Integration and Causality in International Freight Markets – Modeling with Error Correction and Directed Acyclic Graphs

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100 Word Abstract: Using Directed Acyclic Graphs (DAG's) and Error Correction Models we study the dynamics of the notoriously volatile international freight prices that comprise the Baltic Panamax Index, the index on which freight futures trading is based. The DAG's are used to make definitive statements about the contemporaneous correlations between prices and allow us to address the construction of the data-determined orthoganization on contemporaneous innovation covariance, critical in providing sound inference in innovation accounting techniques. Our results provide a rich source of information on price discovery over various time horizons and suggest that the index may not be appropriately comprised and weighted.

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Integration and Causality in International Freight Markets – Modeling with Error Correction and Directed Acyclic Graphs

Using Directed Acyclic Graphs (DAG's) and Error Correction Models we study the dynamics of the notoriously volatile international freight prices that comprise the Baltic Panamax Index, the index on which freight futures trading is based. The DAG's are used to make definitive statements about the contemporaneous correlations between prices and allow us to address the construction of the data-determined orthoganization on contemporaneous innovation covariance, critical in providing sound inference in innovation accounting techniques. Our results provide a rich source of information on price discovery over various time horizons and suggest that the index may not be appropriately comprised and weighted.

I. Introduction

Neoclassical economic thought has long recognized the significance of transportation in the marketing process. In a rudimentary sense, commodities will be transported from high supply to low supply regions if equilibrium conditions between the markets generate a large enough price differential to cover the cost of the transportation. The world's ocean shipping fleet functions under this very fundamental premise. The price of ocean freight is, however, notoriously volatile and the costs associated with the shipment of goods can often be quite substantial. This is particularly true for lower valued commodities, like grains, where the cost of shipment can be substantial portion of the underlying commodity price (Moneta, 1953, Dunn, 1987).[1]

In January 1985, the Baltic Exchange developed the then known Baltic Freight Index (BFI) which in May 1985 would become the underlying asset of the Baltic International Freight Futures Exchange (BIFFEX) contract, a contract designed to hedge uncertainty associated with volatile freight rates. On the basis of their exposure to the risk of adverse freight rate fluctuations, ship owners and charterers could buy or sell BIFFEX contracts so as to protect their freight rate revenue or control their freight rate cost, respectively. In addition to its use for futures trading, the BFI was also considered to be the leading indicator of the condition in the dry-bulk shipping markets. On a daily basis, it provides accurate information about the level of freight rates across a variety of shipping routes, worldwide. This information is extremely valuable for shipping market agents and is an invaluable tool in their decision making process particularly, for an industry such as shipping where trades are being concluded across the globe and there is not a central reporting place to record and monitor the level of activity in the markets. As Gray (1990) points out " *the clarity of vision [provided by the BFI] is a very useful service to the shipping industry.* "

The current article makes significant contributions to the literature from several angles. While several studies (outlined below) have attempted to measure the degree of interconnectivity between the freight markets, to date, no research has estimated the relationships in a truly dynamic manner and have, as such, failed to discuss the implications for commodity futures and physical trading. Therefore it is the principal objective of this paper to assess the degree of interconnectivity between the major shipping routes over various time horizons. To this end, we employ for the first time, Directed Acyclic Graphs (DAG's), which have not, until now, been extensively utilized in economics and finance.

Based on an Error Correction Model (ECM), we develop a framework for estimating forecast error decompositions and impulse responses, which combined, provides a rich source of information on market linkages in both the short, intermediate and long run. Following Spirtes et al., (1993) we examine the contemporaneous relationships among the variables based on the variance covariance matrix from the innovations (residuals) from an ECM by employing DAG's. The application of innovation accounting and impulse response in this study is different from most other studies in the sense that we address the construction of the data-determined orthoganization on contemporaneous innovation covariance critical in providing sound inference in innovation accounting techniques used to assess short, intermediate and long run relationships among the prices (Swanson and Granger, 1997). From a practical standpoint, this information is crucial in assessing the information flows from the shipping markets and once combined with the DAG analysis, allows us to make an assessment on whether the index, on which the futures is traded, is correctly composed. Indeed, our analysis provides a mechanism for deciding upon the correct index and has obvious, yet profound implications for other research in the area of index construction.

Our results suggest that over the longer term all freight prices are interconnected, verifying the suggestion that the dry bulk shipping market is efficient and bulk tonnage is moved effectively between markets stabilizing freight rates. However, through our unique application of DAG analysis we find a strong geographical pattern to information linkages, and that some routes are dominant in terms of 'price leadership'. The results also indicate that from a futures contract design standpoint, some routes are 'redundant' in terms of information flow and could have been effectively dropped from the index, as information from these markets is already captured in other markets. These redundant routes, have therefore diluted the index, making the hedging strategy less effective, perhaps helping to explain the demise of the freight futures market and the consequent growth in the Over the Counter (OTC) market. Importantly, the DAG analysis provides guidance into what should be the appropriate compilation and weighting of the index.

The rest of the paper is as follows. Section II offers a brief overview of the international ocean freight market, previous attempts to model freight markets, and a discussion of freight indices. Section III outlines the methodologies employed in the paper, including an introduction to DAG's, and section IV provides describes the underlying properties of the data series. Section V presents the empirical results, and the last section, section V1, concludes.

II. The International Ocean Freight Market and Freight Indices

Despite the fact that freight rates are highly volatile and unpredictable, the vast majority of empirical research in international trade generally assumes the existence of a frictionless environment where commodities move freely between regions. However, as shown by Goodwin, Grennes and Wohlgenant (1990) failure to account for the highly variable freight rates can lead to false conclusions in empirical research, illustrating the point by finding strong support for the Law of One Price (LOP), only after they included non-constant transportation costs. Only a handful of papers have attempted to include transportation costs into their analysis with examples coming from Geraci and Prewo (1977) and Roehner (1996). They both provide evidence that trade is quite responsive to transportation costs, and that it is vital that transportation costs be included in the study of trade flows.

Independent of the limited trade research that accounts for freight costs, one area of freight price analysis that has generated interest in recent years has been forecasting future freight rates, and assessing the level of volatility in the freight markets. Examples of freight price forecasting are provided by Binkley and Bessler (1983), Cullinane (1992), Denning et al. (1994), Venstra and Franses (1997), Kavussanos and

Nomikos (1999) and Haigh (2000). In general, these authors conclude that forecasting freight rates is particularly difficult, evidently confirming the inherent instability in ocean transport markets. Indeed, in his 1996 study, Kavussanos models the volatility directly of various types of ship prices (e.g., spot versus time-charter) and discovers that the various prices have all exhibited consistently large periods of volatility (that tend to time-cluster). The research also indicates that there are some slight differences in the level of volatility depending on the shipping arrangement, with time-charter ship prices illustrating greater instability.

Without a completely articulated theory the strong presumption is that spot rates and time charter rates ought to be related to one another in a systematic way (in a similar way that short and long bonds are related via the 'term-structure' of interest rates). Indeed, the freight market is often judged as being the textbook example of efficient and competitive in the sense that the available tonnage is moved effectively from market to market to meet demand which stabilizes and links freight rates together (Berg-Andreassen, 1997). As such, in their quest to support this theory, several studies have sought to analyze the relationships between various shipping prices. While Hale and Vanags (1989) reject the hypothesis that spot and time-charter rates are interconnected, the findings of Berg-Andeassen (1997) confirm the perception in the shipping industry that changes in the spot rate impact the movement of time-charter rates.

Several authors, including Binkley and Harrer (1981), Binkley (1983), and Beenstock and Vergottis (1989) have provided important research in the area of ocean freight price determination. Indeed, within the area of freight price determination, attempts have been made to decipher exactly which variables affecting the level of freight prices, are the most volatile (see for instance, Hse and Goodwin (1995)). All the studies point out that equilibrium shipping rates are determined through a complex interaction of supply and demand conditions for the shipping services. The demand for shipping is quite simply a function of the level of international trade and thus is influenced by the usual factors that affect the excess supply and demand of these globally traded commodities. The supply of shipping is principally a function of the existing shipping capacity and the input costs associated with operating a vessel (e.g., fuel prices).

What contributes significantly to the variability of freight rates is the fact that there is limited scope for capacity expansion in the short run due to lengthy construction lags. The major means of expanding short run capacity is through more intensive shipping use, entailing an increase in bunker fuel prices and hence freight rates. This combined with the effect of changing conditions in the world economy, political events, port conditions and even the weather create an unstable, unpredictable shipping environment.

Given the levels of volatility evidenced in the freight markets, the benefits of providing a futures market in freight rates had been obvious to market practitioners in the shipping industry since the 1960's. However, such a market was eventually established only in 1985 (Gray, 1990). The reason is that the underlying asset of the market - the service of seaborne transportation - is not a physical commodity that can be delivered at the expiry of the futures contract. By its very definition, a futures contract is an agreement to deliver a specified quantity and grade of an identifiable commodity, at a fixed time in the future. This obstacle was overcome with the introduction of the cash settlement procedure for the stock index futures contracts in 1982. When the underlying commodity is not suitable for actual physical delivery then an alternative is to deliver the cash value of the commodity at that time. The development of the cash settlement procedure led to the creation, on 1 May 1985, of the BIFFEX contract. The underlying asset, which is delivered at the settlement date, is the cash value of a freight rate index, originally known as the Baltic Freight Index (BFI), now known as the Baltic Panamax Index (BPI).

The BPI is calculated every London business day by the Baltic Exchange, from data supplied by a panel of fourteen international shipbrokers, and is reported in the market at 1 p.m. London time. The panel is composed of companies who " … *are deemed by the Baltic Exchange to be of sufficient size, reputation and integrity to be good independent arbiters of the market*" (Gray, 1990). Each shipbroking company submits its view of that day's rate on each of the BPI constituent routes, at 12 a.m. London time. These rates are based either on actual shipping fixtures concluded in the market, or in the absence of an actual fixture, reflect the panelist's expert view of what the rate would be on that day if a fixture had been concluded. As a precautionary measure to prevent any individual broker influencing the market, the highest and lowest assessments for each trade route are excluded and a simple arithmetic average is taken of those that remain. The resulting route averages are used in the computation of the BPI.

