Railroad wheat transportation markets in the central plains: modeling with error correction and directed graphs

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Abstract

Time series methods are used to study the dynamics of regional, export-wheat, railroad rates linking seven central US regions to Texas Gulf ports. Research focuses on the extent and nature of regional rate interactions to determine whether regional rail transportation rates are established independently, through interaction and/or dominated by several regional leaders. Analysis is carried out on 1988–1994 public waybill data for seven Business Economic Areas (BEA) located in Kansas, Oklahoma, Texas and Colorado: these regions originate virtually all of the eight million tons of hard red winter wheat annually shipped to Texas Gulf ports. Results show all rail transportation markets linked in varying degrees. Some regions are near-independent or highly exogenous regarding rate-setting, while others interact with and to rates established in other regions. Regions that are dominated by a single carrier tend to be more independent and insulated regarding rate-setting. Export rates in regions dominated by the Union Pacific (UP) generally account for a significant variation in the rates of other regions. Data show the UP to have been aggressive in providing incentives for country elevators to consolidate for purposes of making unit train shipments, thus their presumed influence on rates of other regions. As expected, export rates for regions with substantial storage and transhipment facilities are sensitive to export rates of regions which ship to the transhipment facilities. Finally, results suggest that rate-setting in a particular region is in part a function of the dominant railroad’s management and its aggressiveness, an expected outcome in an oligopolistic market. © 1999 Elsevier Science Ltd. All rights reserved.

The Staggers Rail Act of 1980 dramatically altered government policy toward the railroad industry by adopting a market-oriented paradigm that relaxed restrictions on pricing and capital disinvestment. Most evidence suggests the experiment has been a success. Railroads have reduced employment and increased labor productivity, rationalized capital, and lowered real rates while...
increasing rates of return and profitability (MacDonald and Cavalluzzo, 1996; Wilson, 1994; Friedlaender et al., 1992; Winston et al., 1990; Winston, 1993).

Many economists correctly predicted that railroad deregulation would lower rates for many products. However, an exception to the general accuracy of these forecasts was with regard to bulk products (grain) where it was thought that shippers could expect higher rates (Levin, 1981). It was argued that railroad rates in the Great Plains would increase *ex post* regulation because of ineffective intermodal competition. However, in contrast to expectations, relatively large declines in rates occurred after deregulation. MacDonald (1989) offers, what is perhaps, the most comprehensive and definitive analysis. MacDonald uses 1981–1985 waybill data, in combination with selected control variables and regression methods to show that effective inter-rail competition was introduced into much of the Plains as a result of deregulation. Virtually all studies into the effect of deregulation on Great Plains grain rates analyzed a similar period and regardless of data or method generated findings that corroborate those of MacDonald (Hauser, 1986; Sorenson, 1984; Fuller et al., 1987).

Previous studies into the effect of deregulation on Plains railroad grain rates focused on rate trends and competitive forces affecting rate levels. In contrast, this study examines the dynamic relationships among regional rail transportation rates that link seven central plains wheat production regions with export facilities on the Texas Gulf. The objective of this research is to determine whether export-wheat rates in Plains transportation markets are established independently, through interaction and/or dominated by several regional leaders. Further, because selected railroads have dominant market shares in most regions, the results are expected to offer a perspective on railroad company pricing. This study is of particular interest since the analyzed period (1988–1994) reflects important railroad consolidations and possible sophistication in price-setting that may not have been captured by previous studies that focused on the period immediately after deregulation.

Analysis is carried out on public waybill data that identifies the origin of shipment by Business Economic Area (BEA). Seven BEA regions were found to virtually originate all wheat shipments to Texas Gulf ports; they included two regions that encompassed the western two-thirds of Kansas (northcentral and northwest (Salina, Kansas), and southcentral and southwest Kansas (Wichita, Kansas)), a region located in northwest and central Oklahoma (Enid, Oklahoma), a region including the northeast quadrant of Colorado (Denver, Colorado), a region including the Texas (Amarillo, Texas) and Oklahoma panhandles and two regions centered about Kansas City and Dallas-Ft. Worth. Each of the Kansas regions and the Oklahoma region ship about 20% of Texas port receipts while the north Texas region (Dallas-Ft. Worth) contributes about 15%. Remaining economic regions shipped about equal portions (8%) to Texas ports. The regions centered about Kansas City and Dallas-Ft. Worth do not produce important quantities of export destined wheat but, do include important secondary storage facilities that receive from the other five areas.

During the study period, the Atchinson, Topeka and Santa Fe (ATSF); Union Pacific (UP); Burlington Northern (BN); Kansas City Southern (KCS) and the Southern Pacific (SP) railroads dominated in mainline, gathering system and in carriage of wheat to Texas ports. The UP system includes considerable mainline/gathering trackage in northcentral and northwest Kansas and Colorado as well as north/south trackage extending from northcentral Kansas (Salina) and Kansas City region to Texas ports (Fig. 1). The UP includes trackage in all study regions except
Fig. 1. Railroad network of primary carriers in the study region.

Atchison, Topeka & Santa Fe

Burlington Northern

Union Pacific
the region comprising the Texas/Oklahoma panhandles. Based on waybill distance data and knowledge regarding location of major shipping sites, it was estimated that the UP transported about two-thirds of the export-destined wheat in northcentral and northwest Kansas and the Colorado region.

