MPHIL THESIS

EMPIRICAL COMPARISON OF NON-NESTED ENCOMPASSING TEST: APPLICATION TO INFLATION FUNCTION

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CERTIFICATE

This is to certify that this thesis entitled: **"Empirical Comparison of Non-Nested Encompassing Test: Application to Inflation Function"** submitted by Mr. Jawad Yasir Hadi is accepted in its present form by the Department of Econometrics and Statistics, Pakistan Institute of Development Economics (PIDE), Islamabad as satisfying the requirements for partial fulfillment of the degree in **Master of Philosophy in Econometrics**.

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بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

Dedicated to my beloved Father Hussain Bakhsh and

Mother Zarina Bano

My Inspiration, My Support & My World.

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Jawad Yasir

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List of abbreviations

ADF	Augmented Dickey Fuller
S2G	Simple to General
G2S	General to Specific
Y*	Potential GDP
OG	Output Gap
DGP	Data Generating Process
LDGP	Local Data Generating Process
GUM	General Unrestricted Model
ECM	Error Correction Model
FRMSE	Forecast Root Mean Square Error
SE	Standard Error

Abstract

Model selection is a fundamental issue in econometrics analysis. A major goal of econometric analysis is to develop an optimal model for observable phenomenon among various models. There are lots of procedures and criteria utilized for selecting model. Choice of model selection criteria depends on subjective judgement. General to specific methodology is theoretically superior wherever models could be nested in single large model. However general to specific is not feasible when the nested model becomes very large. In this situation, non-nested encompassing can be used for selecting models and is recommended by several authors.

However, it is generally not known that how good non-nested encompassing is, in terms of selecting good model. The aim of this study is to examine the performance of non-nested hypothesis test for model selection and to select better model through encompassing on the basis of forecast performance of the models.

On Forecast RMSE we found that Cox, Ericsson, Joint test have same power , and they chose the correct model for 13 out of 16 countries indicating 81 % power. Whereas, Sargan test chose the correct model for 11 out of 16 countries indicating 68 % power. So, Sargan is less suitable test for model selection than Cox, Ericsson, and Joint test.

Keywords: model selection criteria, nested encompassing, non-nested encompassing, forecasting.

Chapter 1

Introduction

1.1. Background of the study

Model selection is a fundamental issue in econometrics analysis. A lot of work has been carried out in the field of model selection literature but for model selection no strategy is considered to be the best in absolute terms because every criterion has some pros and cons.

A major goal of econometric analysis is to develop a model for observable phenomenon. There are lots of procedures and criteria utilized for selecting model. Choice of model selection criteria depends on subjective judgement and on the purpose of the model selection. The model selection procedures include:

Maximizing R Square /Minimizing SSE (Theil 1961), Stepwise selection which include forward selection and backward deletion, Information Criterion which include Akaike's Information Criterion (1973, 1974), Bayesian Information Criterion (1978), Focused Information Criterion (2003), Final Prediction Error (1970), Hannan-Quinn Criterion (1979), Efficient Determination Criterion (2001) etc., data mining, and encompassing.

The encompassing methodologies can further be divided into two i.e. nested encompassing which is also called general to specific and non-nested. There is lots of literature on general to specific methodology and many econometrician prefer this strategy over the alternatives. General to specific methodology is theoretically superior regarding nested encompassing[1]. However general to specific i.e. nested encompassing is not feasible when there are large number of determinants and the data is relatively small [Charemza and Deadman (1997)]. In

[1] For details see Charemza & Deadman (1997). New directions in econometric practice. *Books*.

such cases, the model becomes very large and cannot be easily handled through nested encompassing. Therefore, in this situation researcher has to choose non-nested encompassing. Another associated problem is that in real data, the true DGP is unknown and one can't use accuracy as a measure of performance. This is because it is not possible to determine whether or not the methodology has find the right model. However, in such situation forecast performance can be used as a measure of performance of selected model. The forecasting is the ability of the model to predict for the data that was never used in estimating the model. If the model is working better for the data it haven't seen, this means there is something better in the estimated model than the rival models. Therefore we will use forecast performance as measure of performance in terms of selecting the appropriate model.

To illustrate this, we use inflation modelling as case study. There are many models for inflation and choice of the right model is a point of concern for economists. We will investigate how good non-nested encompassing is for the choice of model for inflation.The appropriateness of model selection will be judged through forecast performance. The model having best forecast performance would be considered as the optimal model.

The non-nested encompassing test having highest probability of finding optimal model would be treated as optimal encompassing test.

1.2. Objective of the Study

The objective of our research is to examine the performance of non-nested hypothesis test for model selection and to select better model through encompassing on the basis of forecast performance of the models. We want to show how good non-nested encompassing criteria is in terms of selection of appropriate model for inflation. Among the four non-nested encompassing test, the test which will select best model most frequently on the basis of lowest S.E can be thought as best test.

1.3. Significance of the Study

Our study will help econometrician in selecting appropriate model selection strategy in a situation where nested encompassing fails. However general to specific i.e. nested encompassing is not feasible when the model becomes very large [Charemza and Deadman (1997)], so in this situation non-nested encompassing criteria can guides the researcher in selection of a good model.

As discussed, non-nested encompassing can be used as model selection strategy, however the properties of such tests are not known. This study will help researcher in choice of appropriate model selection strategy.

1.4. Organization of the study

This research is divided into five chapters. Chapter one is the introduction, objectives, and with the significance of this study, chapter two highlights the literature review, chapter three discussed the Econometric methodology and also discussed data and its construction. Chapter four deals with results and discussion and chapter five emphases on summary, conclusion and recommendation.

Chapter 2

Literature review

2.1. Background

The econometric analysis depends heavily on the accuracy of model selection. It is a fact that if a significant regressor is omitted from a regression equation, the results can be completely wrong and misleading (Zaman, 2017). But how can we tell whether or not a significant variable has been omitted? The regression itself will not provide us with any clues. All of the statistics can be very healthy, with high R-squares, significant t-statistics for all regressors, the correct signs, and everything else one could hope for in a regression. The missing variable does not signal its absence by any observable defects in the estimated equation. There is one situation where problems posed by the Axiom of Correct Specification have a potential solution. This is when theory and empirical evidence inform us that there is a very small set of regressors which determine the dependent variable (Zaman, 2017).

As we have discussed, omitted variables pose a significant threat to regression models, and imply that the original regression could be a purely nonsense regression. A natural way to try to solve this problem would be to add potentially relevant regressors to the set of regressors into a regression model. If at least one of the regressors proves significant, then it is immediately obvious that the original model is missing significant regressors. So far, this reasoning is correct, but the natural remedy of adding variable to fix the problem is not correct. That is because the significance of the added variable does not imply that, that specific variable is the missing variable. As we have seen, once an important variable is missing, any other variable which is correlated with the missing variable will appear to be significant (Zaman, 2017).

The fact that inferences can change dramatically if we change the sets of regressors was noted by Leamer (1978), and labelled the ‘fragility’ of conventional inference. The methodological theory taught in textbooks demands that a well specified model should exist in advance of empirical estimation; that is, we must know the true model, before we run the regression. The reality is very different. In practice, applied econometricians search through hundreds of models, looking for coefficients which match their presuppositions.

