Revised October 1998
Bibliography not included

Forecasting Inflation Using VAR Analysis

by
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Given certain limitations of structural modelling, this paper explores the use of an alternate Vector Autoregressive Regressive (VAR) model, augmented by an error correction term to forecast inflation. The model used monthly observations on the consumer price index, monetary base, exchange rate, interest rate on Government of Jamaica treasury bills, imported inflation and a proxy for gross domestic product. The model exhibited greater predictive accuracy when compared to other models. The impulse response functions 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. Exchange rate stabilization was found to be the most effective means of short term stabilization.

[1] The views expressed in this paper are not necessarily those of the Bank of Jamaica.

1. Introduction

Given the objective of price stability, the ability to predict the process of price adjustments is essential. From a policy perspective, an understanding of the interactions and transmission process between the main macroeconomic variables and prices serves to guide the process of policy formulation and implementation. In understanding and predicting inflation in Jamaica it is necessary to understand the importance of shocks and the underlying process. Critical elements of these are the persistent components such as expectations, indexation and the structural factors such as the openness of the economy, as well as the production function. This paper explores these interrelations and attempts to provide an alternative means of forecasting inflation by employing a Vector Autoregressive (VAR) model. In so doing it attempts to elucidate some aspects of the transmission process.

Previously, forecasting and policy analyses have been conducted using structural macroeconomic models developed along the lines of the Cowles Commission approach. These structural models, using hypothesized theoretical relations, show the main linkages in the economy. These models thus rely on economic theory to determine the number of variables and their influence.

The initial relative success of this approach led to the development of large scale models, the most noted of which were the MIT, Penn State and the Federal Reserve models. During the late seventies, however, these models were criticized by Lucas as being highly inappropriate for policy analysis as they violated the 'policy invariance' property. More recently, Sims(1980) in a seminal critique argued that the restrictions applied to structural models in the estimation procedure were 'incredible' and could not be properly tested.

Under the Cowles Commission approach, if a particular structural form or parametization that is derived from economic theory, fails to be identified by the data, the parameter space is then transformed such that each point uniquely represents distinct behavioural patterns. This as Sims(1980) notes is termed normalization. Generally such normalization involves the estimation of the reduced form of the structural model. Sims (1980) argues however that "having achieved identification in this way, the equations of the model are not products of distinct exercises in economic theory."[2] The fact is that in structural models, to achieve identification, restrictions are often imposed which have no theoretical justification. Further, and more importantly, Sims asserts that such restrictions are not necessary for the intended use of macromodels (i.e. forecasting and policy analysis).

Alternatively, he suggested that, "instead of using reduced forms one could normalize by requiring the residuals to be orthogonal across equations and the coefficient matrix of current endogenous variables to be triangular."[3] This led to the development of VAR modelling, which has proven to be quite useful in short term forecasting. VAR models have increasingly been used in macroeconomic research over the last decade or so, especially in the United States.[4] Currently VARs are used by the various branches of the Federal Reserve Bank and the Bank of England for forecasting economic trends.

Because many variables do affect inflation, and are in turn affected by inflation, it is possible to identify a small selection of economic variables, movements in which appear to have been highly correlated with inflation in the past and as such may then be useful in forecasting future inflation. The VAR approach provides a convenient means of accomplishing this, as it relies on the causal and feedback relation amongst variables.

The paper is organized as follows. The first section briefly overviews the more recent models of price behaviour. These will be used as benchmarks for comparison with the VAR model. Section Two looks at a theoretical overview of the methodology while Section Three looks at the empirical model and its results. In this section a comparison of the forecasting performance of the VAR model with other time series models is done. The paper concludes by looking at the implication of the results.

2. Recent Models

Various economists have attempted to empirically analyze the issues outlined in the previous section. Earlier studies, such as Bourne and Persaud(1977) and Holder and

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[2] Sims (1980), **Macroeconomics and Reality**, Econometrica vol.48 pg. 2

[3] ibid pg. 2

[4] See for example Sims (1980), Rosenweig and Tallman (1993), Blanchard and Quah (1989) and Quah and

Worrell(1985), emphasized the role of structural influences and cost push inflation. More recent studies have found that monetary disequilibrium and exchange rate changes are significant in explaining the behaviour of prices in the Jamaican economy[5]. The link between the money stock and inflation occurs via a monetary transmission process whereby the amount of money economic agents desire to hold is less than the available money stock. Assuming a stable demand for money, this serves to reduce the value of money (in terms of goods) thus increasing the price level.

Ganga(1992) estimated a model similar to the Harberger model using two-stage least squares. The results using annual data were

$$lnp = 0.066 - 0.112\ln(ms) + 0.167 \ln(ms_{t-1}) - 0.137\ln(wg) + 0.315\ln(pm) + 0.338\ln(xrate) - 0.378\ln(rgdp) + 0.229 \ln(P_{t-1})$$

Only the contemporaneous money stock and wage rate had unexpected signs and were insignificant. The results suggest that output fluctuations and exchange rate changes had the largest impact on price changes. These results of course are highly influenced by the unique features of the sample period. Using monthly data from 1990 to 1992 the estimated model was

$$lnp = 0.007 + 0.156\ln(xrate_{t-1}) + 0.285\ln(ms_{t-1}) + 0.006INT_{t-1} + 0.554\ln(p_{t-1})$$

which suggest that inflation is highly influenced by lagged money supply and exchange rata changes[6]. These results also highlight the significant role of inflationary expectations.

