Relative Price Dynamics and Monetary Policy: Evidence from Directed Graphs

by

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1. Introduction

The nature of the dynamic linkages between monetary policy and the agricultural sector has been one of the most debated in the recent past, yet with little consensus. Central to this debate is the question of whether the responses of agricultural prices to monetary policy shocks differ from the responses of prices in the rest of the economy. This question is important given the increasing dependence of agriculture on international markets and the potential impacts of changes in macroeconomic variables such as interest rates, exchange rates, and foreign income growth patterns. The importance of macroeconomic policy linkages to agriculture and trade is further emphasized by the reduction in foreign demand for U.S farm exports in the aftermath of the recent Asian financial crisis. Although most theoretical models advocate money neutrality (i.e. money does not affect prices) in the long, Bordo's work showed that changes in the money supply can induce changes in the relative prices in the short-run.

Currently there are several alternative approaches used by researchers to evaluate the timing and magnitude of macroeconomic policy variables on agriculture. On the one hand, there are models based on Granger's approach to testing for causality. Within this scheme, F-tests could be used to infer the direction of causality between U.S. money supply and agricultural prices (Barnett, Bessler, and Thompson; Lapp). On the other hand, the approach favored by most researchers is to use vector autoregression (VAR) or its variants (error correction and cointegration models) to identify the response of agricultural prices to changes in macroeconomic variables (Bessler; Devadoss and Meyers; Taylor and Spriggs; Orden and Fackler; Robertson and Orden; Robertson and Orden; Saghaian, Reed, and Marchant).

VAR models are widely used in empirical research because they require the use of minimal zero restrictions in contrast to more traditional over-identified and less dynamic econometric models. Some (Cooley and Dwyer; Cooley and LeRoy) have argued that, while VAR models may be useful for forecasting, they are not appropriate for policy analysis. As VARs represent summaries of the correlation structure embedded in observational data (non-experimental data), they cannot be interpreted independently of a maintained structural model. In other words, explicit zero-type restrictions will need to be imposed on at least some components of the VAR. Standard practice is to identify VAR models through Choleski decomposition of the covariance matrix. This is implicitly imposing a recursive structure for the economy.

Sims (1986) and others have noted that when there is contemporaneous correlation among variables, the choice of an ordering in the Choleski decomposition may make a significant difference for interpretation of impulse responses and forecast error variance decompositions. As an alternative to the Choleski decomposition, some researchers (Sims, 1983; Bernanke; Blanchard and Quah) suggest the use of orthogonalizations that allow the researcher to impose over-identifying restrictions on the model. We follow the literature and label these models as structural vector autoregressions (SVARs) as they rely on prior theory as the source of their identifying restrictions. Bernanke's approach achieves identification via the assumption that distinct, mutually orthogonal, behavioral shocks drive the model, and that lagged relationships among the variables are not restricted. Although the "Bernanke decomposition" relaxes the assumption of a just-identified structure for the VAR innovations, it still requires imposing a particular causal ordering of the variables which may be itself arbitrary, as theory may not always yield a clear identifying structure (Cooley and Dwyer).

The purpose of this paper is to reinvestigate the question of how agricultural prices respond to monetary policy relative to nonagricultural prices, while improving on previous work through the application of recent advances in time series statistical techniques that involves the combining of error correction modeling and directed acyclic graphs. Specifically, the proposed method consists of supplementing Johansen's cointegration procedure with a directed acyclic graph-based decomposition and rules of inference in linear time-series with unit roots. Although pplications of directed graphs to VAR model identification are not commonplace, a similar procedure has been suggested in Swanson and Granger. Their procedure considers only first order conditional correlation, and involves more subjective insight by the researcher to achieve a "structural recursive ordering". One advantage of using directed graphs is that results based on properties of the data can be compared to *a priori* knowledge of a structural model suggested by economic theory or subjective intuition. Specifically, identification is achieved by modeling the contemporaneous innovations from a VAR model with directed acyclic graphs, as recently presented in Spirtes, Glymour, and Scheines (2000). Before discussing model specification and estimation, a brief overview of directed acyclic graphs is presented.