The BPI currently comprises 7 seaborne trade routes. The underlying trade routes and their respective weightings in the composition of the BPI have been substantially revised on a number of occasions to ensure that the index provides a sound basis for the effective functioning of the BIFFEX market. These revisions in the composition of the index, since its inception in January 1985, are presented in Table 1 and schematically in Figure 1; the notes, in the same table, describe some minor amendments to the composition of the index. [2]

We can broadly identify four different periods corresponding to differing compositions of the underlying index. During the first period (January 85 to August 90), the index consisted of capesize, panamax and handysize spot freight rates. [3] For the period up to 3 November 1988, there were 13 routes, of which, 3 were capesize routes (routes 6, 8 and 10 representing 15% of the index composition), 5 were panamax routes (routes 1, 2, 3, 7 and 9 which made up 65% of the index) and the remaining 5 were handysize routes (routes 4, 5, 11, 12 and 13 which accounted for the remaining 20%). After 4 November 1988, route 13 was deleted and the number of the index constituent routes was reduced to 12. The composition of the index was altered again on 6 August 1990 with the introduction of three time-charter routes (routes *1A*, *3A* and *5*). [4] The index was revised once more on 5 February 1991 when the panamax route 7 was replaced by a capesize route and a new time-charter route (route 2A) was introduced. An additional time-charter route was introduced on 5 February 1993 (route 9). The four handysize routes (i.e. routes 4, 5, 11 and 12) were eventually excluded from the composition of the index in November 1993 and the number of the index routes was reduced to 11. Finally, in November 1999, the capesize routes were removed from the underlying index and since then the index consists of panamax routes only.

These revisions have been driven by the intention to generate an underlying index which promotes the effective functioning of the BIFFEX contract. For instance, Gray (1990) indicates that time-charter routes were introduced in order to facilitate market participants who wanted to hedge their freight rate risk on these routes. Similarly, Cullinane et al. (1999) indicate that the exclusion of the handysize routes was implemented in response to pressure from market agents, operating on panamax and capesize trade-routes, who wanted to increase the panamax and capesize representation on the index so as to enhance the performance of their hedges. Finally, the exclusion of the capesize routes from the BPI, followed after an extensive review and consultation of the London International Financial Futures Exchange (LIFFE) with BIFFEX market participants, who "*put a Panamax index at the top of their list of requirements*" since this was expected to increase the performance of hedges on the panamax routes.[5]

The question of whether or not the BIFFEX contract provides effective freight risk management has been analyzed extensively in the literature by different researchers including Kavussanos and Nomikos (1999, 2000) and Haigh and Holt (2000). These studies invariably indicate that BIFFEX is not a very effective hedging instrument; since it does not provide risk protection to the degree that is evidenced in other commodity and financial futures markets. The underlying reason behind this is that the BIFFEX contract is based on an index comprising the routes and as such, provides a cross-hedge against these shipping routes; this makes the hedge less appealing, and the volume of trading lower. However, despite the numerous revisions in the composition of the BPI, trading volume in the market has remained at low levels and, as a result, in June 2001, LIFFE, the authority regulating the BIFFEX contract, announced that trading in the BIFFEX contract would cease in April 2002.[6] Whether the index is correctly composed and whether there are any obvious patterns or redundancies within the index is the question we attempt to address next.

III. Models and Methodologies

Cointegration and Error Correction Framework

The development of cointegration modeling stems largely from the work of Granger (1986) and Engle and Granger (1987). Although the estimated coefficients can be shown to be consistent, the associated standard errors may be misleading for any hypothesis testing (Hall (1986), Stock (1987)), and as such much work on applied cointegration analysis has relied on Johansen's multivariate approach (Johansen, 1988, 1991; Johansen and Juselius, 1990). 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, X_t, (n = 7 here) that is generated by an autoregressive form depicted as:

$$X_t = w + \sum_{i=1}^{k} \Pi_i X_{t-i} + e_t \quad t = 1,2,...,T \, , \tag{1}$$

$e_t \sim Niid(0, \Sigma)$,

where X_t is an n x 1vector of the I(1) variables (seven routes comprising the BPI), Π_i is an n x n matrix of parameters, w is a vector of constants, and e_t is a random error term. Johansen and Juselius (1990) prove that eq. (1) can be rewritten as error-correction representation as follows:

$$\Delta X_t = \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-1} + e_t \, , \tag{2}$$

with

$$\Gamma_i = -(I - \Pi_1 - \Pi_2 - ... - \Pi_i)(i = 1...k-1) \, , \tag{3}$$

and

$$\Pi = -[I - \Pi_1 - ...\Pi_k] \; . \tag{4}$$

Eq. 2 resembles a Vector Autoregression (VAR) (in fist differences), with an inclusion of the lagged-level component, also known as the Error Correction Term (ECT). Since e_t is stationary, the rank of the 'long-run' matrix, Π, determines how many linear combinations of X_t are stationary. We know that the rank of any matrix is equal to the number of characteristic roots that are different from zero, and so the rank of Π determines the number of cointegrating vectors. In practice, we can obtain only estimates of Π and its characteristic roots, and once these are estimated we can test for the number of characteristic roots (Johansen (1991)). If Π is full rank (Π =7), then the freight price series are jointly stationary and a VAR (levels) is the appropriate model to use to study the relationships between the freight prices. If the rank of Π is positive and less than n, then cointegration is present, and there exist matrices ab', with dimensions n x r, where r is the number of cointegrating relationships, such that Π = ab'. The matrix b is the matrix of cointegrating parameters and the matrix a is the matrix of weights (also known as the speed of adjustment parameters) with which each cointegrating vector enters the *n* equations.

All the parameters within the ECM can provide information on both the long run and the short run nature of the relationships between the freight prices. First, the long-run structure can be identified by testing hypothesis associated with b. Detailed examination on the cointegration space spanned by b provides rich information on the long-run relationships and market structure of the freight prices. Indeed, hypothesis testing allows us to determine whether some markets may be excluded from the long run relations. The short run dependencies among the prices can also be identified through hypothesis testing on a and Γ_i. Hypothesis testing on a, the short run adjustment to the long run relationships, can be conducted in a similar way to that used for hypothesis testing on b. This allows 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 may be the best way to describe the short run structure and interdependencies among the freight prices (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 seven freight 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 (Phillips, 1998).

However, the basic problem of the orthoganalization of residuals from the ECM remains unresolved. Most studies employing ECM or VARs have yet to fully address the problem associated with the contemporaneous relationships among variables. Despite this, innovation accounting (impulse responses) requires 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 the Choleski factorization 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 the correct structural model may not be known to the researcher. Therefore, 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 which, until now, have been largely ignored in the economics and finance literature. It is to a brief explanation of DAG theory that we now turn.

Directed Acyclic Graphs

For three variables A, B and C, illustrate a causal fork, A causes B and C, as: B ← A → C. The unconditional association between B and C is nonzero (as both B and C have a common cause in A), but the conditional association between B and C given knowledge of the common cause A, is zero. This is one screening off property associated with causal relations: *common causes screen off associations between their joint effects*. Illustrate the inverted causal fork, A and C cause B, as: A→ B ←C. Here the unconditional association between A and C is zero, but the conditional association between A and C given the common effect B is not zero. A second screening off property associated with causal relations is: *common effects do not screen off association between their joint causes*. These screening off phenomieina are captured in the literature of *Directed Acyclic Graphs*.[7]

A Directed Acyclic Graph is a picture illustrating causal flow between variables with lines with and without arrowheads. Variables connected by a line are said to be adjacent. If we have a set of variables {A,B,C,D,E}: (i) the undirected graph contains only undirected lines (e.g., A — B); (ii) a directed graph contains only directed lines (e.g., B → C); (iii) an inducing path graph contains both directed lines and bi-directed lines (C $\leftrightarrow$ D); (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 DAG is a graph that contains no directed cyclic paths (an acyclic graph contains no directed path from a variable that returns to itself). Only acyclic graphs are used in the paper.

Directed Acyclic Graphs represent conditional independence as implied by the recursive product decomposition:

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

where Pr denotes probability. The symbol pa_i refers to the realization of some subset of the variables that precede (come before in a causal sense) n_i in order $(n_1, n_2, ..., n_n)$. 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) provide a proof of this proposition. D - separation characterizes the conditional independence relations given by equation (5). If we formulate a Directed Acyclic Graph 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, X and Y are in V, and Z is also in V, then G linearly implies the correlation between X and Y conditional on Z is zero if and only if X and Y are d-separated given Z.

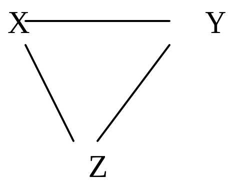
Spirtes, et al. (1999) consider the relationship between directed graphs and the counterfactual random variable model (the random assignment experimental model) of Rubin (1978) and Holland (1986). For one (causal relationships summarized by directed graphs on observational data) to imply the other (causal relationships revealed in a random assignment experiment) one needs three conditions. First, one needs to focus on *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 omit X from 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.

Causal sufficiency suggests that one finds a sufficiently rich set of theoretically relevant variables upon which to conduct 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. Spirtes, Glymour and Scheines (1993) note that the Markov condition has been questioned in quantum mechanical experiments. Failure to require the condition would require us to ignore statistical dependency even in experimental designs (Spirtes, Glymour and Scheines 1993, p. 64). Finally, the faithfulness condition may not hold if parameter values cancel one another. For example the following two equations describe the underlying model that generates X, Y, and Z:

$$X = 20Y + 2Z + e_X$$

$$Z = -10Y + e_Z$$

where e_X and e_Z are uncorrelated noise terms, each not correlated with its associated right hand side variables (e_X is not correlated with Y or Z and e_Z is not correlated with Y). If this is 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 are 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. However, 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 even with the unstable correlation structure; 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).

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 $\rightarrow$ Y $\leftarrow$ Z if Y is not in the sepset of X and Z. If X $\rightarrow$ Y, Y and Z are adjacent, X and Z are not adjacent, and there is no arrowhead at Y, then orient Y — Z as Y $\rightarrow$ Z. If there is a directed path from X to Y, and a line between X and Y, then direct (X — Y) as: X $\rightarrow$Y.

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

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

and n is the number of observations used to estimate the correlations, $r(i,j|k)$ 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, the distribution of $z(r(i,j|k),n) - z(r(i,j|k),n)$ 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. When sample size falls below 100 observations significance levels as high as .20 are recommended (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).

As previously suggested, applications of DAG's 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."

IV. Data

Daily data from February 2nd 1996 through to May 7th 2001 are collected from the Baltic Exchange. The starting date of February 2nd 1996 is chosen, as this is the last date that a major change was made to the BPI.[8] Focusing on this period allows us to concentrate on the interactions of the freight prices when there have been no major changes occurring to any of the underlying routes.