Shaw(1992), starting from the hypothesis of the Quantity Theory, estimated the relationship between money supply and prices in Jamaica between 1982 and 1992. The changes in prices were examined as a function of changes in the money supply(M2), previous price changes and changes in the exchange rate. Using quarterly data, the estimated model most preferred was

$$p_t = 0.27 + 0.28\Delta ms_{t-2} + 0.38\,\Delta p_{t-1} + 0.24\,\Delta ex_t$$

From this he concludes the inflation rate is influenced by changes in the money supply, but not directly as the Quantity Theory purports. Monetary changes affect inflation indirectly because of the prevalence of mark-up pricing. This also provides the channel for the impact of exchange rate

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Vahey (1995).

[5] See for example Worrell, Watson and Scantlebury-Mynard (1992).

[6] Ghartey (1994) found that changes in the exchange rate can be linked to monetary dynamics. consequently he suggests that monetary policy can be employed to control the exchange rate.

adjustments (i.e. changes in the exchange rate affect variable cost) and lagged prices.

Thomas (1994) attempts to capture the dynamics of the inflationary process and the relationship with respect to policy shocks in a monetarist framework. He employed a hybrid methodology which combined a distributed lag specification with an error-correction approach. The distributed lag - polynomial lag, was used to capture the short run impact of policy shocks.

Theoretically, he used a small country assumption in which the economy is a price taker in the international market. Thus the domestic price level, by the law of one price is given by

$$P = eP^*$$

where P^* is the international price level and e is the exchange rate. Given this his model is specified as

$$P = p(e, P^*, c, f)$$

the steady state long run model is

$$P_t = 80.34 + 6.88e_t + 0.002c_t + 0.80I_t - 0.80\, P_t^* + 0.02f_t$$

the short run polynomial lag model is

$$\Delta P_t = -1.67 + 20.84 \sum \Delta e_{t-i} + 0.0003 \sum \Delta i_{t-i} + 1.10 \sum \Delta P_{t-i}^* - 0.32 \sum \Delta T_{t-i}$$
$$+ 0.001 \sum \Delta f_{t-i} - 0.385\, u_{t-1}$$

Thomas concluded from these results that exchange rate changes exert the most dominant influence. This is however against the results of insignificant coefficient estimates for the short run model. The model in itself maybe subject to over paramatization. The model selection criterion used may not be the most appropriate in an ECM framework.

Downes, Worrell and Scantlebury-Maynard (1992) estimated an encompassing model of inflation for Jamaica, which incorporated both structuralist and monetarist features. The functional structure of their model is given as

$$\dot{P} = p(\dot{er}, \dot{usp}, \dot{m}^s, \dot{r}, \dot{wr}, \dot{prod}, s)$$

Changes in the price level ($\dot{P}$) are modelled as being positively related to the changes in the money stock ($\dot{m}^s$), exchange rate ($\dot{er}$), U.S. inflation ($\dot{usp}$), lending rate ($\dot{r}$), domestic wage rate ($\dot{wr}$), factors which cause domestic inflation to deviate from purchasing power parity equivalent (s) and negatively related to changes in productivity (prod).

Using annual data, the results of the static long run equation suggest that cost push variables such as the loan rate and the wage rate do not influence the inflation rate in the long run. Using the generalized instrumental variable estimator technique, the short run dynamic error correction model was

$$dlp = -0.03 + 0.22\,dler + 1.65\,dlusp + 0.39\,dlm1 - 0.15\,HURDUM - 1.03ec(-1)$$

which suggests that changes in the exchange rate, U.S. inflation and monetary changes have significant effect on the inflation rate.(HURDUM is a dummy variable for hurricane.) In the short run therefore the model emphasized the role of monetary variables as against structural variables.

For the purpose of this paper a monthly version of this all encompassing model (ECPM) was estimated. The long run static model in logs was found to be (the t-statistics are given in parentheses)

$$\underset{(-0.2)}{lp = -0.005} + \underset{(19.3)}{1.39lp_{t-1}} \underset{(-1.93)}{-0.238lp_{t-2}} - \underset{(-3.1)}{0.2133lp_{t-3}} + \underset{(4.6)}{0.03ler} + \underset{(3.3)}{0.02lm2} + \underset{(3.6)}{0.0129lwr}$$

$$adj\ R^2 = 0.99 \quad SER = 0.011 \quad SC(\chi^2_1) = 0.0038 \quad D\text{-}F = -5.52$$

and the short run error correction model was

$$\Delta lp = \underset{(0.64)}{0.0009} + \underset{(5.9)}{0.94\Delta lp_{t-1}} - \underset{(-1.1)}{0.13\Delta lp_{t-2}} + \underset{(5.9)}{0.098\Delta ler} + \underset{(1.95)}{0.039\Delta lm2_{t-1}} + \underset{(1.4)}{0.005\Delta lwr} - \underset{(-2.9)}{0.51ecm_{t-1}}$$

$$adj\ R^2 = 0.60 \quad SER = 0.01 \quad F(1, 183) = 45.3 \quad SC(\chi^2_1) = 3.3 \quad HET[F(27, 160)] = 1.4 \quad RESET(\chi^2_1) = 0.87$$

M1 was replaced by M2 in this monthly model as it was found to be more relevant. The model maintained the basic characteristics in the short run as Worrell's(1992) model.

