Forecasting Accuracy of Error Correction Models: International Evidence for Monetary Aggregate M2

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Abstract: It has been argued that Error Correction Models (ECM) performs better than a simple first difference or level regression for long run forecast. This paper contributes to the literature in two important ways. Firstly empirical evidence does not exist on the relative merits of ECM arrived at using alternative co-integration techniques particularly with Autoregressive Distributed Lag (ARDL) approach of co-integration. The three popular co-integration procedures considered are the Engle-Granger (1987) two step procedure, the Johansen (1988) multivariate system based technique and the recently developed ARDL based technique of Pesaran et al. (1996, 2001). Secondly, earlier studies on the forecasting performance of the ECM employed macroeconomic data on developed economies i.e. the US, the UK and the G-7 countries. By employing data from a broader set of countries including both developed and developing countries and using demand for real money balances this paper compares the accuracy of the three alternative error correction models in forecasting the monetary aggregate (M2) for short, medium and long run forecasting horizons. We also compare the forecasting performance of ECM with other well-known univariate and multivariate forecasting techniques which do not impose co-integration restrictions such as the ARIMA and the VAR techniques. The results indicate that, in general, for short run forecasting non co-integration based techniques (i.e. unrestricted VAR and ARIMA) result in superior forecasting performance whereas for long run forecasting ECM based techniques perform better. Among the co-integration based techniques, our analysis provides evidence of comparatively superior forecasting performance of the ARDL based error correction model.

Keywords: Co-integration, Error correction models, ARIMA, VAR.

JEL Classification: C1, C22, C32, C53, E47

1. Introduction

Having reliable forecasts of macroeconomic variables is key information for forming sound macroeconomic growth oriented policies useful for governments. These are equally useful for planning and development agencies, central banks, long term direct and portfolio investors and other relevant stakeholders. As pointed out by Amato and Swanson (1999) both the central banks and researchers have interest in the money aggregate M2 which have a potential role in the conduct of monetary policy either as an intermediate target or simply as an information variable. Much applied research in money demand is devoted to its specification. Money demand functions have long been known to be unstable (Judd and Scadding, 1982). The existence of a stable money demand function for any country is important, so it has always been a classic case for application of econometric methodologies. In recent years, the error-correction approach to modeling on macroeconomic data has not been an exception, and applications to money demand specification and estimation exist for most countries. This popular specification has the advantage of containing both long-run levels and short-run first differences of non stationary variables.

The Co-integration in a vector time series (Engle and Granger, 1987) has a number of implications for work in empirical macroeconomics. Co-integration transforms the linear combination of two non-stationary time series into a stationary one. In economics co-integration is referred to as a long-run equilibrium relationship. The intuition is that non-stationary time series with a long-run equilibrium relationship cannot drift too far apart from the equilibrium because economic forces will act to restore the equilibrium relationship. Therefore one of the purported advantages of co-integration in an integrated vector process is that it will result in improved forecasting performance in long horizon. In an extremely influential and important paper, Engle and Granger (1987), (henceforth referred to as EG) showed that co-integration implies the existence of an error correction model (ECM) that describes the dynamic behavior of two non-stationary series. The ECM links the long-run equilibrium relationship implied by co-integration with the short run dynamic adjustment mechanism that describes how the variables react when they move out of long-run equilibrium. This ECM makes the concept of co-integration useful for modeling and inference for macroeconomic time series. This paper demonstrates which error correction techniques yield better forecast of the macro variables. Forecasts are based on information contained in the historical data. If forecasts are too far away from the historical trends, they are indicative of important information regarding some events which have altered the historical path of the economy.

As co-integration and ECM provides a unified framework of modeling both long and short run an interesting question for researcher was whether incorporating the long-run restriction through an error correction model yields superior forecast in comparison with pure first difference model which do not impose co-integration restriction. On a theoretical ground co-integration is expected to yield better forecast as pointed by Stock (1995, p-1) who asserts that “If variables are co-integrated, their values are linked over the long run, and imposing this information can produce substantial improvement in forecast over long horizons”. This assertion is based on theoretical results by Engle and Yoo (1986) that long horizon forecasts from the co-integrated systems satisfy the co-integration relationship exactly and that the co-integration combination of variables can be forecast with finite long-horizon forecast error variance.

A simulation study by Engle and Yoo (1987) shows that the two step EG ECM provide better forecast compared to unrestricted VAR particularly at longer horizons while a similar simulation study by Chambers (1993) further corroborated this result using a non-linear one-step ECM. Using the same experimental set up as in Engle and Yoo, Clements and Hendry (1995) find that over-differencing the system results in inferior forecasting performance. In a simulation study using a four-dimensional VAR(2) Reinsel and Ahn (1992) show that forecast gains from co-integrated system depends on proper specification of the number of unit roots and under specifying the number of unit roots results in poor performance for ten to twenty five steps ahead forecasts whereas over-specification results in inferior short-term forecasts.

In the literature some studies have compared forecast ability of the error correction models resulting from the Engle-Granger and the Johansen VECM technique. However the literature does not provide empirical evidence regarding the forecast accuracy of the ARDL based error correction model and its comparison with EG and Johansen techniques. In addition, most of the empirical evidence employing real data in forecast comparison using error correction models comes from the developed economies. This paper provides empirical evidence of forecasting performance of the alternative error correction models resulting from the three techniques as well as from non co-integration based techniques using the data from a broader set of countries including both developed and developing countries (except European countries for which data series on monetary aggregates discontinue after formation of European Monetary Union in 1999).

