Causality and Price Discovery: An Application of Directed Acyclic Graphs

by

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Directed Acyclic Graphs (DAG's) and Error Correction Models (ECM's) are employed to analyze questions of price discovery between spatially separated commodity markets and the transportation market linking them together. Results from our analysis suggest that these markets are highly interconnected but that it is the inland commodity market that is strongly influenced by both the transportation and commodity export markets in contemporaneous time. However, the commodity markets affect the volatility of the transportation market over longer horizons. Our results suggest that transportation rates are critical in the price discovery process lending support for the recent development of exchange traded barge rate futures contracts.

Key Words: Barge Rate Futures, Directed Acyclic Graphs, Causation, Integration.

I Introduction

To date, a large amount of research has been undertaken to evaluate the extent to which spatially separated markets are integrated. The popularity of the subject matter is driven in part by the fact that finding continual deviations from the equilibrium level of integration might imply that riskless arbitrage opportunities exist. However, despite the fact that freight rates are notoriously volatile, and the fact that over 5.5 billion tonnes, or 98% of annual world trade is carried by sea, the role of the transportation market in testing for integration within the marketing channel has been largely ignored in the literature.[1] A few notable exceptions do exist. For instance, important research undertaken by Geraci and Prewo (1977) confirmed that it is vital to include transportation costs in the study of integration among spatially separated markets. Goodwin, Grennes and Wohlegant (1990) conclude that failing to account for volatile freight rates can lead to erroneous conclusions in empirical trade research. They carefully demonstrate this point by finding stronger support for the Law of One Price only after they accounted for shipment costs.

Only a handful of studies have directly isolated the effect that volatile freight prices might have on the price discovery process. These include Haigh and Holt (2000), Hauser and Neff (1990) and Haigh and Bryant (2001). While the first contribution emphasized the importance of ocean freight volatility within the marketing channel, it was the latter contributions that isolated the extent to which domestic freight volatility (specifically volatile barge rates) contributed to the level uncertainty. However, both studies failed however to discuss in any detail exactly how the prices were linked and did not assess in any detail issues relating to causality among the markets.

Because of the importance of transportation rates in the price discovery process, there has always been considerable amount of interest in developing a forward/futures market for transportation services (Hauser and Buck, 1989). Indeed, in May of 1985 the BIFFEX freight futures contract was launched at the London International Financial Futures Exchange (LIFFE). The contract, based off an index of shipping prices compiled by the Baltic Exchange was designed to hedge freight price risk in the dry-bulk sector of the ocean shipping markets. Indeed, because of its uniqueness (it was the only futures contract on a service) and because of its potential importance, several researchers have investigated its use from a hedging standpoint. Examples include Thuong and Visscher (1990), Kavussanos and Nomikos (1999, 2000) and Haigh and Holt (2000). These studies invariably conclude that the BIFFEX market is not a particularly effective hedging instrument and does not provide the price risk protection evidenced in other futures markets. Each concludes that its weak performance as a hedging instrument is due to the fact that the contract was based on an index of shipping routes making the hedge less appealing and hence the trading volume lower. As anticipated, in June 2001 LIFFE announced that trading in the BIFFEX contract would cease in April 2002 because of low trading volumes.[2] It seems therefore that there is no way to predict with any degree of accuracy whether or not a new futures contract will be successful.

It may be possible however to provide some quantitative indicators of how important that market is likely to be especially if it influential or highly influenced in the price discovery process within a marketing channel.[3] Indeed, the current study makes significant contributions to this issue from several angles. Using recent high frequency price data we adopt a new framework to analyze the relationship between inland grain prices in Illinois, export grain prices at the U.S. Gulf and the barge market that links them together. In particular, we analyze the degree of interdependence and direction of causality at three time horizons: contemporary, short run and long run. To this end, we employ Directed Acyclic Graph (DAG) theory which, to date, has been surprisingly underutilized in both the economics and finance fields.[4] The unique methodology allows us to examine the causal pattern of contemporary relationships among the innovations in the three markets, based off of the familiar Error Correction Model (ECM). The ECM approach (whose existence is dependent upon the notion of cointegration) and the resulting innovation accounting techniques allow us to address both the short run and long run causality. Critically, our DAG analysis allows us to address the construction of the data-determined othoganization on contemporaneous innovation covariance, critical in providing sound inference in innovation accounting (Swanson and Granger, 1997). From a practical standpoint, the contemporary, short and long run information provides a unique assessment of the degree of interconnectivity and direction of causation within the marketing channel, important to physical traders in this marketplace.

It is also the objective of this study to focus on the importance of the barge market and explain in detail its role in the price discovery mechanism of the export marketing channel. Indeed, data provided by the United States Federal Grain Inspection Service over the period May 6th 1999 – May 3rd 2001 (the same time period analyzed in this study) suggest a priori, the relative importance of the barge market. For instance, the total amount of grain exported out of the U.S. within this time period was 258.84 million tonnes of grain on 16586 different vessels to a total of 131 different countries. Of that total number, 134.26 million tonnes (51.9% of the total) was shipped out of the U.S. Gulf (the vast majority of which originated via barges along the Mississippi River) on 7187 different vessels to 101 different countries. [5] Isolating the importance of the barge market is of particular interest here simply because trading in barge futures contracts for the particular stretch of river analyzed in this study began at the St. Louis Merchants exchange in December of 2000.[6]

The rest of the paper is organized as follows. Section II provides an overview of the econometric methodologies employed in the paper. Section III describes the data, and Section IV presents the empirical results. The last section, Section V, concludes.

II Econometric Methods

A considerable amount of research has attempted to evaluate the degree of interconnectivity between markets employing time-series techniques appropriate for non-stationary and cointegrated data. In particular, much work on applied cointegration analysis has relied on Johansen's multivariate approach (Johansen, 1988, 1991; Johansen and Juselius, 1990). Examples of papers employing such techniques include Chowdhury (1991) and Goodwin and Piggott (2001).

