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Market Adjustments over Transportation Networks: A Time Series Analysis of Grain Movements on the Mississippi Inland Waterway System

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Abstract

Transport occurs over a network and involves a multitude of different origins, destinations, and modes, which complicates the estimation of structural models. However, an understanding of the type and level of market adjustments among key transport statistics is central to analysing the effects of policy and to forecasting. Time-series techniques are used to characterise the relationship between key transport statistics such as movements on a waterway and shocks to barge rates. Generally, the results suggest that the approach is useful in uncovering complicated relationships over networks and that it is well suited to forecasting.

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1.0 Introduction

Theoretical and empirical analysis of transport markets is an extremely complicated undertaking. Transport markets are defined over a network involving multitudes of commodities, origins, and destinations. Trades are typically negotiated between heterogeneous demanders and suppliers of differentiated products that provide (or can provide) service to a multitude of different destinations. Theoretically, market adjustments to exogenous changes are non-trivial and result from a computable general equilibrium framework. Empirically, the analysis is compromised by a lack of sufficiently detailed data across the different modes and through the spatial environment.

Despite the lack of sufficiently detailed data, evaluation of market adjustments remains central to policy evaluation. For example, the Army Corps of Engineers maintains the US waterways. The relationship between river traffic and economic variables such as modal and port prices plays a key role in determining the potential benefits of waterway projects to increase the volume of traffic. In Army Corps planning models, these relationships are identified and examined using static structural models. However, the National Research Council and others have noted a number of concerns with this approach. These concerns relate largely to assumptions regarding the structure of demand and the lack of representation of important substitution patterns across space, modes and alternative markets (for example, National Research Council, 2000; Berry *et al*., 2000). In this study, time-series techniques are used to model transport market adjustments and substitution patterns across both modes and alternative markets. The results suggest that there are strong substitution patterns for each.

In addition, not only are the techniques well suited to identifying important substitution patterns, they are also extremely useful for forecasting. To this end, out-of-sample forecasts for exogenous shocks are made and their efficiency evaluated. The results suggest that forecasts of both outputs and prices can be made with a high degree of precision especially in the short run.

The time-series model used in this paper allows the data to identify important patterns between the level of river traffic and the interrelationship with terminal prices, barge rates, rail rates, rail deliveries, and ocean freight rates. In addition, the model is useful for understanding how river transport is affected by shocks to barge prices as well as shocks to prices and quantities of products shipped down the river and prices and quantities of competing transport modes. Further, demanders and suppliers of river transport services often make decisions based upon future expectations of such variables and the model developed here is capable of uncovering such relationships over time. This is important because, as recent experience from the Mississippi suggests, changes in variables such as ocean freight rates can have large and dramatic influences on river traffic and little is known about how these variables are related. Also, events such as unexpected lock closings can be captured within the model used here and the effects of such closures on prices and quantities of transport services can be determined. Such information is useful not only to understand the relevant patterns of substitution, but also to understand the dynamic adjustments to key variables which can be used to frame transport decisions.

Throughout the paper, the analysis is conducted using vector autoregressions (VARs). This approach is designed partially to address problems with traditional static and dynamic structural forecasting and modelling.[1] As is well known, forecasts based upon structural models are often poor due to lack of knowledge regarding the true structure and because of changes in structure not incorporated into the model. In the case of river transport, structural models forecast the demand for river transport from forecasts of the demand for products that use river transport such as grains and industrial products (for example, Baumel, 2000; Sparks Companies Inc., 2002). These demands are then allocated to individual locations (a pool) on the river using historical patterns. Such an approach is a large and complicated task that requires many simplifying assumptions that are mandated by the lack of available sufficiently disaggregated data on commodity movements, and lack of data on the many influences on the demand for each of the products transported on the river. The difficulty of modelling disaggregate markets theoretically, together with the lack of sufficient data, make structural modelling of network markets such as transport exceedingly complex.

In this study, the pitfalls of structural modelling are avoided through the use of an approach common in the time-series econometrics literature to understand the patterns of market adjustments in transport markets, in particular with respect to waterway transport.[2] While this procedure identifies structural shocks by imposing restrictions on the variance–covariance structure associated with the reduced form model, recovery of

[1]Most forecasting models of river traffic rely on structural modelling. Structural econometric models have as their basic building blocks behavioural equations, equilibrium conditions, and accounting identities derived from theoretical models. This results in restricted models, with the restrictions often in the form of the exclusion of some variables from some equations. Identification restrictions often result in further exclusions, often without theoretical support. Vector autoregressive models do not impose any exclusion restrictions upon the data; instead, they generally rely upon restrictions on contemporaneous causal relationships or assume zero long-run effects of particular types of shocks. Thus, in these models structural shocks are still identified, but through a different set of identifying assumptions that do not involve excluding variables from particular equations.

[2]For in depth discussions of the advantages and disadvantages of the VAR versus structural approaches, see Anderson (1979), Sargent (1979), and Stock and Watson (2001).

the structural parameters themselves, and hence the demand curves, is not a feature of this estimation procedure. What the models do provide is a means of informing the future construction of dynamic structural models.

2.0 Time Series Analysis

Economists commonly use time-series techniques to understand and forecast variables of interest. These models are used for forecast horizons that extend far into the future and also for shorter horizons, as short as days or even minutes in the financial literature. Error correction and vector autoregressive (VAR) models are often used in this type of analysis. Formally, these models are interpreted as general reduced form structural models.[3] The models arise from the idea that the identification restrictions present in most structural econometric models are arbitrary and not supported by underlying theoretical models. If the identification restrictions used to estimate structural econometric models are suspect, then it is not surprising that these models do not produce reliable forecasts. An alternative is to rely on a different identification scheme and forgo the troublesome identification restrictions present in structural econometric models.

This led researchers to consider VAR, and later error-correction models, as alternatives to structural modelling. Under this approach, a very general reduced form is posited that allows each endogenous variable to depend upon every other endogenous variable in the model as well as any exogenous variables.[4] Estimation allows the data to impose restrictions as required to achieve the best fit. This is in contrast to the structural approach where such restrictions are imposed as maintained hypotheses. Forecasts of the endogenous variables can then be derived from the estimated time-series models. More importantly, and central to this paper, once the model is estimated it can be used to simulate the reaction of key variables to shocks (that is, the response to positive orthogonalised innovations; the response to a negative shock would be the opposite) to other variables and produce estimates of how key variables are related (impulse response functions) and evaluate the importance of each variable (variance decompositions).

