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Monetary Conditions & Core Inflation: An Application of Neural Networks

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Abstract

This paper assesses the predictive power of a neural network model of inflation relative to other time series models. Over the last two decades there has been increased research on conditions under which various forecasting methods perform best. While no single method dominates, it has been established that simple and parsimonious models are robust under a wide range of conditions. To that end, the forecasting performance for core inflation in Jamaica from an articifical neural network model (ANN) was compared with those from an autoregression moving average model ARIMA (1,1,0)) and a vector error correction model (VECM). The within sample prediction of the ANN model was most robust, while an ARIMA model performed marginally better than the VECM within sample. However, the ARIMA model provided the best out of sample projections. The ANN model although projecting a higher core inflation outturn, captured all of the major turning points.

Keywords: neural network, forecasting, core inflation
JEL Classification: C45, C53, E31

[1] The views expressed are those of the author and does not necessarily reflect those of the Bank of Jamaica

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1.0 *INTRODUCTION*

Previous approaches to forecasting inflation by the Bank of Jamaica (BOJ) employed a Vector Error Correction Model (VECM) (Robinson 1997) and a model that decomposes inflation into its local and foreign cost components. These models have been complemented by conjectural analysis and rely on a diverse set of indicators. The BOJ models are used for the short-term forecasting of headline inflation.

However, it is generally accepted that monetary policy should focus on underlying or core inflation. Roger (1995) suggests that shocks to the general price level, which are perceived as one-time events, should not have a lasting effect on the inflation rate, and as such, it would be inappropriate for the policy makers, who are targeting the inflation rate, to respond. Similarly, Motley (1997) argues that temporary price shocks are often due to supply shocks, such as unusual weather, which affect harvests. These supply shocks while affecting the level of prices do not necessarily affect its long-run growth rate. Thus, if the goal of policy makers is to control inflation, core inflation should be selected as the policy target, in preference to headline, as the former inherently avoids shocks or disturbances that add noise to measured inflation.

Accordingly, this paper develops and assesses the forecast performance of various models for core inflation. The remaining sections of the paper are organized as follows. Section 2 gives a brief discussion on the history of core inflation in Jamaica. Section 3 describes methodological issues relating to the neural network model. Section 4 presents the results and evaluates the competing model forecasts. The conclusion is presented in the final section.

2.0 *INFLATION IN JAMAICA*

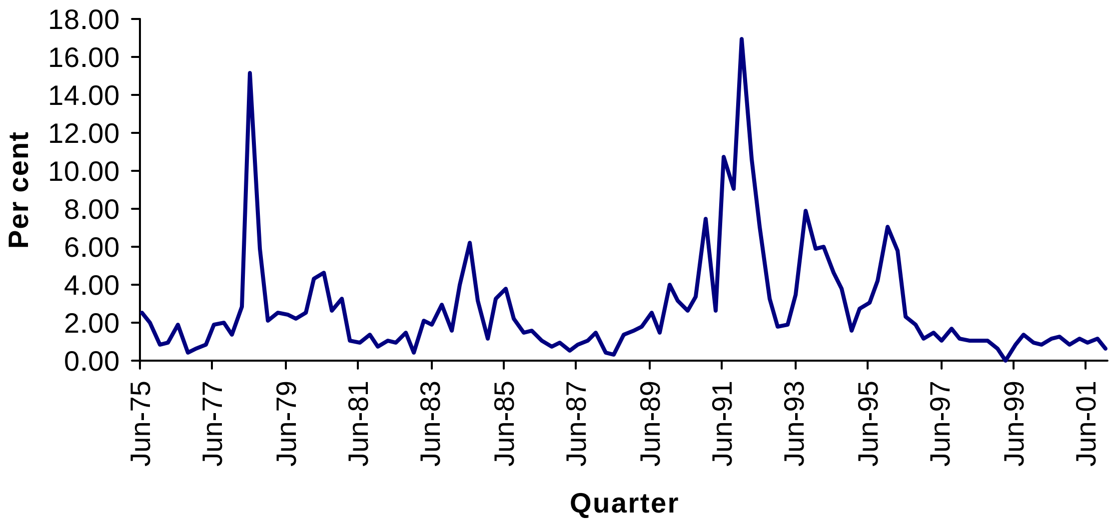
The quarterly trend in core inflation[2] in Jamaica between 1975 and 2001 is depicted in figure 1. The average quarterly core inflation over the period was 2.7 per cent. With the exception of 1978 and 1984, core inflation was fairly stable over the period 1975 and 1990. The 1978 hyper inflationary episode resulted from the devaluation of the exchange rate due to the abolition of the dual exchange rate regime and the implementation of a crawling peg regime. Similarly, the rise in inflation in 1984 coincided with a change in the exchange rate regime and the introduction of the foreign exchange auction mechanism in March of that year, which saw the devaluation of the exchange rate. Core inflation peaked in 1991, following the liberalization of the foreign exchange rate regime. It is important to note that the incidence of inflation over the review period has been associated with strong money growth, which has served to undermine the stability of the exchange rate regime. The average quarterly expansion of the monetary base between 1975 and 2001 was 5.8 per cent, with particularly strong growth being recorded between 1982 and 1984.

Since 1997, core inflation has been fairly stable, reflecting the Central Bank's focus on containing underlying inflation. This trend in core inflation has occurred alongside major changes in the Jamaican economy, including substantial reductions in tariffs, partial elimination of price controls, subsidies and quantitative restrictions on commodity trade.

[2] The measure of core used in this paper is the trimmed mean. See Allen (1997)

Figure 1

Core Inflation in Jamaica:
(1975 - 2001)



There are many different theories as to the causes of inflation, but there is no universally accepted theory that explains inflation in all countries. For our purposes, our variable selection process will be guided by previous empirical work done on inflation in Jamaica, which was essentially based on the monetarist views.

Bourne and Persaud, in 1977, conducted one of the first econometric investigations of inflationary sources in the Jamaican economy. The study showed that a devaluation of the local currency and increased foreign prices were the main causes of inflation in Jamaica in the 1960 and 1970. Downes (1992) examined a structural/monetarist model of inflation in Jamaica, among other countries using an error correction model. He found that monetary policy, the exchange rate vis-à-vis the United States of America (USA) dollar and USA price inflation were significant in explaining inflation in Jamaica, with the monetary policy variable being the most important. Using monthly data for the period 1978:1 to 1990:6, Thomas (1994) employed a monetarist model to evaluate the impact of changes in the exchange rate, net domestic credit, foreign assets and international prices on Jamaica's inflationary process. He found the Treasury Bill rate, exchange rate, foreign prices and net foreign assets to be the important variables in elucidating long-run price behaviour in Jamaica. However, he found net domestic credit to be insignificant in explaining inflation in Jamaica. Robinson (1995) tested for cost-push against demand-pull inflation using a model developed by Harberger in 1963. Over the sample period, 1986 to 1994, he found a bi-directional causation between prices and wages. He concluded that, " Excessive cash holdings are translated first into consumer demand, then into higher prices and then into higher wages and then into higher prices". This suggests that wages do not necessarily initiate inflation in the Jamaican economy. The dominant result he found was that current money supply changes were most significant.