Summary statistics on the prices are presented in Table 2 along with the correlations among the freight prices. As observed by the coefficient of variation, the spot routes (*R1*, *R2* and *R3*) show less variability than the time charter rates (*R1A*, *R2A*, *R3A* and *R4*). This reflects the higher volatility of time-charter routes compared to the underlying spot routes. Turning next into the correlation coefficients, we can note that the highest correlation coefficients are evidenced between the spot and their corresponding time-charter routes (that is routes *R1* and *R1A*, routes *R2* and *R2A* and routes *R3* and *R3A*). This is not surprising given that the definitions of spot routes are very similar to those of the corresponding time-charter routes. Take for instance routes *R1* and *R1A*. Route *R1* reflects cargo movements of grain from US Gulf to Belgium or Holland; route *R1A* on the other hand is a time-charter route for a round-trip voyage from north-west Continent (Europe) to US and back to north-west Continent. Therefore, route *R1A* consists of two legs; a ballast leg from Europe to US - as there are few dry bulk cargoes originating in Europe - and a laden leg from US to Europe. Similarly, route *R2* (Grain from US Gulf to Japan) is similar to route *R2A* (timecharter route from Continent to the Far East via US Gulf). Therefore, route *R2A* consists of a ballast leg from the Continent to US Gulf and a laden leg from US Gulf to Japan as is route *R2*. Turning now into routes *R3* and *R3A* we can see that they are also linked. More specifically, route *R3* represents the shipping freight cost of transporting grain from North Pacific to Japan while route *R3A* typically represents cargo flows from Japan to North Pacific for the transportation of grain and then back to Japan. Finally, route *R4* comprises a ballast leg from Japan to North Pacific to load coal and then back to the European continent. These similarities in the definitions of the BPI routes are manifested by the high values of correlation coefficients evidenced in Table 2. The high degree of association between spot and timecharter rates is also confirmed by the time series plots of time charter price series (panel A) and the spot freight price series (panel B) in Figure 2. The discussion above indicates that the underlying BPI shipping routes are linked. However, it does not provide detailed evidence on the dynamics of these linkages as well as on the existence of causation between them. These are addressed in the following section.

V. Empirical Results

Unit root tests (Dickey and Fuller, 1981) on the levels and first differences of the Baltic routes, presented in Table 3, indicate that the series in levels follow unit root processes at the 5% level, with the exception of route *R*3A which has a unit root at the 1% level. As a result, cointegration techniques are used to examine the existence of a long-run relationship between the shipping routes. The lag length (k) in the VECM of equation (2), chosen on the basis of the Schwarz Bayesian Information Criterion (SBIC) (Schwarz, 1978), is 2. The VECM of equation (2) is then estimated using the maximum likelihood estimation procedure of Johansen and Juselius (1990).[9] The estimated λ_{max} and λ_{trace} statistics, in Table 4, indicate that there are three cointegrating relationships between the underlying freight rate routes, since the first failure to reject the null hypothesis of no cointegration is when testing for $r \leq 3$ with the λ_{trace} test and when testing for $r = 3$ with the λ_{max} test; therefore, for the remainder of the study an ECM with three cointegrating relationships is modeled. After imposing the three cointegrating vectors the estimated matrices associated with (2) using data from February 2nd 1996 through to May 7th 2001 are as follows:

$$\Pi = a\,b'\,X_{t-1} = \begin{bmatrix} .00086 & .00025 & -.00002 \\ (4.796) & (1.394) & (-.097) \\ .00032 & -.00027 & -.00037 \\ (1.497) & (-1.221) & (-1.698) \\ .00086 & -.00002 & .00004 \\ (4.822) & (-.098) & (.233) \\ .00111 & -.00008 & .00042 \\ (4.604) & (-.349) & (1.756) \\ -.00035 & .00023 & .00055 \\ (-2.492) & (1.629) & (3.889) \\ .00035 & -.00119 & .00074 \\ (1.409) & (-4.757) & (2.954) \\ .00055 & .00013 & .00038 \\ (2.226) & (.549) & (1.550) \end{bmatrix} \mathrm{X}$$

$$\begin{bmatrix} -11.649 & 28.308 & -10.495 & -20.547 & 21.075 & 7.440 & -17.611 & 3.449 \\ -5.658 & 10.571 & 5.008 & -15.706 & -17.829 & 21.007 & -4.409 & 7.163 \\ 5.745 & 6.202 & 13.874 & -14.985 & -22.902 & 10.040 & -1.274 & 3.172 \end{bmatrix} \begin{bmatrix} R1_{t-1} \\ R1A_{t-1} \\ R2_{t-1} \\ R2A_{t-1} \\ R3_{t-1} \\ R3A_{t-1} \\ R4_{t-1} \\ 1 \end{bmatrix}$$

and

$$\Gamma = \begin{bmatrix} .389 & .136 & .159 & .032 & .036 & -.017 & .028 \\ (9.942) & (3.498) & (3.704) & (.815) & (.764) & (-.510) & (.840) \\ .283 & .300 & .213 & .094 & .085 & -.016 & .013 \\ (5.709) & (6.074) & (3.915) & (1.888) & (1.417) & (-.369) & (.307) \\ .055 & .021 & .490 & .112 & .006 & .013 & .024 \\ (1.425) & (.547) & (11.476) & (2.873) & (.119) & (.402) & (.719) \\ .211 & .057 & .319 & .342 & .078 & -.026 & .029 \\ (3.892) & (1.061) & (5.356) & (6.308) & (1.182) & (-.551) & (.608) \\ .066 & -.056 & .102 & -.012 & .455 & .076 & .075 \\ (1.989) & (-1.700) & (2.798) & (-.371) & (11.231) & (2.675) & (2.596) \\ .205 & -.217 & .123 & .036 & .223 & .388 & .263 \\ (3.409) & (-3.620) & (1.854) & (.590) & (3.046) & (7.546) & (5.040) \\ .196 & -.192 & .160 & -.021 & .235 & .162 & .491 \\ (3.293) & (-3.234) & (2.444) & (-.356) & (3.240) & (3.172) & (9.526) \end{bmatrix}$$

The first matrix is the factorized matrix of long-run coefficients, $\Pi = ab'$, multiplied by the vector of lagged variables, X_{t-1}, which includes an intercept term. The Π matrix has been factorized as ab' where a captures the short-run adjustment toward the long-run equilibrium and b' is the vector of cointegrating relationships. Indeed, perturbations in the long-run equilibrium are given by $b' X_{t-1}$. As the t - statistics associated with the corresponding a coefficients suggest, many of the markets seem to respond to adjustments in the equilibrium relationship (using a critical t-value of 1.96 (5%)). In order to test formally whether freight rates for a route respond to the long-run information generated from all the other freight routes, we perform hypothesis tests on whether an entire row of a equals zero. Results from these tests, do not provide conclusive evidence as to whether any of the freight rates are weakly exogenous at the most stringent levels of significance (i.e., 1% level). This indicates that all routes react to shocks in other markets, a finding consistent with the efficient market theorem provided by Berg-Andreassen (1997).[10]

Additionally, we also test restrictions associated with the long run parameters (b) which allows us to make more concrete statements about the nature of the cointegrating vectors. Indeed, we may find a stable cointegrating vector holding the series together, but this may be due to a smaller sample of the seven series rather than all seven together. Therefore, we formally test the hypothesis that each of the seven series is not in the cointegrating space, or in other words, is not present in any of the three cointegrating vectors. At stringent levels of significance (i.e., 1% level) we find that each of the series belongs in the larger system that links the freight prices together.

While testing whether each of the series is part of the entire cointegrating system is informative, it is also interesting to test other hypotheses associated with the long-run relationships. That is to test whether groups of freight prices may belong to one particular vector, whereas other groups may belong to another vector. For instance, Bessler and Fuller (2000) impose restrictions on the long run relationships of various rail rates based on their physical characteristics. In our case, we have shipping routes with common geographical characteristics (e.g. shipping routes originating in the Atlantic or Pacific basins) or contract types (e.g. time-charter vs. spot) or even route coverage (for instance, route 2 and route 2A). Therefore, we also test for restrictions along these lines within the cointegrating space.

We test for overidentifying restrictions on the cointegration space (as outlined in Hansen and Juselius, 1995). Focusing such restrictions on time-charter versus spot and on geographical characteristics resulted in no clear overidentifying restrictions. Henceforth we therefore continue to employ the 'unrestricted' cointegrating matrix. This finding indicates that these markets are efficient in the sense that available tonnage is moved effectively from market to market to meet the demand and a consequence stabilizing the freight markets, thus ensuring that over the longer term, their prices move together.

Turning next into the Γ matrix, containing the coefficients of the lagged freight rates given above, we note that most of the coefficients are statistically significant. Interestingly, the coefficients associated with $R2$ (Grains from US Gulf – Japan) are highly significant across all the estimated equations, with coefficients ranging from .123 on $R3A$ to .319 on $R2A$. Such a finding suggests the importance of this particular freight route since all the other shipping routes seem to be significantly affected by this route.

The preceding analysis indicates that it is quite difficult to discern the short run patterns of responses to strengths of the dependencies by either focusing on individual parameter estimates whether they are derived from the Γ or the a matrix. Therefore, to address this issue we turn our attention to the innovation accounting techniques which are described next.

Innovation Accounting

A more detailed insight on the causal relationship between freight rates is obtained by analyzing the decompositions of forecast errors generated from the ECM of equation (7). Critical to such analysis is the treatment of contemporaneous innovations in the time series (Sims, 1980). In this paper, we follow the factorization commonly referred to as the "Bernanke ordering". Consider the innovation vector (e_t) from the ECM as: **?** $e_t = v_t$, where **?** is a 7 x 7 matrix of coefficients and v_t is a 7 x 1 vector of orthogonal shocks. To illustrate, a general description of the model being considered here is given in Equation (7) below:

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} & a_{15} & a_{16} & a_{17} \\ a_{21} & a_{22} & a_{23} & a_{24} & a_{25} & a_{26} & a_{27} \\ a_{31} & a_{32} & a_{33} & a_{34} & a_{35} & a_{36} & a_{37} \\ a_{41} & a_{42} & a_{43} & a_{44} & a_{45} & a_{46} & a_{47} \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & a_{56} & a_{57} \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} & a_{67} \\ a_{71} & a_{72} & a_{73} & a_{74} & a_{75} & a_{76} & a_{77} \end{bmatrix} \begin{bmatrix} e_{11t} \\ e_{21t} \\ e_{31t} \\ e_{41t} \\ e_{51t} \\ e_{61t} \\ e_{71t} \end{bmatrix} = \begin{bmatrix} n_{11t} \\ n_{21t} \\ n_{31t} \\ n_{41t} \\ n_{51t} \\ n_{61t} \\ n_{71t} \end{bmatrix}. \tag{7}$$

Here $e_{11t}, e_{21t}, e_{31t}, e_{41t}, e_{51t}, e_{61t}$, and e_{71t} are observed (non-orthogonal) innovations in the series differenced freight prices $\Delta X_1, \Delta X_2, \Delta X_3, \Delta X_4, \Delta X_5, \Delta X_6$, and ΔX_7 in period *t*; $n_{11t}, n_{21t}, n_{31t}, n_{41t}, n_{51t}, n_{61t}$, and n_{71t} are orthogonal innovations for the same series in period t, where orthogonalization is obtained via the matrix **A**. As documented by Doan (1992), a factorization is identified if there is no combination of *i* and *j* ($i \neq j$) for which both $\{a_{ij}\}$ and $\{a_{ji}\}$ are non-zero (where $\{a_{ij}\}$ is element *i,j* of the matrix) **A**.

