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MACRO-ECONOMETRIC ANALYSIS OF THE EFFECTS OF DOMESTIC CREDIT CONDITIONS AND MONETARY INNOVATIONS ON AGRICULTURE BY VECTOR-AUTOREGRESSION METHODS: UNITED KINGDOM, JAPAN, AUSTRALIA, AND NIGERIA

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University Microfilms International 300 N. Zeeb Road, Ann Arbor, MI 48106
Macro-econometric analysis of the effects of domestic credit conditions
and monetary innovations on agriculture by vector-autoregression
methods: United Kingdom, Japan, Australia, and Nigeria

by

T. A. Sanni

A Dissertation Submitted to the
Graduate Faculty in Partial Fulfillment of the
Requirements for the Degree of
DOCTOR OF PHILOSOPHY

Major: Economics

Approved

Signature was redacted for privacy.

In Charge of Major Work

Signature was redacted for privacy.

For the Major Department

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For the Graduate College

Iowa State University
Ames, Iowa

1986
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DEDICATION

This work is dedicated to Dr. Earl O. Heady.
GENERAL INTRODUCTION

Structural econometrics

Consider equation (1) below as estimating the variable X:

\[ X = q_1 X_{t-1} + q_2 Y_t + q_3 Y_{t-1} + q_4 Z_{t-1} \]  \hspace{1cm} (1)

To the extent that a policy simulation yields consistent estimates of X conditional on Y, then equation (1) may be a structural relation. However, this depends on the "true" structure of the economy and on the process that generated Y in the sample period.

Posit the accurate functional form of (1) as

\[ X_t = q_1 X_{t-1} + q_2 Y_t + q_3 Y_{t-1} + q_4 Z_{t-1} + U_t \]  \hspace{1cm} (2)

and policy set by

\[ Y_t = r_1 Y_{t-1} + r_2 X_{t-1} + r_3 Z_{t-1} + V_t \]  \hspace{1cm} (3)

Suppose \( V_t \) is uncorrelated with \( U_t \) thereby indicating that we have pure Y shocks or completely randomized experiments. Suppose further that \( q_4 = 0 \) and \( Z_{t-1} \) is uncorrelated with \( U_t \) in which case \( Z_{t-1} \) is an instrumental variable and further implying that even if the experiments are not random (e.g. they may be conditional on \( Z_t \)). Such experiments are informative about the role of Y because \( Z \) does not affect \( X \) directly.

Structural econometric models have traditionally made exclusionary restrictions on variables such as \( Z \).
In the place of (2) consider

\[ X_t = Q_1X_{t-1} + Q_2(Y_t - Y^e_t) + U_t \]  \hspace{1cm} (4)

Where \( Y^e_t \) is expected \( Y \), so that \( X \) fluctuates according to unanticipated \( Y \) shocks. From (3) and (4) one may obtain

\[ X_t = (Q_1 - Q_2r_2)X_{t-1} - Q_2r_1Y_{t-1} + Q_2Y_t - Q_2r_3Z_{t-1} + U_t \]  \hspace{1cm} (5)

which clearly indicates that \( X \) and \( Y \) depend on the policy rule itself so that although \( X_t \) is independent of the \( Y \) rule, a naive estimation of (5) will suggest otherwise.

In conclusion, the reduced form estimate (1) will say nothing useful about the effects of a change in \( Y \) supply rule (that is, a change in \( r_1, r_2, r_3 \)) on \( X \). The issue discussed so far is the famous Lucas Critique.

**New directions in applied econometrics**

Forecasting and policy analysis are the goals of most macroeconometric formulations for economic data observed in aggregate time frames. Structural econometric models can only demonstrate that a statistically significant relationship exists between two (or more) variables. Such models are not powerful enough to draw the stronger conclusion that changes in one variable caused changes in the other.

Innovative atheoretical macroeconometrics have been developed. This new direction is commonly employed for exogeneity testing based on impulse response analysis as well as policy analysis using estimated vector autoregressions. In fact, the reduced forms of so-called
traditional simultaneous equation econometric models are special cases of vector autoregressions. Such models are simply estimated and identified through the imposition of huge numbers of exclusionary restrictions implied by the categorization of variables into exogenous and endogenous.

**Vector Autoregressions**

Unconstrained vector autoregression (VAR) modeling may be construed as a direct response to the criticism by rational expectationists and other economists of standard structural multiple-equation macro-econometric models. The unconstrained VAR allows all variables to enter the system with equal "interactional weights." That is, unrestricted VAR imposes no prior restrictions on the interactions among variables. It thus makes possible the exploitation of the full range of possible interrelationship over time among economic variables.

Litterman (1979) argues that the noise to signal ratio present in aggregate economic time series is high. He has suggested the use of Bayesian priors, which filter the useful signal from the accompanying noise and produce biased but mean squared error superior forecasts. Litterman's Bayesian procedure can be conceived of as a compromise between the extremes of standard structural specification (with highly objectionable priors) and unrestricted VARs (with no variable interactional weights).

Vector autoregression specification is very general. It is capable of modeling arbitrarily well any covariance stationary stochastic process. The main weakness of this specification, and the
reason it has not been used extensively in the past for economic forecasting, is that the number of free parameters increases quadratically with the number of variables in a system, and for even moderately-sized systems the model becomes highly overparameterized relative to the number of available observations. Each element of a vector of economic variables of interest is regressed on its own lagged values and the lagged values of every other variable in the system.

Several common types of macroeconomic models may be viewed as vector autoregressions with particular classes of restrictions. As we argued in the previous section, the reduced forms of traditional simultaneous equation econometric models are special cases of vector autoregressions. Such models are estimated and identified through the imposition of huge numbers of exclusionary restrictions on structural equations and the restrictions implied by the categorization of variables into exogenous and endogenous.

Another common forecasting method, the autoregressive-integrated-moving-average (ARIMA) models, generate stochastic processes which, under the usual invertibility assumption, have autoregressive representations. Though ARIMA models have theoretical virtues and are capable of capturing long lag distributions with parsimonious parameterizations, they have several drawbacks. It is the addition of a moving average, which differentiates ARIMA models from vector autoregressions, that causes a loss of linearity which makes estimation, statistical inference, interpretation, and prediction more difficult even in the univariate case. These difficulties increase dramatically
with multivariate ARIMA models. In fact, the univariate ARIMA models which are common in the literature may be viewed as multivariate models which have severe cross-equation exclusionary restrictions.

The equilibrium solutions of rational expectation models are another special case of vector autoregressions. Here, the assumption of optimizing behavior of agents in the economy generally leads to a set of complicated, cross-equation restrictions. In this dissertation work, unconstrained vector autoregressions are estimated using differing data, time periods, and different countries.

**VAR technique**

In standard structural macroeconometric models, the usual method of imposing restriction seems to be to assume that no variables enter a particular equation other than those for which there is a particular economic theory to justify their inclusion.

However, in macroeconometric models which involve conditioning expectations on the past values of all variables in the system, enter decision functions, then the opposite assumption would seem to be more appropriate that in general it is likely that movements of all variables affect the behavior of all other variables. The latter assumption happens to be the thrust of vector autoregression estimation. The remainder of this sub-section deals with the theoretical and methodological issues surrounding vector autoregression estimation.
Consider an equation in the vector autoregressive model.

\[ w_t = a_{11}(L) w_{t-1} + a_{12}(L) x_t + a_{13}(L) y_t + a_{14}(L) z_t + w^* \]  

(1)

Application of ordinary least squares (OLS) to the above equation yields the following:

\[ \hat{q}_t = \hat{a}_{11}^m(L) w_{t-1} + \hat{a}_{12}^n(L) x_t + \hat{a}_{13}^p(L) y_t + \hat{a}_{14}^r(L) z_t + w^*_t \]  

(2)

In an equation such as (2), the superscripts \( m, n, p, \) and \( r \) denote the order of lags in \( a_{11}(L), a_{12}(L), a_{13}(L), \) and \( a_{14}(L), \) respectively. While \( \hat{a}_{11}^m(L), \hat{a}_{12}^n(L), \hat{a}_{13}^p(L), \hat{a}_{14}^r(L), \) and \( \hat{q}_t \) are least squares estimates.

1. A non-trivial question immediately comes to mind on the appropriate specification of our VAR model as depicted by the system (1) above. Such a question concerns the choice of an appropriate lag length. In other words, what are realistic or reasonable values for \( m, n, p, \) and \( r \) in an equation such as (2)?

In attempts to answer the foregoing question, several criteria have been suggested for choosing appropriate lag length. First, there is an intuitive argument that regularities in economic data may be missed by using less than an annual lag structure such as 4 quarters or 12 months depending on the frequency of observations. Second, one may compare two specific lag lengths and then use the asymptotic chi-square distribution of the log likelihood ratio to test the null hypothesis of zero sum of
coefficients on terms excluded from the constrained model. It is well-known that asymptotically, under a null hypothesis that the omitted lags from the constrained model truly have zero coefficients, 

\(-2\log(\text{likelihood ratio})\) is distributed chi-square with \((k_{U} - k_{R})\) degrees of freedom, where \(k\) is the number of variables in the model while \(k_{U}\) and \(k_{R}\) are the number of lags of each variable included in the unrestricted and restricted model, respectively. Third, Akaike (1974) and Schwarz (1978) have proposed criteria for choosing lag length based on maximizing the log likelihood function while adjusting for the number of parameters to be estimated. Indexing models of different lag lengths by the subscript \(q\) if we have \(T\) observations and \(K_{q}\) parameters to estimate, Akaike proposes that one chooses the model that maximizes \(\log(L_{q} - K_{q})\) where \(L_{q}\) is the likelihood function maximized with respect to parameters estimated. Schwarz proposes choosing \(q\) to maximize \(\log(L_{q} - K_{q}) \log T/2\). It has been observed however that this criterion of Schwarz have the tendency to favor models with fewer lags!

2. The time series data used in vector autoregression estimation is always assumed to represent a covariance stationary stochastic process. A vector stochastic process is stationary if \(EX_{t} = \mu(\text{the mean of } X_{t})\) and \(Var(X_{t}) = \frac{2}{\lambda} < \), \(cov(X_{t}, X_{s}) = \rho_{t-s}\). In essence, all that is involved here is that a stationary process will have mean and variance that do not change through time, and the covariance between values of the process at two points in time depends solely on the distance between those two points in time, and not on time itself. Essentially, the stationarity assumption is equivalent to saying that
the generating mechanism of the process is itself time invariant, so that neither the form nor the parameter values of the generation procedure changes through time. The issue, therefore, is that without doubt no one can claim that an assumption of stationarity is generally realistic.

Not surprisingly, therefore, it is widely observed that empirical data available to the economic analyst often will exhibit seasonality, indicating that such raw data does not in fact represent a covariance stationary stochastic process. In vector autoregression literature, the usual practice in this situation is to transform the data for example by taking logs. Alternatively, one may include seasonal dummies or time trend as righthand variables in an attempt to derive a data set that can be represented by stationary stochastic process.

3. Another methodological issue with respect to VAR is that of homogeneity, in the sense that a priori we do not always know whether the parameters of a VAR model are stable over time. According to Lucas (1976), for any structural equation to be identified it should uniquely remain invariant in spite of "interventions," e.g., substantially different regimes. Hence, if we suspect that our historical data spans eras of substantially different policy regimes, or if an economy is characterized by structural changes, then it might be necessary to test for homogeneity.

4. Another by no means trivial methodological issue with regards to VAR is its excessive data demand and the large number of parameters to estimate. This has led Litterman (1979) to suggest that to attain a
A reliable forecasting model requires a minimum of 30 observations per parameter estimated. Sims (1978) suggested the use of index models. Index models require all cross-variable relations in an n variable autoregressive as common dependence of the n variables on k "indexes" which are themselves linear combinations of past values of variables in the VAR system. Litterman (1979) argues that the noise to signal ratio present in aggregate economic time series is high. He suggested the use of Bayesian prior which filters the useful signal from the accompanying noise, which though give biased but mean squared error superior forecasts. In this Bayesian approach, there is a prior distribution emphasizing short lag univariate representations of each variable and cross variable relations entering only if they are strongly suggested by the data.

**Monetary impacts on agriculture**

Chambers and Just (1982) formulated a model to assess the effects of macro monetary factors on U.S. agricultural markets. These authors subjected the model to dynamic multiplier analysis to examine the effects of the level of domestic credit, identified as money supply widely defined (M2), on the agricultural sector. Their results suggested that the dynamic response of agricultural prices and exports to a decrease in the money supply is eventually elastic, and that anti-inflationary policies such as a contraction of the money supply may seriously affect the competitive position of the U.S. agricultural sector in the world market. Chambers (1984) then developed a theoretical model to address the questions of whether and how variations
in the money supply relate to agricultural aggregates. In an empirical analysis of his model, Chambers demonstrated that in the short run, a restrictive open market policy may depress the agricultural sector, affecting agricultural trade, agricultural prices, and agricultural income. Again, analysis was limited to the United States.

In this dissertation work, I applied Chambers' model to study the same kind of monetary impacts on the agricultural sectors of the postwar United Kingdom, Japan, and Nigeria. Those applications are contained in Sections I, II, and IV, respectively.
DYNAMIC MODELING OF TRIVARIATE MONETARY
AND AGRICULTURAL TIME SERIES OBSERVATIONS
ON UNITED KINGDOM POSTWAR ECONOMY

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SECTION I. DYNAMIC MODELING OF TRIVARIATE MONETARY AND AGRICULTURAL TIME SERIES OBSERVATIONS ON THE UNITED KINGDOM’S POSTWAR ECONOMY

Introduction

Chambers and Just (1982) in their study on the effects of monetary factors on United States Agriculture contend that, the long-run effect of a sustained change in the level of domestic credit identified as money supply, can have a significant impact on the agricultural sector of the economy—especially on agricultural prices. These authors found grain prices to be very responsive to fluctuation in the level of domestic credit. For instance, their results suggested that,

a sustained ten percent reduction in domestic credit eventually evokes more than a seventeen percent change in the level of wheat price, a seven percent change in corn price, and an eleven percent change in soybean price (p. 244).

Chambers and Just also argues that, a contraction of domestic credit by appreciating the exchange rate worsens the competitive position of the United States' agricultural sector in the world market. However, these authors observed a shift from exports to domestic consumption of wheat, corn, and soybean though, not sufficient to compensate for the decrease in exports. Consequently, domestic agricultural prices were seriously deflated.

Sanni (1985c) in a recent study on monetary impacts on Japanese agriculture, proposed a vector autoregressive (VAR) model. I then employed the innovation—accounting and computation of orthogonal innovation techniques pioneered by Sims (1980a, 1980b) and further
developed by Doan and Litterman (1983) to uncover very interesting
dynamic relationships between money supply (defined as (M1) and
alternatively, (M2)) on both the Food Component of the Consumer Price
Index (FCPI) and an index of price received by farmers (IPR).

A major conclusion of my study is that the proportion of FCPI
forecast error variance attributable to changes in the triangularized M1
innovation becomes progressively larger: only about 4 percent initially
to 27 percent by the 12th month horizon. FCPI innovations accounted for
by FCPI itself steadily declined from 98.2 and 71.9 percent for the 4th
and 12th months, respectively. And, finally, FCPI accounts for roughly
13 percent for the 4th through the 12th months of the triangularized M1
innovations.

The author is primarily interested in studying the impacts of macro
monetary factors on agriculture (see Sanni (1985a, 1985b, and 1985c);
Sanni and Calkins (1985); and Sanni, Calkins, and Shelley (1985)).

The present paper is an attempt at dynamic modeling of trivariate
monetary and agricultural time series observations on the United
Kingdom's postwar economy. We employed the Vector Autoregression (VAR)
methodology. The paper is organized into five sections. The second
section is on VAR methodology while the third section contains the
model, data, and sources. The fourth section is on empirical analysis.
A brief summary of major findings as well as concluding remarks is the
subject of the fifth and final section.


**VAR methodology**

Analysis in the framework of a standard macroeconometric model proceeds on the basis of restrictions among variables imposed a priori so that a particular "structural" model is presented. Reduced-form equations are then derived on the basis of the assumed structural model.