The literature reviewed above suggests that monetary policy changes, exchange rate movements and foreign inflation have been the more dominant factors in explaining inflation in Jamaica. Underlying inflation is generally determined by demand pressures primarily associated with output gaps and monetary impulses. However given the absence of consistent intra-year data on aggregate supply and demand and consistent with the previous studies on inflation in Jamaica, the explanatory variables used in this study are base money to capture monetary policy changes, the exchange rate and foreign prices. The impact of imported inflation is captured mainly by oil prices as it was found that domestic inflation reacted more significantly to oil prices relative to general foreign consumer prices. In addition the 30- day treasury-bill rate is included to capture shifts in monetary policy[3].

[3] See Robinson(1998)

3.0 *NEURAL NETWORK MODEL*

Over the last two decades there has been increased research on the forecasting performance of various time series models. (Makridakis et al. (1982, 1986)). It has been found that no single method dominate the forecasting landscape. However, it has been established that simple and parsimonious models are robust under a wide range of conditions.

Recently, Artificial Neural Network models (ANN) have emerged as an alternate forecasting tool. Remus & O'Connor (1998) indicate that ANN model excel in pattern recognition and forecasting from pattern clusters. The ANN models have two advantages when compared with other traditional methods of forecasting. Firstly, they are universal approximators of functions in that they can approximate whatever functional form best characterizes the time series. In this context, they are inherently non-linear, but can overcome the limitations of linear forecasting models. Secondly, ANN models have been proven to be better than traditional forecasting methods for ***long term*** forecast horizons, but are often as good as traditional forecasting methods over shorter forecast horizons.

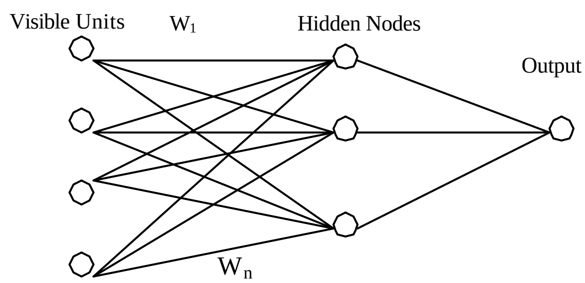
McCulloch's (1943) paper laid the theoretical basis for the development of ANN models. Minsky (1954) developed the computing platform on which current ANN models are processed. Analysis using ANN was further enhanced with the development of the back-propagation technique (Rumelhart & McClelland, 1986).

ANN models are inspired from biological neural networks. They are developed using software that attempt to mimic the human brain's ability to classify patterns or to make predictions or decisions based on past experience (Gately, (1996)). While the human brain relies on inputs from the five senses, ANN uses inputs from data sets.

3.1 *Architecture of ANN Models*

ANN models typically contain three or more layers consisting of input (visible), hidden and output units.

Figure 2
Typical Neural Network Architecture



Input layers receive input patterns directly, while hidden layers neither receive inputs directly nor are given direct feedback. Hidden units are the stock of units from which new features and new internal representations can be created. In a neural network model, the user may specify a pattern of inputs to the visible units but not the external inputs to the hidden unit. The hidden unit net input is based only on the outputs from other units to which they are connected. In this paper, the exchange rate, base money, three seasonal factors, a pulse dummy and an autoregressive term were specified in the input layer. The exchange rate and base money were differenced before they entered the model.

3.2 *Interactive Activation*

The units in a neural network take on continuous activation values between a maximum and minimum value, though their output – the signal they transmit to other units – is not necessarily identical to their activation. In the ANN model, output = $[a_j]^+$. Here, a_j refers to the activation of unit j, and the expression $[a_j]^+$ has value $a_j > 0$; and zero otherwise. The index j ranges over all units with connections to unit 'i'.

Units change their activation based on the current activation of the unit and the net input to the unit from other units, or from outside the network. The net input to a particular unit (say unit i) is the weighted sum of all the output from other units plus any external input:

$$\text{net}_i = \sum_j w_{ij} output_j + extinput_i \qquad (1)$$

In general the weights (w_{ij}) can be positive or negative.

Once the net input into a unit has been computed, the resulting change in the activation of the unit is as follows:

$$\Delta a_i = \begin{cases} (\max - a_i) net_i - decay(a_i - rest) & \text{if } (\text{net}_i > 0) \\ (a_i - \min)\; net_i - decay(a_i - rest) & \text{otherwise} \end{cases}$$

where max, min, rest and decay are all parameters. In particular, we choose max = 1, min ≤ rest ≤ 0, and decay between 0 and 1. Note also that a_i is assumed to start, and to stay within the interval [max, min].

The optimal activation of the unit occurs when the incremental activation of the unit is zero. Setting $\Delta a_i = 0$ and rearranging expression 2 results in the following equilibrium condition for the activation of the unit:

$$a_i = \frac{(\max)(net_i) + (rest)(decay)}{net_i + decay} \qquad (3)$$

Using max = 1 and rest = 0, this simplifies to

$$a_i = \frac{(net_i)}{net_i + decay} \qquad (4)$$

Equation 4 indicates that the equilibrium activation of a unit will always increase as the net input increases, however, it can never exceed 1 (or, in the general case, max). The decay term acts as a kind of restoring force [as an equilibrating force] that tends to bring the activation of the unit back to zero (or to rest in the general case). Decreasing the value of this decay parameter increases the equilibrium activation of the unit.

3.3 *Learning*

Neural network models are of interest because they learn, naturally and incrementally, in the course of processing. One classical procedure for learning (i.e. understanding the data generation process) is the error correcting or delta learning rule as studied by Widrow and Hoff (1960) and by Rosenblatt (1959). The delta rule in its simplest form, can be written as

$$\Delta w_{ij} = \varepsilon \delta_\iota a_j \qquad 5$$

where ε is the value of the learning parameter and δ_i, the error for unit *i,* is the difference between its teaching input (t_i) and its obtained activation (a_i)

$$\boldsymbol{d}_i = t_i - a_i \qquad 6$$

Note that if $\boldsymbol{d}_{pi} < 0$, the adjustment to weight w_{ij} will be negative so that the influence of input *i* is reduced. The system chooses a set of weights to minimize the error. The procedure used is the gradient descent, in which the weights themselves are minimized. The system is then said to decline in weight-space and attains equilibrium when all the weights have been minimized.

