Impact of Macroeconomic Policies on Agricultural Prices

Titus O. Awokuse

Existing empirical evidence on the impact of macroeconomic variables on agriculture remains mixed and inconclusive. This paper re-examines the dynamic relationship between monetary policy variables and agricultural prices using alternative vector autoregression (VAR) type model specifications. Directed acyclic graph theory is proposed as an alternative modeling approach to supplement existing modeling methods. Similar to results in other studies, this study's findings show that over the time period analyzed (1975–2000), changes to money supply as a monetary policy tool had little or no impact on agricultural prices. The primary macroeconomic policy instrument that affects agricultural prices is the exchange rate, which is shown to be directly linked to interest rate, a source of monetary policy shock.

Key Words: agricultural prices, cointegration, directed acyclic graphs, monetary policy, VAR

Over the past few decades, there has been a growing interest in the nature of the dynamic relationship between agriculture and the general economy. This issue is of importance given the increasing dependence of agriculture on international markets and the potential and wide-ranging 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 potential reduction in foreign demand for U.S. farm exports in the aftermath of financial crisis in export markets. Schuh's (1974) seminal paper played a pivotal role in initiating the subsequent empirical analyses in this area. The majority of the recent investigations of the agriculture-macroeconomy nexus later focused on the timing and magnitude of the causal relationship between monetary policy and agricultural prices. 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.

Unfortunately, economic theory is ambiguous on the nature of the causal relationship between agriculture and the rest of the macroeconomy. Although most theoretical models advocate money neutrality (i.e., money does not affect prices) in the long run, Bordo (1980) showed that changes in the money supply could induce changes in the short-run movement of relative prices. Furthermore, Chambers and Just (1982) argue that expansionary monetary policy could have a positive effect on agriculture (and vice versa). Hence, much of the debate has been informed by empirical analyses of historical agricultural time-series data. However, the existing empirical evidence on the relationship between agricultural prices and monetary policy has been mixed and inconclusive. The purpose of this paper is to re-examine the dynamic relationship between agricultural prices and monetary policy, with an emphasis on improving on the specification of previous empirical models based on time-series techniques.

There are several alternative approaches used by researchers to evaluate the effect of changes in macroeconomic policy variables on agriculture. On the one hand, there are models based on Granger's (1969) approach to testing for probabilistic causality. Within this scheme, Wald tests could be used to infer the direction of causality between money supply and agricultural prices (Lapp 1990). On the other hand, the approach favored by most researchers is the use of vector autoregression (VAR) or its variants (error correction and cointegration models) to identify the response of agricultural prices to changes in mac-

Titus O. Awokuse is Assistant Professor in the Department of Food and Resource Economics, University of Delaware. The author thanks three anonymous reviewers for their helpful comments which improved the quality of the paper. The usual disclaimer applies.

roeconomic variables (Bessler 1984; Devadoss, Meyers, and Starleaf 1990; Orden and Fackler 1989; Dorfman and Lastrapes 1996; Saghaian, Reed, and Marchant 2002; Saghaian, Hasan, and Reed 2002). Of all the previous works that used VAR-type models to analyze the agricultural price overshooting hypothesis, only Saghaian, Hasan, and Reed (2002) directly addressed the issue of identification via the application of directed graphs, as proposed in this paper. However, their paper focused only on Asian economies and not on U.S. agricultural prices.

One major criticism of previous works based on VAR-type models is the way that variables responding to shocks are identified in the system. 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 researchers have argued that while VAR models may be useful for forecasting, they are not appropriate for policy analysis (Cooley and LeRoy 1985, Cooley and Dwyer 1998). 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. A common 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 (Bernanke 1986, Blanchard and Quah 1989) suggest the use of orthogonalizations that allow for imposing over-identifying restrictions on the model. In the literature, these models are labeled as structural vector autoregressions (SVARs) as they rely on prior economic theory as the source of their identifying restrictions. Bernanke's (1986) 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 itself be arbitrary, as theory may not always yield a clear identifying structure (Cooley and LeRoy 1985, Cooley and Dwyer 1998).

