PROCEEDINGS ICE 2017 P43 – P56
ISBN 978-967-0521-99-2

FORECASTING OF MONEY DEMAND IN MALAYSIA USING NEURAL NETWORKS AND ECONOMETRIC MODEL

Norlin Khalid
Pusat Pengajian Ekonomi, Fakulti Ekonomi dan Pengurusan,
Universiti Kebangsaan Malaysia
Email: nrlin@ukm.edu.my

Muhammad Harunurashid Thelata
Kementerian Kewangan Malaysia
Email: harunurashid.thelatha@treasury.gov.my

Nur Fakhzan Marwan
Jabatan Ekonomi, Fakulti Pengurusan Perniagaan,
Universiti Teknologi MARA, Kedah
Email: nurfakhzan@kedah.uitm.edu.my

Zulkefly Abdul Karim
Pusat Pengajian Ekonomi, Fakulti Ekonomi dan Pengurusan,
Universiti Kebangsaan Malaysia
Email: zak1972@ukm.edu.my

ABSTRACT

This paper aims to evaluate the out-of-sample forecasting performance of estimated money demand function in Malaysia by comparing Vector Error Correction Model (VECM) with Multilayer Feed Forward Neural Network (FFNN) method. Real income, interest rate and inflation were used as determinant variables for money demand. The period study covers monthly data from 1997 until 2015. Forecast errors were generated using in sample results, 3, 6, 12 and 24 months ahead. Our main finding show FFNN yielded a better out of sample forecast performance than VECM. These findings are strongly recommended to policy makers, academicians and investment firms in Malaysia.

Keywords: Money demand, forecasting, Neural Networks, Error Correction Model.

1.0 Introduction

Economic forecasting such as forecasting of money demand is critical to the tactical, operational and strategic decision making of the central bank, considering future consumption, investment, or a basis on policy instrument. Since maintaining price stability and sustaining long run economic growth are the main objectives for monetary authority; estimating and forecasting money demand is therefore crucial in selecting appropriate monetary policy actions. In Malaysia's experience, the Bank Negara Malaysia (BNM) has switched its monetary policy strategy from monetary targeting towards interest rate targeting in November 1995. Hence, the ability to predict the future money demand is now becoming a central concern for policy makers due to combination of money supply and money demand determines interest rates and thus affects the final goals of monetary policy. In other words, knowing the future characteristics of money demand will give some insights to policy makers in designing their optimal policy rules in order to achieve the target level of inflation rate and higher economic growth.

However, forecasting an accurate money demand is not an easy task as it is hard to find estimation that yield an acceptably accurate forecast output for money demand. Based on these problems, few issues have been raised. Although many models have been developed to estimate money demand, most of them are in sample. How about the out of sample data to predict money demand? What method can be used to compare the performance of money demand forecasting? On the ground of better policy implication, an accurate forecast of money demand is needed for the purpose of controlling inflation. With a better method consists of lower forecast error criterion, policy makers may have more accurate pictures of current economics, thus will formulate and implement more appropriate rules and regulation in order to achieve their targets.

Empirically, various methods have been applied in estimating and forecasting economic and financial variables such as econometric methods, which are ranging from univariate, to multivariate regression model i.e., VAR models. Among the newest method in time series forecasting is a neural network. The interests in neural network for forecasting have dramatically increased as can be seen by a growing number of papers published in journals from various disciplines. Shaikh A. Hamid (2004) surveys a huge number of papers that used neural networks for forecasting wide-ranging fields in economic and finance. Indeed, neural networks have been successfully applied in many areas such as exchange rate, stock movement, domestic debt, and earning yield. Vishwakarma, (1994) and Qi (2001) have found neural networks to be useful in predicting business cycle turning points. In addition, three studies by Swanson and White (1995, 1997a, b) find that nonlinear neural networks are useful in economic time series forecasting of interest rates, unemployment, GNP, etc.

The theory of money demand plays an important role in a monetary policy formulation. There were some discussions on the theory of money demand, which was originally started by a classical theory in the early of 20th century by economists such as Fisher (1911), Pigou (1917), and Marshall (1923). Next, Keynes (1936) established his own money demand theory and later Friedman (1956) developed the Quantity Theory of Money. As a result, money demand function that emerges from the literature was a mixture of various theories. Nevertheless, all theories on money demand agreed on the standard functional form of money demand in which the demand for real balances is a function of economic activity and the opportunity cost, in which commonly proxy by the real GDP and interest rates respectively. Following that, money demand functions have been estimated empirically by using different countries and dataset, model specification as well as econometric methodology.[20] Empirically, the behavior of money demand is approximately influenced by certain variables, such as real income, interest rate, and price level.