For a simple network with say two input units and a single output unit, learning occurs by activating each unit, preparing an output, and then comparing this output with the teaching input. The error between the teaching input and the output of the network is then used to adjust the weights through the fixed learning parameter. The correct set of weights is approached asymptotically if the training procedure is continued through several sweeps, each of these sweeps being referred to as a ***training epoch***. Each epoch results in, theoretically, a set of weights that is closer to the perfect solution. To get a measure of the closeness of the approximation to a perfect solution, we can calculate the total sum of squared errors that result on each epoch. This measure of the state of learning of the network gets smaller over each epoch, as do the changes in the strength of the connections. Minsky and Papert (1969) have shown that the error correcting rule will find a set of weights that drives the error as close to zero as desired, provided that such a set of weights exist.

It should be noted that such weights as described above exists only if for each input-pattern – target-pair, the target can be predicted from a linear combination of the activation units. That is, the weights must satisfy the linear predictability constraint:

$$t_{ip} = \sum_j w_{ij} a_{jp} \qquad 7$$

for output unit *i* in all patterns *p*. This constraint can be overcome by the use of hidden units, which in turn introduces problems relating to the training of the network.

3.4 *Training Hidden Units: Back Propagation*

The application of the back propagation rule involves two phases. In the first phase, the input is propagated forward through the network to compute the output value a_{pj} for each unit (we will assume a single output unit for simplicity). This output is then compared with the target, resulting in a δ term for the output unit.

$$\delta_{pi} = (t_{pi} - a_{pi})\, f'_i\, (net_{pi}) \qquad 8$$

where $net_{pi} = \sum_j w_{ij} a_{pj} + bias_i$ is the activation function, and $f'_i(net_{pi})$ is the first derivative of the activation function with respect to a change in the net input to the unit. The second phase involves a backward pass through the network (analogous to the initial forward pass) during which the δ term is computed for each unit in the network. In the case of the hidden units, there is no specified target so that δ is determined recursively in relation to the δ terms of the units to which they directly connect and the weights of those connections. That is

$$\delta_{pi} = f'_i(net_{pi})\sum_k \delta_{pk} w_{ki} \qquad 9$$

Once these two phases are complete, we can compute the weighted error derivative for each weight. These weighted error derivatives can then be used to compute actual weight changes on a pattern by pattern basis, or they may be accumulated over the ensemble of patterns.

4.0 *RESULTS*

This section presents the predictions from the estimated neural network model. These are compared with the forecasts from a univariate ARIMA model and a VECM. The ARIMA was estimated using the Box-Jenkins (1976) methodology and the best model was chosen using the Schwartz Bayesian Criteria. With respect to the VECM, the likelihood ratio test was employed to determine the most appropriate lag length.

As noted previously, the variables considered are core inflation (CORE), base money (BAS), exchange rate (EXR), oil prices (OIL) and the Treasury bill rate (TBILL). All variables are measured in logs covering the period March 1975 to December 2001. Except for oil prices, which were taken from West Texas Intermediate Crude Oil Price listings, all the variables were taken from the Bank of Jamaica's database. For the core series, initial work had been done for the period 1992 to 1999. For the purpose of this paper, the CPI was collected from the Statistical Institute of Jamaica (STATIN) for the period 1975 to 1998 and the index extended using the same methodology currently employed by BOJ in reporting core inflation. Table A, Appendix I, gives the results of the unit root tests, which indicate that all the variables are I(1).

4.1 *Neural Network*

The network was trained in RATS. One hidden layer with three nodes was specified along with an R-square of 0.95 as the convergence criteria. The network converged after 15,587 epochs. The most parsimonious model included the exchange rate and base money, at four lags, three seasonal factors, the pulse dummies, and an autoregressive term. The Treasury Bill rate was found to be insignificant.

The Llung-Box Q-statistic indicates the presence of mild serial correlation in the error term of the neural forecast. Perhaps, one way to remedy this would be the specification of a more complex network or to use alternative learning algorithms such as the feedforward training techniques. RATS unfortunately does not cover multi-layer network design, nor does it contain alternative algorithms to the back-propogation technique. For more in depth work on neural nets, software such as "Matrix Backpropagation", "WinNN" or

"The Brain" would be required[4]. The presence of serial correlation indicates that the estimates from the ANN model will not have minimum variance.

4.2 *ARMA*

Table B in Appendix I gives the SBC results of the various Box-Jenkins models, which indicate that an ARIMA (1,1,0) model was favoured. Two pulse dummies were created to take account of the two one - off shocks to core inflation. The first pulse dummy was used to capture the effect of the 1978 shock, equalling one in June 1978 and zero elsewhere. The second is a combination of a gradually changing and prolonged pulse dummy, equalling one in December 1991, and a half (0.5) in June and September 1991 and March and June 1992. Three seasonal dummies were also created to capture the seasonal patterns in the data. In addition, a time trend was included in the model.

The results of the ARIMA model are contained in table 1. The two pulse dummies were found to be statistically significant, as well as the filtered series and the AR component. The Llung-Box Q-Statistics (Table 1) indicated the absence of serial correlation along with the Breusch-Godfrey serial correlation LM Test (F statistics of 0.65 and probability of 0.69), while the White's test (Table 1) suggested that the error term was homoskedastic.

[4] WinNN, for example, is a Neural Networks package for windows 3.1 and above. WinNN incorporates a very user-friendly interface with a powerful computational engine. It provides an alternative to using more expensive and hard to use packages. WinNN can implement feed forward, multi-layered NN and uses a modified fast back-propagation for training. It also has various neuron functions. It allows testing of the network performance and generalization. All training parameters can be easily modified while WinNN is training. Results can be saved on disk or copied to the clipboard. It also supports plotting of the outputs and weight distribution.