2. The Literature

Hoffman and Rasche (1996) compared the forecasting performance of a co-integrated system relative to the forecasting performance of a comparable VAR that fails to recognize that the system is characterized by co-integration. They considered co-integrated system composing three vectors, a money demand representation, a Fisher equation, and a risk premium captured by an interest rate differential. The data were from the US economy. They found that the advantage of imposing co-integration appears only at longer forecast horizon and this is also sensitive to the appropriate data transformation. They considered eight years out-sample forecast horizon.

Jansen and Wang (2006) investigated the forecasting performance of the error correction model arising from the co-integration relationship between the equity yield on the S&P 500 index and the bond yield relative to that of univariate models. They found that the Fed Model improves on the univariate model for longer-horizon forecasts, and the nonlinear vector error correction model performs even better than its linear version. They considered ten years forecast horizon.

Wang and Bessler (2004) employed five agriculture time series from the US. They used annual data from 1867 to 1966 for model specification and the data for 1966 to 2000 were used for out-of sample forecast evaluation. Their results favored ECM for three to four year ahead forecast. However the differences in forecast obtained from various models were not statistically significant.

Lin and Tsay (1996) considered both simulated data and financial and macroeconomic real data from the UK, Canada, Germany, France and Japan and interest rate data from the US and Taiwan. Their results are contradictory as the simulated data yield better forecast from the ECM whereas the performance of ECM for real data is mixed. They attribute this contradiction to deficiency in forecast error measure which does not recognize that forecast are tied together in the long-run.

This brief literature review indicates that at best the results on relative merit of imposing co-integration constraint are mixed. If there is some advantage of using the ECM it occurs at longer horizon only. This review also indicates that very few studies employ data from the less developed economies such as the Asian, African and Latin American countries. Also no study has yet considered forecasting performance of the newly developed ARDL based co-integration. It has been argued (e.g. Narayan and Narayan, 2005) that ARDL has important advantages over the Engle-Granger and Johansen approaches. Firstly, it can be applied regardless of whether underlying variables are I(0) or I(1). Secondly, ARDL based co-integration tests have better small sample properties than the EG and Johansen co-integration tests. Thirdly appropriate modification of the orders of the ARDL model is sufficient to simultaneously correct for residual serial correlation and the problem of endogenous variables.

3. Forecasting Techniques

3.1. Co-integration Based Techniques and ECM

The Granger Representation Theorem (Engle and Granger, 1987) enables simultaneous modeling of first difference and the level of the variables using an error correction mechanism which provides the framework for estimation, forecasting and testing of co-integrated systems. If X_t and Y_t are co-integrated and individually I(1) variables with co-integration vector $(1,-\beta_0,-\beta_1)$ the general form of the ECM can be expressed as

$$A(L)\Delta Y_t = \delta + B(L)\Delta X_t + \alpha(Y_{t-1} - \beta_0 - \beta_1 X_{t-1}) + u_t \tag{1}$$

with the lag polynomials

$$A(L) = 1 - a_1 L - a_2 L^2 - \ldots - a_p L^p \,;\, B(L) = b_0 + b_1 L + b_2 L^2 + \ldots + b_q L^q$$

where the lag operator is defined as $L^i Y_t = Y_{t-i}$. In this model the coefficients in the *A(L)* and *B(L)* represent the impact of short run changes while the long run effects are given by the co-integration vector $(1,-\beta_0,-\beta_1)$ and the α controls the speed of adjustment of short run changes towards long run path.

After the pioneering two-step estimator of the ECM parameters proposed by EG several ECM techniques have been developed. The EG technique can identify only a single equilibrium relationship among the variables under study. Johansen (1988) proposed a framework of estimation and testing of vector error correction model (VECM) based on vector auto regression (VAR) equations. The VECM can be expressed as:

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{j=1}^{p} \Gamma_j \Delta Y_{t-j} + u_t \tag{2}$$

The Π is a $g \times g$ matrix containing the long-run parameters. If there are r co-integration vectors then Π can be expressed as a product of two matrices as $\Pi = \alpha\beta'$ where both α and β are $g \times r$ matrices. The matrix β contains the coefficients of long-run relationship and α contains the speed of adjustment parameters which are also interpreted as the weight with which each co-integration vector appears in a given equation. This approach can accommodate multiple equilibrium relationships in the VECM.

Both of these estimation techniques assume that the variables to be modeled are I(1). Recently Pesaran, Shin and Smith (1996) and Pesaran (2001) proposed a technique based on Autoregressive Distributed Lag (ARDL) model which allows both I(0) and I(1) variables thus potentially avoids pre-test bias.

To explain the three main techniques of error correction model we consider the real money balance relationship. The long run relationship is expressed as:

$$MP_t = \beta_0 + \beta_1 y_t + \beta_2 i_t + u_t \tag{3}$$

where *MP = log(M2/CPI), y = log(output), i =nominal interest rate*
The Engle Granger technique uses residuals $EC_t = \hat{u}_t = MP_t - \hat{\beta}_0 - \hat{\beta}_1 y_t - \hat{\beta}_2 i_t$ from the long run equation (3) and test for stationarity of the residuals. Co-integration exists if EC_t is stationary. The error correction model will then be formulated as:

$$\Delta MP_t = \gamma_0 + \sum_{i=1}^{m_1} \gamma_{1i} \Delta MP_{t-i} + \sum_{i=1}^{m_2} \gamma_{2i} \Delta y_{t-i} + \sum_{i=1}^{m_3} \gamma_{3i} \Delta i_{t-i} + \alpha\, EC_{t-1} + v_t \tag{4}$$