The gathering system of the ATSF railroad was the most extensive of any railroad serving the study region (Fig. 1). During much of the study period, the ATSF included a substantial gathering/mainline system in the south Kansas and Oklahoma regions, with an estimated market share of about 75% (Ruppel et al., 1990). The ATSF has a strong presence in the Texas/Oklahoma region, a region shared with the Burlington Northern and in the Dallas-Ft. Worth region, a region served by all major carriers. The Burlington Northern system tends to operate on the periphery of the most intensive wheat producing regions (Fig. 1). Regardless, it is estimated to have a significant market share in the Texas/Oklahoma region and in the Colorado and Dallas-Ft. Worth regions. The Colorado market is shared with the UP and ATSF, but with the UP presumed to be the dominant carrier. The Kansas City Southern railroad is limited to north/south track extending from Omaha, Nebraska to Texas Gulf ports but is an important carrier of export-destined wheat from the Kansas City market to Texas ports. The SP includes mainline in the Texas/Oklahoma panhandle and south Kansas regions, but lacks direct links to Texas ports, thus its minor role in the transportation of export-destined wheat from the study region.

1. Method of analysis

Our plan is to study the dynamic relations present in observational data on seven regional rate series. Rather than attempt to model the detailed demand and supply structure of (and transportation linkages between) each market, we propose to summarize the time series regularities within and among each market. Our ability to capture ceteris paribus conditions embedded in structural demand and supply models on data observed over a seven year period is judged to be weak. Accordingly, we look to summarize the regularities present in these data and attempt to test restrictions defined in terms of observable rates rather than the unobservable parameters of demand and supply.

The public waybill file was the source of rate data for the study. The waybill sample reports the date, number of cars per shipment, miles of haul, weight, region of origin and destination, and revenue generated for a selected shipment. These files represent a stratified random sample of nonproprietary shipments. Some suggest (Wolfe and Linde, 1997) the public waybill may not accurately reflect railroad rates since it may not include all records contained in the master waybill file and railroads may mask contract revenues at the three digit STCC level. Because the master file is confidential, most transportation research is based on the public file thus, potential concern regarding these analyses. Regardless, ALK Associates, Princeton, New Jersey indicate that at the national level over 99% of the files in the master file are included in the public file. Further, research based on the public waybill has generally been accepted by peers as credible and insightful (Fuller et al., 1987; Kwon et al., 1994). The analyzed railroad rates were obtained for each of the seven BEA regions by segregating export shipments to Texas Gulf ports and then calculating a monthly, volume-weighted average rate that reflected the unequal sampling rate for entries in the
waybill sample. The nominal monthly rate data extend from 1988 through 1994, thus 84 rate observations on each region.

A Vector Autoregressive (VAR) representation and, if appropriate, its derivative error correction model, are particularly useful for efficiently summarizing dynamic influences and will be applied here. The VAR representation will be entertained as a starting point; however, we expect to see cointegrating (long-run) relations in the data, as rail rates are prices and each geographical location is (potentially) connected by competition by other carriers or other modes (truck).

The maximum likelihood methods of Johansen (1992 and 1995) and Johansen and Juselius (1990) are used in this paper. They consider the cointegration problem as one of reduced rank regression. Let $x(t)$ be the vector of series under investigation, with the following error correction representation:

$$
\Delta x(t) = \mu + \Gamma(1)\Delta x(t - 1) + \cdots + \Gamma(k - 1)\Delta x(t - k + 1) + \pi x(t - 1) + \Psi D_t + u(t),
$$

where

$$
\Gamma(i) = -[\pi(i + 1) + \cdots + \pi(k)] \quad \text{for } i = 1, \ldots, k - 1
$$

and

$$
\pi = -[I - \pi(1) - \cdots - \pi(k)].
$$

Here the $\pi(i)$ are $(p \times p)$ matrices of autoregressive parameters from a VAR in levels of $x(t)$ of lag order $k$, $\mu$ a constant, $D_t$ a set of predetermined variables (seasonal dummy variables or intervention dummy variables), $\Psi$ the associated parameter(s) on these predetermined variables and $u(t)$ a white noise innovation term.

Eq. (1) resembles a VAR model in first differences, except for the presence of the lagged level of $x(t - k)$. Its associated parameter matrix, $\pi$, contains information about the long-run (cointegrating) relationship between the variables in the vector $x$. There are three possibilities of interest:

(a) if $\pi$ is of full rank, then $x(t)$ is stationary in levels and a VAR in levels is an appropriate model;
(b) if $\pi$ has zero rank, then it contains no long-run information, and the appropriate model is a VAR in differences; and (c) if the rank of $\pi$ is a positive number, $r$, and is less than $p$ (here in our case $p = 7$), there exist matrices $z$ and $\beta$, with dimensions $p \times r$, such that $\pi = z\beta'$; the latter case, $\beta' x(t)$, is stationary, even though $x(t)$ is not.

In case (c), the long-run equilibrium between the series is summarized by the vector $\beta$. The rate at which each series adjusts to perturbations in this equilibrium is given by the $z$ matrix. Analysis of the elements of $z$ and $\beta$, are fundamental to our understanding of long-run relations present in our data.

