Forecasting Agricultural Commodity Transportation Costs:

Mississippi River Barge Rates

Brian Wetzstein, Zen-Noh Grain Corporation

Brian.wetzstein@zgcusa.com

Brian.wetzstein@gmail.com

Selected Paper prepared for presentation at the
2016 Agricultural & Applied Economics Association
Annual Meeting, Boston, Massachusetts, July 31-August 2

Forecasting Agricultural Commodity Transportation Costs: Mississippi River Barge Rates

A commodities trader's success is directly tied to his/her ability to foresee future changes in the marketplace and to adapt a position accordingly. This is especially true in trading of agricultural commodity markets that are characterized by low margins and high volumes. Intuition and experience may provide a sense for the current feel of the market or even into the future; however it is often difficult to convert feelings into numerical forecasts. Traders may then base decisions on gut feelings or non-quantitative predictions based on intuition. A case in point is commodity trading where transaction and transportation costs are generally a major variable-cost component of the commodity being traded. These costs can represent a significant portion of commodity-procurement costs, and in the case of Mississippi River barge shipping can be highly volatile. Persistent changes in price volatility can heighten the risk exposure of both agricultural producers and procurers, which negatively impacts efficiency by presenting a barrier to more efficient trading and reduce the efficiency and competitiveness of U.S. exports. Organizations augmenting their intuition with quantifiable predictions of commodity-procurement costs (barge rates for example) may enhance their returns. Further, the Army Corps of Engineers as well as state and federal governments are interested in barge rate forecasts as they are essentially predictions of river traffic and commerce levels. These forecasts relate directly to the health of the U.S. agricultural export market and domestic farmers.

When looking at how barge rates may behave in the future, many current traders rely simply on a historical average or the barge rate in the previous period, which are naïve forecasting scenarios that are unable to account for a changing market or external factors. An alternative is developing an economic forecasting model to which improve the accuracy and reliability of forecasts. Developing a simple model that yields more accurate forecasts than the current naïve scenarios can increase trading profitability and transportation efficiency. However, the worth of developing such a model extends farther than just improving trading efficiency and profitability. It provides a case study on how applied economists are market engineers in designing tools for improving efficiency. The real test of economic theory is not only how well it provides an understanding of how an economy operates, but how well economists can apply the tools developed from it to solve practical questions in a real world environment.

Thus, the aim of this analysis is to investigate the supply and demand dynamics of agricultural commodity barge transportation and to produce simple spatial forecasts of barge rates. These forecasts, along with increased understanding of variables affecting barge rates, can lead to potential efficiency and monetary gains. The main goal is to predict barge rates and their associated volatilities by river segment. The testable hypothesis is a simple spatial forecasting model will out preform a naïve model in terms of yielding higher commodity trading returns from taking advantage of more accurate barge rate forecasts.

For forecasting barge rates by sector, a spatial vector autoregressive model is developed with the dependent variables measuring the prices of barge transportation. Prices are in terms of five distinct river segments: St. Louis, Illinois, Upper Ohio, Lower Ohio, and Lower Mississippi (MTCT). The lagged spatial vector characteristics of the model capture segment price interaction through time and space. In addition, exogenous variables of barge draft depth, Mississippi River imports and exports, Midwest diesel prices, and first differenced corn prices are also included.

One-, two-, and five-week forecasts are constructed for an out-of-sample period. The effectiveness and accuracy of the forecasts are then compared on the basis of RMSE, RMSPE, stochastic dominance analysis, and the Henriksson-Merton test. Trader's returns are then conducted based on the resulting forecasts and the associated returns of conducting trades during a period of low barge rates. Results support the hypothesis by indicating the forecasts have the ability to improve on returns relative to a naïve forecasting scenario.

Literature

A wealth of literature exists on agricultural commodity pricing with the classic Tomek and Robinson book as a foundation (Tomek and Robinson, 1972). Brandt and Bessler (1983) were one of the first applications to apply time series analysis for forecasting agricultural commodity prices. This was followed by efforts including Yang and Brorsen (1992) and Ramirez and Fadiga (2003) who employ a GARCH model in forecasting. This research has resulted in regular agricultural commodity price forecasts by various agencies including the World Bank (World Bank, 2015).

