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INTERACTIONS AMONG MONEY, EXCHANGE RATES, AND COMMODITY PRICES

by

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I. INTRODUCTION

A cursory examination of the literature on the effects of macroeconomic variables on agriculture reveals much speculation and confusion. Empirical results range from a significant relationship between the size of the money supply and real commodity prices (Chambers and Just, 1982) to no relationship (Batten and Belongia 1984). Some frameworks in the literature only admit forward linkages from money, exchange rate, and nonagricultural good markets to commodity and food markets. In contrast, other frameworks admit backward linkages from commodity and food markets to the both real and financial macroeconomic phenomena. Still, other empirical studies have argued that the linkages with the general economy place agriculture in a cost-price squeeze. In contrast, other studies have argued that agricultural prices, especially at the farm level, respond faster to changes in money supply than nonfarm prices. In a flex-fixed price world other studies have argued that commodity prices will overshoot their long-run equilibrium and, as a result, only during periods of monetary contraction do you expect a "cost-price squeeze" to be imposed upon the agricultural sector; during periods of monetary expansion, the reverse would be expected to hold.

The conflicting inferences that exist in the agricultural economics literature on the role of macroeconomic phenomenon are often based on vector autoregressive (VAR) or multivariate time-series models. Time-series models have been used to recover plausible behavioral interpretations of reduced-form relationships based on minimal restrictions, as opposed to often-overidentified econometric models. Yet, time-series models have been criticized on the grounds that identifying restrictions are required to give structural interpretation to an reduced-form empirical evidence. In practice, identification in multivariate time-series models is obtained by choice of a certain decomposition of the covariance matrix of the one-step-ahead forecast errors, which implies a recursive structure of the model. Such a recursive structure is, of course, questionable and must rely on some structural characterization of the economy.

Recent papers by Bernanke (1986) and Sims (1986) have argued that the contemporaneous structure of the system need not be recursive for VAR models to be identified. If the innovations are mutually orthogonal and all lagged relationships among the endogenous and the exogenous variables are left unrestricted, then a VAR model can be identified by restrictions placed on the contemporaneous interactions among the endogenous variables. Basically, the idea is that an economic structure can be identified from the estimated innovation covariance matrix of a VAR system, which is then to be interpreted (ex post) as the reduced form of a structural model. Since different decompositions will arise from different orderings of the endogenous variables, the "structural" interpretation of a VAR system is thus appropriate to discriminate among competing structural hypothesis.

Since the publication of Sims' article on the money-to-income Granger causality (1972), VAR models have been applied to a variety of macroeconomic monetary models (Sims 1980a, 1980b, 1986, 1989; Hsiao 1981; Thorton and Batten 1985; Litterman and Weiss 1985; Bernanke) and to models on the effects of money on agriculture (Bessler 1984; Orden 1986; Saunders 1988; Orden and Fackler 1989). Despite their similar specifications, all these studies have often yielded conflicting results. Granger (1988) and Stock and Watson (1989), among others, have suggested that this may have been caused in part by the failure to adequately consider the time-series properties of the data or to account for the implications of unit-root nonstationarity for model specification and hypothesis testing (Nelson and Plosser 1982; Stock and Watson 1988, 1989; Engle and Granger 1987).

The issue of unit-root nonstationarity has been widely debated in recent years, particularly with respect to its macroeconomic implications. Findings of nonstationarity due to one or more unit roots in the autoregressive representations of several macroeconomic time series (e.g., Nelson and Plosser) have given support to the hypothesis that the observed series have trends which are nondeterministic. If a series has one unit root, then its first difference is stationary, and the series is said to be *integrated of order 1 (I(1))*. More generally, a series is I(d) if its *d*th difference is stationary. An I(0) series has spectrum bounded from above and is positive at all frequencies. Its first and second moments are time invariant and so it is *second-order stationary*, i.e., its generating mechanism can be approximated by a stationary invertible ARMA (p, q) process, with p and q finite (Box and Jenkins 1976)[1].

If two or more series are I(1) with no trends in mean, so that their changes are I(0) with zero means, usually any linear combination of them will also be I(1). However, if there exists a linear combination which is I(0), then the variables are said to be *cointegrated* (Granger 1983). Engle and Granger have shown that, if a Nx1 vector x_t of I(1) variables is cointegrated with cointegrating rank r,[2] then there exists a VAR representation,

$$A(L)x_t = \varepsilon_t,$$

such that A(1) has rank, r, and A(O) = I_N, and a vector error correction (VEC) representation

$$A^*(L)(1-L)x_t = -\gamma z_{t-1} + \varepsilon_t,$$

where $z_t = \alpha x_t$ and α is the cointegrating vector, and A*(0) = I_N. As Engle and Granger point out, "vector autoregressions estimated with cointegrated data will be misspecified if the data are differenced, and will omit important constraints if the data are used in levels" (p. 259).

A VEC model is a VAR model in the first differences of the series where lagged deviations from the stationary long-run equilibrium among the variables (captured by the cointegrating relationship) affect the dynamics of the system. The failure to impose the restrictions implied by cointegration on a VAR in levels simply yields an estimated model where significant constraints have not been imposed. However, the estimation of a model in levels of I(1) variables gives unreliable results. Conversely, the failure to recognize cointegration among the variables in differencing the individual series to obtain stationarity yields a misspecified VAR model in first differences.

This result has important consequences for the correct specification of the reduced form to be estimated through a VAR formulation. If all the endogenous variables are I(1), then they should be first differenced; and a VAR model in the first differences should be estimated. Failure to do so would result in spurious regression estimation. Moreover, if the N components of a vector x_t of endogenous variables are I(1) and cointegrated, then they should be first differenced and a VEC model should be estimated. Failure to include an error-correcting term in a VAR in first differences would otherwise result in a misspecified model.

In this paper, the above issues are analyzed for U. S. agriculture using a four-variable reduced-form model of the dynamic interactions among money (m), the exchange rate (3), manufacturing prices (p_B) and agricultural prices (p_A). It will be shown that the empirical results are very sensitive to the treatment of the time series properties of the data, casting doubt on many conclusions previously drawn in the literature. In particular, since the four endogenous variables will appear to be nonstationary and cointegrated, a VEC model (as opposed to a VAR model in the differences) will be the most appropriate dynamic representation of the system.

II. Analytical Framework

Let us denote with Y the vector, $[\bar{p}_A, \bar{p}_B, \bar{e}, \bar{m}]$, and with ε the vector, $[u_{pA}, u_{pB}, u_e, u_m]'$. Then we can write a class of structural models as:

(1)
$$A_0 Y_t = A(L) Y_{t-1} + \varepsilon_t$$
$$\varepsilon_t = C(L)\varepsilon_{t-1} + \eta_t$$

where A(L) and C(L) are infinite polynomial of nxn and qxq matrices, respectively, in the lag operator,

(2) $$A(L) = \sum_{i=1}^{n} A^i L^{i-1}$$

$$C(L) = \sum_{i=1}^{q} C^i L^{i-1}$$

and η is white noise.