A common practice in early VAR-type analysis was to rely on a Choleski factorization, so that the **A** matrix is lower triangular in order to achieve a just-identified system in contemporaneous time. In the ensuing analysis we employ the directed graphs algorithms given in Spirtes et al. (1993) to place zeros into the **A** matrix (a similar suggestion was made by Swanson and Granger (1997)). A DAG is an assignment of causal flow (or the lack thereof) among a set of variables (vertices) based on identifying restrictions in the following innovation correlation matrix (Σ) from the ECM (where we represent the innovations as e_{it}). Our seven variable ECM results in the following innovation correlation matrix where lower triangular entries only are printed in the order, *R1*, *R1A*, *R2*, *R2A*, *R3*, *R3A* and *R4*.

$$\Sigma(e_t) = \begin{bmatrix} 1.00 & & & & & & \\ 0.72 & 1.00 & & & & & \\ 0.59 & 0.67 & 1.00 & & & & \\ 0.65 & 0.80 & 0.76 & 1.00 & & & \\ 0.39 & 0.43 & 0.44 & 0.44 & 1.00 & & \\ 0.40 & 0.48 & 0.41 & 0.49 & 0.71 & 1.00 & \\ 0.37 & 0.46 & 0.40 & 0.44 & 0.70 & 0.82 & 1.00 \end{bmatrix}. \tag{8}$$

The off-diagonal elements of the scaled inverse of the $\Sigma(e_t)$ (or any other correlation matrix) are in fact the negatives of the partial correlation coefficients between the corresponding pair of variables (in our case, freight rates) given the remaining variables in the matrix (Whittaker 1990, p.4). To illustrate, if we were interested in computing the conditional correlation between innovations in $R2\,(e_{3t})$ and $R2A\,(e_{4t})$ given innovations in $R3(e_{5t})$ and $R3A\,(e_{6t})$ we would calculate the inverse of the following matrix $\Sigma_1(e_t)$ (taking the corresponding elements from $\Sigma(e_t)$):

$$\Sigma_1(e_t) = \begin{bmatrix} 1.00 & & & \\ 0.76 & 1.00 & & \\ 0.44 & 0.44 & 1.00 & \\ 0.41 & 0.49 & 0.71 & 1.00 \end{bmatrix}. \tag{9}$$

The matrix $\Sigma_1(e_t)$ is the 4 x 4 matrix with lower triangular elements associated with the $R2$, $R2A$, $R3$ and $R3A$ given in (8) above. The off-diagonal elements of the scaled inverse of the $\Sigma_1(e_t)$ matrix, denoted by $\Sigma_1^*(e_t)$, (where the * indicates that we have scaled the inverse matrix) are the negatives of the partial correlation coefficients between the corresponding pair of variables given the remaining variables. In this case:

$$\Sigma_1^*(e_t) = \begin{bmatrix} 1.00 & & & \\ .68 & 1.00 & & \\ .17 & -.01 & 1.00 & \\ -.05 & .23 & .63 & 1.00 \end{bmatrix}. \tag{10}$$

For instance, the partial correlation between innovations in rates in one market ($R2$) and innovations in another market ($R2A$), given innovations in markets $R3$ and $R3A$ is 0.68. Under the assumption of multivariate normality, Fisher's z - test (Eq.6) can be applied to test for significance from zero. In this particular instance, the correlation between routes $R2$ and $R2A$ given $R3$ and $R3A$ (0.68) is significantly different from zero at all conventional significance levels, whereas the correlation between $R2A$ and $R3$ given $R2$ and $R2A$ (-.01) is not significantly different from zero (the marginal significance level is 0.703). So we can say that innovations in the *R2* and *R2A* rates are related in contemporaneous time whereas innovations in *R2A* and *R3* are not.

Directed graphs provide an algorithm for removing edges between markets (similar to that described above) and also directing the causal flow of information between the markets. The algorithm starts with a complete undirected graph (like the one shown in the top panel of Figure 3) where innovations in every market are connected with innovations in every other market. The algorithm removes edges based on vanishing correlation and partial correlation, the latter measured based on the scaled inverse correlation matrix (which is derived from the complete contemporaneous variance-covariance matrix from the ECM as explained above). Edges between the variables are sequentially removed based on either vanishing zero order correlation (unconditional correlations) or vanishing conditional correlations, where conditioning is done on all possible sets with members 1,2,…,k – 2, where k is the number of variables studied (7 in this case).

The middle panel of Figure 3 gives the pattern on innovations based on the seven-freight market ECM (Eq.8). We see two undirected edges in panel B: *R1 – R2* and *R4 – R3A*. Here Tetrad is not able to direct the edges but some other interesting and intuitively pleasing patterns emerge.[11] The first observation is that there are no complete 'sinks' whereby a particular route only receives information from other routes, but does not generate any information to other routes. This first observation leads us to conclude that no routes are redundant in terms of generating information in contemporaneous time. However, some routes seem to 'receive' more information from other markets rather than generate information. For instance, the graph illustrates that *R1* is led in contemporaneous time by *R1A* and *R2A* but does not 'lead' any other route. That is, we do not have a directed edge away from that route. Additionally, we can note that *R1* and *R2* are clearly linked together although we are not able to distinguish the direction of causality between them. Despite this undirected edge, it is clear that *R1* does not seem to be leading other shipping routes in terms of information discovery.

Turning next into *R1A* we can note that while it leads *R1*, it is also influenced by *R2* (grains from US Gulf to Japan) and *R4*, the eastern hemisphere time charter route, which does ultimately connect

Japan, Australia and European Continent (the same destination as *R1A*). On the other hand, *R2*, which is considered by shipping practitioners as being the benchmark route, is clearly a dominant route in contemporaneous time. This is verified by observing the number of directed edges leaving that route and influencing other routes. As can be seen *R2* leads *R1A*, *R2A* and *R3* in contemporaneous time, and is also linked with *R1*, although we can not determine the direction of causation in this case. While DAG's alone seem to verify the importance of *R2* in the price discovery process, data provided by the United States Federal Grain Inspection Service (FGIS) - which provides data on volume of trade and number of ships leaving the U.S. ports - also point out the significance of *R2* in the world sea borne trade. To illustrate, between Feb 2nd 1996 and May 7th 2001 (the period of time studied here), a total of 86.5 million tones of grain was transported from the U.S. Gulf to South Japan (*R2*) on 4556 different vessels. This compares to a total of 14.5 million tones of grain being transported from the U.S. Gulf to the Amsterdam-Rotterdam-Antwerp (ARA) region of Europe (*R1*) on 414 vessels, and 37 million tonnes were shipped from the US. North Pacific to South Japan (*R3*) on a total of 1908 vessels. Using *R2* as the base route, we can see that in terms of tonnage shipped, volume does have some influence on price leadership. In particular volume on *R1* is only about 17% of that shipped to Japan via *R2* and volume on *R3* is about 43% of the total volume that is shipped via *R2*. Focusing our attention on the time charter routes, we see that *R2A*, 'leads' *R1* in contemporaneous time, but it is clearly influenced (being led) by both *R2* and *R3A*. This is in contrast to *R2A*'s spot equivalent, *R2*, which is a more dominant route in terms of price leadership.

Not surprisingly routes *R4*, *R3A* and *R3* are all linked together. The common characteristic of these routes is that they reflect trading in the Pacific basin. Interestingly, this group of routes is also connected via R2A to the U.S. Gulf region. This is expected as the physical movement of goods within the U.S. to competing ports links the prices in a way described in Berg-Andreassen (1997). For instance, route *R3A* leads *R2A* but both these routes have the common characteristic that they are routes that ultimately head for Japan/South Korea. *R4* also seems to lead route *R1A*. Intuitively, these routes originate in very different parts of the globe but have the common feature that their final destination is North Continent.

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 4 respectively. The forecast error decomposition allows us to consider which freight rates are statistically exogenous or endogenous relative to each other at differing forecast horizons. A freight rate would be considered statistically exogenous if most of the variance of its forecast error is due to its own innovations rather than the innovations originating from the other freight prices in the system. A truly exogenous freight rate should explain 100% of its forecast error variance at all forecast horizons. In this study we provide horizons from 1,2,3 and 5 days (the very short run) to intermediate run (10 days) to the long run (30 and 60 days). The maximum forecast horizon is set to 60 days since this is the typical duration of hire in the time-charter routes of the Baltic Panamax Index**.** The first column in the output is the standard error of forecast for each particular route. The remaining columns provide the error decompositions. Each row should add up to 100% (but may not due to rounding). Calculation of the impulse responses on the other hand, enables us to evaluate the dynamic paths of adjustment of each of the freight prices to shocks in the data series.

Looking for instance at the forecast decompositions for *R1*, we can note that this route is quite heavily influenced by *R1A* and *R2* which combined explain almost 61% of the uncertainty in *R1* after just 1 day and their impact is even stronger when we consider the longer term. This finding is not surprising given the results from the DAG's as well as the relatively low level of physical trading activity on this route. Indeed, as suggested by the directed graph analysis, *R1* acts as a "near sink" since it is quite unimportant in generating information affecting other markets. This pattern is also verified by looking at the influence that *R1* exerts on the forecast errors of the remaining routes, in the second column of Table 5, where the greatest influence of *R1* into any other route across all forecast horizons is only 5.56% (R3A for 60 days ahead). Finally, recall that DAG's suggest we cannot assign the direction of causation between *R1* and *R2* in contemporaneous time. However, we can see from the error decompositions that *R2* explains up to 49.00% (after 10 days) of the variation in *R1*, whereas *R1* explains at most 0.81% of the variation in *R2*. Therefore, *R2* dominates *R1* in terms of information discovery across all forecast horizons.

