117	0.143	0.137	0.116	0.143	Model 5
Hungary	3.34837	2.875	2.988	2.702	2.882	2.889	Model 4
India	0.069	0.058	0.062	0.06	0.054	0.071	Model 5
Indonesia	0.101	0.132	0.1495	0.157	0.195	0.13	Model 1
Iran	0.213	0.26	0.201	0.254	0.296	0.194	Model 6
Japan	0.091	0.072	0.095	0.089	0.08	0.078	Model 2
Luxembourg	0.101	0.087	0.12	0.091	0.098	0.088	Model 2
Malaysia	0.07	0.054	0.089	0.091	0.073	0.042	Model 6
Maldives	0.089	0.111	0.093	0.103	0.12	0.107	Model 1
Mexico	0.121	0.095	0.137	0.086	0.087	0.116	Model 4
Morocco	0.441	0.078	0.096	0.094	0.264	0.246	Model 6
Nepal	0.067	0.079	0.07	0.073	0.075	0.073	Model 1
Netherland	0.098	0.051	0.063	0.057	0.099	0.108	Model 2
New Zealand	0.103	0.088	0.087	0.086	0.095	0.097	Model 4
Norway	0.083	0.056	0.057	0.052	0.069	0.081	Model 4
Pakistan	0.064	0.068	0.054	0.053	0.075	0.074	Model 4
Peru	0.109	0.076	0.094	0.067	0.076	0.121	Model 4
Paraguay	0.148	0.096	0.113	0.107	0.097	0.11	Model 2

Country Name	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Best Model
Philippines	0.07	0.077	0.066	0.075	0.075	0.064	Model 6
Portugal	0.104	0.061	0.061	0.051	0.097	0.116	Model 4
Qatar	0.114	0.102	0.12	0.094	0.066	0.078	Model 5
South Africa	0.127	0.058	0.083	0.072	0.119	0.121	Model 2
Sri Lanka	0.041	0.058	0.053	0.045	0.063	0.068	Model 1
Switzerland	0.102	0.054	0.056	0.048	0.082	0.098	Model 4
Sweden	0.115	0.049	0.06	0.056	0.095	0.114	Model 2
Turkey	0.086	0.122	0.124	0.105	0.104	0.112	Model 1
United States	0.016	0.015	0.016	0.009	0.011	0.015	Model 4
United Kingdom	0.089	0.057	0.055	0.053	0.077	0.088	Model 4
Uruguay	0.099	0.095	0.128	0.073	0.076	0.111	Model 4

Table: 12 Results of Testing Hypothesis from Non-Nested Encompassing (Growth Modeling)

Country Name	Model 5 ⊃ Model 1	Model 5 ⊃ Model 2	Model 5 ⊃ Model 3	Model 5 ⊃ Model 4	..	Model 5 ⊃ Model 6
Argentina	-1.524 [0.1276]	-1.852 [0.0641	-1.187 [0.2352]	-1.274 [0.2026]	..	-2.535 [0.0112]*
Testing Hypothesis	Model 3 ⊃ Model 1	Model 3 ⊃ Model 2	..	Model 3 ⊃ Model 4	Model 3 ⊃ Model 5	Model 3 ⊃ Model 6
Australia	-1.084 [0.2784]	-2.702 [0.0069]**	..	-3.029 [0.0025]**	-6.215 [0.0000]**	-4.222 [0.0000]**
Testing Hypothesis	Model 5 ⊃ Model 1	Model 5 ⊃ Model 2	Model 5 ⊃ Model 3	Model 5 ⊃ Model 4	..	Model 5 ⊃ Model 6
Austria	1.056 [0.3842]	0.1508 [0.8802]	0.5088 [0.6109]	1.587 [0.1124]	..	0.6202 [0.5351]
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Bangladesh	-2.902 [0.0037]**	-3.077 [0.0021]**	-5.175 [0.0000]**	..	-15.46 [0.0000]**	-11.88 [0.0000]**
Testing Hypothesis	Model 5 ⊃ Model 1	Model 5 ⊃ Model 2	Model 5 ⊃ Model 3	Model 5 ⊃ Model 4	..	Model 5 ⊃ Model 6
Belgium	0.4812 [0.6303]	1.607 [0.1081]	1.958 [0.0503]	-0.1123 [0.9106]	..	-0.1571 [0.8752]
Testing Hypothesis	Model 2 ⊃ Model 1	..	Model 2 ⊃ Model 3	Model 2 ⊃ Model 4	Model 2 ⊃ Model 5	Model 2 ⊃ Model 6
Bhutan	0.6420 [0.5209]	..	-0.4124 [0.6801]	-0.2139 [0.8306]	-6.122 [0.0000]**	-4.037 [0.0001]**
Testing Hypothesis	Model 2 ⊃ Model 1	..	Model 2 ⊃ Model 3	Model 2 ⊃ Model 4	Model 2 ⊃ Model 5	Model 2 ⊃ Model 6

Country Name	Model 5 ⊃ Model 1	Model 5 ⊃ Model 2	Model 5 ⊃ Model 3	Model 5 ⊃ Model 4	..	Model 5 ⊃ Model 6
Bulgaria	-2.026 [0.0427]*	..	-2.198 [0.0279]*	-2.070 [0.0385]*	-1.239 [0.2153]	-1.816 [0.0694]
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Brazil	-3.095 [0.0020]**	-1.190 [0.2341]	-3.083 [0.0021]**	..	-2.948 [0.0032]**	-5.849 [0.0000]**
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Canada	1.049 [0.2942]	1.602 [0.1091]	0.002086 [0.9983]	..	-2.072 [0.0383]*	0.09950 [0.9207]
Testing Hypothesis	Model 5 ⊃ Model 1	Model 5 ⊃ Model 2	Model 5 ⊃ Model 3	Model 5 ⊃ Model 4	..	Model 5 ⊃ Model 6
China	-0.8182 [0.4132]	-1.953 [0.0508]	-0.3222 [0.7473]	-0.4732 [0.6361]	..	0.01299 [0.9896
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Chili	2.641 [0.0083]**	-8.537 [0.0000]**	-4.078 [0.0000]**	..	0.3567 [0.7213]	-2.246 [0.0247]*
Testing Hypothesis	Model 2 ⊃ Model 1	..	Model 2 ⊃ Model 3	Model 2 ⊃ Model 4	Model 2 ⊃ Model 5	Model 2 ⊃ Model 6
Denmark	-5.006 [0.0000]**	..	-0.2485 [0.8038]	-3.033 [0.0024]**	-0.5273 [0.5980]	0.4855 [0.6273]
Testing Hypothesis	Model 2 ⊃ Model 1	..	Model 2 ⊃ Model 3	Model 2 ⊃ Model 4	Model 2 ⊃ Model 5	Model 2 ⊃ Model 6
France	-3.531 [0.0000]**	..	0.1443 [0.8853]	-4.513 [0.0000]**	-3.443 [0.0006]**	-1.980 [0.0477]*
Testing Hypothesis	Model 2 ⊃ Model 1	..	Model 2 ⊃ Model 3	Model 2 ⊃ Model 4	Model 2 ⊃ Model 5	Model 2 ⊃ Model 6
Germany	-1.321 [0.0009]**	..	-4.731 [0.0000]**	-5.836 [0.0000]**	-2.639 [0.0083]**	-0.7262 [0.4677]
Testing Hypothesis	Model 5 ⊃ Model 1	Model 5 ⊃ Model 2	Model 5 ⊃ Model 3	Model 5 ⊃ Model 4	..	Model 5 ⊃ Model 6
Ghana	-1.263 [0.2066]	-5.805 [0.0000]**	-0.6658 [0.5055]	-1.160 [0.2461]	..	-0.02662 [0.9788]
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Hungary	-1.733 [0.0832]	-6.007 [0.0000]**	-3.311 [0.0009]**	..	-4.349 [0.0000]**	-2.338 [0.0194]*
Testing Hypothesis	Model 5 ⊃ Model 1	Model 5 ⊃ Model 2	Model 5 ⊃ Model 3	Model 5 ⊃ Model 4	..	Model 5 ⊃ Model 6
India	0.9661 [0.3340]	-3.861 [0.0001]**	-0.1389 [0.8895]	-0.7905 [0.4293]	..	0.5447 [0.5860]
Testing Hypothesis	..	Model 1 ⊃ Model 2	Model 1 ⊃ Model 3	Model 1 ⊃ Model 4	Model 1 ⊃ Model 5	Model 1 ⊃ Model 6
Indonesia	..	-1.004 [0.3151]	-0.7010 [0.4833]	-4.440 [0.0000]**	-2.245 [0.0248]*	-4.989 [0.0000]**
Testing Hypothesis	Model 6 ⊃ Model 1	Model 6 ⊃ Model 2	Model 6 ⊃ Model 3	Model 6 ⊃ Model 4	Model 6 ⊃ Model 5	..
Iran	-7.054 [0.0000]**	-11.88 [0.0000]**	-8.914 [0.0000]**	-8.080 [0.0000]**	-8.456 [0.0000]**	..
Testing	Model 2 ⊃	..	Model 2 ⊃	Model 2 ⊃	Model 2 ⊃	Model 2 ⊃