The Johansen's (1988) technique employs the Vector Error Correction Model (VECM)

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{k} \Gamma_i \Delta Y_{t-1} + \omega_t \tag{5}$$

Where 'Π' and 'Γ_i' are square matrices whose elements depend on the coefficients of long run model and Y_t contains the endogenous variables of the model. In present case of money balance equation, $Y_t = [MP_t \;\; y_t \;\; i_t]'$. A test of rank of '$\Pi$' then establishes the number of co-integration relationships to enter in the VECM equation. If there are '*r*' co-integration relationships, the matrix Π' is expressed as product of two matrices each of which is of order $g \times r$ i.e. $\Pi = \alpha\beta'$. For example if *r* = 1, the VECM will be written as (for *g* = 3 variable system)

$$\Delta Y_t = \begin{bmatrix} \alpha_{11} \\ \alpha_{12} \\ \alpha_{13} \end{bmatrix} (\beta_{11} y_{1t-1} + \beta_{12} y_{2t-1} + \beta_{13} y_{3t-1}) + \sum_{i=1}^{k} \Gamma_i \Delta y_{t-1} + \omega_t \tag{6}$$

where $y_1 = MP$ and $y_2 = y$ and $y_3 = i$
For testing co-integration the ARDL technique specifies the dynamic equation as

$$\Delta MP_t = \gamma_0 + \sum_{i=1}^{m_1} \gamma_{1i} \Delta MP_{t-i} + \sum_{i=1}^{m_2} \gamma_{2i} \Delta y_{t-i} + \sum_{i=1}^{m_3} \gamma_{31} \Delta r_{t-i} + \alpha\, MP_{t-1} + \beta\, y_{t-1} + \delta\, i_{t-1} + \eta_t \tag{7}$$

If there is no co-integration, $\alpha = \beta = \delta = 0$. The corresponding F-test has non-standard asymptotic distribution. Pesaran et al. (1996) provide two sets of asymptotic critical values for the test. One set assumes that all variables are I(0) and the other assumes they are all I(1) variables. If the computed F-statistic falls above the upper bound critical value, then the null of no co-integration is rejected. If it falls below the lower bound, then the null cannot be rejected. Finally, if it falls inside the critical value band, the result would be inconclusive. These two sets of critical values refer to two polar cases but actually provide a band covering all possible classifications of the variables into I(0), I(1) or even fractionally integrated variables. Once co-integration is established the error correction model is formulated as:

$$\Delta MP_t = \delta_0 + \sum_{i=1}^{m_1} \delta_{1i} \Delta MP_{t-i} + \sum_{i=1}^{m_2} \delta_{2i} \Delta y_{t-i} + \sum_{i=1}^{m_3} \delta_{3i} \Delta r_{t-i} + \phi\, EC_{t-1} + \eta_t \tag{8}$$

where error correction term EC_t is formulated by normalizing the long run coefficients of lagged variables in (7). In all these cases the optimal lags m_1, m_2 and m_3 may be selected by employing information criteria.

3.2. Non Co-integration Based Techniques

3.2.1 ARIMA

Among statistical time-series techniques, the ARIMA models achieve extensive use and acceptance. The ARIMA models are widely used in forecasting economic and financial time series such as exchange rates (e.g. Meese and Rogoff, 1983). The ARIMA models attempt to predict a variable using only information contained in its past values. The ARIMA models as conceptualized by Box et al. (1994) associate autoregressive with moving average terms after differencing d times to transform the series to stationarity denoted by ARIMA *(p, d, q),* that is, it is an autoregressive integrated moving average time series, where p denotes the number of autoregressive terms, d is the number of times the series has to be differenced before it becomes stationary, and q is the number of moving average terms. To represent the model we consider the real money aggregate MP_t.

$$\phi(L)(1-L)^d MP_t = \mu + \theta(L)u_t \qquad (9)$$

where μ is the intercept term

$$\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \phi_3 L^3 - \ldots - \phi_p L^p$$
$$\theta(L) = 1 - \theta_1 L - \theta_2 L^2 - \theta_3 L^3 - \ldots - \theta_q L^q$$

The ARIMA modeling process includes evaluation the stationarity of the time series, identification of the order of autoregression and moving average components by observing the autocorrelations, partial autocorrelations, Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) and then estimation of the autoregression and moving average parameters is carried out as described by Box et al. (1994).

3.2.2 VAR

Vector autoregression (VAR) is a widely used econometric technique for multivariate time series modeling. Vector autoregression provide a convenient representation for both estimation and forecasting of systems of economic time series. Vector autoregressive (VAR) models are, as suggested by their name, models of vectors of variables as autoregressive processes, where each variable depends linearly on its own lagged values and the lagged values of the other variables in the vector. This means that the future values of the process are a weighted sum of past and present values plus some noise. The two simple VAR models used in this paper are VAR at level of the data and VAR at first difference respectively. A vector autoregressive model at level of order p is VAR*(p)* has the following general form:

$$X_t = A_0 + \sum_{j=1}^{p} A_j X_{t-j} + u_t \qquad (10)$$

or

$$X_t = A_0 + A_1 X_{t-1} + A_2 X_{t-2} + A_3 X_{t-3} + \ldots + A_p X_{t-p} + u_t$$

where X_t is a vector of p variables, A_0 is the $(p \times 1)$ constant term vector, $A_0, A_1, A_2, ..., A_k$ are $(p \times p)$ matrices of coefficients to be estimated, and u_t is a vector of innovations with mean zero and covariance matrix Σ.
A vector autoregressive model at first difference of order p has the following general form:

$$\Delta X_t = A_0 + \sum_{j=1}^{p} A_j \Delta X_{t-j} + u_t \qquad (11)$$

or

$$\Delta X_t = A_0 + A_1 \Delta X_{t-1} + A_2 \Delta X_{t-2} + A_3 \Delta X_{t-3} + ... + A_p \Delta X_{t-p} + u_t$$

where ΔX_t is a vector of p variables after taking first difference, A_0 is the $(p \times 1)$ constant term vector, $A_0, A_1, A_2, ..., A_k$ are $(p \times p)$ matrices of coefficients to be estimated, and u_t is a vector of innovations with mean zero and covariance matrix Σ.