However, fitting econometric models based on supposed a priori knowledge or economic theory does not resolve controversy surrounding competing theories of economic activity. For example, there is much disagreement among economists on the role of money supply (see Brunner and Meltzer (1966); Friedman (1970); and Tobin (1970)).

Also, in standard econometric modeling there is a dichotomy between endogenous and exogenous variables. This division of variables into a group considered exogenous and a group considered endogenous presupposes that shocks to endogenous variables do not affect exogenous variables. And changes in exogenous variables are treated as mutually independent. This is the basis on which interim multipliers trace the effects on endogenous variables of a change in a specific exogenous variable, and on which reduced-form equations of the model are used to decompose historical movements in predicted values of endogenous variables into components attributed to observed changes among exogenous variables.

Standard econometric models, therefore, provide little distinction between expected paths and unexpected shocks in the evaluation of effects of changes in exogenous variables on endogenous variables. This should not be surprising, because treatment of exogenous variables as non-stochastic precluded such a distinction. The asymmetry imposed by
the dichotomy between endogenous and exogenous variables in standard econometric models often results in an equivalent asymmetry in interpretation of the model. *Analysis based on reduced-form equations focuses exclusively on the effects of changes in exogenous variables on endogenous variables.* Hence, usual reduced-form analysis provides no basis for evaluating the effects of shocks to endogenous variables on other endogenous variables. Comparison of the relative impacts among factors affecting an endogenous variable is thus restricted to comparisons only among exogenous variables.

I contend that the magnitude of the effects of shocks to variables treated as endogenous relative to the effects of shocks to variables treated as exogenous is relevant—particularly in the case in standard macroeconometric models developed to evaluate the effects of macroeconomic versus sectoral factors on agricultural markets. Such an asymmetry may severely constrain the utility of an analysis.

Recently developed and popularized by Sims (1980a, 1980b) there is a general strategy for estimating profligately as opposed to parsimoniously parameterized macro-models. It is thus increasingly feasible to estimate large-scale macro-models as unrestricted reduced forms, treating all variables as endogenous. This approach is called VECTOR AUTOREGRESSION (VAR).

The statistical model underlying the vector autoregression procedure is a linear dynamic system with an n x 1 vector of outputs, Y, (say) which is generated by a stochastic difference equation. Each variable is treated as a linear function of its own lagged values
and lagged values of each of the other variables plus a random disturbance.

If we assume that Y is generated by a \( m \)-th order stochastic difference equation of the form

\[
Y(t) = D(t) + B_1 Y(t-1) + \ldots + B_m Y(t-m) + \epsilon(t)
\]  \hspace{1cm} (1)

where \( D(t) \) is the deterministic component of \( Y(t) \), and typically might include a polynomial in \( t \) as well as seasonal dummies.

Under mild regularity conditions, the \( B_j \)'s are uniquely determined by the population orthogonality conditions

\[
E (\epsilon(t)' Y(t-j)) = 0 \quad j = 1, 2, \ldots, m
\]  \hspace{1cm} (2)

or more compactly

\[
(I - B(L)) Y(t) = D(t) + \epsilon(t)
\]  \hspace{1cm} (3)

where \( B(L) = \sum_{j=1}^{m} B_j L^j \), and \( L \) is the lag operator defined by

\[
L^j(Y(t)) = Y(t-j).
\]

The non-deterministic part of \( Y \) is given by

\[
Z(t) = Y(t) - (I - B(L))^{-1} D(t)
\]  \hspace{1cm} (4)

which has the moving average representation
\[ Z(t) = (I - B(L))^{-1} \xi(t) \]

\[ = M(L) \xi(t) \]

\[ = \sum_{j=0}^{\infty} M_j \xi(t-j) \quad (5) \]

where each \( M \) is an \( n \times n \) matrix and \( M_0 = I \). Note that the \( M \)'s and \( B \)'s are related by the matrix Fourier transform relation

\[ (I - B_1 e^{-iw} - \ldots - B_m e^{-iw_m})^{-1} \]

\[ = \sum_{j=0}^{\infty} M_j e^{-iw_j} \quad (6) \]

The autoregressive representation generates a broad class of stochastic processes.

According to a theorem by Wold (1938), any stationary process can be represented as the sum of a deterministic component which is representable as a moving average. Thus, all stationary stochastic processes for which the moving average is invertible can be represented as an infinite-order autoregression and approximated arbitrarily well by finite-order autoregressions.

The optimal linear projection property of the vector autoregressive representation for covariance processes is an important motivation for the choice of autoregressive estimators.

In a vector autoregressive system with \( n \) variables, there are \( n \) separate equations, each of which has the same explanatory variables.
In a system with \( m \) lags of each variable and deterministic component \( D(t) \), a function of \( n \times d \) matrix of parameters \( c \), the \( i^{th} \) equation has the following scalar form:

\[
Y_i(t) = d_i^1(t) + b_{i1}^1 Y_1(t-1) \\
+ b_{i2}^1 Y_2(t-2) + \ldots + b_{im}^1 Y_m(t-m) \\
+ b_{i1n}^2 Y_1(t-1) + \ldots + b_{imn}^2 Y_m(t-m) \\
+ \ldots + Y_{n(t-m)} + \ldots + Y_{n(t-m)} + \epsilon_i(t) 
\]  

(7)

where \( b_{jk}^i \) above is the \( k^{th} \) element of the \( i^{th} \) row of \( B_j \) in matrix notation, and \( d_i^1(t) \) is the \( i^{th} \) element of the deterministic component.

We now derive the conditional likelihood function. Suppose we have observations on

\[
Y(t), t = -m+1, -m+2, \ldots, 0, \ldots, T
\]

generated by a stationary time series of norm

\[
\|Y\|^2 = E(Y' Y) 
\]

(8)

where \( E \) is the expectation operator. Let

\[
\epsilon(t) = u(t) 
\]

(9)

where \( u(t) \) is distributed as multivariate normal

\[
N(0, G_u) 
\]

(10)
independent in time.

The log likelihood for $u(t)$ is

$$L(u(t)) = -\frac{n}{2} \log 2\pi - \frac{1}{2} \log |G_u|/ - \frac{1}{2} u(t)' G_u^{-1} u(t)$$ (11)

and the joint log likelihood is

$$L(u(t)), t=1, \ldots, T)$$

$$= -\frac{Tn}{2} \log 2\pi - \frac{T}{2} \log |G_u|/$$

$$- \frac{1}{2} \sum_{t=1}^{T} u(t)' G_u^{-1} u(t)$$ (12)

when $Y(-m+1), \ldots, Y(0)$ are taken as fixed, (8) defines a 1-1 transformation of

$$Y(1), \ldots, Y(T)$$

into $u(1), \ldots, u(T)$

with unit Jacobian. Thus, we can substitute

$$((I - B(L)) Y(t) - D(t))$$

(13)

for $u(t)$ and write the log likelihood for $Y(1), \ldots, Y(t)$ given $Y(-m+1), \ldots, Y(0)$ as
L(y(t), t=1, ..., T/G_u, B(L), C)

\[ L(y(t), t=1, ..., T/G_u, B(L), C) = -\frac{\text{Tn}}{2} \log 2\pi - \frac{T}{2} \log G_u/ \]

\[ -\frac{1}{2} \sum_{t=1}^{T} (\text{I} - B(L)) Y(t) - D(t))' G_u^{-1} (\text{I} - B(L)) Y(t) - D(t) \]  

(14)

\( G_u \) will be positive definite at a maximum, so that a condition for \( L \) to be maximized with respect to \( G_u \) is that \( dL/dG_u^- = 0 \).

Let

\[ u(t, B(L), C) = \tilde{u}(t) \]

\[ u(t) = ((1 - B(L)) \eta(t) - D(t)) \]  

(15)

Then a first-order condition for the maximization of \( L \) is given by

\[ \frac{dL}{dG_u^{-1}} = \frac{T}{2} G_u + (\frac{d}{d} \text{i} \text{j}) (-\frac{1}{2} \sum_{t=1}^{T} \sum_{i=1}^{n} \sum_{j=1}^{n} \tilde{u}_i(t) \sigma_{ij} \tilde{u}_j(t)) = 0 \]  

(16)

where \( G_u^{-1} = (\sigma_{ij}) \).

Let \( S = \frac{1}{T} \sum_{t=1}^{T} \tilde{u}(t) \tilde{u}(t)' \)

then, (16) implies \( G_u = S \), which is true for any values of B(L) and C.
We can then form the concentrated log likelihood function $L^*$ by substituting $S$ for $G_u$ to get

$$L^*(Y(t), t = 1, \ldots, T / B(L), C)$$

$$= - \frac{Tn}{2} \log 2\pi - \frac{T}{2} \log \det S$$

$$- \frac{1}{2} \sum_{t=1}^{T} \hat{u}(t)' S^{-1} \hat{u}(t)$$

$$= - \frac{Tn}{2} \log 2\pi - 1 - \frac{T}{n} \log \det S$$

(17)

In general, we minimize $\log \det S$ with respect to $B(L)$ and $C$ in order to maximize the likelihood function.

It is a standard result that when the right hand-side variables are the same in all equations, as they are in unrestricted VAR which we have in (8), minimization of $\log \det S$ is solved by minimizing the sum of squared residuals in each equation separately.

Therefore, ordinary least squares (OLS) estimates, equation by equation are maximum likelihood estimates conditioned on the initial observations (Litterman, 1979).

Model, data, and sources

For the present multivariate case, as well as in the univariate case, the vector autoregression methodology for estimating the moving average representations of a vector stochastic process is to first estimate the coefficients of the autoregressive representation and then
compute moving average representation coefficients from the estimates. For an n variable system, we begin with n equations, each equation expressing the current value of one of the variables in the system as a function of lagged values of all variables in the system plus an error term.

The current paper employed a three-variable autoregressive model with three components (w, x, y):

\[
\begin{align*}
\begin{bmatrix}
w_t \\
x_t \\
y_t
\end{bmatrix}
&= 
\begin{bmatrix}
a_{11}(L) & a_{12}(L) & a_{13}(L) \\
a_{21}(L) & a_{22}(L) & a_{23}(L) \\
a_{31}(L) & a_{32}(L) & a_{33}(L)
\end{bmatrix}
\begin{bmatrix}
w_t \\
x_t \\
y_t
\end{bmatrix}
+ 
\begin{bmatrix}
w^*_t \\
x^*_t \\
y^*_t
\end{bmatrix}
\end{align*}
\]

(18)

where \( w_t = M_i (i = 1, 2) \), \( x_t = \text{EXCH} \), \( y_t = \text{FCPI} \), and

\[
a_{ij}(L) = \sum_{i=1}^{M_{ij}} a_{ij1} L^1,
\]

\( w^*_t, x^*_t, y^*_t \), are zero-mean white noise innovations with constant covariance matrix

\[
E(w^*_t x^*_t y^*_t)' (w^*_t x^*_t y^*_t) = d_{L,s} M
\]

(19)

We estimated the parameters of each equation by ordinary least squares (OLS). This procedure was justified in the previous section.

For this study, we identified monthly observations on the following variables:

M1 = money supply defined as currency in circulation plus demand deposits in millions of pounds sterling,
M2 = money supply defined as M1 plus savings deposits and small
denomination time deposits in millions of pounds sterling,
EXCH = exchange rate for the United Kingdom measured as the ratio
of US dollars to pound sterling (period average),
FCPI = food component of the consumer price index, 1974 = 100.

M1, M2, and EXCH were obtained from various issues of International
Monetary Fund (IMF) International Financial Statistics (IFS)
publications. FCPI figures were obtained from the Central Statistical
Office, Great George Street, London, England in an internal memo of 11
October 1984.

Table 1 presents annual monthly averages of our time series data
for 1972 to 1979.

M1 increased from 11,187 million pounds in 1972 to 15,144 million
pounds by 1975. This figure grew to 17,608 million pounds by 1976 and
finally stood at 26,957 million pounds by 1979.

M2 increased from an annual monthly average of 22,491 million
pounds in 1972 to 37,617 million pounds by 1975. Very similar to M1
movements, M2 grew from 41,659 million pounds in 1976 to 57,662 million
pounds by 1979.

FCPI annual monthly average stood at 78.2 percent in 1972, 133.3
percent in 1975, and 159.9 percent by 1976. This figure steadily
increased to 228.3 percent by 1979.

EXCH annual monthly average was 2.5018 in 1972. This figure
decreased to 2.2218 by 1975. EXCH annual monthly averages were 1.8062
and 2.1216, respectively, for 1976 and 1979.
Table 1. Annual monthly averages of M1, M2, EXCH, and FCPI 1972–1979

<table>
<thead>
<tr>
<th>Year</th>
<th>Money Supply M1</th>
<th>Money Supply M2</th>
<th>Price indices FCPI (1974=100)</th>
<th>EXCH (US $/Pound)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1972</td>
<td>11,187</td>
<td>22,491</td>
<td>78.2</td>
<td>2.5018</td>
</tr>
<tr>
<td>1973</td>
<td>12,303</td>
<td>28,687</td>
<td>89.9</td>
<td>2.4522</td>
</tr>
<tr>
<td>1974</td>
<td>12,737</td>
<td>34,300</td>
<td>100.0</td>
<td>2.3390</td>
</tr>
<tr>
<td>1975</td>
<td>15,144</td>
<td>37,617</td>
<td>133.3</td>
<td>2.2218</td>
</tr>
<tr>
<td>1976</td>
<td>17,608</td>
<td>41,659</td>
<td>159.9</td>
<td>1.8062</td>
</tr>
<tr>
<td>1977</td>
<td>19,903</td>
<td>45,161</td>
<td>190.3</td>
<td>1.7455</td>
</tr>
<tr>
<td>1978</td>
<td>24,030</td>
<td>51,793</td>
<td>204.0</td>
<td>1.9195</td>
</tr>
<tr>
<td>1979</td>
<td>26,957</td>
<td>57,662</td>
<td>228.3</td>
<td>2.1216</td>
</tr>
</tbody>
</table>


**Empirical analysis**

The proposed relationship between M1, (and, alternatively, M2) EXCH, and FCPI is

\[ A(L) Y_t = e_t \]  \hspace{1cm} (20)

Where \( Y_t \) is a covariance stochastic process, \( e_t \) is white noise error process and \( L \) is the lag operator defined such that \( L Y_t = Y_{t-1}, L^n Y_t = Y_{t-n} \), and \( A(L) \) is a general matrix polynomial in \( L \) such that

\[ A(L) = I + A_1 L + A_2 L^2 + \ldots + A_n L^n \]
the above Equation (20) can be expressed as

\[ Y_t = A^{-1}(L) e_t \]  

(21)

or equivalently

\[ Y_t = \sum_{i=1}^{\infty} B_i e_{t-i} \]  

(22)

which is simply, the moving average representation of the stochastic process \( Y_t \).

As a practical matter, in estimating a VAR model, one assumes that the infinite lagged autoregressive representation can be approximated well by a finite lag model.

Our first task is thus to estimate the \( B_i \) matrices as well as decide upon a realistic choice of lag lengths of the autoregressive parameters. The way we have always done this is, to estimate the autoregressive model by unconstrained least squares and then use \( A(L) \) to approximate the matrices \( B_i \). Consequently, we regress each dependent variable upon lagged values of all the variables in the system to approximate \( A(L) \). All variables in our regressions are converted to natural logarithms. We also included a constant as well as a trend term in order to transform our series to stationary processes.

One way for the choice of lag lengths, is to compare two specific lag lengths and then use the asymptotic chi-square distribution of the log likelihood ratio to test the null hypothesis of zero sum of coefficients on terms excluded from the constrained model. It is well
known that asymptotically, under a null hypothesis that the omitted lags
from the constrained model truly have zero coefficients

-2log(likelihood ratio) is distributed chi-square with \((k l_U - k l_R)\)
degrees of freedom, where \(k\) is the number of variables in the model
while \(l_U\) and \(l_R\) are the number of lags of each variable included in
the unrestricted and restricted model, respectively.

In the case of the VAR system containing M1, EXCH, and FCPI, the
value of -2log(likelihood ratio) was calculated to be 14.01815 with
18 degrees of freedom. Thus, we could not reject a null hypothesis of
the appropriateness of four lags at reasonable levels of significance
(note that chi-square of 18 degrees of freedom at 5 percent significance
level is 28.869).

