**The Causal Structure of Land Price Determinants**

by

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**Abstract**

This paper investigates causation contemporaneously and over time to elucidate the persistent lack of agreement about what "causes" changes in farmland prices. Using recently developed causal modeling framework of directed acyclic graphs (DAGs) and cointegrated (VAR) techniques, the assumed causal structures of existing structural and empirical models are tested directly. The results validate concerns about the nonstationarity of these series. Land price changes are found to respond to a small subset of the oft-cited causes of price change, including macroeconomic variables.

**Key words**: Causality, cointegration, directed acyclic graphs, land prices, VAR.

# The Causal Structure of Land Price Determinants

## Introduction

Contradictions persist in the literature explaining the relative and absolute importance of the various causes of farmland price changes. In part, such disagreements can be attributed—without necessarily citing methodological fault—to the idiosyncrasies of ad hoc modeling, fundamental differences between theoretical and data-driven approaches (i.e., structural versus empirical modeling), and the temporal or spatial differences in the data studied in empirical models. Within the last decade, however, two active strains in this research stand out for their inability to approach an externally (or even internally) recognized consensus.

The first strain sought to better understand the explanatory failures of the present-value model (Johnson; Lloyd; Tegene and Kuchler; Hallam; Falk and Lee; Lence and Miller), while the second offered improved structural models (Just and Miranowski; Chavas and Thomas).[1] These studies prompted others that use empirical models to question the robustness of the structural efforts (Lence 2001) and the conclusions of the empirical efforts. Thus, although the analysis of farmland price changes continues to be a vibrant area of study, greater clarity would improve the practical value of the results and more consistent structural and empirical modeling is an important first step toward achieving this clarity. The research presented in this paper comprehensively tests for causal structure of the determinants of fluctuations in farmland prices and thereby provides new insight on the appropriateness of many alternate modeling strategies.

The analysis of causal structure is not an entirely new area of research on land prices. Several studies have considered causation with respect to price or price changes. Falk and Lee argue that early structural models failed to predict well because of the inelasticity of supply made the simultaneous equations approach inappropriate. Not surprisingly, studies in the last 20 years all assume price is endogenous and few reflect on the possibility of simultaneous or reverse causation between price and quantity (or other variables).[2] The present paper tests for and cannot reject the endogeneity of price.

Several authors have also examined, or at least questioned, the relationships among independent variables. Specifically, potentially important explanations for the persistent controversy about the importance of various causal factors include: (1) non-spurious relationships among the independent variables; (2) correlations with omitted variables; and (3) the fit of land-price models with nonstationary price data. This paper examines these issues. In addition, structural models differ in that they start by specifying most of the causal relationships among variables, while empirical studies often focus on a small set of explanatory variables. This paper will be the first to examine the joint consequences of these two sets of assumptions.

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 (DAG), a recent and powerful modeling technique for analyzing contemporaneous causal structure (Spirtes et al. 2000; and Pearl 1995, 2000). Although some authors have applied this methodology to economic issues (Swanson and Granger, 1997, Bessler and Akleman, 1998), this study is the first to apply DAG to the causal structure of the key determinants of farmland prices.

Using data for the U.S. and three representative agricultural states (Iowa, Kansas, and Georgia)—substantially the same as used by Just and Miranowski—the analysis of DAGs rejects the contemporaneous causation by all of the commonly cited exogenous causes of land-price changes except a small subset of financial variables. The results suggest that land price changes are caused only by two macroeconomic variables: capital gains and real estate debt. Quantity variables are insignificant and, surprisingly, inflation and returns only indirectly affect land price changes. Results from the DAG and cointegrated vector autoregression (VAR) models suggest that the data warrant a simple model where macroeconomic variables cause land price changes. The collective results of these models thus simplify contemporaneous causal modeling and suggest that spurious correlations may indeed be a problem in the formulations of some existing models. The identified macroeconomic variables explain changes contemporaneously and over time, while many other determinants of farmland prices (conditioned on other variables) are found to have insignificant impact on farmland prices. The rest of the paper is organized as follows. Section 2 provides a brief discussion of the commonly cited determinants of farmland price changes and describes the data (variables) used in analysis. Then, the third and fourth sections present the empirical methods and analysis of causation using DAG and cointegrated VAR models, respectively. The fifth section concludes the paper.

**Determinants of Land Prices**

Several papers have investigated the causal effects of various variables on the observed fluctuations in farmland prices. The commonly used "explanatory" variables can be grouped into these categories: measures of government programs, measures of net return to agriculture, measures of land quantity, and measures of financial (credit market constraints) and/or macroeconomic activity. Gardner (2001) used cross-sectional, farm-level data to investigate the role of government programs in explaining changes in farmland prices and concluded that government payments have no significant impact on farmland prices in the past three decades. Phipps (1984) and Melichar (1979) concluded in separate analyses that relative to measures of net return to agriculture, non-farm variables are not as important in explaining changes in farmland prices.

In contrast, others (Alston; Burt; Hallam et al.; Just and Miranowski) found that macroeconomic variables such as inflation, interest rates on debt, and measures of capital gains are important determinants of changes in land prices. Castle and Hoch identified a “real capital gains” component, which cause real price changes as land increases or decreases in value relative to general price levels. Castle and Hoch argued that the capitalization of real capital gains may explain up to 50 percent of fluctuations in land prices and that the landowner treats these gains as income, thus reinforcing the image of farmer-landowners participating simultaneously in land markets (as investor) and commodity markets (as suppliers). Since land can be regarded as a financial investment asset, Castle and Hoch and Hallam et al. also identified interest rates (opportunity cost of capital) and the real value of debt arising from general price level (inflation) as key determinants of changes in land prices.

Just and Miranowski synthesized the literature by developing a theoretical framework that combines most of these variables in a single model of farmland changes. *A priori*, their model assumes that price is endogenous and excludes all other potential causal interactions except the unidirectional causation of the “explanatory” variables on price. Just and Miranowski concluded that macroeconomic variables are the dominant explanatory factors responsible for changes in farmland prices; although the assumed structural relationships are not without basis, it is valuable nonetheless to test these maintained hypotheses. To consider a contrasting model without any prior causal assumptions, consider Figure 1. Figure 1 would require data or theory to remove initial casual associations. Since economic theory does not always give clear and unambiguous direction on causal paths, it is reasonable to explore causal information contained in observed data with modeling techniques such as the DAG combined with cointegrated VAR analyses.

This study follows the variable definitions and annual data sources[3] from 1963 to 1983 as outlined in Just and Miranowski and extended their data to cover the 1961 to 1995 period using the same (or similar) variables. These variables go well beyond farm-firm income and capture the various explanations for land price changes in the literature. Annual data were obtained for the U.S. and three representative agricultural states (Iowa, Kansas, and Georgia) for the following thirteen variables: land value per acre (LPRICES), acreage in farms (ACRE), number of farms (NFARM), real estate debt (DEBT), real estate tax rate (RETAX), net returns per acre to farming with government payments (RETURNG), net returns per acre to farming without government payments (RETURN), implicit GNP price deflator (INFLATION), average interest rate on farm real estate debt (IDEBT), interest rate on savings or interest rate on muni-bonds (IRATE), proportion of farmland financed by debt (PFDET), average tax rate (AVTAX), and the proportion of current land value attributable to capital gains (CAPGAINS). All data series, except interest rates, are in natural logarithms.