It must be noted that whilst these models examine the determinants of inflation it may be argued that they do not fully explore the causal relationship between the variables. Simple correlation does not necessarily indicate causation. Against this back-ground, S. Nicholls, J.Nicholls and H.Leon(1995) investigated the money price causation in four CARICOM economies. Granger causation was found to run from base money and the narrow definition of money to prices between 1973 to 1995. This did not hold, however, for intervening periods. Causation from base money and broad money was found in the 1981 to 1989 period. Causation was found also to run from prices to broad money and M2. Ganga(1992) found no causal relation between prices, money supply and exchange rate using annual data from 1970 to 1990. Using monthly data from December 1990 to February 1992, however, he found significant unidirectional causality from money supply and exchange rate to prices.

The foregoing would suggest that whilst certain variables have relatively more influence on the behaviour of prices, the theoretical postulate underlying the behaviour of prices in the Jamaican economy remains partially obscure as the precise causal relations still require further analysis. VAR models as proposed by Sims(1980) circumvent these problems *initially,* as they do not impose strict theoretical priors. That is, VARs avoid any *a priori* endo-exogenous division of variables, consequently the Sims methodology is referred to by Cooley and LeRoy (1985) as atheoretical macroeconometrics. For short run forecasting purposes this approach avoids the need for explicitly forecasting the exogenous variables, a limitation of conventional models.

3.0 Empirical Methodology

VAR modelling has its theoretical genesis in the time series analysis of Wold Taio, Box and Jenkins. They basically modeled the moving average and autoregressive components of a time series, which can then be used to predict future movements in the variables. The most widely used model was the Box and Jenkins autoregressive integrated moving average (ARIMA) models.

If x_t is a stationary variable, the moving average process of order p, MA(p), ignoring the deterministic component, is

$$x_t = \varepsilon_t + \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + \ldots\ldots\ldots + \phi_q \varepsilon_{t-q}$$

$$= (1 + \phi_1 L + \phi_2 L^2 + \ldots\ldots\ldots\ldots + \phi_p L^q) \varepsilon_t$$

$$= \phi_q (L) \varepsilon_t \qquad [1]$$

where L is the log operator and ε_t is the white noise error. Thus ε_t is expressed as the

weighted sum of random shocks. The AR representation is

$$x_t = \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \ldots\ldots\ldots + \alpha_p x_{t-p} + \varepsilon_t$$

This can be expressed in terms of the random shocks to x_t where

$$\varepsilon_t = x_t - \alpha_1 x_{t-1} - \alpha_2 x_{t-2} - \ldots\ldots\ldots - \alpha_p x_{t-p}$$

$$= (1 - \alpha_1 L - \alpha_2 L^2 + ... + \alpha_p L^p)\, x_t$$

$$= \alpha_p(L)\, x_t \qquad [2]$$

Substituting [2] into [1] we obtain an ARMA(p q) model.

Suppose we have a dependent variable in the form

$$y_t = y_{t-i} + x_t$$

Then this is equivalent to

$$(1 - L)^d y_t = x_t \qquad [3]$$

which is stationary, where d denotes the amount of time y_t would have to be differenced for stationarity to hold. But since x_t follows an ARMA (p q) process then equation [3] can be written as an ARIMA(p, d, q) model by combining equations [1], [2] and [3]. i.e.

$$(1 - L)^d y_t = \frac{\phi_q(L)}{\alpha_p(L)} \varepsilon_t$$

Thus y_t is given as a function of its own lags and a series of innovations in x_t.

VAR models extend this by incorporating similar expressions for x_t, (i.e. x_t becomes endogenous), thus forming a system of equations. In matrix form the VAR model is

$$Y_t = AY_{t-1} + e_t \qquad [4]$$

where Y is a vector of variables (y and x in the case above) and A is a matrix of poly-nomials in the lag operator and e_t is a vector of random errors. Therefore VAR models are simple multivariate models in which each variable is explained by its own past values and the current and past values of all other variables in the system.

Much of the appeal of VAR stems from Sims (1980) critique of structural models. He basically questioned the theoretical validity of the restrictions imposed on the structural models of the time. Sims favoured an atheoretical approach to modelling based on vector autoregressions, in which the data generation process determines the model.

Therefore we may start from a structural hypothesis or model in matrix form such that

$$HY_t + JX_t = k\varepsilon_{it} \qquad [5]$$

and $E(\varepsilon_{it}\, \varepsilon'_{it}) = I$ (i.e. the errors are homoskedastic). Y and X are vectors of endogenous and exogenous variables respectively. If we endogenize the X matrix, we can
write Y such that H becomes

$$H = H_1 + LH_2$$

where H_1 is a matrix whose elements give the contemporaneous relation between the variables and H_2 gives the relation with the lag variables where L is the lag operator. Given this, equation [5] becomes

$$H_1 Y_t + H_2 Y_{t-1} = k\varepsilon_{it}$$

Assuming that H is a positive definite matrix and thus invertible we can solve for Y_t to obtain

$$Y_t = - H^{-1}_1 H_2 Y_{t-1} + H^{-1}_1 k\varepsilon_{it}$$

This can be rewritten as

$$Y_t = A^* Y_{t-1} + e^*_t$$

which is of the same form as the VAR expression in equation [4]. The variance covariance matrix however is no longer $E(\varepsilon_{it}\, \varepsilon'_{it}) = I$ but

$$E(e_t\, e'_t) = E[H^{-1}_1 k\varepsilon_{it} (H^{-1}_1 k\varepsilon_{it})']$$
$$= \Omega$$

consequently[7] care must be taken in making inferences about the response of the system to disturbances. This is the result of the fact that the elements in the A* matrix are not impact multipliers but reduced form coefficients. Further the estimated coefficients on successive lags tend to oscillate and they tend to incorporate complicated by cross-equation feedbacks.