There is a chance of arriving at a good approximation to the true model. Thus The Axiom of Correct Specification requires that all relevant regressors must be included in a valid regression model. The best strategy currently in existence for finding the right regressors is the General-to-Simple modelling strategy of David Hendry. This is the opposite of standard simple-to-general strategy advocated and used in conventional econometric methodology. There are several complications in applying this strategy, which make it difficult to apply. It is because of these complications that this strategy was considered and rejected by econometrician. For one thing, if we include a large number of regressors, as GETS required, multicollinearities emerge which make all of our estimates extremely imprecise. Hendry’s methodology has resolved these, and many other difficulties, which arise upon estimation of very large models. This methodology has been implemented in Autometrics package within the PC-GIVE software for econometrics. This is the state-of-the-art in terms of automatic model selection, based purely on statistical properties. However, it is well established that human guidance, where importance of variables is decided by human judgment about real-world causal factors, can substantially improve upon automatic procedures.

The aim of econometric analysis in the model selection process is to develop a model for observable phenomenon and to discover true DGP. The key issue in the model selection literature is that: Are the models are ever true, or are the selected model exhibit full reality?

Data analysis practitioners say that surely models are only approximation to full truth [Burnham, *et al*. (2004)]. George Box made the famous statement, “All models are wrong but some are useful. So full reality is not extracted by any selected model by any selection strategy but we can find the model which is closest to the reality.

2.2. Stepwise Regressions

These include general to specific and specific to general procedure.

2.2.1. Forward Selection (Specific to General)

In this approach the most significant omitted explanatory variable is added to the model, one at a time. This selection stops when no further significant variable can be found. Forward selection method include variables early which in the long run we don’t desire to select in the model so results are misleading and biased i.e. Lovell biased occurs (1973).

General to specific modelling does seem to represent major advance over simple to general approaches, where models are successively complicated. Thus, for example, there is little theoretical justification for the common practice of adding new variables to a model because of evidence of serial correlation in the errors of fitted equation. Not only are conventional test statistics normally invalid in models with omitted variables, but there is no reason why two investigator starting from the same simple model will converge on the same final equation. If a test suggests an extension to a model, and subsequently another test on this extended model indicates some misspecification, then clearly the original decision to change the model in the way indicated was wrong. Accordingly, the entire approach is questionable. The major problem in simple to general approaches to econometric modelling is that if one starts with a misspecified model, then the attempt to improve upon this model by extending it on the basis of the statistical tests is likely to be based on erroneous statistical procedures. It was unstructured data mining and simple to general approach that led to the existence of a plethora of alternative models which so undermined the credibility of the econometrics to many people.

2.2.2. Backward Deletion (General to Specific)

If we start with all explanatory variable in the model and remove insignificant variables from the model one by one then it is backward deletion approach. Backward deletion excludes variables that are not the significant determinants of the dependent variable.

There is lots of literature on general to specific methodology and many econometrician prefer this strategy over the alternatives. General to specific methodology is theoretically superior regarding nested encompassing. However general to specific i.e. nested encompassing is not feasible when the model becomes very large, so in this situation non-nested encompassing is superior.

In Econometric model building, we can derive a good model by starting with the general model and finally reduced it by a sequence of tests of economically sensible restrictions. However, there need not be a unique model reduction sequence that leads from a general model to a specific form. The strength of general to specific modelling is that model construction proceeds from a very general model in a more structured, ordered fashion, and in this way avoids the worst excesses of data mining.

The charge of data mining that can be directed against the general to specific methodology seems to be potentially more serious where the investigator does not have a clear idea as to the specific form that the investigator should lead to. For example there were ten economically plausible models presented which could be derived from a general model. If the investigator were interested in only one of these, where the specific form of the general model was known. However, if the investigator has no firm view as to the specific form of the final model to be considered, the interesting question remains as to whether general to specific modelling can be viewed as a method of model simplification, that is as a method of discovery, rather than of confirmation. There is clear dilemma here. With a number of economic theories acceptable to the investigator, it seems inevitable that a data mining problem exists.

General to specific modelling may well lead to multiple admissible models not nested within each other. There is no systematic way of ordering the sequence of tests in general, but the particular sequence adopted could be crucial in the selection of the specific form finally selected. Charemza, we can have single model that leads to a variety of theoretical models, this provides natural way of selection among the rival models.

2.3. Non-nested encompassing tests

2.3.1. Cox Test (1961, 1962)

Cox (1961, 1962) presented influential work in the field of non-nested hypothesis testing. According to Cox the selected model should be as effective to foresee the pertinent traits of alternative models. Cox type of tests are effective when the functional form of models are different. Here H_0 is our null hypothesis and H_1 is our alternative hypothesis. Likelihood ratio test give us relative analysis of real performance of H_1 with the expected performance of the $H_1E\ (H_1)$ under H_0. A correct null hypothesis H_0 will not misinterpret the actual performance of the alternative hypothesis H_1.

The design of Cox's test is based on likelihood ratio test statistic. Cox test statistics display that log-likelihood ratio and the expected log-likelihood ratio are extricate under H0. Let hypothesize H_0, $L_0\ (\hat{\theta}_0)$ is the MLE of a given set of values "y" and hypothesize H_1, $L_1\ (\hat{\gamma}_1)$ is the MLE of a given set of values "y".

Separate families hypothesis are as follows:

$$H_0: \quad y = Xb_0 + u_0;\ u_0 \sim N(0, \sigma_0^2 I) \text{ ------------- } (i)$$

$$H_1: \quad y = Zb_1 + u_1;\ u_1 \sim N(0, \sigma_1^2 I) \text{ ------------- } (ii)$$

$$\hat{l}_{01} = lnL_0(\hat{\theta}_0) - lnL_1(\hat{\gamma}_1) \text{ -------------- } (iii)$$

Cox test statistic's numerator is the difference of log likelihood ratio and expected log-likelihood ratio under the null.

$$T_0 = \hat{l}_{01} - E(\hat{l}_{01}) \text{ -------------- } (iv)$$

Now Cox test statistics is obtained by dividing above equation by standard deviation.

$$N_0 = \frac{T_0}{\sqrt{[V(T_0)]}} \sim N(0, 1) \text{ ------------- } (v)$$

2.3.2. Pesaran (1974)

The work of Pesaran (1974) was the extension of the Cox's (1961, 1962) work. He proposed a methodology for testing non-nested models and innovated modified likelihood-ratio test different from classical likelihood-ratio test.

First of all we have to set a comprehensive model, this model will contain both the models H_0 and H_1 and after that likelihood-ratio test can be applied. Likelihood function of model, H_0 is denoted by $\bar{L}_0(\alpha/y)$ and H_1 is denoted by $\bar{L}_1(\beta/y)$, so in general for comprehensive model can be written as follow:

$$\bar{L}(\alpha, \beta, \theta/y) = F(L_0, L_1, \theta)$$

Following are the hypothesis belonging to separate families:

$$H_0: \quad y = Xb_0 + u_0;\ u_0 \sim N(0, \sigma_0^2 I) \text{ ------------- } (vi)$$

$$H_1: \quad y = Zb_1 + u_1;\ u_1 \sim N(0, \sigma_1^2 I) \text{ ------------- } (vii)$$

$\therefore z_t = \gamma x_t + v_t$

In this paper Cox test is employed according to the need. X and Z are independent of each other i.e. they are non-nested. Following limits are to be imposed while moving forward in this analysis.