V(.) in Equations (1) and (2) contains the contemporaneous correlation (zero order) matrices for the thirteen variables, for the Unites States and Iowa, respectively. These zero-order correlation matrices are used as the starting point in the analysis of causal structure inherent to the data. The order of the variables is given as listed above the matrix. As shown in equation (1), there is a relatively high unconditional correlation between land prices (LPRICES) and the other variables in the system. For example, the unconditional correlation between LPRICES and DEBT is 0.98 while the correlation between LPRICES and CAPGAINS is 0.73. Furthermore, consider the correlation matrix in equation (2), the Iowa farmland data used in Just and Miranowski. All 12 explanatory variables have correlation coefficients in excess of 0.33 with price. Yet, they are also correlated with each other; only 16 of the 65 correlations are below 0.30 and, without AVTAX, PFDET, and CAPGAINS, all correlations exceed 0.30. Hence, there is a real need to consider all possible relationships among the variables and exclude certain associations in a systematic manner.

$$(1)\quad V(U.S.) = \begin{array}{c} \begin{array}{ccccccccccccc} \text{LP} & \text{ACRE} & \text{NFARM} & \text{REDET} & \text{RETAX} & \text{NETRg} & \text{NETR} & \text{INFL} & \text{IREDET} & \text{ISAV} & \text{AVTAX} & \text{PFDET} & \text{CGAIN} \end{array} \\ \begin{pmatrix} 1.00 & & & & & & & & & & & & \\ 0.98 & 1.00 & & & & & & & & & & & \\ 0.98 & 1.00 & 1.00 & & & & & & & & & & \\ 0.98 & 1.00 & 1.00 & 1.00 & & & & & & & & & \\ 0.88 & 0.90 & 0.90 & 0.90 & 1.00 & & & & & & & & \\ 0.67 & 0.71 & 0.71 & 0.71 & 0.60 & 1.00 & & & & & & & \\ 0.55 & 0.57 & 0.57 & 0.57 & 0.46 & 0.96 & 1.00 & & & & & & \\ 0.98 & 1.00 & 1.00 & 1.00 & 0.90 & 0.71 & 0.57 & 1.00 & & & & & \\ 0.95 & 0.94 & 0.94 & 0.94 & 0.83 & 0.71 & 0.60 & 0.95 & 1.00 & & & & \\ 0.58 & 0.52 & 0.52 & 0.53 & 0.54 & 0.46 & 0.49 & 0.54 & 0.66 & 1.00 & & & \\ 0.44 & 0.41 & 0.41 & 0.41 & 0.41 & 0.59 & 0.63 & 0.42 & 0.45 & 0.43 & 1.00 & & \\ 0.90 & 0.95 & 0.95 & 0.95 & 0.82 & 0.75 & 0.59 & 0.94 & 0.88 & 0.44 & 0.40 & 1.00 & \\ 0.73 & 0.60 & 0.60 & 0.61 & 0.53 & 0.32 & 0.31 & 0.60 & 0.61 & 0.53 & 0.44 & 0.44 & 1.00 \end{pmatrix} \end{array}$$

Furthermore, high collinearity is observed among ACRE, NFARM, and DEBT. Both ACRE and NFARM are essentially measuring the same economic activity: quantity of land in agriculture. This initial inspection of the unconditional correlation matrix suggests that potential determinants of land prices are some measures or proxy for quantity of farmland, real estate debt, net cash rent, inflation rate, interest rate, and taxation. As DAG investigates the conditional correlation among these variables, one reasonably expects that some of the variables' effect on variability in farmland prices will cancel out each other.

$$
(2)\quad \mathrm{V}(\mathit{Iowa}) = \begin{array}{c}
\begin{array}{ccccccccccccc}
\mathbf{LP} & \mathbf{ACRE} & \mathbf{NFARM} & \mathbf{REDET} & \mathbf{RETAX} & \mathbf{NETRg} & \mathbf{NETR} & \mathbf{INFL} & \mathbf{IREDET} & \mathbf{ISAV} & \mathbf{AVTAX} & \mathbf{PFDET} & \mathbf{CGAIN}
\end{array} \\
\begin{pmatrix}
1.00 & & & & & & & & & & & & \\
0.96 & 1.00 & & & & & & & & & & & \\
0.96 & 1.00 & 1.00 & & & & & & & & & & \\
0.96 & 1.00 & 1.00 & 1.00 & & & & & & & & & \\
0.67 & 0.65 & 0.65 & 0.65 & 1.00 & & & & & & & & \\
0.71 & 0.78 & 0.78 & 0.78 & 0.46 & 1.00 & & & & & & & \\
0.53 & 0.58 & 0.58 & 0.58 & 0.31 & 0.90 & 1.00 & & & & & & \\
0.96 & 1.00 & 1.00 & 1.00 & 0.65 & 0.78 & 0.57 & 1.00 & & & & & \\
0.93 & 0.94 & 0.94 & 0.95 & 0.61 & 0.78 & 0.62 & 0.95 & 1.00 & & & & \\
0.57 & 0.52 & 0.52 & 0.53 & 0.41 & 0.52 & 0.51 & 0.54 & 0.66 & 1.00 & & & \\
0.33 & 0.31 & 0.31 & 0.32 & 0.48 & 0.26 & 0.22 & 0.31 & 0.29 & 0.12 & 1.00 & & \\
0.56 & 0.74 & 0.74 & 0.74 & 0.41 & 0.70 & 0.50 & 0.73 & 0.64 & 0.26 & 0.18 & 1.00 & \\
0.40 & 0.16 & 0.16 & 0.17 & 0.15 & -0.02 & 0.01 & 0.16 & 0.21 & 0.28 & 0.21 & -0.44 & 1.00
\end{pmatrix}
\end{array}
$$

## Analytical Framework and Methodological Issues

This section provides a brief discussion of the two methodological approaches adopted in this study for the analysis of the causal structure of the determinants of land prices. The conceptual framework for DAG is discussed first because it determines the contemporaneous causal relationship among the variables. Then, an abbreviated synopsis of the cointegrated VAR modeling techniques is offered, since this technique is more common in the literature than DAG.

### *Directed Acyclic Graphs (DAG) Theory*

Structural models, such as Just and Miranowski's, often rely on prior economic theory as the source of their identifying restrictions for edge removal and assigning the direction of causal flow among the variables in the system. However, in some cases, this practice may itself be arbitrary, as theory may not always yield a clear identifying structure. The DAG bridges the gap between theory and practice by allowing theory to suggest which variables to initially include in the system. Then, the data-based DAG algorithm uses the inherent data-generating process to help assign causal flow on observational (non-controlled) data.

The most commonly used definition of causality is that proposed by Granger, which exploits the asymmetry that a cause precedes its associated effect (and not vice versa). Granger formally defined cause as follows: $Y_n$ is said to cause $X_{n+1}$ if $[P(X_{n+1} \in A| \Xi_n)] \neq [P(X_{n+1} \in A| \Xi_n - Y_n)]$, for some A, where $X_n$ and $Y_n$ are time ordered sets of variables defined for time = $-\infty, \ldots, 0, 1\ldots, n$, and $\Xi_n$ is the set of non-redundant information available in time n. Alternatively, X Granger-causes Y, if a series Y is better predicted by its complete past information set than by that universe less the series X. More recently, Spirtes et al. (2000), and Pearl (1995, 2000) describe DAGs—a non-time sequence asymmetry in causal relations as an alternative and more comprehensive approach for investigating causal relationships. This new approach can be used as an alternative (or complement to) Granger's time sequence asymmetry in causal systems.

A DAG is a picture representing the causal flow among a set of variables such that there are no directed cycles, i.e., it is not possible to start at a vertex and follow a directed path back to the same vertex. The vertices (nodes) of these graphs represent variables on which data has been obtained, and line segments connecting vertices (directed edges or arrows) are generated by calculations of conditional statistical dependence or independence among pairs of variables (ceteris paribus).