VAR and error-correction models are often called atheoretical models, but this can be misleading. The models are atheoretic in the sense that variables are not arbitrarily excluded from structural equations to obtain

[3]A seminal article in this area is Sims (1980).
[4]Thus, there are no exclusion restrictions as would exist under the structural approach.

identification, and reduced forms rather than behavioural relationships are the focus of the modelling effort. However, identification assumptions are still required in order to identify structural disturbances, and the identification of structural disturbances is a necessary component in estimating and properly interpreting the impulse response functions and variance decompositions used in this paper. In the time-series literature, such restrictions are generally restrictions upon contemporaneous relationships, as in this paper, or restrictions regarding the long-run effects of particular shocks.

In previous work, De Vany and Walls (1996, 1999) demonstrate the usefulness of VAR models to quantify equilibrium dynamics over power and natural gas networks. As they note in their 1999 paper, the structure of networks is sufficiently complicated so as to preclude direct theoretical and empirical modelling of each and every relationship in each and every market, and the data requirements to do so are extreme, and the problems with modelling market adjustments in transport markets are analogous. In such cases, theory can be used to guide the construction of VAR models, which can then be used to uncover network adjustments. As noted by DeVany and Walls:

> 'To quantify power price dynamics on the WSCC network, we employ a flexible statistical model that allows us to characterize the joint distribution of power price changes with few a priori constraints. The statistical model — an unrestricted vector autoregression — encompasses the type of complex price dynamics that are characteristic of electrical networks, and this type of model has been used to quantify price dynamics in other network markets.' (De Vany and Walls, 1999, p.128)

In their 1996 paper, De Vany and Walls also note the usefulness of VAR models for capturing multilateral spatial relationships in power and natural gas networks:

> 'The sophistication of econometricians in quantifying the strength of spatial market linkages has increased in step with time-series methodology; however, the current statistical tests for market linkages consider only pairs of markets. In fact, most markets that are dispersed geographically contain many trading locations that are connected in different ways; some pairs have many paths between them whereas others are only indirectly linked.' (De Vany and Walls, 1996, p.56)

To our knowledge, VAR and error-correction models have not been used to examine transport networks even though the structural analysis of transport markets share many, if not all, of the difficulties of structural modelling in other network industries, including those analysed by De Vany and Walls.

The analysis in this paper focuses on grain transport markets with a special focus on barge transport on the Mississippi river. Grain flows consist primarily of wheat, corn and soybeans to the Gulf, the Pacific Northwest, and a variety of different inland locations. The grain flows enter the river at a wide number of different locations, and there are a number of alternative markets for grain, some of which do not require barge movements. The large number of entry points, alternative terminal markets, and modal alternatives requires an excessive amount of data not all of which are available, and the underlying equilibrium structure is exceedingly complex. Because of this, in general, previous models examining transport market adjustments resort either to a focus on a narrow set of markets or commodities, or to simulation models somewhat like the Army planning models discussed earlier. Indeed, there are few studies that model transport equilibria theoretically or empirically.[5]

In the next section, a time-series model is constructed and the available data are described. The model contains data for movements of multimodes, transport rates, prices of commodities at spatially separated markets, and ocean freight rates. Each of these variables has some relation to the underlying formal structural model, and as such are important variables to include in the model. More specifically, the model consists of lockages on the Mississippi river, rail deliveries of grain to export points, rail rates for grain to export points, the bid price for grain at export points, ocean freight rates from export points, and barge rates on the Mississippi river. The first two categories, lockages and rail deliveries, involve quantities, while the last four, rail rates, grain bids, ocean freight rates, and barge rates, involve prices.

The model developed here is used to produce impulse response functions and variance decompositions as well as out-of-sample forecasts. The former indicate how particular variables in the model respond to unexpected changes in other variables in the model, and how important each type of shock is in explaining variance of the variables in the model. A central result is that barge demand and lock supply shocks as well as other demand and supply shocks have significant effects. These results are presented in Section 4, while variance decompositions are presented in Section 5. The model can also be used to forecast out-of-sample. In

[5]Wilson *et al*. (1988) estimate a structural supply and demand model for rail and truck markets for a narrowly defined market; that is, grain transport of North Dakota origins. Friedlaender and Spady (1981) estimate supply and demand models separately, then combine them to simulate outcomes of rail and truck markets.

Section 6, related research on forecasting in transport markets is summarised along with evidence on the performance of the model developed in this paper.

3.0 Data and Econometric Model

The time-series model and associated impulse response functions, variance decompositions, and out-of-sample forecasting statistics are constructed as follows.

First, data on river traffic through each lock and prices of commodities from various geographic regions are obtained from the Lock Performance Monitoring System (LPMS) as reported in the United States Department of Agriculture (USDA) *Grain Transportation Report*. Commodity price and other data are also in the USDA's *Grain Transportation Report*, which is available on a weekly basis. The nineteen variables available for use in the analysis are shown in Table 1. The data are available consistently from the first week of 1999 through the 20th week (the last week of May) of 2003.[6]

There are six categories of variables in the table, lockages, rail deliveries, rail rates, grain bids, ocean freight rates, and barge rates. Within each category the variables are highly collinear and nineteen variables is a relatively large number for the type of analysis used here, so representative variables from each category are used in the model. These data are used, in customary log form, in a six variable time-series model. In particular, the variables are: the log of lockages at Mississippi lock #27, which is located near St. Louis and shown in Figure 1; the ratio of grain deliveries by rail to the Gulf of Mexico to grain deliveries by rail to the northwest; the ratio of the rail delivery rate from Kansas City to the Gulf of Mexico to the rail delivery rate from Kansas City to Portland; the ratio of the price of wheat in the Gulf to the price of wheat in Portland; the ratio of the ocean freight rate from the Gulf to Taiwan to the ocean freight rate from Portland to Taiwan; and the barge rate from St. Louis to Cairo.

The order of the variables in the VAR model is the same as in the table, lockages, rail deliveries, rail rates, grain prices, ocean freight rates, and barge rates. Weekly dummies are added as deterministic variables to

[6]While these data have been collected for a longer time period, the variables are not consistently measured throughout the sample period, and in some cases are only available for a sub-period, limiting the extent of the sample. To conserve on space, figures containing each of the variables used over time are provided in an unpublished appendix (Appendix A) available from the authors.