Table 1
Result of ARIMA (1,1,0) model
Sample 1975:1, 1998:4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.0002	0.006	0.030	0.976
Dummy 1	0.103	0.012	8.708	0.000
Dummy 2	0.110	0.013	8.194	0.000
Q1	0.001	0.003	0.210	0.834
Q2	0.001	0.003	0.435	0.665
Q3	0.002	0.003	0.795	0.429
Filter Core	0.834	0.193	4.064	0.000
Core(1)	0.430	0.095	4.533	0.000
Llung-Box				
Period	Q-Stastistic	Probability		
4	0.34	0.95		
8	5.19	0.64		
12	13.87	0.24		
16	15.58	0.41		
	F Statistics	R Squared	Probability	
White's Test	1.59	12.23	0.14	

R-squared 0.80
SBC -5.61

4.3 *VAR*

Based on the time series properties of the variables a VECM was estimated to capture both the long and short run dynamics of core inflation. The likelihood ratio tests indicated an optimal lag length of two (Table D, Appendix I). The Johansen Cointegration test (Table C, Appendix I) on the variables revealed one cointegrating equation at the 5% significance level.

The long-run equilibrium results (Table 2) of the VECM indicate the nature of the relationships between core inflation and its specified determinants. The exchange rate, base money, and foreign prices all have positive effects on core inflation, with the exchange rate having the greatest impact. This is consistent with *a priori* expectations. A one-unit shock to the exchange rate causes core inflation to increase by 49 per cent over the long run, while shocks to the Treasury Bill rate causes core inflation to decline marginally by 1 per cent. The effects of oil prices in the long run appear to be relatively strong.

Table 2
Normalised Long Run Coefficients

Core Index	Ex-rate	Tbill	Base Money	Oil Prices
1.000	0.490	-0.090	0.095	0.206
Standard Error	0.263	0.034	0.205	0.139

The impulse responses from the VECM are shown in figures A, B and C (Appendix I). The effect runs from oil prices to base money to Treasury bill rate to exchange rate and to core inflation. A unit shock to the exchange rate has a positive impact on core inflation. This impact is highly significant for the first six quarters, after which it dies out at approximately the 34th quarter. A unit shock to base money, has a positive impact on core inflation in the second quarter after the shock, which lasts for as much as seven quarters. This is consistent with Allen (1997), where it was found that core inflation responded within three to six months after a shock to the monetary base. Likewise, a unit shock to foreign prices has a positive impact on core inflation, peaking in the second quarter before settling to its equilibrium level. A unit shock to the Treasury bill rate has a cyclical effect on core inflation up to the 38th quarter, after which it peters out. Shocks to core inflation from itself have the most significant influence, suggesting that the inflationary process in Jamaica has significant inertia. A unit shock to core inflation has an immediate, positive and significant effect on itself over the first five quarters.

Based on the impulse responses in figures B and C (Appendix I), base money has a significant impact on the exchange rate, while the exchange rate has a marginal impact on base money. By deduction, the causation appears to run from base money to the exchange rate, and finally to prices. These results are consistent with those found by Robinson (1997), which showed that expansionary monetary policy has an unambiguous expansionary effect on prices, the lag effect of monetary policy was found to be at least two months and exchange rate stabilization was found to be the most effective means of short-term stabilization.

To determine the contribution of each variable to the core inflation process, the paper assesses the variance decomposition for the sixty-step-ahead forecasts. The results (Table E, Appendix I) show that most of the variability in core inflation was caused mainly by shocks to itself, base money and the exchange rate, throughout the period. Shocks associated with foreign prices have a marginal effect on core inflation over the forecast horizon.

4.4 *Forecast Evaluation*

Tables F and G (Appendix I) provide a comparison of the forecasting accuracy of the three models under consideration. Based on these statistics, the ANN model has the greatest predictive power for in-sample forecasts. It has the lowest mean squared error (MSE), root mean squared error, and mean absolute error.

Figures 3, 4, and 5 show the (in sample) forecasts compared with the actual series for the three models. All the models captured the shock to core inflation in 1978. The ANN model captured the major turning points in core inflation well, although there are indications that between 1986 and 1989 and towards the end of the period it over-estimated the series. The other two models appear to have done better over these periods. Of note, the ARIMA model captured the dynamics in core inflation best, towards the end of the period. Also, the liberalization effect was best captured by the ANN model, followed by the ARIMA model. The VEC model (and to some extent the ARIMA model) did not capture the full effect of this policy, and apparently did a poor job at estimating the second to last and last spikes during the period.

Figure 3

**ARIMA Forecast of Core Inflation.
(In-sample)**

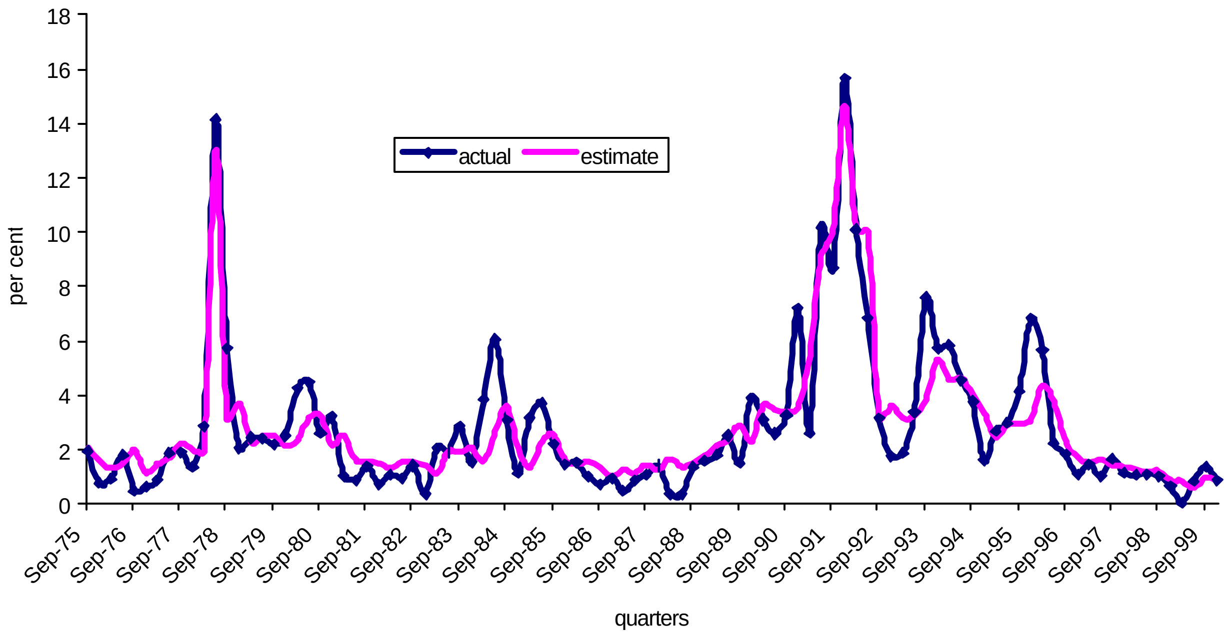


Figure 4
VEC Forecast of Core Inflation.
(In-sample)