As for the VAR system containing M2, EXCH, and FCPI, we obtained
the value of -2log(likelihood ratio) to be 16.44817 with 18 degrees
of freedom. Therefore, a null hypothesis of the appropriateness of four
lags was not rejected again, at reasonable levels of significance (note
that chi-square with 18 degrees of freedom at 5 percent significance
level is 28.869).

Very similar with the analysis of Japanese data (see Sanni,
1985c), I employed the innovation accounting techniques of Sims
(1980a) to describe in some details dynamic impacts of random monetary
shocks on the exchange rate and aggregate food price variables.

Table 2 is constructed to facilitate our discussion of the effects
of unexpected changes in M1 on the rest of the variables of the system.
The table lists the forecast error variances and their decompositions
for time horizons of 1, 4, 8, and 12 months. The vector autoregressions was triangularized in order from highest to lowest as follows: M1, EXCH, and FCPI.

Table 2 shows that M1 may be exogenous in this short run analysis. The major portion of forecast error variance (90 percent) is accounted for by its own innovations at a 4-month lag, at 8 months 75.5 percent and at 12 months about 70.3 percent. Close perusal of Table 2 indicated that M1 explains successively less of the forecast variance in M1 itself (This is documented in various other studies we mentioned earlier!). M1 innovations accounted for by EXCH increased from 7 percent, 11.9 percent and to 13.1 percent, respectively for the 4th, 8th, and 12th months horizons. A more interesting case is for FCPI, which accounted for only 3 percent of the M1 innovations by the 4th month but nearly to 17 percent by the 12th month.

For EXCH, there is a considerable reduction in forecast error variance accounted for by its own innovations from 99.8 percent in the first month to approximately 56 percent by the 12th month. The proportion of EXCH forecast error variance attributable to changes in the triangularized M1 innovations becomes progressively larger: almost zero initially to 6.2 percent by the 12th month. More interesting results are found for FCPI. EXCH innovations accounted for by FCPI was about 4 percent at the 4th month but increased impressively to 25.3 and 38.2 percent at the 8th and 12th months, respectively.
Table 2. Proportion of forecast error variance k-months-ahead produced by each innovation

<table>
<thead>
<tr>
<th>Triangularized innovation</th>
<th>k</th>
<th>Ml</th>
<th>EXCH</th>
<th>FCPi</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecast error in:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ml</td>
<td>1</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.900</td>
<td>0.070</td>
<td>0.030</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>0.755</td>
<td>0.119</td>
<td>0.126</td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>0.703</td>
<td>0.131</td>
<td>0.167</td>
</tr>
<tr>
<td>EXCH</td>
<td>1</td>
<td>0.002</td>
<td>0.998</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.026</td>
<td>0.936</td>
<td>0.039</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>0.043</td>
<td>0.704</td>
<td>0.253</td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>0.062</td>
<td>0.555</td>
<td>0.382</td>
</tr>
<tr>
<td>FCPi</td>
<td>1</td>
<td>0.014</td>
<td>0.00003</td>
<td>0.986</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.038</td>
<td>0.098</td>
<td>0.864</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>0.124</td>
<td>0.185</td>
<td>0.691</td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>0.187</td>
<td>0.276</td>
<td>0.537</td>
</tr>
</tbody>
</table>

The proportion of FCPi forecast error variance attributable to FCPi itself declines steadily, from 98.6 percent in the 1st month to 86.4, 69.1, and 53.7 percent by the 4th, 8th, and 12th months, respectively. Again, the FCPi forecast error variance attributable to Ml innovations becomes steadily larger, from a little over 1 percent at the 1st month to 12.4 and 18.7 percent at the 8th and 12th months, respectively.
Similarly, to the case of M1, EXCH accounts for practically, zero percent of the forecast error variance for FCPI. This increased progressively to 18.5 and 27.6 percent at the 8th and 12th months, respectively.

Figure 1 displays the plots of the effects of innovation in M1 on M1, EXCH, and FCPI. The figure is self-explanatory. Note that the contemporaneous effect of M1 innovations on EXCH is positive for the 1st through the 12th months period, except a very small negative effect of the 2nd month! The contemporaneous effect of M1 innovations on FCPI is crystal clear. The contemporaneous effect is positive throughout a 24-month horizon but Figure 1 is limited to only the first twelve months.

To evaluate the effects of unexpected changes in M2 on the rest of the variables, we constructed Table 3 which lists the forecast error variances and their decomposition for time horizons of 1, 4, 8, and 12 months. The triangularization order was M2, EXCH, and FCPI.

Clearly, M2 tends to be more exogenous since it accounts for relatively more of its own innovations as time wears on. At the 4-month lag 94.4 percent of M2 innovations was accounted for by M2 itself. This decreased slightly to 91.3 and 88.5 percent, respectively by the 8th and 12th months. Again, while M2 explains successively less of the forecast variance in M2 (less so than for M1) but more and more of the forecast variance in EXCH and FCPI. M2 innovations accounted for by EXCH at the 4th, 8th, and 12th months, increased from 2 to 3.7, and finally to 6.0 percent, respectively. Similarly, M2 innovations accounted for by FCPI were 3.5, 5.0, and 5.5 percent for the 4th, 8th, and 12th months period.
Figure 1. Effect of innovations in M1 on M1, EXCH & FCPI
### Table 3. Proportion of forecast error variance \( k \)-months-ahead produced by each innovation

<table>
<thead>
<tr>
<th>Forecast error in:</th>
<th>M2</th>
<th>EXCH</th>
<th>FCPI</th>
</tr>
</thead>
<tbody>
<tr>
<td>( k )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>4</td>
<td>0.944</td>
<td>0.020</td>
<td>0.035</td>
</tr>
<tr>
<td>8</td>
<td>0.913</td>
<td>0.037</td>
<td>0.050</td>
</tr>
<tr>
<td>12</td>
<td>0.885</td>
<td>0.060</td>
<td>0.055</td>
</tr>
<tr>
<td>EXCH</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.087</td>
<td>0.913</td>
<td>0.00</td>
</tr>
<tr>
<td>4</td>
<td>0.082</td>
<td>0.902</td>
<td>0.016</td>
</tr>
<tr>
<td>8</td>
<td>0.054</td>
<td>0.761</td>
<td>0.185</td>
</tr>
<tr>
<td>12</td>
<td>0.042</td>
<td>0.608</td>
<td>0.350</td>
</tr>
<tr>
<td>FCPI</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.039</td>
<td>0.002</td>
<td>0.959</td>
</tr>
<tr>
<td>4</td>
<td>0.018</td>
<td>0.100</td>
<td>0.882</td>
</tr>
<tr>
<td>8</td>
<td>0.022</td>
<td>0.146</td>
<td>0.831</td>
</tr>
<tr>
<td>12</td>
<td>0.051</td>
<td>0.197</td>
<td>0.752</td>
</tr>
</tbody>
</table>

EXCH forecast error variance attributable to EXCH itself were 90.2, 76.1, and 60.8 percent for the 4th, 8th, and 12th months period. Surprisingly, EXCH forecast error variance attributable to changes in the triangularized M2 innovations actually declined from 8.2 to 5.4, and 4.2 percent for the 4th, 8th, and 12th months, respectively. Again, very interesting results are found for FCPI. EXCH innovations accounted
for by FCPI was about 2 percent at the 4th month but increased dra-
matically to about 19 percent at the 8th and 12th months, respectively.

In the case of the system containing M2, the proportion of FCPI
forecast error variance attributable to FCPI itself gradually declines,
from 95.9 percent in the 1st month to 88.2, 83.1, and 75.2 percent by
the 4th, 8th, and 12th months, respectively. Similar to the case for
M1, but less so, FCPI forecast error variance attributable to M2
innovations becomes steadily larger, from about 2 percent at the 4th
month to 5 percent by the 12th month. EXCH accounts for 10, 14.6, and
19.7 percent for the 4th, 8th, and 12th months, respectively, of the
forecast error variance for FCPI.

Figure 2 shows the effect of innovations in M2, EXCH, as well as
FCPI. The figure illustrates the contemporaneous effect of M2 on itself
as well as other variables in the triangularized system. Note that the
contemporaneous effect of M2 innovations on EXCH is negative for a 24
month horizon, though the figure is limited to only the first 12 months!
However, the contemporaneous effect of M2 innovations on FCPI is less
clear cut. The contemporaneous effects is negative for the first four
lag periods but clearly positive thereafter.

**Summary of findings and concluding remarks**

In the second section of this paper, a fairly rigorous exposition
on the theoretical justification of the application of ordinary least
squares to estimate an unconstrained vector autoregressive system was
presented. I then applied VAR to study the dynamic relationship
between money, exchange rate and aggregate food price variables, using
Figure 2. Effect of innovations in M2 on M2, EXCH & FCPI
the United Kingdom's postwar time series data, for the period 1972 to 1979. I found that the time series data admits a 4-lag specification for the system containing M1, EXCH, and FCPI as well as the system containing M2, EXCH, and FCPI.

A major finding of this study is that the proportion of FCPI forecast error variance attributable to changes in the triangularized M1 innovations becomes progressively larger: slightly above 1 percent initially to almost 19 percent by the 12th months horizon. More interesting, FCPI forecast error variance attributable to changes in the triangularized EXCH innovations were clearly larger more so than for M1: from practically zero initially to almost 28 percent by the 12th months horizon.

However, the proportion of FCPI forecast error variance attributable to changes in the triangularized M2 innovations was an average of only 3.25 percent for the entire 12 months period. FCPI forecast error variance attributable to changes in EXCH innovations still dominates that of M2. This proportion was an average of 11.125 percent for the 12 months.

Changes in FCPI triangularized innovations accounted for over 38 percent of EXCH forecast error variance at the 12th months horizon in the system containing M1, EXCH, and FCPI. This was about 35 percent of EXCH forecast error variance at the same 12th months horizon for the system containing M2, EXCH, and FCPI.

This study strongly suggests that the exchange rate may have more econometrically measurable impacts on aggregate food price, for the period May 1972 to December 1979, than money supply.
References cited


International Monetary Fund (IMF), international financial statistics, various issues.


A MACROECONOMETRIC ANALYSIS OF MONETARY IMPACTS ON JAPANESE AGRICULTURE

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SECTION II. A MACROECONOMETRIC ANALYSIS OF MONETARY IMPACTS ON JAPANESE AGRICULTURE

Introduction

The vector autoregressive (VAR) method is a novel development in the econometric modeling of time series data. Christopher Sims has forcefully argued against the standard approach to modeling economic relationships, particularly in a dynamic context.

Using the vector autoregressive methodology, Chambers (1984) uncovered some interesting dynamic relationships between monetary and agricultural variables. His conclusions could, if generally upheld, have a significant influence on activist monetary policies. One way of examining the strength of Chambers' results is to replicate the exercise in other contexts and using differing data and time periods.

The purpose of this paper is to investigate the effects of monetary factors on Japanese agriculture using vector autoregression techniques.

The paper is divided into six sections. A brief discussion of two main arguments against standard econometric practice as well as concrete advantages of VAR is contained in section 2. In section 3, we discuss multivariate vector autoregression methodology. Section 4 is on model identification for our particular case, data, and sources. The empirical analysis and results are in section 5. Finally, in section 6, we state our conclusions and suggestions for further research.
**VAR preference**

Analysis in the framework of standard macroeconomic model proceeds on the basis of restrictions among variables imposed *a priori*, so that a particular "structural" model is presented. Reduced form equations are derived on the basis of the assumed structural model. However, policy analysis based on supposed *a priori* knowledge or economic theory is subject to a serious attack by the rational expectations school (see for example, Lucas (1976) and Sargent (1978)).

One line of attack is what Sims (1980) called "incredible restrictions" which the standard econometric model employ to preclude interactions among economic variables. Such models, according to Sims, are thus infected by spurious constraints.

The second line of attack is that of "identification." As correctly stated by Sims (1980), a model is identified if distinct points in the model's parameter space imply observationally distinct patterns of behavior for the model's variables. Sims argued that "claims for identification in large macro models cannot be taken seriously" and that "a more systematic approach to imposing restrictions could lead to capture of empirical regularities which remain hidden to the standard procedures and hence, lead to improved forecasts and policy projections."

The VAR equations are conceived as unrestricted reduced forms where all variables are treated as endogenous. The VAR model is thought of as an initial step in describing the average behavior of the system over the observation period.
Concrete advantages of the VAR as opposed to standard econometric techniques include the following:

1. VAR offers an opportunity for the econometrician to drop the restrictions based on supposed a priori knowledge or economic theory as severely criticized by Sims and others. Note that, tests of economically meaningful hypotheses can still be carried out at a second stage.

2. A VAR model can be used for controller design. Suppose some of the variables under consideration are government instruments while some are target variables. Then, the model can be easily recast into a state space representation. Once a loss function is specified, say of a quadratic form, the optimal values for the instruments over time can be resolved.

3. By testing the upper-or-lower-block triangularity of the autoregressive operator, a VAR model provides a reasonably powerful test of exogeneity of variables under consideration.

4. Fischer (1981) observed that the VARs are "... a convenient way of summarizing empirical regularities and perhaps suggesting predominant channels through which relations work" p. 402.

5. Lastly, Sims (1982) said in a discussion of VAR results that "... careful attention to the historical data exerts an important discipline on what can plausibly be asserted about the way the economy works" p. 138.
All economic theory consists of comparative static propositions while historical data are designed by a dynamic economy which don't bear evidence on comparative static propositions of economic theory. The VAR approach is consistent with the conceptual notion that current behavior of economic agents in a dynamic setting reflects their expectations about the future, and that current values of observed economic variables reflect such expectations. In this setting, the effects of unexpected shocks to particular variables on their own expected future path and the expected future path of other variables is of central interest. The magnitude of such effects can be estimated on the basis of historical data in a VAR framework.

**Methodology**

The moving average representation of stationary stochastic processes is

\[ X_t = \text{I}e_t + D^1e_{t-1} + D^2e_{t-2} + \ldots = D(L) e_t \]  

where \( X_t = (X_{t,1}, X_{t,2}, \ldots, X_{t,m})' \) i.e., an \( m \times 1 \) vector of observations on \( m \) variables (say) at time \( t \) and \( e_t = (e_{t-1}', e_{t-2}', \ldots, e_{t-m}') \) i.e., an \( m \times 1 \) vector of one-step ahead prediction errors for \( X_t \) given all observations \( (X_{t,1}, X_{t,2}, \ldots, \) and for all \( t \) and \( s \).

Suppose the contemporaneous covariance of the untransformed innovations is \( M \). Then assume that
\[ Ee_t = 0 \quad (2) \]
\[ \text{cov}(e_t) = M \quad (3) \]
and
\[ E(e_t e_s) = 0, \; t \neq s \quad (4) \]

(4) is the assumption of zero serial correlation of errors.

\[ D^S = \text{an m x m matrix of moving average coefficients such that} \]

\[ D(L) = \sum_{j=0}^{\infty} D^S L^j \quad (5) \]

In a multivariate moving average representation \( D^S_{1j} \) gives the effect on variable \( i \) at time \( t \) of a one unit shock to variable \( j \) at time \( t-s \).

So, the matrices \( (D^S)_{1j} \) form an impulse response function. Thus, in the vector model we can trace the effects on future values of a variable of today's shocks to all other variables in the system.

Very similar to the univariate case, one solution to the problem of contemporaneous correlations among the prediction errors is to choose a particular order of the \( m \) variables in the vector \( X_t \), out of initial ordering \( X_{t,1}, X_{t,2}, \ldots, X_{t,m} \), and then remove from the shock to each variable that portion that is explained by contemporaneous shocks to variables earlier in the ordering.

Consider shocks of the form:
A shock to a particular variable at time $t$ is now defined as only that portion of the value of the variable at time $t$ that was not predicted from historical data and contemporaneous shocks to variables earlier in the ordering. Such shocks are called "orthogonal innovations."

To compute the orthogonal innovations, we decompose the covariance matrix $M$ as follows:

$$M = CC'$$  \hspace{1cm} (7)$$

where $C$ is lower triangular and invertible. For a given $M$ this decomposition is unique. And it enables the econometrician to express the random vector $e_t$ as a linear combination of independent random variables:

$$e_t = CV_t$$  \hspace{1cm} (8)$$

where $\text{cov}(V_t) = I$.