$$lim_{n\to\infty}\left(\frac{X'X}{n}\right) = \Sigma X'X$$

$$lim_{n\to\infty}\left(\frac{Z'Z}{n}\right) = \Sigma Z'Z$$

$$lim_{n\to\infty}\left(\frac{X'Z}{n}\right) = \Sigma X'Z$$

$\therefore\ the\ matrices\ \Sigma X'X\ and\ \Sigma Z'Z\ are\ non-singular\ and\ \ \Sigma X'Z\ \neq 0$

To test the hypothesis H_i = *(H_0, H1)*, Pesaran used the cox statistics which are as follow:

$$N_i = \frac{\boldsymbol{T_i}}{\sqrt{[\boldsymbol{\hat{V}(T_i)}]}} \sim N\ (0, 1) \text{ ------------- } (viii)$$

Where,

$T_0 = \frac{n}{2}\ \ln(\frac{\hat{\sigma}_0^2}{\hat{\sigma}_{10}^2})$,

$\hat{V}_0 = (\frac{\hat{\sigma}_0^2}{\hat{\sigma}_{10}^4})\hat{\beta}_0' X_0' M_1 M_0 M_1 X_0 \hat{\beta}_0$,

$\hat{\sigma}_{10}^2 = \hat{\sigma}_0^2 + \frac{n}{2}\hat{\beta}_0' X_0' M_1 X_0 \hat{\beta}_0$,

$M_0 = I_n - X_0(X_0' X_0)^{-1}$

2.3.3. Sargan Test (1958, 1959)

Sargan had an extensive work on instrumental variables statistics. He developed the test statistics in 1958. Basic purpose of his paper was to deal with measurement error and simultaneity problem in exogenous variables. As linearity can be a major cause of measurement error in models. So Sargan developed another paper in 1959 extended his work of 1958 in which he took instrumental variable models that were linear in variables but non-linear in parameters.

Following are the test statistics used:

$$c_0 = \frac{y'(N - Q_0)y}{\hat{\sigma}_0^2}$$

$y = X_i a_i + \mu_i$

$N = Z(Z'Z)'Z'$

$Q_i = NP_i = NX_i(X_i'NX_i)^{-1}X_i'N \qquad i = 0$

$\tilde{\sigma}_0^2 = (y - X_0\tilde{a}_0)'(y - X_0\tilde{a}_0)/(n - k_0)$

2.3.4. Ericsson Test (1983)

Ericsson in his paper tested non-nested hypothesis for which he developed statistics based on Instrumental Variables, asymptotic distribution of both IV statistics and ML statistics are derived and at the end a comparison is made between the non-nested and nested tests on the basis of their asymptotic power.

Following are the hypothesis and test statistics and its explanation used is this paper:

$$H_0: \quad y=X_0 a_0 + u_0;\ u_0 \sim N(0,\sigma_0^2 I) \text{ -------------(x)}$$

$$H_1: \quad y=X_1 a_1 + u_1;\ u_1 \sim N(0, \sigma_1^2 I) \text{ ------------- (xi)}$$

$$t_6 = \frac{v'(Q_1 - P_0'Q_1P_0)v}{2\tilde{\sigma}_0\{v'P_0'P_1'(N-Q_0)P_1P_0v\}^{1/2}} \quad \text{------------- (xii)}$$

Where,

$N = Z(Z'Z)'Z'$

$P_i = X_i(X_i'NX_i)^{-1}X_i'N$

$Q_i = NP_i = NX_i(X_i'NX_i)^{-1}X_i'N \qquad i = 0,1,2$

$$\tilde{a}_{\iota} = \{X_i' Z(Z'Z)^{-1}Z'X_i\}^{-1}X_i'(Z'Z)^{-1}Z'v$$

$$\tilde{\sigma}_i^2 = \frac{(v-X_i\tilde{a}_i)'(v-X_i\tilde{a}_i)}{(n-k_i)}$$

$$\tilde{\mu}_i = v - X_i\tilde{a}_{\iota}$$

$$v = X_i a_i + \mu_i$$

2.4. Comparison of Model Selection Strategies

There are different comparison exists in the Econometrics literature.

2.4.1. Comparison of Information Criteria

Econometrician proposed different methods and estimation technique to select the appropriate model with respect to time. Most of the procedures involved minimizing the loss information based on the least square and maximum likelihood.

The mostly used model selection criteria are Akaike information criterion (1973, 1974), Bayesian information Criterion (1978), cross-validation methods [Golub, *et al*. (1979)] etc. These criteria are not enough to guarantee the congruence of the model and it is also possible to select the miss-specified models [Bontemps and Mizon (2008)]. Models should not be selected on the basis of model fit criteria [Hendry and Krolzig (2005)] as model selection criteria's are not enough to select suitable model.

There is a vast literature available on the Bayesian model selection procedure. The assumption of prior probabilities for the individual models are required by the Bayesian model selection procedure and the posterior probabilities are derived from the model and their parameters. Mixture of models are selected by Bayesian method and it can create uncertainty (see for detailed Raftery and Volinsky 1999). The extreme bound analysis is developed by Leamer (1978, 1983, and 1985) and this is another form of Bayesian procedure. He disagreed that inference is only robust if the specification assumption is enough to nest the data generating process. Hendry and Mizon (1990) and Breush (1990) has disapproved this method. Hendry and Mizon (1990) disagreed that conventional procedure do not exhibit the issues of model selection as a results most of the economic models are miss-specified in empirical studies.

2.4.2. Comparison of Forward Selection / Backward Deletion

2.4.2.1. Forward Selection

For model selection simple to general is another technique, in which simple model is tested against the data successively. The deficiency identified by Hendry and Krolzig (2001) of this approach is as follows:

There is no ending point for model specification in simple to general technique if the model is supposed to be outside the sample and many rejection of tests may be possible. It is not clear that which factor cause to reject the test if one or more tests reject. So misspecification problem arises and we cannot apply restrictions to final model.

This strategy starts from the theoretical model with many auxiliary assumptions. When model is poorly fit to data than we relax auxiliary assumption by using the statistical tests for a more general model and patching the original theoretical model [Gilbert (1986)].

2.4.2.2. Backward Deletion

Hendry methodology, London schools of economics (LSE) methodology and PcGets are different names of general to specific approach. The London School of econometrics proposed the empirical modelling methodology. The theory of reduction exhibits how statistical models are basically a kind of empirical model derived from the data generating process. Empirical model are based on the theory of reduction. The main purpose of the theory of reduction is to analyze probability concept that is used in a simplification method of the empirical model [Hendry (1995)]. In general to specific modelling Data generating process (DGP) is changed by the idea of local data generating process (LDGP) in G2S. The LDGP is the joint distribution of the subset of variables under analysis [Hendry (2000b)].

In practice econometrician obtain final model by the use of general-to-specific approach which follow the theory of reduction. The paper of Davison et al (1978) is the base of general to specific modelling. The general to specific methodology is a realistic example of the theory of reduction which is related to the DGP [Hendry (1983)].

The general unrestricted model (GUM) is prepared on the theoretical basis and then the GUM is reduced step down by testing the realistic economic restrictions to get parsimonious model.

There is lots of literature on general to specific methodology and many econometrician prefer this strategy to the alternatives. General to specific methodology is theoretically superior regarding nested encompassing. However general to specific i.e. nested encompassing is not feasible when the model becomes very large, so in this situation non-nested encompassing becomes the feasible option.

2.4.3. Comparison of Information Criteria / Forward Selection

Information based criterion are not sufficient to ensure the congruence of the model and it is also possible to select the miss-specified models [Bontemps and Mizon (2008)]. These criteria's are not enough to select the appropriate model because model should not be selected on the basis of model fit criteria [Hendry and Krolzig (2005)].