Because of the advantages of the Johansen methodology, this technique is adopted in the ensuing analysis. First, assume an *n*-dimensional vector of nonstationary time series, Y_t, (n = 3 here) that is generated by an autoregressive form depicted as:

$$Y_t = \omega + \sum_{i=1}^{K} \Pi_i Y_{t-i} + \varepsilon_t \ , \qquad (1)$$
$$\varepsilon_t \sim Niid(0, \Sigma)$$

where Y_t is an n x 1vector of the I(1) variables (the prices in the export marketing channel), Π_i is an n x n matrix of parameters, ω is a vector of constants, and ε_t is a random error term. Johansen and Juselius (1990) prove that eq. (1) can be rewritten as error-correction representation as follows:

$$\Delta Y_t = \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \Pi Y_{t-k} + \varepsilon_t \ , \qquad (2)$$

with

$$\Gamma_i = -(I - \Pi_1 - \Pi_2 - \ldots - \Pi_i)(i = 1 \ldots k-1) \ , \qquad (3)$$

and

$$\Pi = -[I - \Pi_1 - \ldots \Pi_k] \ , \qquad (4)$$

Equation (2) is nothing more than Vector Autoregression (VAR) (in first differences), with an inclusion of the lagged-level component, which is known as the Error Correction Term. The combination is simply known as an Error Correction Model (ECM). Since ε_t is stationary, the rank of the 'long-run' matrix, Π, determines how many linear combinations of Y_t are stationary. It is commonly known that the rank of any matrix is equal to the number of characteristic roots that are not equal to zero, and so the rank of Π determines the number of cointegrating vectors. Should the rank of Π be positive and less than n, then cointegration is said to be present. Should this be the case, then there exist matrices $\alpha\beta'$, with dimensions n x r, (where r is the number of cointegrating relationships), such that Π may be factored as $\alpha\beta'$. The β matrix is a matrix of cointegrating parameters and the matrix α is a matrix of weights (also known as the speed of adjustment parameters) with which each cointegrating vector enters the n

equations. Testing hypothesis, and examining the cointegrating space associated with β can help identify the long-run structure and provide rich information on the long-run relationships and market structure of the prices. Indeed, hypothesis testing allows us to determine whether some markets may be excluded from the long run relations.[7]

The short run dependencies among the prices can also be identified through hypothesis testing on α and Γ_i. Hypothesis testing on α (the short run adjustment to the long run relationships) can be conducted in a similar way to that used for hypothesis testing on β. The α vector is the measure of the average speed of convergence towards the long-run equilibrium and plays a crucial role in analyzing how each of the price series will respond to deviations from the long-run equilibrium relationship. These tests permit the researcher to make inferences regarding the short run adjustment processes of each series. It also enables the researcher the ability to test whether a particular market is weakly exogenous with regard to other markets (if those market prices are unresponsive to the deviation from long-run relationships).

The parameters associated with Γ_i define the short-run adjustment to the changes of the process (Juselius, 1995). Hypothesis tests can also be conducted on these matrices. However, as is the case of standard VAR's, the individual coefficients associated with the ECM can be somewhat difficult to interpret, particularly those associated with the short-run dynamics captured within Γ_i. Consequently, innovation accounting techniques may be the best way to describe the short run structure and interdependencies among the prices within the export marketing channel (Swanson and Granger, 1997). Therefore, given the ECM, impulse response analysis can be undertaken (based on an equivalent levels VAR) to summarize the short run dynamic interrelationships among the prices. Undertaking the impulse response analysis in this way addresses the necessity of imposing the cointegrating relationships into the system, which has very recently been proven to be crucial in yielding consistent impulse responses and forecast error decompositions (Philips, 1998).

However, the basic problem of the orthoganalization of residuals from the ECM remains somewhat unresolved. Most studies employing ECM or VAR's have yet to fully address the problem associated with the contemporaneous relationships among variables. Despite this, innovation accounting techniques require that a causal assumption about contemporaneous correlation be made. Early work in this area employed the Choleski factorization, with more recent applications concentrating on a 'structural' factorization suggested by Bernanke (1986) and Sims (1986) simply because researchers may not view the world may not be viewed as being recursive (Cooley and Leroy (1985)). However, the problem with both the Bernanke (1986) and Sims (1986) approach is that it is assumed that the researcher has knowledge of the correct structural model (which is unlikely to be the case). As such, following Spirtes et al, 1993 in this study we examine the contemporaneous relationships among the variables based on the variance covariance matrix from the innovations (residuals) from the ECM by employing DAG's. It is to a brief explanation of DAG theory that we now turn.

Directed Acyclic Graphs

Consider first the non-time sequence asymmetry in causal relations. For a causally sufficient set of three variables X, Y and Z, illustrate a causal fork, X causes Y and Z, as: Y $\leftarrow$X $\rightarrow$ Z. Here the unconditional association between Y and Z is nonzero (as bothY and Z have a common cause in X), but the conditional association between Y and Z given knowledge of the common cause X, is zero: *common causes screen off associations between their joint effects.* Illustrate the inverted causal fork, X and Z cause Y, as: X$\rightarrow$ Y $\leftarrow$Z. Here the unconditional association between X and Z is zero, but the conditional association between X and Z given the common effect Y is not zero: *common effects do not screen off association between their joint causes*. This screening off phenomina is captured in the literature of *directed graphs*.[8]

Variables connected by a line are said to be adjacent. If we have a set of variables {V,W,X,Y,Z}: (i) the undirected graph contains only undirected lines (e.g., V — W); (ii) a directed graph contains only directed lines (e.g., W $\rightarrow$ X); (iii) an inducing path graph contains both directed lines and bi-directed lines (X $\leftrightarrow$ Y); (iv) a partially oriented inducing path graph contains directed lines ($\rightarrow$), bi-directed lines ($\leftrightarrow$), non-directed lines (o—o) and partially directed lines (o$\rightarrow$). A directed acyclic graph is a graph that contains no directed cyclic paths (an acyclic graph contains no directed path from a variable that returns to the same variable). Only acyclic graphs are used in the paper.

DAG's represent conditional independence as implied by the recursive product decomposition:

$$\Pr(v_1, v_2, v_3, ..., v_n) = \prod_{i=1}^{n} \Pr(v_i \mid pa_i) \qquad (5)$$

where Pr denotes the probability. The symbol pa_i refers to the realization of some subset of the variables that precede (come before in a causal sense) v_i in order ($v_1, v_2 ..., v_n$). The symbol $\prod$ refers to the product (multiplication) operator. Pearl (1986) proposes d-separation as a graphical characterization of conditional independence. Verma and Pearl (1988) give a proof of this proposition. That is, d-separation characterizes the conditional independence relations given by equation (5). If we formulate a DAG in which the variables corresponding to pa_i are represented as the parents (direct causes) of V_i, then the independencies implied by equation (5) can be read off the graph using the criterion of d-separation (defined in Pearl (1995)).

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

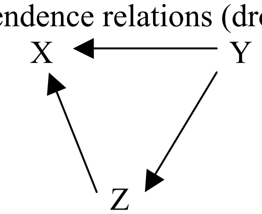
Geiger, Verma and Pearl (1990) demonstrate that there is a one-to-one correspondence between the set of conditional independencies, $X \perp Y \mid Z$, implied by equation (5) and the set of triples (X, Y, Z) that satisfy the d-separation criterion in graph G. If G is a directed acyclic graph with variable set V, A and B are in V, and H is also in V, then G linearly implies the correlation between A and B conditional on H is zero if and only if A and B are d-separated given H.