In contrast, a review of the literature on forecasting within country U.S. agricultural commodity transportation costs associated with barge transportation revealed no pertinent articles. This is surprising given that transportation costs can represent a major proportion of commodity costs (Schnepf, 2006; Volpe et al., 2013). A commodities trader considering future purchases in the grain market for shipment to the Gulf of Mexico must forecast the cost of transporting the grain from point-of-sale to the export port destination. Forecasting accuracy of barge transportation rates directly impacts potential returns. There are some research efforts in forecasting global rates of the large ocean going Panamax vessels. These include Batchelor et al. (2007), Chang et al. (2012), and Chen et al. (2012) who employ VECM, ARIMA, and VARX approaches, respectively, to forecast seaborne freight rates.

In terms of spatial econometrics, Kuethe and Pede (2011) indicate that estimating a spatial VARX or SpVARX model for housing prices produced significantly more reliable short-term forecasts than a conventional VARX model based on the mean-square forecast error. While the variables affecting barge freight rate and housing prices are different, the underlying methodology leading to a SpVARX model is still applicable. In a similar manner that nearby housing prices can affect each other, barge rates in neighboring river segments do as well. The inclusion of a spatial weight matrix to capture spillover effects in barge freight can aid in improved model specification and the resulting forecasts.

Instead of developing improved methods or model specifications for predicting Mississippi River barge rates, the literature improving the efficiency of river trade generally focuses on infrastructure improvements to the lock and dam system. Current estimates from the Corps of Engineers (2010) indicate it would cost approximately $3 billion dollars to renovate the aging lock system to full working order. Yu et al. (2006) link lock delays to barge transportation efficiency by employing a VAR model. Results suggest the strongest relation affecting barge rates in different segments, apart from their own lagged values, are the lagged values of barge rates in neighboring segments. If a segment’s barge rate can be reduced by increasing barge supply, barge rates in neighboring segments will also decline. This suggests spatial characteristics and interactions, which may be captured with a SpVARX model.

Barge Rates and Draft Depth

For analysis, the river is dissected into five distinct segments consisting of the Illinois, Upper Ohio, Lower Ohio, Lower Mississippi (MTCT), and St. Louis rivers (Figure 1). This collection of river segments comprises over 2000 miles of barge navigable waterways whose locks, dams, and channels are maintained by the Army Corps of Engineers. The cost to ship commodities between a specified river segment and a demand node to a Gulf port is given by lock tariff rates. The Waterways Freight Bureau (WFB) was originally set up to regulate barge pricing. Each lock had its own tariff rate measured as a dollar per ton cost to ship commodities between that lock and a destination Gulf port. Since 1976, WFB no longer exists and market forces are allowed to determine barge rates with 1976 tariffs as benchmarks.

Barge operators on the Mississippi River employ a barge percent-of-tariff (BPOT) as the price of traversing the river. Market forces then result in stochastic barge rates over time. Multiplying the stochastic BPOT rate at a given time by the fixed historic tariff rate for a specific lock within a given segment provides a dollar/ton price for shipping commodities. This price is the cost per ton to ship a commodity from its starting location to a Gulf port. Overall, the rates vary from approximately $2.00 to $7.00 per ton and are higher the farther north the lock location. Figure 2 displays the barge rates in a dollar per ton value over the five river segments.

Market Structure

Miljkovic et al. (1999) concluded barge rates are determined by market forces with no information asymmetries. Thus, the main elements to include in a forecasting model of barge rates are variables influencing barge supply and demand. The list of the included variables along with their expected signs are listed in Table 1.

One variable which influences the supply of barge transportation in the market is how heavily barges can be loaded depending on current river conditions. The Army Corps of Engineers attempt to maintain a minimum river channel depth of nine feet through dredging policies, but are not always able to do so during drought or irregular river flow. However, most of the volatility in loaded draft depth arises when natural river conditions permit barges to be loaded deeper than nine feet. When river conditions are calm and sufficiently deep, barges can be loaded to a maximum draft of around 12½’ to 13’. In these cases, theory would predict potential lower barge rates as each barge can accommodate larger loads requiring fewer barges to be contracted, and in essence increasing total barge transportation supply.

Another supply determinant is the availability of barges on a specific river segment. Grain movements can serve as a proxy for segment supply availability. The U.S. Agricultural Marketing Service tracks grain barge movements, which is similar to the barge count variable employed by Yu et al. (2006). The main input price supply shifter is diesel prices where an increase in fuel prices can negatively affect the availability of barges.