The interest among economists in forecasting money demand has increased dramatically. In spite of large number of studies to estimate the money demand functions from various countries and samples, researchers have not been successful in providing an accurate representation of the central bank behaviour in terms of elasticity of the scale variables included in the money demand. Although there have been a considerable amount of research studying a correct specification of the money demand using various econometric techniques such as error correction model, VARs etc., these methods have not been

[20] For instance, Sriram (1999, 2001) highlights extensive literatures on modeling and estimating money demand including selection of scale variables and estimation techniques chosen for various range of industrial and developing countries.

successful in reducing the out-of-the-sample forecast error. A common feature to these techniques is the assumption of a linear long run relationship between money balances and its determinants. However, as highlighted in Sriram (1999), money demand relationship may generate a nonlinear structures due to specification of microeconomic behavior, aggregation and the role of financial intermediation[21]. Therefore, in this study we test the possibility of nonlinearities in the demand for money for the case of Malaysia. Following this background, the main objective for this study is to evaluate the out-of-sample forecasting performance of estimated money demand function in Malaysia by comparing Vector Error Correction Model (VECM) with Multivariate Feed Forward Neural Network (FFNN) method.

Our work differs from previous studies in several ways. First, our focus is on constructing multivariate time series forecasting models using both neural network and econometric methods. This is achieved by linking real money balances with some chosen determinants variables that has proven to be important in determining money demand from previous literatures. Second, we examine both short-term and longer-term forecasts in which the forecast errors are generated using in sample results, 3, 6, 12 and 24 months ahead. Third, we compare the performances of linear (VECM) and nonlinear (FFNN) model by using a different criterion to capture both in sample and out of sample forecasting namely Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Theil's U-Statistic.

The plan of the paper is as follows. Section 2 briefly discusses the specification of money demand, data used and methodology employed. The result of the empirical estimation is illustrated in section 3. Finally, section 4 concludes the paper and suggests a few recommendations for future research directions.

2.0 Model Specification and Methodology

2.1 Money Demand Function

The concept of money demand is similar to the concept of demand of other things, the desire to own something is supported by purchasing power. Hence, the demand for money is the public's desirability to hold total assets in the form of money at a level of wealth or income at a certain price level. In an economy, the main owners of money are the households and financial institutions. The households need money because money can provide certain services that yield satisfaction to the owners while the financial institution needs money to enable smooth business transactions. Furthermore, the services provided by money are normally associated with the functions of money as a medium of exchange, store of value and unit of measurement.

The general specification form of money demand usually begins with the relationship between the demand for real balances and economic activity and the opportunity cost of holding money (Sriram, 2001). Denote Y as economic activity and R as the opportunity cost of holding money, the general form of money demand is given as:

$$\frac{M}{P} = f(Y, R) \qquad (1)$$

This study mainly focuses on the neural network forecasting on behavior of money demand in Malaysia. For the econometric model associated in forecasting money demand, Vector Error Correction Modeling (VECM) is used. VECM, or multivariate modeling is constructed based on the fundamentalist point of

[21] A neural network is non-linear forecasting and has been used rapidly due to growing evidences that found macroeconomic data follow non-linear processes.

view that the behavior of money demand is determined by macro variables in economics. For the neural networks however, Multilayer Feed Forward Neural Network (FFNN) will be applied.

The data sets of this study include the real money balances, real income, interest rate, and inflation. The proxy for real money balances is M2 monetary aggregate at constant price, where M2 is believed as the most appropriate proxy for money demand for Malaysia as a developing country and moving towards developed country. Real income is proxied using Industrial Production Index (IPI) at constant price. IPI is the best measurement of economic growth in short term. Meanwhile, the proxy for interest rate is Malaysia interbank rate for three months. Inflation/Price level is proxied using Consumer Price Index (CPI) published monthly by Department of Statistics Malaysia (DOSM). Data is divided into two sets. First, from August 1993 to March 2013 for training/modeling or 236 observations, second from April 2014 to March 2015 or 24 observations for testing/forecasting

Prior to forecasting money demand using VECM and FFNN methods, several pre modeling tests will be conducted as it will provide the right choice of model selection. Among pre modeling tests are chaotic behavior using Brock Dechert Scheinkman test (BDS, 1996) to check the evidence of nonlinearity of the data, and Variance Ratio Test introduced by Lo and Mackinlay (1998) to examine the predictability of data by comparing variance of differences of the data calculated over different intervals.