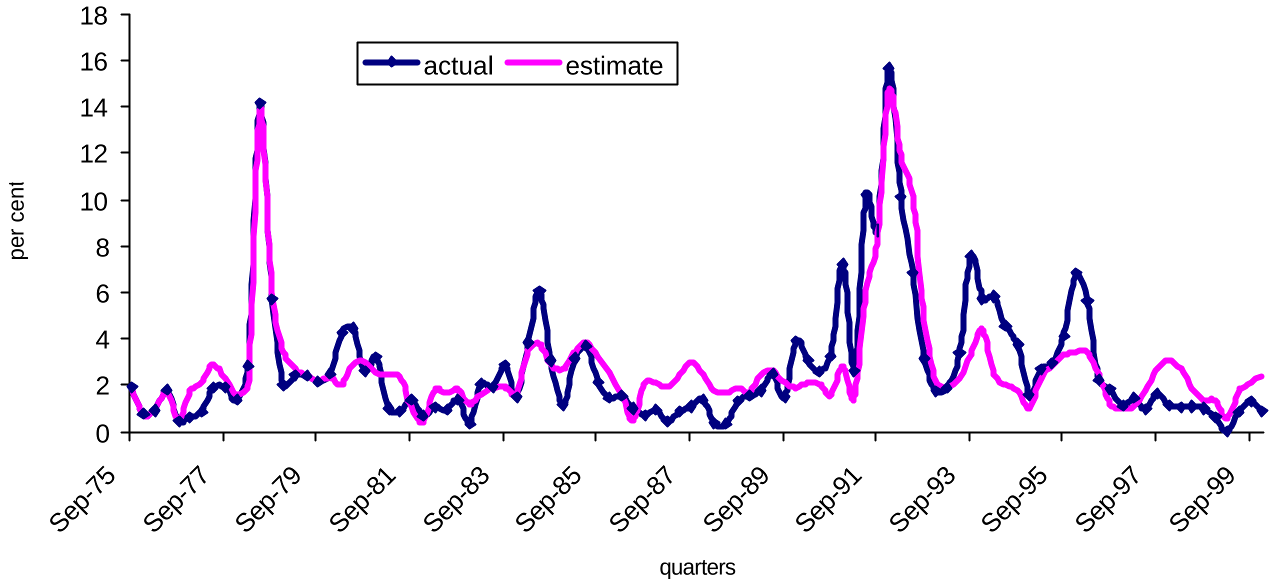
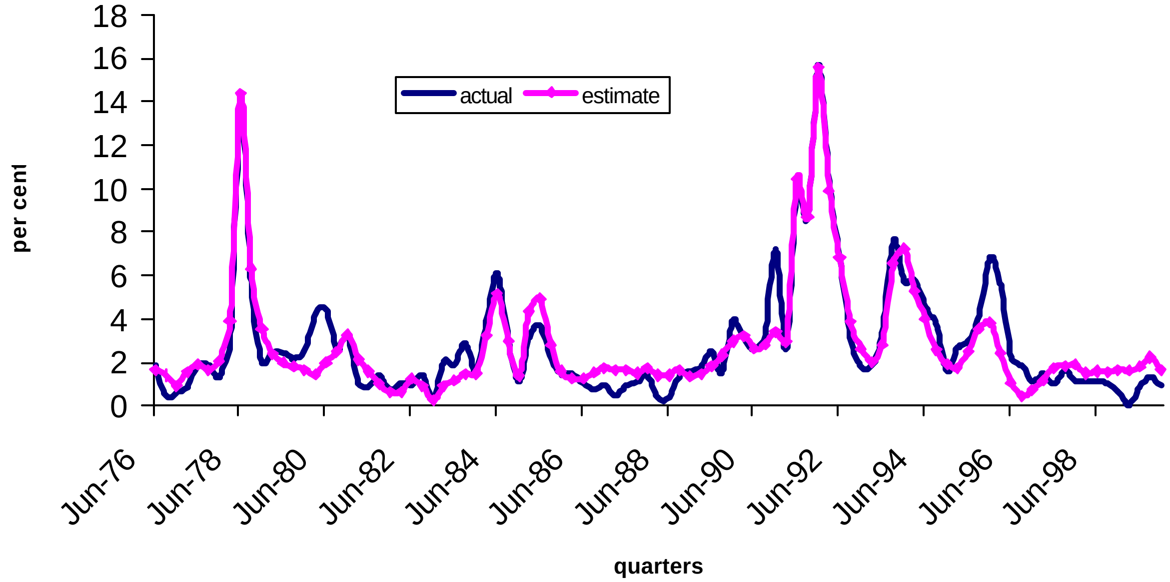


Figure 5

ANN Forecast of Core Inflation.
(In-sample)



A forecast encompassing test was also used to assess the ARIMA and ANN forecasting abilities. If one model forecast encompasses another, that model's forecast is said to be unbiased, contains all the information present in the other, but contains more useful information. Failure of one model's forecasts to encompass another indicates that it is possible to gain by combining the forecasts. The results in table H (Appendix I) indicated that the ANN model forecast encompasses the ARIMA model.

Despite the fact that the ANN model dominated the in-sample forecast performance, the ARIMA and VEC models did a better job with the out-of-sample forecast. Significantly, the Janus quotient (J-Quotient) for the ARIMA model was approximately seven times smaller than the quotient for the ANN model. It should be noted that the Janus quotient is a more robust estimator than the Theil-U coefficient when dealing with out-of-sample forecast evaluations.