This study extends the literature and makes important contributions in several ways. First, it exploits the inherent causal information contained in the data to test for contemporaneous causation with the analysis of directed acyclic graphs (DAGs), a modeling technique for analyzing contemporaneous causal structure (Spirtes, Glymour, and Scheines 2000; Pearl 1995; Pearl 2000). Thus, DAGs, an alternative data-based approach, are used to provide identification for responses to shocks in a VAR-type model of the agriculture-macroeconomy nexus. Second, in contrast to most previous studies that focused on a closed economy, this is one of the few studies that also captures the role of international macroeconomic linkages and trade effects through the inclusion of an exchange rate variable in the system. Third, this is the first study to apply DAG identification approach to U.S. data on the agriculture-macroeconomy nexus. 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. Relative to the recursive identification scheme, the data-determined identification approach based on directed graphs is shown to offer a plausible explanation of the impact of changes in monetary policy on agricultural prices.

The rest of the paper is organized as follows. In the section below, a brief overview of directed graph theory is provided. Then, a discussion of the empirical methods and results are provided. The final section concludes the paper.

Directed Acyclic Graphs (DAGs)

Directed acyclic graph (DAG) theory is an increasingly popular sub-field of discrete mathematics with numerous applications to various practical problems in the natural 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, especially in the analysis of causal relationships. The majority of past investigations of causal relationships among economic variables use the Granger (1969) causality framework. This approach exploits the asymmetry that results from the fact that a cause precedes its associated effect. But recently, Spirtes, Glymour, and Scheines (2000) and Pearl (1995, 2000) proposed directed graphs as a more general framework for describing causal relationships.

In contrast to Granger's (1969) definition of causality, directed acyclic graphs allow for non–time-sequence asymmetry in causal relations. The concept of conditional independence forms the foundation for understanding directed acyclic graphs. A DAG can be defined as a picture using arrows and vertices to represent the causal flow among a set of random variables. The vertices (variables) of these graphs can represent random variables on which data has been obtained. The line segments connecting vertices (directed edges or arrows) are generated by calculations of conditional statistical dependence or independence among pairs of variables (ceteris paribus). Alternatively, a DAG is a graph that contains only directed acyclic paths (i.e., no variable is allowed to be a direct or indirect cause of itself). Two vertices (variables) are connected, only if a direct association exists between them. However, two variables cannot be connected if they are conditionally independent, given other variables in the system.

For example, if there is a directed edge $Q \rightarrow P$, the variable Q is described as the parent of P, while P is described as the child (or descendant) of Q. In this case, Q is a direct cause of P. In addition, a graph represented by $P \leftarrow X \rightarrow Q$ implies that the three variables—P, Q, and X—have a relation such that X causes P and Q. This causal relationship implies that the unconditional association between P and Q is nonzero but that the conditional association between P and Q, given knowledge of the common cause X, is zero. The common cause X can potentially screen off associations between their joint effects. Alternatively, if we have a scenario where both X and Q cause P, represented as $X \rightarrow P \leftarrow Q$, then the unconditional association between X and Q is zero. However, the conditional association between X and Q, given the common effect P, is not zero.

Following Pearl (1995, 2000) and Spirtes, Glymour, and Scheines (2000), directed acyclic graphs can be used as an analytical tool to represent conditional independence as implied by the recursive product decomposition:

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

where Pr is the probability of vertices $x_1, x_2, x_3, \ldots x_n$, and pa_i represents the realization of some subset of the variables that precede x_i in order ($x_1, x_2, x_3, \ldots x_n$). Pearl (1995, 2000) showed that the conditional independence relations given by equation (1) could be represented by *d*-separation. Pearl's (1995, 2000) concept of *d*-separation (directional separation) can be illustrated as follows. For any three disjoint subsets X, Y, Z vertices in a DAG, Z is said to *d*-separate X from Y if there is no active causal link from X to Y given Z. The concept of *d*-separation is a graphical characterization of conditional independence summarized in DAGs. Pearl's (1995, 2000) work on *d*-separation is significant because it shows the link between the causal graphs and the underlying probability distribution of the data-generating process.