Country Name	Model 5 ⊃ Model 1	Model 5 ⊃ Model 2	Model 5 ⊃ Model 3	Model 5 ⊃ Model 4	..	Model 5 ⊃ Model 6
Hypothesis	Model 1		Model 3	Model 4	Model 5	Model 6
Japan	0.1379 [0.8903]	..	-0.8707 [0.3839]	-1.175 [0.2401]	-1.313 [0.1890]	-1.810 [0.0702]
Testing Hypothesis	Model 2 ⊃ Model 1	..	Model 2 ⊃ Model 3	Model 2 ⊃ Model 4	Model 2 ⊃ Model 5	Model 2 ⊃ Model 6
Luxembourg	4.350 [0.0000]**	..	0.5534 [0.5800]	-2.618 [0.0088]**	-0.8845 [0.3764]	-6.001 [0.0000]**
Testing Hypothesis	Model 6 ⊃ Model 1	Model 6 ⊃ Model 2	Model 6 ⊃ Model 3	Model 6 ⊃ Model 4	Model 6 ⊃ Model 5	..
Malaysia	3.420 [0.0006]**	-9.715 [0.0000]**	-1.041 [0.2980]	-3.136 [0.0017]**	-4.076 [0.0000]**	..
Testing Hypothesis	..	Model 1 ⊃ Model 2	Model 1 ⊃ Model 3	Model 1 ⊃ Model 4	Model 1 ⊃ Model 5	Model 1 ⊃ Model 6
Maldives	..	-2.826 [0.0047]**	-9.967 [0.0000]**	-4.829 [0.0000]**	0.1378 [0.8904]	-8.152 [0.0000]**
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Mexico	-0.4716 [0.6372]	-2.028 [0.0426]*	1.267 [0.2053]	..	-3.259 [0.0011]**	1.281 [0.2000]
Testing Hypothesis	Model 6 ⊃ Model 1	Model 6 ⊃ Model 2	Model 6 ⊃ Model 3	Model 6 ⊃ Model 4	Model 6 ⊃ Model 5	..
Morocco	-4.558 [0.0000]**	-22.30 [0.0000]**	-17.06 [0.0000]**	-18.35 [0.0000]**	-1.181 [0.2376]	..
Testing Hypothesis	..	Model 1 ⊃ Model 2	Model 1 ⊃ Model 3	Model 1 ⊃ Model 4	Model 1 ⊃ Model 5	Model 1 ⊃ Model 6
Nepal	..	-0.3532 [0.7239]	-4.032 [0.0001]**	-3.392 [0.0007]**	-1.753 [0.0795]	-2.498 [0.0125]*
Testing Hypothesis	Model 2 ⊃ Model 1	..	Model 2 ⊃ Model 3	Model 2 ⊃ Model 4	Model 2 ⊃ Model 5	Model 2 ⊃ Model 6
Netherland	0.6651 [0.5060]	..	-0.6500 [0.5157]	-2.638 [0.0083]**	-0.8125 [0.4165]	-0.4269 [0.6695]
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
New Zealand	1.706 [0.0879]	-2.000 [0.0455]*	-2.093 [0.0363]*	..	-7.903 [0.0000]**	-4.379 [0.0000]**
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Norway	21.015 [0.0071]**	-1.270 [0.2040]	-1.975 [0.0483]*	..	-2.008 [0.0447]*	0.1659 [0.8682]
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Pakistan	-3.263 [0.0011]**	-0.03716 [0.9704]	-2.590 [0.0096]**	..	1.351 [0.1766]	-0.1120 [0.9109]
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Peru	-0.7935 [0.4275]	-4.416 [0.0000]**	-2.149 [0.0316]*		-5.209 [0.0000]**	-0.8842 [0.3766]
Testing	Model 2 ⊃	..	Model 2 ⊃	Model 2 ⊃	Model 2 ⊃	Model 2 ⊃