Substituting into our moving average representation, we obtain:

$$X_t = CV_t + D^1 CV_{t-1} + D^2 CV_{t-2} + \ldots = D(L)CV_t$$  \hspace{1cm} (9)$$

To evaluate the effects of shocks typical of those that have occurred historically, we take as a shock to the $j^{th}$ variable the $j^{th}$
column of \( C \). The matrix element \( C_{jj} \) takes on the value of a one standard deviation orthogonal innovation in variable \( j \), while \( C_{ij} \) measures the effect on variable \( i \) of a standard deviation shock to variable \( j \). Since \( C \) is lower triangular, a shock to the first variable in the ordering may affect all of the following variables, while a shock to the last variable in the ordering has no contemporaneous effect on other variables in the system.

The effects of current shocks on future values of variables (the impulse responses) are generated as vector products. For example, the effect of a shock to variable \( j \) at time \( t+k \) is given by the product of the \( i^{th} \) row of \( D^{s} \) and the \( j^{th} \) column of \( C \).

Impulse responses generated in this fashion should more realistically reflect the historical evidence than would non-orthogonal impulse responses generated by \( (D^{s})^{k}_{s=1} \) matrices alone.

Consider the forecast error variance in a vector model. We have

\[
\text{Var}(X_{t+k} / X_t, X_{t-1}, \ldots) = \sum_{s=0}^{k-1} D^{s} M D^{s}
\]

which is simply a matrix measure of the \( k \)-step ahead forecast variance, with the \( i^{th} \) diagonal element of the matrix being a measure of forecast variance for \( X_{t+k,i} \).

If \( M \) is a diagonal matrix (that is, the components of \( e_t \) are uncorrelated contemporaneously) then, forecast error variances can be proportioned into components due to shocks to each variable. If \( M \) is
not diagonal, such a decomposition is not directly attainable since each forecast variance will include contemporaneous covariance terms whose assignment to a specific variable is problematic!

Again, we may order the variable and use orthogonalized innovations to attain the decomposition of variance from

\[
\text{Var}(X_{t+k} / X_t, X_{t-1}, \ldots) = \sum_{s=0}^{k-1} (D^s C) (D^s C)' \quad (11)
\]

If we let \( d^{s}_{c_{ij}} \) be the \( i,j^{th} \) element of \( D^s C \), the \( i^{th} \) diagonal element of \( (D^s C)'(D^s C)' \) is simply the sum of squared terms \( (d^{s}_{c_{ij}})^2 \), \( j = 1, \ldots, m \). Hence, the component of variance in the \( k \)-step ahead forecast of \( X_{t+k,i} \) due to orthogonal innovations in variable \( j \) is

\[
\sum_{s=0}^{k-1} (d^{s}_{c_{ij}})^2 \quad (12)
\]

In this way, the econometrician can apportion forecast variance to orthogonal innovations in different variables.

**Model, data, and sources**

As in the univariate case, the vector autoregression methodology for estimating the moving average representations of a vector stochastic process is to first estimate the coefficients of the autoregressive representation and then compute moving average representation coefficients from these estimates. For an \( m \)-variable system we begin
with \( m \) equations, each equation expressing the current value of one of the variables in the system as a function of lagged values of all variables in the system plus an error term. The current paper employed a three-variable autoregressive model with three components \((w, x, y)\):

\[
\begin{bmatrix}
    w_t \\
x_t \\
y_t
\end{bmatrix} = \begin{bmatrix}
a_{11}(L) & a_{12}(L) & a_{13}(L) \\
a_{21}(L) & a_{22}(L) & a_{23}(L) \\
a_{31}(L) & a_{32}(L) & a_{33}(L)
\end{bmatrix} \begin{bmatrix}
w_t \\
x_t \\
y_t
\end{bmatrix} + \begin{bmatrix}
w_t^* \\
x_t^* \\
y_t^*
\end{bmatrix}
\]

where \( w_t = M_{i}(i = 1, 2, \ldots) \),

\[ x_t = FCPI, y_t = IPR, \text{ and} \]

\[ a_{ij}(L) = \sum_{i=1}^{M_{ij}} a_{ij1} L^1, \]

and \( w_t^*, x_t^*, y_t^* \) are zero-mean white noise innovations with constant covariance matrix

\[
E(w_t^* x_t^* y_t^*)' (w_t^* x_t^* y_t^*) = d_t, M
\]

We then estimated the parameters of each equation by ordinary least squares (OLS). We chose this method because application of ordinary least squares separately to each equation gives estimates that are consistent and asymptotically normally distributed.

For this study, we identified monthly observations on the following variables:
M₁ = money supply defined as currency in circulation plus demand deposits in billion of Yen.

M₂ = money supply defined as M₁ plus savings deposits and small denomination time deposits in billions of Yen.

FCPI = food component of the consumer price index, 1975 = 100.

IPR = index of price received by farmers, 1980 = 100.

M₁ and M₂ monthly time series data were obtained from the International Monetary Fund (IMF) through an internal memo of September, 1984. FCPI and IPR Series were obtained through an internal memo of December, 1984 from the Japan Trade Center, Tokyo, via their Chicago office.

Table I presents annual monthly averages of our time series data for 1972 to 1982.

M₁ increased from 28,300 billion Yen in 1972 to 44,550 billion Yen by 1975. This figure grew to 66,333 billion Yen by 1979, and finally M₁ stood at 74,260 billion Yen by 1982.

M₂ increased from an annual monthly average of 72,940 billion Yen in 1972 to 114,137 billion Yen by 1975. Very similar to M₁ movements, M₂ grew from 182,291 billion Yen in 1979 to 233,307 billion Yen by 1982.

FCPI annual monthly average stood at 61.73 percent in 1972, 100.00 percent in 1975 (the base year!) and 123.06 by 1979. This figure steadily increased to 140.24 by 1982.

IPR started out with 48.05 percent in 1972. This figure increased to 79.00 percent by 1975. IPR annual monthly averages were 95.68 and 102.75, respectively, for 1979 and 1982.
Table 1. Annual monthly average of M1, M2, FCPI, and IPR^a

<table>
<thead>
<tr>
<th>Year</th>
<th>Money Supply (billion Yen)</th>
<th>Price indices</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M1</td>
<td>M2</td>
</tr>
<tr>
<td>1972</td>
<td>28,300</td>
<td>72,940</td>
</tr>
<tr>
<td>1973</td>
<td>35,699</td>
<td>89,710</td>
</tr>
<tr>
<td>1974</td>
<td>40,392</td>
<td>101,244</td>
</tr>
<tr>
<td>1975</td>
<td>44,550</td>
<td>114,137</td>
</tr>
<tr>
<td>1976</td>
<td>50,892</td>
<td>131,503</td>
</tr>
<tr>
<td>1977</td>
<td>54,456</td>
<td>146,545</td>
</tr>
<tr>
<td>1978</td>
<td>60,336</td>
<td>164,004</td>
</tr>
<tr>
<td>1979</td>
<td>66,333</td>
<td>182,291</td>
</tr>
<tr>
<td>1980</td>
<td>66,866</td>
<td>196,663</td>
</tr>
<tr>
<td>1981</td>
<td>69,355</td>
<td>213,911</td>
</tr>
<tr>
<td>1982</td>
<td>74,260</td>
<td>233,307</td>
</tr>
</tbody>
</table>

^aColumns 2 & 3 from an internal memo from International Monetary Fund (IMF), September, 1984. Columns 4 & 5 from an internal memo from Japan Trade Center, Tokyo, of December, 1984.

**Empirical analysis and results**

Based on plots of the above series (not included here), our statistical analysis was done on monthly series for the period May 1972 to December 1980.

The following hypotheses will be tested in the empirical analysis:
1. In a three-variable VAR System containing M1, FCPI, and IPR, a four-lag formulation is appropriate for our time series data.

2. In a three-variable VAR System containing M2, FCPI, and IPR, a four-lag formulation is appropriate for our time series data.

3. M1 has a statistically measurable impact on the agricultural aggregates.

4. M2 has a statistically measurable impact on the agricultural aggregates.

5. Unexpected changes in M1 have a perceptible influence on agriculture.

6. Unexpected changes in M2 have a perceptible influence on agriculture.

The proposed relationship between M1, (and, alternatively, M2), FCPI, and IPR is

\[ A(L) X_t = e_t \]  \hspace{1cm} (15) \]

where \( X_t \) is a covariance stochastic process, \( e_t \) is white noise error process and \( L \) is the lag operator defined such that \( LX_t = X_{t-1} \), \( L^nX_t = X_{t-n} \) and \( A(L) \) is a general matrix polynomial in \( L \) such that

\[ A(L) = I + A_1 L + A_2 L^2 + \ldots + A_n L^n \]

The above equation (15) can be expressed as

\[ X_t = A^{-1}(L) e_t \]

or, equivalently,
\[ X_t = \sum_{i=1}^{\infty} B_i e_{t-i} \tag{16} \]

which is simply the moving average representation of the stochastic process \( X_t \).

Our first hypothesis concerns the estimation of the \( B_i \) matrices. One way is to estimate the autoregressive model by unconstrained least squares and then use \( A(L) \) to approximate the matrices \( B_i \). Consequently, we regress each dependent variable upon lagged values of all the variables in the system to approximate \( A(L) \). (n=4 and to test our hypothesis, we estimated a version of the model with n=6). All variables in our regressions are converted to logarithms. We also included a constant as well as a trend term, (to transform the series to stationary processes). We then employ the asymptotic chi-square distribution of the log likelihood ratio to test the null hypothesis of zero sum of coefficients on the terms excluded from the constrained model. It is well-known that asymptotically under a null hypothesis that the omitted lags from the constrained model truly have zero coefficients \(-2\log(\text{likelihood ratio})\) is distributed chi-square with \((k \cdot l_u - k \cdot l_r)\) degrees of freedom where \( k \) is the number of variables in the model while \( l_u \) and \( l_r \) are the number of lags of each variable included in the unrestricted and restricted model, respectively.

In the case of the system containing ML, FCP, and IPR, the value of \(-2\log(\text{likelihood ratio})\) was calculated to be 21.48586 with 18 degrees of freedom. Thus, we could not reject the null hypothesis of
four lags at reasonable levels of significance. (Note that chi-square of 18 degrees of freedom at the 5 percent significance level is 28.869.)

The second hypothesis of four versus six lags was tested for the system containing M2, FCPI, and IPR. In this case, we obtained the value of $-2\log(\text{likelihood ratio})$ to be 27.46788 with 18 degrees of freedom. Therefore, we could not reject the null hypothesis of the appropriateness of four lags again, at reasonable levels of significance. (Note that chi-square with 18 degrees of freedom at 3 percent significance level is 28.869.)

Our third hypothesis concerns whether M1 has any statistically measurable impact on the behavior of the agricultural aggregates. In the VAR framework, this is interpreted to mean that the coefficients of the lags of M1 in all the agricultural aggregate regressions are not significantly different from zero. Therefore, we estimated one form of the model incorporating the stated restrictions and then conducted a standard likelihood ratio test for the entire system. In this particular case, the $-2\log(\text{likelihood ratio})$ was calculated to be 19.19525 with 8 degrees of freedom. We clearly reject the null hypothesis of no M1 effects upon agriculture, at reasonable levels of significance. (Note that chi-square for 8 degrees of freedom at 5 percent is 15.51.)

The fourth hypothesis also posited that the coefficients of the lags of M2 in all agricultural aggregate regressions were not significantly different from zero. Consequently, we estimated a version of the model incorporating the stated restrictions and then conducted a
standard likelihood ratio test for the entire system. In this case, we obtained the value of \(-2\log(\text{likelihood ratio})\) to be 25.22362 with 8 degrees of freedom. This clearly rejects the null hypothesis of no M2 effects upon agriculture at reasonable levels of significance. (Note again that chi-square with 8 degrees of freedom at the 5 percent level of significance is 15.51.)

Having established the fact that money, whether defined as M1 or M2, has an econometrically measurable impact on the agricultural aggregates, we describe in some more detail the nature of the dynamic relationship in what has been described as "innovation accounting" and forecast error variance decomposition in VAR literature. Those are the issues involved in the last two hypotheses listed above.

Table 2 is constructed to facilitate our discussion of the fifth hypothesis of the effects of unexpected changes in M1 on the rest of the variables in the system. The table lists the forecast error variances and their decompositions for time horizons of 1, 4, 8, and 12 months. The vector autoregression was triangularized in order from highest to lowest as follows: M1, FCPI, and IPR.

Table 2 indicates very strongly that M1 may be essentially exogenous in this analysis. This is because it accounts for over 80 percent of its own innovations remarkably steadily for the 4th through the 12th months' forecast horizons.

While FCPI accounts for roughly 13 percent for the 4th through the 12th month, IPR accounts for less than 5 percent for the same period of the triangularized M1 innovations.
FCPI innovations accounted for by FCPI itself steadily declined from 98.2 to 71.9 percent for the 2nd and 12th months, respectively. Interestingly (and as documented in other studies), the proportion of FCPI forecast and variance attributable to changes in the triangularized M1 innovation becomes progressively larger: only about 4 percent initially to 27 percent by the 12th month.

Table 2. Proportion of forecast error variance k-months-ahead produced by each innovation

<table>
<thead>
<tr>
<th>Triangularized innovation</th>
<th>k</th>
<th>M1</th>
<th>FCPI</th>
<th>IPR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecast error in:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M1</td>
<td>1</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.798</td>
<td>0.154</td>
<td>0.048</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>0.820</td>
<td>0.129</td>
<td>0.051</td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>0.821</td>
<td>0.133</td>
<td>0.046</td>
</tr>
<tr>
<td>FCPI</td>
<td>1</td>
<td>0.037</td>
<td>0.963</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.017</td>
<td>0.982</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>0.143</td>
<td>0.849</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>0.268</td>
<td>0.719</td>
<td>0.013</td>
</tr>
<tr>
<td>IPR</td>
<td>1</td>
<td>0.016</td>
<td>0.464</td>
<td>0.520</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.011</td>
<td>0.464</td>
<td>0.524</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>0.057</td>
<td>0.470</td>
<td>0.474</td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>0.120</td>
<td>0.477</td>
<td>0.403</td>
</tr>
</tbody>
</table>
The proportion of IPR forecast error variance attributable to IPR itself is considerably low, 52 percent in the 1st month and 40 percent in the 12th. Again, IPR forecast error variance attributable to changes in M1 innovations becomes progressively larger, from 2 percent in the first month to 12 percent by the 12th month.

Figure 1 displays the plots of the effect of innovation in M1 on M1, FCPI, and IPR. The figure is largely self-explanatory. Note that the contemporaneous effect of M1 innovations on IPR is positive from the 1st through the 12th lag periods. However, the contemporaneous effects is negative for the first three lag periods but positive thereafter.

To evaluate the sixth and final hypothesis regarding the effects of unexpected changes in M2 on the rest of the variables, we constructed Table 3 which lists the forecast error variances and their decomposition for time horizons of 1, 4, 8, and 12 months. The triangularization order was M2, FCPI, and IPR.