Table 1
Weekly Data from 1999:01 through 2003:20 Collected from the USDA's Grain Transportation Report Used in the VAR Model

A. Lockages
Total lockages on the Illinois at Lock #8
Total lockages on the Mississippi at Lock #15
Total lockages on the Mississippi at Lock #27
B. Rail Deliveries
Rail deliveries to Texas
Rail deliveries to Mississippi
Rail deliveries to the Pacific
C. Tariff Rail Rates
The tariff rail rate for wheat from Kansas City to Houston
The tariff rail rate for wheat from Kansas City to Portland
D. Grain Bid Prices
The bid price for Portland HRW
The bid price for Gulf HRW
The bid price for Gulf SRW
The bid price for LA Corn Portland
E. Ocean Freight Rates
The Gulf to Taiwan ocean freight rate for heavy grain
The PNW to Taiwan ocean freight rate for heavy grain
F. Barge Rates
Barge rates for the Mid-Mississippi (percent of tariff from Davenport, IA)
Barge rates for the Illinois (percent of tariff for the Illinois River, Peoria, IL)
Barge rates for St. Louis–Cairo (percent of tariff from St. Louis)
Barge rates for Lower Ohio (percent of tariff from Lower Ohio)
Barge rates for Cairo–Memphis (percent of tariff from Cairo)

capture any seasonal effects over the year. For example, the first equation of the VAR model is Total Lockages on the Mississippi at Lock #27 regressed upon a constant, the weekly dummies, and lags of each of the six variables in the model.[7] The second equation is the ratio of rail deliveries regressed upon the same set of independent variables, a constant, the weekly dummies, and lags of each of the six variables in the model, and so on, until the last equation which has the St. Louis to Cairo barge rate as the left-hand side variable.

Before proceeding, the time-series properties of the individual series, in particular the stationarity or unit root properties, as well as any co-integrating

[7]The six variables used in the model, namely: the log of lockages at Mississippi lock #27; the ratio of grain deliveries by rail to the Gulf of Mexico to grain deliveries by rail to the northwest; the ratio of the rail delivery rate from Kansas City to the Gulf of Mexico to the rail delivery rate from Kansas City to Portland; the ratio of the price of wheat in the Gulf to the price of wheat in Portland; the ratio of the ocean freight rate from the Gulf to Taiwan to the ocean freight rate from Portland to Taiwan; and the barge rate from St. Louis to Cairo, are derived from data in Table 1.

Figure 1
Lock #27 on the Mississippi Waterway System

relationships that might exist among the variables, are examined. However, before these tests can be performed, the lag structure of the variables needs to be determined.

Table 2 presents two sets of system-wide lag length tests, the Akaike information criterion (AIC) and a likelihood ratio test with the degrees of freedom correction suggested by Sims (1980). As shown in the table, both tests select the same lag length, two, and this is the number used below.

The next step is to perform unit root tests to determine if the variables in the model are stationary or contain unit roots. These are presented in Table 3. It is not expected that the variables that are ratios will contain unit roots as the prices ought to move together in the long run. The main concern is to check for unit roots in the non-ratio variables, lockages and barge rates. The tests are conducted using augmented Dickey–Fuller tests with the lag length of two determined by the tests shown in Table 2. The table shows that for all series except the grain price ratio the assumption of stationarity in log levels is warranted.[8] In addition, the result for the grain price ratio is not robust to changing the number of lags and other changes so that the result for this series appears anomalous, a view that is confirmed from visual inspection of the series. Thus, the model estimated is in log levels.

In order to identify structural shocks in the model, the disturbances must be orthogonalised. The orthogonolisation of the shocks in the model is performed in the usual manner using the Choleski decomposition.[9]

[8]There are two columns in Table 3 for tests conducted with and without a trend term. For all variables, except rail rates where it is not clear which to use, the model without a trend used to obtain the results in the right-hand column is appropriate.

[9]An unpublished appendix (Appendix B), available from the authors, contains an example of the Choleski decomposition for a two variable model with one lag illustrating the identification assumptions.

Table 2
Akaike Information Tests for Lag Length

Lags	*AIC*	*(H_0 vs. H_1)*	*LR test*	*P-value*
1	−41.3854			
2	−41.8265*	1 vs. 2	146.0140	0.0000
3	−41.7453	2 vs. 3	29.1745	0.7828
4	−41.6333	3 vs. 4	22.5233	0.9611
5	−41.5438	4 vs. 5	27.7086	0.8374
6	−41.3417	5 vs. 6	3.2302	1.0000
7	−41.2397	6 vs. 7	25.4444	0.9051
8	−41.2247	7 vs. 8	44.5287	0.1557

*Indicates number of lags used in Table 3.

With this decomposition, which imposes a recursive structure, the variables least likely to be affected by contemporaneous shocks to other variables come first in the ordering, and those variables most likely to be affected contemporaneously are placed last. Note that quantities appear in the model ahead of prices so that the identification assumption used here is that quantity supplied responds with at least a one period lag to changes in demand. That is, during the period of the shock, the supply curve is vertical so that any changes in quantity arise solely from shocks to the supply curve, but after one week supply can respond to the change in demand. Prices, however, respond to both supply and demand shocks since a shift in supply or demand will change the equilibrium price. Under this assumption, shocks in the model associated with quantities (that is, the first two of equations for lockages and rail deliveries) can be interpreted as supply shocks (that is, rightward shifts of supply) and

Table 3
Augmented Dickey–Fuller Unit Root Tests

	AR model with constant and trend	*AR model with constant*
MISS27	−6.80977*	−6.71253*
RAILDEL	−4.17093*	−3.83966*
RAILRATE	−2.81547	−2.91771**
GRAINPRICE	−2.67985	−1.55565
OCEANRATE	−2.93297	−2.76668***
BARGERATE	−3.58555**	−3.56752*

Note: The critical values for the first column are −4.00, −3.43, −3.14; for the second column −3.46, −2.87, −2.57 for 1 per cent, 5 per cent and 10 per cent levels of significance. *Indicates significant at 1 per cent, **5 per cent and ***10 per cent. The number of lags is two as determined by Table 2. All variables are seasonally adjusted.

those with prices (that is, the last four of equations) as demand shocks (that is, rightward shifts of demand).

The model is estimated using the data described above and the estimated model is used to produce impulse response functions (IRFs), variance decompositions (VDCs), and out-of-sample forecasts.[10] The IRFs show the impact that an unanticipated structural shock to one variable has on the time path followed by another. For example, an IRF can plot the effect that a shock in the barge rate between two points has on the amount of traffic through a lock. In the model, a shock to barge rates emanates from a rightward shift in the barge demand function. Such a shift should increase rates (or, at least, not decrease rates), and therefore, should increase lockages.