Covered dry cargo barge demand is primarily driven by the international transfer of grain (Miljkovic et al., 1999), which is transported by ocean vessels. Over 90% of all U.S. corn and soybean exports from the River Gulf area are transported there by barge. The number of oceangoing grain vessels in the Gulf region can capture the quantity of covered cargo barge transportation demand. The USDA Grain Inspection, Packers, and Stockyards Administration, provides weekly measures of the number of oceangoing grain vessels scheduled for filling at the Gulf Coast ports. Thus, larger numbers of vessels scheduled for filling at the gulf relate to increased overall barge demand.

Available from the National Agricultural Statistics Service is the current level of U.S. corn storage. With corn as main agricultural commodity transported by the barge type under study, corn storage accounts for many of the seasonal characteristics of bar rates. When corn stocks are trending down (up) this would suggest an increase (decrease) in barge demand.

The grain movements, national stock, and export variables focus on the downstream movement of agricultural commodities. Variables specifically relating to the upstream transportation of covered hopper barges are not included as there barge operate on a separate price structure. Other than diesel prices, previous efforts addressing agricultural commodity barge rates do not include specific variables to account for upstream transportation (Haigh and Bryant, 2001; Fuller and Grant, 1993; Miljkovic et al., 1999). In addition with the majority of upstream covered hopper barges empty, diesel prices capture a major portion of the upstream transit cost. Further, once barges are loaded, it is rare the cargo does not travel the length of the river as over 90% of agricultural commodity River Gulf exports are fed by barge. This downstream dynamic is inherently included in the barge rate pricing system. The barge percent of tariff barge rate of a specific lock is the cost of transportation between that specific lock location and a downstream Gulf coast export location.

These downstream interactions yield a one directional relation where lower segments are not affected by upper segments. This results in barge rate equation where a barge rate in a given segment is a function of its own lagged price and the lagged price of segments below it. An increase in barges rates in a segment downriver will stimulate up-bound barges to stop and conduct business. This reduces the barge supply upriver. In contrast, if the barge rate were to increase upriver, the supply of empty barges must still pass by the lower segments and will not impact their barge supply.[1] The interactions among segment draft depths are also a one directional relation. Barge operators are only concerned with river levels downstream of their loading site as this analysis deals with down bound barge rates.

Methodology

In econometrics, a spatial weight matrix is a tool used to identify possible spatial influences within different portions of a system. It is often defined as a nonnegative matrix W_{ij}, which accounts for the spatial influence of unit *j* on unit *i* for *n* different spatial units (Bhattacharjee and Jensen-Butler, 2013). In a distance based spatial weight matrix, neighboring segments are assigned weights based on their relative distance. The weight is the inverse of their distance. For barge freight, this distance is measured in river miles between the midpoints of respective segments. A spatial weight matrix is then employed to examine how the percent of tariff barge rate in one segment is related to current and past values of percent of tariff and draft depths in neighboring segments. This is consistent with (Ollier et al., 2003), who employ a spatial weight matrix to study the relation of segments sharing a common endpoint, as is the case with barge rates in neighboring segments.

In order to include a weight matrix in the analysis and examine the effects of segment interaction, *s* spatial cross-regressive lags are added to a VARX model (SpVARX). The SpVARX*(p,s)* contains N segments, which are specified as linear functions of p own lags and p lags of the other $N-1$ segments which are thought to influence it. Thus, which segments are considered neighbors and how the neighbors are defined to effect each other are determined by the structure of the weight matrix and the number of cross regressive lags. If a SpVARX(3,1) is specified with $s=1$, segments are considered neighbors only if they meet at a common point in addition to the previously described one way interaction of only segments downstream affecting ones upstream. This yields:

$$Y_{n,t} = c_n + \sum_{p=1}^{3}(\alpha_{n,p}\,Y_{n,t-p}) + \gamma_n W Y_{n,t-1} + \beta_n W D_{n,t-1}$$

$$+\sigma_n X_{n,t-1} + \varepsilon_{n,t},\ n = 1,\ \ldots,\ 5,$$

where $Y_{n,t}$ is segment *n* barge rates observed in time $t = 1, \ldots, T$, W is a spatial weight matrix, $D_{n,t-1}$ is a 5×1vector of draft depths by segment lagged one time period, $X_{n,t-1}$ denotes a 5×1vector of exogenous conditioning variables (draft depth, diesel price, ocean vessel count, grain movements, and national corn stock) lagged one time period, c_n is a constant term, α, β, γ, and σ are parameters to be estimated, and $\varepsilon_{n,t}$ is a white noise error term.