Country Name	**Model 5 ⊃ Model 1**	**Model 5 ⊃ Model 2**	**Model 5 ⊃ Model 3**	**Model 5 ⊃ Model 4**	**..**	**Model 5 ⊃ Model 6**
Hypothesis	Model 1		Model 3	Model 4	Model 5	Model 6
Paraguay	-0.4010 [0.6885]		-2.149 [0.0316]*	-3.405 [0.0007]**	-6.861 [0.0000]**	-3.400 [0.0007]**
Testing Hypothesis	Model 6 ⊃ Model 1	Model 6 ⊃ Model 2	Model 6 ⊃ Model 3	Model 6 ⊃ Model 4	Model 6 ⊃ Model 5	..
Philippines	-1.829 [0.0674]	-0.5689 [0.5694]	-2.026 [0.0428]*	-3.048 [0.0023]**	-2.373 [0.0176]*	..
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Portugal	1.790 [0.0735]	1.790 [0.0735]	4.2524 [0.0244]*	..	-1.821 [0.0686]	0.9842 [0.3250]
Country Name	Model 5 ⊃ Model 1	Model 5 ⊃ Model 2	Model 5 ⊃ Model 3	Model 5 ⊃ Model 4	..	Model 5 ⊃ Model 6
Qatar	3.4821 [0.0142]*	-3.655 [0.0003]**	-2.405 [0.0162]*	-3.467 [0.0005]**	..	-0.6991 [0.4845]
Testing Hypothesis	Model 2 ⊃ Model 1	..	Model 2 ⊃ Model 3	Model 2 ⊃ Model 4	Model 2 ⊃ Model 5	Model 2 ⊃ Model 6
South Africa	0.9443 [0.3450]	..	-0.6909 [0.4896]	-2.839 [0.0045]**	-2.271 [0.0231]*	-2.041 [0.0412]*
Testing Hypothesis	..	Model 1 ⊃ Model 2	Model 1 ⊃ Model 3	Model 1 ⊃ Model 4	Model 1 ⊃ Model 5	Model 1 ⊃ Model 6
Sri Lanka		-3.997 [0.0001]**	-4.961 [0.0000]**	-4.961 [0.0000]**	-0.2751 [0.7832]	0.5417 [0.5880]
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Switzerland	0.8319 [0.4055]	-3.749 [0.0002]**	-1.117 [0.2638]	..	-0.4449 [0.6564]	0.2620 [0.7933]
Testing Hypothesis	Model 2 ⊃ Model 1	..	Model 2 ⊃ Model 3	Model 2 ⊃ Model 4	Model 2 ⊃ Model 5	Model 2 ⊃ Model 6
Sweden	3.430 [0.0006]**	..	-0.06186 [0.9507]	-4.363 [0.0000]**	-0.3404 [0.7335]	4.1073 [0.0273]*
Testing Hypothesis	..	Model 1 ⊃ Model 2	Model 1 ⊃ Model 3	Model 1 ⊃ Model 4	Model 1 ⊃ Model 5	Model 1 ⊃ Model 6
Turkey	..	-1.420 [0.1556]	-7.584 [0.0000]**	-3.263 [0.0011]**	-2.807 [0.0050]**	-5.444 [0.0000]**
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
United States	0.1010 [0.9195]	0.1902 [0.8492]	0.5792 [0.5625]	..	-0.02044 [0.9837]	1.525 [0.1273]
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
United Kingdom		-2.034 [0.0419]*	-7.078 [0.0000]**	..	-1.310 [0.1901]	0.7930 [0.4278]
Testing Hypothesis	Model 4 ⊃ Model 1	Model 4 ⊃ Model 2	Model 4 ⊃ Model 3	..	Model 4 ⊃ Model 5	Model 4 ⊃ Model 6
Uruguay	-5.262 [0.0000]**	-2.402 [0.0163]*	-0.5995 [0.5489]		-11.04 [0.0000]**	-2.714 [0.0066]**

Table: 13 Results of Retained Model Non-Nested Encompassing (Growth Modeling)

Country Name	**Argentina**	**Australia**	**Austria**	**Bangladesh**	**Belgium**	**Bhutan**	**Bulgaria**	**Brazil**	**Canada**	**China**	**Chilli**
Variables											
Constant	-4.0471 (0.0430)	-22.636 (0.0212)	-1.449 (0.8237)	15.908 (0.1357)	-0.8754 (0.9149)	7.434 (0.0419)	51.936 (0.2326)	2.851 (0.4538)	-5.491 (0.8349)	-1.673 (0.0123)	-123.706 (0.0100)
LNGDP_1	0.921 (0.0000)	0.674 (0.0061)	0.605 (0.0007)	0.367 (0.0466)	0.793 (0.0000)	0.731 (0.0000)	0.077 (0.7413)	0.862 (0.0000)	0.659 (0.0015)	0.817 (0.0000)	0.616 (0.0000)
FDI(inf)	0.012 (0.2854)	0.007 (0.4086)	-0.002 (0.2250)	0.002 (0.9095)	0.002 (0.5536)	0.007 (0.3258)	-0.003 (0.6201)	0.004 (0.7358)	0.001 (0.4676)	0.0151 (0.3688)	-0.001 (0.7427)
FDI(inf)_1	0.022 (0.0688)	0.008 (0.2891)	-0.0091 (0.6796)	-0.046 (0.0176)	6.327 (0.9867)	-0.005 (0.3197)	0.008 (0.2034)	-0.010 (0.3352)	-0.001 (0.6238)	0.0327 (0.0685	0.007 (0.0915)
TOP	-9.169 (0.0000)	2.573 (0.0454)	-4.715 (0.0005)	-7.739 (0.0000)	0.033 (0.9709)	-0.288 (0.0292)	..	-14.369 (0.0000)	-14.008 (0.0000)	0.058 (0.8491	..
TOP_1	9.483 (0.0000)	2.597 (0.0232)	1.796 (0.2092)	2.707 (0.1924)	0.416 (0.6234)	-0.270 (0.1015)	..	10.929 (0.0001)	7.460 (0.0126)	-0.380 (0.1640)	..
LG	1.168 (0.8227)	5.173 (0.1669)	0.728 (0.4357)	0.426 (0.1428)	0.587 (0.3441)	0.115 (0.6925)	..	0.099 (0.6702)	-0.031 (0.9070)	0.113 (0.7867)	..
LG_1	-23.665 (0.0002)	7.114 (0.5841)	-0.538 (0.5708)	-84.835 (0.7738)	-0.560 (0.4026)	96.265 (0.7801)	..	0.041 (0.8910)	458.524 (0.1146)	0.113 (0.7804)	..
DI	0.001 (0.5494)	0.059 0.0080	-0.538 (0.5708)	..	-0.036 (0.9447)	0.004 (0.6660)	-0.003 (0.4517)	1.486 (0.0734)	-0.002 (0.6351)	0.013 (0.2031)	0.005 (0.0495)
DI_1	-0.002 (0.2203)	0.002 (0.9699)	2.499 (0.2561)	..	0.0235 (0.9648)	0.016 (0.0547)	0.011 (0.0991)	2.421 (0.6708)	-0.001 (0.6498)	- 0.001 (0.8893	-0.005 (0.0013)
LnGCF	1.042 (0.0000)	0.015 (0.3872)	1.105 (0.0036)	0.411 (0.0784)	0.816 (0.0371)	0.149 (0.1144)	-0.045 (0.8407)	0.657 (0.0001)	0.259 (0.0101)	0.255 (0.586)	..
LnGCF_1	-0.811 (0.0000)	-0.016 (0.3753)	-0.420 (0.2427)	-0.301 (0.1554)	-0.599 (0.0658)	0.014 (0.8893)	0.053 (0.8311)	-0.556 (0.0003)	-0.090 (0.4934)	0.009 (0.9436)	..
TDebtS	..	..	..	0.003 (0.8027)	..	..	-0.014 (0.1295)	-0.008 (0.1343)	0.060 (0.3070)	..	15.453 (0.0013)
TDebtS_1	..	..	..	0.042 (0.1091)	..	..	0.014 (0.1108)	0.010 (0.0613)	-0.054 (0.3670)	..	-15.948 (0.0010)