2. Directed Graphs (DAG) Theory

Graph theory is an increasingly popular sub-field of discrete mathematics with numerous applications to various practical problems in the sciences and social sciences. Graph theory can be divided into two branches: areas of undirected graphs and directed graphs (or digraphs). Although undirected graphs have been studied more extensively in the natural sciences, directed graphs have more relevant applications to economics and other social sciences. Many of the literature on directed graphs contain, "not only interesting theoretical results, but also important algorithms as well as applications." (Ban-Jensen and Gutin, 2001)

Directed acyclic graphs exploit a non-time sequence asymmetry in causal relations. Consider a causally sufficient set of three variables X, Y and Z. We illustrate a causal fork, X causes both Y and Z, as: Y ←X → Z. Here the unconditional association between Y and Z is nonzero (as both Y and Z have a common cause in X), but the conditional association between Y and Z given knowledge of the common cause X, is zero: *a common cause screens-off association between its joint effects.* Illustrate the inverted causal fork, both X and Z cause Y, as: X→ Y ←Z. Here the unconditional association between X and Z is zero, but the conditional association between X and Z given the common effect Y is not zero: *a common effect does not screen-off association between its joint causes*. These *screening-off* attributes of causal relations are captured in the literature of *directed graphs*.

A directed graph G is a picture representing the causal flow among a set of variables. More formally, it is an ordered triple <V,M,E> where V is a non-empty set of elements called vertices (variables), M is a non-empty set of marks (symbols attached to the end of undirected edges), and E is a finite set of ordered pairs of elements E called edges. We call V the vertex-set of G and E the edge-set of G. Vertices connected by an edge are said to be adjacent. If we have a set of vertices {A, B, C, D, E}: (i) the undirected graph contains only undirected edges (e.g., A — B); (ii) a directed graph contains only directed edges (e.g., B → C); (iii) an inducing path graph contains both directed edges and bi-directed edges (C ↔ D); (iv) a partially oriented inducing path graph contains directed edges (→), bi-directed edges (↔), non-directed edges (o—o) and partially directed edges (o→). A directed acyclic graph is a directed graph that contains no directed cyclic paths (an acyclic graph contains no vertex more than once). Only acyclic graphs will be used in this study.

Directed acyclic graphs are designs for representing conditional independence as implied by the recursive product decomposition:

$$\Pr(x_1, x_2, x_3, \ldots x_n) = \prod_{i=1}^{n} \Pr(x_i \mid pa_i), \qquad (1)$$

Where Pr is the probability of vertices $x_1, x_2, x_3, \ldots x_n$ and pa_i the realization of some subset of the variables that precede (come before in a causal sense) X_i in order $(X_1, X_2, \ldots, X_n)$. Pearl proposes d-separation as a graphical characterization of conditional independence. That is, d-separation characterizes the conditional independence relations given by equation (1). If we formulate a directed acyclic graph in which the variables corresponding to pa_i are represented as the parents (direct causes) of X_i, then the independencies implied by equation (4) can be read off the graph using the notion of d-separation (defined in Pearl):

Definition: *Let X, Y and Z be three disjoint subsets of vertices in a directed acylic graph G, and let p be any path between a vertex in X and a vertex in Y, where by 'path' we mean any succession of edges, regardless of their directions. Z is said to block p if there is a vertex w on p satisfying one of the following: (i) w has converging arrows along p, and neither w nor any of its descendants are on Z, or, (ii) w does not have converging arrows along p, and w is in Z. Further, Z is said to d-separate X from Y on graph G, written* $(X \perp\!\!\!\perp Y \mid Z)_G$ *, if and only if Z blocks every path from a vertex in X to a vertex in Y.*

Geiger, Verma and Pearl (1990) show that there is a one-to-one correspondence between the set of conditional independencies, $X \perp\!\!\!\perp Y \mid Z$, implied by equation (4) and the set of triples (X, Y, Z) that satisfy the d-separation criterion in graph G. Essential for this connection is the following result: if G is a directed acyclic graph with vertex set V, A and B are in V, and H is also in V, then G linearly implies the correlation between A and B conditional on H is zero if and only if A and B are d-separated given H.

Spirtes, Glymour and Scheines have incorporated the notion of d-separation into an algorithm (PC Algorithm) for building directed acyclic graphs, using the notion of sepset (defined below). The PC algorithm is an ordered set of commands that begins with a general unrestricted set of relationships among variables and proceeds step-wise to remove edges between variables and to direct "causal flow." The algorithm is described in more details by Spirtes, Glymour, Scheines.