2. Results

We identify each of the seven regions using a city name identifier: Kansas City, Missouri; Dallas-Ft. Worth, Texas; Amarillo, Texas; Enid, Oklahoma; Wichita, Kansas; Salina, Kansas; and Denver, Colorado (Table 1). Kansas City and Dallas-Ft. Worth are not major producing regions; however, they include non-trivial amounts of grain storage, which receive wheat from other production regions for storage and subsequent shipment to Texas Gulf ports. We use the logarithmic transformation to account for percentage changes in rates. Fig. 2 gives the historical
levels of the log transformed data. The level of each series appears to vary with geographical distance from the port, with Denver generally being the highest rate ($\mu_{\text{Denver}} = 3.00$, mileage = 1140, where $\mu$ indicates the mean log rate in the Denver region over the 1988–1994 period and mileage is the approximate mileage to the Houston Gulf port), followed by Salina

Table 1
Likelihood ratio tests on seasonal binary variables and order of lag in a levels VAR

<table>
<thead>
<tr>
<th>Lag</th>
<th>T</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>87.47</td>
<td>0.00</td>
</tr>
<tr>
<td>1</td>
<td>117.53</td>
<td>0.00</td>
</tr>
<tr>
<td>2</td>
<td>102.48</td>
<td>0.00</td>
</tr>
<tr>
<td>3</td>
<td>104.74</td>
<td>0.00</td>
</tr>
</tbody>
</table>

(Lags)

<table>
<thead>
<tr>
<th>k vs. k+1</th>
<th>T</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 vs. 1</td>
<td>178.23</td>
<td>0.00</td>
</tr>
<tr>
<td>1 vs. 2</td>
<td>47.62</td>
<td>0.53</td>
</tr>
<tr>
<td>2 vs. 3</td>
<td>50.69</td>
<td>0.41</td>
</tr>
</tbody>
</table>

Tests on seasonal dummy variables are conducted without and with eleven monthly binary variables, at lags zero, one, two, and three. The test at each lag is on the eleven monthly indicator variables in a VAR in levels (undifferenced data) at each lag 0, 1, 2, 3. Tests on lags are on lags $k$ versus $k + 1$ in a VAR in levels (undifferenced data) fit with eleven monthly indicator variables and a constant. Tests on unit roots are conducted following Beaulieu and Miron (1993). These tests are conducted with a constant and eleven seasonal dummy variables, with no trend (see Beaulieu and Miron, especially Table A.1, for details). We reject, at a 5% significance level and lower, seasonal unit roots at several of the frequencies $\pi$, $\pi/2$, $2\pi/3$, $\pi/3$, $5\pi/6$ and $\pi/6$ for all series. In addition, we find no rejections at the 5% level of significance of unit roots at the zero frequency for all series except Dallas-Ft. Worth. On Dallas-Ft. Worth data, we do not reject non-stationarity at the zero frequency at 0.025 level.

Fig. 2. Log rates for rail transport of wheat from seven hinterland markets, 1988–1994 (log $$/ton).
(μ_{Salina} = 2.94, mileage = 800), Wichita (μ_{Wichita} = 2.73, mileage = 700), Amarillo (μ_{Amarillo} = 2.65, mileage = 690), Enid (μ_{Enid} = 2.59, mileage = 600), Kansas City (μ_{KC} = 2.47, mileage = 850) and Dallas-Ft. Worth (μ_{DFW} = 2.04, mileage = 300). Kansas City is the exception to our mean rate and is a positive function of distance observation.

While the means of the market rates may be helpful in understanding the overall level of rates, each series is not particularly wedded to its historical mean. Further, rates in each market are not randomly distributed around their individual means, as rates that are above the market mean in period t appear likely to be followed in time by rates that are also above the market mean (rate in period t + 1 will also be highly likely to be above the historical mean). In short, these data appear to have time series attributes. In Table 1 we consider likelihood ratio tests on monthly (seasonal) dummy variables and orders of lags in VARs on levels of log rates in each market. In the first panel of results labeled “seasonals” we consider VARs at consecutive lags: no lags, t − 1, t − 2, and t − 3, each with eleven monthly indicator variables (dummy variables). The null hypothesis at each lag is that the eleven dummy variables, as a group have coefficient values equal to zero. We strongly reject the null at each length of lag, indicating that the data have seasonal regularities. The second panel of tests presented under the label “lags” are likelihood ratio tests on the order of lag in a VAR, given a constant and eleven monthly “dummy” variables. Here the null hypothesis is that the coefficients at lag k + 1 are, as a group, equal to zero. (Lutkepohl (1985) has considered tests of this type and suggests a critical p-value of 0.01 be used to select lags.) Notice here that the coefficient matrix at lag one is significantly different from zero at a very low p-value (<0.01), while matrices at lags two and three require p-values in excess of 0.10 to reject the null hypothesis.

Given the results presented in Table 1 (a VAR of lag order one with seasonal dummy variables), we next consider the number of long-run “stationary” relations present in this seven variable data set. Here we consider tests on the number of non-zero eigenvalues present in the π matrix of the error correction representation of the form:

$$\Delta x(t) = π x(t - 1) + (Ψ_i + Ψ_{i-1}) + u(t).$$

Here π = −(I − π1), where π1 is the parameter matrix on VAR with one lag fit with levels data, I the identity matrix, Ψ_i and Ψ_{i-1} the monthly dummy coefficients associated with month i and month i − 1 corresponding with x_i and x_{i-1} in a levels VAR, and u(t) a white noise innovation term. (Notice that we have no I(1)Δx(t − 1) term from Eq. (1), as our VAR in levels is of order k = 1, so our error correction model will have k − 1 = 0 lags of first differences.)

Table 2 gives trace test statistics on the rank of π, the number of cointegrating vectors (r) present in this seven variable set. We offer tests for both a constant in the cointegrating vector (T* tests) and for a constant outside the cointegrating vectors (T tests), as we did not test for time trend in our levels VAR (Table 1). Following the sequential testing procedure suggested by Johansen (1992), we see in Table 2 that we have six cointegrating vectors with a constant included in the cointegrating space.