Figure 6

Out-of-sample Forecasts of Core Inflation

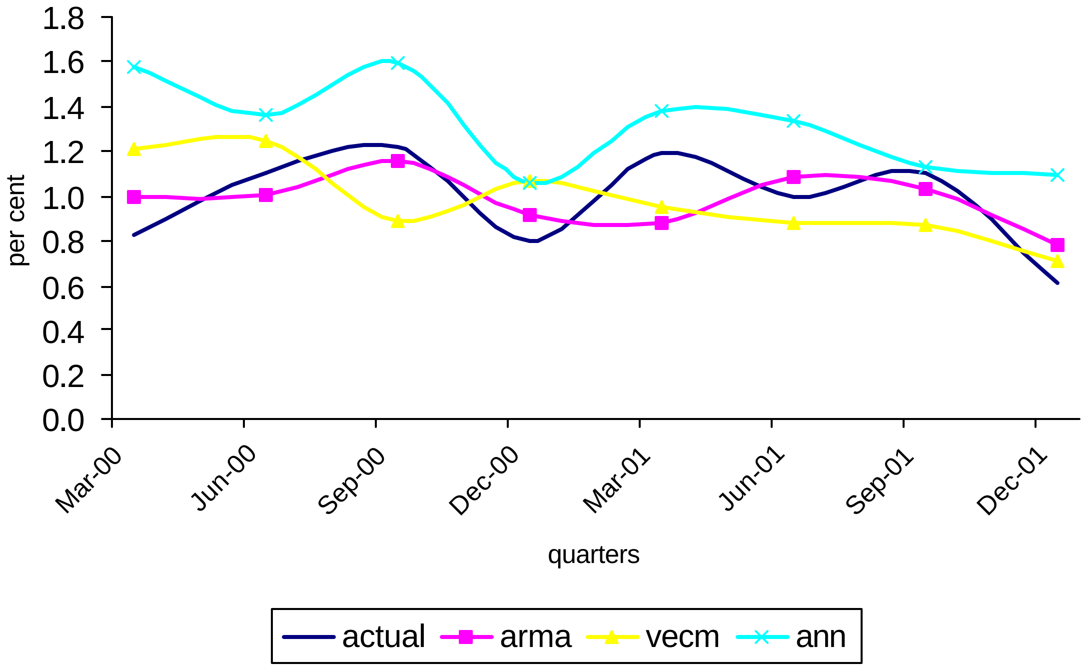


Figure 6 shows the out-of-sample forecast. The graph indicates that the ARIMA and VECM models remain closest to the actual core inflation out-turn between the first quarter of 2000 and the last quarter of 2001. The ANN model, although suggesting a higher inflation out-turn, captured the major turning points in the core series. The ARIMA model captured only the first turning point in core inflation while the VECM model did not capture any of the major turning points. Thus although the statistical measures suggest that the forecasts from the univariate model is superior, the ANN model seems to have been able to capture the data generating process more adequately. The omission of an income variable and possible shifts in the relations among the macroeconomic variables over time may have limited the forecasting power of the multivariate models.

5.0 *CONCLUSION*

Based on the results from the models, volatility in core inflation was due mainly to innovations to itself, to base money, the exchange rate, and to a lesser extent foreign prices. The results of the impulse responses indicated that core inflation responded immediately to a shock to base money.

Of the three models estimated the ANN model was the most appropriate in making in-sample forecast of core inflation. The ARIMA model performed marginally better than the VECM for in-sample forecasts. In addition, the ARIMA model performed better than the VECM when making out-of-sample forecast. The ANN model was the only model that captured the major turning points in core inflation when making out of sample forecast. Whilst further work is required in terms of the type of propagation mechanism to be used, the analysis suggests that ANN model can be a useful addition to the set of tools used in analyzing and forecasting inflation in Jamaica.

APPENDIX

Table A

Augmented Dickey-Fuller Test			
	T statistics		
Variables	Levels	First Difference	lag
Core	-1.85	-3.8	1
Base Money	-0.46	-3.65	4
Exchange Rate	-2.58	-5.23	1
TBILL	-1.44	-4.6	9
Oil Prices	-2.25	-8.09	1
5% critical value	-3.45	-3.45	N/A
1% critical value	-4.04	-4.04	N/A

Table B

Model Selection using AIC and SBC criteria.
Box-Jenkins Models

Models	***AIC***	***SBC***
arima(1,1,1)	-5.802	-5.565
arima(1,1,2)	-5.803	-5.566
arima(1,1,0)	**-5.823**	**-5.612**
arima(1,1,4)	-5.803	-5.565
arima(0,1,4)	-5.639	-5.43

Table C

JOHANSEN COINTEGRATION TEST

Sample 1976:4 to 1999:04

Null Hypothesis	Eigenvalue	Likelihood Ratio	5% Crtical Value	1% Crtical Value
$r = 0$	0.605	117.146	68.52	76.07
$r < 1$	0.174	34.425	47.21	54.46
$r < 2$	0.15	17.401	29.68	35.65
$r < 3$	0.033	2.973	15.41	20.04

Likelihood ratio test indicates one cointegrating equation at the 5% significance level

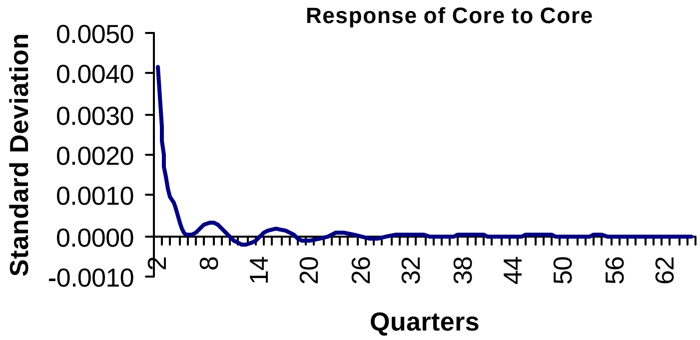
Table D

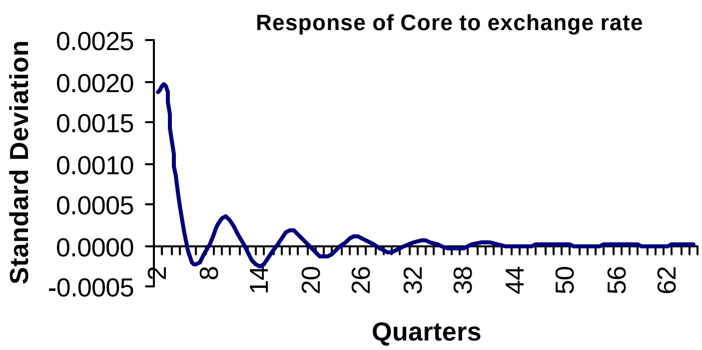
Results of Likelihood Ratio Test

Lag Lengths	Chi-square ratio	Significance Level
8 vs 4	90.39	0.74
4 vs 2	57.64	0.21
2 vs 1	76.03	0.00
	SBC	
2	-5.12	
4	-4.73	
8	-3.96	