Because a shock to any one variable can affect all other variables, there are $(6)(6) = 36$ impulse responses. Because the number is large, the discussion below focuses on a subset of the responses.[11] The VDCs complement the IRFs. The IRFs show the pattern of the response over time of one variable brought about by a structural shock to another variable. The VDCs assess the importance of the shock in explaining the variance of the responding variable at each point in time. Thus, the IRFs give the sign and the pattern of the response while the VDCs assess the importance of the structural shock in explaining the variability of a particular variable at each point in time after the shock occurs.

4.0 Impulse Response Functions

There are six variables in the model, lockages, rail deliveries, rail rates, grain bids, ocean freight rates, and barge rates. In the following, it is important to recall that IRFs for shocks to quantities (lockages and rail deliveries) reflect supply shocks — for example, a shock to barge lockages is a rightward shift in the supply of barge lockage services. Shocks to prices (rail rates, grain bids, ocean freight rates, and barge rates) reflect demand shocks under the identification scheme used in the estimation. Thus, for example, a shock to the barge rate represents a rightward shift in barge demand. In the subsections below the IRFs are first presented for the quantity shocks and then for the price shocks.

[10]An unpublished appendix (Appendix C), available from the authors, contains all the parameter estimates.

[11]To conserve space, only a subset is considered. An unpublished appendix (Appendix D), available from the authors, contains the entire set.

The following figures show examples of the results for each of the six types of shocks, two for each type. All figures show the impulse responses along with confidence bands as suggested by Sims and Tao (1999).

4.1 Shocks to total lockages

Lockages are subjected to a one standard deviation shock.[12] As discussed above, this is a supply shock, a rightward shift in the supply function of lockages. Figures 2a and 2b show the response of the rail rate ratio and the ocean freight ratio to the shock. In the case of rail rates, the increase in the supply of lockages induces a rise in the rail rate ratio. This

Figure 2a
Response of Lockages to a Shock to Lockages

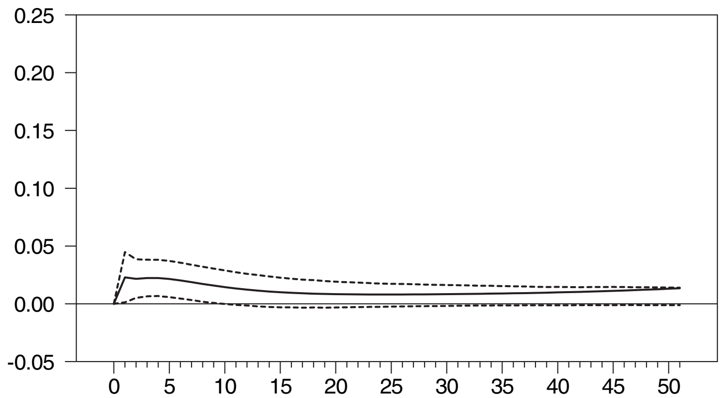
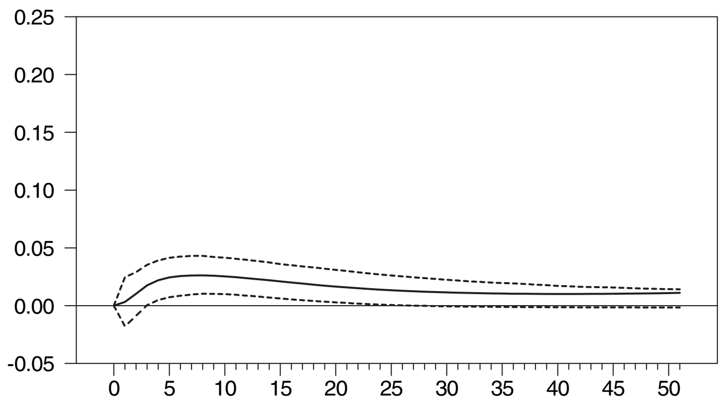


Figure 2b
Response of Rail Delivery Ratio to a Shock to Lockages



[12]The size of the shock, one standard deviation, is customary.

could arise, for example, from increased demand for rail services arising from the increased flow of traffic down the river brought about by the supply shock.

The response of ocean freight rates is also positive, though the effect is delayed and it is not significant until after the third week following the shock. Once again, the rise in ocean freight rates can be explained by increased demand for ocean freight services due to the increased flow of traffic on the river.

4.2 Shocks to the rail delivery ratio

Figures 3a and 3b show the consequences of a shock to the rail delivery ratio, a supply shock. In Figure 3a, the response of the grain bid ratio is shown. The supply shock to rail deliveries causes the grain bid ratio to

Figure 3a
Response of Rail Rate Ratio to a Shock to Lockages

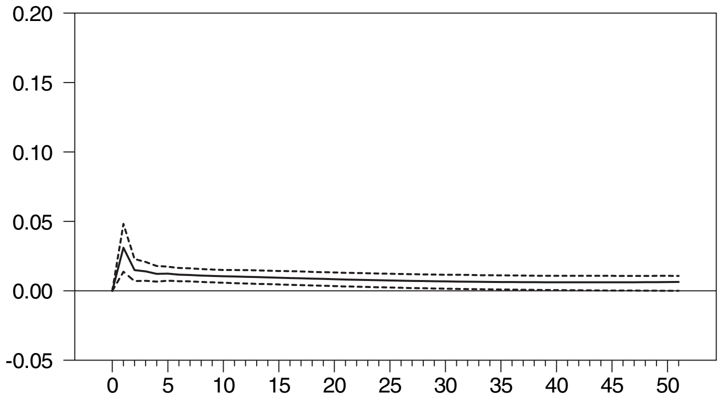
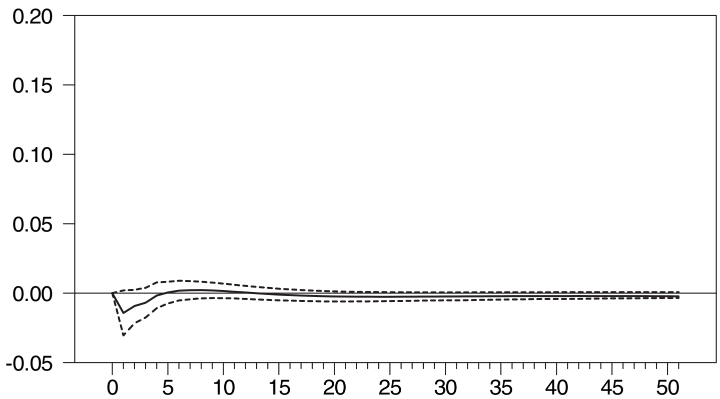


Figure 3b
Response of Grain Bid Ratio to a Shock to Lockages



increase immediately, and then return to the initial value slowly over time. In Figure 3b, which shows the response of the barge rate, the effect is negative as expected if traffic is diverted to rail due to the supply shock, but it is not significant.