Clearly, M2 is not as exogenous as M1. This is because, by the 4th through the 12th month, it accounts for an average of 76 percent of its own innovations. The proportion of FCPI forecast error variance attributable to FCPI itself is fairly high, 94 percent in the first month and 95 percent in the 4th. This proportion fell to 92 percent and 85 percent in the eighth and 12th months, respectively. Very similar to the case of M1, the FCPI forecast error variance attributable to changes in the triangularized M2 innovations becomes progressively larger, from about 6 percent at the first month to 12 percent by the 12th month.
Figure 1. Effect of innovations in M₁ on M₁, FCPI & IPR
Table 3. Proportion of forecast error variance k-months-ahead produced by each innovation

<table>
<thead>
<tr>
<th>Triangularized innovation</th>
<th>k</th>
<th>M2</th>
<th>FCPI</th>
<th>IPR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecast error in:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M2</td>
<td>1</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.750</td>
<td>0.166</td>
<td>0.084</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>0.760</td>
<td>0.136</td>
<td>0.103</td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>0.778</td>
<td>0.122</td>
<td>0.100</td>
</tr>
<tr>
<td>FCPI</td>
<td>1</td>
<td>0.057</td>
<td>0.943</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.053</td>
<td>0.946</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>0.069</td>
<td>0.921</td>
<td>0.010</td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>0.124</td>
<td>0.852</td>
<td>0.024</td>
</tr>
<tr>
<td>IPR</td>
<td>1</td>
<td>0.0005</td>
<td>0.439</td>
<td>0.561</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.011</td>
<td>0.407</td>
<td>0.582</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>0.033</td>
<td>0.406</td>
<td>0.562</td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>0.057</td>
<td>0.415</td>
<td>0.528</td>
</tr>
</tbody>
</table>

IPR accounts for only 56 percent of its own forecast variance in the first month and 53 percent by the 12th. Again, the proportion of IPR forecast error variance attributable to changes in the triangularized M2 innovations becomes progressively greater, but less so than for M1. This was approximately zero by the first month but 6 percent by the 12th.
Figure 2 shows the effect of innovations in M2 on M2, FCP, as well as IPR. The figure illustrates the contemporaneous effect of M2 on itself as well as other variables in the triangularized system. Note, however, that the contemporaneous effect of M2 innovations on both FCP and IPR are less clear cut. The contemporaneous effect is negative for the first four lag periods for FCP but positive thereafter. For IPR, the contemporaneous effect is positive at the first month (though very small), negative for the following two months and positive thereafter.

Conclusions and suggestions for further research

In this paper, we presented a brief discussion on two standard arguments against standard econometric modeling practice to study economic relationships. We listed five concrete advantages of the vector autoregressive (VAR) methodology which remains a novel development in the statistical analysis of time series data. We then applied VAR to study the relationship between money and agricultural variables, using Japanese data, for the period 1972 to 1980. We found that our time series data admits a 4-lag specification for the system containing M1, FCP, and IPR as well as the system containing M2, FCP, and IPR. We also found that both M1 and M2 have statistically significant impact upon the behavior of the agricultural variables. And, finally, we found that unexpected changes in both M1 and M2 have perceptible influence on the agricultural variables. Our empirical results strongly support a contention that money matters for the agricultural sector of Japan.
Figure 2. Effect of Innovations in MZ on M2, PPI & IPR

Change in logged values of M2, ITR & FCPI

Month

M2

PPI

IPR

I
For the United States' economy, evidence is increasingly accumulating on the whole issue of macroeconomic impacts on the U.S. agricultural sector. Chambers and Just (1982) lamented the fact that monetary policy actions "such as reducing domestic credit are only rarely, if ever, recognized as having any impact on the agricultural sector of the economy" p. 245. Chambers (1984) has pioneered an interesting discussion of financial market interactions with agricultural markets. As we argued in the beginning of this paper, Chambers' conclusions could, if generally upheld, have a significant influence on activist monetary policies. We added that one way of examining the strength of Chambers' results is to replicate the exercise in other contexts and using differing data and time periods. The present paper is an attempt in that direction. Another attempt of ours was for the Australian economy (see Sanni and Calkins, 1985).

This study is extremely limited in scope. We have used only money supply (M1 and, alternatively, M2) as the primary measure of monetary impacts. We have also used food component of consumer price index and an index of price received by farmers as indicators of agricultural sector responses to monetary impulses. Obviously, this study can be extended by the inclusion of more financial as well as agricultural sector variables in our VAR model.

Such a task is by no means as easy one. This is because of disaggregated time series data such as non-food consumer price index, total value of agricultural exports, total value of agricultural imports, etc., for the Japanese Economy, may not be readily available.
References—cited


Japan Trade Center, Tokyo, Japan. Internal memo of December 1984.


A maximum likelihood estimation of the dynamic relationship between money and agriculture in Australia

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SECTION III. A MAXIMUM LIKELIHOOD ESTIMATION OF THE DYNAMIC RELATIONSHIP BETWEEN MONEY AND AGRICULTURE IN AUSTRALIA

Abstract

This paper uses a maximum likelihood estimation procedure to investigate the dynamic relationship between money and agriculture in Australia. Bivariate causality tests were conducted among the variables in a vector autoregressive system, yielding interesting results. Using quarterly time series data for the period third quarter, 1969 up and until second quarter, 1984, we confirm an earlier contention that money matters for the agricultural sector of Australia.

Introduction

In a recent study on Australia, Sanni and Calkins (1985) presented a vector autoregressive (VAR) model to study the importance of domestic credit conditions proxied by money supply (AM1 and, alternatively, AM2) on agricultural aggregates such as agricultural trade balance (ATB) and relative agricultural prices (RAP). We assumed that all the variables entering our VAR system have identical lag lengths. Using n=4 quarters versus n=6 quarters, we further assumed that the shorter lagged model is a constrained version of the more generously lagged model. We then employ the asymptotic chi-square distribution of the log likelihood ratio to discriminate against the longer lagged model. Our major conclusion is that money supply is important for the agricultural sector of Australia.

Conventional research on the determination of the best order of lags for the multivariate autoregressive model cast serious doubts on
the appropriateness of the assumption that all variables entering the VAR system should have identical lag lengths. Therefore, in this paper, I follow a sequential procedure proposed by Gaines, Keng, and Sethi (1981) to reexamine the impacts on money supply on the agricultural sector of Australia.

The paper is divided into four sections. The second section is a fairly detailed discussion of Caines et al. extension of Hsiao (1981) sequential method for multivariate vector autoregressive identification. The third section is on the application of the Caines et al. procedure to Australian data. Our summary of findings and concluding remarks are contained in the fourth section.

**VAR system identification: Pairwise causality analysis and specific gravity ordering**

The empirical analysis of Caines et al. employs the Akaike (1969, 1970) final prediction error (FPE) criterion in a preliminary investigation of the optimal lag lengths for each variable in the VAR system. Consequently, overly generous lag lengths are avoided thus preserving degrees of freedom, while biased estimates of lag parameters are avoided by including lags of a sufficient length. This procedure, which is summarized below, is applicable to stationary time series:

1. For a pair of stationary processes \((X, Y)\) construct bivariate models of different orders, then compare the multivariate final prediction error (MFPE) of these models, and choose the model of order \(k\), possessing minimum MFPE to be the optimal model for the pair of processes \((X, Y)\).
2. Construct bivariate restricted autoregressive models of order k, i.e., AR(k), both causal models and non-causal (independent models) for (X, Y), and apply the stagewise causality detection procedure to determine the endogeneity, exogeneity, or independence relations between X and Y.

3. If a process X has n multiple causal variables, \( y_1, y_2, \ldots, y_n \), we rank these multiple causal variables according to the decreasing order of their specific gravities.

4. For each caused (endogenous) process X, we first construct the optimal univariate autoregressive model using the FPE criterion, then we include X's multiple causal variables one at a time, according to their causal ranks, and use the FPE criterion to determine the optimal orders of the models at each step.

Suppose X has two causal variables \( y_1 \) and \( y_2 \) with causal ranks second and first, respectively. We first use the FPE criterion to determine the optimal order of the autoregressive model for X, say

\[
x(t) = w_o(k_o) x(t) + w_1(k_1) y_2t.
\] (1)

Second, we introduce \( y_2 \) to the model and again use the FPE criterion to determine the optimal order \( k_1 \), thus we get

\[
x(t) = w_o(k_o) x(t) + w_1(k_1) y_2t + w_2(k_2) y_1t
\] (2)

and third, we introduce \( y_1 \) so that, finally, we get the optimal ordered univariate multivariate autoregressive model of X against its
causal variables as follows:

\[ x(t) = w_0(k_0)x(t) + w_1(k_1)y_{2t} + w_2(k_2)y_{1t} \]  \hspace{1cm} (3)

5. Pool all the optimal univariate autoregressive models constructed in (4) and apply full information maximum likelihood (FIML) methods to estimate the system. Finally, carry out diagnostic checking treating the system as a maintained hypothesis.

In anticipation of our application to Australian data, consider a threevector process \( X_t \) with elements \( X_{1t}, X_{2t}, \) and \( X_{3t} \). The \( X_i \) are assumed to have been prefiltered by appropriate differencing or detrending to yield the series. Estimation of the vector autoregressive process proceeds as follows:

(a) Fit the autoregressives for \( i = 1, 2, 3 \)

\[
X_i = \sum_{s=1}^{M} a_s X_{i,t-s} + U_i
\]  \hspace{1cm} (4)

From \( m=1, \ldots, M \), where \( M \) is specified \textit{a priori} to be the maximum length of the autoregressive process.

(b) Next, examine the FPE.

\[
FPE_{X_i} = \frac{T + m + n + 1}{T - m - n - 1} \cdot \frac{S_s S_{\text{res}}}{T}
\]  \hspace{1cm} (5)

where for the present \( n=0 \) and \( S_s S_{\text{res}} \) is the residual sum of squares and \( T \) is the sample size. Choose \( m_i \) for the values of \( m \) which
minimizes the FPE.

(c) Fit the following regressions for all pairs of variables

\[ X_i = \sum_{s=1}^{m_i} a_{i,s} X_{i,t-s} + \sum_{r=1}^{n} b_{r} X_{j,t-r} + U_i' \]  

for \( n=1, \ldots, M \) and pick \( n_j \) as the value of \( n \) which minimizes the FPE.

(d) For each pair of variables \( X_i \) and \( X_j \) consider the following model.

\[
\begin{bmatrix}
X_i \\
X_j
\end{bmatrix} = \begin{bmatrix}
A(L) & B(L) \\
C(L) & D(L)
\end{bmatrix} \begin{bmatrix}
X_i \\
X_j
\end{bmatrix} + \begin{bmatrix}
U_i' \\
U_j'
\end{bmatrix}
\]  

(7)

where

\[
A(L) = a_1 L + a_2 L^2 + \ldots + a_{m_i} L_{i}^{m_i}
\]

\[
B(L) = b_1 L + b_2 L^2 + \ldots + b_{n_j} L_{j}^{n_j}
\]

\[
C(L) = c_1 L + c_2 L^2 + \ldots + c_{m_j} L_{j}^{m_j}
\]

\[
D(L) = d_1 L + d_2 L^2 + \ldots + d_{n_i} L_{i}^{n_i}
\]

A(L), B(L), C(L), and D(L) represent the lag polynomials fit in (6) above.

Using these polynomials as the maintained hypotheses, alternatively test for the hypothesis that unidirectional causality runs from \( X_j \) to \( X_i \), and lastly that \( X_i \) and \( X_j \) are independent of one another. These hypotheses are tested using a standard likelihood ratio test.

For example, let \( G \) be the estimated variance-covariance matrix of
residuals from system (7) above. Then, to test for unidirectional causality for \( X_i \) and \( X_j \), constrain \( B(L) = 0 \), and suppose \( G' \) is the resulting variance-covariance matrix, under the null

\[-2\log(\text{likelihood ratio}) \text{ is asymptotically distributed as chi-square with } d \text{ degrees of freedom where } d \text{ is the number of imposed restrictions, and of course likelihood ratio } = \left( \frac{\det(G')}{\det(G)} \right)^{-T/2}. \]

(e) Given the bivariate causality results, Caines et al. define the specific gravity of \( X_i \) with respect to \( X_j \) as the reciprocal of the final prediction error in the \( X_j \) equations. The specific gravity can then be computed for each \( X_j, j \neq i \).

To be concrete, suppose the specific gravity of \( X_{j1} \) with respect to \( X_i \) is larger than that of \( X_{j11} \), then \( X_{j1} \) in general provides better information on \( X_i \) than does \( X_{j11} \). Then, given the univariate process for \( X_i \) which yields the lowest FPE, begin by adding the \( X_j \) with the highest specific gravity, searching over the lag lengths for the lowest FPE. Next, given that bivariate lag length, continue adding in order of decreasing specific gravities additional \( X_j \)'s which in the analysis of (d) above cause \( X_i \). Of course, if some particular \( X_j \) does not lower the FPE of \( X_i \) then that \( X_j \) is excluded from the equation for \( X_i \).

(f) After performing the analysis of (e), for each \( X_i \) which is caused by some other variable in the system, pool all the individual equations and estimate by full information maximum likelihood techniques as earlier mentioned.

(g) Given the parameter estimates as a result of (f), perform diagnostic checking by under- and over-fitting the model, by analyzing
the residuals, and so on.

Maximum likelihood estimation

**Data transformations** The data set on AM1, AM2, ATB, and RAP were converted to natural logarithms. Then, we investigated the first and second differences of each series. These transformations were necessary in order to transform our series to stationary stochastic processes. We found that the first differences of the logs of all the variables produced series with no significant trend. We substantiate this claim by regressing these variables on time (regression results are presented in tables, in a technical appendix available on request from the author).

**Estimation procedure** The next step in the sequential method proposed by Caines et al. (1981) is to determine the order of the one-dimensional autoregressive process for all the variables using the FPE criterion. In this study, the estimation period is third quarter, 1969 through second quarter, 1984. We thus have 60 observations. M is chosen to be 14.

Table 1 presents the FPE of fitting a one-dimensional autoregressive process for AM1, AM2, ATB, and RAP (detailed calculations of the FPEs are available in the technical appendix available on request from the author). The minimum final prediction error of $2.939 \times 10^{-4}$ for AM1 was achieved at the 12th order of lags, while $4.203 \times 10^{-4}$ was the minimum FPE achieved for AM2 at the 11th order of lags. ATB and RAP achieved their lowest FPEs of $8.296 \times 10^{-3}$ and $2.967 \times 10^{-4}$, respectively, at the 1st lag in each case.
The next step according to Gaines et al. is to treat $X_i$ as the only output of the system and assume $X_j$ as the manipulated variable which controls the outcome of $X_i$, then use the FPE criterion to determine the lag order of $X_j$, assuming that the order of the lag operator on $X_i$ is the one specified in the previous step above.

Table 1. FPE of fitting a one-dimensional autoregressive process for AM1, AM2, ATB, and RAP

<table>
<thead>
<tr>
<th>The Order Of Lags</th>
<th>FPE of AM1*10^{-4}</th>
<th>FPE of AM2*10^{-4}</th>
<th>FPE of ATB*10^{-3}</th>
<th>FPE of RAP*10^{-4}</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>9.425</td>
<td>7.973</td>
<td>8.296(^{a})</td>
<td>2.967(^{a})</td>
</tr>
<tr>
<td>2</td>
<td>6.083</td>
<td>5.214</td>
<td>8.558</td>
<td>3.026</td>
</tr>
<tr>
<td>3</td>
<td>4.991</td>
<td>4.914</td>
<td>8.769</td>
<td>3.128</td>
</tr>
<tr>
<td>4</td>
<td>5.038</td>
<td>4.652</td>
<td>9.021</td>
<td>3.233</td>
</tr>
<tr>
<td>5</td>
<td>3.740</td>
<td>4.569</td>
<td>9.150</td>
<td>3.272</td>
</tr>
<tr>
<td>6</td>
<td>3.450</td>
<td>4.676</td>
<td>9.431</td>
<td>3.275</td>
</tr>
<tr>
<td>7</td>
<td>3.521</td>
<td>4.785</td>
<td>9.679</td>
<td>3.375</td>
</tr>
<tr>
<td>8</td>
<td>3.221</td>
<td>4.802</td>
<td>9.974</td>
<td>3.223</td>
</tr>
<tr>
<td>9</td>
<td>3.288</td>
<td>4.795</td>
<td>10.141</td>
<td>3.237</td>
</tr>
<tr>
<td>11</td>
<td>3.186</td>
<td>4.203(^{a})</td>
<td>10.680</td>
<td>3.393</td>
</tr>
<tr>
<td>12</td>
<td>2.939(^{a})</td>
<td>4.315</td>
<td>10.995</td>
<td>3.513</td>
</tr>
<tr>
<td>13</td>
<td>3.005</td>
<td>4.465</td>
<td>11.366</td>
<td>3.634</td>
</tr>
<tr>
<td>14</td>
<td>3.108</td>
<td>4.609</td>
<td>11.513</td>
<td>3.765</td>
</tr>
</tbody>
</table>

\(^{a}\)Minimum FPE indicating optimal order of the process.
Table-2 presents the optimum lags of the manipulated variable and the FPE of the controlled variable. (Again, more detailed calculations of the FPEs are available in the technical appendix available on request from the author.)