Figure A

Response of Core Inflation to One S.D. Innovation





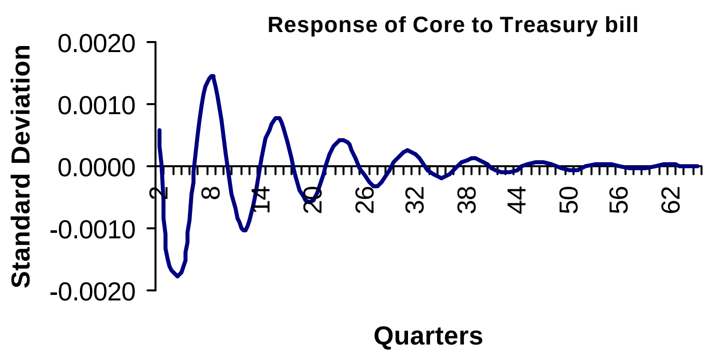
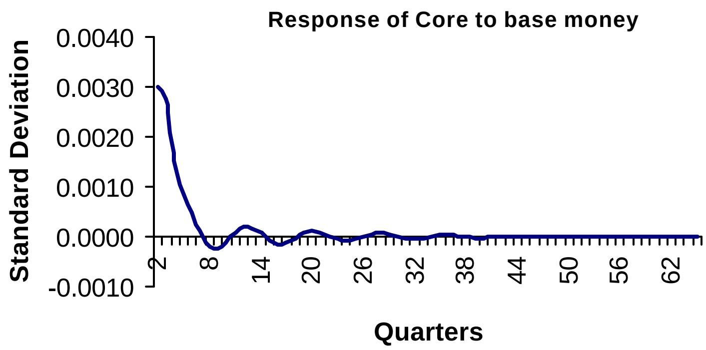


Figure A (cont)



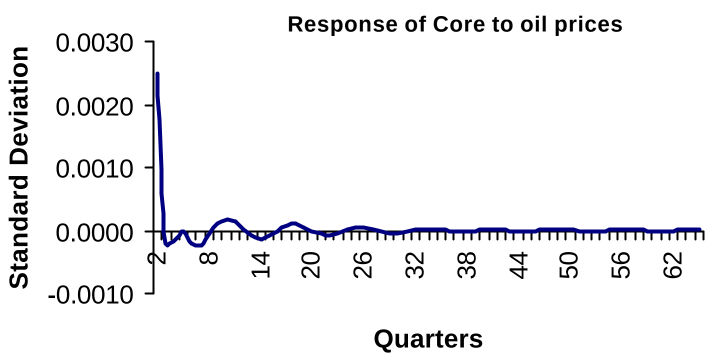
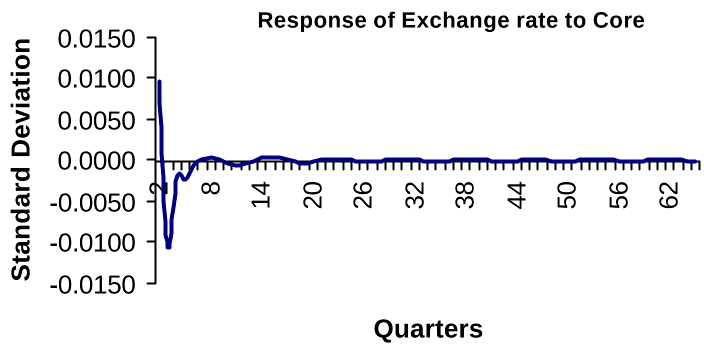
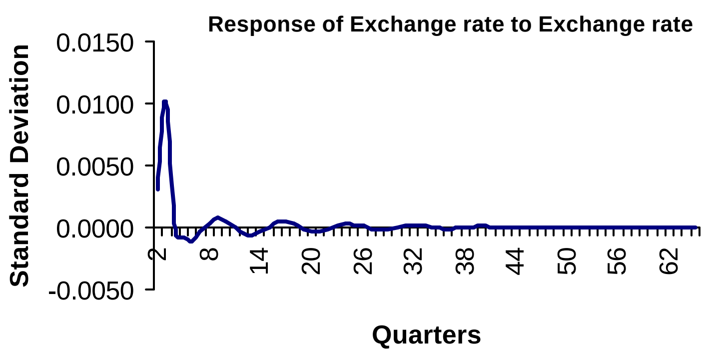


Figure B

Response of Exchange Rate to One S.D. Innovation





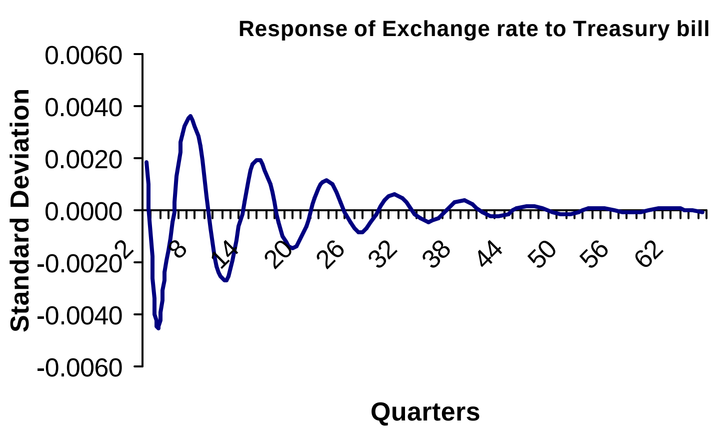
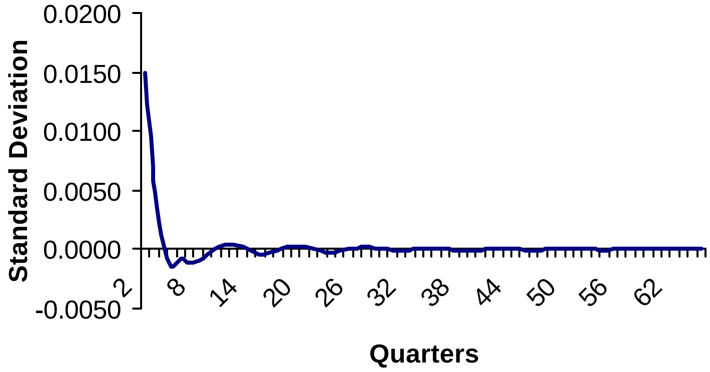


Figure B(cont)