Instead the response to shocks can be assessed using innovation analysis This involves using the Ω matrix to generate variance decompositions and impulse response functions. This however depends on the causal order of the impact or the transmission mechanism. Sims proposed ordering the variables from the most pervasive, in which the shocks to the variables have an immediate impact on all other variables in the system, to the least pervasive. In practice, ordering is done by a Choleski decomposition of the covariance matrix Ω. This produces a lower triangular matrix such that $\Omega = \lambda\lambda'$ holds, where $\lambda = H^{-1}_1 k$. This allows the effects of

[7] Proof : $E(e_t\, e'_t) = E[H^{-1}_1 k\varepsilon_{it} (H^{-1}_1 k\varepsilon_{it})']$

$$= E[H^{-1}_1 k\varepsilon_{it}\varepsilon_{it}' k' (H^{-1}_1)']$$

Taking expectations we have

$$E(e_t\, e'_t) = E[H^{-1}_1 kk' (H^{-1}_1)'] E(\varepsilon_{it}\varepsilon_{it}')$$

but $E(\varepsilon_{it}\varepsilon_{it}') = I$, thus shocks to each variable in the system to be identified. In which case they can then be interpreted as structural shocks. In the case where the possible number of orderings maybe large, 'structural' VAR (SVAR) models have been proposed in which economic theory is used to determine the order.

The exercise will therefore involve the estimation of a compact reduce form system explaining the predictable co-movements amongst the variables. The unexplained portion, is then given a structural interpretation, in the framework of a SVAR, whereby identifying assumptions are placed on the pattern of correlation among the residuals.

The main problem with estimating VARs however, is that the number of variables and lags may lead to over parametization. This causes multicollinearity between the different lagged variables and poor out of sample forecasts (although the within sample fit maybe good). Bayesian vector autoregression (BVAR) has been used to overcome this. Also Gilbert (1995) has suggested combination of VAR estimation and state space model reduction techniques in determining the model.

Alternatively minimizing the Schwartz criterion given as

$$sc = T\ln\hat{\sigma}^2 + n\ln T$$

can be used to reduce the parameters. This paper along with using the Schwartz criterion will employ a likelihood ratio test which tests the appropriateness of one lag length over another. If Ω^* is a M*M covariance matrix based on a lag length 'p', and Ω is a contending residual covariance matrix of lag length 'p-i', then the likelihood ratio statistic is given as

$$\lambda = T(\ln|\Omega| - \ln|\Omega^*|)$$

where T is the number of observations and $\ln|\Omega|$ represents the log determinant of the matrix. Because the traditional χ^2 and F distributions in a VAR framework are subject to asymptotic biases, T is modified by a multiplier correction, which simply adjusts the statistics according to the sample size and the number of estimated coefficients. This can be used to test the hypothesis that the coefficients of the i lags are zero. It is distributed χ^2 with M^2 degrees of freedom.

This test is applied iteratively until the most appropriate lag, given the data generation

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$E(e_t e'_t) = E[H^{-1}_1 kk'(H^{-1}_1)']I = \Omega$

process, is obtained. In the first stage, a hypothetical lag structure[8] is assumed, which is then tested against an alternative to derive an initial lag length. This is then tested against smaller alternatives. The process is repeated until the most suitable length is found.

3.1 Cointegration and Error Correction

Traditional economic theory has been applied on the assumption that economic series have a constant mean and finite variance. That is, the variables are stationary. (A non-stationary series on the other hand is characterized by a time-varying mean or variance, and thus any reference to it must be within a particular time frame.) In practice, however, most economic series are not stationary and consequently OLS estimation will lead to spurious results. Recent developments however, notably Engle and Granger (1987), have shown that OLS estimation may still be valid if a linear combination of any non-stationary series is stationary. In which case the variables are said to be cointegrated.[9]

If the variables are stationary then the VAR can be estimated, in which case any shock to the stationary variables will be temporary. If the variables are nonstationary and not cointegrated, then they have to be transformed into stationary variables by differencing, before the VAR can be estimated. Shocks to the differenced variables will have a temporary effect on the growth rate but a permanent effect on its level. Cointegrated non-stationary variables require the inclusion of a vector of cointegrating residuals (adjustment matrix) in the VAR with differenced variables. This is known as a vector error correction model (VECM).[10] This is necessary as the Granger Representation Theorem notes that cointegrated variables are related through an error correction mechanism.

To test for stationarity[11] or the absence of unit roots, an alternate test for unit roots developed by Phillips and Peron(1988) is used. Consider the autoregressive model

$$y_t = r y_{t-1} + \varepsilon_t \qquad t = 1,2,.......$$

In the limit, the time series y_t converges to a stationary series if and only if $| r | < 1$.

[8] This is essentially an unresticted VAR.

[9] Please see K. Holden , and J. Thompson , **Co-Integration: An Introductory Survey**. British Review of Economic Issues June 1992, for a simple overview of stationarity and cointegration theory.

[10] Testing and analysing cointegration in a VAR model is often considered more robust than the Engle - Granger single equation method. See S. Johansen (1991), **Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models**. Econometrica 59.