This approach has criticized by the Hendry and Mizon (1990) and Breush (1990). Hendry and Mizon (1990) argued that conventional criteria do not address the issues of model selection as a results most of the economic models are miss-specified in empirical studies.

On the other hand S2G model strategy has no ending point for model specification if the model is supposed to be outside the sample and many rejection of tests may be possible. It is not clear that which factor cause to reject the test if one or more tests reject. So misspecification problem arises and we cannot apply restrictions to final model.

2.4.4. Model Selection and Encompassing literature

Hendry, *et al*.(2011), highlighted three different criteria to gauge any method of model selection that is the local data generation process (LDGP) can be retrieved when begins from the LDGP itself; the operating characteristics of the selection procedure match their required properties; and the method finds a well-specified, undominated model of the LDGP. They concluded that model selection based on *Autometrics* using relatively tight significance levels and bias correction is a successful approach to selecting dynamic equations even when commencing from very long lags to avoid omitting relevant variables or dynamics.

Fugen Song, *et al*. (2014), worked over single forecasting model selection in combination forecasting through cointegration test first and encompassing test method then and concluded that the forecasting accuracy has improved to a certain extent after single model selection.

Kato, *et al*. (2005), worked over Bayesian selection of models that can be specified using inequality constraints among the model parameters and concluded that Bayes factor for the encompassing and a constrained model has a very nice interpretation. They used three examples: an analysis of variance with ordered means; a contingency table analysis with ordered odds-ratios; and a multilevel model with ordered slopes and concluded that for a specific class of models, selection based on encompassing priors will render a virtually objective selection procedure.

Busetti, *et al*. (2013) analysed the size and power properties of several tests of equal Mean Square Prediction Error (MSPE) and of Forecast Encompassing (FE) are evaluated, using

Monte Carlo simulations and concluded that for nested models, the F-type test of forecast encompassing proposed by Clark and McCracken (2001) displays overall the best properties. Empirically he take the nested and non-nested models for GDP in Italy and the euro-area. For comparison he used the following tests: the standard Diebold Mariano test of equal MSPE; the $MSE - t$ and the $MSE - F$ modifications of McCracken (2007) for nested models; the forecast encompassing test of Harvey, Leybourne and Newbold (1998); the *ENC –t,* and *ENC - F* modifications of Clark and McCracken (2001); the forecast encompassing test of Chao, Corradi and Swanson (2001) for nested models.

2.5. Literature Gap

Non-nested encompassing performance has not been evaluated for real data. There are various non-nested encompassing tests are available in literature but mutual comparison does not exist. Busetti, *et al*. (2013) take the nested and non-nested models for GDP in Italy and the euro-area using Monte Carlo simulations and concluded that for nested models, the F-type test of forecast encompassing proposed by Clark and McCracken (2001) displays overall the best properties. Alam (2017) have made the comparison of non-nested encompassing tests and he compared these tests by Monte Carlo simulation technique which will lead to the power and size performance of the tests but in our study I compare non-nested encompassing tests on the basis of prediction error for real data.

Chapter 3

METHODOLOGY AND DATA DESCRIPTION

3.1. Methodology

We want to evaluate and compare performance of various non-nested encompassing tests on the basis of their performance in real data. We are using the inflation function for this comparison. There are many models for inflation. If models are estimated with few observations left for forecast evaluation, the forecast can help to choose best model. We will use inflation data in such a way that 90 % observations are used to estimate and select models, whereas remaining 10 % are used to evaluate performance. For this we utilize the approach which is summarized as under:

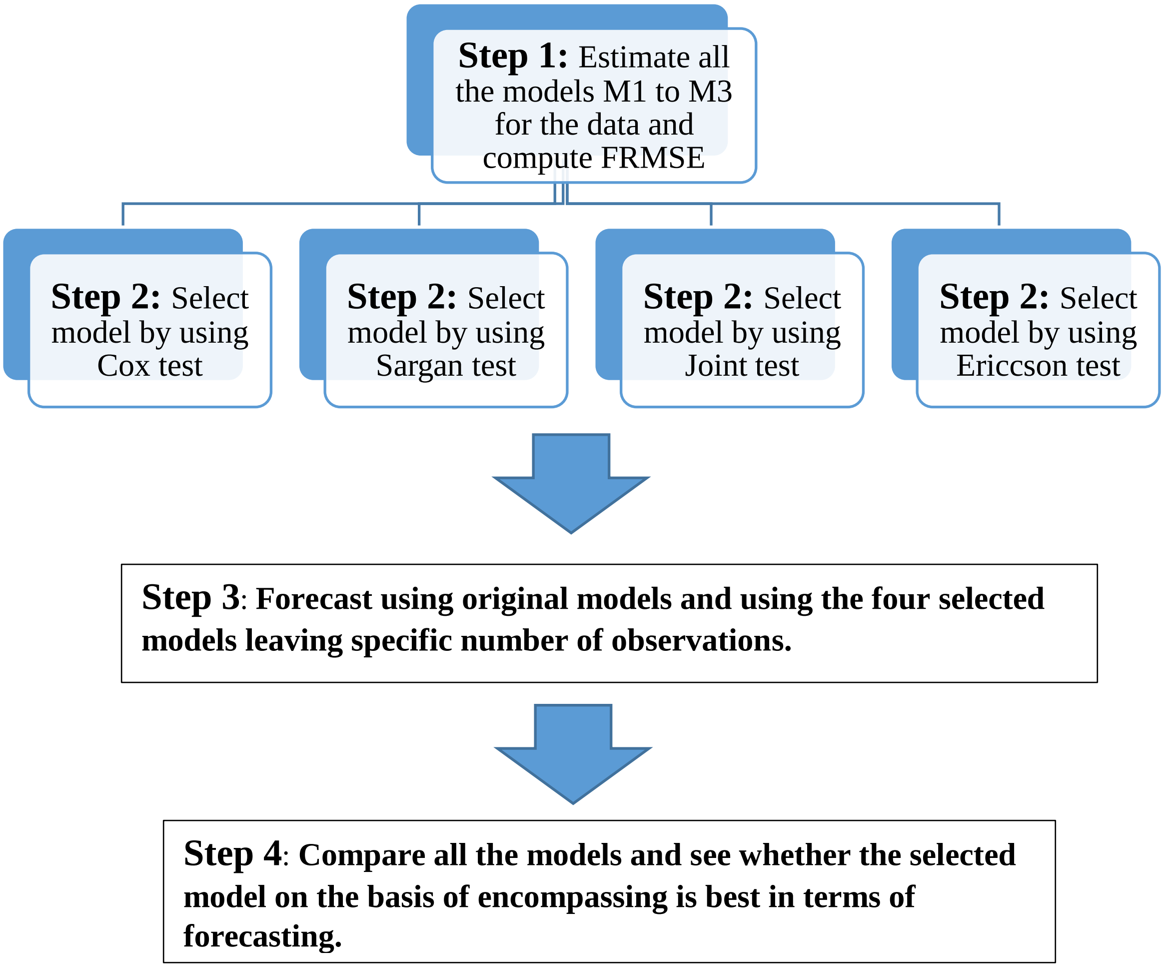
In step 1 we will estimate all the three non-nested models and estimate their forecast root mean square error (FRMSE) and standard error of regression. Rank Standard error of regression and select the model with minimum SE. In step 2 we will apply four non-nested encompassing tests on the three non-nested models of inflation and select four models whether different or same. The model selected by Cox test will name as M*c. Similarly the models selected by Cox (1961), Sargan (1958), Joint test [Davidson and MacKinnon (1981)] and Ericcson (1983) tests named as M*c, M*s, M*j and M*e respectively. Find the FRMSE of the four selected models by encompassing tests.