Spirtes, et al. (1999) show the connection between directed graphs and the counterfactual random variable model (the random assignment experimental model) of Rubin (1978) and Holland (1986). First, one needs to focus on observational data a *causally sufficient* set of variables. This means that there are no omitted variables that in fact cause any two of the included variables under study. If variable X causes both Y and Z and we leave X out of the analysis, then an apparent causal flow from Y to Z (or vice versa) may be due to the fact that X causes both Y and Z, so the causal flow identified as running from Y to Z would be spurious (Suppes 1970). Second, one needs to constrain herself to causal flows that respect a *causal Markov condition.* That is to say, if X causes Y and Y causes Z, we can factor the underlying probability distribution on X, Y and Z as $Pr(X,Y,Z) = Pr(X)Pr(Y|X)Pr(Z|Y)$. Finally, the probabilities, Pr, we attempt to capture by graph G are *faithful* to G if X and Y are dependent if and only if there is an edge between X and Y.

The causal sufficiency condition suggests that one find a sufficiently rich set of theoretically relevant variables upon which to conduct her analysis. Failure to include a relevant variable may lead one to put a line between two variables when in fact both are effects of an omitted third variable. Failure of the Markov condition has been noted in quantum mechanical experiments (see Spirtes, Glymour and Scheines 1993). Failure to require the condition would require us to ignor statistical dependency even in experimental designs (Spirtes, Glymour and Scheines 1993, p. 64). The faithfulness condition can be violated if parameter values just happen to be of the correct magnitude to cancel one another. If, for example the following two equations describe the underlying model that generates X, Y, and Z:

$$X = 10Y + 2Z + \varepsilon_X$$
$$Z = -5Y + \varepsilon_Z$$

where ε_X and ε_Z are uncorrelated noise terms, each not correlated with its associated right hand side variables (ε_X is not correlated with Y or Z and ε_Z is not correlated with Y). If this is the "deep parameter" representation of the "true" generating process on X, Y and Z, it has a directed acyclic graphical representation with no conditional independence relations (dropping the noise terms):



Yet, X and Y will be uncorrelated. If we rely on correlation and partial correlation stucture based on observational data on X, Y and Z to remove edges between variables, we would mistakenly remove the edge between X and Y, even though the data generating process requires it to be present. The exact off-setting of parameter values in the "true" model, while possible, seems unlikley. Slight variations in any of the linear coefficients show X and Y to be correlated, so that the correlation structure in the model is unstable (Glymour 1997, p. 209). [Of course the experimentalist can find the causal model behind X and Y by breaking the connection between Y and Z through random assignment in a controlled experiment].

Spirtes, Glymour and Scheines (1993) have applied the notion of d-separation into an algorithm (PC Algorithm) for building directed graphs. PC algorithm is a sequential set of commands that begin with an unrestricted graph where every variable is connected with every other variable and proceeds step-wise to remove lines between variables and to direct "causal flow." The algorithm is described in detail in Spirtes, Glymour, and Scheines (1993, p.117).

Briefly, the algorithm (we will summarize only the generic aspects of PC algorithm) begins with a complete undirected graph G on the vertex set **X**. The complete, undirected, graph shows an undirected line between every variable of the system (every variable in **X**). Lines between variables are removed sequentially based on zero correlation or partial correlation (conditional correlation). *The conditioning variable(s) on removed lines between two variables is called the sepset of the variables whose line has been removed (for vanishing zero order conditioning information the sepset is the empty set).* Edges are directed by considering triples X — Y — Z, such that X and Y are adjacent as are Y and Z, but X and Z are not adjacent. Direct lines between triples: X — Y — Z as X → Y ← Z if Y is not in the sepset of X and Z. If X → Y, Y and Z are adjacent, X and Z are not adjacent, and there is no arrowhead at Y, then orient Y — Z as Y → Z. If there is a directed path from X to Y, and a line between X and Y, then direct (X — Y) as: X →Y.

In applications, Fisher's z is used to test whether conditional correlations are significantly different from zero. Fisher's z can be applied to test for significance from zero; where:

$$z(\rho(i,j\mid k),n)=\left[\frac{1}{2}\sqrt{n-|k|-3}\right]\ln\left\{\frac{|1+\rho(i,j\mid k)|}{1-\rho(i,j\mid k|)}\right\}, \tag{6}$$

and n is the number of observations used to estimate the correlations, $\rho(i,j\mid k)$ 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, the distribution of $z(\rho(i,j\mid k),n)-z(r(i,j\mid k),n)$ is standard normal. PC algorithm and its more refined extensions are marketed as the software TETRAD II (Scheines, et al 1994).

Monte Carlo studies with small sample sizes suggest that Tetrad II works well, if the researcher applies an inverse relationship between sample size and significance level on line removal test. They recommend when sample size falls below 100 observations researchers use significance levels as high as .20 (Sprites, et. al. 1993, Chapter 5). As sample size grows above 100, the suggestion is to drop the applied significance level to more traditional values (e.g., .10 or .05).

Applications of directed graphs in economics and finance are not commonplace. Recently, however, Swanson and Granger (1997) suggested a similar procedure to sort-out causal flow on innovations from a vector autoregression (VAR). Their procedure considers only first order conditional correlation, and involves more subjective insight by the researcher to achieve a "structural recursive ordering."

III Description of the Data

The data for this study cover a two-year time period, from May 6th, 1999 to May 3rd 2001, totaling 520 daily observations for each of the time-series. The mid point of the original daily closing Illinois and Gulf soybean bid prices were provided by the Illinois Department of Agriculture and the USDA Agricultural Marketing Service respectively. Grain barge rate data covering the same period were also collected for the stretch of river beginning south of Peoria. Specifically, first, weekly barge rate information was collected from the USDA, Agricultural Marketing Service, Transportation and Marketing Division. This weekly rate (Wednesday quote) reflects the current rate as a percent of the historic benchmark tariff rate (southbound barge freight call session basis trading benchmark (July 1979)). From this figure the dollar per ton rate was obtained by multiplying the quoted rate (a percentage of the benchmark rate) by the historic benchmark rate associated with the south of Peoria region. Such a data series was used Haigh and Bryant (2001). Then daily rate data was also collected from a large grain trading company that transports grain on a daily basis along this stretch of the river. The data cannot be shared for confidentiality reasons, but to ensure its reliability the Wednesday daily price from the grain trading company was correlated with the USDA price. Because both series were found to be highly correlated (ρ = 0.983) the daily grain and daily barge rates were used throughout.[9]

Summary statistics on all the prices are presented in Table 1. As one might expect, the average (mean) grain price at the Gulf is greater than that at Illinois, with the difference being slightly greater than the barge rate linking the two together. Indeed, Figure 1 Panel A plots the daily grain prices at Illinois and the Gulf, and illustrates their strong correlation (ρ = 0.970). The spread (Gulf – Illinois) and the barge rate are presented in Panel B. This graph also illustrates the strong degree of interconnectivity between these price series commanding a strong correlation of ρ = 0.949. As can be seen in Table 1 the degree of volatility varies among the price series with the grain price series exhibiting identical levels of uncertainty (as measured by the Coefficient of Variation). Interestingly, barge rate volatility is several times as great as the grain price volatility. Haigh and Byrant (2001) also found the excess volatility found in this market (relative to other markets). The discussion above indicates that the barge prices and the grain prices are linked together. However, it does not provide detailed evidence on the dynamics of these linkages as well as on the existence of causation among them. It is those issues that we now turn to.