The spatial weight matrix, W, defines which segments are considered neighbors. The spatial cross regressive lags are obtained by multiplying each temporal lag term by the spatial weight matrix. These cross regressive lags represent the average barge rates of neighboring segments in a previous time period. One commonly employed weighting system for spatial analysis is a binary contiguity matrix where neighboring regions take a value of one with zero otherwise. A second weighting scheme employed is an inverse distance based weight matrix. Each non-zero element between two neighboring segments is assigned the value of 1/distance. Here, distance is defined as the distance in river miles between the midpoints of each segment. The weight matrixes are then row standardized to create proportional weights. Both weighting schemes yield similar empirical results and forecasts, so only the weighting scheme analyses are presented using row standardized weight matrices.

Data

For all the variables (barge rates, draft depths, diesel prices, corn storage, grain movements, and ocean vessels) weekly data are collected from January 2003 to June 2014, yielding 594 observations. The units of measurement and definitions are listed in Table 2 with summary statistics provided in Table 3.

Barge rates have a relatively high variance with both a positive skewness and kurtosis. This indicates river segment price distributions with right tails and frequent peaked high values. In contrast, draft depths have left tail distributions with no consistency in the peaks. In terms of the conditioning variables, ocean vessels have a relatively large standard deviation with close to a normal distribution which is caused by the highly seasonal nature of agricultural commodity exports. This is in contrast to diesel prices with relatively small standard deviations, but high kurtosis.

Results

Table 4 lists the results of the SpVARX employing row standardized inverse distance weight matrices.[2] All of the self-lagged barge rates are significant at the 1% level with dynamics indicating an adjustment process. The once lagged barge rates have a positive correlation with current barge rates, followed by a negatively correlated second lag and positively correlated third lag. The once lagged barge rates in neighboring segments representing price interaction terms are also all significant at the 1% level. In terms of draft depth interaction terms, only the Lower Ohio and St. Louis once lagged values of the draft depth interactions are significant. A segment's own lagged draft depth is significant with the hypothesized negative relation for the Lower Ohio, St. Louis, and MTCT segments. A significant positive relationship at the 5% level between barge rates and draft depth is associated with the Illinois segment and appears counter to the expected coefficient sign. A hypothesis for this phenomenon is barges originating in the far northern region of the Illinois are not constrained by draft depth. The average draft depth for this segment is lower than the draft depth for the other segments (Table 3). Barge operators may load barges originating in the Illinois segment only partially full with the idea that elevators farther south will add cargo. Thus, a lower initial draft in Illinois could indicate decreased barge demand in the Illinois segment compared to downriver segments and would reduce the barge rate in the Illinois segment.

Each of the significant exogenous variables has the hypothesized sign with the exception of diesel prices on the St. Louis segment. The lack of a significant diesel price relation for four of the segments and a negative relation for the St. Louis segment indicates a weak adjustment process of barge supply to input price changes. Barge rates appear slow to adjust to input price changes. Input prices in general and diesel prices in particular appear to be less understood and could be a point for further research and analysis.

Forecasting

In order to assess the predictive value of the model, One-, two-, and five-week forecasts are constructed for an out-of-sample period. For out-of-sample forecasts, the last 20% of the 594 weekly observations are withheld in estimating the model. This yields an out-of-sample forecasting range beginning in the seventh week of 2012 and continuing until the end of the full data set in week 23 of 2014. The Appendix Table A.1 lists estimation results, which are then employed to estimate one-, two-, and five-week forecasts for the remaining 20% of the data. Comparing the coefficients in Table 4 (the full sample) with Table A.1 (data-constrained sample) reveals the stability of the results.

As a visual comparison, the predicted one-, two-, and five-week values are plotted against their actual values for each river segment (Figures 3-5). The forecasts appear to track relatively well for the one-week forecasts; deviations in their tracking exist as the forecasts are extended to two and five weeks.

For numerical comparisons the root mean squared error (RMSE) and percent error (RMSPE) are calculated along with the mean and variance for each forecast (Table 5). These values are compared to a naïve forecasting model where the price in the next week is assumed to be the price in the current week. Considering the one-week forecast, the naïve forecast is close to the SpVARX forecast performance, although the SpVARX still dominates in terms of mean-variance analysis. This close comparison does not continue to hold as the forecast length increases. At the five-week forecast, the naïve forecasts deviate considerably from the actual barge rates and the associated SpVARX forecasts. If there were only an interest in one-week forecast, then the naïve forecasts would generally suffice. However, for any longer forecasting period, a SpVARX type forecast is warranted.