As mentioned earlier, this paper seeks to obtain an accurate forecast of the money demand by comparing the performance of econometric techniques, which concentrates on linear model with a nonlinear dynamic time series known as a neural network. In doing so, we first review several steps involved in testing and forecasting demand for money for each methods. Then, various performance criterions to compare and evaluate the out-of-sample forecasting performance will be discussed.

2.2 Estimation using VECM

We utilize cointegration and Vector Error Correction Model (VECM) to estimate money demand function for both short-run and long run and thus give forecast over different horizons. In order to test for cointegration, i.e., long run interaction between money demand and macro variables, Johansen-Juselius cointegration method is used. Below are several steps involved in forecasting money demand using VECM method.

Prior to test for a long run relationship, the unit root test is conducted to test the order of integration, I, for each variable using the Augmented Dickey-Fuller (ADF) approach. The cointegration method requires each series of the variables to be integrated at the same level, I(1). The idea is, even if the variable is not stationary, but a linear combination of two or more variables may be stationary.

ADF test is an enhanced test of DF test (1979) to test whether a unit root is present in the series or not. A time series which is stationary after one differencing is said to be integrated of order one, I(1) and if the series is stationary without differencing is called I(0).

$$\Delta Y_t = b_0 + \beta Y_{t-1} + \alpha_1 \Delta Y_{t-1} + \ldots + \alpha_n Y_{t-n} + \varepsilon_t \qquad (2)$$

Next, if all series of variables are integrated at first difference, a cointegration test to determine the long run interactions between money demand and its determinants will be conducted. Johansen test is a procedure for testing cointegration of several time series. Johansen and Juselius (1990) show that the hypothesis of the existence of the maximum *r* cointegrating vectors can be tested by using two likelihood test statistics as follows:

$$\lambda_{trace}(r) = -T\sum_{i=r+1}^{n}\ln(1-\hat{\lambda}_i) \quad (3)$$

$$\lambda_{\max}(r, r+1) = -T\ln(1-\hat{\lambda}_{r+1}) \quad (4)$$

T is the number of observations used and λ are the eigenvalues of the matrix obtained from π. λ_{trace} test statistic (r) will test the null hypothesis which states that the number of cointegrating less than r, the number of cointegration against the alternative hypothesis of equal or greater with $r + 1$.

If two variables are cointegrated, it implies the existence of a long-term relationship if it has at least one Granger cause either one direction or both directions. Vector Error Correction (VEC) characterization limited to long-term behavior of the endogenous variables to converge to the cointegrating relationships while allowing for dynamic adjustment of the short term. VEC equation is as follows

$$\Delta M2_t = \alpha_1 + \lambda_{M2}\varepsilon_{t-1} + \sum_{i=1}^{n}\delta_{1i}\Delta M2_{t-i} + \sum_{i=1}^{n}\phi_{1i}\Delta Y_{t-i} + \sum_{i=1}^{n}\gamma_{1i}\Delta R_{t-i} + \sum_{i=1}^{n}\rho_{1i}\Delta I_{t-i} + \nu_{1t} \quad (5)$$

The symbol Δ is the first difference term, M2 is real money demand, Y is the Industrial Production index (IPI) which is the measure of economic growth in short term, R is the monthly interest rate on Malaysia Government Securities (MGS) 10 year, and I is the inflation, proxy by Consumer Price Index (CPI). Terms ε_{t-1} is the error correction term deferred the error from the cointegrating vectors equation produced by the Johansen cointegration test.

F-test and t-test are causality tests between sampling periods and do not explain the benchmark for dynamic nature of the system. Hence, variance decomposition (VDC) test will be performed to show the percentage of forecast error variance for each variable that refers to the shock to the system and fluctuations in other variables. Money demand is predicted using ordinary least squares method, but the equation used is taken from the equation that was generated through an error correction model.

2.3 Designing and Programming FFNN Model

Commended by Kaastra and Boyd (1996), four important steps in designing neural networks forecasting will be discussed below:

Step 1: *Topology network*

Through the first step, the number of neurons in the input layer, the number of neurons in the hidden layer, the type of network, and the activation function have to be determined. In time series modeling and forecasting, a single hidden layer of feed forward neural network is mostly used, which has three layers of simple processing units connected by acyclic links

$$y_t = w_0 + \sum_{j=1}^{q} w_j . g\left[w_{oj} + \sum_{i=1}^{p} w_{i,j} . y_{t-i} \right] + \varepsilon_t \quad (6)$$

where $w_{i,j}$ and w_j symbolize the connection weights, p is number of input nodes, q is number of hidden nodes, and ε_t is random error term.