If $|r| = 1$, the series is not stationary with its variance being a function of time t. The series is said to follow a random walk or possess a unit root. If $|r| > 1$, the series is also non-stationary with its variance increasing exponentially as time passes, that is the series explodes.

The Phillips-Perron test, like the Dickey-Fuller test, tests the hypothesis that $r = 1$ in the equation

$$\Delta y_t = \mu_t + r y_{t-1} + \varepsilon_t$$

Unlike the ADF test, there are no lagged difference terms on the left hand side. The equation is estimated by ordinary least squares and then the t-statistic of the coefficient is corrected for serial correlation, using the Newey-West procedure. All that is required is to specify the autoregressive structure to be used by the Newey-West procedure. This yields the Z_t statistic, where

$$Z_t = \left(\sum_{2}^{T} y^2_{t-1}\right)^{0.5} (r - 1) s^{-1}_{Tl} - (0.5)(s^2_{Tl} - s^2_k)\left[s_{Tl}\left(T^{-2} \sum y^2_{t-1}\right)^{0.5}\right]^{-1}$$

and

$$s^2_k = T^{-1} \sum_{2}^{T} y^2_t$$

$$s^2_{Tl} = T^{-1} \sum_{1}^{T} y^2_t + 2\, T^{-1} \sum_{s=1}^{l} w_{sl} \sum_{t=s+1}^{T} y_t\, y_{t-s}$$

for some choice of lag window such as $w_{sl} = 1 - s/(l+1)$

3.2 Variable Selection

The previous discussions on inflation and recent empirical work suggest that both monetary and to a lesser extent structural variables are relevant to the model. For parsimony however the variables selected are the logs of the consumer price index(CPI)
(in which case the difference gives the inflation rate), exchange rate (xrate) , gross domestic product (GDP), imported price index[12] (ipi) to capture imported inflation, interest rate on Jamaican treasury bills (ijt) and the money base (bm). Imported inflation and GDP represent the structural influences on inflation whilst the interest rate on treasury bills and base money

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[11] See T. Agbeyegbe(1996) for a discussion on testing for stationarity in price series in the Caribbean.
[12] Imported inflation is derived from an imported price index, which is a weighted average of the export prices

represents the monetary policy stance.

Block exogeneity tests are used to determine how these variables enter the model. Block exogeneity tests are the multivariate generalization of the Granger causality tests. It has as its null hypothesis, that the lags of a set or block of variables do not enter the equations of the other variables, and thus it is exogenous to the model.

It maybe argued that some measure of fiscal policy, such as the deficit or central bank advances to government, should be included. However to attain parsimony such variables are excluded. Further, it can be shown that changes in base money do capture fiscal policy influences.

4.0 Results

Table i shows the results of the unit root tests with the 5% Mackinnon critical values. The table shows that all the variables are non-stationary, specifically, the variables are I(1). Consequently they have to be differenced once to become stationary. Further Table ii shows the results of the Johansen tests for cointegration amongst the variables. The results indicate that there are at most two cointegrating vectors.

Table i

Phillips-Peron Unit Root Test

Variable	Level	1st Difference
LCPI	-1.25	- 7.82
LGDP	-2.19	-10.77
LIPI	-1.89	-13.42
LXRATE	-2.31	- 9.37
LBM	-3.21	-16.25
LIJT	-3.25	-10.38

of the major trading partners and the price of oil.

MacKinnon 5% critical value = -3.4344

Table ii

Johansen Cointegration Test

	Eigenvalue	Likelihood Ratio	5% Critical value	1%Critical value
r = 0	0.274	149.4	102.1	111.01**
r ≤ 1	0.189	89.6	76.1	84.45 **
r ≤ 2	0.135	50.4	53.1	60.16
r ≤ 3	0.068	23.6	34.9	41.07
r ≤ 4	0.036	10.1	19.9	24.60
r ≤ 5	0.017	3.3	9.2	12.97

*(**) denotes rejection of the hypothesis at 5%(1%) significant level.

Given the above results a VECM was estimated. Because we are using monthly data an initial lag length of twelve lags (unrestricted VAR) versus smaller lags VARs was tested. Initially the Likelihood ratio favoured seven lags chosen. Further iterations however based on the likelihood ratio and the Schwartz criterion favoured a four lag VAR[13].

The block exogeneity tests indicated that base money, interest rate, exchange rate and gross domestic product should enter the model at four lags. This would suggest that Granger causality runs from these variables to the inflation rate. The most significant variables were base money and exchange rates. The evidence for imported inflation was weak. It was replaced by wages, however the out of sample forecasting accuracy of the VECM declined significantly. This is probably the result of a poor monthly wage series. Imported inflation, to the extent that its impact would reflect structural influences, was therefore retained in the model. The full VECM

[13] The Likelihood Ratio for twelve versus seven lags was χ^2 (112) = 91.1 with a significance level of 0.9267. At Four lags the Likelihood Ratio χ^2 (64)= 62.32 with a significance level of 0.536. We therefore cannot reject the null hypothesis that the restrictions hold, and thus conclude that four lags are sufficient. The

results are given in Appendix ii.