Country Name Variables	Argentina	Australia	Austria	Bangladesh	Belgium	Bhutan	Bulgaria	Brazil	Canada	China	Chilli
Inf	..	-0.040 (0.0058)	..	0.003 (0.0662)	..	-0.002 (0.3222)	2.848 (0.9596)	..	-0.001 (0.9654)	..	-0.005 (0.3163)
Inf_1	..	-0.019 (0.0742)	..	0.002 (0.2346)	..	-0.010 (0.0009)	-5.696 (0.8480)	..	-0.004 (0.1226)	..	0.018 (0.0000)
LnTLF	..	-47.418 (0.5860)	..	4.874 (0.7743)	..	-8.130 (0.7724)	-0.187 (0.2166)	..	-27.795 (0.1147)	..	0.008 (0.5083)
LnTLF_1	..	47.371 (0.5861)	..	-4.935 (0.7716)	..	7.810 (0.7803)	0.085 (0.5412)	..	27.802 (0.1144)	..	-0.0082 (0.6188)
LnTOTP	..	4.702 (0.4017)	..	-16.124 (0.0374)	..	..	6.929 (0.4382)	..	3.063 (0.1775)	..	40.592 (0.0024)
LnTOTP_1	..	-3.486 (0.5279)	..	15.926 (0.0383)	..	..	-9.313 (0.3354)	..	-2.124 (0.3812)	..	-33.237 (0.0171)
Edu	-0.045 (0.0884)	-0.139 (0.0517)	..	-0.038 (0.3560)	..	0.021 (0.4573)	-0.066 (0.1289)	-0.042 (0.0011)	-0.003 (0.8102)	..	0.001 (0.8607)
Edu_1	0.002 (0.9221)	-0.006 (0.9289)	..	-0.0475 (0.2890)	..	-0.005 (0.8103)	-0.006 (0.8870)	0.030 (0.0143)	0.007 (0.6536)	..	0.0094 (0.2790)
LnRExp	..	0.421 (0.0039)	..	0.557 (0.0000)	..	..	0.387 (0.0947)	0.853 (0.0000)	0.763 (0.0000)	..	0.664 (0.0000)
LnRExp _1	..	-0.3085 (0.1186)	..	-0.041 (0.7865)	..	..	0.041 (0.8584)	-0.671 (0.0003)	-0.500 (0.0016)	..	-0.196 (0.1505)
GEXP	..	-0.021 (0.0507)	..	0.0005 (0.7258)	..	0.001 (0.0624)	0.004 (0.2388)	..	0.001 (0.5265)	..	-0.004 (0.2890)
GEXP_1	..	-0.006 (0.5743)	..	-0.009 (0.3428)	..	0.005 (0.6053)	-0.005 (0.8707)	..	0.001 (0.6337)	..	0.007 (0.8866)
P(remi)	..	-0.280 (0.2400)	..	-0.024 (0.0182)	..	..	-0.055 (0.2844)	-0.012 (0.4407)	0.003 (0.4420)	..	-1.905 (0.2848)
P(remi)_1	..	0.076 (0.7141)	..	0.012 (0.1181)	..	..	0.021 (0.4788)	0.049 (0.0024)	0.002 (0.2225)	..	7.430 (0.0001)

Country Name Variables	Denmark	France	Germany	Ghana	Hungary	India	Indonesia	Iran	Japan	Luxembourg	Malaysia
Constant	7.673 (0.0014)	-6.570 (0.8054)	37.211 (0.3607)	9.808 (0.3970)	41.221 (0.0680)	24.409 (0.2192)	18.111 (0.0001)	51.697 (0.0000)	-29.139 (0.6814)	-3.201 (0.8830)	11.526 (0.5302)
LNGDP_1	0.379 (0.0250)	0.421 (0.1405)	-0.076 (0.6161)	0.538 (0.0040)	0.056 (0.7750)	0.165 (0.4428)	0.259 (0.1407)	-0.200 (0.1198)	0.775 (0.0000)	0.382 (0.1635)	0.598 (0.0171)
FDI(inf)	-0.001 (0.1451)	-0.001 (0.5212)	0.006 (0.0020)	-0.036 (0.1614)	1.508 (0.9400)	0.003 (0.8913)	0.031 (0.0041)	0.060 (0.2700)	-0.0154 (0.8739)	-0.002 (0.3024)	0.003 (0.5078)
FDI(inf)_1	-0.007 (0.6147)	0.001 (0.6605)	0.004 (0.0167)	0.020 (0.3551)	-0.001 (0.6421)	0.023 (0.3235)	-0.010 (0.2504)	-0.111 (0.0268)	0.022 (0.8275)	-0.0001 (0.6507)	-0.003 (0.2455)
TOP	..	-17.338 (0.0000)	-13.172 (0.0000)	-7.707 (0.0086)	-12.598 (0.0000)	-0.273 (0.8643)	-11.330 (0.0000)	-11.177 (0.0000)	..	-10.146 (0.0000)	-10.966 (0.0000)
TOP_1	..	7.474 (0.1400)	-2.135 (0.4100)	3.422 (0.2343)	0.085 (0.9736)	-1.455 (0.2485)	0.160 (0.9406)	-4.293 (0.0385)	..	3.258 (0.2644)	6.318 (0.0518)
LG	..	-0.248 (0.2176)	0.857 (0.4405)	0.495 0.6512	0.675 (0.5136)	-0.441 (0.0675)	-0.228 (0.6664)	-1.001 (0.0117)	..	..	0.101 (0.5380)
LG_1	..	911.756 (0.5249)	1160.18 (0.4977)	-207.247 (0.9192)	132.664 (0.9175)	9.921 (0.9912)	-1.611 (0.0065)	134.780 (0.5561)	..	..	-127.300 (0.6836)
DI	-0.567 (0.1852)	0.006 (0.9578)	0.128 (0.9047)	-0.004 (0.9490)	-0.006 (0.8638)	0.216 (0.7843)	-0.006 (0.0092)	-0.008 (0.2566)	..	-7.296 (0.8609)	0.001 (0.8691)
DI_1	0.6794 (0.0754)	0.012 (0.3080)	-1.486 (0.1443)	-0.003 (0.6110)	9.318 (0.9801)	-0.602 (0.4081)	0.004 (0.0422)	-0.004 (0.1927)	..	2.501 (0.7516)	-0.004 (0.3484)
LnGCF	-0.149 (0.0513)	0.327 (0.0602)	-0.184 (0.0789)	-0.096 (0.0206)	0.151 (0.0380)	0.684 (0.0000)	-0.012 (0.5592)	-0.002 (0.6256)	..	0.079 (0.3946)	0.173 (0.0008)
LnGCF_1	0.210 (0.0026)	-0.321 (0.0443)	0.099 (0.2593)	-0.012 (0.7876)	-0.063 (0.3378)	0.054 (0.8033)	0.064 (0.0071)	0.020 (0.0039)	..	0.063 (0.3916)	-0.110 (0.1355)
TDebtS	-4.065 (0.0014)	0	-1.330 (0.4394)	..	..	..	..	-0.033 (0.0099)	..	-1.663 (0.8830)	0
TDebtS_1	4.065 (0.0014)	-0.027 (0.5354)	0	..	..	..	..	0.0057 (0.6704)	..	1.663 (0.8830)	-0.017 (0.9825)
Inf	-0.033 (0.0011)	0.013 (0.0680)	0.004 (0.9269)	-0.001 (0.1936)	-0.001 (0.5060)	0.003 (0.3325)	0.147 (0.3753)	0.001 (0.3887)	0.015 (0.5032)	-0.007 (0.2100)	-0.002 (0.4843)