As in Awokuse and Bessler (2003), the Fisher's z statistic can be used to test estimated sample correlations and conditional correlations against zero. Fisher's z is expressed as

$$(2) \qquad z(\rho(i,j \mid k), n) = \left[\frac{1}{2}\sqrt{n - |k| - 3}\right] \ln\left\{\frac{|1+\rho(i,j \mid k)|}{1-\rho(i,j \mid k)}\right\},$$

where 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, and $|k|$ is the number of variables in k. 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. Similar to Swanson and Granger (1997), the causal path suggested by this data-driven approach is then used in a vector autoregression (VAR) model in the construction of forecast error variance decompositions.

Spirtes, Glymour, and Scheines (2000) developed a causal search algorithm (PC algorithm) for building directed acyclic graphs. The PC algorithm uses a stepwise testing of conditional independence for removing statistically insignificant edges (causal links) between variables and directing causal flow of information between the variables. Edges among a set of *N* variables (e.g., residuals from a VAR) are removed sequentially based on the observed zero correlation and partial correlation (conditional correlation). 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 in the system. Then, the algorithm removes edges sequentially between variables. Next, the direction of causal flow is assigned between variables which remain connected after all possible conditional correlations have been determined to be nonzero. The PC algorithm and its more refined extensions are available with the software *TETRAD II* (see Scheines et al. 1994). Also, more detailed discussions of DAG and its applications can be found in the writings of Pearl (2000), Spirtes, Glymour, and Scheines (2000), and Bessler and Yang (2003).

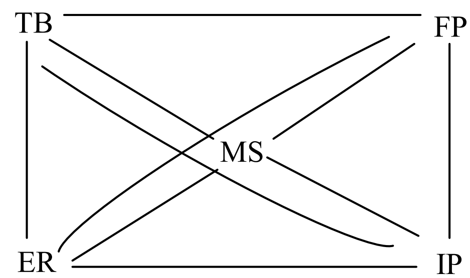

Figure 1. Complete Undirected Graph on Innovations from VECM

Notes: *MS* = money supply, *TB* = interest rates, *ER* = exchange rates, *FP* = agricultural prices, *IP* = industrial prices.

Empirical Model and Analysis

Data and Integration Properties

The data series used in this study are as follows: auction average interest rate on three-month treasury bills (*TB*); weighted average of the currencies of ten major trading partner countries versus the U.S. dollar (*ER*); money stock, in billions of U.S. dollars (*MS*); industrial prices, measured as the producer price index (*IP*); and agricultural prices, measured as prices received by farmers for crops (*FP*). The data for money supply, interest rate, exchange rate, and industrial prices are from the Federal Reserve Bank in St. Louis, Missouri, and the agricultural prices are from the U.S. Department of Agriculture. The data set is monthly and covers the period January 1975 to December 2000. The choice of variables included in the analysis is based on conventions common to previous studies (see Bessler 1984, Orden and Fackler 1989, Saghaian, Reed, and Marchant 2002). All data series (except *TB*) 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 (1979) test and the Phillips and Perron (1988) non-parametric test. Both testing procedures are based on the null hypothesis that a unit root exists in the autoregressive representation of the series. The null hypothesis should be rejected if the test statistic is greater than the critical value. Results shown in Table 1 suggest that the null hypothesis of a unit root cannot be rejected at the 5 percent significance level for each of the series in levels. However, the null hypothesis of a unit root could be rejected for the series in first differences. Thus, unit root test results indicate that the time series are integrated of order one. This finding suggests the need to test for cointegration as there may be long-run co-movement among the variables.

A common method for testing for cointegration between economic series is the Johansen and Juselius (1990) maximum likelihood (ML) procedure, which allows for simultaneous analysis of both short-run and long-run phenomenon. Johansen and Juselius (1990) 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

$$(3) \qquad \Delta X_t = \mu + \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-1} + \varepsilon_t \,,$$

Table 1. Tests for Unit Root

Variable	Augmented Dickey-Fuller (DF)	Phillips-Perron (PP)
Levels		
MS	0.81	1.86
MS	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		
Δ*MS*	-5.56**	-9.70**
Δ*TB*	-8.12**	-11.84**
Δ*ER*	-8.40**	-12.87**
Δ*FP*	-9.31**	-15.43**
Δ*IP*	-4.43**	-8.24**

Notes: ** denotes that a test statistic is significant at the 5 percent 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; the conclusions are robust for an adjustment with lags of two to six.

where $\boldsymbol{X_t}$ is an $(n \times 1)$ column vector of p variables, μ is an $(n \times 1)$ 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 contains information about the long-run relationships.