As we can see, expectations are not written out explicitly in (1) since we assume they have already been eliminated from the model. In order to move from the structural model to the reduced form, we premultiply both sides of (1) by [1-C(L)]:

(3) $$A_0 Y_t = \{C(L)A_0 + [1 - C(L)]A(L)\} Y_{t-i} + \eta_t$$

and then we premultiply both sides by A_0^{-1} (assuming A_0 is nonsingular),

(4) $$Y_t = D(L) Y_{t-i} + \varepsilon_t$$

where

(4a) $$D(L) = A_0^{-1}\{C(L)A_0 + [1 - C(L)]A(L)\}$$

(4b) $$\xi_t = A_0^{-1}\eta_t.$$

In the present context, our ultimate interest would be about the own and cross dynamics of prices, exchange rates, and money, that is, A_0, A(L) and the covariance matrix of ξ_th. Also, we assume that C(L) is diagonal, i.e., each structural disturbance depends only on its lagged values and not on the lagged values of the other disturbances. Since the disturbances in each equation represent the effect of the omitted variables *other than* m, e, p_A, and p_B, this implies that all the *residual* effects on m, e, p_A, and p_B are uncorrelated.

Taking first differences of any of the variables in (4) would imply assuming the presence of unit roots, i.e., nonstationarity in the mean, in [I-D(L)]. Unit roots in [I-D(L)] could arise from unit roots in [A_0-A(L)] or from unit roots in the disturbances, i.e., [I-C(L)]. However, since we are assuming, in the absence of other disturbances, that the economy will tend toward the steady state, we can rule out the possibility of unit roots in [A_0-A(L)]. That is, we can rule out unit roots in the own and cross dynamics of prices, exchange rates, and money. Accordingly, unit root in [I-D(L)] must arise from unit roots in the disturbances-generating process, [I-C(L)]. Since the disturbances, by their own nature, include all the omitted and unexplained effects, this is not unreasonable. Unit roots can arise from productivity shocks, random supply shocks, etc.

If [I-D(L)] has one or more unit roots, then the appropriate specification of (4) should be as given by the Granger Representation Theorem (Engle and Granger). Suppose [I-D(L)] has r unit roots, with r = 1, 2, 3. Then (4) must be rewritten as

$$\Delta Y_t = D'(L)\Delta Y_{t-1} + UY_{t-1} + \xi_t \tag{5}$$

where $\Delta Y_t = Y_t - Y_{t-1}$, D'(L) has all its roots outside the unit circle and U is of rank 3-r (U is the cointegrating vector). Hence, only if each of the three disturbances has a unit root would it be appropriate to estimate (4) as

$$\Delta Y_t = D'(L)\Delta Y_{t-1} + \xi_t \tag{6}$$

If there are less than three unit roots, (5) is the correct specification and it is also more efficient. If the main source of nonstationarity in the disturbances is in exogenous shocks to the system, then we would expect it to affect all the variables; if the shocks "cancel" each other out, then it is possible that less than all variables will be affected. A reasonable estimation strategy would then be to check the estimated roots of the system, perform the unconstrained estimation of (6), and then compare the results of the unconstrained with the constrained specification (5).

III. THE TIME-SERIES PROPERTIES OF THE DATA

We chose quarterly data for the period, 1972:1-1988:3 (the data sources and the actual variables are described in the Appendix), to implement the empirical analysis. Money supply stock is measured by M_2, the exchange rate by the trade-weighted nominal exchange rate,[3] farm prices by the index of prices received by farmers, and manufacturing prices by the consumer price index, all items less food. All variables were transformed in logarithms and defined as follows: LM2 indicates log of money supply, LER indicates log of exchange rate, LFP indicates log of farm price, LNP indicates log of manufacturing (nonfarm) price.

A number of statistics have been proposed as tests for unit roots in the autoregressive representation of a time series. Many of these are actually modifications of the "t-like" tests proposed by Dickey and Fuller (1979). A Dickey-Fuller test (DF) for

$$(1-L)y_t = \rho y_{t-1} + \varepsilon_t \tag{7}$$

is a test of the null hypothesis that $\rho = 0$. Under the null, the t-statistic of the estimated ρ (denoted as τ) is not distributed as a Student t; its critical values are given in Fuller (1976, p. 373). An "Augmented" Dickey-Fuller test (ADF) is a test of the same null hypothesis in the regression:

$$(1-L)y_t = \rho y_{t-1} + \sum_{i=1}^{p} \beta_1 \Delta y_{t-i} + \varepsilon_t \tag{8}$$

with p = 4, where lags of Δy are included to represent more of the dynamics. Slightly different is a test of the same null hypothesis in the regression:

$$(1-L)y_t = \mu + \rho y_{t-1} + \varepsilon_t. \tag{9}$$

Here, a constant is included so that a test for a unit root is actually a test of the null hypothesis that $\rho = 0$, conditional on $\mu = 0$. The t-statistic is denoted as τ_{μ}. It has a different distribution from τ, and its values are tabulated in Fuller (table 8.5.2, p. 373). This same test applies to the augmented version,

$$(1-L)y_t = \mu + \rho y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + \varepsilon_t. \tag{10}$$

Finally, a test of the hypothesis that the series has a unit root with a non-zero drift and a linear deterministic trend can be conducted from the regression,

$$(1-L)y_t = \mu + \alpha t + \rho y_{t-1} + \varepsilon_t. \tag{11}$$

Here, the test for the presence of one unit root is actually a test of the null hypothesis that $\rho = 0$, conditional on $\mu = 0$ and $\alpha = 0$. The t-statistic is denoted as τ_{τ}, and its critical values are given in Fuller (table 8.5.2, p. 373) The same hypothesis is also tested through the augmented version,

$$(1-L)y_t = \mu + \alpha t + \rho y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + \varepsilon_t. \tag{12}$$

Results for the three DF and ADF tests are summarized in table 1 and table 2, respectively. They suggest, almost uniformly, that the null hypothesis that the individual series have one unit root cannot be rejected even at the 10 percent significance level. Thus, we can conclude that the money supply (as measured by M_2), the U. S. exchange rate, and the farm and manufacturing price series appear to be nonstationary over the period 1972:1-1988:3; and that, therefore, a VAR model estimated in levels would be incorrect. As first differencing of the four is then required in order to induce stationarity, we need to examine multivariate representations of the four series to see if a VAR model in first differences, as opposed to a VEC model, would be appropriate.

table 1

DF tests

Sample period: 1972:2 1988:3 - OBS: 65

Δy_t LABEL	$\hat{\rho}$	$\hat{\tau}$
LM2	.001376939	3.944462
LER	-.000136615	-.1341539
LNP	.000848783	2.392095
LFP	.001862330	3.628100

Δy_t LABEL	$\hat{\rho}$	$\hat{\tau}_\mu$
LM2	-.003242065	-1.498871
LER	-.059912210	-1.854569
LNP	-.004166762	-1.663254
LFP	-.016535920	-3.231151

Δy_t LABEL	$\hat{\rho}$	$\hat{\tau}_\tau$
LM2	-.046913240	-1.077990
LER	-.068875300	-1.980608
LNP	-.011743110	-.8064899
LFP	-.038504920	-1.749294

Critical Values (50 obs)

	5%	10%
τ	-1.95	-1.61
τ_μ	-2.93	-2.60
τ_τ	-3.50	-3.18

table 2

ADF tests

Sample period: 1972:1 1988:3 - OBS: 62

Δy_t LABEL	$\hat{\rho}$	$\hat{\tau}$
LM2	.001283489	2.534805
LER	-.000001551	-.0014378
LNP	.000609151	1.500332
LFP	.000815008	1.402850

Δy_t LABEL	$\hat{\rho}$	$\hat{\tau}_\mu$
LM2	-.002774095	-1.143140
LER	-.079513770	-2.191781
LNP	-.006424105	-2.340190
LFP	-.014643050	-2.171359

Δy_t LABEL	$\hat{\rho}$	$\hat{\tau}_\tau$
LM2	-.062297420	-1.056653
LER	-.098639540	-2.391551
LNP	-.024246080	-1.473865
LFP	-.063340090	-2.563237

Critical Values (50 obs)

	5%	10%
τ	-1.95	-1.61
τ_μ	-2.93	-2.60
τ_τ	-3.50	-3.18

If there are still four unit roots in the multivariate AR representation of the four variables, then a VAR in first differences is the appropriate model. Conversely, if there are less than four unit roots, then the four series are cointegrated and the vector of first differences does not not have a VAR representation with an invertible moving average (it is overdifferenced), and a VEC model is appropriate.