Step 2: *Preparation of data to build a network*
Data will be modified through the process of normalization. Range of new data that are used in the neural network is 0 to 1. If the existing data already in that range, it will also be normalized. One reason why normalized data is needed is problem which may occur to activation function for a data set with a larger range, besides to help the network to learn the data more efficiently and quickly. Range 0 to 1 can be used if the activation function used is the sigmoid type.

$$sig(x) = \frac{1}{\left(1+e^{-n}\right)} \tag{7}$$

Step 3: *Training, validation and testing the network*
Data is divided into three parts, testing (in samples), validation and prediction (outside the sample). For FFNN, all layers except the input layer receives the weight of the previous layer. Generally, the FFNN is composed of three main layers; input, hidden, and output. Input layer has a number of neurons equal to the number of explanatory variables, thus the selection of macro variables based on solid economic theory is important. Hidden layer (one or more) are between the input layer and output layer, to identify, modify and generalized the previous data to new input. Number of neurons in the hidden layer is determined experimentally, and there is still no strong guidance so far. Output layer consists of one neuron only. Next, learning coefficient, the number of iterations, and learning method will be determined. In this study, Levenberg-Marquadt is used as a learning method.

Step 4: *Implementation*
Finally, a good model should be robust with respect to retraining frequency. It is recommended that the frequency of retraining for the deployed network should be the same that is used during testing on the final model.

Figure 1: Example of Multilayer Feed Forward Neural Network (FFNN)

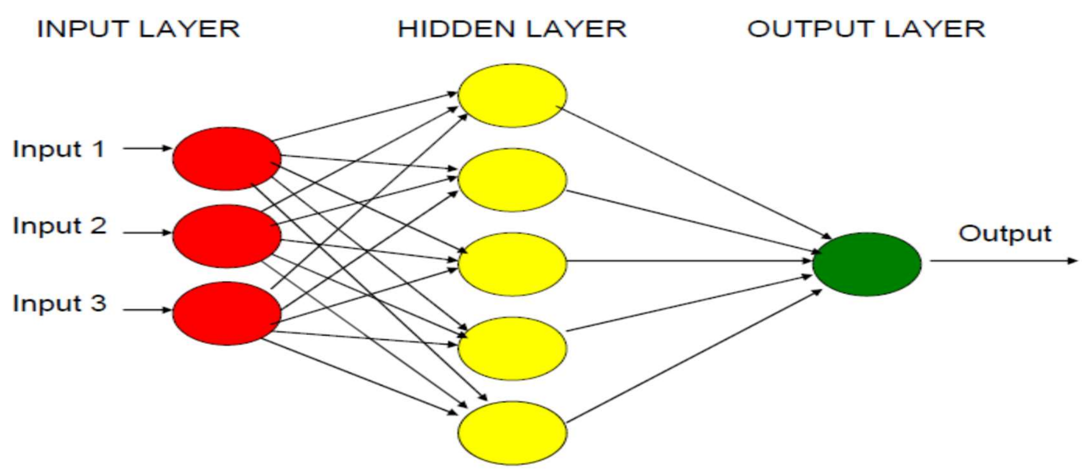

Figure 1 shows the example of Multilayer Feed Forward Neural Network (FNNN), where the above four steps are implemented.

2.4 Performance Comparison

In order to evaluate the performance of linear (VECM) and nonlinear (FFNN) model, different criterion are used for both in sample and out of sample forecasting such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Theil's U-Statistic. For all following criterion, *X* denotes actual value, *F* denotes forecasted value, and *n* denotes the number of observations.

$$RMSE = \left(\left[\sum_{t=1}^{n} \frac{(F_t - X_t)^2}{n} \right] \right)^{1/2} \tag{8}$$

$$MAE = \frac{1}{n} \sum_{t=1}^{n} \left| F_t - X_t \right| \tag{9}$$

$$MAPE = 100 * \frac{\left[\sum_{t=1}^{n} \left| \frac{F_t - X_t}{X_t} \right| \right]}{n} \tag{10}$$

$$U = \sqrt{\frac{\sum_{t=1}^{n} (F_t - X_t)^2}{n}} \Bigg/ \left[\sqrt{\frac{\sum_{t=1}^{n} (F_t)^2}{n}} + \sqrt{\frac{\sum_{t=1}^{n} (X_t)^2}{n}} \right] \tag{11}$$

In order to determine whether the differences between the performance criteria for the two models are statistically significant, the predictive accuracy is evaluated using the Diebold Mariano (1995) test as follows:

$$DM = \frac{\bar{d}}{\left[\frac{2\pi \hat{f}_d(0)}{T} \right]^{1/2}} \tag{12}$$

3.0 Empirical Findings

3.1 Pre-modeling Test

To ensure that the data series is nonlinear, BDS test has been performed (see Table 1). M2 is nonlinear over the period study, since the calculated z–Statistics and probability value is large enough to reject the null, thus the application of nonlinear models for money demand forecasting is justified.