Considering stochastic dominance, a commodity trader's gamble is choosing when to purchase barge transportation based on assumption of how rates will change in the future. For example, if barge rates are predicted to decline, a trader can gamble and delay commodity transportation. Figure 6 illustrates the distribution of squared error terms for the one- and five-week forecasts for a SpVARX model and the naïve forecasting case. All of the squared error values for each forecast are sorted from low to high. With 120 out-of-sample forecasts and five segments, there are 600 squared error terms for each forecast. The x-axis represents the squared error terms y-axis is the accumulative probability from 1/600 to one. Thus, if a forecast's accumulative probability is farther to the left relative to another forecast's, then it has a lower squared error value for a higher percentage of its 600 observations. From Figure 6, the SpVARX forecasts exhibit second-order stochastic dominance over the naïve forecasts. This supports their numerical dominance presented in Table 5.

As a final comparison of the forecasts, the generalized Henriksson-Merton test is employed as a market timing test to determine whether a forecast moves in the same contemporaneous direction as the actual out-of-sample barge rates. Specifically, assuming no preference symmetry on the part of traders, then

$$r_{f,t+1} = c + \beta r_{a,t+1} + \varepsilon_{t+1},$$

where $r_{f,t+1}$ and $r_{a,t+1}$ denote the change in the forecast and actual barge rates from time t to t + 1, respectively, c and β are parameters to be estimated, and ε_{t+1} is the error term. The test results reveal the β's are positive and significant at the 1% level for the one-, two-, and five-week forecasts. While the constants, c's, are not significant. If there is no difference in the actual and forecast barge rates values, the constant is zero. However, a trader with preference symmetry would value these forecasts in terms of a positive significant relation between the first differenced actual and forecasted values. When the actual barge rates increase (decrease) the forecasted barge rates also increase (decrease) and there is not a significant constant, which would imply a gap between their values.

Returns from Out-of-sample Forecasts

The results of the Henriksson-Merton test indicate the SpVARX forecasts have the ability to improve commodity traders' returns as the forecasted barge rates and actual barge rates tend to move in the same direction. Traders could optimize their shipping schedule by correctly predicting the directional change of future barge rates. As an initial indication of the magnitude of these potential enhanced returns, consider decision-making scenarios listed in Table 6 for a two-week forecast. Let $\widehat{P}_{t+i}$, $i = 1, 2$, be the forecasted barge rate in time $t + i$ and P_t and P_{t+i} be the actual barge rates in time t and $t + i$, respectively. For simplicity, assume transaction and storage costs are zero or constant. This allows focusing solely on transportation cost savings when the trader is able to accurately take advantage of lower future barge rates. As indicated in Table 6, this provides an examination of the potential savings or losses, which occur when a trader uses the forecasted barge rates to take adjust their shipping schedule to take advantage of lower rates.

The decision-making process is extrapolated to the case of a five-week forecast. When confronted with predicted barge rates for future periods, the lowest forecasted barge rate is compared to the current barge rate. Thus, if a forecasted barge rate is lower than the current, in this scenario the trader will chose to postpone shipment. The amount that the hypothetical trader will ear/loss by adjusting their shipping schedule is the difference between the current barge rate where they chose not to ship, and the actual observed barge rate when the forecasts implied barge rates will be lower and when the trader in fact chose to ship. Table 7 lists the savings for a five-week inverse distance based SpVARX forecast.

The predicted profit tally for each future time $t + i$, $i = 1, \ldots, 5$ is the number of occurrences that a forecasted barge rate in a set of 5 week forecasts is the lower than the current barge rate. For $t + 1$, the predicted profit tally is the number of occurrences where $\widehat{P}_{t+1} = \min(\widehat{P}_{t+i} \,|\, i = 1, \ldots, 5)$, and likewise for the other four future time periods. Commodity traders have a potential to earn increased returns by transporting their goods during this forecasted lower barge rate period. This predicted profit tally is mated to the actual profit tally where the actual barge rate was indeed the lowest. For $t+1$, it is the number of occurrences where $P_{t+1} = \min(P_{t+i} \,|\, i = 1, \ldots, 5)$. When the forecast of the lowest future barge rate matches (does not match) the actual week with the lowest rate, the trader experiences a savings (loss) in barge rates. The average savings (loss) is then calculated based on the savings (loss) for each occurrence where $\hat{P}_{t+i} - P_{t+1} < 0$ ($\hat{P}_{t+i} - P_{t+1} > 0$). The overall average represents the average cost of barge transportation that is saved or lost if these forecasts are followed. It represents the increase in dollars per ton returns, which commodity traders would realize if they were to consistently adjust their shipping schedule based on the SpVARX forecasts. Dividing this average overall savings value by the average barge rate in the respective segment (Table 3) results in the average percentage saved.