A way of testing for cointegration and indirectly checking for the number of unit roots is to regress any of the four variables on the other three. The residuals from each regression should then be tested for stationarity through a DF test of the type developed by Engle and Granger and Engle and Yoo (1987). If r of those residuals are stationary, there will be r cointegrating vectors, and r will be the rank of the error-correcting term to be included in the VEC representation. For a vector time series, Y_t with N components and r cointegrating vectors gathered together into the array, U–the rank of U is r, which is also the "cointegrating rank" of Y_t. The dimension of U is Nxr for all t; and the error-correcting term, $X_t = U'Y_t$, has dimension (rxN)x(Nx1) = rx1 for all t. In the VEC representation,

$$\Delta y_t = D^*(L)\Delta Y_{t-1} + \gamma U' Y_{t-1} + \zeta_t \tag{13}$$

the vector of coefficients, γ, has dimension Nxr, and $\gamma U'Y_{t-1}$ is Nx1 for all t. In practice, for each t, the rows of the error-correcting term, $X_t = U'Y_t$, are given by the residuals of the r cointegrating regressions, which implies that each of the N components of ΔY_t in (13) must be regressed against the lagged components of ΔY_t and r residuals from the cointegrating regressions.

Results for a whole set of cointegrating regressions are reported in table 3. Each variable is regressed in turn against the others in two-variable systems (left, upper part of table 3), three-variable systems (right, upper part of table 3), and four-variable systems (central lower part of table 3). The residuals from each regression are then tested for stationarity through the DF and the ADF tests outlined in Engle and Granger, whose critical

table 3

Co-integration regressions
Sample period: 1972:1 1988:3 - OBS: 67

VARIABLES		t-tests*		VARIABLES		t-tests*	
LHS	RHS	DF	ADF	LHS	RHS	DF	ADF
LM2	LER	-.643	-.811	LM2	LER LNP	-.499	-2.042
LM2	LNP	-.424	-2.135	LM2	LER LFP	-.854	-3.097
LM2	LFP	-1.100	-2.905*	LM2	LNP LFP	-.408	-2.147
LER	LM2	-1.116	-2.438	LER	LM2 LNP	-1.202	-2.415
LER	LNP	-1.145	-2.439	LER	LM2 LFP	-.969	-2.474
LER	LFP	-1.160	-2.410	LER	LNP LFP	-1.567	-2.684
LNP	LM2	-.547	-2.329	LNP	LM2 LER	-.660	-2.202
LNP	LER	-.974	-1.216	LNP	LM2 LFP	-2.346	-2.456
LNP	LFP	-2.838	-3.174**	LNP	LER LFP	-2.941	-3.723*
LFP	LM2	-1.562	-3.236**	LFP	LM2 LER	-1.353	-3.377*
LFP	LER	-1.810	-1.128	LFP	LM2 LNP	-3.094	-3.492*
LFP	LNP	-3.100*	-3.483**	LFP	LER LNP	-3.176	-4.075**

VARIABLES		t-tests*	
LHS	RHS	DF	ADF
LM2	LER LNP LFP	-.625	-1.971
LER	LM2 LNP LFP	-1.684	-2.647
LNP	LM2 LER LFP	-2.796	-2.948
LFP	LM2 LER LNP	-3.225	-4.058**

Critical values (50 obs) for the t-tests

	with 2 variables			with 3 variables			with 4 variables		
	1%	5%	10%	1%	5%	10%	1%	5%	10%
DF	-4.07	-3.37	-3.03	-4.84	-4.11	-3.73	-4.94	-4.35	-4.02
ADF	-3.77	-3.17	-2.84	-4.45	-3.75	-3.36	-4.61	-3.98	-3.67

* Note: 't-tests' are the 't-statistics' of the coefficient of lagged residuals on differenced residuals. Residuals are from the co-integrating regressions. A star and a double star indicate rejection of the null at the 10% and at the 5% level respectively.

values have been reported in Engle and Yoo (tables 2 and 3, pages 157 and 158). As the results suggest, there is some evidence of cointegration among the four variables, LM2, LER, LNP, and LFP.

In a bivariate context, money and farm prices, as well as manufacturing and farm prices, appear to be cointegrated over the period, 1972:1-1988:3. Conversely, money and manufacturing prices do not seem to be cointegrated, and the exchange rate is not cointegrated with any of the other three variables. In a trivariate context, there is stronger evidence of cointegration among the four series. Farm prices are cointegrated with money and the exchange rate, with money and manufacturing prices, and with the exchange rate and manufacturing prices.

For the four-variable system, we are able to reject the null hypothesis of non-cointegration in one case (at the 10 percent level), implying that money supply, the exchange rate, farm prices, and manufacturing prices are cointegrated within the sample period, 1972:1-1988:3. Therefore, the assumption that there are less than four unit roots is verified, which means that a VAR representation in the first differences of the four variables is misspecified. In particular, there appear to be $N - r = 4 - 1 = 3$ unit roots, so that a VEC representation with a 1x1 error-correcting term appears appropriate.

These results contrast with many conclusions that emerge from previous studies. On one hand, they show that studies that have estimated VAR models in levels have been incorrect because they neglect the issue of nonstationarity (Sims 1980a, 1980b; Hsiao; Thorton and Batten ; Litterman and Weiss; Bernanke; Bessler; Orden; and Devadoss and Meyers 1987; among others). On the other hand, they confirm the findings on the cointegration between money and prices as found in Robertson and Orden (1989) for New Zealand (although it appears that some of their conclusions on money neutrality pointed out by the use of a VEC representation as opposed to a VAR in first differences would not apply as automatically to the U. S. case [4] Conversely, these results do not sconfirm some of the findings of non-cointegration between the exchange rate and other fundamentals, as shown recently in Meese and Rose (1989).

IV. A Vector-Error-Correcting Model

In the estimation of a general vector-error correcting model, the first step concerns the identification of the lag structure on the endogenous variables. Lag order identification is generally performed through a series likelihood-ratio tests for linear restrictions. One such test is Sims' (1980a, p. 17) modified likelihood ratio test:

$$(T-k)\left\{\log\left[\det(D_R)\right]-\log\left[\det(D_U)\right]\right\} \tag{14}$$

where D_R is the matrix of cross products of residuals when the model is restricted and D_U is the same matrix for the unrestricted model. Two models with different lag orders are estimated, and the specification with the lower order is tested as a restriction of the one with the higher order. The modified likelihood ratio test is distributed as a $\chi^2(h)$, where h is the number of restrictions being tested (i.e., the number of lags that are not present in the lower order specification).