IV Empirical Application

In order to implement our ECM we first check the order of integration of each of the price series within the marketing channel. As can be seen from Table 2, each series is integrated of the first order confirming that the analyses will be conducted on the differenced price series. The ECM was then estimated using the maximum likelihood technique outlined by Johansen and Juselius (1990). The lag length order was selected based on the Schwarz-loss criterion, (as shown in Table 3). Consequently, our ECM is as follows:

$$\Delta Y_t = \Gamma \Delta Y_{t-1} + \Pi Y_{t-1} + \varepsilon_t, \tag{7}$$

where Π is a (3 x 3) matrix of coefficients relating lagged levels of grain and barge prices measured at time t, Γ is a (3 x 3) matrix of coefficients relating changes in grain and barge prices lagged one period to current changes in the prices and ε_t is a (3 x 1) vector of innovations (residuals).[10] As previously mentioned, if we find that Π is of reduced rank ($0 < r < p$) (where p = 3 here) we can test the individual elements of β' against zero in the factorization $\alpha\beta' = \Pi$. We can also investigate the possibility of weak exogeneity of each of the series (testing whether each element of the α vector is equal to zero). Therefore, given this feature, equation (7) can be written as:

$$\Delta Y_t = \Gamma \Delta Y_{t-1} + \alpha\beta' Y_{t-1} + \varepsilon_t. \tag{8}$$

Table 3 (top panel) presents the decision rule based on the trace tests for the number of cointegrating vectors. Using critical values provided by Osterwald-Lenum (1992) we first fail to reject the null hypotheses on $r \leq 1$and so the ECM is modeled with one cointegrating vector. The lower part of Table 3 explores some exploratory tests on the long run structure of interdependence between the prices. Indeed, our purpose is to make a more definitive statement about the nature of the cointegrating vector. In particular, the middle panel explores the possibility that one of the three series is not in the cointegrating space. Under the null hypothesis that price *i* is not present in the cointegrating space, the test statistic is distributed chi-squared with one degree of freedom. We firmly reject the null for each series. With respect to the short-run adjustment toward the long run relationships, α, we also test for weak exogeneity on each market. For each market we test for whether or not it responds to perturbations in the cointegrating space. Recall our long run relationship is represented by $\Pi Y_{t-1} = \alpha\beta' Y_{t-1}$. Perturbations in the long run equilibrium are given by $\beta' Y_{t-1}$ and so the question of interest is whether or not an entire row of α equals zero. Testing this suggests that a price corresponding to that particular row is not responding to the long-run information from the rest of the prices. Under the null hypothesis that a price does not respond to shocks in the long-run equilibrium, the test statistic is also distributed chi-squared with one degree of freedom. Inspection of the lower panel of Table 3 suggests that both the Illinois and Gulf markets are weakly exogenous and the barge market does all the adjusting to the long-run equilibrium. Accordingly, the following factorization of Π into $\alpha\beta'$ is given below in equation (9) where each element has been normalized on the Illinois price:

$$\alpha\beta' = \begin{bmatrix} .000 \\ (.000) \\ -3.474 \\ (-6.304) \\ .000 \\ (.000) \end{bmatrix} \left[1.000 + .066 - 1.061\right]. \tag{9}$$

Perturbations in this equilibrium relationship are then represented as z_t = Illinois - .066(Barge)-1.061(Gulf), where z_t represents stationary deviations in the long-run equilibrium between the two sets of prices. The t – statistic associated with the barge market suggests that the transportation market does respond to the export marketing channel equilibrium. Put simply, if the price of the Illinois market is high relative to its long-run equilibrium, the barge market responds downwards in period t + 1. This is an especially intuitive result given that one would expect the demand for barges to decrease (and hence prices fall) if the price of grain in Illinois increased.

The other part of the ECM framework that isolates the short run dynamics is through the Γ matrix, a (3 x 3) matrix of coefficients relating changes in prices lagged one period to current prices. The estimated coefficients associated with this matrix are:

$$\Gamma = \begin{bmatrix} -.112 & -.024 & .057 \\ (-.820) & (-1.930) & (.392) \\ .167 & .218 & .011 \\ (.298) & (4.348) & (.018) \\ .155 & -.000 & -.193 \\ (1.222) & (-.039) & (-1.418) \end{bmatrix}. \tag{10}$$

Casual inspection of the reported t – statistics associated with this matrix suggests that the dominant market is the barge market. The coefficient associate with the lagged differences from the barge market is significant on itself and the Illinois market. Interestingly changes in the Illinois and Gulf markets in period t - 1 enter no market in period t with a statistically significant coefficient.

As previously mentioned, the short run patterns of response and strengths of the relationships among the prices that make up the export marketing channel are quite difficult to decipher by focusing on the individual coefficients separately, either through the speed of adjustment parameters, α_i or through the short run dynamics matrix, Γ. A more suitable way to summarize the dynamic relationships between these markets is through well-known innovation accounting techniques, applied to the ECM outlined in equation (7). However, as previously mentioned, crucial to such analysis is the method used to treat contemporaneous innovation. In this study we adopt the factorization known as the "Bernanke ordering". Write the innovation (residual) vector (ν_t) from the ECM as $\mathbf{A}\nu_t = \varepsilon_t$, where $\mathbf{A}$ is a 3 x 3 matrix and ε_t is a 3 x 1 vector of orthogonal shocks. As illustrated by Doan (1992, 8 – 10), if there is no combination of i and j ($i \neq j$) for matrix $\mathbf{A}$ where both $\{a_{ij}\}$ and $\{a_{ji}\}$ are non-zero where $\{a_{ij}\}$ is an element i,j of matrix $\mathbf{A}$ in this instance. Here we employ the DAG algorithm presented in Spirtes et al. (1993) in order to place zeros in the $\mathbf{A}$ matrix. Swanson and Granger (1997) made a similar suggestion.