3. Identification

Results presented thus far are summarized as follows: we have six long-run relations in our rate data from seven markets. Here we make use of theory to provide identifying information on the
nature of these six long-run relationships. A priori, theory provides expectations on the behavior of rail rates from alternative locations to a common port. One plausible hypothesis, which is consistent with the result we find here, is that for ‘markets connected by competition (a free flow of information and the possibility of arbitrage – in our case it is plausible that grain could be moved by truck from one market to another), we should observe $p \leq 1$ (independent) long-run relationships ($z_1, z_2, \ldots, z_p \leq 1$). For example, if we have rates from three efficient markets, $r_1, r_2$, and $r_3$, arbitrage would dictate that two independent vectors hold these three markets together:

$$
\begin{bmatrix}
Z_1 \\
Z_2
\end{bmatrix} =
\begin{bmatrix}
b_{11} & b_{21} & 0 & c_1 \\
0 & b_{22} & b_{32} & c_2
\end{bmatrix}
\begin{bmatrix}
r_1 \\
r_2 \\
r_3 \\
1
\end{bmatrix}.
$$

In our seven market case, we expect to see, as we do, six cointegrating vectors connecting the seven markets. Further, knowledge of six of these rates and competition would be sufficient to give long-run information (up to a constant) on the seventh. Actually, Samuelson (1952) derives the $p - 1$ restrictions for the case of the price of a commodity in $p$ markets connected by fixed transportation rates. In our application, transportation to the Texas Gulf is the commodity and each market is connected to the other via rail or truck transportation. His restrictions would result in $p - 1$ pairwise equality restrictions and a non-zero constant in the cointegrating vector, the latter to account for differences in marginal cost related to distance. We explore these below.

The long-run restrictions that the $r$ cointegrating vectors reflect such pairwise restrictions (without imposing equality) suggest a just identified cointegrating space (for details on identification of the cointegration space see Johansen (1995)).
The estimated error correction model from these just identified restrictions is given in Eq. (3). The \( x_i \)'s correspond to each market as follows: \( x_1 = \) Kansas City; \( x_2 = \) Dallas-Ft. Worth; \( x_3 = \) Amarillo; \( x_4 = \) Enid; \( x_5 = \) Wichita; \( x_6 = \) Salina; and \( x_7 = \) Denver. The first matrix on the right-hand side of the equal sign gives the \( z \) matrix of Eq. (1), which summarizes the weights with which perturbations in the long-run-equilibrium enter each of the \( \Delta x_i \)'s (left-hand side of the equal sign). The second matrix on the right-hand side of the equal sign gives \( \beta' \) of Eq. (1), the cointegrating vectors, so that \( \beta' x(t - 1) \) give perturbations in the long-run equilibrium. Finally, the last matrix gives estimated coefficients associated with the seasonal dummy variables. Parentheses give \( t \)-statistics for parameter estimates on \( z \) and the seasonal dummy variables.

Residuals in Eq. (3) are reasonably well-behaved. Lagragian multiplier-type tests on first and fourth order autocorrelation on residuals (chi-squared tests, see Godfrey (1988) for description) reject the null of white noise residuals at \( p \)-values of 0.20 and 0.62, respectively. Lagragian multiplier-type tests on first order ARCH residuals (see Hansen and Juselius, 1995, p. 76 for discussion of the test statistic) from each equation result in the following statistics (and \( p \)-values from the chi-squared distribution with one degree of freedom): 0.03 (0.86), 0.10 (0.75), 13.3 (0.000), 0.14 (0.71), 1.0 (0.31), 0.2 (0.65) and 4.3 (0.04) for the Kansas City, Dallas-Ft. Worth, Amarillo, Enid, Wichita, Salina and Denver equations, respectively. These statistics do suggest a non-constant variance in the innovations from the Amarillo equation. (Further analysis of the Amarillo

\[
\begin{pmatrix}
\Delta x_1(t) \\
\Delta x_2(t) \\
\Delta x_3(t) \\
\Delta x_4(t) \\
\Delta x_5(t) \\
\Delta x_6(t) \\
\Delta x_7(t)
\end{pmatrix} = 
\begin{pmatrix}
-0.54 & 0.28 & 0.30 & 0.60 & 2.63 & 0.06 \\
(5.8) & (2.2) & (2.1) & (2.5) & (2.8) & (0.5) \\
-0.14 & -0.79 & -0.64 & -0.78 & -2.83 & -0.08 \\
(1.8) & (7.1) & (5.3) & (3.8) & (3.4) & (0.7) \\
-0.07 & 0.13 & -0.54 & -0.76 & -3.07 & -0.11 \\
(0.6) & (0.9) & (3.2) & (2.7) & (2.7) & (0.7) \\
-0.06 & 0.06 & 0.15 & -0.52 & -1.78 & 0.01 \\
(0.8) & (0.6) & (1.3) & (2.8) & (2.4) & (0.1) \\
0.00 & -0.01 & 0.03 & 0.05 & -0.20 & -0.10 \\
(0.1) & (0.1) & (0.4) & (0.4) & (0.4) & (1.7) \\
0.05 & 0.17 & 0.17 & 0.44 & 1.6 & -0.18 \\
(0.9) & (2.2) & (2.1) & (3.1) & (2.9) & (2.5) \\
-0.09 & 0.35 & 0.35 & 0.55 & 2.22 & 0.41 \\
(2.0) & (5.5) & (4.9) & (4.6) & (4.6) & (6.6)
\end{pmatrix}
\]