Country Name Variables	Denmark	France	Germany	Ghana	Hungary	India	Indonesia	Iran	Japan	Luxembourg	Malaysia
Inf_1	-0.004 (0.6805)	-0.010 (0.0726)	0.002 (0.4760)	-0.009 (0.3783)	-0.001 (0.5733)	0.001 (0.7850)	-0.150 (0.3626)	-0.001 (0.1836)	-0.037 (0.1206)	-0.002 (0.7448)	-0.001 (0.7570)
LnTLF	0.05 (0.1422)	-53.393 (0.5250)(	-66.186 (0.4991)	13.219 (0.9194)	-8.619 (0.9178)	-0.537 (0.9907)	..	-8.319 (0.5495)	-0.063 (0.6718)	-0.007 (0.3532)	8.070 (0.6831)
LnTLF_1	0.018 (0.6483)	53.418 (0.5250)	66.639 (0.4963)	-13.256 (0.9192)	8.569 (0.9183)	0.485 (0.9916)	..	8.084 (0.5607)	0.089 (0.4997)	0.006 (0.2406)	-8.078 (0.6834)
LnTOTP	2.243 (0.6194)	3.682 (0.5136)	-0.429 (0.5913)	-28.723 (0.5052)	-3.613 (0.6372)	-98.156 (0.0302)	..	5.094 (0.3623)	2.653 (0.8849)	-7.052 (0.1152)	-5.156 (0.4289)
LnTOTP_1	-0.250 (0.9654)	-2.319 (0.6857)	1.508 (0.0273)	29.516 (0.4926)	2.609 (0.7268)	97.430 (0.0311)	..	-5.52350 (0.3147)	-0.765 (0.9674)	6.972 (0.1289)	5.032 (0.4799)
Edu	..	-0.050 (0.1007)	-0.003 (0.9002)	..	-0.007 (0.7559)	..	-0.010 (0.1395)	-0.045 (0.0307)	..	-0.012 (0.5167)	-0.002 (0.8069)
Edu_1	..	0.003 (0.8936)	0.014 (0.7199)	..	0.017 (0.3446)	..	-0.008 (0.8964)	-0.017 (0.2778)	..	-4.256 (0.9981)	-0.014 (0.1681)
LnRExp	0.978 (0.0000)	0.952 1 (0.0000)	1.052 (0.0000)	..	0.871 1 (0.0000)	..	0.851 (0.0000)	0.600 (0.0000)	..	0.911 (0.0000)	0.882 (0.0000)
LnRExp _1	-0.321 0.1292)	-0.302 (0.3094)	0.104 (0.5115)	..	0.016 (0.9286)	..	-0.010 (0.9604)	0.214 (0.0395)	..	-0.301 (0.2464)	-0.537 (0.0384)
GEXP	-0.002 (0.6736)	-0.007 (0.0577)	0.002 (0.9030)	0.003 (0.0819)	3.704 (0.9793)	0.001 (0.5755)	..	-0.001 (0.5973)	0.062 (0.0081)	-0.006 (0.0320)	0.002 (0.1491)
GEXP_1	0.0043 (0.2394)	-0.002 (0.7216)	-0.007 (0.7881)	0.001 (0.3696)	-0.002 (0.1107)	-0.009 (0.6727)	..	0.001 (0.6378)	-0.048 (0.0456)	-0.008 (0.0469)	0.001 (0.1981)
P(remi)	-0.012 (0.8798)	0.005 (0.9471)	0.008 (0.8969)	..	-0.017 (0.1558)	..	0.003 (0.8479)	-0.074 (0.0768)	..	-0.001 (0.4357)	0.001 (0.8964)
P(remi)_1	0.066 (0.4594)	-0.012 (0.1440)	0.358 (0.0013)	..	0.001 (0.9156)	..	0.067 (0.0025)	0.013 (0.6947)	..	0.001 (0.5249)	0.002 (0.8219)

Country Name	Maldives	Mexico	Morocco	Nepal	Netherland	New Zealand	Norway	Pakistan	Peru	Paraguay	Philippines
Variables											
Constant	0.002 (0.9997)	-16.873 (0.0510)	23.478 (0.0086)	12.767 (0.1506)	18.861 (0.3610)	19.777 (0.0488)	11.979 (0.1242)	1.606 (0.5018)	5.259 (0.4917)	17.996 (0.0224)	3.983 (0.3862)
LNGDP_1	0.739 (0.0000)	1.017 (0.0000)	0.464 0.0258	0.342 (0.1073)	0.380 (0.0329)	0.316 (0.1769)	0.7487 (0.0001)	0.832 (0.0001)	0.197 (0.4029)	0.342 (0.1073)	0.655 (0.0039)
FDI(inf)	-0.007 (0.2274)	-4.788 (0.996)8	-0.015 (0.0917)	0.058 (0.5249)	-0.003 (0.6141)	2.257 (0.8704)	0.001 0.9724	-0.007 (0.7860)	-0.005 (0.4051)	-0.004 (0.7155)	-0.012 (0.3870)
FDI(inf)_1	-0.014 (0.0235)	-0.015 (0.2094)	-0.006 0.4143	0.065 (0.4718)	-0.002 (0.7421)	-2.789 (0.7800)	0.004 (0.4609)	0.014 (0.6094)	-0.005 (0.9354)	-0.016 (0.1878)	0.033 (0.0211)
TOP	-7.455 (0.0000)	-9.411 (0.0000)	-12.580 (0.0000)	-5.487 (0.0317)	..	-12.0731 (0.0000)	-19.307 (0.0003)	..	-8.837 (0.0002)	-11.820 (0.0000)	-13.581 (0.0000)
TOP_1	6.022 (0.0060)	15.674 (0.0000)	2.399 (0.4103)	2.707 (0.4130)	..	3.438 (0.2532)	12.034 (0.0294)	..	2.744 (0.3962)	2.596 (0.3670)	11.154 (0.0032)
LG	..	-2.139 (0.0002)	..	..	..	0.399 (0.4034)	-0.131 (0.7808)	..	-1.935 (0.5224)	-0.021 (0.9703)	0.103727 (0.8494)
LG_1	..	238.240 (0.3129)	..	..	..	-184.793 (0.5975)	-0.586 (0.1443)	..	84.579 (0.7114)	-59.648 (0.5884)	1.025 (0.1325)
DI	-0.001 (0.8916)	0.004 (0.0596)	-0.016 (0.2541)	2.550 (0.4286)	..	-0.002 (0.2435)	-0.005 (0.4699)	0.000 (0.9622)	0.001 (0.9081)	-0.008 (0.0054)	0.015 (0.0622)
DI_1	-0.004 (0.5977)	-0.001 (0.4917)	0.010 (0.4403)	2.726 (0.4003)	..	0.001 (0.5767)	0.005 (0.5974)	0.001 (0.9347)	-0.002 (0.8565)	-0.001 (0.9778)	0.007 (0.1419)
LnGCF	-0.007 0.9561	0.541 (0.0008)	0.502 (0.0003)	0.035 (0.3994)	-0.133 (0.5133)	0.063 (0.2868)	0.599 (0.0001)	0.257 (0.2626)	0.400 (0.0000)	0.259 (0.0028)	0.188 (0.0212)
LnGCF_1	-0.018 (0.8932	-0.421 (0.0068	-0.307 (0.0419	0.004 (0.9213	0.204 (0.3443	-0.035 (0.4757	-0.427 (0.0262	-0.351 (0.1541	0.005 (0.9650	-0.070 (0.5078	-0.095 (0.2602
TDebtS	-8.559 (0.9894)	..	0.012 (0.1409)	-0.120 (0.2138)	..	..	..	-0.019 (0.2396)	..	..	..
TDebtS_1	0.001 (0.8038)	..	-0.001 (0.8131)	0.0169 (0.8710)	..	..	-0.022 (0.9074)	0.011 (0.4506)	..	..	..
Inf	..	-0.006 (0.0004)	-0.003 (0.6221)	-0.003 (0.4665)	-0.033 (0.0086)	-0.009 (0.7025)	-0.004 (0.4692)	0.001 (0.6723)	-0.0001 (0.7611)	0.006 (0.0067)	0.009 (0.6437)
Inf_1	..	0.005 (0.0072)	0.001 (0.7773)	-0.002 (0.6072)	0.005 (0.7481)	0.002 (0.3894)	0.001 (0.7674)	-0.004 (0.3690)	0.001 (0.8428)	-0.002 (0.8961)	-0.006 (0.6567)