The above tests were performed, based on the general VEC model,

$$\Delta Y_t = D^*(L)\Delta Y_{t-1} + \gamma U' Y_{t-1} + \xi_t \tag{15}$$

which is equivalent to that in (13). An eight-order lag specification was chosen as the unrestricted model and tested in turn against lower order (restricted) specifications of seven, six, five, four, three, and two lags, respectively. The different models were estimated over the quarterly sample period, 1972:1-1983:3. The results show that, while an eighth-order lag can be rejected in favor of a third order specification, it cannot be rejected against a fourth order. The results of the estimation of the basic VEC model with no exogenous variables and a fourth-order lag specification are summarized in table 4. In the first section, the coefficients

table 4

ESTIMATION OF A FOURTH-ORDER VEC MODEL

RHS variables (lsgs)	LHS variables Coefficients (standard errors) DLM2	DLER	DLFP	DLNP
DLM2 (1)	.351(.143)	.059(.830)	.222(.228)	.135(.117)
DLM2 (2)	.124(.152)	-.532(.878)	-.023(.241)	-.134(.123)
DLM2 (3)	-.167(.150)	.733(.866)	.153(.238)	.295(.122)
DLM2 (4)	.256(.136)	-.471(.787)	.026(.216)	-.165(.110)
DLER (1)	.023(.024)	.344(.143)	-.025(.039)	.013(.020)
DLER (2)	.011(.026)	.055(.153)	-.085(.042)	-.022(.021)
DLER (3)	-.022(.026)	.024(.151)	.031(.041)	.013(.021)
DLER (4)	-.016(.025)	.071(.147)	.018(.040)	-.018(.020)
DLFP (1)	-.207(.079)	-.650(.457)	.319(.122)	.242(.064)
DLFP (2)	.237(.090)	.853(.523)	.141(.143)	-.118(.073)
DLFP (3)	-.229(.096)	.771(.554)	.120(.152)	.146(.078)
DLFP (4)	.090(.097)	.223(.564)	.285(.155)	.057(.079)
DLNP (1)	-.587(.175)	-.694(1.012)	.199(.278)	.714(.142)
DLNP (2)	.686(.208)	-1.762(1.203)	-.176(.330)	-.386(.169)
DLNP (3)	-.393(.221)	.880(1.279)	.513(.351)	.434(.180)
DLNP (4)	.446(.175)	1.660(1.010)	-.530(.277)	-.130(.142)
Constant	.008(.004)	-.014(.027)	-.006(.007)	-.002(.003)
EC (1)	.009(.029)	-.206(.170)	-.111(.046)	.038(.024)

F tests (significance levels)

Coefficients on lagged values of: DLNP in equation with LHS variable:	DLM2	DLER	DLFP	DLNP
DLM2	3.794(.009)	.630(.643)	3.817(.009)	5.143(.002)
DLER	.245(.911)	2.121(.092)	1.830(.138)	1.900(.126)
DLFP	.639(.637)	1.556(.201)	5.320(.001)	.955(.441)
DLNP	2.069(.099)	.508(.729)	6.204(.000)	11.399(.000)

Standard errors of the innovations and their correlation matrix

SEE		DLM2	DLER	DLFP	DLNP
.00649	DLM2	1.00	-.13	.05	-.27
.03748	DLER		1.00	.00	.24
.01030	DLFP			1.00	-.17
.00528	DLNP				1.00

of lagged vales of DLM2, DLER, DLFP, and DLNP [the coefficients of D*(L)] and the coefficient of the error-correcting (EC) term, γ, are reported; standard errors are in parentheses. In the second section, test results on lagged values of DLM2, DLER, DLFP, and DLNP, respectively, have zero coefficients in each of four normalized equations. In the third section, standard errors of the estimates and the correlation matrices of the reduced-form disturbances are reported.

Lagged changes in money, farm prices, and manufacturing prices have a significant effect on money growth and manufacturing prices. Conversely, only the own lagged changes appear to have a significant effect (block-wise) on exchange rate growth and farm prices. Note, however, that the coefficient estimates in vector autoregression frameworks are difficult to interpret and that the block F-tests, in particular, are not useful in analyzing the dynamic interactions. In contrast, impulse response functions and the variance decompositions reported in the following sections allow more definitive assessments.

The Impulse Response Functions

In order to trace the dynamic effects of random shocks to money, the exchange rate, manufacturing prices, and farm prices, the estimated fourth-order VEC model can be reparameterized to an equivalent VAR formulation in the levels of the variables. With this reparameterization, the error-correction term is incorporated into the lagged variables of the autoregressive model. The latter model can be inverted to obtain impulse response functions based on the moving average representation which tracks the effects of an initial shock on the long-run equilibrium values of the variables.

Consider again the model in (15) rewritten more compactly as

$$D^{+}(L)\Delta Y_t = \gamma U' Y_{t-1} + \xi_t \tag{16}$$

where $D^{+}(L) = I-D^{*}(L)$, i.e., $D_0^{*} = I$. The lag polynomial $D^{+}(L)$ is full of rank, and all its roots lie outside the unit circle. We need to recover a VAR formulation of (16) in levels such that

$$D(L)Y_t = \xi_t \tag{17}$$

where D(L) is invertible. This will occur by reparameterizing $D(L)Y_t$ as

$$D(L)Y_t = I(Y_t - Y_{t-1}) + [I + D_1 + \ldots + D_P]Y_{t-1} + \ldots + [-D_P](Y_{t-(P-1)} - Y_{t-P}). \tag{18}$$

Since $U_i'Y_t \neq 0$, by comparing (16) with (18), we can see that

$$-\gamma U' = [I + D_1 + \ldots + D_P] = D(1) \tag{19}$$

as stated in the Granger Representation Theorem (Engle and Granger). A simple VAR in levels such as (17) with no reparameterization of D(L) (as in (19)) would omit the rank-reducing constraints in D(1). This is due to cointegration and, as a result, the nonreparameterized lag operator matrix would be noninvertible since it would miss the error-correcting term (the cointegrating vector).

Impulse response functions can be obtained by inverting D(L), i.e., through its moving average representation. Thus we can refer to $D(L)^{-1}$ as the MA representation of the reduced-form model. This gives the dynamic effects of each reduced-form disturbance, setting all others equal to zero. The "shocks" are positive residuals of one standard deviation unit in each equation of the system. These are referred to as "innovations" since they represent that component of the endogenous variable which is not being predicted from the past values of the variables in the system.

In order to fully characterize the distinct dynamic patterns of the system it is useful to transform the residuals to their orthogonal form. Since the residuals in our analysis show very little correlation across equations, this will have almost no effect on the contemporaneous interactions among the variables. Orthogonalization, of course, requires the assumption of a recursive order by hich to triangularize the system. This implies that "the residuals whose effects are being tracked are the residuals from a system in which contemporaneous values of other variables enter the right-hand-sides of the regressions with a triangular array of coefficients" (Sims 1980a, p. 21). Thus, the first-variable equation is left unaltered while the last-variable equation will include contemporaneous values of all other right-hand-side variables. In any event, comparison among alternative recursive orderings shows that various identifying assumptions on the contemporaneous interactions among the variables make very little difference. This is primarily because of the low cross correlation among the residuals.

Money innovations have very persistent effects on both money and prices. A 1 percent increase in this source in the first quarter induces a 2 percent increase in money and farm prices and a 4 percent increase in nonfarm prices after five years. In other words, a monetary shock raises the levels of money supply and agricultural prices by the same amount and manufacturing prices by a larger amount in the long run. This implies that money is neutral with respect to the farm sector but not with respect to the manufacturing sector. Moreover, manufacturing prices seem to be more responsive to money innovations than agricultural prices. Since nonfarm prices move toward the new long-run equilibrium faster than farm prices, it can be argued that positive monetary shocks induce shifts in relative prices in favor of the nonfarm sector both in the short and the long run. Also farm prices do not respond more than proportionally to a positive monetary shock in the short run, nor do they overshoot their own long-run equilibrium level.