\[
\begin{pmatrix}
1.00 & 0.64 & 0 & 0 & 0 & 0 & 0 & -3.79 \\
0 & 1.00 & -0.91 & 0 & 0 & 0 & 0 & 0.36 \\
0 & 0 & 1.00 & -1.75 & 0 & 0 & 0 & 1.88 \\
0 & 0 & 0 & 1.00 & -4.13 & 0 & 0 & 8.73 \\
0 & 0 & 0 & 0 & 1.00 & -0.10 & 0 & -2.46 \\
0 & 0 & 0 & 0 & 0 & 1.00 & -1.38 & 1.20
\end{pmatrix}
\]

\[
\begin{pmatrix}
x_1(t - 1) \\
x_2(t - 1) \\
x_3(t - 1) \\
x_4(t - 1) \\
x_5(t - 1) \\
x_6(t - 1) \\
x_7(t - 1)
\end{pmatrix}
\]
perturbations in the first cointegrating vector and significant positive responses to perturbations in each beta vector.

The test on first order ARCH residuals falls to 1.92, with an associated p-value of 0.165. However, we reject weak exogeneity (the zero restrictions on $x$) at a $p$-value of 0.000; suggesting that Amarillo is best not modeled as weakly exogenous. We did not take further steps to model ARCH-like effects in the Amarillo residuals.

Responses to perturbations in each of the long-run relations are given in the first matrix on the right-hand side of Eq. (3); where perturbations in the long-run equilibrium are given by $\beta' x(t - 1)$, the second matrix and vector on the right-hand side of Eq. (3). We list $t$-statistics on alpha matrix entries in parentheses, which are relevant to the particular identifying restrictions imposed. Interpretation of each alpha magnitude is interpretable, given the particular normalization used on each beta vector.

Changes in the rate in Kansas City ($\Delta x_1(t - 1)$) show a significant negative response to perturbations in the first cointegrating vector and significant positive responses to perturbations in
the next four cointegrating vectors. For our first cointegrating vector normalization is with respect to the Kansas City rate in period $t - 1$: $x_1(t - 1) + 0.64x_2(t - 1) - 3.79 = z_1(t - 1)$, where $z_1(t - 1)$ is used to represent perturbations in the first long-run equilibrium and $x_1(t - 1)$ and $x_2(t - 1)$ represent the Kansas City and Dallas-Ft. Worth rates, respectively. When the Kansas City rate is high relative to its historical, long run, relation to the Dallas-Ft. Worth rate, the Kansas City rate falls in the subsequent period by 0.54 $z_1(t - 1)$. Similar interpretations exist for the response of the Kansas City rate for perturbations in the long-run relations between Dallas-Ft. Worth and Amarillo, Amarillo and Enid, Enid and Wichita, and Wichita and Salina rates. Interestingly, Kansas City does not respond significantly to perturbations in the Salina–Denver long-run equilibrium.

Dallas-Ft. Worth shows a significant negative response to disturbances in the second, third, fourth and fifth long-run relations. For our second cointegrating vector the normalization is with respect to the Dallas-Ft. Worth market: $x_2(t - 1) - 0.91x_3(t - 1) + 0.36 = z_2(t - 1)$, where $z_2(t - 1)$ is used to represent perturbations in the second long-run equilibrium and $x_2(t - 1)$ and $x_3(t - 1)$ represent the Dallas-Ft. Worth and Amarillo rates, respectively. If the Dallas-Ft. Worth rate is high relative to the long-run equilibrium (if $z_2(t - 1)$ is positive) then the Dallas-Ft. Worth rate decreases by 0.79 $z_2(t - 1)$. Similarly, if the Amarillo rate is high in period $t - 1$, relative to the long-run equilibrium with Enid, $x_3(t - 1) = 1.75x_4(t - 1) + 1.88 = z_3(t - 1)$, then the Dallas-Ft. Worth rate in period $t$ falls by 0.64 $z_3(t - 1)$. Similar interpretations exist for Dallas-Ft. Worth’s response to the Enid–Wichita equilibrium and the Wichita–Salina equilibrium. Dallas-Ft. Worth does not respond significantly to disturbances in the Salina–Denver long-run equilibrium.

The Amarillo market responds significantly negative with respect to shocks in the third long-run equilibrium: $x_3(t - 1) - 1.75x_4(t - 1) + 1.88 = z_3(t - 1)$, so that when Amarillo is high relative to its long-run relation with Enid in period $t - 1$, the Amarillo rate in the subsequent period falls by 0.54 $z_3(t - 1)$. Amarillo responds negatively, as well, to perturbations in the fourth long-run equilibrium: $x_4(t - 1) - 4.13x_5(t - 1) + 8.73 = z_4(t - 1)$, so that when Enid is high relative to its long-run equilibrium with Wichita, the Amarillo rate responds negatively by 0.76 $z_4(t - 1)$. Similarly, Amarillo responds negatively with respect to the Wichita–Salina equilibrium.

Enid responds significantly negative to perturbations in the fourth and fifth cointegrating vectors (the Enid–Wichita and Wichita–Salina equilibria). Wichita shows only a weak negative response ($t$-statistic of 1.7) to shocks in the Salina–Denver equilibrium; so that when Salina is high relative to its long-run equilibrium with Denver, the rate in Wichita falls in the subsequent period. It is interesting that all other responses of the Wichita rate to shocks in long-run relations are not significantly different from zero. Salina responds significantly in a positive manner to shocks in the second, third, fourth and fifth vectors and negatively to shocks in the last vector. Finally, Denver responds positively (significantly so at usual levels) with respect to perturbations in all five vectors.