Johansen and Juselius's (1990) cointegration methodology requires the estimation of the VAR equation (3); 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 $\boldsymbol{X_t}$. The first test that considers the hypothesis that the rank of Π is less than or equal to r cointegrating vectors is given by the trace test below:

$$\text{Trace} = -T \sum_{i=r+1}^{n} \ln(1-\lambda_i)\,. \tag{4}$$

The second test statistic below is known as the maximal eigenvalue test and computes the null hypothesis that there are exactly r cointegrating vectors in $\boldsymbol{X_t}$:

$$\lambda_{\max} = -T\ 1n(1-\lambda_r)\,. \tag{5}$$

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 based on 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 (1978) BIC and Hannan-Quinn (1979) HQ information criteria suggest using a lag length of two (which has white noise residuals). Subsequent analysis proceeds with the use of a VAR model with lag length $k=2$.

Results of a cointegration test 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 are at most three cointegrating vectors present in the system. Since the variables in the system are cointegrated, it is appropriate to estimate models with error correction terms included to capture long-run relationships. Therefore, a five-variable (*MS, TB, ER, IP,* and *FP*) error correction model was estimated in natural logarithm levels (except interest rate, *TB*, which is in levels) over the period January 1975 to December 2000.

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 Reimers 1992, Swanson and Granger 1997, Phillips 1998). The choice 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 is sensitive to the ordering of variables when the residual covariance matrix is non-diagonal. In this study, 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 graph analysis of the correlation (covariance) matrix (Swanson and Granger 1997, Bessler and Yang 2003).

Table 2. Multivariate Cointegration Test Results

# of cointegrating vectors	Eigenvalues	Trace statistics	$C(5\%)$	λ-max statistics	$C(5\%)$
$r = 0$	0.203767	166.11**	76.07	70.41**	34.40
$r \leq 1$	0.137431	96.70**	53.12	45.68**	28.14
$r \leq 2$	0.094476	50.02**	34.91	30.67**	22.00
$r \leq 3$	0.041164	19.35	19.96	12.99	15.67
$r \leq 4$	0.020375	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 percent critical values.

The structural factorization approach commonly referred to as "Bernanke ordering" was applied. This requires writing the innovation vector ($\mathbf{e}_t$) from the estimated error correction model as $Ae_t = v_t$, where, in our case, **A** is a 5×5 matrix and $\mathbf{v}_t$ is a 5×1 vector of orthogonal shocks. It was common in earlier VAR-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. Directed graph algorithms as discussed above were used 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 (3), fit to 312 data points, are given as equation (6). Equation innovations for each column across the top of the matrix are as follows: *MS* = 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 *MS* and *FP*.

$$(6) \qquad \begin{array}{cc} & \begin{array}{ccccc} MS & TB & ER & IP & FP \end{array} \\ \mathbf{V}(corr) = & \begin{bmatrix} 1.00 & & & & \\ -0.16 & 1.00 & & & \\ -0.07 & 0.32 & 1.00 & & \\ 0.12 & -0.02 & -0.10 & 1.00 & \\ 0.01 & 0.14 & 0.02 & 0.15 & 1.00 \end{bmatrix} \end{array}$$

The innovation correlation matrix given by equation (6) 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 (2000), alternative levels of significance are considered in an attempt to achieve an unambiguous causal structure of the variables in contemporaneous time. Presenting results for alternative levels of significance allows the researcher to quantitatively assess the robustness of results with respect to significance levels.