Innovations from our ECM give us the contemporaneous innovation correlation matrix, Σ (representing the innovations as ν_i). The equation below (11) presents the lower triangular elements of the correlation matrix on innovations ($\hat{\nu}$) from equation (7) where the entries are presented in the order, Illinois, Barge and Gulf:

$$\Sigma(\hat{\nu}_t) = \begin{bmatrix} 1.00 & & \\ -.084 & 1.00 & \\ .919 & .049 & 1.00 \end{bmatrix}. \tag{11}$$

DAG theory points out that the off-diagonal elements of the scaled inverse of the $\Sigma(\hat{\nu}_t)$ matrix are in fact the negatives of the partial correlation coefficients between the corresponding pair of variables given the remaining variable(s) in the matrix (Whittaker 1990, p.4). The off-diagonal elements of the scaled inverse of the $\Sigma(\hat{\nu}_t)$ matrix, denoted by $\Sigma^*(\hat{\nu}_t)$, where the * indicates that we have scaled the inverse matrix:

$$\Sigma^*(\hat{\nu}_t) = \begin{bmatrix} 1.00 & & \\ -.327 & 1.00 & \\ .927 & .321 & 1.00 \end{bmatrix}. \tag{12}$$

For example, the partial correlation between innovations in prices in the Illinois market and the barge market, given innovations in the Gulf market is -.327. Under the assumption of multivariate normality, Fishers z statistic can be applied to test for significance from zero (see Equation (6)). In this case, the correlation between Illinois and the barge market (-.327) is significantly different from zero at all conventional significance levels (with an associated p - value = .000). Interestingly, in this case all conditional partial correlations are significantly different from zero. That is, the partial correlation between the Illinois market and the Gulf market given innovations in the barge market is .927 (p - value of .000) and the partial correlation between the barge market and the Gulf market given innovations in the Illinois market is .321 (again a p-

value of .000). Curiously, the partial correlations between the Illinois and the barge market and the Gulf and the barge market are of the intuitively correct sign. That is, one would expect an increase in Illinois prices to cause a decrease in barge prices (less demand for barges given the higher price of grain for export), a result found previously when we standardized the cointegrating vector on the Illinois price. Moreover we find here that an increase in Gulf prices tends to cause an increase in barge prices; a result consistent with the notion that increase in demand for barges would drive these prices upwards given the higher export prices at the Gulf.

DAG's as given in Spirtes et. al (1993) provides an algorithm for removing edges between different markets but also directs causal flow of information between markets. The algorithm starts with a complete undirected graph (like the one shown in the top panel of Figure 2) where innovations in every market are connected with innovations in every market. The algorithm then starts to remove edges based on simple correlations. Indeed, in this analysis, it was found that the sample correlation between the Gulf market and the barge market could be removed in contemporaneous time ($\rho_{B,G}$= .0486 with a *p* - value of .2681). However, the sample correlation between the Gulf price and Illinois and the barge price and Illinois could not be removed. As such, only the edges connecting the barge market to Illinois and the Gulf market and Illinois remain. The next step of removing edges is based on the partial correlations. Here, correlations between the Gulf price and the Illinois price conditional on the barge rate and between the barge rate and the Illinois price conditional on the Gulf price are found to be non-zero. Accordingly, we can not remove the edges Illinois — Barge and Illinois — Gulf.

Edge removal, based on correlations and partial correlation results in the triple: Gulf — Illinois — Barge, using the notation from Figure 2. Since the edge between Gulf and Barge was removed using the unconditional correlation test (recall $\rho_{B,G}$= .0486 with a *p* - value of .2681), we can direct this remaining triple as: Gulf $\rightarrow$ Illinois $\leftarrow$Barge, as we show in Panel B of Figure 2. Here, Illinois is a collider – receiving information from both the Gulf market and the barge market. As such (as a collider) it opens up the information flow between the Gulf and barge markets. Recall from Equation 12, the conditional correlation between the Gulf market and the barge market is .321 and has a p – value of .000.

Forecast error decompositions and impulse responses (one standard deviation shocks from the ECM's) based on the DAG's are provided in Table 4 and Figure 3 respectively. The forecast error decompositions allows us to consider which prices within the export marketing channel are statistically exogenous or endogenous relative to each other at differing forecast horizons. One particular price series within the system would be considered to be statistically exogenous if most of the variance of its forecast error could be attributed to its own innovations rather than originating from one of the other price series within the system. Indeed, a truly exogenous price series should explain 100% of its forecast error variance at all forecast horizons. As can be seen from Table 4 we analyze a forecast horizon up to 14 days – more than enough time for a barge to travel from this part of the Illinois River (South of Peoria) to the U.S. Gulf. The impulse responses, which allow us to evaluate the dynamic paths of adjustment of each of the prices to shocks in the data series, are illustrated in Figure 3. They too allow a 14-day window.

The first column in the output for the forecast error decompositions is the standard error of the forecast for each particular price series. The remaining columns illustrate the error decompositions. As usual, each row should add up to 100 (but may not here due to rounding). As can be seen, the Illinois market is very heavily influenced by the Gulf market whereby the Gulf explains 84.78% of the variation in the Illinois market after just one-day. Recall, our results from the DAG analysis suggest that the Gulf market 'causes' the Illinois market in contemporaneous time, and apparently continues to do so in the short run (1 day) out to the longer term of 14 days, where it still explains over 78%. The barge market has some influence on the Illinois market, although its effect is not as large as the Gulf's. Indeed, the barge market explains about 1.6% of the variation after 1 day and finishes at about 3.9% after 14 days. Once again, this result is consistent with the DAG analysis. There, the barge market 'caused' the Illinois market in contemporaneous time. The remaining portion of the variation is attributed to the Illinois market itself (13.6% after 1 day and about 17.7% after 14 days).

Perhaps the most interesting finding is associated with the forecast error decompositions associated with the barge market. Consistent with the DAG graphs analysis, the barge market is not influenced by either the Illinois or the Gulf markets in the very short run (1 day). Indeed, after 1 day the barge market is exogenous, as it explains 100% of its own variation. Over time, however, a different pattern emerges. While some of the variation can be explained by the Gulf market at time passes, the vast majority of the variation of the barge rate can be attributed to the Illinois market. Indeed, after the 14 days have passed about 58% of the variation can be attributed to the Illinois market. Clearly, over time, the barge market is susceptible to large volatility shocks arising from the very market that it serves.

The Gulf market is also 100% exogenous in the short run a result consistent with the direction of causality in the DAG analysis. Indeed, as time passes, while not being completely exogenous, very little of the variation in the market is being explained by the domestic influences of the Illinois market and the barge market that connects the two together. It seems to be a plausible hypothesis therefore that the Gulf market is being influenced by other global factors, but it in turn affects the Illinois market which then influences the barge market as time passes. Put another way, the Gulf price does not seem to influence the barge rate directly, but rather its informational effect is transmitted through the Illinois market and then onto the barge market shortly thereafter.

Focusing our attention on the impulse responses in Figure 3 we see an identical pattern emerge. For instance, the left-hand panel of the chart illustrates the response of each market to a shock in the Illinois market. While the Illinois and Gulf markets are somewhat affected by a shock from the Illinois market, it is the barge market that is most heavily influenced, a finding consistent with the error decompositions. Indeed, it is only after about the 14 days that the barge market stabilizes, yet still remains affected. Clearly a shock from the Illinois market creates considerable volatility in the barge industry, which could, if unhedged, be extremely detrimental to physical traders in this industry. Interestingly, the sign of the shock is as one might expect (negative), a result consistent with the finding of a negative conditional correlation between the markets. That is, an increase in Illinois prices should correspond with a decrease in barge rates (as explained previously). Note also that while the barge rate is affected by the Illinois price over time, it starts out at zero, a finding consistent with the DAG analysis whereby the Illinois market does not affect the barge market in contemporaneous time. This can also be said about the affect of the Illinois market on the Gulf market. An innovation in the barge market has almost no affect the Gulf market (bottom graph of the middle panel), just like the innovation in the Illinois market had no affect. Once again, the Gulf market can be deemed to be exogenous to the other domestic linkages. However, as shown by the top graph in the middle panel, the Illinois market is somewhat affected by the barge market, and the sign of the response (negative) is, once again, consistent with earlier intuition.