4. The Data and the Economic Models

4.1. The Model

The economic model we considered is the demand for real money balances function.
According to economic theory demand of real money balances '*M/CPI*' depends positively on transaction volume i.e. output level '*Y*' and negatively on cost of holding cash i.e. nominal interest rate '*i*' i.e.

$$\log(M_t / CPI_t) = \beta_0 + \beta_1 \log Y_t + \beta_2 i_t + u_t \qquad (12)$$

Thus the task is to forecast money stock (M2) from the alternative ECM resulting from the three co-integration techniques as well as from non co-integration based techniques.

4.2. The Data and Their Sources

We considered quarterly data from 1970Q1 to 2010Q4. For model specification and estimation we employ data from 1970Q1 to 2009Q4 for one year (4 quarters) ahead forecast (short run forecasting) and the forecast evaluation is conducted for the period 2010Q1 and 2010Q4. For medium run forecasting i.e. three years ahead forecast the data of 1970Q1 to 2007Q4 are employed and the forecast evaluation is conducted for the period 2008Q1 and 2010Q4. For the long run forecasting five years (20 quarters) the data for 1970Q1 to 2005Q4 are used in estimation of the models and the forecast evaluation is conducted for the period 2006Q1 and 2010Q4.

The quarterly data (1970Q1-2010Q4) from a broader set of countries including both developed and developing countries are employed including the following countries. 1. Australia 2. Barbados 3. Canada 4. Colombia 5. Denmark 6. Iceland 7. India 8. Indonesia 9. Israel 10. Japan 11. Jordan 12. Korea 13. Kuwait 14. Malaysia 15. Mexico 16. Morocco 17. New Zealand 18. Nigeria 19. Norway 20. Pakistan 21. Philippines 22. Senegal 23. Singapore 24. South Africa 25. Sweden 26. Switzerland 27. Thailand 28. Trinidad and Tobago 29. Turkey 30. UK 31. Uruguay 32. US.

Interest rate is measured by discount rate, lending rate or money market rate (whichever is available for full sample period). Output is measured by manufacturing production index or GDP which indicate significant seasonality in some countries so quarterly dummies are added in estimation. The data comes mostly from International Financial Statistics (IFS).

We employ Mean Absolute Percentage Error (MAPE) to evaluate the forecast accuracy. This measure eliminates the effect of scaling of variables so that forecast error from countries is comparable. The MAPE is given by:

$$MAPE = 100 \times \frac{1}{H}\sum_{t=1}^{H} \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right| \quad (13)$$

where Y_t and $\hat{Y}_t$ represent actual and forecast respectively and H represent forecast horizon.

5. Results and Discussion

5.1 Unit Root and Co-integration Tests

The empirical analysis involves certain challenges e.g. EG and the Johansen techniques require the pre-testing for unit root in the variables and, strictly speaking, are valid if variables are I(1). However ARDL does not need such pre-testing. Unit root tests on all the series were conducted. Unit root tests are applied to check whether the time series is stationary. Many unit root tests are proposed in the literature. In this paper we used three tests namely ADF (Augmented Dickey Fuller) test, Phillips-Peron test and KPSS (Kwiatkowski, Phillips, Schmidt and Shin, 1992) test.

The Dickey-Fuller test is based on testing the hypothesis that series contains unit root against the series is stationary under the assumption that errors are white noise. The test may be carried out using a conventional *t* statistic. However, the tests do not follow the standard student t distribution so the critical values for the test are obtained by simulation. An extension which will accommodate some forms of serial correlation is the augmented Dickey–Fuller test.

Phillips and Perron (1988) and Perron (1988) suggested non-parametric test statistics for the null hypothesis of a unit root that explicitly allows for weak dependence and heterogeneity of the error process. The advantage is that these modified tests eliminate the nuisance parameters that are present in the DF statistic if the error process does not satisfy the i.i.d. assumption.

KPSS proposed an LM test for testing trend and/or level stationarity. That is, now under the null hypothesis the series is assumed stationary, whereas in the former tests it was a unit root process. Taking the null hypothesis as a stationary process and the unit root as an alternative is in accordance with a conservative testing strategy. One should always seek tests that place the hypothesis we are interested in as the alternative one. Hence, if we then reject the null hypothesis, we can be confident that the series indeed has a unit root. Therefore, if the results of the tests above indicate a unit root but the result of the KPSS test indicates a stationary process, one should be cautious and the stationarity should be investigated further taking into account the autocorrelation structure of the series.