Briefly, one forms a complete undirected graph G on the vertex set V. The complete undirected graph shows an undirected edge between every variable of the system (every variable in V). Edges between variables are removed sequentially based on zero correlation or partial correlation (conditional correlation). *The conditioning variable(s) on removed edges between two variables is called the sepset of the variables whose edge has been removed (for vanishing zero order conditioning information the sepset is the empty set).* Edges are directed by considering triples X — Y — Z, such that X and Y are adjacent as are Y and Z, but X and Z are not adjacent. Direct edges between triples: X — Y — Z as $X \rightarrow Y \leftarrow Z$ if Y is not in the sepset of X and Z. If $X \rightarrow Y$, Y and Z are adjacent, X and Z are not adjacent, and there is no arrowhead at Y, then orient Y — Z as $Y \rightarrow Z$. If there is a directed path from X to Y, and an edge between X and Y, then direct (X — Y) as: $X \rightarrow Y$

In applications, Fisher's z is used to test whether conditional correlations are significantly different from zero. Fisher's z can be applied to test for significance from zero; where $z(\rho(i,j|k)n) = 1/2(n-|k|-3)^{1/2} \times \ln\{(|1 + \rho(i,j|k)|) \times (|1 - \rho(i,j|k)|)^{-1}\}$ and n is the number of observations used to estimate the correlations, $\rho(i,j|k)$ is the population correlation between series i and j conditional on series k (removing the influence of series k on each i and j), and |k| is the number of variables in k (that we condition on). If i,j and k are normally distributed and

$r(i,j|k)$ is the sample conditional correlation of i and j given k, then the distribution of $z(\rho(i,j|k)n) - z(r(i,j|k)n)$ is standard normal.

PC algorithm can commit type I and type II errors on both edge existence (PC algorithm can fail to include an edge when it should include it and can include an edge when it should not) and edge direction (PC algorithm may fail to put an arrowhead at vertex A when it should put it at vertex A and PC algorithm may put an arrowhead at A when, in fact, it should not have put an arrowhead there). Sprites, Glymour and Scheines have explored several versions of PC algorithm on simulated data with respect to errors on both edge inclusion (yes or no) and direction (arrowhead at A or not). They conclude that there is little chance of the algorithm including an edge that is not in the "true" model. However, there is, with small sample sizes (less than say 200 observations) considerable chance that the algorithm will omit an edge that belongs in the model.

Further, arrowhead commission errors (putting an arrowhead where it does not belong) appear to be more likely than edge commission errors (putting an edge where it does not belong). Accordingly, the authors conclude: "In order for the method to converge to correct decisions with probability 1, the significance level used in making decisions should decrease as the sample size increases, and the use of higher significance levels (e.g. 0.2 at sample sizes less than 100, and 0.1 at sample sizes between 100 and 300) may improve performance at small sample sizes." (Sprites, Glymour and Scheines, p. 116)

3. Empirical Model and Analysis

Data and Integration Properties

The data set used in this study are money supply, M1, short-term interest rates, TB, real trade weighted exchange rates, ER, industrial prices, IP, agricultural prices, FP. The data are from the Federal Reserve Bank, St. Louis and the USDA. The data set is monthly and covers the period 1975:1 to 2000:12. All data series are in natural logarithms. In order to determine the order of integration, two univariate unit root tests were examined for each of the five series: the augmented Dickey-Fuller test (Dickey and Fuller) and the Phillip and Perron non-parametric test. Both testing procedures are based on the null hypothesis that a unit root exists in the autoregressive representation of the series. Results shown in Table 1 suggest that all the variables are non-stationary in levels, but the null hypothesis of a unit root could not be rejected for the first differences. Unit root tests results indicate that the time series are integrated of order one. This finding suggests that cointegration (or an error correction) model specification is appropriate for investigating the dynamic relationships among the variables in this system of five variables.