Similar conclusions about *R1* emerge when we consider the impulse response functions. Reading along the columns from the left hand side of figure 4 to the right hand side we can assess the effect of shocking each market (along the top) and the resulting response on the other markets down the left hand side. Shocking *R1* for instance, has some effect on itself and a slight effect on the other routes although the effect dies out fairly quickly which confirms the fact that *R1* is relatively unimportant in terms of price discovery.

Turning next to the forecast decompositions for *R1A*, we can note that it is heavily influenced by *R2* in the short run, and continues to be influenced by this widely regarded influential market into the much longer term, although at that time the Far-Eastern routes (*R3*, *R3A* and *R4*) also help explain some of the variation. In the short run, (1 day) *R4* influences *R1A*, accounting for 15.9%. Interestingly, this complements the findings from DAGs that *R1A* is affected by *R4* in contemporaneous time. We can also note that *R1A*, unlike its 'spot' counterpart (*R1*), does influence other markets particularly in the longer term (explaining 27.113%, 12.109% and 28.313% in *R1*, *R2* and *R2A*, respectively after 60 days). The superior importance of *R1A* in information discovery is also confirmed by the impulse response functions in Figure 4 which show that *R1A* has a bigger effect on other routes and the shocks do not die out as quickly as its spot counterpart, *R1*. Therefore, these findings indicate that *R1A* is more influential, in terms of information dissemination, compared to *R1*. This is expected given the scope of trading reflected in route *R1A*. Typical routes reflected within the definition of route *R1A* include Continent – North America for grains and back to Continent or Continent – East Coast of South America for grains or coal and then back to the Continent. Therefore, *R1A* represent the wider North and South Atlantic to Continent trade, as opposed to the US Gulf – Continent trade only reflected in *R1*, and hence reflects more accurately the trading conditions in the Atlantic basin. As a result, it should exert greater influence on other routes, compared to *R1*.

Perhaps the most expected result is confirmed by the error decompositions of *R2*. As previously explained, *R2* is the most significant route in terms of price discovery and results from the DAG analysis illustrate its influence in contemporaneous time. However, *R2* is highly exogenous in the short run meaning that it explains 100% of its own variation after 1 day, and continues to explain over 90% of its own variation after 5 days. In the intermediate to long-run, *R2* is affected by other markets, most notably *R1A* and *R3A*, however their combined effect accounts for only 24.3% of the total variation in *R2* after 60 days. Interestingly, it takes quite a long time for these markets to influence *R2*, but this is commensurate to the period of time taken for the ships to move between these regions so as to exploit any differences in the level of freight rates. Turning next into the impulse response functions, we can note that a shock in *R2* affects all the other freight rates, with the effect of the shock not truly stabilizing until the maximum horizon of 60 days. What is surprising however is that even though *R2* seems to have the greatest influence on other markets, in contemporaneous time, short, intermediate and the long-term, its weighting in the BPI is identical to *R2A* (12.5%) which seems to be less influential. Indeed, *R2A* (the time-charter equivalent of *R2*) is most heavily influenced by *R2* in the short run, but is also influenced by *R1A* particularly for the longer horizons. This is because, *R1A* and *R2A* link the Atlantic and Pacific trades and a degree of substitutability exists between these routes. For instance, vessels which are available in the Continent, will choose to trade either in the Atlantic basin (*R1A*) or the Pacific basin (*R2A*) depending on the level of freight rates prevailing in these two regions. Therefore, any imbalance in the relative level of freight rates between these regions will be ironed out by a corresponding adjustment of the supply of tonnage in each region. However, given the timescales involved in the time charter routes, these adjustments will take place in the medium to long-run, that is in excess of 30 days, which explains why the impact of *R1A* on *R2A* is greater for the longer horizons.

However, like *R1*, *R2A* does very little in explaining the variability of other routes across different horizons. For instance, it has very little influence on *R3* and only explains a little over 2% of its forecast error after 60 days. Correspondingly, as illustrated by the impulse response analysis, a shock in *R2A* has the least effect on all other routes. For instance, shocking *R2A* has almost no effect on *R1A*. These results compliment the DAG analysis where it was found *R2A* has very little influence in other markets, and even though it 'directs' *R1* in contemporaneous time its influence on *R1* after 1 day is just 1.86% and falls to 0.19% after 60 days. *R2A* is therefore, by all accounts a relatively insignificant route, obviously not 'deserving' an equivalent weighting in the BPI as *R2*, which is clearly the more dominant route.

As one might expect, once we turn our attention to the markets that are related to the Pacific Basin (*R3*, *R3A* and *R4*) we see a similar geographical divide in the short run that was found in the U.S. Gulf. According to the forecast error decompositions, after 1 day, *R3* is only influenced by itself (41.563%) and by *R3A* (54.371%). Interestingly, its effect on other routes is fairly small. For instance, over the longer term it explains, 3.65%, 5.46%, 7.39% and 5.13% of the "US Gulf-routes" (i.e. *R1*, *R1A*, *R2*, *R2A*) and has a similar affect on the other West Coast routes (4.43% and 4.73% on *R3A* and *R4*, respectively). Similar conclusions emerge when we consider the impulse responses. That is, while a shock in *R3* has some effect on some routes, compared to more significant routes, like *R1A* or *R2*, this effect is small.

Focusing now on *R3A*, this time-charter route represents cargo voyages between Japan and the U.S. west Coast (or British Columbia) and back, or between Japan and Australia and back thus, in description, being quite different from the other routes, as it may never link to the U.S. Not surprisingly, the short-run forecast error decompositions, indicate that the route is quite exogenous in the short-run since it explains 100% of its forecast error for the 1-step ahead forecast; for longer horizons however, it tends to be influenced by other routes, most notably *R2*. Indeed within 60 days about 23% of *R3A*'s variability is explained by *R2* reflecting once again that over time arbitrage should link the freight markets together. We can also note that, unlike its spot counterpart *R3*, *R3A* has a clear influence on other markets. Focusing on the longer term (60 days), *R3A* explains 13.32% of the variation in *R1*, 12.85% in *R2A*, 50.34% of the variation in *R3*, and almost 50% of the variation in *R4*. The impulse responses also verify the importance of this route. A shock in *R3A* has a significant effect in all markets, with the larger effects occurring in *R3*, *R3A* and *R4*. This is consistent with the results from DAG analysis which suggests that there is an obvious consistency between the methodologies. Indeed, in contemporaneous time, *R3A* and *R4* are connected (but not directed), and *R3A* causes both *R3* and *R2A* in contemporaneous time. Therefore, *R3A* is an important route, perhaps as important as R2, in terms of information discovery.

Finally, *R4*, typically comprises a ballast leg from Japan to North Pacific to load coal and then back to the Continent. The short-run forecast error decompositions, indicate that the route is quite exogenous. It explains about 87% of its own variation after one day but is also affected by *R3A* (about 11.9%) – which also is linked to Japan. The DAG suggests that we cannot sign the causation in contemporaneous time, but results here seem to indicate that *R3A* affects *R4* in the longer term (50.34%) much more than *R4* affects *R3A* in the long term (3.21%). The impulse response graphs also suggest most influence comes from *R3A*. Interestingly, *R3* has a little affect on *R4* in the short, intermediate and longer term, even though, as seen in the DAG, there is a contemporaneous causality suggesting *R3* causes *R4*. Once again, like other routes, *R2* affects *R4* as time passes, accounting for about 11.36% after 60 days.

In summary therefore, given the competitive nature of the ocean shipping market we should expect to find that all routes move together, a result confirmed by the cointegration analysis, and should influence one another (albeit by different degrees) a result confirmed by the DAG analysis, the forecast error decompositions and impulse response analysis. The results, from these tests indicate that there are some leading routes, like *R2* and *R3A* which dominate the other routes in terms of information dissemination. However, while *R3A* seems to be appropriately weighted within the BPI, *R2* is under weighted relative to its importance. In addition, it seems that the information provided by *R1* is already reflected in other routes (like *R1A* and *R2*) and could conceivably be ignored as a means of providing new information not captured in other markets. Indeed, *R1* follows rather than leads in contemporaneous time, the short, intermediate and long run. The same seems to be true for *R2A*. These two routes together comprise, almost a quarter of the weighting of the BPI (22.5%), yet their influence is trivial. To illustrate this point, we exclude routes *R1* and *R2A* from the estimation process and re-estimate the ECM of equation (2) using the modeling procedure described in section 2. The ensuing pattern is presented in Figure 3, Panel C. We can clearly see that innovations in most freight rates are linked between each other. In fact, with the exception of the *R1A* - *R3*, *R2* - *R4* and *R2* - *R3A* pairs of routes, the remaining combinations of pairs are connected between them. This indicates that the flow of information between the routes has increased following the exclusion of the two redundant routes from the system. In addition, the fact that none of the connected pairs are directed indicates that there is a balance in the flow of information within each pair of routes since none of the routes leads any of the other routes. Therefore, these findings suggest that *R1* and *R2A* do not contribute any new information to the system of freight rates and, as a result, should not be included in the calculation of the index. From a practitioner's standpoint, this implies that the current index may have been diluted by redundant routes, thus deterring hedging activity in a way suggested by Haigh and Holt (2000) and Nomikos and Kavussanos (2000).

VI. Conclusions

While there have been several attempts in recent years to study the level of interconnectivity and linkages within the volatile dry-bulk ocean freight industry to date, no study has conducted an analysis in a truly dynamic nature. Underutilized in both finance and economics, the unique contribution of this research is to employ Directed Acyclic Graphs (DAG's). The DAG's allow us to assess causation and linkages among the world's major shipping routes for the first time. The DAG analysis also allows us to address issues surrounding the causal ordering on innovations from a VAR or an Error Correction Model from which we generate familiar forecast error decompositions and impulse responses.

Our results verify previous research on international shipping freight markets in that freight rates are very much linked which suggests that shipping markets are highly efficient and tonnage is shifted from market to market thus stabilizing and linking freight rates together. Indeed, we confirm using a variety of methodologies, that over time, markets that are geographically separated, do begin to significantly influence one another by the time that it takes to physically move the commodity from one region to another.

Our DAG (contemporaneous) analysis combined with the short, intermediate and long run analysis also confirm that some routes are dominant in terms of price discovery and lead many other routes. This is true in particular for *R2* (Grains from US Gulf to Japan), which is known throughout the industry as the 'benchmark' route. This route leads many other routes in contemporaneous time, and impacts other routes for long periods of time if it is shocked. While the analysis confirms that several of the routes comprising the BPI are appropriately weighted, *R2* seems to have a relatively low weight, whereas *R1* and *R2A* seem to provide no unique information since their information is captured within the information provided by other routes. These routes are quite possibly redundant in the index, or at best have a weight that is too high.