3.2 Vector Error Correction Model

The results of ADF unit root test for all series are presented in Table 2. The test is implemented without and with a time trend. As can be seen from Table 2, all variables which are the money demand, real income, interest rate and inflation are found to be stationary at first difference based on ADF test. However, for stationary test in level, ADF test for both without and with time trend cannot reject the null hypothesis of nonstationarity. Thus, solid evidence are found that all variables are stationary when expressed in first difference, except M2 and Y variables using constant and trend criteria. Thus these variables seems to be integrated of order one, I(1).

Since the results from the integration tests suggest the possibility of long run relationship among the variables, we proceed to cointegration test by applying Johansen and Juselius procedure. The cointegrating result is summarized in Table 3. Based on Table 3, there is at least one cointegrating vector among the variables. Both trace and maximum eigenvalue tests indicate a unique cointegrating vector governing the long run relationship among the variables. The implied long run coefficients from the estimated by normalizing on the money demand are also reported. Specifically, the long run normalized cointegrating regression for money demand using M2 can be written as:

$$M2 = 1.156937Y - 0.020499R + 4.690179I$$

Several interesting results are notable from the long run equation. In the long run, increase in real income (Y) seems to be associated with the real money demand growth. Following theory, the long run association between the money demand and interest rate (R) is negative. This should be expected as the increase in interest rate made people to spend less their money, so less demands the money. Finally, money demand has a positive relationship with inflation (I). When inflation increases, the purchasing power falls, hence more money is needed to buy the same things.

Then, an error correction term has been calculated in order to see the long run equilibrium when there is a shock in the series. Based on Table 4, the error correction term for money demand (M2) is significant at 5% significance level indicating that there exist long-run equilibrium. We can also said that money demand (M2) will response about 50% when there is a shock. The negative value of its error correction also indicates that the speed of adjustment for money demand (M2) achieve its equilibrium when there is a shock is about two months.

To determine the short-run causality and the dynamics between these series, a Granger causality test has been conducted and the results are presented in Table 5. From the results, significant probability values denote rejection of the null hypothesis of non-causality. We found that inflation (I) granger cause money demand (M2) unidirectional at 10% significance level. This implying that past values of inflation (I) has a predictive ability in determining the present value of money demand (M2). Furthermore, the results also shows a causality running from money demand (M2) towards real income (Y) and causality from inflation (I) towards real income (Y).

In order to provide further insight into the dynamic relationships of the variables in the system, the forecast error-variance decomposition is calculated. The variance decomposition shows the proportion of the forecast error of each endogenous variable that is accounted by each of other variables. The results of the variance decomposition of the forecast-error for 24 months are shown in Table 6. The results shows that interest rate (R) relatively the leading variable, being the most exogenous of all. This is because after 24 months (2 years), about 95 percent of the forecast error variance of interest rate is explained by its own shock compared to other variables. The result also shows that money demand (M2) is relatively endogenous as only about 72 percent of the variance explained by its own shock.

3.3 Multilayer Feed Forward Neural Network (FFNN)

Multilayer Feed Forward Neural Network (FFNN) is applied to predict the money demand using real income, interest rate and inflation as input. A network consisting of three layers is constructed which includes one input layer with three neurons, one hidden layer with five neurons and one output layer with one neuron. Sigmoid function is used for activation of neurons in hidden layer and output layer respectively.

Levenberg–Marquadt training is used for the network train for both in sample and out sample forecasting. The number of iterations (epochs) is 21. Meanwhile, mean square error is used as the error minimization function as it is universal and commonly used. Figure 2 shows the neural networks diagram. Figure 3 and Figure 4 respectively show the original money demand series and return (actual), forecasted money demand series and return via VECM (FVECM) and forecasted money demand series and return via FFNN (FFFNN). The better fit by FFNN is the outcome of pattern recognition advantage by neural networks.

3.4 Forecasting using VECM and FFNN

For prediction purpose, we then estimate the money demand equation obtained in VECM via Ordinary Least Square (OLS) to check the goodness of fit for the equation using Ljung – Box serial correlation test. Since the data under consideration is monthly, therefore the value of Q-Statistic for lag number 3, 6, 12, and 24 are reported. Table 7 reports that there is no correlation in the model, and is adequate to be utilized for prediction.