We have seven models named as M1[2], M2[3], M3[4], M*c, M*s, M*j and M*e. Now compare all the seven models on forecast performance and see whether the selected model on the basis of encompassing test is best in terms of forecasting.

[2] M1 is Model 1 based on Quantity Theory of Money.
[3] M2 is Model 2 Macroeconomics based inflation model.
[4] M3 is Model 3 P-Star Inflation model.

If all the tests or at least two tests end up with same model that is they have same forecast root mean square error, this would mean that they have same performances.

Detail of methodology by flow chart.



Explanation of each of non-nested encompassing test in **step 2** is as follows:

1. Assume that we have M1, M2…. Up to Mn non-nested models used in our study.
2. Now estimate all the given set of models M1, M2….Mn for the data and compute standard error (S.E) of regression. Select that model which has lowest standard error of regression because the model which encompasses other rival models must have lower standard error of regression (Hoover and Perez, 1999).

3. Suppose M_i is the model which has lowest S.E of Regression, then we will proceed as follows.

$$H_0(1): M_i \text{ encompass } M_1$$

$$H_0(2): M_i \text{ encompass } M_2$$

$$H_0(\text{n}): M_i \text{ encompass } M_n$$

We apply non-nested test statistics Cox (1961), Sargan (1958), Joint test [Davidson and MacKinnon (1981)] and Ericsson (1983). All the models which are encompassed by M_i are considered as less predictive power than M_i and M_i represent their prediction power. The model whose H_0 is rejected will be considered as not encompassed by M_i.Suppose that model is M_k, and its prediction power is not represented by M_i.

4. For optimal model we will take union of M_i and M_k.

Explanation of **step 3** is as follows:

1- The selection shall be done separately with four encompassing tests and optimal model shall be obtained from all four tests.

2- Let M*c denote the model selected by Cox test, M*s denote the model selected by Sargan test, M*e denote the model selected by Ericsson test, and M*j denote the model selected by Joint test.

3- The model M1, M2, M3 and the models M*c, M*s, M*j and M*e shall be re-estimated leaving five observations for testing the forecast performance.

4- The Forecast Root Mean Square Error (FRMSE) shall be calculated using the original observations and the forecasts for the observations reserved for forecasting.

3.2. Various theoretical models of inflation and detail of models used in our study

There are mainly two types of models that are used by the researchers, one based on theories known as structural modeling and second based on the behaviour of the data is known as time series modeling. In time series modeling researcher assume that the data have all the related and enough information to interpret the behaviour of a variable.

As required by the encompassing methodology, we plan to compare all these models within a common framework. Our approach is non-nested, where we compare theoretic models without attempting to nest them.

Among the structural model, I will use models based on quantity theory of money, aggregate demand -aggregate supply model, P-star model.

3.2.1. Model based on Quantity Theory of Money

The quantity theory of money (QTM) was proposed by Irving Fisher in the beginning of 20's century states that money supply and price level has a direct, positive relationship. This theory relates money supply (M), velocity of money (V), prices (P), real income (Y) and can be written as

$$PY = MV \qquad 3.1$$

Taking log on both sides we have

$$p = m + v - y \qquad 3.2$$

By differentiating on both side we have

$$\frac{1}{P}\frac{dP}{dt} = \frac{1}{M}\frac{dM}{dt} + \frac{1}{V}\frac{dV}{dt} - \frac{1}{Y}\frac{dY}{dt}$$

$$\frac{P^{\cdot}}{P} = \frac{M^{\cdot}}{M} + \frac{V^{\cdot}}{V} - \frac{Y^{\cdot}}{Y}$$

$$g_p = g_m + g_v - g_y \qquad 3.3$$

Equation (3.3) shows that growth in prices (g_p) is function of growths of money supply (g_m), growth of velocity(g_v) , and growth in real income(g_y) . Quantity theory identifies that money supply is the key factor that effects the changes in price level as V and Y remain almost constant. Econometric counterpart of (3.3) is as follows.

$$\pi_t = \beta_0 + \beta_m g_m + \beta_v g_v + \beta_y g_y + \vartheta \qquad 3.4$$

Equation (3.4) shows that growth in money supply, growth in real income, growth in velocity and some other hidden factors determine the CPI inflation(π_t). Theory suggests that $\beta m > 0$ $and\ \beta v > 0$ whereas $\beta y < 0$. As growth of real income is determined by labor, capital and technology, these factors are independent of growth of money. Growth of velocity of money is a function of financial structure, budget deficit etc. These are relatively unaffected by the growth of real money supply. Equation (3.4) will be used for estimation and further research.

3.2.2. Macroeconomics based inflation model

Another approach to determine the major factors governing the behaviour of inflation is based on aggregate supply and demand based macroeconomic models. It is based on the theory of John Maynard Keynes presented in his work The General Theory of Employment, Interest and Money.

$$\pi_t = \gamma_1 Y_t^g + \gamma_2 m_t - \gamma_3 Y^* + \varphi \sum_{i=0}^{n} \theta_i \pi_{t-1-i} + \vartheta_t \qquad 3.5$$

Equation (3.5) states that current inflation (π_t) depends upon output gap(Y_t^g), aggregate amount of money in circulation for given period of time in an economy(m_t), lagged values of inflation (π_{t-1-i})and potential output (Y*). Usually researchers take import prices as a supply side shock as it is exogenous and independent of domestic economic environment. The equation (3.5) will become

$$\pi_t = \gamma_1 Y_t^g + \gamma_2 m_t - \gamma_3 Y^* + \varphi \sum_{i=0}^{n} \theta_i \pi_{t-1-i} + \gamma_4 Imp_t + \epsilon_t \qquad 3.6$$

We will use this equation for estimation and encompassing purpose.

3.2.3. P-Star Inflation model

Halman, Porter and Small (1989) developed the P-Star model. They said that the price level is determined by the ratio of money stock to potential output and long run equilibrium level of velocity of money. It is developed on the long-term QTM and therefore combines the factors of the price level in long term with changes in current inflation in short term. In P-Star model price level is define as the total money stock in an economy per unit of potential output.

$$P^* = MV^*/Y^* \qquad 3.7$$

Where M is the total domestic money stock and V^* and Y^* are respectively values of the velocity of M and potential output in long run.

The central idea of the P-Star model is that the price level converges to an equilibrium which is largely determined by the domestic liquidity. A consequence of this outcome is that the price gap- is supportive in forecasting future inflation. However the crucial conclusion is that the changes in money stock can influence the CPI and, thereby, the long run price level.

In the P-star model, prices follow the error-correction mechanism" (ECM) to adjust to the potential level. The P-star model is usually estimated as:

$$\pi_t = \alpha_0 + \alpha_1 (p_{t-1} - p_{t-1}^*) + \sum_{i=0}^{n} \beta_i \pi_{t-1} + \mu_t \qquad 3.8$$

The coefficient α_1 is the speed of adjustment of prices to P* and the coefficients of β_i represent the lag of the actual rate of inflation. We will use this model for estimation and encompassing.