As we would expect, a positive monetary shock induces an initial depreciation in the exchange rate (a balance-of-payment effect) which is followed by an almost proportional appreciation in the long run (income effect). An exchange rate innovation also has fairly persistent effects both on the exchange rate and on prices. An initial 1 percent appreciation induces a 1.6 percent decrease in farm prices and a 2.0 percent decrease in nonfarm prices after five years. It also produces an overshooting effect whose extent is not very large (it is less than 1.9 percent after nine quarters) but which lasts for more than five years. Conversely, the effect on money is less than proportional and, once five years has passed, it appears to be fully reabsorbed.

Manufacturing price innovations have persistent but less than proportional effects on money, the exchange rate, and agricultural prices. A positive 1 percent shock to nonfarm prices induces a reduction in the money supply and a depreciation in the exchange rate in the first two years. This can be explained in terms of an accommodating anti-inflationary monetary policy and by a trade-balance effect, respectively. In the long run, the two effects are reversed in sign. The new long-run equilibrium level of manufacturing prices appears to be much higher than the initial level, indicating that spiraling inflationary effects may be operating. Also, since agricultural prices respond at a much slower pace, a positive increase in manufacturing prices pushes the farm sector in a cost-price squeeze which does not tend to disappear, even in the long run.

Farm price innovations have persistent effects both on prices and on the exchange rate. A 1 percent increase in farm prices in the first quarter induces a more than proportional increase in nonfarm prices (5.2 percent) and a less than proportional increase in the exchange rate (2.6 percent) in the long run. Money supply shows a significant short-run decreasing response which again can be explained in terms of an accommodating anti-inflationary policy pursued by the monetary authority. Also, farm prices increase initially at a faster pace than manufacturing prices. Nevertheless, this short-run shift in relative prices in favor of agriculture is reversed after eight quarters; and in the long run, the farm sector is placed in the cost-price squeeze noted above.

A number of empirical results were generated from three different recursive orderings and orthogonal decompositions of the innovation covariance matrix. The first ordering runs from money to exchange rates to manufacturing prices to agricultural prices; the second, from exchange rates to money to manufacturing prices to agricultural prices; and the third is the reverse ordering of the first. All of these orderings have different implications in terms of Granger's causality. In any case, the results obtained from these specifications are qualitatively similar to the nonorthogonal case. The timing of the adjustment process differs for each of the three representations, but the overall pattern is much the same. However, there are two differences worth noting in the timing of the adjustment process.

First, manufacturing and agricultural price short-run responses to money innovations are different under the three representations. Under the first and second ordering (DLM2-DLER-DLNP-DLFP and DLER-DLM2-DLNP-DLFP, respectively) farm prices increase more than nonfarm prices in the short run (i.e., they move at a faster pace toward their new long-run equilibrium value). Under the third ordering (LFP-LNP-LER-LM2), the short-run responses of the two prices are almost the same. Albeit the long-run responses turn out to be qualitatively similar in all four cases, one should, of course, be aware of the short-run implications of the different ordering. If we were to choose a money-to-prices causation ordering, then we would conclude, as in Robertson and Orden, that "positive monetary shocks induce a shift in relative prices in favor of agriculture in the short run.[5] Conversely, if we were to choose a prices-to-money causation ordering, then we would assume that the short-run price responses are the same while, in the long run, agriculture is pushed into a cost-price squeeze.

Second, exchange-rate responses to manufacturing price innovations follow a slightly different pattern in the three representations. With nonorthogonal innovations, the response was initially negative and positive in the long run. The same pattern is maintained under the third ordering, although the extent of depreciation here is very small. Under the first and second ordering following a manufacturing price shock, the exchange rate initially depreciates, returning to its previous equilibrium value in the long run. In other words, there is overshooting in the exchange-rate response. Farm-price responses to manufacturing price innovations also are basically different. If, in the nonorthogonal case, they were positive both in the short and the long run, in the orthogonal cases they are positive in the short run but negative in the long run with some overshooting along the way.

The Variance Decompositions

Variance decompositions provide a useful way to analyze the main channels of dynamic interactions in the model. The decomposition of the variance is just the attribution of the variance of the error to the components of the (orthogonal) innovations. In practice, it gives the proportions of forecast error *k* quarters ahead produced by each innovation. While the variance itself does not depend on the factorization of the covariance matrix, the decomposition does. As we have argued, the orderings chosen for the factorization of the covariance matrix have strong causal and structural implications. Thus, variables that are not expected to have any significant explanatory power on other variables should be placed lower in the ordering.

By definition, the first variable in the ordering explains all of its one-step-ahead variance. The first-step variance, due to own variations, will be higher the lower the correlation between the residuals of a variable and the residuals of variables that come first in the ordering. With low correlation among innovations in the variables, the decomposition of the one-step variance should not depend on the order of factorization. Variance decompositions can also be used as a basis for determining whether or not a variable behaves exogenously by putting it first in the ordering and then checking if its variance is explained primarily by its own innovations.

Table 5 displays the results of the variance decompositions carried on the MA representation of the nonorthogonalized (original) basic VEC model. The percentages of forecast errors *k* quarters ahead produced by each innovation on the four variables, DLM2, DLER, DLNP, and DLFP show some interesting characteristics of the system over the period, 1972:2-1988:3. For the nonorthogonalized MA representation, 100 percent of the

Table 5

DECOMPOSITION OF THE k-QUARTER-AHEAD FORECAST ERROR VARIANCE
NONORTHOGONALIZED INNOVATIONS

Proportion of variance of DLM2 due to innovations in:

STEP	DLM2	DLER	DLNP	DLFP
1	100.00	.00	.00	.00
2	75.99	1.25	15.44	7.31
3	74.76	2.56	14.98	7.68
4	71.09	3.99	14.28	10.62
8	64.20	4.92	17.98	12.88
12	62.53	4.86	19.26	13.33
16	60.66	5.23	19.40	14.69
20	59.67	5.70	19.01	15.60

Proportion of variance of DLER due to innovations in:

STEP	DLM2	DLER	DLNP	DLFP
1	.00	100.00	.00	.00
2	.00	96.40	.82	2.75
3	1.19	85.02	11.10	2.68
4	1.17	82.97	11.73	4.11
8	2.00	75.35	14.39	8.25
12	3.19	68.06	13.43	15.31
16	5.06	63.87	12.76	18.30
20	6.25	62.37	12.40	18.95

Proportion of variance of DLNP due to innovations in:

STEP	DLM2	DLER	DLNP	DLFP
1	.00	.00	100.00	.00
2	1.56	.52	85.26	12.64
3	1.85	.87	83.11	14.16
4	6.25	2.27	73.34	18.12
8	10.20	7.39	48.33	34.06
12	14.63	9.66	38.85	36.84
16	17.02	10.76	35.84	36.36
20	18.06	11.10	35.03	35.79

Proportion of variance of DLFP due to innovations in:

STEP	DLM2	DLER	DLNP	DLFP
1	.00	.00	.00	100.00
2	1.73	.75	.91	96.59
3	2.15	9.53	.91	87.39
4	3.57	9.47	5.93	81.01
8	9.51	9.93	5.44	75.11
12	11.72	10.65	5.15	72.46
16	12.58	10.83	5.13	71.44
20	12.82	10.87	5.19	71.10

variance of the one-step-ahead forecast error in each variable is due to innovations in the variable itself.