Long-run Analysis

The concept of cointegration is intuitively appealing because it is supported by the notion of long-run equilibrium in economic theory. While variables in a system may fluctuate in the short-run, they are expected to return to their steady state in the long-run. A common method for testing for cointegration between economic series is the Johansen (1991) and Johansen and Juselius (1992) maximum likelihood (ML) procedure which allows for simultaneous analysis of both short-run and long-run phenomenon. Johansen and Juselius (1992) modeled time series as reduced rank regression in which they computed the ML estimates in the multivariate cointegration model with Gaussian errors. The model is a reformulation of a VAR(k) into a vector error correction (VECM) representation given by:

$$\Delta X_t = \mu + \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-1} + \varepsilon_t \qquad (2)$$

where X_t is an (nx1) column vector of p variables, μ is an (nx1) vector of constant terms, Γ and Π represent coefficient matrices, Δ is a difference operator, k denotes the lag length, and ε_t is i.i.d. p-dimensional Gaussian error with mean zero and variance matrix Λ (white noise disturbance term). The coefficient matrix Π is known as the impact matrix and it contains information about the long-run relationships.

Equation (2) resembles a VAR model in first differences, except for the inclusion of the lagged level of X_{t-1}, an error correction term, which will contain information about the long-run among variables in the vector X_t. This way of specifying the system contains information on both the short- and long-run adjustment to changes in X_t through the estimates of Γ and Π respectively. The VECM equation above allows for three model specifications: (a) if Π is of full rank, then X_t is stationary in levels and a VAR in levels is an appropriate model; (b) if Π has zero rank, then it contains no long-run information, and the appropriate model is a VAR in first differences (implies variables are not cointegrated); (c) if the rank of Π is a positive number, r and is less than p (where p is the number of variables in the system), there exists matrices α and β, with dimensions (p x r), such that $\Pi = \alpha\beta'$. In this representation β contains the coefficients of the r distinct long-run cointegrating vectors that render $\beta' X_t$ stationary, even though X_t is itself non-stationary, and α contains the short-run speed of adjustment coefficients for the equations in the system.

Johansen's methodology requires the estimation of the VAR equation (2) and the residuals are then used to compute two likelihood ratio (LR) test statistics that can be used in the determination of the unique cointegrating vectors of X_t. The first test which considers the hypothesis that the rank of Π is less than or equal to r cointegrating vectors is given by the trace test below:

$$Trace = -T \sum_{i=r+1}^{n} \ln(1 - \lambda_i) \tag{3}$$

The second test statistic is known as the maximal eigenvalue test which computes the null hypothesis that there are exactly r cointegrating vectors in X_t and is given by:

$$\lambda_{\max} = -T \ln(1-\lambda_r). \tag{4}$$

The distributions for these tests are not given by the usual chi-squared distributions. The calculations for the asymptotic critical values for likelihood ratio tests were done via numerical simulations by Johansen and Juselius (1990) and Osterwald-Lenum (1992).

Two alternative order selection criteria are applied to an unrestricted VAR model in order to determine the appropriate lag length. Both the Schwarz BIC, Hannan-Quinn HQ information criteria suggest using a lag length of two (which has white noise residuals). Subsequent analysis proceed with the use of VAR with lag length k=2. Results of cointegration rank by the Johansen and Juselius (1990) approach are presented in Table 2. Evidence from both the trace and $\lambda_{\max}$ test statistics suggests that there is at most one cointegrating vector present in the system. This finding is consistent with results from similar analysis by Saghaian, et al. that also found evidence of three cointegration vectors. Since the variables in the system are cointegrated, it is best to estimate models with error correction terms included to capture long-run relationships.

Therefore a five-variable VECM was fitted to natural logarithms of the 1975-2001 monthly data for the following variables: M1, TB, ER, IP, and FP (as previously defined).

Short-run dynamics

Like the standard VAR, the individual parameter estimates of the VECM are difficult to interpret. Rather, innovation accounting is the commonly used method by most researchers to describe the dynamic relationship among time series (Sims, 1980; Lutkepohl and Rheimers; Swanson and Granger; Phillips). The proper treatment of contemporaneous innovation correlation is very important to innovation accounting analysis. As noted previously, earlier application of VAR models can be improved upon since innovation accounting based on the Choleski decomposition are sensitive to the ordering of variables when the residual covariance matrix is non-diagonal. In this study, analysis of forecast error variance decomposition is used to summarize the dynamic relationship between monetary policy variables and agricultural prices. The contemporaneous causal structure on innovations can be identified through the directed graphs analysis of the correlation (covariance) matrix (Spirtes, Glymour, and Scheines; Pearl; Swanson and Granger; Bessler and Yang). The application of directed graphs provides a data-determined solution to the basic problem of orthogonalization of residuals from the ECM and thus is potential helpful in obtaining more accurate impulse response analysis or forecast error variance decompositions of a cointegrated VAR. First, a data-based identification approach using information from directed acyclic graphs is used. Then, the standard identification scheme with the Choleski decomposition technique is applied to identify short-run dynamic structure. Finally, implications of the results for money neutrality hypothesis is examined by the comparing between the conclusions from the forecast error variance decompositions produced by both the directed graphs-based Bernanke factorization and the Choleski factorization approaches.