<table>
<thead>
<tr>
<th>Controlled Variable</th>
<th>Manipulated Variable</th>
<th>Optimum Lag of Manipulated</th>
<th>FPE*10^-4</th>
</tr>
</thead>
<tbody>
<tr>
<td>AM1(12)</td>
<td>ATB</td>
<td>12</td>
<td>1.700</td>
</tr>
<tr>
<td>AM2(11)</td>
<td>RAP</td>
<td>14</td>
<td>2.738</td>
</tr>
<tr>
<td>AM2(11)</td>
<td>ATB</td>
<td>14</td>
<td>3.316</td>
</tr>
<tr>
<td>AM2(11)</td>
<td>RAP</td>
<td>1</td>
<td>4.222a</td>
</tr>
<tr>
<td>ATB(1)</td>
<td>AM1</td>
<td>1</td>
<td>0.748</td>
</tr>
<tr>
<td>ATB(1)</td>
<td>AM2</td>
<td>11</td>
<td>0.758</td>
</tr>
<tr>
<td>ATB(1)</td>
<td>RAP</td>
<td>3</td>
<td>0.784</td>
</tr>
<tr>
<td>RAP(1)</td>
<td>AM1</td>
<td>4</td>
<td>2.259</td>
</tr>
<tr>
<td>RAP(1)</td>
<td>AM2</td>
<td>12</td>
<td>2.161</td>
</tr>
<tr>
<td>RAP(1)</td>
<td>ATB</td>
<td>1</td>
<td>3.033a</td>
</tr>
</tbody>
</table>

Note: Minimum FPE attained by controlled variable not lowered.

We found that when AM1 is treated as the only output of the system, controlled at the 12th order of lags, the lag orders of ATB and RAP were 12 and 14 with FPEs of 1.700 * 10^-4 and 2.738 * 10^-4, respectively.

Whereas when AM2 is treated as the only output of the system, controlled
at 11 lags, the lag orders of ATB and RAP were 14 and 1 with FPEs of $3.316 \times 10^{-4}$ and $4.222 \times 10^{-4}$, respectively.

When ATB is treated as the only output of the system, controlled at the 1st order of lag, the lag orders of AM1, AM2, and RAP were 1, 11, and 3 with FPEs of $0.748 \times 10^{-4}$, $0.758 \times 10^{-4}$, and $0.784 \times 10^{-4}$, respectively. Finally, when RAP is treated as the only output of the system, controlled at the 1st order of lag, the lag orders of AM1, AM2, and ATB were 4, 12, and 1 with FPEs of $2.259 \times 10^{-4}$, $2.161 \times 10^{-4}$, and $3.033 \times 10^{-4}$, respectively.

The next step according to Gaines et al. (1981) is to perform bivariate causality tests for all pairs of variables in the system, using a standard likelihood ratio test. This step was accomplished as follows:

First, to test for unidirectional causality for AM1 and ATB we constrain $b^{12}(L) = 0$ in

$$(AM1) = (a^{12}(L) b^{12}(L)) \begin{bmatrix} AM1 \\ ATB \end{bmatrix} + U_i$$

as the null hypothesis. We obtain the value of $-2\log(\text{likelihood ratio})$ of 6.298535 with 12 degrees of freedom. Consequently, we could not reject the null hypothesis at reasonable levels of significance. Clearly, in this case ATB does not cause AM1. This result is in line with a priori expectations. Second, to test for unidirectional causality for AM1 and RAP we constrain $c^{14}(L) = 0$ in
as the null hypothesis. We obtained the value of -2log(likelihood ratio) of 10.79780 with 14 degrees of freedom. Thus, we could not reject the null hypothesis at reasonable levels of significance. Clearly, we conclude that RAP does not cause AMI, which again is in line with a priori expectations.

Third, to test for unidirectional causality for ATB and AMI, we constrain \( e^1(L) = 0 \) in

\[
(\text{ATB}) = (d^1(L) e^1(L)) \begin{bmatrix} \text{ATB} \\ \text{AMI} \end{bmatrix} + U_i
\]

as the null hypothesis. The value of -2log(likelihood ratio) was calculated to be 11.17551 with 1 degree of freedom. Consequently, we reject the null hypothesis at reasonable levels of significance. In this case, we may conclude that AMI causes ATB. This result confirms our contention in Sanni and Calkins (1985) that M1 matters for ATB in Australia. Fourth, to test for unidirectional causality for RAP and AMI we constrain \( g^4(L) = 0 \) in

\[
(\text{RAP}) = (f^1(L) g^4(L)) \begin{bmatrix} \text{RAP} \\ \text{AMI} \end{bmatrix} + U_i
\]

as the null hypothesis. We obtained the value of -2log(likelihood ratio) to be 22.65083 with 4 degrees of freedom. Hence, we reject the null hypothesis at reasonable levels of significance. In this case, AMI
causes RAP. This result also confirms our contention in Sanni and Calkins (1985) that M1 matters for RAP.

Fifth, to test for unidirectional causality for ATB and RAP we constrain \( h^3(L) = 0 \) in

\[
(\text{ATB}) = \left( d^1(L) h^3(L) \right) \begin{bmatrix} \text{ATB} \\ \text{RAP} \end{bmatrix} + U_i
\]

as the null hypothesis. The value of \(-2\log(\text{likelihood ratio})\) was calculated to be 6.161184 with 3 degrees of freedom. In this case, we could not reject the null hypothesis. We may then conclude that RAP does not cause ATB. Sixth, to test for unidirectional causality for RAP and ATB we constrain \( j^1(L) = 0 \) in

\[
(\text{RAP}) = \left( f^1(L) j^1(L) \right) \begin{bmatrix} \text{RAP} \\ \text{ATB} \end{bmatrix} + U_i
\]

as the null hypothesis. We obtained the value of \(-2\log(\text{likelihood ratio})\) to be 3.596273 with 1 degree of freedom. Thus, we could not reject the null hypothesis at reasonable levels of significance. Again, we may conclude here that ATB does not cause RAP.

Our last two results that RAP does not cause ATB, and that ATB does not cause RAP, strongly imply that the two processes, ATB and RAP, may be unrelated.

Seventh, to test for unidirectional causality for AM2 and ATB we constrain \( j^{14}(L) = 0 \) in
\[ (AM2) = (k^{11}(L) h^{14}(L)) \begin{pmatrix} AM2 \\ ATB \end{pmatrix} + V_i \]

as the null hypothesis. The value of \(-2\log(\text{likelihood ratio})\) was calculated to be 14.91134 with 14 degrees of freedom. Thus, we could not reject the null hypothesis. We may, therefore, conclude that ATB does not cause AM2, which is in line with a priori expectations. Eighth, to test for unidirectional causality for AM2 and RAP, we constrain \(h^1(L) = 0\) in

\[ (AM2) = (k^{11}(L) h^1(L)) \begin{pmatrix} AM2 \\ RAP \end{pmatrix} + V_i \]

as the null hypothesis. We obtained the value of \(-2\log(\text{likelihood ratio})\) to be 2.16493 with 1 degree of freedom. Consequently, we could not reject the null hypothesis at reasonable levels of significance. We may thus conclude that RAP does not cause AM2, which is also in line with our a priori expectations. Ninth, to test for unidirectional causality for ATB and AM2 we constrain \(p^{11}(L) = 0\) in

\[ (ATB) = (d^1(L) p^{11}(L)) \begin{pmatrix} ATB \\ AM2 \end{pmatrix} + V_i \]

as the null hypothesis. The value of \(-2\log(\text{likelihood ratio})\) was calculated to be 18.53122 with 11 degrees of freedom. Consequently, we could not reject the null hypothesis at reasonable levels of significance. We may, therefore, conclude that AM2 does not cause ATB.

The results that ATB does not cause AM2 and that AM2 does not cause
ATB, both strongly suggest that the two processes AM2 and ATB may be unrelated.

Finally, tenth, to test for unidirectional causality for RAP and AM2, we constrain $p^{12}(L) = 0$ in

$$(RAP) = (f^1(L) p^{12}(L)) \begin{bmatrix} RAP \\ AM2 \end{bmatrix} + V_4$$

as the null hypothesis. We obtained the value of $-2\log(likelihood \ ratio)$ to be 24.62914 with 12 degrees of freedom. Thus, we clearly reject the null hypothesis again, at reasonable levels of significance. In this final case, we may conclude that AM2 causes RAP. Thus, again we confirm our contention in Sanni and Calkins (1985), that AM2 matters for RAP.

Table 3 below presents the results of the bivariate causality tests. In summary, we found that there is unidirectional causality from AM1 to ATB, from AM1 to RAP, and from AM2 to RAP. However, RAP and ATB may be unrelated. Also, AM2 and ATB may be unrelated.

The model that emerge from the above procedure is presented below for the system containing LM1D (the first difference of the log of M1), LATBD (the first difference of the log of ATB), and LRAPD (the first difference of the log of RAP).

$$\begin{align*}
\left\{ \begin{array}{c}
LM1D \\
LATBD \\
LRAPD 
\end{array} \right\} &= \begin{bmatrix} a_{11}^{12}(L) & 0 & 0 \\
a_{21}^{11}(L) & a_{22}^{12}(L) & 0 \\
a_{31}^{11}(L) & 0 & a_{32}^{12}(L) 
\end{bmatrix} \begin{bmatrix} LM1D \\
LATBD \\
LRAPD 
\end{bmatrix} + \begin{bmatrix} U_1 \\
U_2 \\
U_3 
\end{bmatrix} \\
\text{(8)}
\end{align*}$$
Table 3. Results of bivariate causality tests

<table>
<thead>
<tr>
<th>Variable</th>
<th>Causal Relationship</th>
<th>Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>AM1</td>
<td>→(^a)</td>
<td>ATB</td>
</tr>
<tr>
<td>AM1</td>
<td>→(^a)</td>
<td>RAP</td>
</tr>
<tr>
<td>RAP</td>
<td>(\downarrow)(^b)</td>
<td>ATB</td>
</tr>
<tr>
<td>AM2</td>
<td>(\downarrow)(^b)</td>
<td>ATB</td>
</tr>
<tr>
<td>AM2</td>
<td>→(^a)</td>
<td>RAP</td>
</tr>
</tbody>
</table>

\(^{a}\) Implies that the left hand side variable "causes" the right hand side variable.

\(^{b}\) Implies that the variables may be unrelated.

Adequacy of model

We estimated the system (8) by full information likelihood procedure as well as by ordinary least squares applied to the system equation by equation. The results from both estimation procedures are practically equivalent. When we tested the identified VAR model against the model postulated by Sanni and Calkins (1985) we obtained a value of -2log(likelihood ratio) to be 18.59615 with 20 degrees of freedom. Consequently, we could not reject the null hypothesis that the model depicted by (8) is acceptable. We have thus achieved a more parsimonious parameterization of our initial model without any loss in efficacy of our results.

We do not need to analyze residuals in this case as further diagnostic test of the appropriateness of our model. This is because, of
the fact that the FPE formulas are derived under the assumption that the residuals are white noise (see Hsiao 1981, page 555).

The second model implied by our procedure above is presented below for the system containing LM2D (the first difference of the log of M2), LATBD, and LRAPD.

\[
\begin{align*}
\begin{bmatrix}
    \text{LM2D} \\
    \text{LATBD} \\
    \text{LRAPD}
\end{bmatrix}
    &=
\begin{bmatrix}
    b_{11}^{11}(L) & 0 & 0 \\
    0 & b_{22}^{1}(L) & 0 \\
    a_{31}^{12}(L) & 0 & b_{33}^{1}(L)
\end{bmatrix}
\begin{bmatrix}
    \text{LM2D} \\
    \text{LATBD} \\
    \text{LRAPD}
\end{bmatrix}
+ \begin{bmatrix}
    V_1 \\
    V_2 \\
    V_3
\end{bmatrix}
\end{align*}
\]  
(9)

**Adequacy of model**

Again, following the suggestion in Caines et al. (1981) we estimated the system (9) by the full information maximum likelihood method, as well as ordinary least squares applied to the system, equation by equation. The results from both estimation procedures were essentially equivalent. When we tested the identified VAR model against the version postulated by Sanni and Calkins. The value of \(-2\log(\text{likelihood ratio})\) was calculated to be 24.32916 with 14 degrees of freedom. Thus, we could not reject the null hypothesis that the model in (9) is adequate.

Also, as in the case of the system containing LM1D, we do not need to analyze residuals as further diagnostic test of the appropriateness of the identified model since the FPE formulas were derived under the assumption that the residuals are white noise.
Conclusion -

This paper presents a maximum likelihood estimation of the dynamic relationship between money and agriculture in Australia. Following the method for fitting multivariate autoregressive processes suggested in Gaines et al. (1981), more parsimonious VAR models were identified. The models were found to be acceptable when compared with earlier versions proposed in Sanni and Calkins (1985) by conventional likelihood ratio tests.

The models were then estimated, using both a full information maximum likelihood method as well as ordinary least squares. We found that, in this particular case, the two procedure produce similar results.

A major conclusion of our present study is to confirm the contention in Sanni and Calkins (1985, page 22) that

domestic credit conditions in Australia (proxied by M1 and alternatively M2) have econometrically measurable impacts on the behavior of agricultural aggregates identified as agricultural trade balance, and relative agricultural prices.

Sherlock Holmes once said, "It is a capital mistake to theorize before one has data. Insensibly, one begins to twist facts to suit theories, instead of theories to suit facts." Sherlock's statement is an adequate illustration of our strategy. Our strategy is to examine facts before formulating appropriate and relevant theories. And so, we will conclude this paper on the same note as we concluded our earlier paper;
In another paper, we hope to present a theoretical model of the interaction between the financial and agricultural sectors of market economies. Such a model will include a wide range of aggregate financial variables such as interest rates and exchange rates and a wide range of agricultural aggregates. Using such an elegant model, we hope to gather more evidence on the macroeconomic effects of domestic credit conditions on agriculture. Such a study will focus on the impacts of the financial variables on the agricultural variables inter-temporally for the United States and possibly for recent periods in other market economies such as West Germany, United Kingdom and Nigeria (Sanni and Calkins 1985, page 23).
References cited


VECTOR AUTOREGRESSION ON NIGERIAN MONEY AND AGRICULTURAL AGGREGATES

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**Introduction**

In the early 1970s, the Nigerian economy became heavily dependent on the oil subsector for its government revenues as well as for its foreign exchange earnings. The dominant role of petroleum in the Nigerian economy was further enhanced, when in 1973-74, Nigeria experienced a significant increase in the prices of its crude oil. OPEC, which Nigeria joined in 1971, successfully raised oil price from 0.84 naira to 7.67 naira per barrel in October 1973. Although Nigeria attained self-sufficiency in crude oil production in October 1960, not until Nigeria joined OPEC did oil replace agriculture as the mainstay of the Nigerian economy.

Nigerian policy makers have been criticized for increasing monetization of petrol-monies (Okigbo 1981). The criticism is hard to dispute. This is because "incredible" increases were observed in the Nigerian money supply, defined as M1 or M2, especially from the early to late 1970s. Incredible increases in the level of money supply may have caused rapid increases in domestic prices which were also observed in Nigeria during the same period. In fact, trends in the money supply and consumer price index have been shown to be closely related (Okigbo, 1981) although there is some lag between the change in prices and the change in money supply. In the study conducted on the Nigerian economy, Oke and Nwade (1977) postulated a linear relationship between price and money supply. These authors then fitted a simple regression...
equation to monthly data on money supply and consumer price index, for the period January 1973 to June 1977. The regression equation (P = 1.21 + 0.063 M1) was found to fit the data admirably. The study indicated that a 100 million naira increase in money supply (e.g., as a result of an increase in government spending) generated a 6.3 percent increase in the price level.

The phenomenon of rapid monetization of Nigerian petrol-monies and consequent increases in domestic prices have serious implications for agricultural trade.

It is reasonable to argue that rising domestic prices (in spite of no currency devaluation) may have caused agricultural production to be less affordable to trading partners. On the other hand, rapid monetization of petrol-monies may have increased private sector disposable incomes thereby increasing agricultural import capacity. Time series data on agricultural trade actually indicated decreasing surpluses from 1963 up and until 1974, and persistent deficits from 1975 to 1979.