The application of directed graphs provides a data-determined alternative approach to addressing the basic problem of orthogonalization of residuals from the ECM. Thus, it is potentially helpful in obtaining more accurate impulse response functions or forecast error variance decompositions of a cointegrated VAR. The DAG given in Figure 2 gives us the following matrix representation on innovations in contemporaneous time:

$$(7) \qquad \begin{bmatrix} 1 & a_{12} & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & a_{32} & 1 & 0 & 0 \\ a_{41} & 0 & a_{43} & 1 & 0 \\ 0 & a_{52} & 0 & a_{54} & 1 \end{bmatrix} \begin{bmatrix} v_{MS} \\ v_{TB} \\ v_{ER} \\ v_{IP} \\ v_{FP} \end{bmatrix} = \begin{bmatrix} e_{MS} \\ e_{TB} \\ e_{ER} \\ e_{IP} \\ e_{FP} \end{bmatrix}.$$

The v_i terms are observed innovations from the error correction model and the e_i terms are orthogonal innovations from each variable. For a five-variable VAR system, there are 10 lower triangular elements which can be non-zero in a just-identified model—i.e., with m equal to the number of series in the VAR, we have $m(m-1)/2$ free parameters. The resulting matrix in (7) produced an over-identified model. The identifying restrictions suggested by TETRAD II's graph in Figure 2 were tested using the likelihood ratio test for over-identification as given in Doan (2004, pp. 341–345). The directed graph restrictions

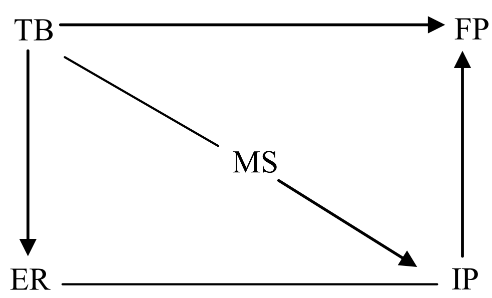

Figure 2. Directed Acyclic Graph on Innovations from VECM (5% level)

Notes: *MS* = money supply, *TB* = interest rates, *ER* = exchange rates, *FP* = agricultural prices, *IP* = industrial prices.

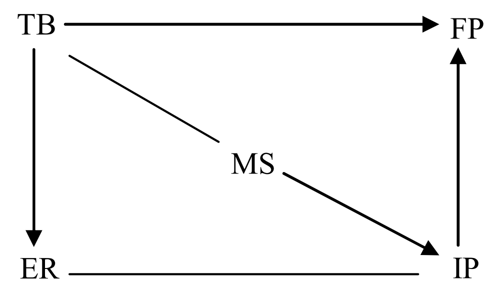

Figure 3. Directed Acyclic Graph on Innovations from VECM (10% level)

Notes: *MS* = money supply, *TB* = interest rates, *ER* = exchange rates, *FP* = agricultural prices, *IP* = industrial prices.

result in a chi-squared statistic of 0.60, with 4 degrees of freedom, and a *p*-value of 0.96. Thus, the restricted model cannot be rejected at conventional significance levels. This suggests that the restrictions based on DAG are consistent with the data. Thus, a data-based identification approach using information from directed acyclic graphs is used. For the sake of comparisons, the common identification scheme with the Choleski decomposition technique is applied to identify short-run dynamic structure. Finally, implications of the results for the money neutrality hypothesis are examined. This is done by comparing the empirical results 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

Figures 2 and 3 present graphs on innovations from the five-variable VECM at the 5 and 10 percent levels of significance, respectively. 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 directed edges 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. In cases of undirected edges, some prior knowledge from theory or conventional wisdom can be used to complement DAG. Alternatively, in cases of small data sets with a limited number of observations, higher significance levels may be explored to sort out the direction of the undirected edges. Subsequent analysis in this paper is based on directed graphs at the 5 percent level. These directed edges, in contemporaneous time, are plausible as they suggest that macroeconomic variables affect agricultural prices (but not vice versa). Conventional wisdom among the majority of economists would be that while agricultural prices may respond to general macroeconomic shocks (money, interest rate, and exchange rate), the reverse feedback from the agricultural sector to the general macroeconomic variables is expected to be rather weak.