In some countries the EG and the Johansen's co-integration is not strictly applicable since the order of integration was not the same for the variables under study in the money demand. Also in some cases EG, Johansen and ARDL co-integration tests could not uncover any co-integration. Such countries are excluded from the analysis. The countries for money demand forecasting which satisfied all prerequisite assumptions (i.e. all the variables in the model appear to be I(1) as evident by at least one unit root test and also indicate significant co-integration from EG, Johansen and ARDL co-integration tests) are 1. Australia 2. Barbados 3. Colombia 4. Denmark 5. India 6. Indonesia 7. Japan 8. Korea 9. Kuwait 10. Malaysia 11. Mexico 12. Morocco 13. South Africa 14. Switzerland 15. Thailand 16. UK (see Table 1).

5.2 Evaluation of Forecast

The following tables (Table 2 through 4) present the comparison of forecast accuracy based on MAPE for short, medium and long run forecasting horizons for money demand model. The best ECM model in each case is highlighted. Generally, for short run forecasting horizon non co-integration based techniques (i.e. unrestricted VAR or ARIMA) yield the lowest forecast errors. For long run forecasting horizon ECM based techniques (i.e. EG, Johansen and ARDL) yield the lowest forecast errors.

Overall, in short run forecasting ARIMA results in the lowest forecast error for Morocco and Thailand (Table 2). In medium run forecasting, the VAR appears to yield the lowest forecast error in both models (Table 3) for Kuwait at first difference. In long run forecasting for Japan the ARDL technique and for Malaysia the Engle Granger two step procedure results in the lowest forecast error (Table 4). For short, medium and long run forecasting for UK ECM based technique results in the lowest forecast error. For Barbados, Malaysia, South Africa and UK the ECM based techniques result in the lowest forecast error for all forecast horizons (Table 2 through 4).

As a summary measure of forecast evaluation we computed mean and median MAPE across the countries which are reported in the bottom part of the tables 2 through 4. The mean and median MAPE are smallest for ARDL based ECM and ARIMA respectively in short run forecasting (see Figure 1 in Appendix). In medium run forecasting, mean and median MAPE are smallest for ARIMA (see Figure 2 in Appendix). In long run forecasting, mean and median MAPE is smallest for EG1 step based ECM (see Figure 3 in Appendix).

Within the ECM based techniques, the best forecasts for Japan are obtained using the Johansen method whereas EG1 step is superior for Switzerland; the EG2 step technique is preferred for Malaysia and the ARDL results in lowest forecast error for Thailand for long run forecasting horizon. Evidence from Kuwait and Barbados shows that the ARDL and the Johansen techniques result in the lowest forecast error respectively (Table 2 through 4). The results for other countries are mixed.

From Table 2 through 4, it appears that the generally the ECM based techniques result in lowest forecast error in long run forecasting. The exceptions are for Australia, Korea, Kuwait, Switzerland and Thailand. The non co-integration based techniques (i.e. unrestricted VAR and ARIMA) result in lowest forecast error in short run forecasting for Colombia, Indonesia, Korea, Kuwait, Mexico, Morocco and Thailand. It can be concluded that ECM based techniques result in lowest forecast error in long run forecasting horizon and the non co-integration based techniques (i.e. unrestricted VAR and ARIMA) result in lowest forecast error in short run forecasting.

6. Conclusion

It is well known that regression analysis on non-stationary time series data may be spurious (non-sense) if the underlying variables are not co-integrated. Error correction models provide a convenient framework for estimation, testing and forecasting. However several co-integration estimation and testing techniques have been developed in the literature. In this paper we have compared the forecasting accuracy of ECM based techniques (i.e. Engle-Granger, Johansen and the ARDL) with non co-integration based techniques i.e. unrestricted VAR and ARIMA. Also three popular error correction models that are derived from the Engle-Granger, Johansen and the ARDL techniques are compared. Overall results indicate that in general for short run forecasting horizon non co-integration based techniques (i.e. unrestricted VAR and ARIMA) whereas for long run forecasting horizon ECM based techniques generate better forecasts.

In short run forecasting, the VAR at first difference and ARDL based ECM results in the best performance in about 31% and 25% of the cases respectively. In medium run forecasting, VAR at first difference results in the best performance in about 44% of the cases, while ARIMA results best performance in 19% of cases. In long run forecasting, the Johansen based ECM results in the best performance in about 25% of the cases. The ARDL and EG1 step based ECM results best performance in 19% of the cases.

Among the co-integration based techniques the results are mixed. In short run forecasting, ARDL based ECM results in the lowest forecast error. The mean and median MAPE is smallest for Johansen and ARDL. In medium run forecasting, ARDL results in the lowest forecast error. The mean and median MAPE are smallest for Johansen and ARDL respectively. In long run forecasting, EG1 step results in the lowest forecast errors.

In summary, for short run forecasting, the ARDL results in best performance in about 44% of the cases, for medium run forecasting Johansen and EG1 step results in best performance in about 31% of the cases. ARDL results in the best performance in about 25% of the cases. In long run forecasting, EG1 step results in best performance in about 38% of the cases whereas the Johansen and the ARDL yield superior performance in about 31% and 25% of the cases respectively.

Thus among the co-integration based techniques, our analysis provides comparatively better forecasting evidence in favor of the ARDL based ECM. Overall the results indicate the superiority of non co-integration based techniques and co-integration based techniques for short run and long run forecasting horizons respectively.