Directed Graphs and Innovation Accounting Analysis

We followed the structural factorization approach commonly referred to as the "Bernanke ordering" which requires writing the innovation vector (e_t) from the estimated error correction model as: $\mathbf{A}e_t = v_t$, where, in our case, **A** is a 5x5 matrix and v_t is a 5x1 vector of orthogonal shocks. It was common in earlier VAR-type (vector autoregression-type) analyses to rely on a Choleski factorization, so that the A matrix is lower triangular, to achieve a just-identified system in contemporaneous time. We apply directed graph algorithms as discussed above to place zeros on the A matrix. A directed graph is an assignment of causal flow (or lack thereof) among a set of variables (vertices) based on observed correlation and partial correlation. The lower triangular elements of the correlation matrix V(corr) on innovations (errors) from the estimated VECM specified by equation (2), fit to 312 data points, are given as equation (5). Here we list the equation innovations for each column across the top of the matrix: M1 = innovations in money supply, TB = innovations in short-term interest rates, ER = innovations in exchange rates, IP = innovations in industrial prices, and FP = innovations in agricultural prices. For instance, the strongest pair-wise correlation (0.32) is between TB and ER. In contrast, the weakest pair-wise correlation (0.01) is between M1 and FP.

$$V(corr) = \begin{array}{c} \begin{array}{ccccc} M1 & TB & ER & IP & FP \end{array} \\ \begin{bmatrix} 1.0 & & & & \\ -0.16 & 1.0 & & & \\ -0.07 & 0.32 & 1.0 & & \\ 0.12 & -0.02 & -0.10 & 1.0 & \\ 0.01 & 0.14 & 0.02 & 0.15 & 1.0 \end{bmatrix} \end{array} \qquad (5)$$

Directed graph theory explicitly points out that the off-diagonal elements of the scaled inverse of this matrix (V or any correlation matrix) are the negatives of the partial correlation coefficients between the corresponding pair of variables, given the remaining variables in the matrix (Whittaker, page 4). Directed graphs as given in Spirtes, Glymour, and Scheines, provided an algorithm (PC algorithm) for removing edges between markets and directing causal flow of information between markets. As shown in Figure 1, the algorithm starts with a complete undirected graph, where innovations from every variable are connected with innovations from every other variable of the system. The algorithm removes edges sequentially between variables based on the observed zero correlation and partial correlation (conditional correlation). Then notion of *sepset* is then used to assign the direction of causal flow between variables which remain connected after all possible conditional correlations have been passed as nonzero.

The innovation correlation matrix given by equation (5) is used as the starting point as the PC algorithm (in TETRAD II software) is applied to these correlations. As suggested by Spirtes, Glymour, and Scheines, various levels of significance are considered in an attempt to achieve an unambiguous causal structure of the variables in contemporaneous time. Figures 2, 3, and 4 present graphs on innovations from the five-variable VECM at the following nominal levels of significance: .05, .10, and .20. As the TETRAD II search algorithm involves multiple hypothesis testing for edge removal, the final significance level is generally larger than that reported as nominal. Although 20 percent is a rather high significance level, it provides important insight on the causal flow from industrial prices to exchange rates. Presenting results for alternative levels of significance allows the researcher to quantitatively assess the robustness of his/her results with respect to significance levels. At the 5 and 10 percent significance levels the directed edges are given in Figures 2 and 3. The resulting graphs are identical, indicating directed edges from interest rates to exchange rates and agricultural prices; directed edges from money supply to industrial prices and from industrial prices to agricultural prices. There were additional edges, though undirected, among industrial prices and exchange rates and among interest rates and money supply. Since there is an undirected edge connecting these variables, we know that there is a relationship between them, but we cannot say which variable is causal. Subsequent analysis in this paper is based on directed graphs at the 5 percent level.