The rest of 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. Table 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

Table 3. Forecast Error Variance Decomposition (directed graphs-based)

Step	Std. error	*MS*	*TB*	*ER*	*IP*	*FP*
			(MS)			
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

months. Money supply is obviously exogenous in contemporaneous time since it explains 100 percent of its own variation at zero-step horizon. But at a longer horizon of 35 months, interest rate alone explained 32.32 percent of the variation in money. Interest rate is also exogenous 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 rate is the only variable that accounts for the observed variation in industrial prices. Exchange rates also account for a notable portion of the variation in agricultural prices.

Similar to earlier results from the DAG analysis, there is no significant empirical evidence indicating feedback effect from agricultural prices to the general macroeconomic variables. Rather, current empirical evidence suggests that agricultural prices respond to macroeconomic variables. In the long run, over 41 percent of the variability in agricultural prices is explained by exchange rates alone. Although to a lesser extent, industrial (input) prices also account for some of the variability in agricultural prices. The role of exchange rates in determining variation in agricultural prices is plausible given the importance of export markets to farm products. This result, showing strong interaction between agricultural prices and the macroeconomic variables, is reasonable and consistent with prior studies on this issue (Orden and Fackler 1989, Lapp 1990).

Table 4 shows the FEVDs based on the standard Choleski decomposition approach. The recursive structural model has the following variable ordering: *MS, TB, ER, IP*, and *FP*. This ordering is consistent with that of the active money hypothesis used in most previous studies (Bessler 1984, Devadoss and Meyer 1987, Orden and Fackler 1989). 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, *MS, 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). The impact of *IP* on *TB* is not surprising given the relative importance of oil and other industrial commodities as factors of production. Very few of the variations in *IP* and *FP* are explained by fluctuations in *MS* or *TB*. Relative to the DAG results, the FEVDs based on Choleski factorization actually provide stronger empirical evidence supporting the contribution of macroeconomic variables in explaining variations in agricultural prices.

Previous studies have shown that money supply and interest rate are relevant monetary policy indicators (Bernanke 1986, Sims 1986, Orden and Fackler 1989, Dorfman and Lastrapes 1996). Similar to results in other studies, current findings show that over the time period analyzed (1975–2001), money supply as a monetary policy tool had little or no impact on agricultural prices or any other variable in the system (Orden and Fackler 1989, Lapp 1990). Rather, the result indicates strong linkages between the other financial variables (interest rate and exchange rate). The primary macroeconomic policy instrument that affects agricultural prices is the exchange rate, which is shown to be directly linked to interest rate, a source of monetary policy shock. The relatively insignificant effect of money supply on agricultural prices does not mean that monetary policy has little effect; rather, it reflects changes in the Federal Reserve Bank's approach to monetary policy in recent years. In the early 1980s, the Federal Reserve Bank shifted its emphasis from money supply as the primary monetary policy instrument to adjustment of the short-term interest rate. Thus, the relative importance of the financial variables (interest rate and exchange rate) in capturing the impact of monetary policy on agricultural prices is plausible.

Summary and Conclusions

Although the impact of monetary policy on agricultural prices has been an issue of great interest among agricultural economists, the nature of the linkage is still controversial. This is due to the ambiguity of economic theory and the existence of mixed and empirical evidence on the matter. This paper re-examines the dynamic relationship between monetary policy variables and agricultural prices using alternative time-series model specifications. 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. Directed acyclic graph theory is proposed as an alternative modeling approach to supplement current methods of analyzing the effect of monetary policy on agricultural prices. The estimated five-variable vector error correction model was based on U.S. data over the period January 1975 to December 2000 for money supply, *MS*, interest rate, *TB*, exchange rate, *ER*, industrial prices, *IP*, and agricultural prices, *FP*. The impact of monetary policy on agricultural prices was investigated through the analysis of forecast error variance decompositions.

Table 4. Forecast Error Variance Decomposition (Choleski-based)

Step	Std. error	*MS*	*TB*	*ER*	*IP*	*FP*
			(MS)			
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

Similar to results in other studies, this study found that money supply as a monetary policy tool had little or no impact on agricultural prices in the past two decades. The primary macroeconomic policy instrument that affects agricultural prices is the exchange rate, which is shown to be directly linked to interest rate, a source of monetary policy shock. The majority of the variability in agricultural prices is explained by exchange rates and industrial (input) prices. The significant impact of exchange rate fluctuations on agricultural prices reflects the increasing importance of export markets for U.S. agricultural products. This result is consistent with the findings in earlier studies that found that agricultural prices respond to changes in interest rate and exchange rate (Orden and Fackler 1989, Lapp 1990).