For the sake of illustration, we assume three economic variables, X, P, and Q. In the first scenario, we assume a causal relation such that X causes P and Q, depicted as: $P \leftarrow X \rightarrow Q$. The existence of a common cause in X implies that the unconditional correlation between P and Q is non-zero, but the conditional correlation between P and Q, given prior knowledge of the common cause X, is zero. This suggests that common causes screen off associations between their joint effects. In contrast, in the case of a second scenario where both X and Q cause P, depicted as X→ P ← Q, then the unconditional correlation between X and Q is zero. However, the conditional association between X and Q, given the common effect P is not zero. This implies that common effects do not screen off association between their joint causes.

Following Bessler and Yang (2003), DAGs can be used to represent conditional independence as implied by the recursive product decomposition:

$$(3) \qquad \Pr(v_1,\ v_2,\ v_3,\ldots v_n) = \prod_{i=1}^{n} \Pr(v_i \mid pa_i)$$

where Pr is the probability of vertices $v_1,\ v_2,\ v_3,\ldots v_n$ and $pa_i$ the realization of some subset of the variables that precede (come before in a causal sense) $v_i$ in order ($v_1,\ v_2,\ v_3,\ldots v_n$). The concept of directional separation (**d-separation**) was first introduced by Pearl (1995) as a graphical representation of conditional independence. Pearl (1995) showed that the conditional independence relations given by Equation (3) could be represented by d-separation. Pearl's (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.

In order to apply the concept of d-separation to observational data, Spirtes et al. (2000) developed an algorithm (PC algorithm) for building directed acyclic graphs. The PC algorithm is collection of commands that determines the causal direction among variables by using a stepwise testing approach to remove edges between variables. Edges among a set of N variables (e.g., residuals from a VAR), are removed sequentially based on zero correlation or partial correlation. PC algorithm and its more refined extensions are available as the software *TETRAD II (see* Scheines, et al. (1994)).

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:

$$z(\rho(i,j\,|\,k),n)=\left[\frac{1}{2}\sqrt{n-|\,k\,|-3}\right]\ln\left\{\frac{|\,1+\rho(i,j\,|\,k)\,|}{1-\rho(i,j\,|\,k\,|)}\right\} \tag{4}$$

and n is the number of observations used to estimate the correlations, ρ( 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(ρ(i,j|k)n) - z(r(i,j|k)n) is standard normal.

### *Cointegrated Vector Autoregression (VAR) Modeling*

Since the cointegration and error correction methodology is fairly commonplace and well-documented elsewhere (Banerjee, et al.; Engle and Granger; Johansen; Johansen and Juselius), only a brief overview is provided. 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. Juselius' maximum likelihood (ML) procedure is a very popular alternative to the Engle-Granger method. The main attraction of this procedure is that it tests for the possibility of multiple cointegrating relationships among the variables. Johansen and Juselius 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 based on the error correction representation given by

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

where $X_t$ is an (nx1) column vector of p variables, $\mu$ is an (nx1) vector of constant terms, $\Gamma$ and $\Pi$ represent coefficient matrices, $\Delta$ is a difference operator, k denotes the lag length, and $\varepsilon_t \sim N(0, \Sigma)$. The coefficient matrix $\Pi$ is known as the impact matrix, and it contains information about the long-run relationships.

Equation (5) 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 $\Gamma$ and $\Pi$ respectively. The error correction model (ECM) equation above allows for three model specifications: (a) If $\Pi$ is of full rank, then $X_t$ is stationary in levels and a VAR in levels is an appropriate model; (b) If $\Pi$ 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); and (c) If the rank of $\Pi$ is a positive number, $r$ and is less than $p$ (where p is the number of variables in the system), there exists matrices $\alpha$ and $\beta$, with dimensions ($p$ x $r$), such that $\Pi = \alpha\beta'$. In this representation $\beta$ 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 $\alpha$ contains the short run speed of adjustment coefficients for the equations in the system.

Johansen's methodology requires the estimation of the VAR Equation (5) and the residuals are then used to compute a likelihood ratio (LR) test statistic that can be used in the determination of the cointegrating vectors of $X_t$. The trace test considers the hypothesis that the rank of $\Pi$ is less than or equal to r cointegrating vectors, and it is expressed as:

$$(6) \qquad Trace = -T \sum_{i=r+1}^{n} \ln(1-\lambda_i)$$

The distribution for this test is not given by the usual chi-squared distributions. The asymptotic critical values for the trace likelihood ratio tests are calculated via numerical simulations (see Johansen and Juselius; Osterwald-Lenum).

## Empirical Analysis and Results

### *Unit Roots*

An important question pertinent to time series data is whether the data series is stationary in levels or stationary after first differencing. If the data series are stationary after first differencing, then cointegration or error correction (ECM) models are needed to analyze the empirical relationships among the variables. Two univariate unit root tests were examined for each of the thirteen series. First, the augmented Dickey-Fuller (ADF) t-tests for the null of non-stationarity (unit roots). Due to the well-known low power of ADF tests, the KPSS test (proposed by Kwiatkowski et al.) was also used to test for the null of stationarity. The combination of ADF and KPSS makes it possible to test for both the null of unit roots and that of stationarity. This approach is very robust in determining the presence of unit roots. Two time trend specifications of both tests were explored: (1) with constant only (without) linear time and (2) with linear time trend. Results for the ADF and KPSS tests are given in Table 1.

Overall, from the combination of the results from both the ADF and KPSS tests, the time series are found to be integrated at most of order one. This implies the possibility of cointegrating relationships among the variables.

***Directed acyclic graphs (DAG) Results*[4]**

Given the presence of unit roots in the undifferenced data, the TETRAD program, a DAG algorithm, was applied to the thirteen variables to remove edges between variables and directing causal flow of information between variables. The PC algorithm removes edges from the complete undirected graph by first checking for unconditional (zero order conditioning) and conditional correlations (first and second order conditioning) between pairs of variables. Edges connecting variables having zero correlation are removed. Remaining edges are then checked for first order partial correlation (correlation between two variables conditional on a third variable) equal to zero. Similarly, edges connecting variables having zero first order conditional correlation are removed. Edges that survive this check of first order conditional correlations are then checked against zero second order conditional correlation, etc.

As suggested by Spirtes et al, various levels of significance are considered in an attempt to achieve an unambiguous causal structure of the variables in contemporaneous time. Figures 2 and 3 present graphs based on unconditional correlation matrices in equations (1) and (2) at the following nominal levels of significance: .10 and .20. As the TETRAD II search algorithm involves multiple hypotheses testing for edge removal, the final significance level is generally larger than that reported as nominal. Presenting results for alternative levels of significance allows one to assess quantitatively the robustness of the results with respect to significance levels. Regarding the significance levels and PC algorithm, Spirtes, Glymour and Scheines (2000, p. 116) suggest that "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. .2 at sample sizes less than 100, and .1 at sample sizes between 100 and 300) may improve performance at small sample sizes."

Since the sample size is limited to 35 observations (1961-1995), this paper presents the 20 percent significance level as the cut off for the removal of edges.[5] This implies that in order for the algorithm to not remove edges, the correlation and conditional correlation between two variables must be significantly different from zero at the 20 percent significance level. Figures 2 and 3 show that at the 10 percent significance levels the directed edges are represented by the arrows with dotted lines while for the 20 percent level, the edges are represented by solid lines. The resulting graphs are identical in most cases. Some of the edges were undirected (ACRE and NFARM, and AVTAX and RETURN). Since there is an undirected edge connecting these variables, there exists a relationship between them, but one cannot say which variable is causal.