4.3 Shocks to the rail rate ratio

The next set of figures, Figures 4a and 4b, show the responses of lockages and barge rates to a shock to the rail rate ratio, a demand shock for rail services. Here, the increased demand for rail services should increase the price of rail services and, if rail and barge transport are substitutes, an increase in the price of a substitute should cause an increase in demand for barge services, which in turn should increase the price and quantity of barge services.

Figure 4a
Response of Ocean Freight Ratio to a Shock to Lockages

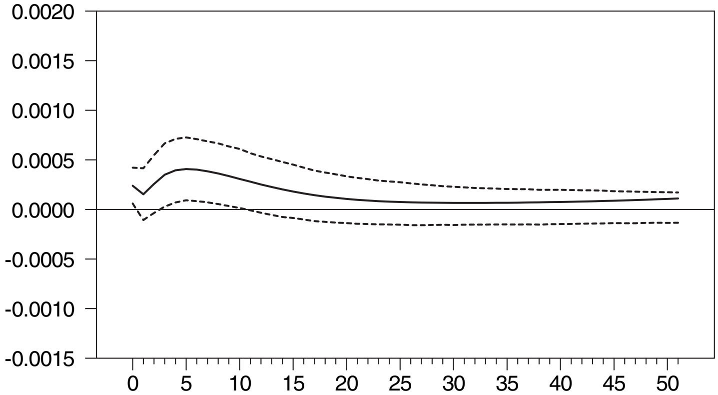
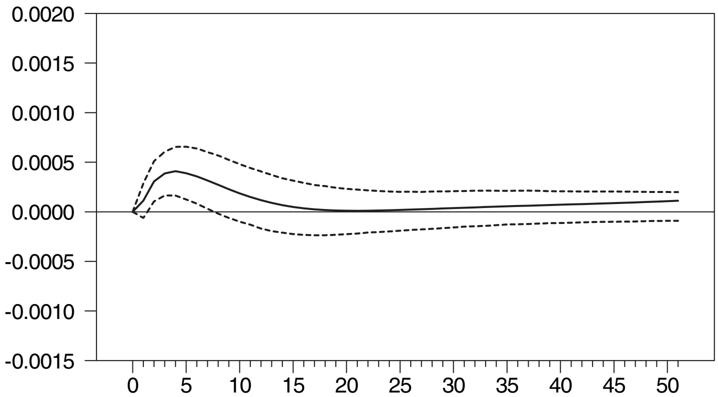


Figure 4b
Response of Barge Rates to a Shock to Lockages



Figures 4a and 4b show that this appears in the results, the increased price of rail services causes both lockages and barge rates to increase. In addition, the results suggest the main impact occurs with a two week delay.

4.4 Shocks to the grain bid ratio

Figures 5a and 5b show the responses of lockages and rail deliveries resulting from a shock to the grain bid ratio. Following the shock, lockages increase significantly for four weeks. Figure 5b shows that rail deliveries also increase following the demand shock, but beyond the first period the effect is insignificant, and it is only marginally significant in the first period.

Figure 5a
Response of Lockages to a Shock to Barge Rates

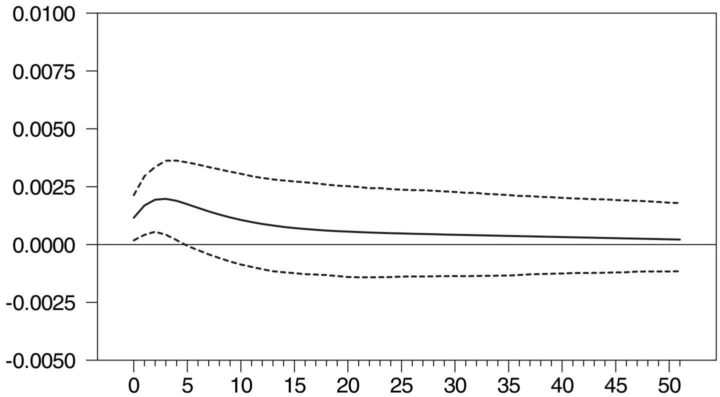


Figure 5b
Response of Rail Delivery Ratio to a Shock to Barge Rates

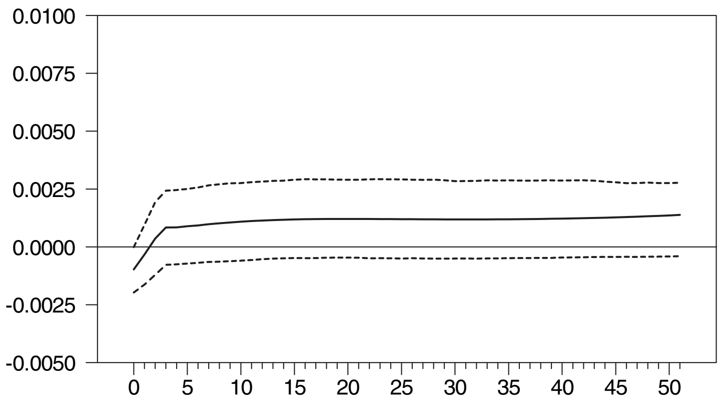


Figure 6a
Response of Rail Rate Ratio to a Shock to Barge Rates

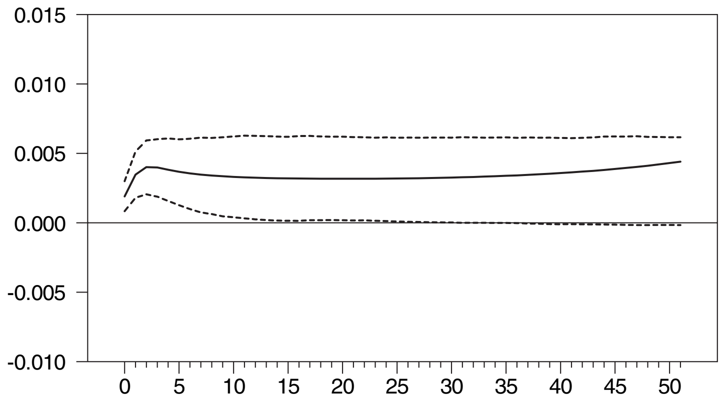
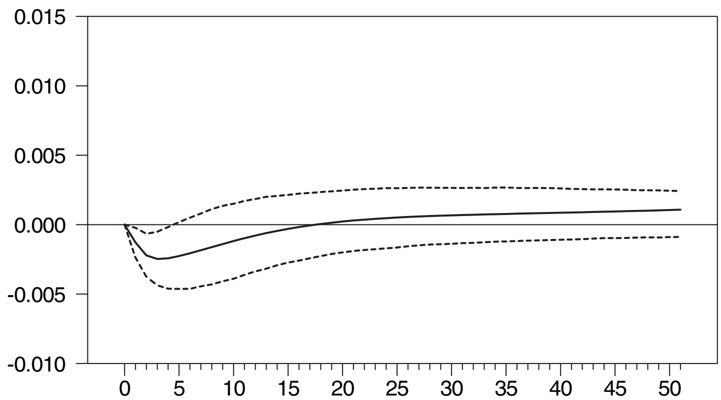