Empirical results from this study show that DAGs can yield results similar to those of a theory-based Choleski approach, even though no prior theoretical restriction is made with DAG. This finding is appealing as DAG could be used as a plausible VAR-identification scheme when theory provides limited or ambiguous priors. Whenever the pair-wise correlations among variables in the variance-covariance matrix are low (as was the case here), results from directed graphs-based factorization tend to be similar to those from Choleski factorization. Given that the conclusions from the empirical results from the two VAR model identification approaches (DAG and Choleski) are similar, the obvious question arises as to why one should not just use Choleski factorization. It may be equally valid to ask an alternative question. Since DAG is data-determined and yields plausible results, why not use DAG? As discussed earlier, the limitations of the Choleski approach and the case for alternative means of identifying VAR models have been well documented (Bernanke 1986, Sims 1986, Blanchard and Quah 1989, Cooley and Dwyer 1998). Identification of vector autoregression (VAR) models through Choleski decomposition of the variance-covariance matrix implicitly imposes a recursive structure for the economy. Since there is no universally accepted *a priori* ordering or sequencing of variables in a system, as is required with the use of the Choleski approach, the final reported estimates are subjective and may vary across researchers.

The DAG methodology proposed in this study has straightforward application to empirical studies of agricultural market performance and efficiency. For example, VAR-type empirical studies on spatial market integration and agricultural price transmission usually make arbitrary assumptions about the contemporaneous causal relationships among various market prices. Future research of this sort can benefit from the application of the DAG method in the specification of a contemporaneous causal relationship that is consistent with the data-generating process. Thus, this data-based identification method is recommended as an empirical tool for identifying future VAR-type time-series models. Finally, directed acyclic graphs are meant to be complementary to (not a substitute for) more established means of identifying VAR models, especially in cases where theory fails to provide a definitive guide as to the causal path of variables in contemporaneous time. Although this data-based methodology has a potentially wide range of applications in econometric modeling, additional research is still needed to assess the robustness of the directed graph technique under alternative assumptions and estimation time periods.

References

Awokuse, T.O., and D.A. Bessler. 2003. "Vector Autoregression, Policy Analysis, and Directed Graphs: An Application to the U.S. Economy." *Journal of Applied Economics* 6(1): 1–24.

Bernanke, B.S. 1986. "Alternative Explanations of the Money-Income Correlation." *Carnegie-Rochester Conference Series on Public Policy* 25: 49–99.

Bessler, D.A. 1984. "Relative Prices and Money: A Vector Autoregression on Brazilian Data." *American Journal of Agricultural Economics* 66(1): 25–30.

Bessler, D.A., and J. Yang. 2003. "The Structure of Interdependence in International Stock Markets." *Journal of International Money and Finance* 22(2): 261–287.

Blanchard, O.J., and D. Quah. 1989. "The Dynamic Effects of Aggregate Demand and Supply Disturbances." *American Economic Review* 79(4): 655–673.

Bordo, M.D. 1980. "The Effect of Monetary Change on Relative Commodity Prices and the Role of Long-Term Contracts." *Journal of Political Economy* 88(6): 1088–1109.

Chambers, R.G., and R.E. Just. 1982. "An Investigation of the Effect of Monetary Factors on Agriculture." *Journal of Monetary Economics* 9(2): 235–247.

Cooley, T.F., and M.D. Dwyer. 1998. "Business Cycle Analysis Without Much Theory: A Look at Structural VARs." *Journal of Econometrics* 83(1–2): 57–88.

Cooley, T.F., and S.F. LeRoy. 1985. "Atheoretical Macroeconomics: A Critique." *Journal of Monetary Economics* 16(3): 283–308.

Devadoss, S., W.H. Meyers, and D.R. Starleaf. 1990. "Impacts of U.S. Monetary Policies on the Farm Sector: An Econometric Analysis." *Applied Economics* 22(11): 1451–1470.