Country Name Variables	Maldives	Mexico	Morocco	Nepal	Netherland	New Zealand	Norway	Pakistan	Peru	Paraguay	Philippines
LnTLF	0.0140 (0.2607)	-13.825 (0.3119)	-0.063 (0.0539)	..	-0.155 (0.0370)	11.730 (0.5972)	..	..	-5.407 (0.6950)	4.182 (0.5865)	..
LnTLF_1	-0.013 (0.2684)	13.859 (0.3123)	0.025 (0.4038)	..	-0.018 (0.8063)	-11.732 (0.5976)	..	..	5.330 (0.7001)	-4.236 (0.5818)	..
LnTOTP	0.100 (0.9683)	25.416 (0.1631)	1.175 (0.9126)	..	5.148 (0.6603)	4.601 (0.1896)	..	..	-0.255 (0.9452)	7.9000 (0.5243)	..
LnTOTP_1	0.201 (0.9346)	-25.041 (0.1636)	-1.859 (0.8598)	..	-5.98300 (0.6164)	-4.747 (0.1948)	..	..	0.719 (0.8454)	-8.171 (0.5009)	..
Edu	-0.017 (0.1251)	..	0.014 (0.6466)	-0.045 (0.1543)	..	-0.004 (0.9800)	-0.016 (0.5838)	-0.057 (0.2447)	-0.007 (0.9715)	0.017 (0.2055)	-0.070 (0.0526)
Edu_1	0.017 (0.0641)	..	0.048 (0.1405)	0.017 (0.5795)	..	-0.002 0.8980	0.015 0.6412	0.041 0.3387	0.025 (0.2339)	-0.012 (0.3789)	0.020 (0.4580)
LnRExp	0.601 (0.0000)	0.638 (0.0000)	0.807 (0.0000)	0.333 (0.0555)	0.740 (0.0000)	0.952 (0.0000)	0.731 (0.0000)	0.194 (0.1103	0.599 (0.0000)	0.849 (0.0000)	0.908 (0.0000)
LnRExp _1	-0.339 (0.0187)	-0.883 (0.0000)	-0.102 (0.5937)	-0.127 (0.5594)	-0.258 (0.1103)	-0.299 (0.1882)	-0.566 (0.0014)	0.020 (0.8953)	-0.176 (0.325)8	-0.155 (0.4901)	-0.599 (0.0175)
GEXP	0.003 (0.2943)	-0.009 (0.0933)	0.001 (0.1771)	..	0.002 (0.6989)	0.003 (0.7429)	..	..	0.001 (0.408)7	0.0001 (0.9616)	..
GEXP_1	0.001 (0.7418)	-0.014 (0.0465)	0.001 (0.4150)	..	0.009 (0.1135)	-0.0008 (0.5782)	..	..	0.001 (0.183)0	0.001 (0.4417)	..
P(remi)	0.004 (0.8175)	-0.042 (0.3215)	0.025 (0.0503)	0.001 (0.9110)	0.001 (0.7119)	-0.096 (0.1837)	0.291 (0.6928)	-0.025 (0.1315)	-0.031 (0.665)6	0.053 (0.0560)	-0.006 (0.5758)
P(remi)_1	0.028 (0.2841)	0.022 (0.6459)	-0.004 (0.6722)	0.008 (0.2474)	-0.008 (0.8471)	0.023 (0.6979)	-1.307 (0.0299)	0.031 (0.0432)	0.027 (0.7038)	0.030 (0.3745)	-0.003 (0.6871)

Country Name / Variables	Portugal	Qatar	South Africa	Sri Lanka	Switzerland	Sweden	Turkey	United States	United Kingdom	Uruguay
Constant	-3.889 (0.1945)	1.958 (0.7037)	30.783 (0.0011)	-10.380 (0.3710)	-1.38 (0.8767)	-22.3 (0.8120)	21.403 (0.0123)	-0.130 (0.6661)	5.357 (0.0826)	..
LNGDP_1	0.792 (0.0000)	-0.51 (0.0885)	-0.210 (0.3204)	0.723 (0.0000)	0.666 (0.0000)	-0.155 (0.4871)	0.294 (0.2631)	0.881 (0.0000)	0.229 (0.2067)	0.199 (0.5033)
FDI(inf)	-8.229 (0.3632)	0.009 (0.4062)	0.004 (0.4181)	-0.014 (0.3939)	-0.001 (0.1941)	-0.001 (0.2094)	0.022 (0.1290)	..	-0.004 (0.2756)	0.004 0.5177
FDI(inf)_1	0.001 (0.2468)	-0.002 (0.7781)	0.003 0.6588)	0.002 (0.8521)	-0.004 (0.7547)	5.894 (0.9439)	-0.010 (0.4609)	..	-0.008 (0.0360)	0.004 (0.4136)
TOP	..	-10.713 (0.0000)	-13.017 (0.0000)	..	..	-12.327 (0.0000)	-14.187 (0.0000)	..	..	-11.821 (0.0002)
TOP_1	..	-4.028 (0.1612)	-3.1314 (0.2777)	..	..	-2.835 (0.3940)	2.145 (0.6300)	..	..	0.227 (0.9359)
LG	..	0.029 (0.8879)	0.363 0.4008	..	..	..	-0.439 (0.6746)	..	..	0.167 (0.5771)
LG_1	..	-527.323 (0.0025)	36.419 (0.8821)	..	..	..	0.208 (0.7645)	..	..	-15 .57 (0.1272)
DI	..	-0.007 (0.5038)	-0.004 (0.1635)	-0.004 (0.2053)	..	-0.001 (0.6550)	-0.003 (0.0228)	..	-0.006 (0.6009)	-0.001 (0.4249)
DI_1	..	0.010 (0.4009)	-0.006 (0.2406)	0.008 (0.0090)	..	-0.002 (0.4333)	0.002 (0.0238)	..	0.011 (0.2692)	-0.002 (0.0605)
LnGCF	0.282 (0.0664)	-0.193 (0.0657)	0.287 (0.01560	0.265 (0.0479)	0.558 (0.0180)	-0.105 (0.2864)	0.078 (0.0974)	0.225 (0.0000)	0.577 (0.0312)	0.372 (0.0655)
LnGCF_1	-0.058 (0.7305)	0.185 (0.1115)	0.167 (0.2597)	-0.089 (0.4253)	-0.416 (0.0540)	-0.148 (0.1193)	-0.078 (0.1399)	-0.124 (0.0054)	0.460 (0.0720)	-0.207 (0.2312)
TDebtS	..	2.458 (0.7038)	..	-0.010 (0.0584)	..	44.0 (0.8117)	-0.021 (0.0120)	..	-5.299 (0.0826)	-13.775 (0.8118)
TDebtS_1	..	-2.458 (0.7038)	..	-0.011 (0.0672)	..	-41.0 (0.8117)	0.009 (0.3672)	..	5.299 (0.0826)	13.230 (0.8192)