The result for in sample forecasting presented in Table 8, and reveals that between VECM and FFNN, in terms of RMSE, MAE, MAPE and Theil's U-Statistic, FFNN has the lower error compared to VECM. The out of sample forecasting results are also provided in Table 9. Comparison between VECM and FFNN for all time horizon prediction suggests that, FFNN easily outperforms the VECM model.

In order to determine whether the differences between the prediction performance criteria for the two models are statistically significant, the predictive accuracy of the models is further evaluated using DM test statistic. The hypothesis testing is as follows:

$H_{0:}$ Equal predictive accuracy between two models
H_1: Better performance in FFNN

Table 10 indicates that at 95% confidence interval, the null hypothesis of no difference in the forecast accuracy of VECM and FFNN are rejected, except for in sample prediction. The positive value of DM test for all series which is greater than the critical value of 1.96 in normal table, except for in sample period, indicates that the VECM model has a higher square error than FFNN and it is statistically significant. The reason why in sample period is not significant might be explained by the fact that VECM is already enough to forecast the money demand compared to FFNN. But if out of sample period is being considered, then FFNN is a better choice than VECM.

4.0 Conclusion

We successfully apply VECM and FFNN in forecasting the money demand. According to the central bank preferences, both models can be used. However, if the predictability of money demand is being considered, FFNN is a better method compared to VECM. The results support the initial finding that the FFNN is a better model for out of sample prediction.

References

Behrooz, G. 2012. Forecasting of exchange rate using intelligence systems and econometric models in ASEAN-5. *PhD thesis*. Not published. Bangi : UKM.

Behrooz, G., Abu Hassan, S. & Najla, S. 2014. Predicting exchange rates using a novel cointegration based neuro – fuzzy system. *International Economics*. 137: 88 – 103.

Brock, W.A., Dechert, W. & Scheikman, J. 1986. A test for independence based on the correlation dimension. *SSRI Working Paper No. 8702*. Department of Economics. University of Wisconsin at Madison.

Diebold, F.X. & Mariano, R.S. 1995. Comparing predictive accuracy. *Journal Business of Economics and Statistics*. 13 (3) : 253 – 263.

Dickey, D. & Fuller, W. 1979. Distribution of the estimators for autoregressive time series unit root. *Journal of American Statistical Association*. 74 (366) : 427 – 431.

Harvey, R.L. 1994. *Neural Network Principles*. New Jersey : Prentice Hall.

Johansen, S. & Juselius, K. 1990. Maximum likelihood estimation and inference on cointegration with applications to the demand for money. *Oxford Bulletin of Economics and Statistics*. 52 (2) : 169 – 210.

Joseph, A., Larrain, M. & Otto, R. 2013. Comparing the forecast of money demand. *Procedia Computer Science*. 20 (1) : 478 – 483.

Kaastra, I. & Boyd, M. 1996. Designing a neural network for forecasting financial and economic time series. *Neurocomputing*. 10 : 215 – 236.

Osterwald Lenum, M. 1992. A note with quantiles of the asymptotic distribution of the maximum likelihood cointegration rank test statistics. *Oxford Bulletin of Economics and Statistics*. 54 (3) : 461 – 472.

Qi, M. (2001), Predicting US recessions with leading indicators via neural network models, International Journal of Forecasting, 17(3), 383-401

Roley, V.V. 1986. Money demand predictability. *NBER Working Paper Series No. 1580*. MA : Cambridge.

Shaikh A. Hamid (2004), Primer on using neural networks for forecasting market variables, Working Paper No. 2004-03, Southern New Hampshire University.

Sriram, S.S. 2001. A Survey of Recent Empirical Money Demand Studies. *IMF Staff Papers*. 47 (3): 334-365.

Swanson, N.R. & H. White. 1995. A model selection approach to assessing the information in the term structure using linear models and artificial neural networks. *Review of Economics and Statistics.* 13: 265-279.

Swanson, N.R. & H. White. 1997a. Forecasting economic time series using adaptive versus nonadaptive and linear versus non-linear econometric models. *International Journal of Forecasting*. 13: 439-461.

Swanson, N.R. & H. White. 1997b. A model selection approach to real-time macroeconomic forecasting using linear models and artificial neural networks. *Review of Economics and Statistics.* 79: 540-550.

Vishwakarma, K. P. (1994), Recognizing business cycle turning points by means of a neural network. Computational Economics 7, 175-185.