For DLM2, DLER, and DLFP, more than 50 percent of the variance at long horizons is accounted for by own innovations (recall that exogeneity is equivalent to the conditions that a variable's own innovations account for all of its variance). Conversely, for DLNP, more than one third of the variance is accounted for by innovations in DLFP over medium and long horizons, while only one third is accounted for by own innovations over long horizons.

The main source of feedback into money supply is price innovations, both manufacturing (less than 20 percent) and agricultural (15 percent). The innovations in nonfarm prices are rather quickly reflected in movements in money supply, whereas the innovations in farm prices take longer. The main source of feedback into the exchange rate is also price innovations, particularly agricultural prices(19 percent). Nonfarm price innovations are more quickly reflected in movements in the exchange rate than farm price innovations. The feedback into manufacturing prices comes basically from all other variables, whereas the (rather small) feedback into agricultural prices comes mainly from money and exchange rate innovations. The farm price variable has a variance over long horizons that is largely accounted for by own innovations (81 percent), at levels tht exceed all other other variables.

The decomposition of the k-quarter-ahead forecast error variance for the various orthogonalizations does not offer any insights. As noted above, for a nearly diagonal covariance matrix, the decomposition of the variance is quite robust to changes in the ordering. As it turns out, some of the effects are only dramatized. Under the prices-to-money ordering, for instance, the feedback from manufacturing price innovations to money long horizons is stronger, accounting for almost one fourth of the forecast error variance of the money variable. Under the money-to-prices ordering, the percentage of 20-quarter-ahead forecast error variance in the manufacturing price variable accounted for by innovations in farm prices is higher, while that accounted for by own innovations is lower.

In summary, money supply changes are rather responsive to inflationary shocks but not as responsive to exchange rate growth. In particular, the money supply growth rate appears to respond quickly to inflationary shocks coming from the nonfarm sector but not as fast to inflationary shocks coming from the agricultural sector. Exchange rate changes also are responsive to inflationary shocks. Inflationary shocks from the manufacturing sector are reflected rather quickly in the dynamic path of exchange rates, although over longer horizons the inflationary shocks coming from the agricultural sector predominate.

Manufacturing price growth is not completely exogenous, and it appears to be strongly influenced by farm price growth,[6] particularly over long horizons. Farm price growth responds rather slowly to money growth shocks and more quickly to exchange rate growth shocks—although overall it does not seem to be particularly responsive. Monetary innovations are, in any case, reflected more substantially in movements in nonfarm price inflation than in movements in farm price inflation.

An Alterative Specification of the Money Variable

Since most VAR models in the literature have been estimated with a different specification of the money variable, we have carried on all the estimations discussed above with an alternative money-supply variable, viz., M_1. This conforms with the majority of the other studies (e.g., Sims 1980b; Litterman and Weiss; Robertson and Orden) and thus makes all the comparisons less "questionable." Since M_2 includes the money supply for financing and investments, it is our view that M_2 is more appropriate for the present purposes.

The implications of the presence of unit roots that were brought about in the case of M_2 still hold for M_1. In particular, the logarithm of M_1 (hereafter, LM_1) appears to be nonstationary under the DF and the ADF tests. There also seems to be, even in this case, at least one cointegrating vector among LM_1 and LER, LNP, and LFP. Therefore, the choice of M_1 instead of M_2 does not make much difference in terms of model specification. A VEC model still proves superior to a VAR, either in first differences or in levels. Lag order selection is also unaffected by the choice of M_1 in place of M_2, as a fourth-order lag VEC is to be preferred on the basis of the results of the likelihood-ratio tests.

The MA representations appear somewhat different, although for most of the response functions the results are basically unaltered.[7] Money supply, as defined by M_1, represents primarily the money for transactional purposes. The largest part of M_2, on the other hand, is represented by nontransactional components.[8] Accordingly, it is quite natural that these two different definitions of the "supply of money" can have different effects on the economy. In particular, they are likely to have different interactions with the exchange rate and both sets of prices. Our results suggest that money supply, as defined by M_1, is less exogenous with respect to farm prices than M_2. As a result of the feedback to money (M_1), farm prices, in turn, appear to be more exogenous than before and to have more explanatory power for the other variables. In contrast, the M_1 money supply appears to have little influence over the remaining variables.

5. Concluding Remarks

As the results of this paper strongly suggest, a correct assessment of the time-series properties of the data is needed in order to proceed with an appropriate form of the vector autoregressive model. Unfortunately, in most of the past studies such an assessment has been generally neglected. The consequences of inadequate assessments and the resulting incorrect model specification are briefly outlined in these concluding remarks.

The fourth-order lag VAR in the levels of the four variables, LM2, LER, LNP, and LFP (over the period, 1972:1-1988:3), is the most common specification that has been examined in the literature (e.g., Bessler; Devadoss and Meyers 1987; Orden and Fackler). Several authors have shown that farm prices respond faster to a change in money supply than nonfarm prices (e.g., Bordo 1980; Devadoss and Meyers; Orden and Fackler). Others have found evidence of Granger-causality from money supply to agricultural prices with no reverse feedback (e.g., Barnett, Bessler, and Thompson 1983; Bessler).

The assumption of money exogeneity with respect to farm prices justifies the causality from money to prices and the absence of causality from prices to money. Apparently this has been shown to hold no matter what definition of money supply was implied (Barnett, Bessler, and Thompson, p. 306). However, as Bessler (p. 29) also acknowledges, this assumption is not neutral with respect to the effect of money supply changes on prices. Under this assumption (i.e., under the assumption of a structural recursive money-to-prices ordering), we find that farm prices respond faster to money innovations than manufacturing prices in the short run while, in the long run, both prices revert to their initial equilibrium level. That is, money is not neutral in the short run, both prices overshoot their long-run value, agricultural prices are more flexible than manufacturing prices, and money has no real effects in the long run.

This result is in line with most of the literature and confirms the findings of Bordo, Bessler, Rausser et al. (1986), Devadoss and Meyers, Orden and Fackler, and Robertson and Orden. However, it is, unfortunately, not very robust as changes in the ordering of the variables have a dramatic effect. In fact, under the assumption of a structural recursive prices-to-money ordering, money is not neutral, even in the long run with respect to farm prices, and farm prices decrease as money increases.[9] Moreover, the assumption of exogeneity of money with respect to farm prices is not fully supported by the data. However, exogeneity of farm prices with respect to money is supported by the data. When money supply is proxied by M_2, the results are certainly more robust to the chosen ordering as all the variables appear to be fairly orthogonal to each other. Neutrality of money is confirmed for the long run but not for the short run. Farm prices do not seem to respond faster than manufacturing prices, neither do they overshoot their long-run equilibrium value.

Three major conclusions can thus be drawn from this discussion. First, the choice of the money supply variable is not irrelevant. Although some of the past results may be misleading because of the incorrect treatment of the data (as in the case of Bordo; Barnett, Bessler, and Thompson; Bessler ; Orden; Devadoss and Meyers), some others appear to be weakened by this lack of robustness with respect to the choice of the money supply variable (e.g., Orden and Fackler; Robertson and Orden).