The last panel of the impulse response graph illustrates the response of the inland markets to a shock in the Gulf market. As can be seen by the top graph, the Illinois market is immediately and strongly affected by a shock originating out of the Gulf. This is a result found previously in both the contemporaneous analyses (the DAG framework) and the forecast error decompositions. A shock to the Gulf market also has an affect on the barge market that feeds it. However, consistent with the contemporaneous analysis, it does not have an immediate affect. However, as time passes, the barge market reacts positively, an intuitively pleasing result.

V Concluding Remarks

In recent years there has been a plethora of research looking at the level of interconnectivity between different yet related markets, but to date, no study has analyzed the degree of interconnectivity within a marketing channel in a truly dynamic manner.

In this study, we apply Directed Acyclic Graphs (DAG's) to make causal statements in contemporaneous time. Applying DAG's to the heretofore well-understand Error Correction Model allows us to address issues surrounding dynamic patterns of price discovery using both forecast error decompositions and impulse responses.

Our results illustrate that regardless of which method is used to analyze the dynamic relationships between the markets information from the Gulf market is critical in the price discovery process in contemporaneous time, the short run and out into the longer term. While the globally influenced Gulf market does not heavily influence the barge market that connects it to its inland grain source at Illinois in contemporaneous time, it is somewhat affected as time passes. However, it is the Illinois market that is immediately influenced by the Gulf. This affect seems to ripple through to the transportation market as time passes reversing the direction of causation from the barge market influencing the Illinois market in contemporaneous time to the Illinois market heavily influencing the barge market out into the longer term. It seems therefore, that over the longer term both the domestic and international markets heavily influence the barge market and shocks to these markets can greatly influence rates, negatively, or positively depending upon where the shock originates. These shocks, whether they originate from the Gulf or inland cause excess volatility in the barge market, which could be detrimental to unhedged physical traders in this marketing channel.

This paper has therefore, not only shed light on the degree of interconnectivity between several important markets using unique econometric methods but also sheds some light on the importance of the barge market critical in linking markets together. Our results seem to support the existence of the newly developed barge rate futures contract, but like so many other futures contracts that are designed, time can only tell whether the market will be successful.

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Table 1. Descriptive statistics and correlation analysis on daily prices

	Illinois	Barge	Gulf
Mean	172.98	8.915	186.34
Median	170.15	8.584	184.28
Standard deviation	10.806	2.228	10.369
CV	0.056	0.250	0.056
m_3	-0.181	-0.531	-0.503
m_4	0.377	0.505	0.186
Min	147.17	5.336	161.11
Max	202.95	16.008	213.41
Unconditional Correlations			
	Illinois	Barge	Gulf
Illinois	1		
Barge	-0.3268	1	
Gulf	0.9700	-0.1003	1

Summary statistics are presented for daily grain and barge prices for the period 6th May 1999 – 3rd May 2001. CV represents the Coefficient of Variation and m_3 and m_4 represent sample skewness and kurtosis respectively.

Table 2. Augmented Dickey-Fuller (ADF) tests for order of integration on prices

Test is on the estimated coefficient θ_1 from the following prototype model:

$$\Delta X_t = \theta_0 + \theta_1 X_{t-1} + \sum_{k=1}^{K} \beta_k \Delta X_{t-k}$$

Price	K	HO: I(1) vs. HA: I(0) ADF	HO: I(2) vs. HA: I(1) ADF
Illinois	0	-2.354	-24.190
Barge	1	-3.158	-18.960
Gulf	0	-2.341	-23.728

Critical values are taken from Fuller (1976). They are –2.57 (10%), -2.88* (5%) and –3.46 (1%). Therefore, based on these results are series are I(1). The optimal lag length (K) was based on the Schwarz Bayesian Criterion (1978).

Table 3. Cointegration analysis of prices

Trace tests on order of cointegration[a]		
λ_{trace} test statistic	H_O:	critical value
103.96	r = 0	29.68
14.21	r ≤ 1	15.41
4.93	r ≤ 2	3.76
Tests for exclusion from the cointegrating vector[b]		
	H_O:	$\chi^2_{(1)}$ value
Illinois	$\beta_I = 0$	79.25
Barge	$\beta_B = 0$	79.17
Gulf	$\beta_G = 0$	78.85
Tests for weak exogeneity[b]		
	H_O:	$\chi^2_{(1)}$ value
Illinois	$\alpha_I = 0$	1.11
Barge	$\alpha_B = 0$	7.57
Gulf	$\alpha_G = 0$	1.85

[a]Tests are on eigenvalues with the Π matrix. The λ_{trace} statistic is $-N(\sum_{i=r+1}^{2} \ln(1-\lambda_i))$, where λ_i are ordered (largest to smallest) eigenvalues on Π. Critical values for the λ_{trace} statistics (at the 10% level) are from Osterwald-Lenum (1992). The optimal lag length (k) is based on the Schwarz Bayesian Criterion (1978). The sample size (N) is equal to 520.

[b]Tests are based on the following: $T = N(\ln(1-\lambda_R) - \ln(1-\lambda_U)$, where λ_R is the eigenvalue calculated with the restriction and λ_U the eigenvalue calculated without the restriction. With one cointegrating vector the critical $\chi^2_{(1)}$ value is 3.84. Based upon these results all prices in the marketing channel appear to be a part of the cointegrating relationship, and both the Gulf and the Illinois prices are weakly exogenous.