Figure 6b
Response of Grain Bid Ratio to a Shock to Barge Rates



4.5 Shocks to the ocean freight ratio
Figures 6a and 6b show how the rail rate ratio and barge rates respond to a shock to the ocean freight ratio. Here there is evidence of a shift in transport demand from the river to rail since rail rates rise following the shock and barge rates fall.

4.6 Shocks to barge rates
Finally, the last two figures, Figures 7a and 7b, show how rail rates and ocean freight rates respond to a demand shock for barge services. Figure 7a shows that rail rates fall substantially and persistently following the shock, indicating a shift away from rail services after the demand shock for barge services.

Figure 7b shows that ocean freight rates move in the opposite direction, increasing following the shock, although the effect is not as persistent as the

Figure 7a
Response of Ocean Freight Ratio to a Shock to Barge Rates

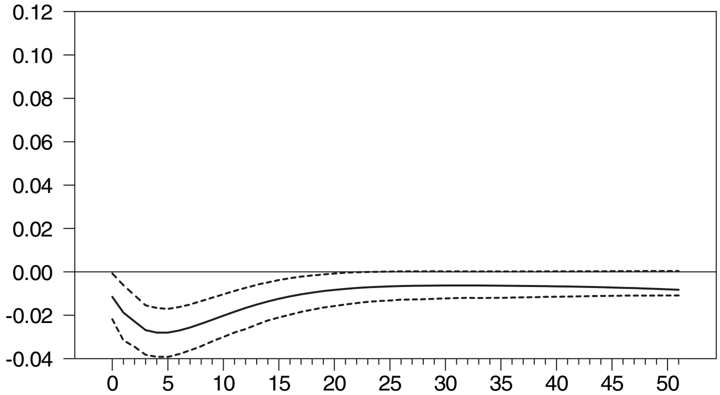
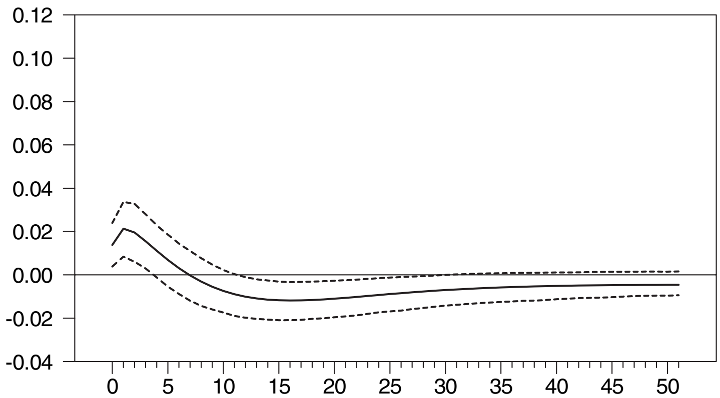


Figure 7b
Response of Barge Rates to a Shock to Barge Rates



decline in rail rates. Thus, an increase in the demand for barge services pulls traffic away from rail, lowering the rates, and increases ocean traffic, increasing rates.

Overall the results are encouraging. The results are significant in a large number of cases and accord with theoretical predictions.

5.0 Variance Decompositions

Impulse response functions document how variables in the model respond over time to their own shocks and to shocks to other variables. However, impulse response functions do not tell us how important the shocks are in explaining variation in the variable under consideration. For example, Figure 7a shows how rail rates respond to a shock to barge rates at various time horizons up to one year after the shock. But among all six shocks identified in the VAR system, how important is this particular shock in explaining variation in lockages at these time horizons? Does a shock to the barge rate ratio cause more or less variation in rail rates than, say, a shock to rail deliveries? Variance decompositions (VDCs), presented in Table 4, can be used to answer these and other questions.

Table 4
Variance Decompositions

Lockages

Step	River locks	Rail deliv.	Rail rates	Grain bids	Ocean rates	Barge rates
1	1.00	0.00	0.00	0.00	0.00	0.00
2	0.99	0.00	0.00	0.00	0.00	0.00
4	0.96	0.01	0.01	0.01	0.01	0.00
8	0.90	0.02	0.03	0.02	0.03	0.00
12	0.88	0.03	0.03	0.02	0.04	0.00
20	0.85	0.03	0.03	0.03	0.06	0.00
26	0.84	0.03	0.03	0.03	0.07	0.00
40	0.83	0.03	0.03	0.03	0.07	0.00
52	0.83	0.03	0.03	0.03	0.07	0.00

Grain Bid Ratio

Step	River locks	Rail deliv.	Rail rates	Grain bids	Ocean rates	Barge rates
1	0.02	0.01	0.00	0.96	0.00	0.00
2	0.04	0.00	0.00	0.95	0.00	0.00
4	0.05	0.00	0.02	0.92	0.00	0.00
8	0.06	0.00	0.05	0.88	0.00	0.00
12	0.06	0.01	0.08	0.85	0.00	0.00
20	0.05	0.01	0.11	0.82	0.00	0.00
26	0.04	0.02	0.12	0.81	0.01	0.00
40	0.04	0.02	0.13	0.79	0.01	0.00
52	0.04	0.03	0.14	0.79	0.01	0.00

Rail Delivery Ratio

Step	River locks	Rail deliv.	Rail rates	Grain bids	Ocean rates	Barge rates
1	0.00	1.00	0.00	0.00	0.00	0.00
2	0.00	0.98	0.01	0.01	0.00	0.00
4	0.00	0.95	0.02	0.02	0.01	0.00
8	0.01	0.91	0.03	0.04	0.01	0.00
12	0.01	0.88	0.03	0.06	0.01	0.00
20	0.02	0.86	0.03	0.07	0.01	0.00
26	0.01	0.85	0.04	0.09	0.01	0.00
40	0.02	0.84	0.04	0.10	0.01	0.00
52	0.02	0.84	0.04	0.10	0.01	0.00