The information from the DAG analysis, forecast error decompositions and impulse response analysis provides a unique insight behind the mechanics of international linkages in freight rates but also provides an indication as to why the volume of trading in freight futures has been declining in recent years. Indeed, we illustrate from a futures trading standpoint, the composition (and weighting) of the index may not be correctly composed (despite being changed several times since its inception). As freight futures trading has declined in recent years, quite possibly due to the development of FFA's, we conclude that the BPI is not the appropriate index to which futures contracts should be linked. Indeed, the results of this study suggest that the composition and weighting of the current BPI may have diluted the hedging effectiveness of the futures contract, or deterred hedging, which may have in part, contributed to its demise.

This research provides a unique, detailed understanding of how these differing freight routes affect one another in contemporaneous time and in the short, intermediate and longer term providing valuable information for the physical traders on the routes analyzed in this study. Moreover, while the DAG and related analysis provided here might be useful from a futures contract design standpoint, this research may have further obvious, yet profound implications in the general area of index construction.

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Table 1. Baltic Panamax Index: Changes in its composition since its inception.

	Vessel Size (dwt)	Cargo	Route	4/01/85 – 3/11/88	4/11/88 – 3/08/90	6/08/90 – 4/02/91	5/02/91 – 4/02/93	5/02/93 – 2/11/93	3/11/93 – 5/05/98	6/05/98 – 29/10/99	From 1/11/99
1	55,000	Light Grain	US Gulf to ARA	20%	20%	10%	10%	10%	10%	10%	10%
1A	70,000	T/C	Trans-Atlantic round (duration 45 – 60 days)			10%	10%	10%	10%	10%	20%
2	52,000	HSS	US Gulf to South Japan	20%	20%	20%	10%	10%	10%	10%	12.5%
2A	70,000	T/C	Skaw Passero to Taiwan – Japan (50-60 days)				10%	10%	10%	10%	12.5%
3	52,000	HSS	US Pacific Coast to South Japan	15%	15%	7.50%	7.50%	7.50%	10%	10%	10%
3A	70,000	T/C	Trans-Pacific Round (35 – 50 days)			7.50%	7.50%	7.50%	10%	10%	20%
4	21,000	HSS	US Gulf to Venezuela	5%	5%	5%	5%	5%			
5	35,000	Barley	Antwerp to Jeddah (Saudi Arabia)	5%	5%						
	38,000	T/C	South America to Far East			5%	5%	5%			
6	120,000	Coal	Hampton Roads (US) to South Japan	5%	7.50%	7.50%	7.50%	7.50%	7.50%		
7	65,000	Coal	Hampton Roads (US) to ARA	5%	5%	5%					
	110,000	Coal	Hampton Roads (US) to ARA				5%	5%	7.50%	7.50%	
8	130,000	Coal	Queensland (Australia) to Rotterdam	5%	5%	5%	5%	5%	7.50%		
9	55,000	Coke	Vancouver (Canada) to Rotterdam	5%	5%	5%	5%				
	70,000	T/C	Japan – Korea to Skaw Passero (50 – 60 days)					5%	10%	10%	15%
10	90,000	Iron Ore	Monrovia (Liberia) to Rotterdam	5%	5%	5%					
	150,000	Iron Ore	Tubarao (Brazil) to Rotterdam				5%	5%	7.50%	7.50%	
11	25,000	Pig Iron	Vitoria (Brazil) to China	5%							
	25,000	Phosphate	Casablanca (Morocco) to West Coast India		2.50%	2.50%	2.50%	2.50%			
12	20,000	Potash	Hamburg (Germany) to West Coast India	2.50%							
	14,000	Phosphate	Aqaba (Jordan) to West Coast India		5%	5%	5%	5%			
13	14,000	Phosphate	Aqaba (Jordan) to West Coast India	2.50%							
14	140,000	Iron Ore	Tubarao (Brazil) to Beilun and Baoshan (China)							7.50%	
15	140,000	Coal	Richards Bay (S. Africa) to Rotterdam							7.50%	

Notes: The following minor amendments of the Index are not presented in this Table.

1. As of 6 May 1998, Routes 2 and 3 refer to a 54,000 dwt panamax vessel. For the period prior to 1 November 1999, the index was known as the Baltic Freight Index (BFI).
2. Routes 1A, 2A, 3A and 9 were based on a 64,000 dwt panamax vessel for the period up to 2 February 1996.
3. Route 5 was 20,000 dwt vessel Barley from Antwerp to Red Sea for the period 1 January 1985 to 4 February 1986.
4. Route 7 was based on a 100,000 dwt vessel for the period 5 February 1991 to 4 February 1993.
5. Route 8 was based on a 110,000 dwt vessel for the period 1 January 1985 to 5 February 1992.
6. Route 10 was based on a 135,000 dwt vessel for the period 5 February 1991 to 2 August 1995.
7. Route 11 was 20,000 dwt Sugar from Recife (Brazil) to US East Coast for the period 1 January 1985 to 8 May 1986.

Table 2. Descriptive statistics and correlation analysis on freight prices.

Descriptive Statistics

	R1	*R1A*	*R2*	*R2A*	*R3*	*R3A*	*R4*
Mean	12.265	9063.49	20.693	10545.81	13.213	9204.88	7656.52
Median	12.397	9338	21.775	11049.5	13.173	9492.5	7003.0
Standard deviation	2.336	2262.55	3.875	2840.83	2.330	2364.16	2374.07
CV	0.190	0.25	0.187	0.269	0.176	0.257	0.310
m_3	-0.947	-0.887	-0.553	-0.530	-1.188	-1.023	-0.762
m_4	-0.240	-0.345	-0.692	-0.308	0.004	-0.297	0.458
Min	7.6	4106	12.314	4143	8.883	3757	3206
Max	16.571	13071	26.929	16386	17.693	13250	12883

Correlations

	R1	*R1A*	*R2*	*R2A*	*R3*	*R3A*	*R4*
R1	1						
R1A	0.942	1					
R2	0.832	0.929	1				
R2A	0.744	0.889	0.957	1			
R3	0.847	0.813	0.742	0.613	1		
R3A	0.819	0.841	0.815	0.739	0.953	1	
R4	0.656	0.555	0.369	0.210	0.865	0.759	1

Summary statistics are presented for daily freight prices for the period 2nd February 1996 – 7th May 2001 (1330 observations). CV represents the coefficient of variation and m_3 and m_4 represent sample skewness and kurtosis respectively.

Table 3. Augmented Dickey-Fuller (ADF) tests for order of integration on freight prices.

Test is on the estimated coefficient $\theta_1$from the following prototype model:

$$\Delta X_t = q_0 + q_1 X_{t-1} + \sum_{k=1}^{K} b_k \Delta X_{t-k}$$

Freight Price	K	HO: *I*(1) vs. HA: *I*(0) ADF	HO: *I*(2) vs. HA: *I*(1) ADF
R1	2	-2.153	-12.539
R1A	2	-2.382	-11.799
R2	1	-2.152	-16.109
R2A	1	-2.679	-17.834
R3	2	-2.398	-11.483
R3A	1	-3.197	-19.120
R4	2	-2.459	-11.527

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 Schwartz Bayesian Criterion (1973).

Table 4. Cointegration analysis of freight rates.

Johansen (1988) tests for the number of cointegrating vectors [a]					
λ_{trace} *test statistic*	$Ho:$	λ_{trace} *critical value*	λ_{max} *test statistic*	$Ho:$	λ_{max} *critical value*
204.96	r = 0	124.25	71.67	r = 0	44.91
133.29	$r \leq 1$	95.18	58.03	r = 1	39.43
75.26	$r \leq 2$	70.60	34.99	r = 2	33.32
40.27	$r \leq 3$	48.28	19.22	r = 3	27.14
21.05	$r \leq 4$	31.52	13.23	r = 4	21.07
7.82	$r \leq 5$	17.95	4.32	r = 5	14.90
3.50	$r \leq 6$	8.18	3.50	r = 6	8.18

[a] r represents the number of cointegrating vectors. $l_{\max}(r, r+1) = -T \ln(1 - \hat{l}_{r+1})$ and $l_{trace}(r) = -T \sum_{i=r+1}^{n} \ln(1 - \hat{l}_i)$ are the estimated (ordered from largest to smallest) eigenvalues on Π matrix in Equation 2. Critical values for the λ_{max} and λ_{trace} and statistics (at the 5% level) are from Osterwald-Lenum (1992). The optimal lag length (k) is based on the Schwartz Bayesian Criterion (1973). The sample size (N) is equal to 1330.

Table 5. Error decompositions.