4.1 Forecasts

Figure viii shows the actual versus the fitted values (within sample) for the inflation rate. Table iii gives a comparison of the forecasting accuracy of the VAR model against an ARMA(4, 3) , Ganga's monthly model and the monthly version of Worrell's (1993) model. The criteria used are the root mean square error RMSE, Theil U statistics and the Janus quotient (J). The Janus quotient looks at the predictive accuracy of the out of sample predictions against the within sample fit. It is given as,

$$J^2 = \frac{\sum_{i=n+1}^{n+m} (P_i - A_i)^2 / m}{\sum_{i=1}^{n} (P_i - A_i)^2 / n}$$

The numerator gives the deviations in the out of sample period whilst the denominator gives the deviations over the sample period. The higher its value the poorer the forecasting performance. If the structure of the model remains constant over the out of sample period then J tends to one. Thus values greater than one indicates the presence of some structural change. This statistic and its interpretation are affected by the size of the out of sample period.[14]

The VAR model has the lowest mean square error in the predictions. Corres-pondingly it possesses the greatest predictive power as evidenced by the Theil U statistics. The ECM is only marginally better than the ARMA model in terms of its forecasting accuracy. Whilst the J-statistic for the VAR model is acceptable (at this point), the ECM exhibits the greatest structural stability. The other models are highly unstable. This highlights the important point that VAR models are suited for short-term forecasting (one to two years). Medium to long term forecast horizons require the use of models such as error correction models.

Table iii

Model	RMSE	Theil U	J

Schwartz criteria for 12, 7 and 4 lags were 46.3, 45.2 and 44.0 respectively.

[14] A more appropriate test would be Chow's predictive test. However the reduction in the sample size, given the number of parameters, would make it difficult to clearly distinguish between instability in the form of occasional outliers and instability in the form of parameter shifts.

VAR	0.004	0.18	0.34
ARMA	0.008	0.38	5.22
ECPM	0.009	0.35	0.90
GANGA	0.036	1.70	2.40

4.2 Impulse Response and Variance Decomposition

This section analyses the dynamic property of the model using variance decomposition and impulse response functions. Figure i shows the response of the inflation rate to a one unit shock to the exchange rate, base money, treasury bill rate, imported inflation and output. The x-axis gives the time horizon or the duration of the shock whilst the y-axis gives the direction and intensity of the impulse or the percent variation in the dependent variable (since we are using logs) away from its base line level.

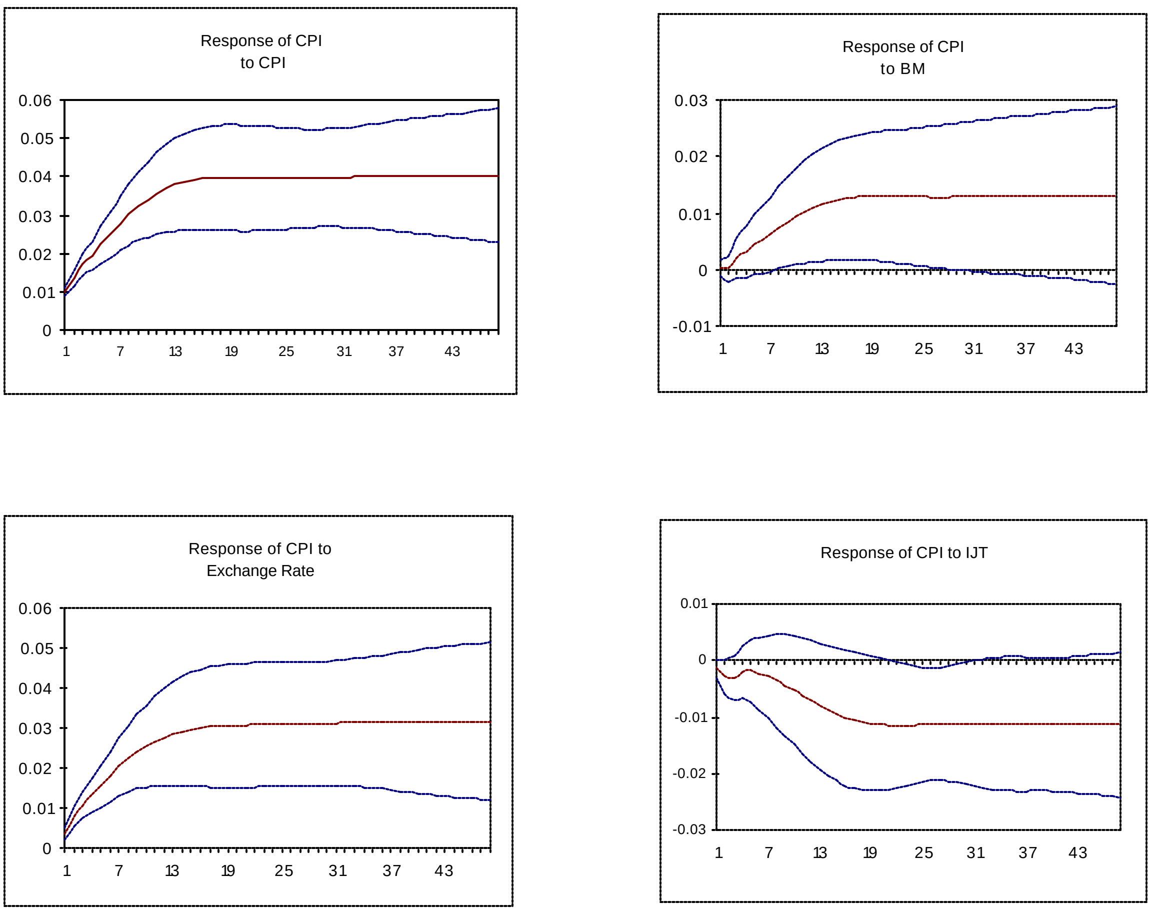
Monte Carlo simulations (with one hundred draws) from the unrestricted VAR were used to generate the standard errors for the impulse response and variance decomposition coefficients. The confidence bands for the response function are 90 % intervals generated by normal approximation. There is no consensus on an explicit criterion for significance in a VAR framework. Sims (1987) however suggests that for impulse responses significance can be crudely gauged by the degree to which the function is bounded away from zero, whilst Runkle(1987) suggests a probability range above 10 percent for variance decompositions.