This section analyzes the dynamic effects of the structural innovations on the endogenous variables. The directed graph is used to specify the causal path for the ordering of the Bernanke decomposition of contemporaneous innovations. Tables 3 contains the forecast error variance decompositions (FEVD) associated with the error correction model under the ordering of innovations as generated by the directed graph given in Figure 2. FEVD is the contribution of each source of innovations to the variance of the n-period ahead forecast error for each endogenous variable for horizons 0, 1, 11, 23, and 35 months. Money supply is obviously exogenous in contemporaneous time since it explains 100 percent of its own variation at zero-step horizon. But at longer horizon of 35 months, about 44 percent of the variation in money is jointly explained by interest rates and agricultural prices. Interest rate is also exogenous at at zero-step horizon. In the long run (3 years), over 35 percent of the variability in interest rates is explained by industrial prices while another 18 percent is explained by exchange rates. Except for the notable contributions from interest rates, variation in exchange rates is mostly determined by its own innovations. This is particularly so in the horizons of 0 and 1 month (87-89 percent).

Industrial prices are nearly exogenous in contemporaneous time, but at longer horizons, exchange rates is the only variable that account for the observed variation in industrial prices. Similarly, exchange rates also account for a notable portion of the variation in agricultural prices. In the long run, over 41 percent of the variability in agricultural prices is explained by exchange rates. The role of exchange rates in determining variation in agricultural prices is plausible given the importance of export markets to farm products. The relatively insignificant contributions from both money supply and interest rates lend support to the money neutrality hypothesis that claims that claims that money does not affect the relative price level in the long run.

Table 4 shows the FEVDs based on the standard Choleski decomposition approach. The recursive structural model has the following variable ordering: M1, TB, ER, IP, and FP. This ordering is consistent with that of active money hypothesis used in most previous studies (Bessler; Devadoss and Meyer; Orden and Fackler). This ordering also reflects an hypothesis of a goods sector with sluggish adjustment. In contrast to relative prices, the monetary macroeconomic variables are assumed to be predetermined. The FEVD results from both decomposition approaches are rather similar. Like the previously reported results based on directed graphs, M1, TB, and ER seem to be exogenous in contemporaneous time. However, at longer horizons, other variables influence these three variables. Particularly, the FEVD results show a stronger influence of IP in explaining the variations in TB (62.2 percent versus 35.8 percent). Very little of the variations in IP and FP are explained by fluctuations in M! or TB. This finding provides empirical support for the money neutrality hypothesis.

4. Concluding Remarks

The objective of the research reported in this paper is to reexamine the dynamic relationship between agricultural prices and monetary macroeconomic policy variables. The main contribution of this study is in introducing an alternative method to identifying contemporaneous correlation structure in VAR-type time series models of the economy. This is accomplished by employing recently developed time series estimation techniques via the combination of error correction modeling and directed graphs techniques. To determine whether money neutrality hypothesis is consistent with U.S. data, initially a vector error correction model was specified for money supply, M1, interest rate, TB, exchange rates, ER, industrial prices, IP, and agricultural prices, FP. The use of an error correction model specification allows us to distinguish between long-run and short-run phenomena.

Long run equilibrium relationship is analyzed by applying cointegration analysis. Johansen's cointegration test result show that three cointegrating vectors are present implying the existence of a long-run steady state among the variables in the system Next, short-run dynamics is investigated through a comparative analysis of two alternative VAR identification approaches: i) Choleski factorization; and ii) Bernanke structural factorization augmented with causal flow information from directed graphs. These two methodological procedures were then used analyze the variance decompositions which then provide insight on the monetary policy impact on agricultural prices. Results from variance decomposition analysis provide empirical support for the money neutrality hypothesis. Additional research is still needed to assess the robustness of the directed graph technique under alternative assumptions and estimation time periods.

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Table 1. Unit Roots Tests

	Dickey-Fuller	Phillips-Perron
Levels		
M1	0.81	**1.86**
TB	-2.52	**-2.51**
ER	-1.35	-1.27
FP	-2.66	-2.80
IP	-2.70	-0.93
First differences		
ΔM1	-5.56 **	**-9.70** **
ΔTB	-8.12 **	**-11.84** **
ΔER	-8.40 **	-12.87 **
ΔFP	-9.31 **	-15.43 **
ΔIP	-4.43 **	8.24 **

Notes:
** denote that a test statistic is significant at the 5 % level. The optimal lag lengths for ADF test statistic was selected based on mimimizing the AIC and BIC criteria using a range of lags. The truncation lag for the PP test was obtained based on the Newey-West adjustment with four lags and the conclusions are robust for an adjustment with lags two to six.