Markets served by the UP (Denver, Salina and Wichita) respond significantly to perturbations in the last vector, which summarizes the long-run relation between Salina and Denver. Rates from Amarillo and Enid, which are not major UP markets, do not respond in this last vector. Vectors four and five (summarizing Enid–Wichita and Wichita–Salina long-run relations) generate significant responses in all markets except Wichita. Finally, the Wichita market which is dominated by the ATSF railroad appears not to respond strongly (or significantly) to perturbations in any of the six long-run relations.
4. Innovation accounting

The error correction model given in Eq. (3) can be used to summarize the period by period influence each market rate has on the other rates of the seven variable system. The strengths of these relationships can be described through analysis of decompositions of forecast error variance (FEV decompositions). Critical to such an analysis is the method for treating contemporaneous innovation correlation. We follow the factorization commonly referred to as the “Bernanke ordering” (see Doan, 1992). Write the innovation vector \((u_t)\) from the error correction model as: \(A u_t = v_t\), where \(A\) is a \(7 \times 7\) matrix and \(v_t\) is a \(7 \times 1\) vector of orthogonal shocks. A general description of the model considered is given in Eq. (4)

\[
\begin{bmatrix}
a_{11} & a_{12} & a_{13} & a_{14} & a_{15} & a_{16} & a_{17} \\
a_{21} & a_{22} & a_{23} & a_{24} & a_{25} & a_{26} & a_{27} \\
a_{31} & a_{32} & a_{33} & a_{34} & a_{35} & a_{36} & a_{37} \\
a_{41} & a_{42} & a_{43} & a_{44} & a_{45} & a_{46} & a_{47} \\
a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & a_{56} & a_{57} \\
a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} & a_{67} \\
a_{71} & a_{72} & a_{73} & a_{74} & a_{75} & a_{76} & a_{77} \\
\end{bmatrix}
\begin{bmatrix}
u_{11t} \\
u_{21t} \\
u_{31t} \\
u_{41t} \\
u_{51t} \\
u_{61t} \\
u_{71t} \\
\end{bmatrix}
= 
\begin{bmatrix}
u_{11t} \\
u_{21t} \\
u_{31t} \\
u_{41t} \\
u_{51t} \\
u_{61t} \\
u_{71t} \\
\end{bmatrix}
\tag{4}
\]

here \(u_{11t}, u_{21t}, u_{31t}, u_{41t}, u_{51t}, u_{61t},\) and \(u_{71t}\) are observed (non-orthogonal) innovations in \(\Delta x_1, \Delta x_2, \Delta x_3, \Delta x_4, \Delta x_5, \Delta x_6,\) and \(\Delta x_7\) in period \(t\); \(v_{11t}, v_{21t}, v_{31t}, v_{41t}, v_{51t}, v_{61t},\) and \(v_{71t}\) are orthogonal innovations in \(\Delta x_1, \Delta x_2, \Delta x_3, \Delta x_4, \Delta x_5, \Delta x_6,\) and \(\Delta x_7\) in period \(t\), where the orthogonalization is obtained via the matrix \(A\). A factorization is identified (see Doan, 1992, 8–10), if there is no combination of \(i\) and \(j (i \neq j)\) for which both \(\{a_{ij}\}\) and \(\{a_{ji}\}\) are non-zero (here \(\{a_{ij}\}\) is element \(i, j\) of matrix \(A\)).

It was common in earlier VAR-type analyses to rely on a Choleski factorization, so that the \(A\) matrix is lower triangular, to achieve a just-identified system in contemporaneous time. We apply directed graph algorithms given in Spirtes et al. (1993) to place zeroes on the \(A\) matrix. (A similar suggestion is made by Swanson and Granger (1997).) A directed graph is an assignment of causal flow (or lack thereof) among a set of variables (vertices) based on observed correlation and partial correlation. Our six variable error correction model based on the identifying restrictions results in the following innovation correlation matrix (lower triangular entries only are printed in order: \(\Delta x_1, \Delta x_2, \Delta x_3, \Delta x_4, \Delta x_5, \Delta x_6,\) and \(\Delta x_7\)):

\[
V = 
\begin{bmatrix}
1.00 & & & & & & \\
0.11 & 1.00 & & & & & \\
-0.05 & -0.10 & 1.00 & & & & \\
0.06 & 0.16 & 0.16 & 1.00 & & & \\
0.10 & 0.29 & -0.12 & 0.07 & 1.00 & & \\
0.02 & -0.21 & 0.02 & -0.10 & -0.05 & 1.00 & \\
0.13 & -0.11 & 0.09 & 0.17 & 0.01 & 0.16 & 1.00 \\
\end{bmatrix}.
\]

Directed graph theory is helpful by explicitly pointing out that the off-diagonal elements of the scaled inverse of this matrix (\(V\) or any correlation matrix) are the negatives of the partial correlation coefficients between the corresponding pair of variables, given the remaining variables in the matrix (Whittaker 1990, p. 4). So, for example, if we wanted to compute the conditional
correlation between innovations in $\Delta x_{1t}$ and innovations in $\Delta x_{2t}$, given innovations in $\Delta x_{5t}$, we would calculate the inverse of the following matrix (taking the corresponding elements from $V$ above):

$$V_1 = \begin{bmatrix} 1.00 \\ 0.11 & 1.00 \\ 0.10 & 0.29 & 1.00 \end{bmatrix}, \quad V_1^* = \begin{bmatrix} 1.00 \\ 0.0851 & 1.00 \\ 0.0716 & 0.2821 & 1.00 \end{bmatrix}.$$