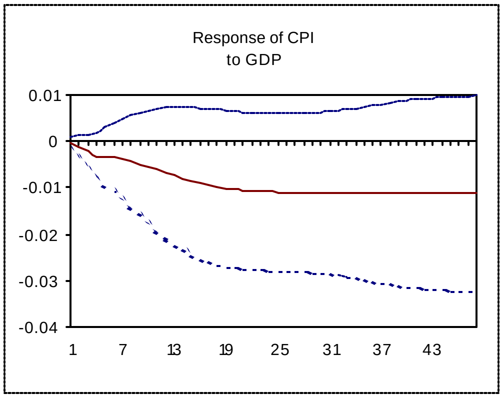
The impulse responses meet *a priori* expectations in terms of the direction of impact. The graphs show that a positive shock to monetary variables or expansionary monetary policy, has a significant expansionary effect on inflation. *The effect of a unit shock to base money on the cpi, occurs after approximately the first one to two months and reaching its peak between ten to twelve months*. Thereafter the cumulative effects of
base money stabilize with the monthly CPI increasing by approximately one percent of its baseline level.

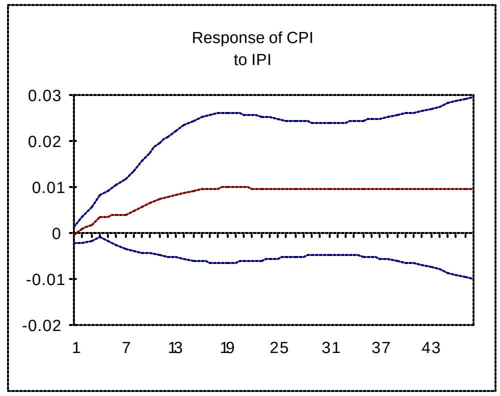
The impact of the exchange rate is rather immediate and long lasting. A unit shock to the exchange rate causes the cpi in the first period to deviate by approximately

0.5 percent from its base level. The inflation rate accelerates rather rapidly in the first ten to twelve months as the CPI tends to a new equilibrium level. *Increases in the interest rates tend to have a contractionary effect on prices*. The more significant impact however manifests itself after five months with the response function trending away from zero.

Figure i
Response of CPI to one s.d. Innovation







The response of direct shocks to the CPI such as expectations and discrete price adjustments resulting from increase markups, removal of subsidies, etc. follows a similar path to the response to exchange rate shocks. The magnitude of the impact of direct shocks, particularly in the first period, is greater for direct shocks to the CPI. The similarity in the paths may stem from the fact that both sources represent some cost push element. The impulse response of CPI to its own innovation however does highlight the role of expectations and the price setting mechanism which includes indexation.

Increases in output do have a significant contractionary effect whilst imported inflation exerts a positive influence after the second month. The impact, particularly of imported inflation seems to be long lived. This is due to the open nature of the economy and the extent to which domestic production relies on foreign inputs.

The foregoing indicates that both cost push and demand pull elements help to explain prices. Having shown the dynamic effects of each disturbance however the next step is to assess their relative contribution to the fluctuations in prices. This is done by decomposing the forecast variance of the inflation rate over different horizons.

Table iv shows the variance decomposition over the short term (6 months), medium term (12 - 24 months) and over the long term (48 months). The statistics indicate the percentage contribution of innovations in each of the variables in the system to the variance of the CPI. *The results show that shocks to the CPI itself and the exchange rate accounts for most of the variability in the CPI over all horizons*. Not much can be attributed to base money, although over longer horizons its relative contribution increases. More importantly, the variance decomposition of the exchange rate (Table v) shows that apart from innovations to the exchange rate itself, base money contributes significantly to the variations in the exchange rate. This supports Ghartey (1995) assessment. *We can conclude that the basic transmission mechanism runs from base money (via interest rates which affect the relative return on financial assets) to the exchange rate and then to prices.*

Further the greater contribution of innovations in the exchange rate in Table v suggests that much of its volatility is the result of exchange rate speculation (even in the long run). One will also note the increasing contribution of the CPI over time. This maybe reflecting the long run phenomena of purchasing power parity (i.e feedback from the CPI to the exchange rate).