Steps ahead	Std.error	*R1*	*R1A*	*R2*	*R2A*	*R3*	*R3A*	*R4*
(*R1*)								
1	0.0203	28.902	20.515	40.429	1.8600	0.0744	1.4924	6.7271
2	0.0371	25.107	21.132	43.231	1.6568	0.1207	1.6654	7.0867
3	0.0531	22.653	21.312	45.245	1.5325	0.1744	1.9251	7.1583
5	0.0824	19.718	21.374	47.654	1.3434	0.2986	2.5893	7.0228
10	0.1410	16.625	21.810	49.001	0.9419	0.6729	4.5551	6.3936
30	0.2685	13.712	25.158	43.957	0.3193	2.1928	10.227	4.4344
60	0.3864	12.295	27.113	39.967	0.1910	3.6523	13.324	3.4577
(*R1A*)								
1	0.0143	0.0000	48.577	33.140	0.0000	0.1761	2.1780	15.929
2	0.0300	1.0546	40.745	41.681	0.2286	0.3243	2.3998	13.567
3	0.0460	1.8502	36.347	46.069	0.4108	0.4406	2.6297	12.252
5	0.0775	2.6051	31.901	50.245	0.5706	0.6521	3.2145	10.811
10	0.1443	2.9650	28.772	52.426	0.5177	1.2116	4.9756	9.1321
30	0.2923	2.3324	30.656	47.559	0.1714	3.4123	9.5108	6.3582
60	0.4245	1.8644	32.303	43.644	0.0921	5.4644	11.480	5.1525
(*R2*)								
1	0.0090	0.0000	0.0000	100.00	0.0000	0.0000	0.0000	0.0000
2	0.0178	0.0762	0.5911	98.641	0.1778	0.0167	0.2518	0.2453
3	0.0270	0.2400	1.4888	96.594	0.3257	0.0717	0.7090	0.5705
5	0.0453	0.5562	3.1409	92.775	0.4016	0.2689	1.8440	1.0138
10	0.0833	0.8124	5.7059	86.349	0.2216	0.9813	4.8064	1.1235
30	0.1598	0.3958	9.9138	73.306	0.6776	4.1273	11.091	0.4887
60	0.2224	0.2150	12.109	66.197	1.3070	7.3926	12.196	0.5840
(*R2A*)								
1	0.0134	0.0000	16.060	50.729	24.633	0.0582	3.2548	5.2662
2	0.0279	0.6208	16.120	57.653	16.860	0.1786	3.1389	5.4288
3	0.0432	1.1550	16.200	60.660	12.939	0.2817	3.3410	5.4225
5	0.0734	1.7442	16.516	62.802	9.0904	0.4773	4.1175	5.2520
10	0.1366	2.0830	17.829	62.441	5.5126	1.0090	6.5804	4.5463
30	0.2691	1.4750	23.788	54.861	2.1760	3.1103	12.285	2.3048
60	0.3859	1.0501	28.313	50.244	1.1591	5.1275	12.851	1.2555
(*R3*)								
1	0.0089	0.0000	0.0000	4.0662	0.0000	41.563	54.371	0.0000
2	0.0168	0.2200	0.0003	6.5251	0.0027	35.892	57.101	0.2595
3	0.0246	0.5701	0.0002	8.7793	0.0103	31.566	58.308	0.7664
5	0.0400	1.2856	0.0100	12.537	0.0242	25.536	58.700	1.9064
10	0.0748	2.4786	0.1428	18.109	0.0150	18.107	57.501	3.6463
30	0.1655	3.8610	1.3715	22.732	0.6352	11.295	56.173	3.9324
60	0.2434	4.7773	4.0919	26.258	2.0626	9.3679	50.341	3.1016
(*R3A*)								
1	0.0140	0.0000	0.0000	0.0000	0.0000	0.0000	100.00	0.0000
2	0.0265	0.7625	0.0000	1.2285	0.0973	0.3828	96.384	1.1451
3	0.0395	1.5544	0.0011	3.0032	0.1633	0.9106	91.880	2.4871
5	0.0656	2.5992	0.0261	6.3272	0.1964	1.7501	84.801	4.3004
10	0.1247	3.7159	0.3151	11.647	0.1197	2.6791	75.806	5.7174
30	0.2671	4.7364	3.0890	17.694	0.3127	3.5431	66.049	4.5759
60	0.3839	5.5585	8.5386	23.763	0.8175	4.4259	53.682	3.2139
(*R4*)								
1	0.0116	0.0000	0.0000	0.0942	0.0000	0.9624	11.901	87.042
2	0.0227	0.8488	0.0065	1.8365	0.0134	2.0379	22.339	72.917
3	0.0344	1.6375	0.0090	3.6396	0.0191	2.8000	29.472	62.423
5	0.0584	2.5584	0.0042	6.3741	0.0131	3.6387	37.609	49.803
10	0.1134	3.3543	0.0802	9.6344	0.0371	4.2400	45.460	37.194
30	0.2446	3.6945	1.2365	10.229	1.4830	4.4368	52.600	26.321
60	0.3447	4.1600	4.0203	11.3607	3.5180	4.7344	49.382	22.824

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 directed graph on observed innovations from the error correction model shown in Equation 2 (with 2 lags). The decompositions may not sum to one hundred in each row due to rounding.

Figure 1. Major revisions of the BFI/BPI Freight Index.

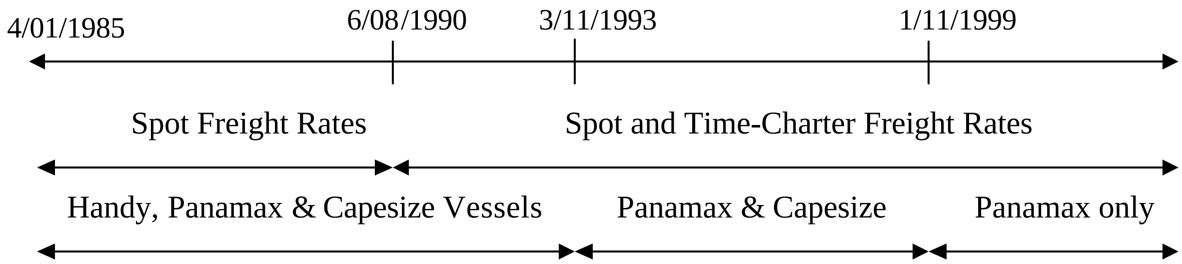
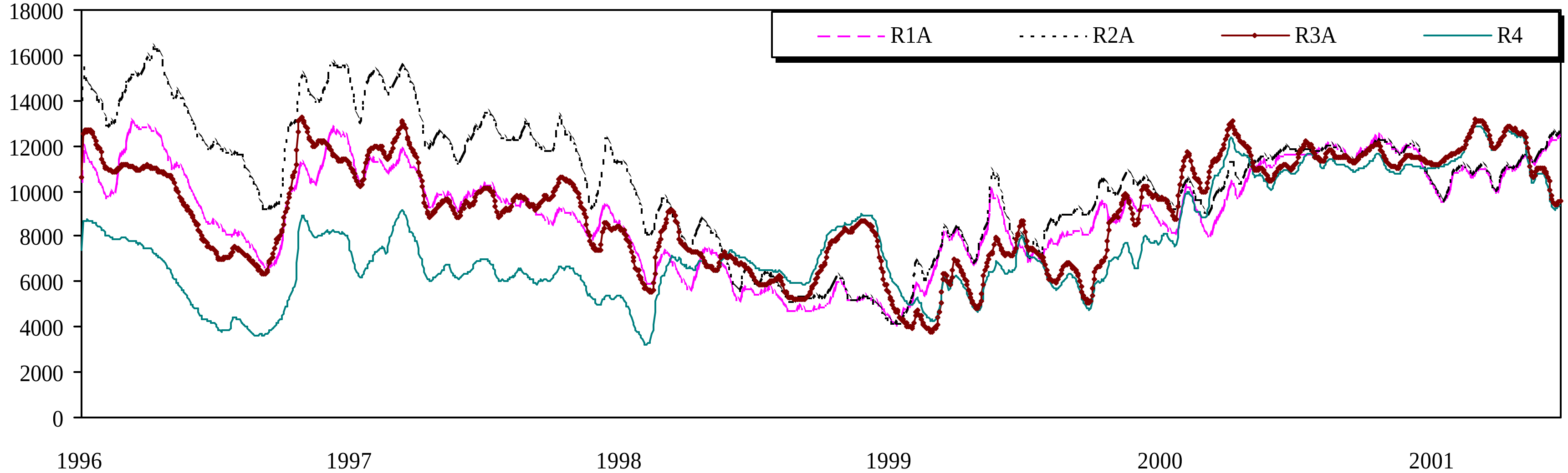
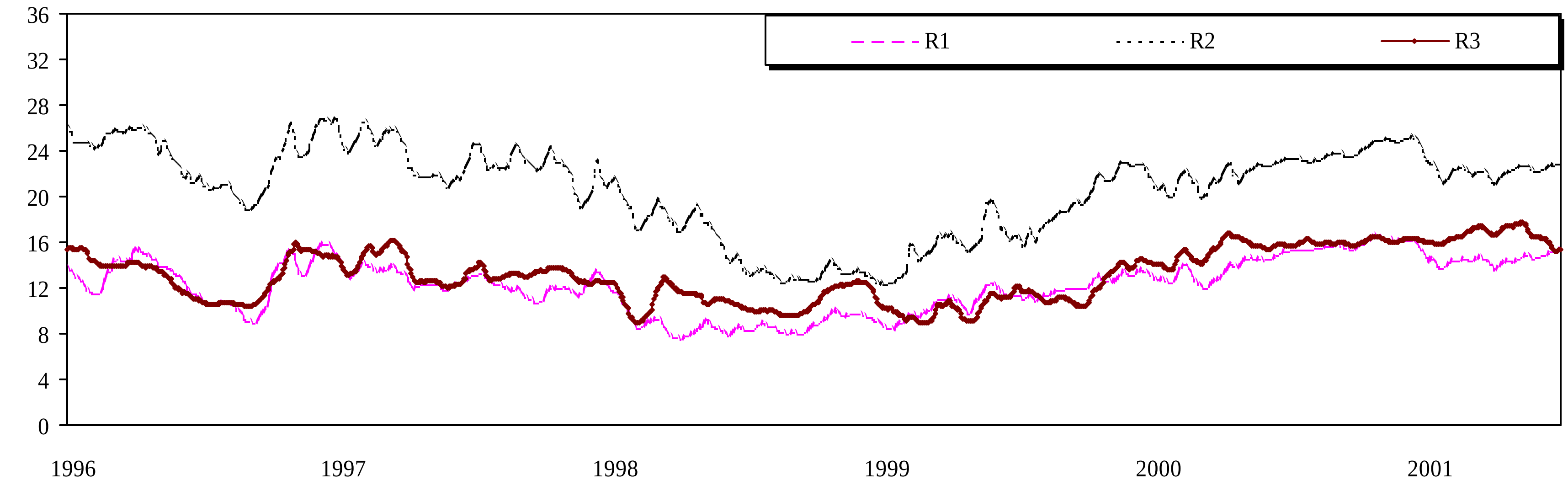


Figure 2. International freight price charts. The sample period is Feb. 2, 1996 through May 7, 2001. Dollars per day.