Table 2. Johansen Cointegration Test Results

# of Cointegrating Vectors	Trace Statistics	C(5%)	λ-max Statistics	C(5%)
r=0	166.11	76.07	70.41	34.40
r≤1	96. 70	53.12	45.68 **	28.14
r≤2	50.02	34.91	30.67	22.00
r≤3	19.35 **	19.96	12.99 **	15.67
r≤4	6.36	9.24	6.36	9.24

Notes:
r denotes the number of cointegrating relationships.
Critical values used are taken from Osterwald-Lenum (1992).
** indicates rejection at the 95% critical values.

Table 3. Variance Decomposition of each series Based on Bernanke Decompositions.

Step	S.E.	M1	TB	ER	IP	FP
			(M1)			
0	0.004	100.000	0.000	0.000	0.000	0.000
1	0.008	96.563	3.184	0.217	0.016	0.021
11	0.025	55.669	34.117	0.584	2.820	6.810
23	0.035	51.401	34.591	0.357	2.655	10.996
35	0.041	53.022	32.322	0.579	1.973	12.105
			(TB)			
0	0.473	0.000	100.000	0.000	0.000	0.000
1	0.779	1.699	94.435	0.111	3.326	0.428
11	1.603	5.014	56.054	4.353	32.137	2.441
23	1.833	3.920	45.924	11.043	36.296	2.816
35	1.987	3.498	39.854	18.149	35.792	2.707
			(ER)			
0	0.016	0.000	10.705	89.295	0.000	0.000
1	0.026	0.106	12.406	86.763	0.024	0.701
11	0.067	0.253	11.636	83.928	1.218	2.965
23	0.082	0.168	13.076	78.618	4.280	3.857
35	0.089	0.154	15.009	71.316	8.903	4.618
			(IP)			
0	0.003	0.905	0.000	0.000	99.095	0.000
1	0.006	1.257	0.158	0.394	98.172	0.019
11	0.024	5.204	5.099	6.960	82.233	0.504
23	0.037	5.793	4.479	16.845	72.353	0.530
35	0.047	5.573	3.282	26.652	64.115	0.378
			(FP)			
0	0.021	0.017	1.523	0.000	1.833	96.628
1	0.031	0.094	1.252	0.265	2.774	95.615
11	0.052	2.868	1.813	8.776	9.125	77.418
23	0.062	2.208	1.372	29.676	13.001	53.742
35	0.070	1.764	1.151	41.414	13.074	42.596

Table 4. Variance Decomposition of each series Based on Choleski Decompositions.

Step	S.E.	M1	TB	ER	IP	FP
			(M1)			
0	0.004	100.000	0.000	0.000	0.000	0.000
1	0.007	95.498	4.126	0.219	0.133	0.023
11	0.030	53.383	33.868	2.755	5.389	4.606
23	0.047	37.884	44.285	4.269	7.237	6.326
35	0.059	32.919	47.370	7.146	5.960	6.605
			(TB)			
0	0.462	2.565	97.435	0.000	0.000	0.000
1	0.789	0.997	95.571	0.224	2.752	0.456
11	1.826	1.459	49.737	2.409	45.319	1.075
23	2.446	1.300	37.516	3.198	57.378	0.608
35	2.920	1.168	32.712	3.507	62.182	0.432
			(ER)			
0	0.016	0.549	9.632	89.819	0.000	0.000
1	0.027	0.226	14.062	84.966	0.133	0.613
11	0.077	0.925	19.243	76.785	0.163	2.884
23	0.111	0.794	23.232	72.509	0.516	2.949
35	0.136	0.673	25.276	70.271	0.880	2.900
			(IP)			
0	0.003	1.386	0.000	0.919	97.695	0.000
1	0.005	1.815	0.019	2.810	95.335	0.022
11	0.029	5.693	2.435	7.932	83.881	0.059
23	0.054	6.889	3.436	11.487	77.852	0.336
35	0.076	6.894	3.761	13.647	75.216	0.483
			(FP)			
0	0.021	0.017	2.195	0.052	2.113	95.622
1	0.030	0.071	2.211	0.028	4.033	93.657
11	0.050	2.070	1.672	9.188	10.771	76.299
23	0.068	1.703	1.189	31.506	24.654	40.948
35	0.087	2.062	0.759	40.299	31.604	25.275