APPENDIX

Figure 2: Feed Forward Neural Network Architecture

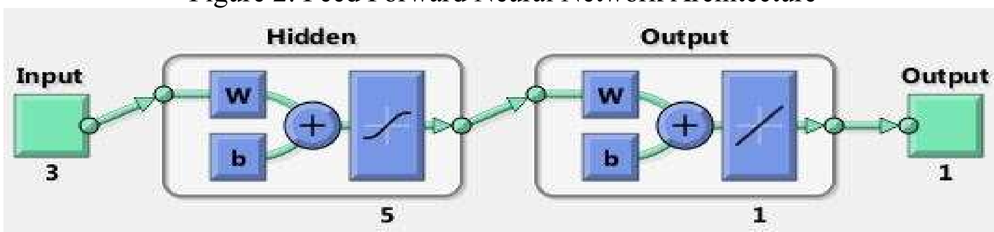

Figure 3: Forecasted Money Demand Series via VECM and FFNN

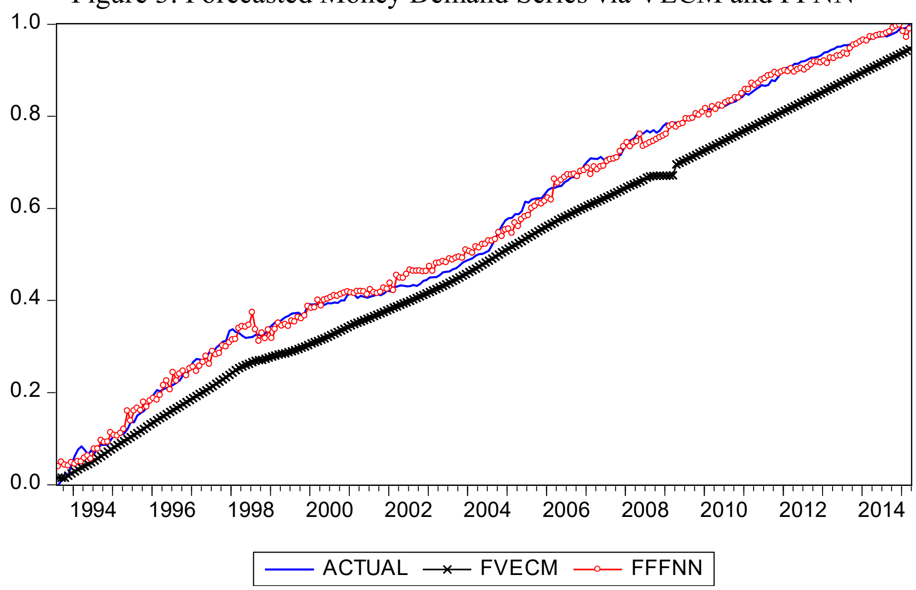

Figure 4: Forecasted Money Demand Return via VECM and FFNN

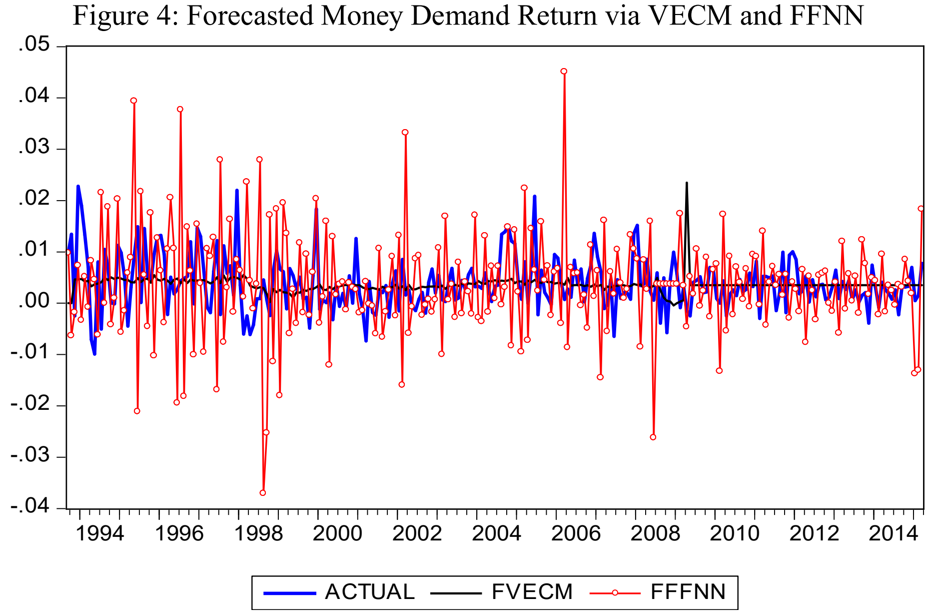

Table 1: BDS Test

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.202499	0.002737	73.98028	0.0000
3	0.344432	0.004349	79.18942	0.0000
4	0.444483	0.005175	85.88574	0.0000