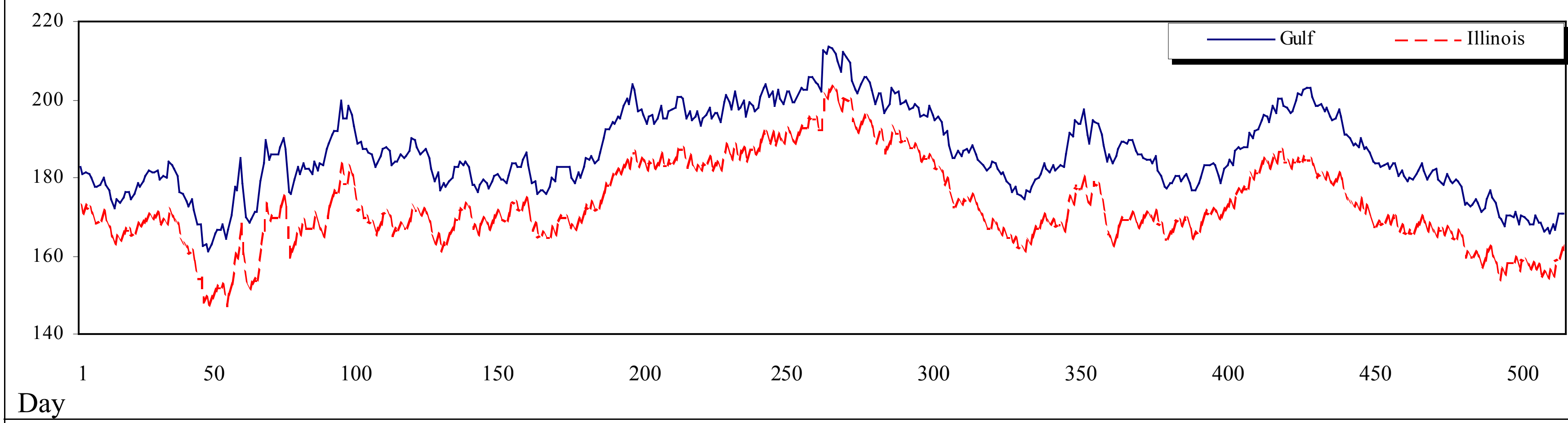
Table 4. Forecast error decompositions

Steps ahead (days)	Std. Error	Illinois	Barge	Gulf
(Illinois)				
1	0.013	13.622	1.598	84.781
2	0.018	11.586	3.689	84.725
3	0.022	12.101	4.335	83.564
7	0.033	14.465	4.545	82.138
14	0.047	17.655	3.933	78.412
(Barge)				
1	0.056	0.000	100.00	0.000
2	0.086	1.990	97.786	0.224
3	0.109	6.195	93.263	0.542
7	0.171	31.405	66.670	1.924
14	0.245	58.334	38.510	3.156
(Gulf)				
1	0.012	0.000	0.000	100.00
2	0.017	0.432	0.004	99.563
3	0.020	0.356	0.032	99.611
7	0.031	0.386	0.051	99.560
14	0.043	0.415	0.057	99.527

The decompositions for each step ahead are given for a Bernanke factorization of contemporaneous covariances, which treats each price series as exogenous in contemporaneous time. The justification for this is based on the DAG on observed innovations from the error correction model shown in equation (7). The decompositions may not sum to one hundred in each row due to rounding.

Figure 1. Daily price data. The sample period is 6th May 1999 – 3rd May 2001 (520 observations):

Panel A. U.S. Gulf and Illinois Soybean Prices (ρ = 0.970).



Panel B. Gulf-Illinois Soybean Price Spread and Mississippi Barge Rate (ρ = 0.949).

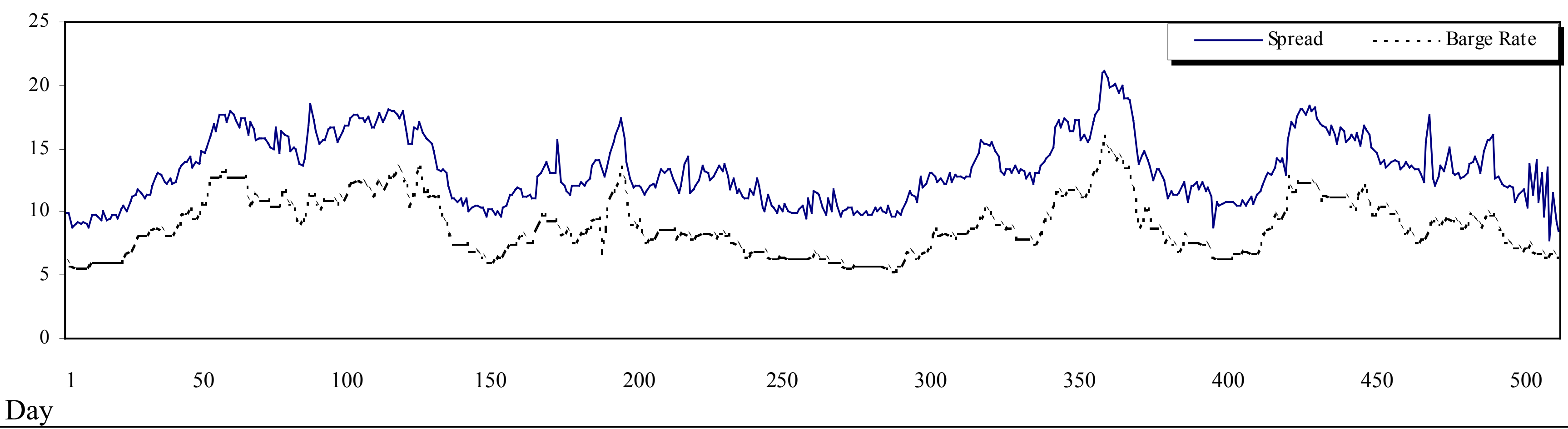
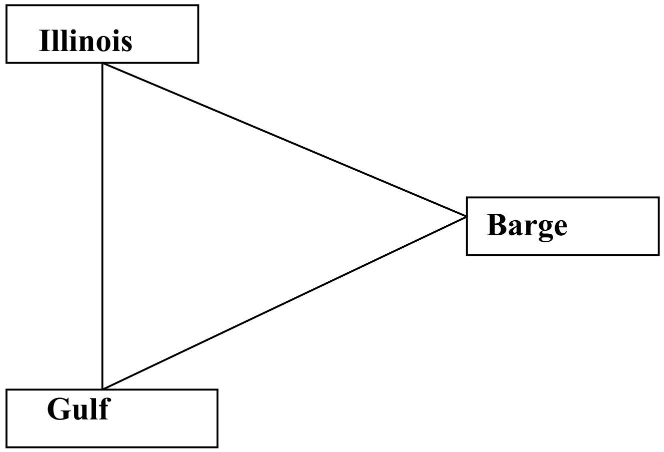


Figure 2. Undirected and Directed Acyclic Graphs

Panel A. Complete undirected graph.



Panel B. Directed graph (lines are significant at the 10% level).