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Table 1: ECM coefficient of co-integration techniques and unit root evidence for money demand model

S.No.	COUNTRIES	UNIT ROOT	EG1	EG2	Johansen Trace Statistic	Johansen Max Statistic	ARDL
1.	Australia	I(1)	0.000155	-0.008613	49.85364*	26.50992*	-0.012737*
2.	Barbados	I(1)	-0.0201*	-0.00687***	30.05361*	18.7646	-0.02115*
3.	Canada	I(1)	-0.01994	-0.02256***	35.23499*	22.01741*	-0.018217*
4.	Colombia	I(1)	-0.02719*	-0.02793**	35.33552*	26.40562*	-0.027189*
5.	Denmark	I(1)	-0.05595*	-0.06425*	48.38142*	30.96582*	-0.075321*
6.	Iceland	I(1)	-0.02112	-0.03562**	34.55416*	20.8995	-0.007115*
7.	India	I(1)	-0.03454*	-0.03509**	39.61226*	23.11082*	-0.039876*
8.	Indonesia	I(1)	-0.09125*	-0.0723*	50.28659*	35.33736*	-0.109112*
9.	Israel	I(0)	-0.06517**	-0.06806**	47.52189*	35.8751*	-0.06778**
10.	Japan	I(1)	-0.0179*	-0.01616**	57.16196*	32.70923*	-0.017859*
11.	Jordan	I(1)	3.03E-05	-0.0649*	32.7945*	22.18915*	-0.025546*
12.	Korea Republic of	I(1)	-0.02302*	-0.02553*	32.73557*	14.0839**	-0.02727*
13.	Kuwait	I(1)	-0.00837***	-0.00877***	35.99209*	25.08678*	-0.008405*
14.	Malaysia	I(1)	-0.03038**	-0.03012***	46.53861*	28.60623*	-0.030378**
15.	Mexico	I(1)	-0.14108*	-0.13851*	33.59998*	23.24584*	-0.181126*
16.	Morocco	I(1)	-0.050017**	-0.05225**	20.44279*	17.11107*	-0.040788***
17.	New Zealand	I(1)	-0.01803	-0.01637	29.5781	21.25815*	-0.014*
18.	Nigeria	I(1)	0.000115	0.002068	21.2492	12.0361	-0.055202**
19.	Norway	I(1)	-3.45E-06	-0.03185	23.9784	12.2342	-0.022329**
20.	Pakistan	I(0)	-0.02909	0.181071	32.07166*	24.49042*	-0.033202
21.	Philippines	I(1)	-0.02425	-0.0203	163.4074*	156.3316*	-0.025744***
22.	Senegal	I(1)	-0.00357	-0.00159	38.01186*	27.88359*	-0.020022***
23.	Singapore	I(1)	-0.0028	-0.00329	20.59232*	19.89945*	-0.005185*
24.	South Africa	I(1)	-0.06661*	-0.0338**	19.53419*	19.40958*	-0.058885*
25.	Sweden	I(1)	0.000114	-0.0015	51.01309*	35.11659*	0.004587*
26.	Switzerland	I(1)	-0.05176***	-0.05037**	4.142259*	4.142259*	-0.057769*
27.	Thailand	I(1)	-0.00608**	-0.00494***	50.79861*	30.0702*	-0.006751*
28.	Trinidad and Tobago	I(1)	-0.01848	-0.01316	15.7656	9.14994	-0.012177**
29.	Turkey	I(1)	1.85E-05	-0.03568	38.97504*	30.64097*	0.002781
30.	UK	I(1)	-0.06543***	-0.06278**	52.12641*	28.1473*	-0.05937**
31.	Uruguay	I(1)	0.0004	0.004032	23.7384	19.46415*	0.007684***
32.	US	I(1)	-0.02567***	-0.01567	45.91367*	33.39467*	-0.010934

* Significant at 1% ** Significant at 5% *** Significant at 10%

Note: In Table 1 the notations EG1 and EG2 refer to the Engle Granger one step and two step procedure respectively. The coefficient of error correction term is reported for the co-integration based techniques for EG1, EG2 and the ARDL techniques. If co-integration is present these coefficients should be negative and statistically significant. For the Johansen approach Trace and Max statistics are reported. For the evidence of co-integration we consider at least one of Trace or Max statistic to be significant. All the countries have significant co-integration from ARDL technique except for Pakistan, Turkey and US. The exceptions for the Johansen technique are from Nigeria, Norway and Trinidad and Tobago. Only for the case of Pakistan and Israel, the variables included in the money demand model do not show that they have unit root from any of the ADF, Phillips-Perron and KPSS tests. This is indicated by the third column using notation I(1) or I(0).

Table 2: MAPE for one year ahead forecast of Money Aggregate (M2)

COUNTRIES	EG 1 step	EG 2 step	Johansen	ARDL	VAR		ARIMA
					level	1^{st} diff	
Australia	3.241	0.921	4.971	0.904	4.86	1.862	1.099
Barbados	19.456	16.189	5.599	16.11	20.349	19.379	13.966
Colombia	2.029	2.081	1.959	1.89	3.126	1.825	1.758
Denmark	1.971	2.649	2.253	1.701	2.713	2.163	1.884
India	0.532	0.685	6.485	0.437	4.165	3.253	1.151
Indonesia	5.884	3.771	4.763	5.331	4.36	2.733	2.742
Japan	0.754	0.68	0.503	0.89	2.315	0.374	0.692
Korea Republic of	1.92	2.692	2.083	1.25	3.195	1.566	0.718
Kuwait	4.075	6.921	5.438	3.867	5.798	2.83	2.324
Malaysia	0.641	0.807	0.968	0.667	0.865	3.347	2.735
Mexico	5.396	9.155	2.107	6.178	2.966	0.799	1.442
Morocco	6.242	4.626	5.872	4.836	6.182	2.538	2.506
South Africa	0.993	2.35	0.741	1.501	1.061	1.724	4.821
Switzerland	1.899	4.101	2.022	3.121	4.456	3.365	2.271
Thailand	9.965	6.443	7.297	8.808	10.107	5.505	4.498
UK	2.405	2.563	4.099	1.762	5	3.918	3.91
Mean MAPE	4.213	4.165	3.573	3.703	5.095	3.574	3.032
Median MAPE	2.217	2.671	3.176	1.826	4.263	2.636	2.298
Mean of Ranks of MAPE	4.000	4.600	4.000	3.400	5.933	3.333	2.733

Notes: The blue highlighter shows the comparison within the co-integration based techniques i.e. EG1, EG2, Johansen and ARDL. The green shade represents the overall best model.