Since the DAG results for both Iowa and the U.S. are very similar at both levels of significance, only the results for U.S. data in Figure 1 are discussed in detail. Relative to the potential 12 edges into LPRICES in the undirected DAG in Figure 1, inspection of the graphs in Figures 2 and 3 reveals that only two edges into LPRICES remain: edges originating from CAPGAINS and DEBT. This implies that only two of these variables are direct and contemporaneous causes of changes in LPRICES. In addition to the two direct edges into LPRICES, there are also possibilities of indirect causes via the direct path from CAPGAINS and DEBT. The notable difference between DAG results for U.S. data (Figure 2) and that for Iowa (Figure 3) is the causal edge between INFLATION and IDEBT. The causal path observed from IDEBT to INFLATION for the U.S data is reversed for the case of Iowa. This may be due to the very small sample size or a reflection of the fundamental differences between in Iowa and U.S. aggregate data.

Relative to results from previous studies emphasizing the role of other variables as determinants of land prices—inflation (in Feldstein; Falk and Lee; Just and Miranowski), net returns to farming (in Phipps; Falk and Lee; Lence and Miller), and interest rates (Alston and Burt)—of particular interest are the results that there are no edges remain between LPRICES and INFLATION, IRATE, and RETURN. Using the 20 percent level of significance the edge between LPRICES and INFLATION is not removed at zero order conditioning, as the correlation (0.962) has a p-value of 0.00. Although the edge connecting LPRICES and INFLATION survives an unconditional test (any test with a p-value greater than 0.2), this edge is removed at first order conditioning as the corr(LPRICES, INFLATION | DEBT) = -0.17, which has a p-value of 0.34 that is well above what is generally considered acceptable. Similarly, the edges connecting LPRICES and IRATE and the edges LPRICES and RETURN, though significant at zero order conditioning, these two edges were also removed at first order conditioning as the corr(LPRICES, IRATE | INFLATION) = 0.21 (p-value = 0.22), and corr(LPRICES, RETURN | DEBT) = -0.13 (p-value = 0.48), respectively. Similar results from the unconditional correlation test are true for the other variables. These outcomes explain why no direct edges exist between LPRICES and all other variables (except CAPGAIN and DEBT) in the system.

Overall, at the 20 percent level of significance, the DAG results shows that land prices in the current time period respond directly to contemporaneous changes in the proportion of capital gains applied to taxable income and real estate debt. Land prices also change, indirectly, in response to same-period changes in a quantity measure—number of farms. A causal path from IRATE to LPRICES was marginally rejected at a 22 percent significance level. The conditional correlations of the other variables were not statistically significant.

These results are a marked departure from many of the structural models, which assumed a richer relationship among the theory-derived explanations of land price changes. Indeed, the DAG analysis suggests that land price models may be comparatively parsimonious. These results, however, do not suggest what variables explain the composition of land prices. Since these explanatory variables do not experience substantive, yearly changes, one would not expect that they explain historical changes in land prices.

Based on the DAG results, a smaller set of variables can be tested for causation over time. This is fortunate given the limited data available. Using these variables and prior knowledge from other studies' findings on the importance of inflation rate, subsequent analysis was performed on the following six variables: LPRICES, NFARM, INFLATION, IRATE, DEBT, and CAPGAINS.

### *Cointegrated VAR Test Results*

Causal information given by DAG results can be used, first, to determine which of the thirteen variables to exclude from the system. Second, the DAG results are also used to assign causal flow for identifying the covariance matrix in a VAR model (Bessler and Akelman). As Table 1 shows, the six variables (LPRICES, NFARM, INFLATION, IRATE, DEBT, and CAPGAINS) suggested by DAG are non-stationary in levels, but stationary in first differences. So, the cointegration relationship among the six variables is investigated.

Following Johansen, tests are performed for both the number of cointegrating vectors and the placement of the constant in the error correction model. Table 2 reports tests on the number of cointegrating vectors for both the constant in the cointegrating vector (*) and the constant outside of the cointegrating vector over 1961 to 1995. For the U.S. dataset, test results from both specifications indicate that there are six cointegrating vectors (full rank). As specified in earlier section, this implies that the appropriate model variant of equation (5) is the VAR in levels. For the Iowa dataset, test results from both specifications suggest the presence of three cointegrating vectors (reduced rank). Also, this implies that the appropriate model variant of equation (5) is the VAR in levels or an error correction model (ECM). As shown in Sims, et al., if the time series are cointegrated, inference based on levels VAR is equivalent to that based on an error correction model (ECM). Throughout the remainder of this paper, the basic model of analysis is VAR in levels.

***VAR-based Innovation Accounting***

The six-variable levels VAR(k) variant of equation (5), comprised of LPRICES, NFARM, INFLATION, IRATE, DEBT, and CAPGAINS, examines the dynamic causal relationship between land prices and the other five variables. The first step is to determine the appropriate lag structure of the VAR using tests such as the Schwartz's (1978) BIC, and Hannan-Quinn (1979) HQ information criteria. Two alternative order selection criteria are applied to an unrestricted levels VAR model in order to determine the appropriate lag length. Both the Schwartz's (1978) BIC and the Hannan-Quinn (1979) HQ information criteria used to determine the order of the VAR suggest that the optimal lag length of two (which has white noise residuals). Subsequent analyses proceed with the use of VAR with lag length k=2.

The rest of this section analyzes the dynamic effects of the structural innovations on each of the variables in the six-variable VAR model for both Iowa and U.S. data. The DAG results in Figures 2 and 3 are used to specify the causal path for the ordering of the Sims-Bernanke decomposition of contemporaneous innovations. Table 3 contains the forecast error variance decompositions (FEVD) associated with the VAR model for U.S. data under the ordering of innovations as suggested by the DAG 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 1 to 7 years.

The first panel contains error decompositions for LPRICES. For U.S. data, the most significant determinant of the variation in LPRICES is the proportion of current land value attributable to capital gains (CAPGAINS). Within the first year, CAPGAINS explains 86.81 percent of the variability in LPRICES while in the long run (7 years later),[6] CAPGAINS still account for 27.88 percent of the variability in LPRICES. The other key determinant of variation in LPRICES in the U.S. data is interest rate on savings or interest rate on muni-bonds (IRATE). IRATE explains about 42.38 percent of the variability in LPRICES in the long run. The only other variable with notable contributions in the long run is real estate debt (DEBT), which account for up to 10.86 percent of the changes in LPRICES for the U.S. data. The relative impact of the other variables is considerably lower.

For completeness, Table 3 also includes results for the remaining panels, which contain error decompositions for NFARM, INFLATION, IRATE, DEBT, and CAPGAINS, respectively. For example, in panel 2 the error decomposition for the returns to farming deflator (RETURN) shows that in the short run, RETURN explains most of its on variation. This suggests that return to farming is exogenous in the very short run. The only other key determinant of returns to farming in this system is real estate debt (DEBT). In the last panel of Table 3, the error decomposition for CAPGAINS shows that it is clearly exogenous, explaining 100 percent of its own variation in the first year and up to 36 percent explained by own innovations in the long run.

Table 4 contains the FEVD associated with the VAR model for Iowa data under the ordering of innovations as generated by the DAG result given in Figure 3. Between 10.41 and 24.10 percent of the variations in LPRICES is explained by own innovations. This implies that land price expectation is an important determinant of LPRICES. The results also reveal that CAPGAINS is an important determinant of the variation in LPRICES. In the first year, CAPGAINS explains 70.35 percent of the variability in LPRICES while in the long run (7 years later), CAPGAINS still account for about 29 percent of the variability in LPRICES. In the long run, the most significant determinant of LPRICES in Iowa is the interest rate on savings or interest rate on muni-bonds (IRATE). The innovation to IRATE explains about 37.54 percent of the variability in LPRICES in year 7. The third variable with significant contributions to variations in LPRICES is returns to farming (RETURN), which account for up to 14.63 percent of the changes in LPRICES for the Iowa data. The effect of implicit GNP price deflator (INFLATION) is relatively minimal at 2.62 percent at the 7-year horizon.