Second, the choice of the ordering is obviously not irrelevant. This is not just a matter of statistical relevance, but it implies theoretical justifications which are, of course, legitimate. What matters here is not which ordering is chosen but how much support is found from the empirical evidence. As M_1 does not appear to be fully exogenous with respect to farm prices, any evidence drawn from that assumption is doomed to have very little robustness. Again, a broader definition of money supply, M_2 instead of M_1, overcomes this drawback. Third, any different set of variables is likely to yield different results. Thus, if some of the results appear to be at odds with past studies, one natural reason is in the nature of the four-variable system we have specified. In most of the literature, in fact, the interactions between money and prices have been analyzed within closed systems. The inclusion of the exchange rate is obviously likely to have a great impact as new channels of influence, which have otherwise been neglected, are taken into account.

To illustrate the importance of the appropriate specification, the correlation matrix of the one-step-ahead forecast errors from the fourth-lag VAR model is reported in table 6. The results of the MA representation of the VAR model in levels with nonorthogonalized innovation covariance matrix are shown in table 7.[10]

The differences with the estimated VEC model are striking (table 8). Money innovations have an increasing effect on prices in the short run but no effect in the long run (in the VEC model, we have an increasing effect which persists in the long run). Thus, under this specification, we would conclude that prices, following a shock to money supply, overshoot their initial long-run equilibrium value. Yet, farm prices do not rise faster than nonfarm prices, and the exchange rate response to a money shock shows some overshooting in the first two years, which is basically the same as in the VEC specification.

Table 6

INNOVATION CORRELATION MATRICES

Model : VAR in levels

	LM2	LER	LNP	LFP
LM2	1.00	-.16	-.20	-.01
LER		1.00	.20	.05
LNP			1.00	-.14
LFP				1.00

Model : VAR in levels with trend

	LM2	LER	LNP	LFP
LM2	1.00	-.16	-.22	-.06
LER		1.00	.20	.07
LNP			1.00	-.19
LFP				1.00

Model : VAR in first differences

	DLM2	DLER	DLNP	DLFP
DLM2	1.00	-.14	-.25	.04
DLER		1.00	.18	.06
DLNP			1.00	-.23
DLFP				1.00

Table 7

MA REPRESENTATION
MODEL : VAR IN LEVELS - NONORTHOGONALIZED INNOVATIONS

Effects of shocks to ξ_{M2} on:					Effects of shocks to ξ_{ER} on:			
LM2	LER	LNP	LFP	Quarter	LM2	LER	LNP	LFP
1.00	.000	.000	.000	1	.000	1.00	.000	.000
1.11	-.038	.178	.030	2	.062	1.15	.153	.003
.969	-.183	.232	.100	3	-.054	1.05	.251	-.111
.649	-.289	.465	.218	4	-.275	.910	.248	-.033
.334	-.328	.712	.364	5	-.433	.717	.255	.016
.240	-.370	.813	.403	6	-.368	.571	.126	-.004
.277	-.350	.837	.461	7	-.210	.483	-.078	-.054
.258	-.271	.926	.533	8	-.058	.442	-.262	-.104
.239	-.176	1.03	.545	9	.056	.416	-.407	-.182
.243	-.084	1.11	.523	10	.151	.378	-.546	-.272
.246	-.003	1.18	.510	11	.221	.317	-.678	-.344
.259	.059	1.24	.493	12	.266	.237	-.796	-.388
.301	.111	1.26	.463	13	.292	.145	-.903	-.414
.356	.158	1.25	.431	14	.299	.051	-.994	-.421
.413	.200	1.23	.397	15	.280	-.036	-1.06	-.410
.471	.238	1.19	.355	16	.239	-.117	-1.09	-.386
.531	.268	1.13	.308	17	.180	-.189	-1.10	-.352
.590	.290	1.06	.261	18	.110	-.252	-1.08	-.308
.647	.302	.974	.214	19	.031	-.304	-1.04	-.257
.699	.305	.877	.169	20	-.051	-.346	-.974	-.201

Effects of shocks to ξ_{NP} on:					Effects of shocks to ξ_{FP} on:			
LM2	LER	LNP	LFP	Quarter	LM2	LER	LNP	LFP
.000	.000	1.00	.000	1	.000	.000	.000	1.00
-.453	-.083	1.56	.049	2	-.408	-.082	.567	1.12
-.337	-.441	1.40	-.008	3	-.498	.057	.791	1.16
-.293	-.517	1.38	.287	4	-.780	.160	1.17	1.17
-.528	-.390	1.62	.542	5	-.810	.225	1.44	1.16
-.503	-.244	1.67	.488	6	-.624	.262	1.56	1.03
-.416	-.039	1.64	.457	7	-.325	.317	1.56	.925
-.460	.169	1.72	.493	8	-.074	.379	1.56	.815
-.445	.324	1.76	.437	9	.157	.440	1.53	.676
-.333	.443	1.70	.346	10	.369	.480	1.46	.524
-.229	.541	1.60	.290	11	.556	.497	1.35	.394
-.129	.615	1.49	.224	12	.717	.492	1.22	.280
-.003	.667	1.33	.129	13	.863	.471	1.07	.179
.128	.702	1.14	.035	14	.983	.440	.899	.095
.246	.717	.932	-.053	15	1.07	.401	.727	.028
.358	.710	.706	-.144	16	1.13	.356	.561	-.026
.463	.684	.465	-.232	17	1.16	.303	.402	-.068
.552	.641	.220	-.308	18	1.17	.246	.256	-.095
.620	.581	-.018	-.373	19	1.16	.185	.126	-.110
.668	.508	-.248	-.427	20	1.14	.121	.016	-.113

Table 8

MA REPRESENTATION - NONORTHOGONALIZED INNOVATIONS

Effects of shocks to ξ_{M2} on:					Effects of shocks to ξ_{ER} on:			
LM2	LER	LNP	LFP	Quarter	LM2	LER	LNP	LFP
1.00	.000	.000	.000	1	.000	1.00	.000	.000
1.35	.010	.166	.140	2	.136	1.34	.096	-.092
1.47	-.116	.245	.236	3	.279	1.52	.015	-.437
1.45	-.096	.561	.397	4	.437	1.64	-.166	-.570
1.42	-.151	.846	.633	5	.337	1.75	-.295	-.585
1.53	-.216	1.00	.758	6	.388	1.78	-.505	-.725
1.61	-.215	1.21	.963	7	.478	1.81	-.788	-.906
1.58	-.128	1.52	1.13	8	.541	1.82	-1.08	-1.00
1.61	-.031	1.83	1.26	9	.546	1.82	-1.28	-1.09
1.64	.028	2.12	1.38	10	.533	1.79	-1.49	-1.20
1.67	.087	2.38	1.52	11	.518	1.71	-1.73	-1.30
1.69	.178	2.66	1.64	12	.486	1.63	-1.95	-1.35
1.73	.279	2.91	1.74	13	.426	1.56	-2.12	-1.39
1.79	.379	3.12	1.81	14	.381	1.49	-2.29	-1.45
1.85	.479	3.33	1.89	15	.336	1.41	-2.45	-1.50
1.91	.579	3.53	1.95	16	.279	1.34	-2.58	-1.52
1.97	.671	3.70	2.00	17	.215	1.28	-2.68	-1.55
2.03	.753	3.84	2.04	18	.160	1.22	-2.78	-1.58
2.09	.832	3.97	2.08	19	.108	1.16	-2.87	-1.60
2.15	.906	4.09	2.11	20	.058	1.11	-2.94	-1.62