The main objective of this paper is to investigate whether money is important for the agricultural sector of Nigeria. Specifically, the effects of M1 and, alternatively, M2 are studied on agricultural aggregates. Also, different lengths of lagged effects are investigated in a vector autoregressive system. And finally, the paper describes in some details the nature of the dynamic relationship among money, prices and agricultural aggregates using Nigerian data.
In this study, the following propositions were tested:

1. In a four-variable vector autoregressive (VAR) system containing M1, agricultural exports (AGE), agricultural imports (AGI), and consumer price index (CPI), a four lag formulation is appropriate for time series data.

2. In a four-variable VAR system containing M2, AGE, AGI, and CPI a four lag formulation is appropriate for time series data.

3. M1 and M2 have statistically measurable impacts upon the agricultural aggregates.

4. Unexpected changes in M1 and M2 have a perceptible influence on the agricultural aggregates.

The paper is divided into six sections. (1) introduction and hypothesis, (2) proposed methodology; (3) model identification for this particular case; (4) time series data, sources, and trends in the data; (5) empirical analysis and results; and (6) conclusion.

**VAR methodology**

According to Burbidge and Harrison (1984), channels of the influence of oil receipts on any economy may be many and varied. Hence, a complete theoretical model to address the question of the impact of oil receipts (oil price) and consequent effect on domestic money supply on domestic economic variables may not be appropriate. Besides, such a model will necessarily be extremely tightly structured (typical of so-called simulation models). And such a model often involves imposing many quite arbitrary restrictions. Therefore, the innovation
accounting techniques pioneered by Sims (1980a and 1980b) and further developed by Doan and Litterman (1983), could be potentially more informative.

The model

The vector autoregression methodology for estimating the moving average representation of a vector stochastic process is to first estimate the coefficients of the autoregressive representation and then compute moving average coefficients from the estimates. Consider an $n$ variable system, beginning with $n$ equations, each equation expresses the current value of one of the variables in the system as a function of lagged values of all variables in the system plus an error term.

This paper employed a four-variable autoregressive model with four components ($w, x, y, z$):

\[
\begin{align*}
    w_t & = a_{11}(L) w_{t-1} + a_{12}(L) y_{t-1} + a_{13}(L) z_{t-1} + a_{14}(L) x_{t-1} + w_t^* \\
    x_t & = a_{21}(L) w_{t-1} + a_{22}(L) y_{t-1} + a_{23}(L) z_{t-1} + a_{24}(L) x_{t-1} + x_t^* \\
    y_t & = a_{31}(L) w_{t-1} + a_{32}(L) y_{t-1} + a_{33}(L) z_{t-1} + a_{34}(L) x_{t-1} + y_t^* \\
    z_t & = a_{41}(L) w_{t-1} + a_{42}(L) y_{t-1} + a_{43}(L) z_{t-1} + a_{44}(L) x_{t-1} + z_t^*
\end{align*}
\]

where $a_{ij}(L) = a_{ij} L^l$, and $L$ is the lag operator so that when applied to a vector process $w_t$, we have $Lw_t = w_{t-1}$ and $L^n w_t = w_{t-n}$. $w_t^*, x_t^*, y_t^*$, and $z_t^*$ are zero-mean white noise innovations with constant covariance matrix

\[
E(w_t^*, x_t^*, y_t^*, z_t^*)' (w_t^*, x_t^*, y_t^*, z_t^*) = d_t, s G.
\]
The parameters of each equation in (1) are estimated by ordinary least squares (OLS). This procedure is justified because theory predicts serially independent error terms and, given that each equation has the same set of variables on the righthand side, OLS applied separately to each equation provides an efficient estimation procedure. In fact, application of OLS gives estimates that are consistent and asymptotically normally distributed.

**Data, sources, and trends**

Table 1 presents annual monthly averages of time series data for 1963 to 1979.

- \( M_1 \) = money supply narrowly defined as currency outside banks and demand deposits.
- \( M_2 \) = money supply widely defined as \( M_1 \) plus savings deposits and small denominated time deposits.
- \( \text{CPI} \) = consumer price index (1980=100).
- \( \text{AGE} \) = total value of agricultural exports in million of naira.
- \( \text{AGI} \) = total value of agricultural imports in million of naira.

\( M_1 \) increased from 223.8 million naira in 1963 to 369.1 million naira in 1969. This was about a 65 percent increase. However, \( M_1 \) increased from 544.2 million naira in 1970 to 1,184.4 million naira in 1974 (about a 118 percent increase) and from its 1974 level to 6,002.6 million naira by 1979. That was a 407 percent increase. The series on \( M_1 \) clearly indicated more rapid increases for the period 1970 to 1979 than for the earlier period.
Table 1. Annual monthly averages of M1, M2, CPI, AGE, and AGI 1963–1979

<table>
<thead>
<tr>
<th>Year</th>
<th>Money Supply (mil naira)</th>
<th>Price Index CPI (1980=100)</th>
<th>Agric. Trade AGE (mil naira)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1963</td>
<td>223.8</td>
<td>17.5</td>
<td>21.2</td>
</tr>
<tr>
<td>1964</td>
<td>264.7</td>
<td>17.7</td>
<td>22.0</td>
</tr>
<tr>
<td>1965</td>
<td>293.6</td>
<td>18.4</td>
<td>24.2</td>
</tr>
<tr>
<td>1966</td>
<td>310.5</td>
<td>20.2</td>
<td>23.9</td>
</tr>
<tr>
<td>1967</td>
<td>331.0</td>
<td>19.4</td>
<td>21.2</td>
</tr>
<tr>
<td>1968</td>
<td>277.2</td>
<td>19.3</td>
<td>21.4</td>
</tr>
<tr>
<td>1969</td>
<td>369.1</td>
<td>21.3</td>
<td>22.3</td>
</tr>
<tr>
<td>1970</td>
<td>544.2</td>
<td>24.2</td>
<td>22.9</td>
</tr>
<tr>
<td>1971</td>
<td>638.4</td>
<td>28.1</td>
<td>20.8</td>
</tr>
<tr>
<td>1972</td>
<td>691.1</td>
<td>29.1</td>
<td>14.4</td>
</tr>
<tr>
<td>1973</td>
<td>813.8</td>
<td>30.7</td>
<td>22.2</td>
</tr>
<tr>
<td>1974</td>
<td>1184.4</td>
<td>34.5</td>
<td>23.4</td>
</tr>
<tr>
<td>1975</td>
<td>2182.9</td>
<td>46.2</td>
<td>18.8</td>
</tr>
<tr>
<td>1976</td>
<td>3286.9</td>
<td>56.0</td>
<td>22.4</td>
</tr>
<tr>
<td>1977</td>
<td>4821.6</td>
<td>68.0</td>
<td>29.4</td>
</tr>
<tr>
<td>1978</td>
<td>5387.8</td>
<td>80.8</td>
<td>36.9</td>
</tr>
<tr>
<td>1979</td>
<td>6002.6</td>
<td>89.7</td>
<td>24.9</td>
</tr>
</tbody>
</table>

^Columns 2, 3, and 4 from International Monetary Funds (IMF) Publications. Columns 5 and 6 from various issues of the Financial and Economic Review of the Central Bank of Nigeria.
M2 increased from an annual average of 316.5 million naira in 1963 to 573.6 million naira in 1969. This was an 81 percent increase. Very similar to M1 movements, M2 increased from 823.4 million naira in 1970 to 1962.7 million naira in 1974 (about a 138 percent increase) and from its 1974 level to 9,029.8 million naira by 1979, a 360 percent increase. Again, M2 has increased more rapidly during the period 1970 to 1979 than for the earlier period.

CPI for 1963 was 17.5. This has increased to 21.3 by 1969 (about a 4 percent rise). But it was 24.2 and 34.5 for 1970 and 1974. That was a 10 percent rise. CPI increased more rapidly, from 34.5 percent to 89.7 percent for 1974 and 1979, a significant 55 percent increase. While price levels have been gradual for the early and late 1960s, it is clear that price movements have been more rapid for the early to late 1970s in Nigeria.

AGE annual monthly average up and until 1975 exceeded those of AGI. While AGE was 21.2 million naira in 1963, AGI was only 4.1 million naira. Also by 1971, AGE was 20.8 million naira while AGI was only 9.5 million naira. However, starting with 1975, AGE was 18.8 while AGI was 35.8 million naira. There have been rapid increases in AGI while AGE has maintained its slow growth. AGI was 1974 and 104.8 by 1978. That was an increase of 445 percent. But AGE of 23.4 million naira in 1974 only rose to 36.9 million naira by 1978, an increase of less than 60 percent.
Empirical analysis and results

The dominance of the role of petroleum in the Nigerian economy began only in the 1970s. For this reason, and because recent data are not available beyond 1979, statistical analysis is done on monthly series for the period 1970 to 1979.

The proposed relationship between M1 (and, alternatively, M2), AGE, AGI, and CPI is

\[ A(L) y_t = e_t \]  

where \( y_t \) is a covariance stationary stochastic process, \( e_t \) is white-noise error process, and \( L \) is the lag operator defined such that \( L y_t = y_{t-1} \), \( L^n y_t = y_{t-n} \), and \( A(L) \) is a general matrix polynomial in \( L \) such that

\[ A(L) = I + A_1 L + A_2 L^2 + \ldots + A_n L^n. \]

The above equation (2) can be expressed as

\[ y_t = A^{-1}(L) e_t \]  

or equivalently

\[ y_t = \sum_{1}^{\infty} B e_{t-1} \]

which is the moving average representation of the stochastic process \( y_t \).

As a practical matter, in estimating a VAR model one assumes that the infinite lagged autoregressive representation (as in (3)) can be
approximated well by a finite lag model.

The appropriate specification of a VAR model, as depicted by system (1) above is an important question to consider, involving the choice of an appropriate lag length.

In attempting to answer this question, several criteria have been suggested for choosing appropriate lag length. First, there is an intuitive argument that regularities in economic data may be missed by using less than an annual lag structure such as 4 quarters or 12 months depending on the frequency of observations. Second, one may compare two specific lag lengths and then use the asymptotic chi-square distribution of the log likelihood ratio to test the null hypothesis of zero sum of coefficients on terms excluded from the constrained model. It is well-known that asymptotically, under a null hypothesis, the omitted lags from the constrained model truly have zero coefficients -2log(likelihood ratio) is distributed chi-square with \((k_l^U - k_l^R)\) degrees of freedom, where \(k\) is the number of variables in the model and \(l_U\) and \(l_R\) are the number of lags of each variable included in the unrestricted and restricted model, respectively. Third, Akaike (1974) and Schwarz (1978) have proposed criteria for choosing lag length based on maximizing the log likelihood function while adjusting for the number of parameters to be estimated. Indexing models of different lag lengths by the subscript \(q\) if we have \(T\) observations and \(K_q\) parameters to estimate, Akaike proposes choosing the model that maximizes \(\log(L_q - K_q)\) where \(L_q\) is the likelihood function maximized with respect to parameters estimated. Schwarz proposed choosing \(q\) to maximize \(\log L_q - K_q \log T/2\).
It has been observed, however, that this criterion has the tendency to favor models with fewer lags. This issue is raised in the first proposition concerning the choice of lags in the VAR system.

For the system containing M1, AGE, and CPI each dependent variable is regressed on lagged values of all the variables in the system. The lag length was chosen to be 4, and to test the first proposition a version of the model with lag length chosen to be 6 was estimated. In this particular case, the value of \(-2\log(\text{likelihood ratio})\) was calculated to be 38.18745 with 32 degrees of freedom. Thus, the null hypothesis of 4 lags is not rejected at reasonable levels of significance. Notice that chi-square with 30 degrees of freedom at 3 percent significance level is 43.773 from any statistical table.

The second proposition of 4 versus 6 lags was tested for the system containing M2, AGE, AGI, and CPI. In this case, the value of \(-2\log(\text{likelihood ratio})\) was calculated to be 33.2834 with 32 degrees of freedom. Thus, the null hypothesis of 4 lags is again not rejected at reasonable levels of significance.

The time series data used in vector autoregression estimation are always assumed to represent a covariance stationary stochastic process. A vector stochastic process is stationary if \(EX_t = u\) (the mean of \(X_t\)) and \(\text{var}(X_t) = \sigma_t < \infty\), \(\text{cov}(X_t, X_s) = Z_{t-s}\). In essence, all that is involved here is that a stationary process will have mean and variance that do not change through time, and the covariance between values of the process at two points in time depends solely on the distance between those two points in time, and not on time itself. Essentially, a stationarity
assumption is equivalent to saying that the generating mechanism of the process is itself time invariant so that neither the form nor the parameter values of the generation procedure changes through time. The issue, therefore is that, without any doubt, no one can claim that an assumption of stationarity is generally realistic.

It is not surprising that empirical data available to the economic analyst often will exhibit seasonality, indicating that such raw data do not in fact represent a covariance stationary stochastic process. In vector autoregression literature, the usual practice in this situation is to transform the data, for example by taking logs. Alternatively, seasonal dummies or a time trend as righthand variables may be included in an attempt to derive a data set that can be represented by a stationary stochastic process.

In this study, all variables in regressions are converted to natural logarithms. Also included are a constant as well as a trend term in each equation of the VAR model in order to convert the series to covariance stationary stochastic processes.

The third proposition concerns whether M1 has any statistically measurable impact on the behavior of the agricultural and price aggregates. In the VAR framework, this is interpreted to mean that the matrices \( A^{-1} \) in equation (3) are block triangular, i.e., the coefficients of the lags of M1 in all the agricultural aggregate regressions are not statistically different from zero. Therefore, a version of the model incorporating the stated restrictions was estimated and a standard likelihood ratio test was conducted for the entire system.
In this particular case, $-2\log(\text{likelihood ratio})$ was calculated to be 37.52292 with 12 degrees of freedom. Thus, the null hypothesis of no $M_1$ effects is clearly rejected at reasonable levels of significance. Notice that chi-square with 12 degrees of freedom at 5 percent is 21.03 from any statistical table.

The part of the third proposition concerning the effects of $M_1$ on the rest of the variables was interpreted similarly to $M_1$ to mean that the coefficients of the lags of $M_2$ in all the agricultural aggregate regressions are not statistically different from zero. Consequently, a version of the model incorporating the stated restrictions was estimated and a standard likelihood ratio test was conducted for the entire system. In this particular case, $-2\log(\text{likelihood ratio})$ was calculated to be 35.21284 with 12 degrees of freedom. This clearly rejects the null hypothesis of no $M_2$ effects at reasonable levels of significance.

Having established the fact that money, whether defined $M_1$ or $M_2$, has an econometrically measurable impact on the agricultural and price aggregates, the nature of the dynamic relationship in what has been described as "innovation accounting" and forecast error variance decomposition are described more completely. These are the issues involved in the last two propositions listed above.

Table 2 is constructed to facilitate the discussion of the fourth proposition concerning the effects of unexpected changes in $M_1$ on the rest of the variables of the system. The table lists the forecast error variances and their decompositions for time horizons 1, 4, 8, and 12.
Table 2. Proportion of forecast error variance \( k \) months ahead produced by each innovation

<table>
<thead>
<tr>
<th>Forecast error in:</th>
<th>M1</th>
<th>AGE</th>
<th>AGI</th>
<th>CPI</th>
</tr>
</thead>
<tbody>
<tr>
<td>( k )</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>4</td>
<td>0.927</td>
<td>0.043</td>
<td>0.019</td>
<td>0.011</td>
</tr>
<tr>
<td>8</td>
<td>0.803</td>
<td>0.045</td>
<td>0.099</td>
<td>0.053</td>
</tr>
<tr>
<td>12</td>
<td>0.708</td>
<td>0.054</td>
<td>0.138</td>
<td>0.099</td>
</tr>
<tr>
<td>AGE</td>
<td>1</td>
<td>0.033</td>
<td>0.967</td>
<td>0.00</td>
</tr>
<tr>
<td>4</td>
<td>0.030</td>
<td>0.922</td>
<td>0.021</td>
<td>0.027</td>
</tr>
<tr>
<td>8</td>
<td>0.035</td>
<td>0.896</td>
<td>0.023</td>
<td>0.046</td>
</tr>
<tr>
<td>12</td>
<td>0.044</td>
<td>0.867</td>
<td>0.029</td>
<td>0.059</td>
</tr>
<tr>
<td>AGI</td>
<td>1</td>
<td>0.005</td>
<td>0.007</td>
<td>0.988</td>
</tr>
<tr>
<td>4</td>
<td>0.006</td>
<td>0.011</td>
<td>0.953</td>
<td>0.029</td>
</tr>
<tr>
<td>8</td>
<td>0.119</td>
<td>0.018</td>
<td>0.825</td>
<td>0.038</td>
</tr>
<tr>
<td>12</td>
<td>0.185</td>
<td>0.027</td>
<td>0.734</td>
<td>0.054</td>
</tr>
<tr>
<td>CPI</td>
<td>1</td>
<td>0.003</td>
<td>0.00005</td>
<td>0.005</td>
</tr>
<tr>
<td>4</td>
<td>0.079</td>
<td>0.015</td>
<td>0.047</td>
<td>0.859</td>
</tr>
<tr>
<td>8</td>
<td>0.302</td>
<td>0.023</td>
<td>0.040</td>
<td>0.636</td>
</tr>
<tr>
<td>12</td>
<td>0.478</td>
<td>0.017</td>
<td>0.050</td>
<td>0.455</td>
</tr>
</tbody>
</table>
The vector autoregression was triangularized in order from highest to lowest as follows: Ml, AGE, AGI and CPI.