The overall conclusions from the variance decomposition results indicate that the following variables are key determinants of changes in farmland prices: land price expectations, the returns to farming, opportunity cost of capital, and capital gains tax variables. This finding is consistent with results from earlier studies by various researchers

(Alston; Burt; Castle and Hoch; Just and Miranowski). The results also suggest that some commonly employed explanatory variables may not have substantively important effects on changes in land prices, over time.

**Concluding Remarks**

Although the causal effects of various variables on the observed fluctuations in farmland prices have been studied before, the results conflict and a lack of consensus persists about what "causes" changes in farmland prices. In order to unravel the causal relation between farmland prices and other variables, past analyses have either relied on static theory-based models or on other empirical models with ad hoc lagged relations. This paper extends previous investigations in this area by employing a combination of cointegrated VAR and directed acyclic graphs (DAG), a recently developed causal modeling technique. This study is the first to apply DAGs to help sort out the causal structure of the key determinants of farmland prices. DAG offers a powerful tool for analyzing the contemporaneous causal structure of farmland prices and its determinants.

This paper used the same annual dataset (extended to cover the 1961 to 1995 period) and the same (or similar) thirteen variables definitions as outlined in Just and Miranowski. Annual data were obtained for the U.S. and three representative agricultural states (Iowa, Kansas, and Georgia), which allowed for the consideration of the main categories of variables often cited as determinants of farmland prices: measures of government programs, measures of net return to agriculture, measures of land quantity, and measures of financial (credit market constraints) and/or macroeconomic activity. DAGs investigated the contemporaneous causal relations among these variables while the cointegrated VAR model (variance decompositions) was used to sort out the lagged causal relationships. Both approaches yield similar results that confirm the importance of measures of net returns to farming, credit market constraints and/or macroeconomic activity as significant determinants of fluctuations in farmland prices.

The results validate concerns about the nonstationarity of these series, which Lence (2001) argued was a shortcoming that undercut the analytical bite of the Just and Miranowski analysis. When causation is studied directly, one finds a much simpler modeling task. Land price changes appear to be sensitive to macroeconomic variables and the net return to farming. This implies that future structural and empirical models can focus more directly on a small set of variables without sacrificing analytical completeness.

The analyses also suggest what appears to be a new implication: some of the variables that affect land price changes might be beyond the scope of agricultural policy. Undoubtedly, this only holds given a continuation of the relatively stable institutional environment, which contributes a substantively important, stable value to agricultural land. Nevertheless, the policy importance of this result should not be underappreciated. If the welfare of farm firms derives from their role as commodity producers and investors in land, then agricultural policy seems mostly incognizant of the role of farmer as investor. Policy interventions that improve socially desirable outcomes vis-à-vis farm firms, but distort agricultural markets, may not be the cost effective. When farm-firm welfare derives in substantial measure from land price changes, which in turn are driven by the macroeconomy, it is important for policy makers to consider policies that mitigate downside risk in land markets. Given the sensitivity of DAG techniques to small sample data size, such as in this study, we recognize that the empirical results from this study must be tempered with caveats about the limitations of the methodology and the limited degrees of freedom available with use of annual time series land data. Future research efforts may address some of the methodological issues and investigate whether farmland relevant policies may have similar substantive effects on farm-firm welfare, but at lower social cost.

**Endnotes**

[1] A third major area of research activity centers on the effect of growth pressure. Since this paper focuses on agricultural land in Iowa, these studies are not reviewed.

[2] Phipps' theoretical model considers and cannot reject the endogeneity of price.

[3] For this kind of analysis, longer duration and higher frequency data series (monthly or quarterly) is usually more desirable for capturing the variability in the series over time. However, data on farmland values at state and national levels are only available annually. So, we note the potential limitations due to data availability for achieving conclusive statistical results.

[4] Although the empirical tests and analyses in this study were performed for three states (Iowa, Kansas, Georgia) and the U.S. aggregate data, to save space, only the empirical results for Iowa and the U.S. are reported. The results for the datasets from Kansas and Georgia, which are available from the authors, are very similar to those for Iowa.

[5] As shown in Figures 2 and 3, even with only 35 observations, most of the edges that remain in the system are very similar at both the 10 and 20 percent significance level. This shows to some degree, the robustness of the edge removal process in the DAG PC algorithm.

[6] The "long run" is arbitrarily set at 7 years, since this is reasonably enough time for the effect of perturbations from various sources to have worked their way through the system.

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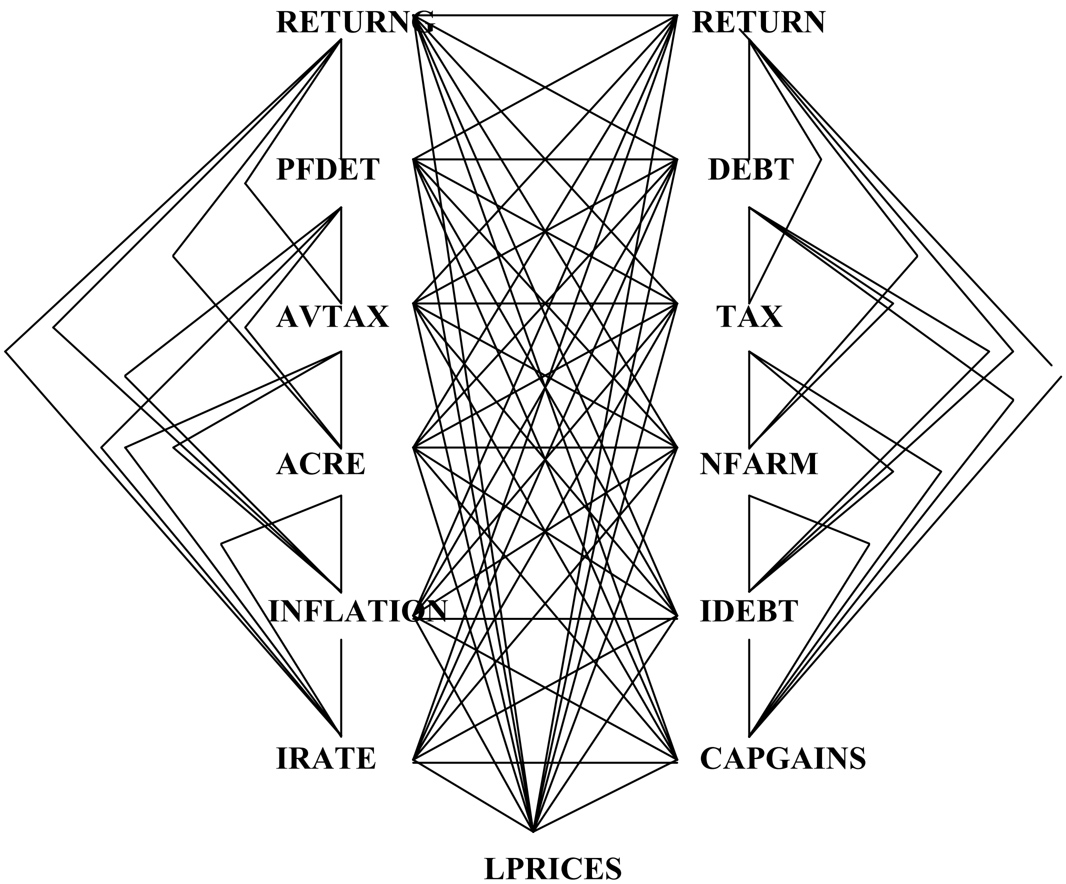