Ocean Freight Ratio

Step	River locks	Rail deliv.	Rail rates	Grain bids	Ocean rates	Barge rates
1	0.00	0.00	0.01	0.00	0.99	0.00
2	0.01	0.01	0.03	0.00	0.95	0.00
4	0.01	0.02	0.10	0.00	0.87	0.00
8	0.01	0.02	0.21	0.00	0.75	0.00
12	0.02	0.03	0.25	0.00	0.70	0.00
20	0.02	0.04	0.25	0.00	0.67	0.01
26	0.02	0.04	0.25	0.01	0.67	0.02
40	0.02	0.04	0.25	0.02	0.65	0.02
52	0.02	0.04	0.25	0.03	0.64	0.02

Rail Rate Ratio

Step	River locks	Rail deliv.	Rail rates	Grain bids	Ocean rates	Barge rates
1	0.04	0.01	0.95	0.00	0.00	0.00
2	0.04	0.05	0.90	0.00	0.01	0.01
4	0.05	0.10	0.81	0.01	0.04	0.01
8	0.06	0.14	0.68	0.00	0.08	0.03
12	0.06	0.15	0.61	0.01	0.09	0.06
20	0.06	0.15	0.56	0.03	0.09	0.10
26	0.06	0.15	0.54	0.05	0.08	0.11
40	0.05	0.15	0.51	0.10	0.08	0.11
52	0.05	0.14	0.49	0.13	0.07	0.11

Barge Rate

Step	River locks	Rail deliv.	Rail rates	Grain bids	Ocean rates	Barge rates
1	0.00	0.00	0.01	0.00	0.02	0.96
2	0.00	0.05	0.01	0.00	0.01	0.92
4	0.01	0.09	0.02	0.00	0.01	0.87
8	0.01	0.11	0.03	0.02	0.00	0.82
12	0.01	0.12	0.05	0.05	0.00	0.76
20	0.01	0.12	0.09	0.12	0.00	0.65
26	0.01	0.12	0.11	0.17	0.00	0.58
40	0.01	0.12	0.13	0.27	0.00	0.47
52	0.01	0.11	0.14	0.31	0.01	0.42

5.1 Variance decompositions for lockages

Variance decompositions provide a delineation of the variance of a particular variable — for example, lockages — at each forecast step (from 1 to 52 in the figures) into the fraction of the variance attributable to shocks to each of the other variables in the model. The first set of numbers in Table 4 presents variance decompositions for the lockage variable at steps of 1, 2, 4, 8, 12, 20, 26, 40, and 52.

Two main conclusions emerge from examination of the VDCs. First, the largest factor affecting the variance of lockages is shocks to lockages. This is not an unusual outcome for VDCs; that is, the largest fraction of the variability at all horizons is explained by a variable's own shocks. Second, setting aside the fraction of the variance of lockages explained by shocks to lockages, ocean freight rates explain the largest fraction of the variance, 7 per cent, at the 52 week horizon, an effect that rises slowly over time. Third, in the initial few weeks, until four weeks after the response, there is very little influence by any variable other than its own past. Finally, the combined amount of influence by rail deliveries, rail rates, and grain bids is 9 per cent, and this too is an effect that rises slowly over time.

5.2 Variance decompositions for rail deliveries

The rail delivery ratio tells a similar story; in the short run rail deliveries are fairly exogenous, but as time passes grain bids begin to have an influence reaching 10 per cent at 52 weeks. The second largest influence comes from rail rates, and there is a small influence from lockages and ocean rates but the response is very small. The notable feature is the short-run exogeneity of rail deliveries, and the rising influence of grain bids and rail rates over time, which account for 14 per cent of the variation at the 52 week horizon.

5.3 Variance decompositions for rail rates

The third set of numbers in Table 4 shows the VDC for the rail rate ratio. In the short run, lockages play the largest role, explaining 4 per cent at the one week horizon, followed closely by rail deliveries at 1 per cent. Thus, changes in quantity variables caused by supply shocks explain most of the variation at this horizon. As the horizon increases, the quantity variables become less important, and changes in price variables due to demand shocks become more important so that, at the 52 week horizon, lockages and rail deliveries explain 19 per cent of the variation, and prices explain 31 per cent with grain bids at 13 per cent, ocean rates at 7 per cent, and barge rates at 11 per cent.

5.4 Variance decompositions for grain bid prices

Interestingly, the results indicate more short-run feedback in the other direction, from lockages to grain bids, but the effect is fairly small at 2 per cent at the one week horizon and 5 per cent at the four week horizon. More influence in variation in grain bids comes from rail rates according to the results, but as in the previous cases, the effect is delayed and only appears after many weeks have passed. At the 52 week horizon, 14 per cent is explained by rail rates, and lockages and rail deliveries combine to explain another 7 per cent.

5.5 Variance decompositions for ocean freight rates

The variance decompositions for ocean freight rates again indicate that in the short run most variability is due to its own past rather than the other variables in the model. However, as time passes, as in previous cases, the effect of rail rates on ocean freight rates rises reaching 25 per cent at the 52 week horizon. The effect of other variables is relatively minor in comparison, and their combined effect of 11 per cent at the 52 week horizon is less than half as large.

5.6 Variance decompositions for barge rates

Barge rates appear to be ‘fairly exogenous’ in the short run; that is, the contemporaneous correlations are small. Thus, it is explained largely by its own past in the short run, while other variables only have a small effect. Over time, however, as with the other decompositions, the effect of other variables rises. In particular, the effect of rail on deliveries comes in at 9 per cent at the four week horizon and rises to 11 per cent at the 52 week horizon. Rail rates and grain bids begin to have explanatory power at the 12–20 week horizon and rise to a combined 45 per cent (14 per cent for rail rates and 31 per cent for grain bids) at the 52 week horizon.