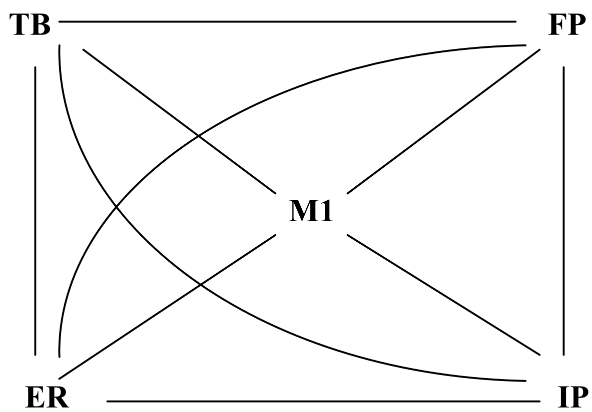

Figure 1. Complete Undirected Graph on Innovations from VECM

M1 = Money Supply; TB = Interest Rates; ER = Exchange Rates; FP = Agricultural Prices; IP = Industrial Prices

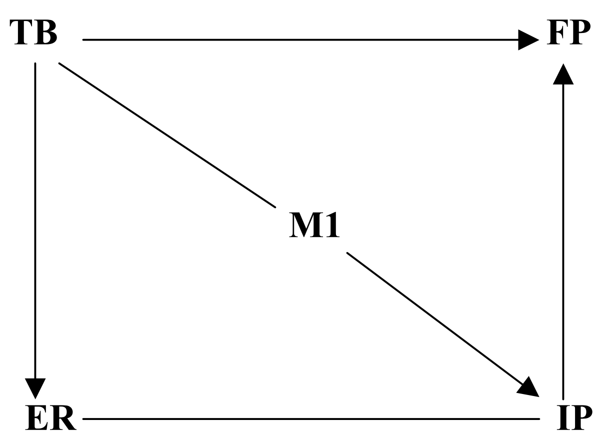

Figure 2. Directed Graph on Innovations from VECM (5% signifiance level)

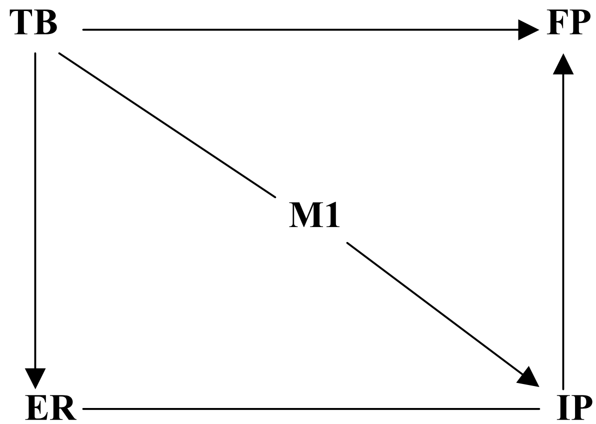

Figure 3. Directed Graph on Innovations from VECM (10% signif. level)

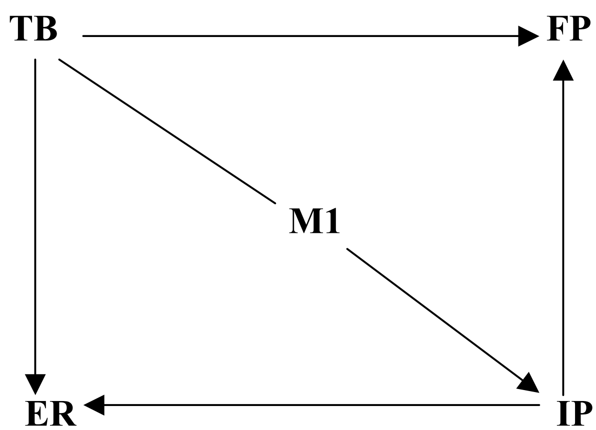

Figure 4. Directed Graph on Innovations from VECM (20% signif. level)