Table iv

Variance Decomposition of the CPI (%)

Horizon	Base Money	CPI	IJT	Ex.Rate	IPI	GDP	Std. Err.
6 mths	1.964	65.289	1.028	29.065	1.440	1.214	0.10237
12 mths	3.724	59.966	1.325	31.585	1.931	1.469	0.14865
24 mths	4.949	55.068	3.121	31.384	2.757	2.719	0.24518
48 mths	5.257	52.967	3.716	31.654	2.92	3.487	0.38501

Table v

Variance Decomposition of the Exchange Rate (%)

Horizon	Base Money	CPI	IJT	Ex.Rate	IPI	GDP	Std. Err
6 mths	7.024	2.538	1.626	86.771	0.742	1.3	0.10237
12 mths	8.414	6.361	5.889	73.484	2.177	3.674	0.14865
24 mths	8.420	7.687	7.226	68.774	2.315	5.576	0.24518
48 mths	8.43	8.9	7.511	66.245	2.399	6.417	0.38501

5.0 Conclusion

The foregoing points to increased forecasting accuracy when a VAR is applied as against other models. VARs avoid the need for an explicit theory (in the initial stages) and information on the exogenous variables over the forecast period. The foregoing results and the experience of a number of economists using VARs however, suggest that VARs are more suited for short term forecasting. Simultaneous and single equation error correction models are more appropriate for longer horizons.

When applied to price behaviour in Jamaica, the VAR model revealed some interesting, though not surprising results, not readily seen with other conventional models. The innovation analysis showed that a positive shock to monetary variables or expansionary monetary policy has an unambiguous expansionary effect on prices. The response functions indicate that monetary policy has a lag effect of 'at least' two months. Further, a decline in the rate of depreciation of the exchange rate will have an immediate dampening effect on prices, particularly in the first twelve months. The response to exchange rate shocks suggests that exchange rate stabilization maybe the most effective way of achieving price stability in the short run. The results of the variance decomposition suggest that monetary stability and the development of an efficient market are essential to exchange rate stability.

The results show that the prices rate do not return to its original level as there is a tendency for inflationary shocks to be long lived. These shocks maybe perpetuated by the nature of the stabilization process, the structure of the economy, the production function, indexation and other institutional factors. Other factors such as the pricing mechanism, expectations and exchange rate speculation, which are captured in the own innovations of the CPI and exchange rate are also very significant and create very strong inertial tendencies. Stabilization policies must therefore be cognizant of these influences that frustrate the stabilization process.

Appendix i : VECM results

	D**lbm**	D**lcpi**	D**lijt**	D**lxrate**	D**lipi**	D**lgdp**
CointEq1	-0.075302	0.002964	0.146435	0.044753	-0.020258	-0.000165
D**lbm**$_{-1}$	-0.245188	-0.011797	-0.147164	-0.030756	0.025457	-0.005908
D**lbm**$_{-2}$	-0.159482	0.024389	-0.306856	0.020044	-0.031585	-0.004351
D**lbm**$_{-3}$	-0.108646	-0.001719	-0.051006	-0.028488	-0.016533	0.003347
D**lbm**$_{-4}$	-0.100600	0.012345	0.065615	0.049860	0.009226	-0.004181
D**lcpi**$_{-1}$	-1.142976	1.463842	1.368287	-0.345637	0.115232	-0.015698
D**lcpi**$_{-2}$	0.280319	0.267643	-0.629099	0.765135	-0.578186	-0.005017
D**lcpi**$_{-3}$	-1.001608	-0.034955	1.396298	-0.369185	0.638502	-0.014165
D**lcpi**$_{-4}$	0.409937	0.130851	0.395987	1.161784	-0.253843	0.016390
D**lijt**$_{-1}$	-0.022102	-0.010753	0.217460	0.048805	-0.005227	0.001611
D**lijt**$_{-2}$	-0.006775	0.015486	0.170529	0.046596	-0.037137	-0.000613
D**lijt**$_{-3}$	-0.069554	0.019427	0.175152	0.018287	-0.022962	-0.000386
D**lijt**$_{-4}$	0.016762	0.004149	0.029963	-0.063263	-0.038822	-0.001489
D**lxrate**$_{-1}$	0.198067	0.083270	-0.078436	0.475685	-0.064791	0.001006
D**lxrate**$_{-2}$	-0.187667	-0.021281	0.485300	-0.246506	0.069509	-0.000535
D**lxrate**$_{-3}$	0.204625	0.029813	-0.034784	0.210878	-0.048689	-0.000745
D**lxrate**$_{-4}$	0.239359	-0.010273	-0.025574	-0.014115	-0.012678	0.000120
D**lipi**$_{-1}$	-0.102374	0.021819	-0.074585	-0.041263	0.147815	-0.001770
D**lipi**$_{-2}$	0.152281	0.012038	-0.144849	0.059797	-0.108635	0.004301
D**lipi**$_{-3}$	0.085430	0.018808	-0.136377	-0.054082	-0.082120	-0.000415
D**lipi**$_{-4}$	-0.019440	-0.022786	-0.094716	-0.021551	-0.149414	0.000587
D**lgdp**$_{-1}$	-1.736537	-0.185210	-0.960204	-0.269209	1.290785	0.379184
D**lgdp**$_{-2}$	2.209432	-0.245179	5.805997	0.292302	0.236400	0.169180
D**lgdp**$_{-3}$	-5.666179	0.104583	-0.017186	-0.367664	-0.228389	0.095328
D**lgdp**$_{-4}$	-1.217771	0.326404	-2.090249	0.498937	2.037606	-0.005652
C	0.065352	0.002740	-0.037944	-0.011772	0.001324	0.001177
Adj. R-squared	0.175903	0.535369	0.283515	0.259193	-0.005172	0.330951
Akaike AIC	-5.502484	-8.813576	-5.141707	-6.178165	-5.859293	-12.00361
Schwartz SC	-5.05323	-8.364331	-4.692462	-5.728920	-5.410048	-11.55437