Some justification of the selected ordering is necessary. It is believed that money supply represents purely a policy variable in this context, to the extent that it is largely determined by government policies and, conceptually, is a reaction function of the Central Bank of Nigeria. Agricultural exports are placed before agricultural imports because it is believed that prices on the world market most likely influence the total value of agricultural exports more than they do agricultural imports. These imports not only depend on the world market prices but also on the flow of foreign exchange earnings available to the country. Definitely the most aggregated of the series is money supply. Agricultural imports could more likely adjust to current shock in agricultural exports than agricultural exports to a shock in agricultural imports. Consumer prices are placed last in the ordering since it is more reasonable to expect prices to respond both to shocks from the agricultural aggregates than vice versa.

Table 2 shows that money supply (Ml), for all practical purposes, is exogenous in this short run analysis. The major portion of forecast error variance (93 percent) is accounted for by its own innovations at a 4-month lag, at 8 months 80 percent and at 12 months about 71 percent. A close perusal of Table 2 indicates that Ml explains successively less of the forecast variance in Ml but more and more of the forecast variance in the agricultural variates. Ml innovations accounted for by AGE at the 4th, 8th, and 12th months were
4.3, 4.5, and 5.4 percent, respectively. Relatively more dramatic, M1 innovations accounted for by AGI were 1.9, 9.9, and 13.8 percent, respectively, for the 4th, 8th, and 12th months. Similarly, M1 innovations accounted for by CPI were 1.1, 5.3, and 9.9 percent by the 4th, 8th, and 12th months, respectively. In a similar study for the United States Chambers explained that

judging what is the short run is difficult; but if it extends to yearly time horizon which because of the long lags inherent in agricultural production seems quite plausible, then unexpected changes in M1 apparently can have perceptible influences on agriculture (Chambers, 1984).

Proportion of AGE forecast error variance attributable to AGE itself is fairly high, from 97 percent in the first month to 92, 90, and 87 percent, respectively, at the 4th, 8th, and 12th months. Interestingly, however, the proportion of AGE forecast error variance attributable to changes in the triangularized M1 innovation becomes steadily increasing from 3.0 percent in the 4th month to 4.4 percent in the 12th.

The proportion of AGI forecast error variance attributable to AGI itself is also considerable, from 98.8 percent in the 1st month to 95.3, 82.5, and 73.4 percent by the 4th, 8th, and 12th months. Again, the AGI forecast error variance attributable to M1 innovations becomes steadily larger, from almost zero at the 1st month to 11.9 and 18.5 percent at the 8th and 12th months.

As for CPI, there is a considerable reduction in forecast error variance accounted for by its own innovations from 99 percent in the
first month to 86 percent by the 8th month, and finally down to 46 percent by the 12th month. Interestingly, however, the proportion of CPI forecast error variance attributable to changes in the triangularized M1 innovations becomes progressively larger: about 0 percent at the 1st month to 8 percent at the 4th month, and 30 to 48 percent by the 8th and 12th months, respectively.

Figure 1 illustrates the contemporaneous effect of innovation in M1 on M1 and AGI. Notice that the contemporaneous effect of M1 on M1 itself is positive for the 12-month period. The contemporaneous effect of M1 innovations on AGI is negative for the first four lag periods but clearly positive, thereafter.

Figure 2 shows the contemporaneous effect of innovation in M1 on AGI and CPI. Again, the contemporaneous effect of M1 on AGI is negative at first (for the first three lag periods) but clearly positive thereafter. The contemporaneous effect of M1 on CPI is negative (though very small) for the first lag period but steadily positive, thereafter.

Table 3 was constructed to confront the fourth proposition on the effects of unexpected changes in M2 on agriculture. The table concerns the decompositions of the error variance again for 1, 4, 8, and 12 month horizons. Table 3 is very similar to Table 2, except that M2 tends to be more exogenous since it accounts for relatively more of its own innovations as time wears on. At a 4-month lag 93.3 percent of M2 innovations were accounted for by M2 itself. This decreased slightly to 89.3 and 82.9 percent by the 8th and 12th months. Again, M2 explains
Figure 1. Effect of innovations in M1 on M1 & AGE
Figure 2. Effect of innovations in M1 on AGI & CPI
successively less of the forecast variance in M2 (less so than for M1) but more and more of the forecast variance in the agricultural and price variables. M2 innovations accounted for by AGE at the 4th, 8th, and 12th months declined from 5.7 to 3.9 and finally to 3.2 percent, respectively. However, M2 innovations accounted for by AGI and CPI increased modestly throughout the 12 month period.

The discussions for AGE, AGI, and CPI closely follow the lines of M1 along with the rest of the variables as discussed above, and will not be repeated here. Figure 3 shows the effects of innovation in M2 on M2 and AGE. Here, as in the case of M1, the contemporaneous effect of M2 on itself is positive for the entire 12 months. However, the contemporaneous effect of M2 on AGE was negative for the first 6 lag periods but clearly positive thereafter.

Figure 4 shows the effects of innovations in M2 on AGI and CPI. Notice that the contemporaneous effects of M2 on AGI are less clear cut. (The contemporaneous effects are first negative, then positive and negative again, for the first, second, and third lag periods, respectively. However, the effects were clearly positive from the fourth period through the rest of the 8 lag periods.) More interesting results were found for CPI. Very small negative contemporaneous effects of M2 innovations on CPI in the first 2 lag periods were observed. These effects were impressively positive, thereafter.
Figure 3. Effect of innovation in M2 on M2 & AGE
Figure 4. Effect of innovation in M2 on AGI & CPI
Table 3. Proportion of forecast error variance $k$ months ahead produced each innovation

<table>
<thead>
<tr>
<th>Forecast error in:</th>
<th>M2</th>
<th>AGE</th>
<th>AGI</th>
<th>CPI</th>
</tr>
</thead>
<tbody>
<tr>
<td>k</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>1.00</td>
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<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>4</td>
<td>0.933</td>
<td>0.057</td>
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<td>0.004</td>
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<tr>
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<td>0.893</td>
<td>0.039</td>
<td>0.036</td>
<td>0.033</td>
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<tr>
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<td>0.829</td>
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<td>0.056</td>
<td>0.083</td>
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</tr>
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<td>0.038</td>
<td>0.963</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
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<tr>
<td>12</td>
<td>0.060</td>
<td>0.886</td>
<td>0.019</td>
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<td></td>
</tr>
<tr>
<td>1</td>
<td>0.004</td>
<td>0.008</td>
<td>0.988</td>
<td>0.00</td>
</tr>
<tr>
<td>4</td>
<td>0.010</td>
<td>0.020</td>
<td>0.944</td>
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<td>8</td>
<td>0.102</td>
<td>0.023</td>
<td>0.848</td>
<td>0.028</td>
</tr>
<tr>
<td>12</td>
<td>0.198</td>
<td>0.026</td>
<td>0.741</td>
<td>0.036</td>
</tr>
<tr>
<td>CPI</td>
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<td></td>
</tr>
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<td>0.002</td>
<td>0.001</td>
<td>0.004</td>
<td>0.993</td>
</tr>
<tr>
<td>4</td>
<td>0.035</td>
<td>0.041</td>
<td>0.045</td>
<td>0.879</td>
</tr>
<tr>
<td>8</td>
<td>0.169</td>
<td>0.065</td>
<td>0.045</td>
<td>0.721</td>
</tr>
<tr>
<td>12</td>
<td>0.342</td>
<td>0.066</td>
<td>0.040</td>
<td>0.556</td>
</tr>
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</table>
Conclusion

Quite understandably, the phenomenon of rapid monetization of Nigerian petrol-monies and the resulting increases in domestic prices may have serious implications for agricultural trade (or for any subsector of the Nigerian economy for that matter). Although agriculture may have contributed less to government revenues and foreign exchange earnings (at least for the period 1970 to 1979), its importance cannot be over emphasized in the Nigerian context because agriculture still employs more than 65 percent of the Nigerian labor force.

Specifically, the time series data admit a 4-lag specification for the VAR system containing M1, AGE, AGI, and CPI as well as the system containing M2, AGE, AGI, and CPI. It was also found that both M1 and M2 have statistically significant impacts on the agricultural and price variables. And, more interestingly, it was found that unexpected changes in both M1 and M2 (defined as random monetary shocks) have perceptible influence on agricultural and price variables. The empirical results strongly support the contention that money does matter for the agricultural sector of Nigeria.

For the United States' economy, evidence is increasingly accumulating on the whole issue of macroeconomic impacts on the U.S. agricultural sector. Chambers and Just (1982) lamented that monetary policy actions "such as reducing domestic credit are only rarely, if ever, recognized as having any impact on the agricultural sector of the economy" (Chambers and Just, 1982). Chambers (1984) has pioneered an interesting discussion of financial market interactions with agricultural
markets. Chambers' conclusions could, if generally upheld, have a significant influence on activist monetary policies.

One way of examining the strength of Chambers' results is to replicate the exercise in other contexts using differing data and time periods. This study is such an attempt. Other attempts of the present author (and his associates) include studies for the Australian economy (see Sanni and Calkins, 1985); the West German economy (see Sanni, Calkins, and Shelley, 1985); the United Kingdom economy (see Sanni, 1985a) and the Japanese economy (see Sanni, 1985b).

To some extent, the results of this study are similar to Chambers' conclusions about the United States. A note of caution here is that money innovations are by definition unpredictable and have little or nothing to do with the effects of anticipated monetary policy changes. Because monetary policy changes are fairly widely publicized in the modern economy, innovation accounting captures only part and not necessarily the most interesting part of the interaction (Chambers, 1984).

This study is extremely limited in scope. Variations in the money supply defined as M1 and alternatively M2 were used as the primary measures of monetary impacts on agricultural trade. Also, total values of agricultural exports and imports were used as indicators of agricultural sector responses to monetary impulses. Obviously, this study can be extended by the inclusion of more financial as well as agricultural sector variables in the VAR model.
Such a task is by no means an easy one because disaggregated time series data such as the food component of the consumer price index, non-food component of the consumer price index, trade weighted index of exchange rates, or effective interest rates for the Nigerian agricultural sector may not be readily available.
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International Monetary fund (IMF). International financial statistics (IFS) [various issues]


SUMMARY AND DISCUSSION

Section I of this dissertation is a seminar paper on "Dynamic Modeling of Trivariate Monetary and Agricultural Time Series Observations on The United Kingdom's Postwar Economy." In that section, vector autoregressive modeling efforts for three variables, money supply (M1 and, alternatively, M2), exchange rate (EXCH), and the food component of the consumer price index (FCPI) indicated that the exchange rate may have more econometrically measurable impacts on aggregate food price for the period May 1972 to December 1979, than money supply.

Section 2 of this work is again a seminar paper on "A Macroeconomic Analysis of Monetary Impacts of Japanese Economy." That section is a rigorous expositonal analysis in the vector autoregressive framework of three important macrovariables: money supply (M1 and, alternatively, M2), food component of consumer price index (FCPI), and an index of prices received (IPR) by farmers. This section concludes that money supply, whether defined narrowly as M1 or widely as M2, have statistically significant impacts upon the behavior of FCPI as well as IPR.

Section 3 of this dissertation is another seminar paper on "A Maximum likelihood estimation of the dynamic relationship between money and agriculture in Australia." The paper is an attempt to investigate the dynamic relationship between money and agriculture in Australia. The variables of interest were money supply (M1 and, alternatively, M2), Agricultural trade balance (ATB), and relative agricultural prices (RAP). Quarterly data for the period third quarter of 1969 through the second quarter of 1984 were used in the analysis.
Interesting results were obtained from bivariate causality tests conducted among the variables in a vector autoregressive framework.

Section 4 of this work is already published in the March 1986 issue of the Canadian Journal of Agricultural Economics. "Vector Autoregression on Nigerian Money and Agricultural Aggregates" employs vector autoregression techniques to analyze monthly time series data on the Nigerian Economy. Four variables were used in the paper. The four variables were money supply (M1 and, alternatively, M2), total value of Agricultural exports (AGE), total value of Agricultural Imports (AGI), and the Consumer Price Index (CPI). The paper established the fact that money matters for the agricultural sector of Nigeria at least for the period May 1970 to December 1979.
LITERATURE CITED


Central Bank of Nigeria (CBN), Lagos. Financial and economic review of the Central Bank of Nigeria [various issues].


ACKNOWLEDGMENTS

Dr. Earl O. Heady, Charles Curtis' distinguished professor of Agriculture, provided genuine inspiration and research assistantship for my pursuit of the Ph.D. degree in Economics at Iowa State University. I am duly honored by his generosity and the guidance of colleagues at the Center for Agriculture and Rural Development (CARD). The genuine inspiration and close supervision was continued by the new director of CARD, Dr. Stanley Johnson. I am very grateful to Dr. Stanley Johnson for his steadfastness and willingness to help in spite of serious odds.

I acknowledge the help of members of my program of study: Dr. Arne Hallam, Dr. James A. Stephenson, Dr. Dudley G. Luckett, and Dr. Mack C. Shelley.

Research Associates at the Bank of England, Threadneedle Street, London England as well as those at the Ministry of Agriculture, Whitehall Place, London, England, provided all of the data for Section I. I am extremely grateful to all of these people.

Research Associates at the Japan Trade Center, Tokyo, Japan, provided most of the data for the second section of this work. My sincere thanks are due to these good people.

Research associates at the Bureau of Agricultural Economics (BAE), Canberra, Australia, and Research Associates at the Reserve Bank of Australia in Sydney, Australia provided the data for the Third Section. I am very grateful to them for their interest and help.

Research Associates at the Central Bank of Nigeria (CBN), Tinubu Square, Lagos, Nigeria, provided most of the data for Section IV of the
dissertation. I appreciate their communication by letter.

Research Associates at the International Monetary Fund (IMF) Washington, D.C., helped provide complete money stock series that supplemented data for all sections of this dissertation. I owe them a lot for their cooperation.

I acknowledge the help of the Oyo State Government of Nigeria for extending scholarships to finance my graduate education at Iowa State University.

I wish to express my sincere thanks to my "God-sent" father, Mr. N. Ade Martins for financing my high school and higher school education in Nigeria and for his moral and financial support during my graduate studies at Iowa State University. I am indebted to him for his genuine interest in me from my youth.

Finally, my darling wife, Mrs. Faosat Joke Sanni (Joke) provided a lot of patience, perseverance, endurance, love, motherly care, and tremendous courage throughout my graduate education, both at the University of Ife, Ile-Ife, Nigeria and in the United States of America. I owe Joke a lot of thanks and sincere appreciation for her genuine interest in my progress in life.

My two beautiful daughters: Busiratu Mobolade Sanni (Bola) and Suebatu Abimbola Sanni (Bimbo) endured my prolonged absence from our humble U.S.A. home (705 Pammel Court, Ames, Iowa) particularly during my research trips to Europe in the summer of 1985. I hereby acknowledge the special help of my two lovely daughters.