Response of Exchange rate to base money



Response of Exchange rate to base money

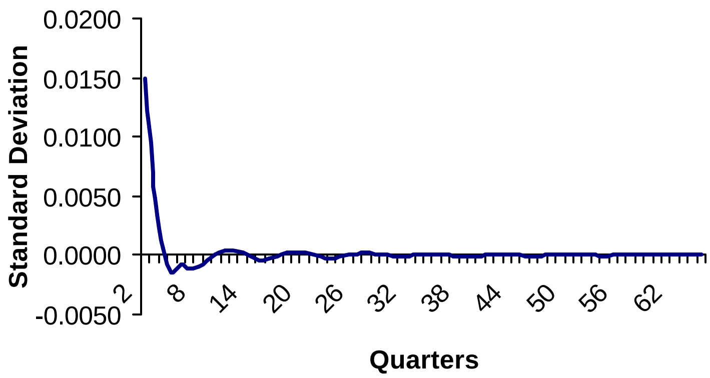
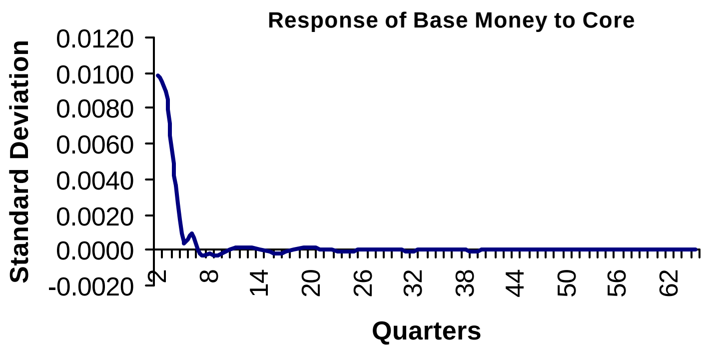
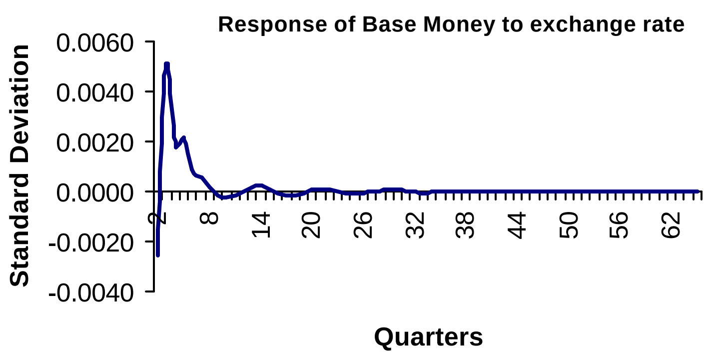


Figure C

Response of Base Money to One S.D. Innovation





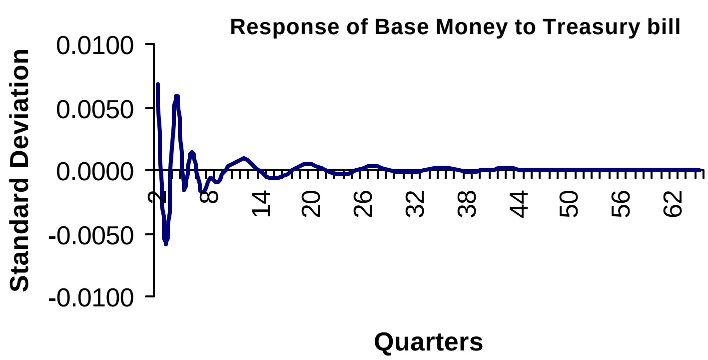
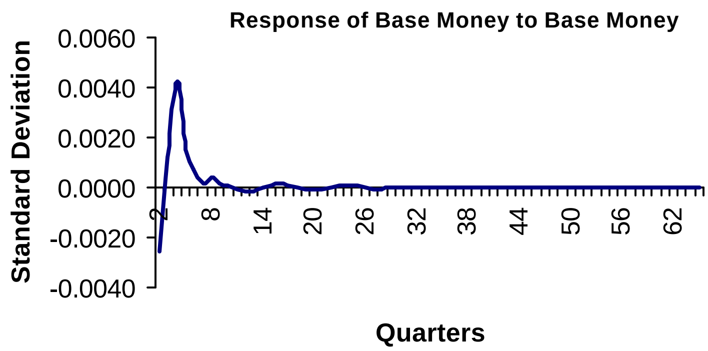


Figure C (cont)



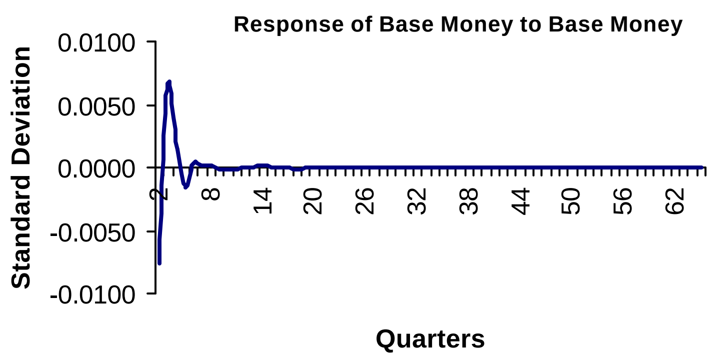


Table E
Variance Decomposition of Core Inflation
(%)

Periods	S.E	Core Inflation	Exchange Rate	Treasury Bill	Base Money	Oil Prices
5	0.04	84.50	3.68	1.50	9.15	1.21
10	0.06	81.14	4.21	1.48	12.27	0.90
15	0.08	79.86	4.60	1.57	13.10	0.86
20	0.09	79.65	4.77	1.38	13.37	0.83
25	0.11	79.41	4.82	1.35	13.61	0.81
30	0.12	79.23	4.89	1.33	13.75	0.80
35	0.13	79.16	4.92	1.29	13.83	0.79
40	0.13	79.08	4.95	1.28	13.91	0.79
45	0.14	79.02	4.97	1.26	13.96	0.78
50	0.15	78.98	4.99	1.25	14.00	0.78
55	0.16	78.94	5.00	1.24	14.04	0.78
60	0.17	78.91	5.01	1.23	14.07	0.77

Table F
Model Forecast Evaluations.
In-sample Forecast.
Sample 1975:1 1999:04

Model	**MSE**	**RMSE**	**MAE**	**Theil U**	**Janus**
ARMA	0.00150	0.013	0.0085	0.16	0.02
VEC	0.00020	0.014	0.0106	0.18	0.03
Neural	0.00010	0.012	0.0072	0.13	0.15

Table G
Model Forecast Evaluations.
Out-sample Forecast.
Sample 2000:1 2001:04

Model	**MSE**	**RMSE**	**MAE**	**Theil U**	**Janus**
ARMA	0.00000	0.0016	0.0014	0.10	0.02
VEC	0.00001	0.0025	0.0023	0.12	0.03
Neural	0.00002	0.0039	0.0034	0.17	0.15

Table H

Forecast Encompassing test results

Sample 1975:1 1999:4

Null Hypothesis	F-Statistics	P-Value
ARMA	3.9294	0.0254
ANN	0.3828	0.6832

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