Country Name Variables	Portugal	Qatar	South Africa	Sri Lanka	Switzerland	Sweden	Turkey	United States	United Kingdom	Uruguay
Inf	-0.016 (0.0110)	-0.002 (0.5246)	-0.006 (0.1185)	0.005 (0.0113)	-0.019 (0.0415)	0.002 (0.3616)	0.001 (0.2423)	-0.002 (0.3839)	-0.005 (0.97370	0.004 (0.1052)
Inf_1	0.014 (0.0104)	0.001 (0.7596)	0.004 (0.2809)	-0.003 (0.1060)	0.007 (0.9331)	0.001 (0.5774)	0.001 (0.8127)	0.002 (0.1662)	0.031 (0.0269)	0.001 (0.2067)
LnTLF		42.100 (0.0025)	-2.171 (0.8850)	-0.002 (0.9665)	-0.066 (0.5269)	0.505 (0.3441)	..	..	0.011 (0.7517)	112.222 (0.1272)
LnTLF_1	..	-42.085 (0.0025	2.271 (0.8799)	-0.065 (0.2249)	0.015 (0.8931)	0.469 (0.4413)	..	..	-0.010 (0.8173)	-112.223 (0.1272)
LnTOTP	..	-1.276 (0.3332	-2.788 (0.6744)	12.800 (0.0384)	13.424 (0.0777)	6.279 (0.0286)	..	..	21.838 (0.3185)	1.244 (0.9127)
LnTOTP_1	..	1.031 (0.4084	2.119 (0.7450)	-12.156 (0.0405)	-13.095 (0.0732)	-7.375 (0.0150)	..	..	-27.197 (0.1808)	4.317 (0.7092)
Edu	0.009 (0.8670)	-0.040 (0.2844	0.006 (0.4570)	-0.048 (0.1241)	..	-0.008 (0.2935)	0.003 (0.8137)	..	0.011 (0.8705)	-0.025 (0.3118)
Edu_1	-0.0791 (0.1185)	-0.038 (0.2287	0.004 (0.6769)	-0.024 (0.2964)	..	-0.003 (0.9704)	-0.005 (0.597)8	..	-0.021 (0.7127)	-0.032 (0.1469)
LnRExp	0.682 (0.0000)	0.505 (0.0000	0.962 (0.0000)	0.067 (0.5542)	0.581 (0.0000)	1.022 (0.0000)	1.035 (0.0000)	0.112 (0.0017)	0.541 (0.0091)	0.796 (0.0003)
LnRExp _1	-0.514 (0.0005)	0.001 (0.9939)	0.265 (0.2256)	0.099 (0.4268)	-0.487 (0.0009)	0.272 (0.2485)	-0.228 (0.4443)	-0.081 (0.0171)	-0.140 (0.5140)	0.061 (0.7840)
GEXP	..	0.376 (0.7404)	-2.733 (0.9911)	0.002 (0.7251)	-0.009 (0.1848)	0.001 (0.4674)	..	..	-0.014 (0.0332)	-0.145 (.0858)
GEXP_1	..	-0.407 (0.8108)	-0.002 (0.2704)	0.002 (0.0068)	0.005 (0.5738)	0.007 (0.0392)	..	..	-0.010 (0.3315)	-0.050 (0.3970)
P(remi)	0.001 (0.5173)	-0.526 (0.0484)	0.122 (0.7162)	-0.045 (0.0137)	-0.070 (0.8539)	-0.149 (0.0674)	0.016 (0.7184)	-0.453 (0.3159)	0.176 (0.4930)	-0.163 (0.4967)
P(remi)_1	-0.001 (0.5330)	-0.353 (0.2162)	-0.516 (0.0804)	0.007 (0.9635)	-0.563 (0.1761)	0.012 (0.8441)	0.007 (0.9822)	0.153 (0.7284)	-0.231 (0.27807)	0.116 (0.6552)

Table: 14 Results of LASSO for Growth Modeling with Final Model Specification

Country	Constant	LNREXP	LNGEXP	LNTLF	LNGCF	TOP	LNTOTP	RMSE
ALGERIA	0.052	0.01	0.1403	0.714	0.055	..	0.08	**0.138**
COLAMBIA	..	0.039	0.036	0.793	0.13	-0.013	0.014	**0.505**
COMBODIA	..	..	..	0.885	..	-0.03	..	**0.221**
COSTARICA	0.049	..	0.8168	..	0.033	..	..	**0.273**
GEORGIA	-0.014	0.044	0.3287	-0.783	0.119	..	0.336	**0.072**
ROMANIA	..	0.073	0.724	-0.261	0.339	..	0.056	**0.339**
Retention Frequency		**4**	**5**	**5**	**5**	**2**	**3**	

Table:15 Results of ALASSO for Growth Modeling with Final Model Specification

Country	Constant	LNGEXP	LNREXP	TOP	LNTLF	LNTOTP	RMSE
ALGERIA	0.077	1.813	2.046	-2.699	0.643	-2.22	**0.417**
COLAMBIA	-0.082	..	..	2.843	..	3.238	**0.504**
COMBODIA	0.809	..	..	..	..	0.1944	**0.26**
COSTARICA	..	3.745	..	..	..	1.593	**0.246**
GEORGIA	0.465	..	-0.598	-0.172	-2.921	..	**0.986**
ROMANIA	6.031	..	0.481	..	-4.44	..	**0.386**
Retention Frequency		**2**	**3**	**3**	**3**	**4**	

Table: 16 Results of Elastic Net for Growth Modeling with Final Model Specification