Effects of shocks to ξ_{NP} on:					Effects of shocks to ξ_{FP} on:			
LM2	LER	LNP	LFP	Quarter	LM2	LER	LNP	LFP
.000	.000	1.00	.000	1	.000	.000	.000	1.00
-.477	-.097	1.71	.102	2	-.328	-.178	.473	1.31
-.475	-.473	1.79	.059	3	-.423	-.112	.658	1.58
-.500	-.593	2.03	.339	4	-.654	.033	1.01	1.84
-.532	-.478	2.37	.435	5	-.825	.168	1.52	2.32
-.303	-.289	2.56	.337	6	-.980	.293	2.10	2.47
-.118	-.205	2.73	.304	7	-1.01	.407	2.45	2.68
-.028	-.137	2.95	.358	8	-1.10	.564	2.86	2.87
.032	-.072	3.17	.376	9	-1.13	.771	3.31	3.08
.125	-.049	3.26	.377	10	-1.10	.970	3.70	3.13
.239	-.020	3.31	.394	11	-1.00	1.13	3.96	3.21
.328	.047	3.39	.435	12	-.948	1.30	4.25	3.29
.406	.113	3.48	.437	13	-.873	1.48	4.51	3.36
.491	.151	3.53	.435	14	-.776	1.62	4.70	3.36
.545	.174	3.58	.459	15	-.660	1.74	4.83	3.38
.580	.198	3.64	.491	16	-.570	1.86	4.96	3.41
.613	.220	3.69	.509	17	-.480	1.96	5.07	3.42
.649	.237	3.72	.528	18	-.392	2.05	5.14	3.41
.676	.258	3.76	.553	19	-.310	2.11	5.19	3.42
.694	.280	3.80	.576	20	-.249	2.17	5.24	3.43

Exchange rate innovations have a decreasing short-run effect on money and both prices. In the long run, following a shock to the exchange rate, money expands, whereas prices tend to adjust backward to their initial equilibrium value. Under the VEC specification, money expands in the short run but not in the long run, whereas prices keep decreasing in the long run. Thus, even in this case, we would conclude that prices, following an exchange rate shock, overshoot their initial equilibrium value. Also, farm prices move more slowly (and less) than manufacturing prices. Interestingly, the overshooting in the exchange rate itself lasts just 2 quarters, as opposed to the more than 20 quarters for the VEC model.

The effect of manufacturing price innovations on money and exchange rate is basically the same as in the VEC model. A manufacturing price shock has an increasing effect on nonfarm prices in the short run, but it is gradually reabsorbed in the long run. The overshooting appears to last for almost 13 quarters. Also, the effect on farm prices is felt only after 5 quarters, but then slowly disappears. Thus, the short-run effects are basically the same as in the VEC model, but this is not the case for the long run.

Farm price innovations have the same effect on the exchange rate as in the VEC model but not on money supply and on the manufacturing price. Following a 1 percent shock to agricultural prices, money supply decreases in the short run and then increases. In the long run, the increase is proportional to the initial shock. Manufacturing prices increase in the short run and then decrease, so that the overall long-run effect is null. Finally, farm prices overshoot their long-run value, but only for a period of 6 quarters. In the VEC model, both prices tend to increase indefinitely.

In summary, the estimation of a VAR model in the levels of the variables gives support to the hypotheses of long-run money neutrality (together with short-run nonneutrality due to some stickiness in prices), and of overshooting in prices and in the exchange rate following any nominal shocks. On the other hand, the hypothesis that farm prices are more flexible than manufacturing price is not supported. The studies that have adopted a VA specification in levels have also yielded similar results—e.g., Bessler, Orden, Devadoss and Meyers, and

Orden and Fackler.[11] However, the differences from the VEC model estimation are dramatic, especially with respect to the long-run respones. For example, the hypothesis of long-run monetary neutrality is not supported.

Since the four variables in the model are actually nonstationary and cointegrated, we know that a VAR in the levels of the variables is incorrect in that the short-run responses may be similar but the long-run responses will differ. Thus, by adopting a VAR specification in levels, false support is presented for the hypothesis that money is neutral in the long run and that prices overshoot their equilibrium value following a monetary shock. The addition of a linear trend variable to the model in levels does not change the substance of the results. As a matter of fact, the inclusion of a linear trend variable incorrectly solves the problem of apparent mean nonstationarity of the variables when such nonstationarity is stochastic. If the variables have "trends in common" which are nondeterministic, the inclusion of a deterministic trend biases the estimated coefficients. Moreover, it does not solve the problem due to the presence of unit roots. If stochastic trends are present and some of them are "in common," then the variables are cointegrated.

In conclusion, the consequences of a incorrect specification of the model are too important to be overlooked. As the results reported in this paper show, the lack of a careful assessment of the time-series properties of the data can lead to very different results. A correct model specification is not just a matter of statistical relevance; the consequences can lead to grossly inaccurate economic interpretations.

FOOTNOTES

[1]The changes of an I(1) series are I(0). I(1) series are nonstationary since their variance is time dependent and the mean is drifting across the sample. Fuller (1976) and Dickey and Fuller (1979; 1981) have shown that the OLS estimator of the first-order autoregressive coefficient does not have the usual distribution (if the series has a unit root) and that the "*t*-statistic" of the estimated coefficient has a nonstandard distribution. Thus, following Box and Jenkins' suggestion, first differences have been advocated as a solution to the presence of unit roots, even in the case of VAR models.

[2]The cointegrating rank, r, is given by the number of linearly independent cointegrating vectors, r, where r cannot be greater than N-1.

[3]Here, a rise in e indicates a revaluation of the exchange rate.

[4]Robertson and Orden (1989) estimate a three-variable system including money, farm and manufacturing prices, finding cointegration for all the possible bivariate systems but not for the trivariate systems.

[5]This statement is at odds with Robertson and Orden's analysis of the effects of a manufacturing price innovation. Their results lead them to conclude that, since farm prices respond slowly to a manufacturing price shock, "the shock to manufacturing prices initially places agriculture in a cost-price squeeze" (1989, p. 13). In our analysis of the nonorthogaonal model, both monetary shocks and manufacturing price shocks imply the same cost-price squeeze effect ordering on agriculture, both in the short and long run, confirming the findings of Tweeten, 1980.

[6]The nonfarm price variable is represented by the Consumer Price Index (all items less food).

[7]The feedback from farm price innovations to the other variables is stronger with M_1 in place of M_2 (24.5 percent versus 15.6 percent for money, 22.6 percent versus 19 percent for the exchange rate, and 49.2 percent versus 35.8 percent for nonfarm prices over long

horizons). Also, the feedback to other variables is much weaker than before (4.5 percent versus 6.3 percent for the exchange rate, 3.1 percent versus 18.1 percent for manufacturing prices, and 2.6 percent versus 12.8 percent for agricultural prices over long horizons). Finally, the feedback from nonfarm price innovations to money is lower than the M_2 formula (6 percent versus 19 percent over long horizons).

[8]In 1988, for instance, the nontransactional components of M_2 (overnight RPs, overnight Eurodollars, money market fund balances, etc.) amounted to $2,279.1 billion, almost 75 percent of total M_2 (Federal Reserve Bulletin, August 1989, Table 1.21). Total M_1 in 1988 was $790.3 billion.

[9]The little robustness of the money-to-prices ordering is acknowledged by Bessler (1984) but not by Robertson and Orden (1989). Conversely, Devadoss and Meyers' (1987) results are consistent under both orderings.

[10]The MA representations with orthogonalized innovations yielded very similar results and thus have not been reported. This, by the way, was to be expected as the innovation correlation matrix in Table 6 is "nearly" diagonal.

[11]Although the latter seems aware of the consequences of unit roots in the variables (p. 498).

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