There are many other models for inflation but most of them are nested in the above models.

3.3. Data description

As the data is available for these countries so, we take annual time series data of 8 lower middle income countries and 8 upper middle income countries of the world from 1980 to 2016 and select the optimal model of inflation for each country included in our research.

The data is collected from International Financial Statistics (IFS) and World Development Indicator (WDI). The software package used in our research is Ox-Metrics and E-views. Countries included in Lower middle income group are India (Ind), Pakistan (Pak), Sri Lanka (Sri), Korea (Kor), Indonesia (Indo), Nigeria (Nig), Cameroon (Cam), Kenya (ken), and countries included in upper middle income group are Turkey (Turk), Thailand (Thai), Paraguay (Parg), Iran (Iran), Colombia (Col), South Africa (S.A), Fiji (Fij), Malaysia (Mal).

Chapter 4

Results and Discussion

4.1. Introduction

In this chapter, we compare our selected model's FRMSE after encompassing with the three model's FRMSE before encompassing and check whether non-nested encompassing approach improves forecasting performance of the models or not. For this purpose we use four non-nested encompassing tests namely Cox, Sargan, Joint and Ericsson.

4.2. Forecast Performance of Lower Middle Income Countries

As given in table 4.2.1 below in case of Indonesia model 1 (M1) has the lowest standard error so, we assume M 1 to be best model, and test whether this model encompasses remaining two models. Results of non-nested encompassing tests that is Cox and Ericsson show that model 1 encompasses model 2 but not encompasses model 3. The finally selected model should also have the variables of M3 and the finally selected model becomes union of M1 and M3. In this case the forecast performance of M1UM3 improves. Whereas Sargan, and joint test show that Model 1 does not encompass model 2 and model 3. The finally selected model should also have the variables of M2 and M3. The finally selected model becomes union of M1, M2, and M3. In this case the forecast performance of M1UM2UM3 improves.

In case of Kenya model 1 (M1) has the lowest standard error so, we assume M 1 to be best model, and test whether this model encompasses remaining two models. Results of all non-nested encompassing tests that is Cox, Ericsson, Sargan, and Joint show that model 1 encompasses other two models. This shows the forecast ability of M2 and M3 is already present in M1, therefore no need of augmentation on M1 and M1 is the finally selected model whose forecasting ability is better than other models.

In case of India model 1 (M1) has the lowest standard error so, we assume M 1 to be best model, and test whether this model encompasses remaining two models. Results of non-nested encompassing tests that is Cox and Ericsson show that model 1 encompasses model 3 but not encompasses model 2. The finally selected model should also have the variables of M2 and the finally selected model becomes union of M1 and M2. In this case the forecast performance of M1UM2 improves. Whereas Sargan and joint test show that Model 1 encompasses other two models. This shows the forecast ability of M2 and M3 is already present in M1, therefore no need of augmentation on M1 and M1 is the finally selected model whose forecasting ability is better than other models**.**

Similarly in case of Pakistan and Nigeria like Kenya, results of all non-nested encompassing tests that is Cox, Ericsson, Sargan, and Joint show that model 1 encompasses other two models and model 1 (M1) is the finally selected model whose forecasting ability is better than other models**.**

Similarly Model (M1) to be best model in case of Sri Lanka, and test whether this model encompasses remaining two models. Results of non-nested encompassing tests that is Cox, Ericsson, and Sargan show that model 1 encompasses other two models so, M1 is the finally selected model whose forecasting ability is better than other models. Whereas joint test show that M1 does not encompass M2. The finally selected model should also have the variables of M2. The finally selected model becomes union of M1 and M2. Result of finally selected model show relatively poor forecast performance. Means null is rejected i.e. best model does not encompass other model. So, in this situation we will take union of both models.

In case of Korea model 1 (M1) has the lowest standard error so, we assume M 1 to be best model, and test whether this model encompasses remaining two models. Results of non-nested encompassing tests that is Cox and Ericsson show that model 1 encompasses model 2 but not encompasses model 3. The finally selected model should also have the variables of M3 and the finally selected model becomes union of M1 and M3. In this case the forecast performance of M1UM3 improves. Whereas Sargan, and joint test show that Model 1 does not encompass model 2 and model 3. The finally selected model should also have the variables of M2 and M3. The finally selected model becomes union of M1, M2, and M3. In this case the forecast performance of M1UM2UM3 improves.

In case of Cameroon model 1 has the lowest standard error so, we assume M 1 to be best model, and test whether this model encompasses remaining two models. Results of non-nested encompassing tests that is Cox and Ericsson show that model 1 encompasses other two models. This shows the forecast ability of M2 and M3 is already present in M1, therefore no need of augmentation on M1 and M1 is the finally selected model whose forecasting ability is better than other models. Whereas Sargan and joint test show that Model 1 encompasses model 3 but not encompasses model 2. The finally selected model should also have the variables of M2 and the finally selected model becomes union of M1 and M2. In this case the forecast performance of M1UM2 improves.

Table 4.2.1 S.E and FRMSE of Lower Middle Income Countries

Countries Names	Models	S.E (FRMSE)	Tests	M1 Encompasses M2	M1 Encompasses M3	Finally Selected Model	S.E (FRMSE) Final Model
Indonesia	M 1	0.024 (0.03)	Cox	-1.290 [0.1969]	3.629 [0.0003]**	M1UM3	0.0145 (0.0069)
	M 2	7.763 (7.40)	Ericsson	1.216 [0.2240]	3.414 [0.0006]**	M1UM3	0.0145 (0.0069)
	M 3	9.088 (3.18)	Sargan	18.51 [0.0024]**	18.03 [0.0004]**	M1UM2UM3	0.0165 (0.0068)
	Optimal Model	M1	Joint	7.414 [0.0002]**	12.97 [0.0000]**	M1UM2UM3	0.0165 (0.0068)
Kenya	M 1	0.025 (0.02)	Cox	-0.7389 [0.4600]	-0.8389 [0.4015]	M1	0.0255 (0.029)
	M 2	8.112 (5.99)	Ericsson	0.6965 [0.4861]	0.7893 [0.4299]	M1	0.0255 (0.029)
	M 3	8.358 (1.91)	Sargan	6.1647 [0.2905]	2.7431 [0.4330]	M1	0.0255 (0.029)
	Optimal Model	M1	Joint	1.2889 [0.2977]	0.90604 [0.4506]	M1	0.0255 (0.029)
India	M 1	0.003 (0.006)	Cox	2.601 [0.0093]**	-1.402 [0.160]	M1UM2	0.0032 (0.0057)
	M 2	2.721 (1.53)	Ericsson	-2.453 [0.0142]*	-1.320 [0.186]	M1UM2	0.0032 (0.0057)
	M 3	2.776 (3.37)	Sargan	10.151 [0.0711]	2.044 [0.5632]	M1	0.0036 (0.006)
	Optimal Model	M1	Joint	2.5132 [0.0542]	0.659 [0.5841]	M1	0.0036 (0.006)
Pakistan	M 1	0.008 (0.006)	Cox	-0.8219 [0.4111]	-1.663 [0.096]	M1	0.0081 (0.0065)
	M 2	3.093 (6.97)	Ericsson	0.7747 [0.4385]	1.564 [0.1178]	M1	0.0081 (0.0065)
	M 3	3.087 (3.43)	Sargan	3.7217 [0.5901]	2.811 [0.4216]	M1	0.0081 (0.0065)
	Optimal Model	M1	Joint	0.70946 [0.6215]	0.9308 [0.438]	M1	0.0081 (0.0065)
Sri-Lanka	M 1	0.014 (0.008)	Cox	-0.3775 [0.7058]	-1.561 [0.1186]	M1	0.0143 (0.0082)
	M 2	4.674 (3.57)	Ericsson	0.3559 [0.7219]	1.46 [0.1420]	M1	0.0143 (0.0082)
	M 3	4.837 (4.49)	Sargan	10.672 [0.0583]	7.087 [0.0692]	M1	0.0143 (0.0082)
	Optimal Model	M1	Joint	2.7022 [0.0418]*	2.766 [0.0604]	M1UM2	0.0121 (0.0205)
Cameroon	M 1	0.026 (0.01)	Cox	1.172 [0.2413]	1.518 [0.1290]	M1	0.0260 (0.014)
	M 2	6.317 (6.05)	Ericsson	-1.105 [0.2691]	-1.429 [0.1529]	M1	0.0260 (0.014)
	M 3	6.287 (1.33)	Sargan	17.72 [0.0033]**	6.3527 [0.0957]	M1UM2	0.0174 (0.0091)