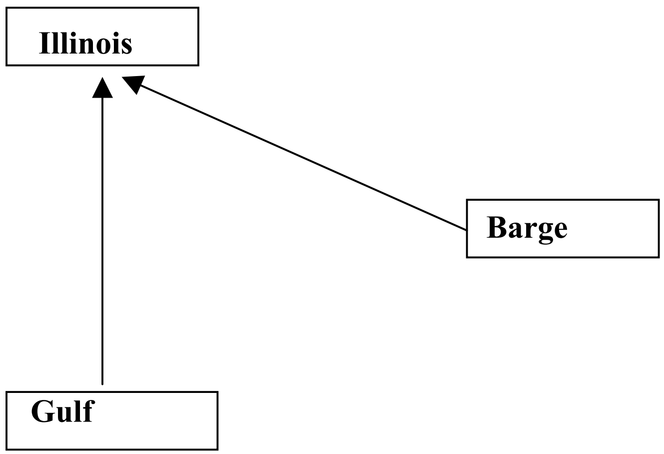
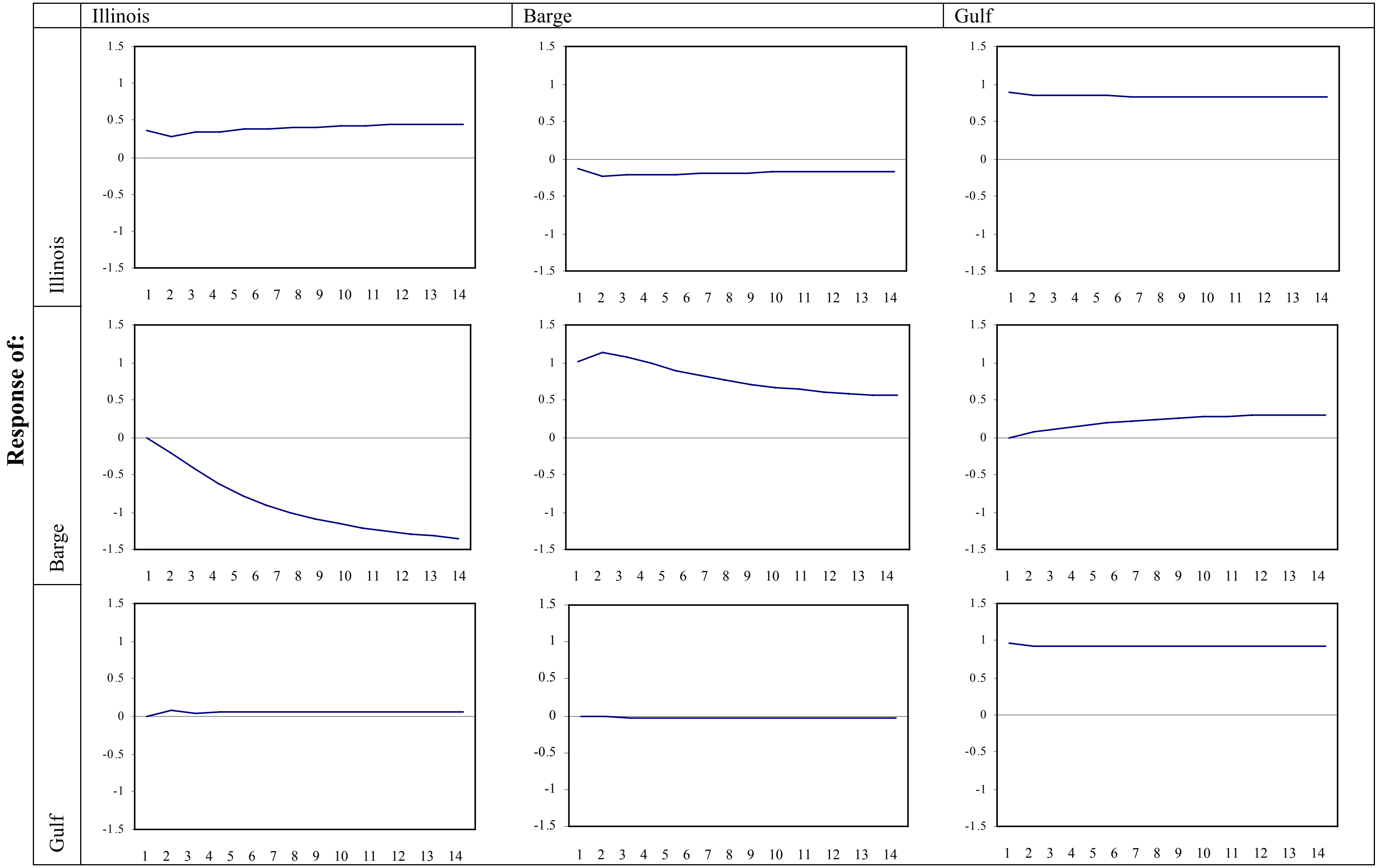


Figure 3. Impulse responses over 14 days from one standard deviation shocks.
Innovation to:



Endnotes

[1] Source: Baltic Exchange, London, UK.

[2] Over its life, the BIFFEX contract has generated a varying degree of trading interest. For instance, at is peak in 1988 the volume reached 97335 contracts (or about 383 contracts per day). However, since November 1999, when the underlying index was changed for the last time (it has been changed a total of 13 times to try and generate trading interest) trading volume only reached an average of 17 contracts a day. Indeed, according to Carlton (1984), 31% of futures contracts introduced in the United States between 1921 and 1983 died within their first two years of trading.

[3] See Carlton (1984) for a description of the important features that a commodity traded on a futures exchange should possess in order to be successful.

[4] Only a handful of papers have employed DAG analysis in economics. Examples include: Bessler and Akleman (1998) and Bessler and Fuller (2000).

[5] For soybeans in particular, which are analyzed in this study, the total tonnage exported out of the U.S. from all ports in this time period was 57.93 million tonnes on a total of 3864 vessels to 44 different countries. However, 40.07 million of those tonnes (or 69.2% of the total) left the U.S. Gulf at New Orleans from the Mississippi River on a total of 1686 vessels to 39 different countries.

[6] Unlike the BIFFEX futures contract, the barge futures contract is not based on an index of prices. Full details on the newly developed barge rate futures contract can be found at the Exchange web site: www.merchants-exchange.com. To date, only one paper has attempted to analyze the feasibility of a futures market for barge freight (Hauser and Buck, 1989). That research, except for some static regression techniques, analyzed the potential role of the market in a largely qualitative manner. The research did recommend that a barge futures contract be developed.

[7] In particular, if we denote $\lambda_1^{'}, \lambda_2^{'}, ..., \lambda_n^{'}$ and $\lambda_1^{*}, \lambda_2^{*}, ..., \lambda^{*}$ as the ordered characteristic roots of the unrestricted and restricted models respectively, then to test the restrictions on β, we can form the test statistic: $T\sum_{i=1}^{r}[\ln(1-\lambda_i^{*})-(1-\lambda_i^{'})]$. Asymptotically, this has a χ^2 distribution with the number of degrees of freedom equaling the number of restrictions placed on β. Large values of λ_i^{*} relative to $\lambda_i^{'}$ (for $i \le r$) imply a reduced number of cointegrating vectors. Therefore, the restriction embedded in the null hypothesis is binding if the calculated test statistic exceeds the tabulated χ^2 value.

[8] Orcutt (1952), Simon (1953), Richenbach (1956), and Papineau (1985) offer similar expressions of asymmetries in causal relations. For a description of various causal asymmetries see Hausman (1998).

[9] These data (like all data used by the authors) are available upon request. A small number of price quotes were missing in each of these markets. On these days, the missing observations were replaced with the most recent price, thus constructing a price series consistent with a random walk.

[10] We excluded the constant from inside the Π matrix due to its statistical insignificance.