For comparison purpose we used mean and median as the average, taken for each technique from the MAPE's of all the countries. The mean of ranks of MAPE is taken by first ranking the MAPE for each country from all technique then taking mean of ranks.

Table 3: MAPE for three year ahead forecast of Money Aggregate (M2)

COUNTRIES	EG 1 step	EG 2 step	Johansen	ARDL	VAR		ARIMA
					Level	1st diff	
Australia	3.469	2.426	6.923	2.981	7.201	5.835	8.085
Barbados	5.665	7.95	3.386	6.41	6.25	5.364	5.134
Colombia	4.556	4.437	1.945	3.954	4.75	1.156	1.816
Denmark	8.01	11.497	10.007	6.931	9.855	9.207	3.288
India	3.088	2.017	2.533	3.032	5.764	1.854	2.332
Indonesia	3.187	5.423	5.569	2.78	6.245	2.149	4.33
Japan	2.504	2.547	0.672	1.354	3.35	0.622	0.699
Korea Republic of	1.283	3.74	2.382	1.913	1.317	1.257	1.73
Kuwait	10.616	12.99	12.584	9.424	11.31	1.733	4.292
Malaysia	5.223	1.206	3.013	5.776	1.585	5.101	3.311
Mexico	5.219	14.572	3.876	5.143	6.633	6.017	3.662
Morocco	6.233	2.156	7.641	2.765	5.581	1.27	3.449
South Africa	10.426	3.555	11.745	5.907	11.953	14.068	13.596
Switzerland	6.837	9.817	7.153	7.062	12.68	8.113	4.269
Thailand	3.419	6.755	5.264	3.227	3.933	10.088	5.226
UK	6.747	7.279	4.5	7.257	11.292	5.145	8.775
Mean MAPE	5.405	6.148	5.575	4.745	6.856	4.936	4.625
Median MAPE	5.221	4.930	4.882	4.549	6.248	5.123	3.966
Mean of Ranks of MAPE	3.933	4.933	4.000	3.600	5.400	3.000	3.133

Notes: The blue highlighter shows the comparison within the co-integration based techniques i.e. EG1, EG2, Johansen and ARDL. The green shade represents the overall best model.

For comparison purpose we used mean and median as the average, taken for each technique from the MAPE's of all the countries. The mean of ranks of MAPE is taken by first ranking the MAPE for each country from all technique then taking mean of ranks.

Table 4: MAPE for Five year ahead forecast of Money Aggregate (M2)

COUNTRIES	**EG 1 step**	**EG 2 step**	**Johansen**	**ARDL**	**VAR**		**ARIMA**
					Level	**1st diff**	
Australia	9.904	21.367	16.051	12.454	13.623	9.342	17.37
Barbados	6.55	13.569	2.296	5.48	14.023	3.97	6.525
Colombia	15.821	12.926	8.653	12.066	13.121	13.512	8.989
Denmark	10.238	13.97	17.953	11.086	16.491	14.643	16.674
India	6.175	7.381	9.194	5.27	11.772	11.394	11.7
Indonesia	4.192	21.49	2.933	9.099	2.958	8.804	7.419
Japan	1.764	1.803	4.688	1.119	2.219	4.95	4.241
Korea Republic of	0.975	3.813	4.557	1.927	0.9	9.96	11.201
Kuwait	19.461	26.27	29.719	14.504	37.834	9.547	19.065
Malaysia	10.501	2.255	10.691	11.952	2.913	2.841	3.432
Mexico	3.822	14.239	7.68	10.839	7.556	6.743	7.298
Morocco	3.291	7.031	3.706	7.227	5.345	9.756	15.616
South Africa	5.546	13.54	12.335	3.95	11.367	6.141	6.747
Switzerland	9.274	14.214	3.251	8.596	12.931	5.53	2.561
Thailand	2.839	15.615	15.675	2.869	2.793	22.894	3.298
UK	10.795	10.163	2.784	11.215	11.2	3.484	4.967
Mean MAPE	7.572	12.478	9.510	8.103	10.440	8.969	9.194
Median MAPE	6.363	13.555	8.167	8.848	11.284	9.073	7.359
Mean of Ranks of MAPE	3.133	4.667	3.933	3.600	4.400	4.067	4.200

Notes: The blue highlighter shows the comparison within the co-integration based techniques i.e. EG1, EG2, Johansen and ARDL. The green shade represents the overall best model.

For comparison purpose we used mean and median as the average, taken for each technique from the MAPE's of all the countries. The mean of ranks of MAPE is taken by first ranking the MAPE for each country from all technique then taking mean of ranks.