	Optimal Model	M1	Joint	6.705 [0.0004]**	2.4056 [0.0884]	M1UM2	0.0174 (0.0091)
Korea	M 1	0.005 (0.01)	Cox	0.9376 [0.3485]	-2.91 [0.003]**	M1UM3	0.0037 (0.0083)
	M 2	1.946 (11.40)	Ericsson	-0.8842 [0.3766]	2.744 [0.006]**	M1UM3	0.0037 (0.0083)
	M 3	2.161 (5.06)	Sargan	19.208 [0.0018]**	13.806 [0.003]**	M1UM2UM3	0.0246 (0.0031)
	Optimal Model	M1	Joint	8.108 [0.0001]**	7.494 [0.0008]**	M1UM2UM3	0.0246 (0.0031)
Nigeria	M 1	0.085 (0.07)	Cox	1.554 [0.1202]	1.566 [0.1173]	M1	0.085 (0.071)
	M 2	14.391 (8.70)	Ericsson	-1.467 [0.1425]	-1.476 [0.1401]	M1	0.085 (0.071)
	M 3	14.229 (9.12)	Sargan	4.1473 [0.5284]	3.2759 [0.3510]	M1	0.085 (0.071)
	Optimal Model	M1	Joint	0.80399 [0.5568]	1.1028 [0.3645]	M1	0.085 (0.071)

4.3. Forecast Performance of Upper Middle Income Countries

As given in table 4.3.2 below in case of Turkey model 1 (M1) has the lowest standard error so, we assume M 1 to be best model, and test whether this model encompasses remaining two models. Results of non-nested encompassing tests that is Cox, Ericsson, Sargan, and Joint tests show that model 1 does not encompass model 2 and model 3. The finally selected model should also have the variables of M2 and M3. The finally selected model becomes union of M1, M2, and M3. Result of finally selected model show relatively poor forecast performance. In case of Thailand model 1 has the lowest standard error so, we assume M 1 to be best model, and test whether this model encompasses remaining two models. Results of non-nested encompassing tests that is Cox, Ericsson, and Sargan show that model 1 encompasses other two models. This shows the forecast ability of M2 and M3 is already present in M1, therefore no need of augmentation on M1 and M1 is the finally selected model whose forecasting ability is better than other models. Whereas joint test show that Model 1 encompasses model 3 but not encompasses model 2. The finally selected model should also have the variables of M2 and the finally selected model becomes union of M1 and M2. Result of finally selected model show relatively poor forecast performance.

In case of South Africa model 1 (M1) has the lowest standard error so, we assume M 1 to be best model, and test whether this model encompasses remaining two models. Results of all non-nested encompassing tests that is Cox, Ericsson, Sargan, and Joint show that model 1 encompasses other two models. This shows the forecast ability of M2 and M3 is already present in M1, therefore no need of augmentation on M1 and M1 is the finally selected model whose forecasting ability is better than other models.

Similarly in case of Paraguay, Iran, Malaysia, Colombia, and Fiji like South Africa, results of all non-nested encompassing tests that is Cox, Ericsson, Sargan, and Joint show that model 1 encompasses other two models and model 1 (M1) is the finally selected model whose forecasting ability is better than other models.

Table 4.2.2 S.E and FRMSE of Upper Middle Income Countries

Countries Names	Models	S.E (FRMSE)	Tests	M1 Encompasses M2	M1 Encompasses M3	Finally Selected Model	S.E (FRMSE) Final Model
Turkey	M 1	0.323 (0.28)	Cox	3.10 [0.001]**	2.70 [0.006]**	M1UM2UM3	0.1735 (0.3511)
	M 2	13.118 (17.38)	Ericsson	-2.96 [0.003]**	-2.57 [0.01]*	M1UM2UM3	0.1735 (0.3511)
	M 3	10.369 (5.47)	Sargan	19.65 [0.001]**	17.1 [0.006]**	M1UM2UM3	0.1735 (0.3511)
	Optimal Model	M1	Joint	8.60 [0.0001]**	11.6 [0.000]**	M1UM2UM3	0.1735 (0.3511)
Thailand	M 1	0.006 (0.007)	Cox	0.1704 [0.864]	1.473 [0.140]	M1	0.0067 (0.0077)
	M 2	1.910 (2.34)	Ericsson	-0.160 [0.872]	-1.38 [0.165]	M1	0.0067 (0.0077)
	M 3	1.996 (2.81)	Sargan	10.916 [0.053]	3.936 [0.268]	M1	0.0067 (0.0077)
	Optimal Model	M1	Joint	2.793 [0.036]*	1.357 [0.276]	M1UM2	0.0035 (0.0094)
South Africa	M 1	0.007 (0.005)	Cox	-1.674 [0.0942]	-0.79 [0.424]	M1	0.0072 (0.0058)
	M 2	2.258 (1.98)	Ericsson	1.577 [0.1149]	0.752 [0.452]	M1	0.0072 (0.0058)
	M 3	2.268 (2.07)	Sargan	6.887 [0.229]	3.550 [0.314]	M1	0.0072 (0.0058)
	Optimal Model	M1	Joint	1.472 [0.231]	1.207 [0.325]	M1	0.0072 (0.0058)
Paraguay	M 1	0.034 (0.04)	Cox	1.565 [0.1175]	0.5269 [0.5983]	M1	0.0340 (0.0421)
	M 2	5.226 (7.27)	Ericsson	-1.478 [0.1394]	-0.4962 [0.6198]	M1	0.0340 (0.0421)
	M 3	4.76 (2.58)	Sargan	10.269 [0.0680]	4.9264 [0.1773]	M1	0.0340 (0.0421)
	Optimal Model	M1	Joint	2.5512 [0.0514]	1.7634 [0.1770]	M1	0.0340 (0.0421)
Iran	M 1	3.05 (0.65)	Cox	-0.0226 [0.981]	-0.2578 [0.7965]	M1	3.05 (0.651)
	M 2	8.495 (10.46)	Ericsson	0.0213 [0.9830]	-0.2444 [0.8069]	M1	3.05 (0.651)
	M 3	8.366 (22.12)	Sargan	1.588 [0.90]	0.099 [0.99]	M1	3.05 (0.651)
	Optimal Model	M1	Joint	0.282 [0.91]	0.030 [0.99]	M1	3.05 (0.651)
Malaysia	M 1	0.007 (0.005)	Cox	1.537 [0.1242]	0.1622 [0.8712]	M1	0.0079 (0.0056)
	M 2	1.483 (1.40)	Ericsson	-1.451 [0.1468]	-0.1527 [0.8787]	M1	0.0079 (0.0056)
	M 3	1.209 (0.62)	Sargan	9.5002 [0.0907]	3.6050 [0.3074]	M1	0.0079 (0.0056)