Country Name	Constant	LNGEXP	LNREXP	TOP	LNGCF	LNTLF	LNTOTP	INF	Tdebts	RMSE
ALGERIA	1.171	-1.047	0.821	0.187	0.836		..	..	1.755	**0.138**
COLAMBIA	4.891	0.482	..	0.418	..	1.747	0.074	..	..	**0.294**
COMBODIA	..	..	0.809		-0.012	..	-0.005	..	..	**0.221**
COSTARICA	0.398	..	0.289	6.081	..	..	..	0.071	..	**0.273**
GEORGIA	..	-0.628	-0.138	..	-1.308	..	..	0.202	..	**1.065**
ROMANIA	2297	0.003	..	1.003	-2.583	1.182	..	..	6.551	**0.705**
Retention		**4**	**4**	**4**	**4**	**2**	**2**	**2**	**2**	

Frequency										

Table: 17 Results of WALS for Growth Modeling with Final Model Specification

Country Name	Constant	LnGCF	LnTLF	LnRExp	TOP	LnTOTP	RMSE
ALGERIA	-3.299	.344	..	.268	..	.678	2.690
COLAMBIA	-7.443	.303	..	..	-.521	1.185	1.969
COMBODIA	3.485	.927	..	..	..	-.147	1.371
COSTARICA	..	.268	1.231	.400	-.441	..	0.473
GEORGIA	31.194	..	-2.022		-.088	1.451	1.108
ROMANIA	27.231	..	..	.124	..	..	0.031
Retention Frequency		04	02	03	03	04	

Table:18 Results of Encompassing for Growth Modeling with Final Model Specification

Country	Constant	LNGDP_1	LnRExp	LnRExp _1	LnGCF	LnGCF_1	TOP	TOP_1	Inf	Inf_1	LnTOTP	LnTOTP_1	RMSE
ALGERIA		0.602	0.367	-0.223	0.224	..	..	-0.146	..	0.007	-4.608	4.630	**1.568**
COLAMBIA	2.695	0.859	0.214	-0.093	0.162	-0.092	..	-0.254	..	-0.001 1	..	-0.234	**1.334**
COMBODIA	4.695	0.178	0.212	..	0.210	0.110	..	..	.. ..	..	1.945	-1.943	**0.422**
COSTARICA	..	0.781	0.314	-0.169	0.215	-0.138	..	-0.368	..	..	..	..	**1.144**
GEORGIA	6.133	1.116	..	..	..	..	-7.079	6.497	..	..	..	..	**0.533**
ROMANIA	..	..	0.123	-0.052	0.186	-0.141	..	..	..	..	..	.160221	**0.989**
Retention Frequency		**5**	**5**	**4**	**5**	**4**	**1**	**4**	**0**	**2**	**2**	**4**	

Table: 19 Results of Autometrics for Growth Modeling with Final Model Specification

Country Name	Constant	LNGDP_1	TOP	TOP_1	LnGCF	LnGCF_1	LnRExp	LnRExp_1	Inf	Inf_1	DI	DI_1	TDebtS	TDebtS_1	RMSE
ALGERIA	-0.851	0.625	..	-0.199	0.2032	..	0.433	-0.241	..	..	-0.066	..	..	..	0.077
COLAMBIA	..	0.902	..	..	0.161	-0.092	0.166	-0.150	..	..	-0.008	..	..	..	0.097
COMBODIA	8.068	0.142	..	..	..	0.150	0.323	..	..	..	0.001	..	..	..	0.022
SCOSTARICA	1.164	0.678	..	-0.390	0.154	-0.093	0.350	-0.141	-0.005	..		..	..	..	2.533
GEORGIA	..	0.883	-0.012	..	..	..	0.058	..	0.001	..	-0.003	..	0.075	..	1.016
ROMANIA	5.698	0.611	..	..	0.200	-0.123	0.098	..	..	..	..	..	..	..	1.826
Retention Frequency		**6**	**1**	**2**	**4**	**4**	**6**	**3**	**2**	**0**	**4**	**1**	**1**	**0**	

Table:20 Results of Extreme Bound Analysis for Growth Modeling with Final Model Specification

			Cons	LNGCF	LNTLF	FDI	TOP	LG	DI	TDebts	INF	LNTOTP	EDU	LNREXP	REMI
			Free	**Focus**	**Focus**	**Focus**	**Free**	**Free**	**Free**	**Free**	**Free**	**Free**	**Free**	**Free**	**Free**
Algeria	LEBA	LEB	-14.0	-1.1	-2.9	-0.5	0.0	-3.4	-0.1	0.4	0.0	0.0	-0.5	0.0	0.0
		UEB	-10.2	1.6	2.9	0.5	0.0	2.0	0.1	0.7	0.0	0.0	0.3	0.2	0.0
	SIMEBA	CDF(beta>0)	0.0	73.1	50.1	51.5	99.9	24.1	48.2	100.0	99.7	54.6	27.0	100.0	1.3
Colombia	LEBA	LEB	-14.5	-0.7	0.0	0.0	0.0	-0.6	0.0	1.0	0.0	0.0	0.0	-0.1	0.0
		UEB	-10.2	0.6	0.0	0.0	0.0	2.9	0.0	1.2	0.0	0.0	0.1	0.0	0.0
	SIMEBA	CDF(beta>0)	0.0	40.5	77.8	10.3	0.4	86.8	25.2	100.0	96.7	0.8	98.7	0.1	100.0
Cambodia	LEBA	LEB	-15.5	0.3	0.0	0.0	0.0	-2.5	-0.3	0.7	0.0	0.0	0.2	-0.1	-0.1
		UEB	-7.9	2.1	0.0	0.0	0.0	0.5	0.1	1.2	0.0	0.0	0.7	0.1	0.1
	SIMEBA	CDF(beta>0)	0.0	100.0	45.3	95.2	87.4	12.1	5.5	100.0	56.2	66.8	100.0	36.0	39.7
Costa Rica	LEBA	LEB	-8.8	-0.3	0.0	0.0	0.0	-0.2	0.0	0.1	0.0	0.0	0.0	-0.8	0.0
		UEB	-1.7	1.4	0.0	0.0	0.0	4.5	0.1	0.8	0.1	0.0	0.4	0.2	0.0
	SIMEBA	CDF(beta>0)	0.0	91.0	4.1	87.9	97.6	98.6	57.3	99.9	96.4	45.5	100.0	48.1	53.1
Georgia	LEBA	LEB	-23.7	-1.5	0.0	0.0	0.0	-2.7	-0.1	0.6	0.0	0.0	0.4	0.0	0.0
		UEB	-11.2	1.1	0.0	0.0	0.0	0.8	0.0	1.6	0.1	0.0	1.1	0.1	0.1
	SIMEBA	CDF(beta>0)	0.0	45.2	73.3	57.0	21.9	18.7	19.7	100.0	83.7	17.4	100.0	97.4	97.2
Romania	LEBA	LEB	-16.6	-0.7	0.0	0.0	0.0	-5.2	0.0	0.7	0.0	0.0	0.2	-0.1	0.0
		UEB	-13.3	1.1	0.0	0.0	0.0	5.6	0.0	1.1	0.0	0.0	0.5	0.1	0.0
	SIMEBA	CDF(beta>0)	0.0	53.6	75.3	63.4	10.8	67.9	89.0	100.0	48.0	52.6	100.0	79.8	42.3