**Figure 1. Complete undirected graph on all thirteen variables.**

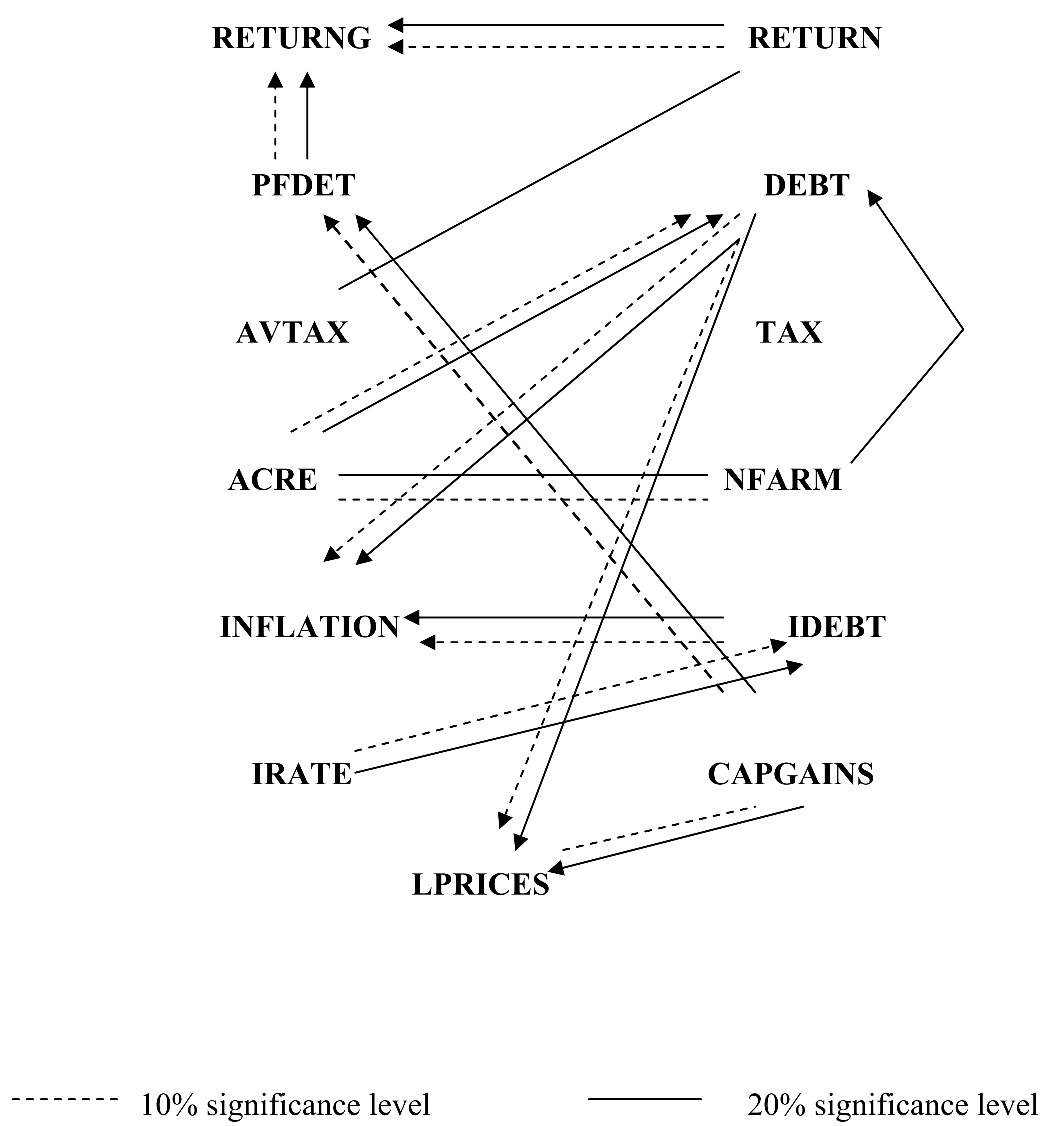


**Figure 2. Directed acyclic graph on all thirteen variables for Unites States, 1961-1995.**

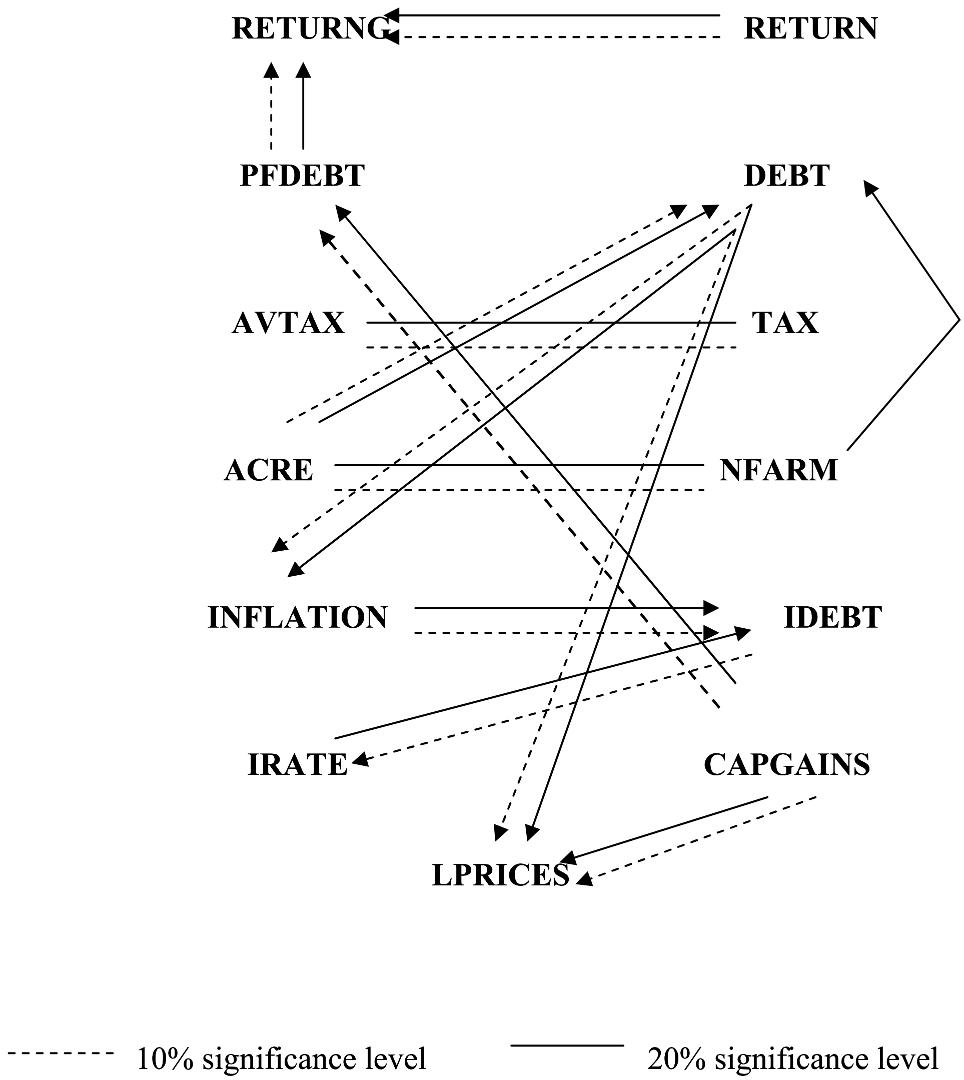


**Figure 3. Directed acyclic graph on all thirteen variables for Iowa, 1961-1995.**

**Table 1. Tests for Unit Roots and Stationarity, 1961 - 1995.**

| | United States | | | | Iowa State | | | |
|---|---|---|---|---|---|---|---|---|
| *Variables* | *ADF constant* | *ADF trend* | *KPSS constant* | *KPSS trend* | *ADF constant* | *ADF trend* | *KPSS constant* | *KPSS trend* |
| LPRICES | -2.061 | -2.010 | 0.814 [b] | 0.364 [b] | -2.332 | -2.242 | 0.360 | 0.328 [b] |
| ACRE | -1.226 | -2.095 | 1.821 [b] | 0.300 [b] | 0.365 | -2.230 | 1.788 [b] | 0.092 |
| NFARM | -3.494 [a] | -0.782 | 1.727 [b] | 0.387 [b] | -3.536 [a] | -1.405 | 1.814 [b] | 0.359 [b] |
| DEBT | -2.085 | -2.287 | 1.575 [b] | 0.404 [b] | -2.439 | -2.743 | 1.526 [b] | 0.397 [b] |
| TAX | 0.311 | -3.654 [a] | 1.821 [b] | 0.202 [b] | -0.071 | -2.859 | 1.792 [b] | 0.116 |
| RETURNG | -1.790 | -3.144 | 1.632 [b] | 0.095 | -2.481 | -4.180 [a] | 1.429 [b] | 0.089 |
| RETURN | -1.965 | -3.656 [a] | 1.587 [b] | 0.143 | -4.064 [a] | -5.446 [a] | 1.049 [b] | 0.137 |
| INFLATION | -1.917 | -1.708 | 1.825 [b] | 0.240 [b] | -1.917 | -1.708 | 1.825 [b] | 0.240 [b] |
| IREDEBT | -1.544 | -1.548 | 1.521 [b] | 0.283 [b] | -1.544 | -1.548 | 1.521 [b] | 0.283 [b] |
| IRATE | -1.600 | -1.137 | 0.946 [b] | 0.293 [b] | -1.600 | -1.137 | 0.946 [b] | 0.293 [b] |
| AVTAX | -2.071 | -1.982 | 0.632 [b] | 0.330 [b] | -1.409 | -1.987 | 0.633 [b] | 0.176 [b] |
| PFDEBT | -2.294 | -2.154 | 0.289 | 0.279 [b] | -3.478 [a] | -3.454 | 0.309 | 0.095 |
| CAPGAINS | -2.390 | -2.624 | 0.623 [b] | 0.304 [b] | -2.501 | -2.741 | 0.539 [b] | 0.215 [b] |

Note: The columns under the heading "ADF constant" refer to the Augmented Dickey-Fuller test with a drift while "ADF trend" contains a linear trend.
[a] Reject the null hypothesis of unit roots for the ADF tests at the 5% significance level.
[b] Reject the null hypothesis of stationarity for the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) tests at the 5% significance level.
Critical values at the 5% level of significance for the ADF (with constant only) and ADF (with linear trend) are: -2.89 and -3.50 respectively.
Critical values at the 5% level of significance for the KPSS (with constant only) and KPSS (with linear trend) are: 0.463 and 0.146 respectively.

**Table 2. Johansen Cointegration Test Results, 1961 - 1995.**

| | Critical values | | United States | | Iowa State | |
|---|---|---|---|---|---|---|
| | | | Trace | Trace* | Trace | Trace* |
| r | C(5%) | C(5%)* | Statistics | Statistics | Statistics | Statistics |
| r=0 | 94.15 | 102.14 | 158.27 [a] | 175.95 [a] | 136.38 [a] | 174.10 [a] |
| r≤1 | 68.52 | 76.07 | 106.42 [a] | 119.91 [a] | 82.74 [a] | 109.40 [a] |
| r≤2 | 47.21 | 53.12 | 67.57 [a] | 78.38 [a] | 42.76 [a] | 68.73 [a] |
| r≤3 | 29.68 | 34.91 | 41.81 [a] | 44.13 [a] | 26.63 | 34.21 |
| r≤4 | 15.41 | 19.96 | 22.55 [a] | 24.70 [a] | 12.99 | 20.42 |
| r≤5 | 3.76 | 9.24 | 9.30 [a] | 11.31 [a] | 5.50 | 7.30 |

Note: r denotes the number of cointegrating vectors for cointegration test with constant within and outside the cointegrating vectors. Johansen's cointegration test follow a sequential process for determination of the cointegration rank. We stop at the first r where we fail to reject the null hypothesis of r numbers of cointegrating vectors. The critical values for the trace tests are taken from Osterwald-Lenum).