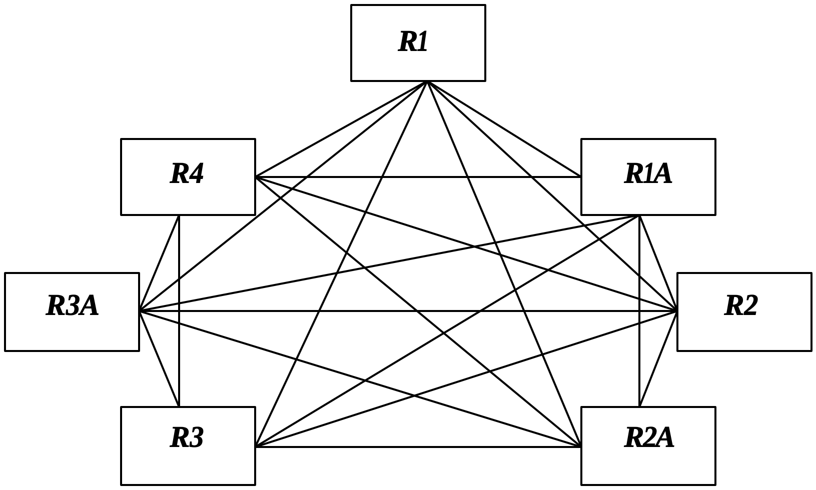
Panel A: Daily time – charter freight prices

Dollars per ton

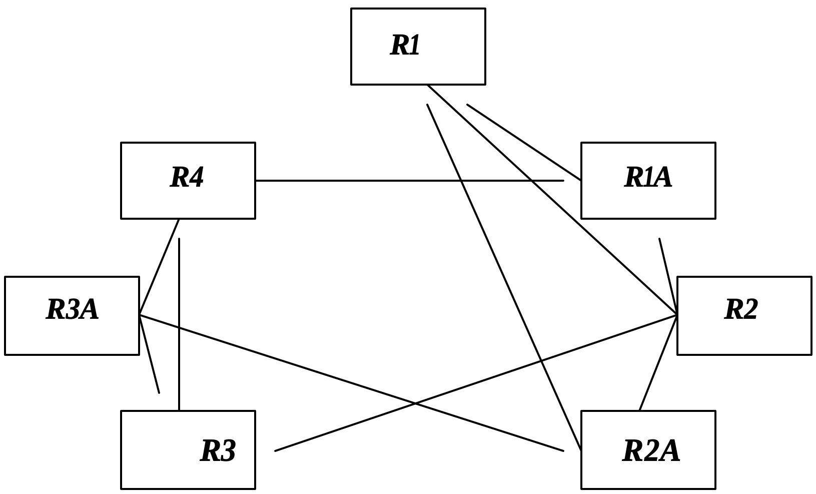


Panel B: Daily spot freight prices

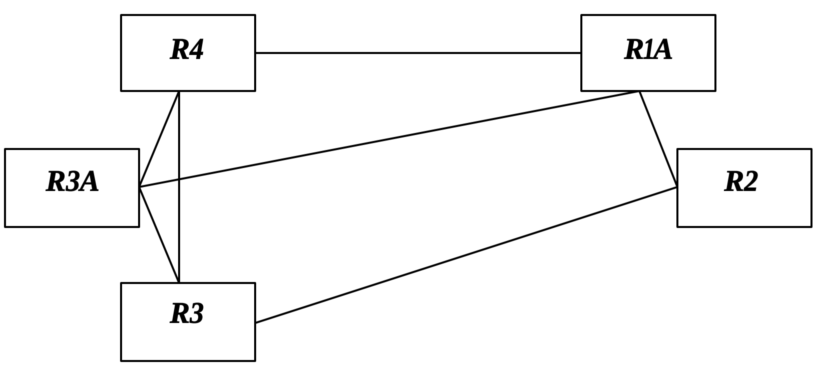
Figure 3: Graphical Representations on Innovations from the Error Correction Models.



Panel A. Complete undirected graph



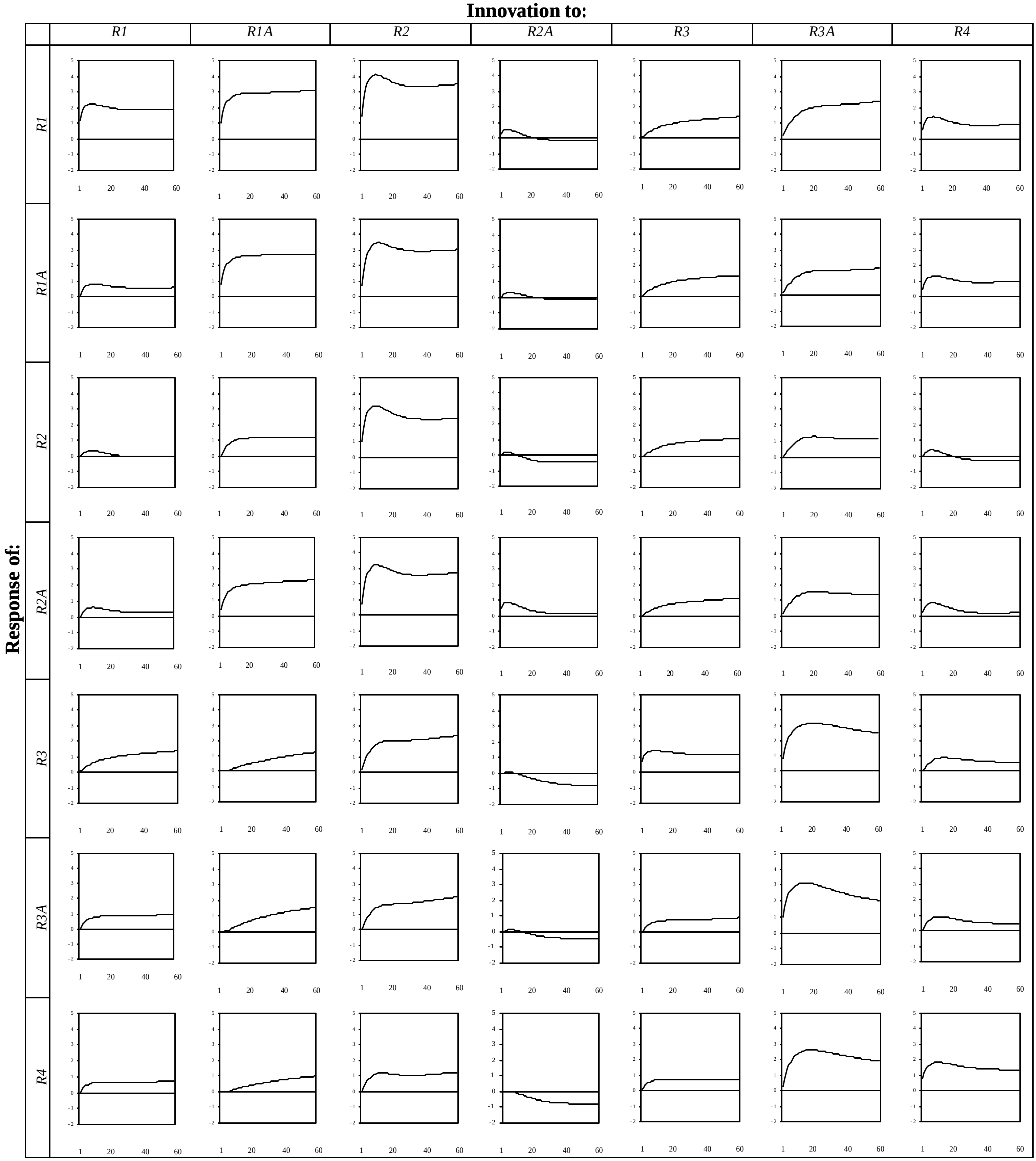
Panel B. Pattern on Innovations



Panel C. Pattern after removing redundant routes

Lines are significant at the 5% level.

Figure 4. Impulse responses to one standard deviation shocks.



Endnotes

[1] For example, ocean freight prices ranged from 3.2% - 12.4% of the value of imported Rotterdam wheat prices between May 1985 and January 1998 (see Haigh and Holt, 2000).

[2] During the period from January 1985 to October 1999, the underlying index of the BIFFEX contract was called the Baltic Freight Index (BFI).

[3] These are the three major classes of vessels, which are used for the transportation of different dry-bulk commodities across different parts of the world. Capesize vessels (around 140,000 dead-weight tons (dwt)) transport iron ore mainly from South America and Australia, and coal from North America, Australia and South Africa. Panamax vessels (around 70,000 dwt) are used primarily to carry grain from North America, Argentina and Australia, and coal from North America, Australia and South Africa. Finally, handysize vessels (around 35,000 dwt) transport grain, mainly from North America, Argentina and Australia, and minor bulk products - such as sugar, fertilizers, steel and scrap, forest products, non-ferrous metals and salt - virtually from all over the world.

[4] Spot charters and time-charters are the two major vessel employment contracts in the shipping industry. In a spot charter, a shipowner undertakes the responsibility to transport a cargo from the loading port to the destination port. The freight paid by the charterers (cargo owners) to the shipowner is expressed as USD ($) per ton of cargo and covers all of the shipowner's expenses in performing that voyage. A voyage charter may be thought of, therefore, as the equivalent of hiring a taxi to take you from A to B. In a time-charter, the shipowner agrees to hire out his vessel to a charterer for a specified time period. The freight rate paid by the charterer in this case is calculated as $ per day of hire. The charterer is directly responsible for all the voyage expenses - such as bunkers, port charges, canal dues etc. - but has much more flexibility, compared to a voyage charter, as to where he trades the ship. A time-charter is therefore, much more akin to hiring a car.

[5] Source: "LIFFE to Introduce new BIFFEX Futures and Options Contracts," LIFFE news, LIFFE Internet Site (www.LIFFE.com), Friday 11 December 1998.

[6] In 1995 trading began in over-the-counter (OTC) derivatives like Freight Forward Agreements (FFA's) and has since seen remarkable growth since that date. Indeed, many practitioners suggest that part of the reason that the BIFFEX futures market has meet its demise is because of the development and subsequent growth in the FFA's. Over the period from February 1996 to June 2000, the average trading volume in the market was only 146 contracts. The monetary value of these contracts roughly corresponds to the average freight cost of transporting 108,000 tons of Grain from US Gulf to Japan (that is, 2 voyages in Route 2 of the BPI); market sources estimate that this level of futures trading activity corresponds to only 10% of the total physical activity in the dry-bulk shipping market. It is also worth noting that the average trading volume after the introduction of the BPI has fallen to only 17 contracts a day.

[7] 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).

[8] As we can see in Table 1, data for the routes that comprise the BPI are available since 5 February 1993, when *R4*, then known as *R9*, was introduced. However, on 2 February 1996 the vessel size for *R1*A, *R2*A, *R3A* and *R4* increased from 64,000 tonnes to 70,000 tonnes causing a jump in the level of freight rates of approximately $1000 a day. Consequently, to avoid this structural break we employ data for the BPI going back only to 2 February 1996.

[9] We also allow for the existence of a constant (m) inside of the Π matrix.

[10] Results from these tests indicate that routes *R1A* and *R4* are individually weakly exogenous at the 5% level of significance. However jointly testing that these shipping routes are weakly exogenous

results in a c^2 value of 13.59 (with an associated p-value of .03). Such a finding does not provide conclusive evidence as to whether the markets are exogenous at stringent statistical levels. Hence, no restrictions on weak exogeneity are imposed in the estimated model. These results, like all other excluded to conserve space, are available upon request.

[11] In subsequent innovation accounting analysis we direct these edges to imply acyclic rather than cyclic graphs. For a discussion of problems arising from cyclic graphs, the reader is directed to Spirtes et al. 1999. The same analysis was conducted at the 1% level of significance. Similar (undirected linkages) are found connecting the markets with the exception of the links between *R4* and *R1A*, *R2* and *R1A* and *R2A* and *R1*.