	Optimal Model	M1	Joint	2.2801 [0.0749]	1.2282 [0.3179]	M1	0.0079 (0.0056)
Colombia	M 1	0.128 (0.01)	Cox	1.188 [0.2349]	0.5196 [0.6033]	M1	0.1286 (0.018)
	M 2	2.925 (5.23)	Ericsson	-1.129 [0.2590]	-0.4907 [0.6236]	M1	0.1286 (0.018)
	M 3	2.923 (2.15)	Sargan	10.244 [0.0686]	1.4811 [0.6866]	M1	0.1286 (0.018)
	Optimal Model	M1	Joint	2.5428 [0.0520]	0.4683 [0.7067]	M1	0.1286 (0.018)
Fiji	M 1	0.011 (0.005)	Cox	-0.4720 [0.636]	1.566 [0.1173]	M1	0.0113 (0.0055)
	M 2	2.084 (3.51)	Ericsson	0.4449 [0.6564]	-1.476 [0.1401]	M1	0.0113 (0.0055)
	M 3	2.262 (1.51)	Sargan	7.6234 [0.1782]	3.2759 [0.3510]	M1	0.0113 (0.0055)
	Optimal Model	M1	Joint	0.8039 [0.5568]	1.1028 [0.3645]	M1	0.0113 (0.0055)

4.4. Comparison of Non-Nested Encompassing Tests

On the basis of lowest S.E among models Cox test select suitable model for 13 countries out of 16 countries except for the countries Sri Lanka, Cameroon, and Thailand. Ericsson test also select suitable model for 13 countries out of 16 countries except for the countries Sri Lanka, Cameroon, and Thailand. Similarly Joint test also select suitable model for 13 countries out of 16 countries except for the countries Indonesia, India, and Korea but Sargan test select suitable model for 11 countries out of 16 countries except for the countries Indonesia, India, Korea, Sri Lanka, and Thailand. On the basis of test performances of tests, Sargan is less suitable for model selection where as other tests used in this study are equally more suitable in model selection.

Chapter 5

Summary and Recommendation

5.1. Summary

There is a large amount of literature on general to specific methodology and many econometricians prefer this strategy over other alternatives. However general to specific i.e. nested encompassing is not feasible when there is large number of determinants and the data is relatively small. In such a case, the model becomes very large and cannot be easily handled through nested encompassing. Therefore, in this situation non-nested encompassing becomes the feasible option. However, it was not known that how good encompassing tests are for the real data.

Our study show that mostly we have good forecasting performance and forecasting serves as a test of model selection because in our study we have found that the model selected through non-nested encompassing is good in forecast performance than the other. Therefore, encompassing should be used when we have multiple models.

The objective of our research is to examine the performance of non-nested hypothesis test for model selection and to select better model through encompassing on the basis of forecast performance of the models. We want to demonstrate the appropriateness of non-nested encompassing criteria in terms of selection of appropriate model for inflation. Now, among the four non-nested encompassing tests, the one which will select best model most frequently on the basis of lowest S.E can be considered as best. We have tested the performance of four encompassing test to the case of inflation modeling.

First we estimated all the three non-nested models and estimate their forecast root mean square error(FRMSE) and S.E, rank S.E and select the model with minimum S.E. Encompass the model of minimum S.E with other models and we have applied four non-nested encompassing tests on non-nested models of inflation and select four models whether different or same. Finally we found the FRMSE of the four selected models by encompassing tests. We compared FRMSE of these models with FRMSE of the three non-nested models estimated before encompassing. In this study we have found that mostly we have good forecasting performance and we have confirmed that encompassing improves forecasting and Forecasting serves as a test of model selection because forecasting performance on the data not used in the model. Since procedure of encompassing improves the forecast ability, than definitely it is good at selecting model and this is being tested.

On Forecast RMSE we found that Cox, Ericsson, Joint test have same power , and they chose the correct model for 13 out of 16 countries indicating 81 % power. Whereas, Sargan test chose the correct model for 11 out of 16 countries indicating 68 % power. So, Sargan is less suitable test for model selection than Cox, Ericsson, and Joint test.

5.2. Recommendation

From the results we have found that non-nested encompassing improves forecasting ability. In this study we found that encompassing test have reasonable power, therefore it can be used for model selection.

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Appendix

Variable Construction

Some variables are readily available from secondary sources for example World Development Indicator (WDI) and International Monetary Fund (IMF). Meanwhile some variables have to be calculated by using formulas.

Price (P)

Consumer prices index (2000=100) is used as a proxy of relative prices. Data source is World Development Indicator (WDI).

Money supply (MS)

Where money supply is the entire stock of currency and other liquid instruments circulating in a country's economy as of a particular time, usually it is taken as M2 and it is also obtained by adding money and quasi money where direct data on M2 of some country are not accessible. For this study Broad Money M 2 (%) has been taken from IFS.

Income (Y)

Income is nothing but simple Gross Domestic Product (GDP). GDP, measured at fixed factor cost.

Velocity of Money

Velocity of money is constructed by the formula $V = \frac{p*q}{m}$ where p is price level, q is real GDP, and m is money supply. $p * q$ is also known as nominal GDP.

Growth of Velocity V (gv)

Growth of velocity is calculated as:

$$\boldsymbol{gv = \left(\frac{V_t - V_{t-1}}{V_{t-1}}\right) * 100}$$

Growth of money supply M (gm)

Growth of money supply is calculated as:

$$\boldsymbol{gm = \left(\frac{m_t - m_{t-1}}{m_{t-1}}\right) * 100}$$

Growth of GDP income Y (gy)

Growth of GDP is calculated as:

$$\boldsymbol{gy = \left(\frac{y_t - y_{t-1}}{y_{t-1}}\right) * 100}$$

Growth of prices that is inflation ($\boldsymbol{\pi_t}$)

Inflation is calculated as:

$$\boldsymbol{\pi_t = \left(\frac{P_t - P_{t-1}}{P_{t-1}}\right) * 100}$$

Import prices (Imp)

Imports prices are defined as Tariff-adjusted import price index of merchandise imports.

Output gap (OG)

The GDP gap or the output gap is the difference between actual GDP or actual output and potential GDP. The calculation for the output gap is Y–Y* where Y is actual output and Y* is potential output and it is obtained using the Hodrick-Prescott filter (1997) with the smoothing parameter set to 100.

Equilibrium price (P*)

Formula of P* is:

$$\boldsymbol{P} * = \frac{\boldsymbol{MV}*}{\boldsymbol{Y}*}$$

Where M is the total domestic money stock and V^* and Y^* are respectively values of the velocity of M and potential output in long run. We take Velocity in this equation as constant.

Price gap $(\boldsymbol{p_{t-1}} - \boldsymbol{p^*_{t-1}})$

This price gap is evaluated in E-views where as it is also evaluated in excel as well. First take natural log of both series i.e. CPI and P*, then take difference of both series and finally take first lag of the resultant series.