The matrix $V_1$ is the $3 \times 3$ matrix with lower triangular elements $V_{1,1}$, $V_{2,1}$, $V_{2,2}$, $V_{3,1}$, $V_{5,2}$; and $V_{5,5}$ of the $V$ matrix given above. The off-diagonal elements of the scaled inverse of the $V_1$ matrix, denoted above by $V_1^*$, are the negatives of the partial correlation coefficients between the corresponding pair of variables given the remaining variables. So, for example, the partial correlation between innovations in rates from market one (Kansas City) and innovations in rates from market two (Dallas-Ft. Worth) given innovations in market five (Wichita) is 0.0851. Under the assumption of multivariate normality, Fisher’s $z$ can be applied to test for significance from zero; where $z = \rho(i, j|k), n = 1/2(n - |k| - 3)^{1/2} \ln \{[1 + \rho(i, j|k)] \times [1 - \rho(i, j|k)]^{-1}]$ and $n$ is the number of observations used to estimate the correlations, $\rho(i, j|k)$ is the population correlation between series $i$ and $j$ conditional on series $k$ (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. In our case, the correlation between innovations in Kansas City and Dallas-Ft. Worth, given innovations in Wichita (0.0851), is not significantly different from zero at 0.05 or 0.10 levels (actually the marginal significance level is 0.449). So at usual levels of significance (say 0.05 or 0.10) we conclude that innovations in the Kansas City rate and the Dallas-Ft. Worth rate are not related in contemporaneous time.

Directed graphs as given is Spirtes et al. (1993) provide an algorithm for removing edges between markets and directing causal flow of information between markets. The algorithm begins with a complete undirected graph, where innovations from every market are connected with innovations with every other market. We represent this complete undirected graph on innovations from the error correction model given in Eq. (3) in Fig. 3, panel a. The algorithm removes edges based on vanishing correlation and partial correlation, the latter measured based on the scaled inverse correlation matrix, as explained above. Edges between variables are removed sequentially based on either vanishing zero order correlation (unconditional correlations) or vanishing conditional correlations, where conditioning is done on all possible sets with members $1, 2, \ldots, K - 2$, where $K$ is the number of variables studied.

Key to assigning direction of causal flow between variables which remain connected after all possible conditional correlations have been passed as non-zero, is the notion of sepset. The conditioning variable ($s$) on removed edges between two variables is called the sepset of the variables whose edge has been removed (for vanishing zero order conditioning information (unconditional correlation) 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 edges 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 $Y\rightarrow Z$. If there is a directed path from $X$ to $Y$, and an edge between $X$ and $Y$, then orient $X\rightarrow Y$. 
Fig. 3 gives both the complete undirected graph and the final directed graph on innovations from our seven market error correction model (Eq. (3)). Panel A is the starting point from which edges are removed and edges directed according to the plan outlined above (actually according to the TETRAD II programs (Spirtes et al., 1993)). Panel B is the ending point. At the five percent level, we have no directed edges. Innovations from the error correction model (Eq. (3)) are independent in contemporaneous time. At a 10% significance level we find the directed edges as given in panel B. Applying a 10% significance level we see edges running between Salina and Wichita to Dallas-Ft. Worth.

We test these restrictions using the likelihood ratio test for over identification given in Doan, 1992. We conduct these tests on two alternative models. Our identification restriction is that we can not have both $a_{ij} \neq 0$ and $a_{ji} \neq 0$ (actually this requirement is overly restrictive, but we maintain it here, see Doan, 1992, pp. 8–10 for discussion). First, is the directed path found at 10%, where innovations from Wichita and Salina cause innovations in Dallas-Ft. Worth in
contemporaneous time. This path implies 19 zero restrictions (there are 21 lower triangular elements or their transpose elements which can be non-zero in a just identified model; the directed graph path found at 10% puts 19 of these equal to zero). These restrictions result in a chi squared statistic of 17.09. With 19 degrees of freedom, we reject these zero restrictions at a p-value of 0.58 (a rather high level), suggesting that the restrictions are consistent with the data. Our second test considers the pattern found at 5.0% (independence). Here we set all 21 lower triangular (and all upper triangular) terms equal to zero. These restrictions result in a chi squared statistic of 27.74; with 21 degrees of freedom, we reject the restrictions at the 0.15 significance level. While independence of innovations in contemporaneous time are not rejected at usual (5%) significance levels, clearly the large difference in level of significance [0.15–0.58] in tests, between the independence ordering and the Salina and Wichita causing Dallas-Ft. Worth ordering in contemporaneous time, suggest we ought to take the latter seriously. The error decompositions associated with this latter ordering of contemporaneous innovations are discussed below.

Error decompositions associated with the error correction model are given in Table 3. Here decompositions are offered under the ordering of innovations in contemporaneous time generated by the directed graph at the 10% level. Responses for the 5.0% directed graph are similar to those offered here and may be obtained from the authors. (Further, responses from a VAR in levels give qualitatively the same results as those reported in Table 3. These too can be obtained from the authors at the address given at the beginning of the paper.)