* denotes test statistics for test results with constant within the cointegrating vectors.

[a] Reject the null hypothesis of cointegration rank r at the 5% significance level.

**Table 3. Decomposition of Error Variance using United States Data.**

| Steps | Std Error | LPRICES | RETURN | INFLATION | IRATE | DEBT | CAPGAINS |
|---|---|---|---|---|---|---|---|
| | | | | **(LPRICES)** | | | |
| 1 | 0.029 | 10.503 | 0.016 | 0.000 | 0.608 | 2.060 | 86.814 |
| 2 | 0.049 | 8.918 | 0.154 | 2.650 | 16.646 | 10.859 | 60.772 |
| 3 | 0.073 | 6.073 | 1.702 | 4.852 | 32.283 | 9.367 | 45.723 |
| 4 | 0.096 | 3.971 | 3.547 | 6.082 | 39.779 | 7.914 | 38.707 |
| 5 | 0.113 | 2.894 | 4.436 | 7.195 | 43.293 | 7.921 | 34.261 |
| 6 | 0.125 | 3.611 | 4.809 | 8.161 | 43.978 | 8.555 | 30.886 |
| 7 | 0.134 | 6.710 | 4.900 | 8.713 | 42.381 | 9.416 | 27.880 |
| | | | | **(RETURN)** | | | |
| 1 | 0.218 | 0.000 | 100.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 2 | 0.264 | 0.431 | 68.569 | 0.556 | 5.587 | 19.882 | 4.975 |
| 3 | 0.283 | 1.444 | 60.791 | 1.266 | 6.646 | 20.544 | 9.309 |
| 4 | 0.288 | 2.175 | 59.317 | 1.231 | 7.234 | 19.919 | 10.125 |
| 5 | 0.295 | 2.675 | 56.646 | 1.255 | 8.324 | 19.765 | 11.336 |
| 6 | 0.301 | 2.844 | 54.466 | 1.242 | 8.185 | 20.572 | 12.691 |
| 7 | 0.302 | 2.817 | 53.939 | 1.253 | 8.107 | 20.929 | 12.956 |
| | | | | **(INFLATION)** | | | |
| 1 | 0.006 | 0.000 | 1.715 | 81.789 | 1.135 | 15.361 | 0.000 |
| 2 | 0.013 | 0.352 | 5.811 | 57.952 | 13.522 | 17.623 | 4.740 |
| 3 | 0.023 | 0.537 | 8.859 | 35.957 | 31.887 | 18.193 | 4.568 |
| 4 | 0.034 | 0.465 | 9.806 | 25.381 | 43.565 | 17.053 | 3.728 |
| 5 | 0.046 | 0.286 | 10.319 | 21.031 | 48.750 | 16.542 | 3.072 |
| 6 | 0.055 | 0.315 | 10.667 | 19.304 | 49.961 | 17.267 | 2.486 |
| 7 | 0.062 | 0.984 | 10.754 | 18.498 | 48.780 | 18.992 | 1.992 |
| | | | | **(IRATE)** | | | |
| 1 | 0.566 | 0.000 | 0.000 | 0.000 | 100.000 | 0.000 | 0.000 |
| 2 | 0.753 | 0.169 | 3.282 | 0.113 | 82.182 | 10.987 | 3.268 |
| 3 | 0.787 | 0.604 | 3.008 | 0.425 | 75.363 | 17.604 | 2.996 |
| 4 | 0.919 | 4.123 | 4.651 | 0.711 | 69.437 | 15.558 | 5.519 |
| 5 | 1.096 | 7.046 | 5.189 | 1.113 | 66.687 | 12.378 | 7.587 |
| 6 | 1.206 | 7.872 | 5.292 | 1.642 | 65.748 | 10.862 | 8.585 |
| 7 | 1.249 | 7.581 | 5.602 | 2.133 | 64.919 | 10.524 | 9.242 |
| | | | | **(DEBT)** | | | |
| 1 | 0.022 | 0.000 | 9.418 | 0.000 | 6.234 | 84.349 | 0.000 |
| 2 | 0.045 | 0.123 | 5.128 | 2.470 | 26.762 | 62.145 | 3.372 |
| 3 | 0.070 | 0.323 | 4.920 | 5.020 | 36.876 | 42.700 | 10.162 |
| 4 | 0.096 | 0.253 | 5.465 | 6.805 | 41.050 | 32.458 | 13.969 |
| 5 | 0.121 | 0.193 | 5.834 | 8.109 | 43.427 | 27.688 | 14.747 |
| 6 | 0.144 | 0.656 | 6.131 | 9.043 | 44.577 | 25.413 | 14.182 |
| 7 | 0.163 | 2.026 | 6.330 | 9.649 | 44.459 | 24.489 | 13.047 |
| | | | | **(CAPGAINS)** | | | |
| 1 | 0.028 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 100.000 |
| 2 | 0.043 | 0.402 | 0.013 | 2.371 | 6.585 | 6.186 | 84.444 |
| 3 | 0.061 | 0.899 | 0.458 | 5.175 | 19.956 | 7.583 | 65.930 |
| 4 | 0.079 | 1.573 | 1.658 | 6.680 | 29.341 | 6.837 | 53.912 |
| 5 | 0.092 | 3.192 | 2.475 | 7.617 | 34.234 | 6.608 | 45.875 |
| 6 | 0.101 | 6.681 | 2.765 | 8.212 | 35.411 | 6.719 | 40.211 |
| 7 | 0.107 | 12.437 | 2.742 | 8.293 | 33.680 | 6.824 | 36.024 |