Devadoss, S., and H.M. William. 1987. "Relative Prices and Money: Further Evidence for the United States." *American Journal of Agricultural Economics* 69(4): 838–842.

Dickey, D.A., and W.A. Fuller. 1979. "Distribution of the Estimators for Autoregression Time Series with a Unit Root." *Journal of the American Statistical Association* 74(366): 427–431.

Doan, T. 2004. *RATS: User's Guide Version 6.0*. Evanston, IL: Estima Press.

Dorfman, J.H., and W.D. Lastrapes. 1996. "The Dynamic Responses of Crop and Livestock Prices to Money-Supply Shocks: A Bayesian Analysis Using Long-Run Identifying Restrictions." *American Journal of Agricultural Economics* 78(3): 530–541.

Granger, C.W.J. 1969. "Investigating Causal Relations by Econometric Models and Cross-Spectral Methods." *Econometrica* 37: 424–438.

Hannan, E.J., and B.G. Quinn. 1979. "The Determination of the Order of an Autoregression." *Journal of the Royal Statistical Society Series* B41(2): 190–195.

Johansen, S., and K. Juselius. 1990. "Maximum Likelihood and Inference on Cointegration: With Applications to the Demand for Money." *Oxford Bulletin of Economics and Statistics* 52(2): 169–210.

Lapp, J.S. 1990. "Relative Agricultural Prices and Monetary Policy." *American Journal of Agricultural Economics* 72(3): 622–630.

Lutkepohl, H., and H.E. Reimers. 1992. "Impulse Response Analysis of Cointegrated Systems." *Journal of Economic Dynamics and Control* 16(1): 53–78.

Orden, D., and P.L. Fackler. 1989. "Identifying Monetary Impacts on Agricultural Prices in VAR Models." *American Journal of Agricultural Economics* 71(2): 495–502.

Osterwald-Lenum, M. 1992. "A Note with Quantiles of the Asymptotic Distribution of the Maximum Likelihood Cointegration Rank Test Statistics: Four Cases." *Oxford Bulletin of Economics and Statistics* 54(3): 461–472.

Pearl, J. 1995. "Causal Diagrams for Empirical Research." *Biometrika* 82(4): 669–710.

____. 2000. *Causality*. Cambridge, MA: Cambridge University Press.

Phillips, P. 1998. "Impulse Response and Forecast Error Variance Asymptotics in Nonstationary VARs." *Journal of Econometrics* 83(1–2): 21–56.

Phillips, P.C.B., and P. Perron. 1988. "Testing for a Unit Root in Time Series Regression." *Biometrika* 75(2): 335–346.

Saghaian, S.H., M.F. Hasan, and M.R. Reed. 2002. "Overshooting of Agricultural Prices in Four Asian Economies." *Journal of Agricultural and Applied Economics* 34(1): 95–109.

Saghaian, S.H., M.R. Reed, and M.A. Marchant. 2002. "Monetary Impacts and Overshooting of Agricultural Prices in an Open Economy." *American Journal of Agricultural Economics* 84(1): 90–103.

Scheines, R., P. Spirtes, C. Glymour, and C. Meek. 1994. *Tetrad II: User's Manual and Software*. Hillsdale, NJ: Lawrence Erlbaum Associates, Inc.

Schuh, G.E. 1974. "The Exchange Rate and U.S. Agriculture." *American Journal of Agricultural Economics* 56(1): 1–13.

Schwarz, G. 1978. "Estimating the Dimension of a Model." *Annals of Statistics* 6(2): 461–464.

Sims, C.A. 1980. "Macroeconomics and Reality." *Econometrica* 48(1): 1–48.

____. 1986. "Are Forecasting Models Usable for Policy Analysis?" *Federal Reserve Bank of Minneapolis Quarterly Review* 10(1): 2–16.

Spirtes, P., C. Glymour, and R. Scheines. 2000. *Causation, Prediction, and Search,* Cambridge, MA: MIT Press.

Swanson, N.R., and C.W.J. Granger. 1997. "Impulse Response Functions Based on a Causal Approach to Residual Orthogonalization in Vector Autoregressions." *Journal of the American Statistical Association* 92(437): 357–367.