Kansas City appears to be near exogeneous in the very short-run, as it explains over 95% of its own variation at horizons 0, 1, and 2 steps ahead. In the longer run, Kansas City rates are modestly explained by innovations in Salina (9.25%) and Dallas-Ft. Worth (4.17%). However, overall, and compared to other markets (Wichita excepted) Kansas City rates are not predominately determined by rates in the other markets. Rates from Dallas-Ft. Worth are most affected (in the long run) by historical shocks from Salina and Wichita. Dallas-Ft. Worth accounts for about 50% of its own variation at the 12 month horizon with these other two markets accounting for in aggregate another 25%. Amarillo appears to be relatively more exogenous than the Dallas-Ft. Worth rate (as over two-thirds of its variation is accounted for by its own past innovations at the twelve horizon). At the long horizon of 12 months innovations in Salina and Dallas-Ft. Worth have the strongest influence on the Amarillo rate.

Decompositions on the Enid market rate look similar to those on the Amarillo rate, about two-thirds of the variation in the Enid rate is accounted for by its own innovations at long horizons. Again innovations in the Salina rate are the next most important factor in the Enid rate; although contributions form the other four markets appear to be almost equally important.

Wichita is clearly the most exogeneous market studied. Over 90% of its variations at all horizons studied is accounted for by variations in its own past. Innovations in the Denver rate series are the next most important series, but these are quite small in importance relative to Wichita’s own historical variation. The Salina market rates show rather strong influences from the Dallas-Ft. Worth innovations, Enid innovations and Denver innovations, besides its own historical innovations. Finally the Denver market rates are influenced most strongly by innovations in the Dallas-Ft. Worth rates and the Salina rates. Denver appears to be the most endogeneous rate series as at the long horizon (12 months) over 60% of its variations is explained by the other six series.
5. Discussion

In this paper we consider the dynamics of export-wheat railroad rates in the central US plains. Our interest centered on rate dynamics, possible leadership in setting rates and interactions among markets in contemporaneous time and subsequent periods.
The error decomposition analysis from an error correction model showed interesting rate dynamics for the two Kansas regions and the Oklahoma region. Results show export rates in the Wichita region to be “highly exogeneous”. Over 90% of the variation in Wichita export rates is accounted for by variations in its own past rates. Several factors may offer partial explanation. The market share of the leading carrier (ATSF) is estimated to be about 75%, the highest market share of any carrier in any region. Possibly the ATSF’s comparatively large market share insulates this region’s export rates from those of other regions. The estimated market share held by the ATSF in the adjacent Oklahoma region (Enid) is also comparatively high (about a two-thirds market share) as is the exogeneity of export rates (66%).

The rate dynamics of the Wichita and Enid regions are in marked contrast to that of the Salina region, the other major shipping region. Export rates in the Salina region account for significant variation in rates of all other regions except Wichita, and rates of three regions account for a portion of long-term variation in Salina rates. The waybill data show the Salina region to make a comparatively large portion of its export shipments from a few sites and to have a higher average number of cars per export shipment. This suggests carriers in north Kansas may have been more aggressive in providing incentives for shippers to consolidate for purposes of making more efficient unit train shipments and abandoning nearby track to increase traffic density. It was estimated that the UP was the primary carrier in the north Kansas (Salina) area with a market share that may have ranged as high as 65%; regardless, the UP would have encountered substantial competition from the ATSF in a portion of the region.

A study by Friedlaender et al. (1992) may offer some explanation: they found the UP to have been particularly successful in the deregulation era at rationalizing its cost structure. In contrast, the ATSF was comparatively poor at reducing costs through rail rationalization. The relatively high market share enjoyed by the ATSF in the Wichita and Enid region in combination with railroad management that was not aggressive regarding rationalization of its cost structure may have led to the observed “highly exogeneous” pricing dynamics. The pricing dynamics of the Wichita and Enid regions are in contrast to those of the Salina region, where the UP is the primary carrier.

Results show the Salina region’s export rates to account for 26% of the variation in the Colorado (Denver) study region export rates, the strongest inter-regional influence identified in the study. This is expected since the UP is the primary carrier in both regions and important consolidated, unit train shippers in western Kansas are in close proximity to a unit train shipper in eastern Colorado, the principal wheat producing region in that state.

The error decomposition results and the directed graph analysis offer supporting evidence that export rates in the two Kansas regions cause Dallas-Ft. Worth export rates in contemporaneous time. The results were anticipated. Although the Dallas-Ft. Worth region produces modest quantities of export-destined wheat, it is an important storage and transhipment site for wheat produced in the two Kansas regions and the Oklahoma regions, the major wheat producers in the study area. Thus, the competitiveness of the Dallas-Ft. Worth region as a transshipment site is affected by export rates that link Kansas and Oklahoma regions with Texas Gulf ports. For example, if railroad rates linking Kansas and Oklahoma regions were lowered without a comparable reduction in Dallas-Ft. Worth export rates, the Dallas-Ft. Worth region would become non-competitive as a transshipment location, in contemporaneous time and the long term. Finally, analysis shows variation in the Dallas-Ft. Worth export rate to account for 17% and 20%
of the variation in the Salina and Denver region export rates. Thus, regions which tranship wheat via the Dallas-Ft. Worth region may find it advantageous to adjust their direct export rates in reaction to Dallas-Ft. Worth export rates. This seems a reasonable rate reaction in view of the above described role of Dallas-Ft. Worth. In fact, it is curious that the other major shipping regions (south Kansas (Wichita), Oklahoma (Enid)) do not also react to Dallas-Ft. Worth rates. Again, the explanation may be a more aggressive railroad management in north Kansas (Salina) and Colorado (Denver), the only two regions where the UP is the primary carrier.

References