APPENDIX

Figure 1: Bar Graph of Median MAPE for one year ahead forecast of Money demand (M2)

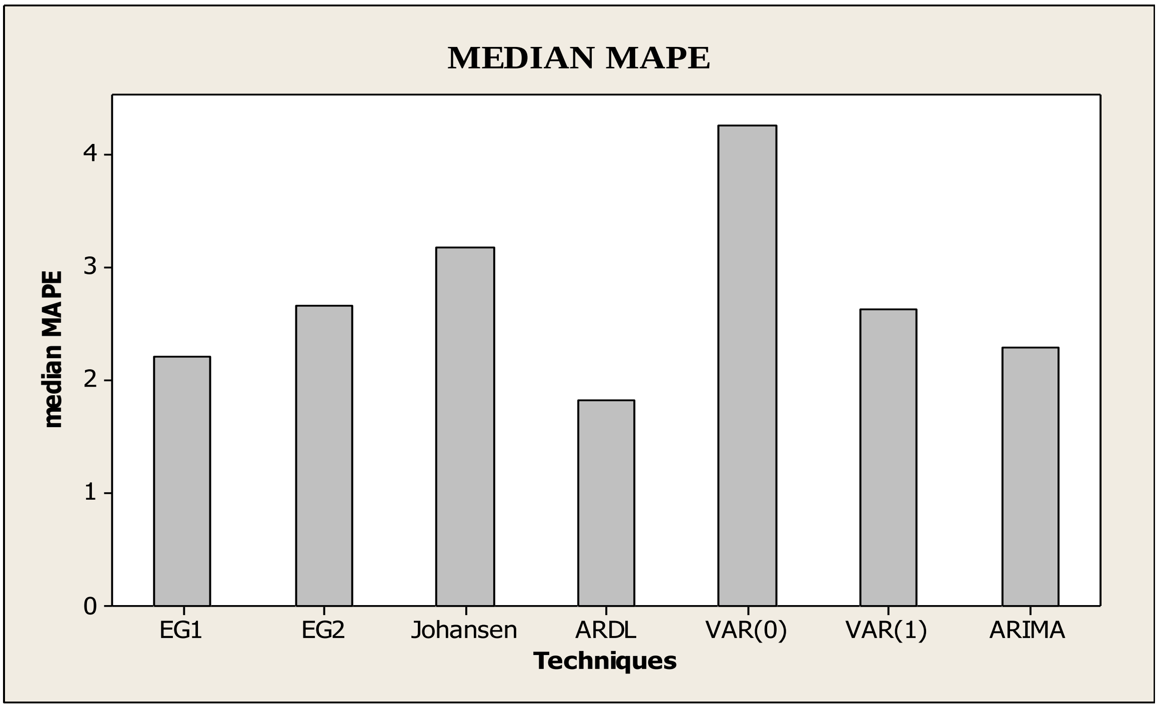

Figure 2: Bar Graph of Median MAPE for three year ahead forecast of Money demand (M2)

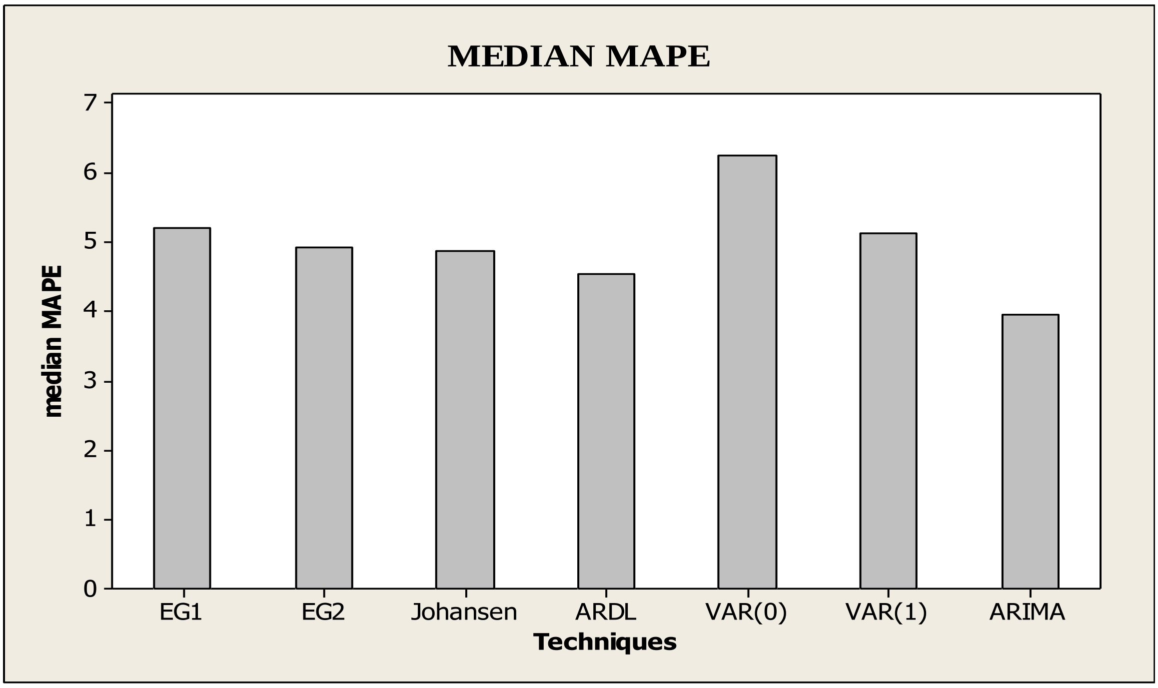

Figure 3: Bar Graph of Median MAPE for five years ahead forecast of Money demand (M2)