6.0 Forecasting Out-of-Sample

The model has uses beyond the identification of patterns of responses over a network to shocks through time — it can also be used for forecasting. There are only a few studies that use time-series techniques to forecast transport markets. Babcock and Lu (2002) use an ARIMAX forecasting model to address what they describe as a neglected area of water transport forecasting, the short-term forecasting of inland waterway traffic. Their paper forecasts grain tonnage on the Mississippi River and finds that the model

Table 5
Out-of-Sample Forecasting Statistics

	RMSE statistics						
	1 step	*2 step*	*3 step*	*4 step*	*5 step*	*6 step*	*Mean*
Lockages	0.06179	0.07413	0.07593	0.08124	0.08542	0.08654	13.29
Rail delivery ratio	0.06721	0.07035	0.06724	0.06771	0.06907	0.06889	1.527
Rail rate ratio	0.00014	0.00019	0.00028	0.00029	0.00030	0.00030	0.7465
Grain bid ratio	0.00296	0.00270	0.00256	0.00363	0.00464	0.00488	0.9588
Ocean freight ratio	0.00309	0.00545	0.00753	0.00881	0.00951	0.00954	1.187
Barge rate	0.01490	0.02085	0.02385	0.02796	0.02580	0.02738	4.837

provides accurate forecasts. Tang (2001) notes that data problems complicate the development of structural economic models and makes forecasting difficult. However, given the focus on short-term forecasting, a time-series model is an attractive alternative. She develops a time-series forecasting model for grain tonnage on the McClellan–Kerr Arkansas River and finds that the models perform well so long as care is taken to identify and model structural breaks in the data.

It would be desirable to directly compare the forecasting ability of the model in this paper to other models such as those just described. Unfortunately, none of these studies is directly comparable to the study used here, so relative forecasting measures are not available. To assess the model's forecasting ability, root mean square error statistics are used. Two types of forecasting statistics can be calculated, in-sample forecasting ability and out-of-sample forecasting ability. The variance decompositions and impulse response functions assess the model's ability to predict in-sample. However, a full assessment of the model's characteristics requires a look at its ability to forecast out-of-sample as well. This is provided in Table 5, which presents root mean square error statistics for horizons of one to six weeks ahead.

For example, the statistic for the one period ahead forecasts are based upon twelve one period ahead out-of-sample forecasts. The first forecast is based upon estimates of the model through time T-1 and the forecast is for time T. The second one period ahead forecast estimates the model through time T-2 and forecasts time T-1. This is repeated until the twelfth forecast is obtained from estimating the model through time T-12 and forecasting T-11. The forecast value for each of the twelve time periods is then used, along with the actual values, to calculate the root mean square error statistics in the table.

For the two period ahead forecasts, the procedure is the same except that the first period estimated is through T-2 for the forecast of period T;

the procedure is the same for the other forecasting horizons with the sample appropriately adjusted. As is evident from a comparison of the root mean square errors to the mean of each series shown in Table 5, the forecasts are fairly accurate in each case, more so, as expected, for shorter horizons.

7.0 Conclusions

Transport markets involve the movement of specific commodities between a multitude of origins and destinations by a variety of modes or combination of modes. Important demand drivers include the prices of the commodity transported and, in international markets, ocean freight rates. Econometric analysis based upon structural models is complicated by the complexity of the interrelationships and by the lack of sufficiently detailed and consistent data across modes. This paper overcomes the structural modelling problem by using complementary time-series techniques, and overcomes the data problem by focusing on key variables implied by the structure. In particular, impulse response functions and variance decompositions are used to characterise relationships among six variables (many are ratios of two variables to capture relative effects) in a VAR model designed to trace the interconnections among variables in the model. The model contains six categories of variables, lockages, rail deliveries, rail rates, grain bids, ocean freight rates, and barge rates, and looks at both short and long horizons.

A central result is that both barge demand and lock supply shocks have significant effects on variables in the model. In addition, the other supply and demand shocks examined have significant effects as well. Generally, the estimated model includes the primary variables affecting transport markets and provides an excellent tool for forecasting. The results suggest that there is a high degree of precision in forecasting out-of-sample. As is common in forecasting, the ability to forecast out-of-sample depends upon how far ahead the out-of-sample forecasts are made. Precision falls when the number of periods increases, but even for six period ahead forecasts, the out-of-sample forecasting performance is strong.

The results are consistent with the notion that quantities adjust to demand shocks, effects that are consistent with the claims of various National Research Council reports and others on the treatment of demand in the various Army Corps planning models. Additional research is mandated, and indeed attempts to measure the structural demand relationships and equilibrium responses that need to be reflected in planning models are currently underway.

References

Anderson, P. A. (1979): 'Help for the Regional Economic Forecaster: Vector Autoregression', *Federal Reserve Bank of Minneapolis Quarterly Review*, 3.

Babcock, M. W. and X. Lu (2002): 'Forecasting inland waterway grain traffic', *Transportation Research – Part E*, 38, 65–74.

Baumel, C. P. (2000): 'Evaluation of the U.S. Army Corps of Engineer Forecasts of U.S. Grain Exports'. Available from: http://www.econ.iastate.edu/faculty/baumel/Baumel/pages/transport.htm.

Berry, S., G. Hewings, and C. Leven (2000): 'Adequacy of Research on Upper Mississippi–Illinois River Navigation Project', Northeast-Midwest Institute, Washington, D.C.

De Vany, A. S. and W. D. Walls (1996): 'The law of one price in a network: Arbitrage and price dynamics in natural gas city gate markets', *Journal of Regional Science*, 36, 555–70.

De Vany, A. S. and W. D. Walls (1999): 'Price Dynamics in a Network of Decentralized Power Markets', *Journal of Regulatory Economics*, 15, 123–40.

Friedlaender, A. F. and R. H. Spady (1981): *Freight transport regulation: equity, efficiency, and competition in the rail and trucking industries*, MIT Press.

National Research Council, Transportation Research Board of the National Academies (2000): *Inland Navigation System Planning: The Upper Mississippi River–Illinois Waterway*, National Academy Press.

Sargent, T. J. (1979): 'Estimating Vector Autoregressions Using Methods Not Based on Explicit Economic Theories', *Federal Reserve Bank of Minneapolis Quarterly Review*, 3.

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

Sims, C. A. and Z. Tao (1999): 'Error Bands for Impulse Responses', *Econometrica*, 67, 1113–56.

Sparks Companies Inc. (2002): *Upper Mississippi River and Illinois Waterway Navigation Study*.

Stock, H. H. and M. W. Watson (2001): 'Vector Autoregression', Working Paper.

Tang, X. (2001): 'Time Series forecasting of quarterly barge grain tonnage on the McClellan-Kerr Arkansas River navigation system', *Journal of the Transportation Research Forum*, 40, 91–108.

United States Department of Agriculture, *Grain Transportation Report January 04, 1999–June 12, 2003* [online]. Available from: http://www.ams.usda.gov/tmdtsb/grain/.

Wilson, W. W., W. W. Wilson, and W. W. Koo (1988): 'Modal Competition in Grain Transport', *Journal of Transport Economics and Policy*, 22, 319–37.