Decompositions at each step ahead are based on Bernanke factorization of contemporaneous innovations using orderings suggested by directed graphs in Figure 2. The decompositions in each row sum to one hundred.

**Table 4. Decomposition of Error Variance using Iowa State Data.**

| Steps | Std Error | LPRICES | RETURN | INFLATION | IRATE | DEBT | CAPGAINS |
|---|---|---|---|---|---|---|---|
| | | | | **(LPRICES)** | | | |
| 1 | 0.062 | 24.102 | 0.070 | 0.000 | 1.864 | 3.615 | 70.349 |
| 2 | 0.105 | 26.086 | 0.841 | 0.812 | 7.257 | 6.396 | 58.607 |
| 3 | 0.153 | 21.697 | 8.028 | 1.482 | 16.755 | 6.250 | 45.788 |
| 4 | 0.202 | 16.757 | 12.205 | 2.013 | 26.749 | 5.835 | 36.442 |
| 5 | 0.240 | 13.338 | 13.480 | 2.256 | 33.587 | 5.767 | 31.572 |
| 6 | 0.264 | 11.189 | 14.450 | 2.392 | 36.641 | 5.806 | 29.522 |
| 7 | 0.276 | 10.409 | 14.625 | 2.622 | 37.536 | 5.837 | 28.972 |
| | | | | **(RETURN)** | | | |
| 1 | 0.368 | 0.000 | 100.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 2 | 0.424 | 0.158 | 85.840 | 3.319 | 8.787 | 0.221 | 1.675 |
| 3 | 0.434 | 0.154 | 83.404 | 3.702 | 9.347 | 0.732 | 2.661 |
| 4 | 0.454 | 0.173 | 83.547 | 4.004 | 8.796 | 0.751 | 2.729 |
| 5 | 0.458 | 0.325 | 83.364 | 4.024 | 8.761 | 0.744 | 2.782 |
| 6 | 0.465 | 0.367 | 83.088 | 3.921 | 9.161 | 0.752 | 2.711 |
| 7 | 0.467 | 0.364 | 82.657 | 3.907 | 9.429 | 0.786 | 2.856 |
| | | | | **(INFLATION)** | | | |
| 1 | 0.006 | 0.000 | 0.008 | 98.866 | 0.105 | 1.022 | 0.000 |
| 2 | 0.012 | 0.009 | 5.150 | 72.207 | 12.469 | 1.511 | 8.654 |
| 3 | 0.021 | 0.032 | 10.464 | 43.592 | 32.030 | 3.780 | 10.102 |
| 4 | 0.033 | 0.049 | 11.475 | 28.563 | 45.160 | 5.601 | 9.152 |
| 5 | 0.044 | 0.031 | 12.411 | 21.347 | 50.579 | 6.744 | 8.888 |
| 6 | 0.054 | 0.066 | 12.921 | 18.163 | 51.946 | 7.495 | 9.411 |
| 7 | 0.063 | 0.364 | 12.580 | 16.969 | 51.625 | 8.049 | 10.413 |
| | | | | **(IRATE)** | | | |
| 1 | 0.549 | 0.000 | 0.000 | 0.000 | 100.000 | 0.000 | 0.000 |
| 2 | 0.705 | 0.509 | 11.757 | 2.137 | 85.519 | 0.002 | 0.075 |
| 3 | 0.715 | 0.599 | 12.515 | 2.485 | 83.075 | 1.206 | 0.120 |
| 4 | 0.830 | 3.371 | 13.784 | 1.850 | 76.311 | 4.085 | 0.599 |
| 5 | 0.997 | 7.133 | 13.664 | 1.287 | 70.423 | 5.835 | 1.659 |
| 6 | 1.118 | 9.473 | 14.246 | 1.033 | 64.897 | 6.654 | 3.697 |
| 7 | 1.193 | 9.920 | 15.214 | 1.017 | 60.256 | 6.996 | 6.597 |
| | | | | **(DEBT)** | | | |
| 1 | 0.022 | 0.000 | 0.688 | 0.000 | 9.227 | 90.086 | 0.000 |
| 2 | 0.044 | 3.174 | 0.688 | 1.645 | 28.379 | 55.473 | 10.641 |
| 3 | 0.075 | 5.935 | 5.431 | 2.369 | 32.437 | 32.578 | 21.251 |
| 4 | 0.111 | 6.268 | 8.398 | 3.187 | 34.560 | 22.161 | 25.425 |
| 5 | 0.147 | 5.440 | 9.830 | 3.835 | 37.086 | 17.205 | 26.603 |
| 6 | 0.181 | 4.265 | 11.030 | 4.268 | 39.315 | 14.560 | 26.562 |
| 7 | 0.209 | 3.250 | 11.657 | 4.673 | 41.122 | 13.092 | 26.207 |
| | | | | **(CAPGAINS)** | | | |
| 1 | 0.081 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 100.000 |
| 2 | 0.122 | 0.138 | 0.497 | 1.467 | 0.422 | 1.730 | 95.747 |
| 3 | 0.155 | 0.366 | 1.018 | 3.314 | 5.992 | 2.757 | 86.553 |
| 4 | 0.190 | 0.430 | 4.891 | 4.166 | 17.112 | 3.052 | 70.348 |
| 5 | 0.220 | 0.330 | 7.216 | 4.387 | 26.985 | 3.100 | 57.983 |
| 6 | 0.236 | 0.515 | 8.307 | 4.397 | 31.651 | 3.054 | 52.077 |
| 7 | 0.242 | 1.957 | 8.500 | 4.454 | 32.200 | 2.950 | 49.938 |

Decompositions at each step ahead are based on Bernanke factorization of contemporaneous innovations using orderings suggested by directed graphs in Figure 3. The decompositions in each row sum to one hundred.