(***) Significant at 1%, (**) Significant at 5%, (*) Significant at 10%

Table 2: Unit Root Test

Variable	Level		First difference	
	Constant	Constant & Trend	Constant	Constant & Trend
M2	0.8675	0.2243	0.0171**	0.0695*
Y	0.5709	0.1444	0.0000***	0.0000***
R	0.3321	0.3064	0.0000***	0.0000***
I	0.3106	0.5398	0.0041***	0.0108**

(***) Significant at 1%, (**) Significant at 5%, (*) Significant at 10%

Table 3: Johansen Juselius Cointegration Test

Null hypothesis	Alternative hypothesis	λ_{trace}	λ_{max}	Critical values (95%)	
				λ_{trace}	λ_{max}
r = 0	r > 0	74.08243**	48.54686**	47.85613	27.58434
r = 1	r > 1	25.53556	14.71059	29.79707	21.13162
r = 2	r > 2	10.82497	8.121338	15.49471	14.26460
r = 3	r > 3	2.703633	2.703633	3.841466	3.841466

(***) Significant at 1%, (**) Significant at 5%, (*) Significant at 10%

Table 4: Error Correction Model

Error correction	DM2	DY	DR	DI
t-statistics	-0.52326**	-0.03893**	-0.47765	2.43525**

(***) Significant at 1%, (**) Significant at 5%, (*) Significant at 10%

Table 5: Granger Causality Test

Dependent variable	ΔM2	ΔY	ΔR	ΔI
ΔM2		0.9916	0.9140	0.0576*
ΔY	0.0027***		0.3112	0.0195**
ΔR	0.9283	0.9602		0.9925
ΔI	0.3772	0.4184	0.4472	

(***) Significant at 1%, (**) Significant at 5%, (*) Significant at 10%

Table 6: Variance Decomposition

Dependent Variable	Periods	M2	Y	R	I
M2	3	98.31969	0.319378	0.026212	1.334723
	6	92.99108	1.099996	0.026568	5.882360
	12	85.14257	2.888049	0.045165	11.92422
	24	72.01984	6.905609	0.058312	21.01624
Y	3	4.014089	90.89387	0.358539	4.733500
	6	5.106438	89.47116	0.377061	5.045343
	12	6.091506	88.40028	0.443567	5.064646
	24	6.557156	87.68119	0.477855	5.283802
R	3	4.639981	0.027833	95.32878	0.003406
	6	4.108621	0.022511	95.85906	0.009807
	12	3.935813	0.013329	96.02862	0.022235
	24	3.983985	0.011389	95.92082	0.083804
I	3	7.257054	1.244273	8.262061	83.23661
	6	4.869476	0.684049	10.24882	84.19766
	12	3.443264	0.743549	12.58668	83.22650
	24	2.327746	6.086500	16.49785	75.08790

Table 7: Ljung – Box Serial Correlation Test

Periods	Q-Statistic	Probability value
3	0.1927	0.979
6	9.9126	0.128
12	20.252	0.162
24	31.547	0.139

(***) Significant at 1%, (**) Significant at 5%, (*) Significant at 10%

Table 8: In Sample Forecasting Results for M2

Model	RMSE	MAE	MAPE	Theil's U-Stat.
VECM	0.242752	0.203818	3.496993	0.021784
FFNN	0.021400	0.016300	0.289100	0.001900

Table 9: Out of Sample Forecasting Results for M2

Model	RMSE	MAE	MAPE	Theil's U-Stat.
		3 months ahead		
VECM	0.248460	0.208038	3.563381	0.022297
FFNN	0.020000	0.019900	0.324000	0.001600
		6 months ahead		
VECM	0.254534	0.212287	3.630182	0.022809
FFNN	0.020500	0.020000	0.325200	0.001700
		12 months ahead		
VECM	0.266392	0.220888	3.765376	0.023839
FFNN	0.014600	0.011100	0.180800	0.001200
		24 months ahead		
VECM	0.291721	0.239128	4.051588	0.026041
FFNN	0.012700	0.009700	0.157500	0.001000

Table 10: Diebold Mariano (DM) Test

Time period	DM (VECM vs. FFNN)
In sample	0.8315
3 months ahead	58.7709**
6 months ahead	39.2173**
12 months ahead	18.9118**
24 months ahead	8.1910**

(***) Significant at 1%, (**) Significant at 5%, (*) Significant at 10%