As indicated in Table 7, there is limited savings associated with the first future period, *t + 1*. In fact, there is only a positive saving for the Illinois and Lower Ohio segments. Following the naïve forecast would then be the recommended strategy. However, proceeding into the future the average percentage saved with the SpVARX forecast generally increases. Consistent with the forecast accuracy results (Table 5 and Figure 6), the SpVARX forecasts can potentially save 17% to 29% on barge rates when forecasts indicate optimal shipping is in the fifth week. If commodity traders are interested in enhancing their returns associated with determining the optimal shipping time, then they may want to consider some simple forecasting model, such as the SpVARX.

Conclusions

The ability to accurately forecast Mississippi River barge rates provides trading advantages as well as increasing market efficiency. This research outlines a forecasting model that can serve as a foundation for agents, including traders, to develop quantifiable predictions of transportation costs (barge rates). Such forecasts provide information to commodity traders when barge rates are likely to be volatile. They can then minimize transportation costs by choosing to ship commodities when rates are predicted to be lower. With these forecasts, traders are able to optimize their shipping schedule by either transporting commodities now or storing them to ship later.

As addressed in the introduction, a major avenue for economists is developing tools, which solve practical questions of microeconomic engineering. One such tool is developing simple forecasting models designed to augment existing future expectations. Specifically, the intricate dynamics of agricultural commodity barge transportation on the Mississippi River is further revealed through the engineering of simple barge-rate forecasts. With a five-week forecast horizon, approximately 20% savings in barrage rates is possible when forecasts indicate lower barge rates in five weeks. This supports the hypothesis that a simple spatial forecasting model can out preform a naïve model. Economic engineering does have market value and suggests agents may want to consider investing in such engineering. In particular, commodity traders can benefit from these simple types of economic engineering.

Footnotes

[1] Similar results are were obtained for a fully constrained and unconstrained model. The downward bound model is presented as a representation.

[2] Forecasting models were also developed based on VARX, directionally constrained VARX, and binary SpVARX approaches. The inverse distance SpVARX model yields superior forecasting performance, and thus, serves as the model for the reported results.

References

Batchelor, R., A. Alizadeh, I. Visvikis. 2007. "Forecasting Spot and Forward Prices in the International Freight Market 23(1):101-114.

Bhattacharjee A, C. Jensen-Butler. 2013. "Estimation of the Spatial Weight Matrix under Structural Constraints." *Regional Science and Urban Economics* 43(4):617-634

Brandt, J., D. Bessler. 1983. "Price Forecasting and Evaluation: An Application in Agriculture," Journal of Forecasting 2(3):237-248.

Chang, C., C. Hsieh, Lin, Y. 2012. "A Predictive Model of the Freight Rate of the International Market in Capesize Dry Bulk Carriers," Applied Economics Letters 19(4):313-317.

Chen, S., H. Meersman, E. Van de Voorde. 2012. "Forecasting spot rates at main routes in the dry bulk market," Maritime Economics and Logistics 14(4):498-537.

Corps of Engineers. 2010. "Regional Supplement to the Corps of Engineers Wetland Delineation Manual: Midwest Region (Version 2.0)." Wetlands Regulatory Assistance Program. U.S. Army Corps of Engineers: Engineer Research and Development Center, August 2010. http://www.usace.army.mil/Portals/2/docs/civilworks/regulatory/reg_supp/erdc-el-tr-10-16.pdf

Miljkovic D, G. Price, R. Hauser, K. Algozin. 1999. "The Barge and Rail Freight Market for Export-Bound Grain Movement from Midwest to Mexican Gulf: An Econometric Analysis." *Transportation Research Part E* 36:127-137.

Ollier S, D. Chessel, P. Couteron, R. Pelissier, J. Thioulouse. 2003. "Comparing and Classifying One-Dimensional Spatial Patterns: An Application to Laser Altimeter Profiles." *Remote Sensing of Environment* 4:453-462.

Ramírez, O., M. Fadiga. 2003. "Forecasting Agricultural Commodity Prices with Asymmetric-Error GARCH Models," Journal of Agricultural and Resource Economics 28(1):71-85.

Schnepf, R. 2006. Price Determination in Agricultural Commodity Markets: A Primer, CRS Report for Congress, RL33204.
http://nationalaglawcenter.org/wp-content/uploads/assets/crs/RL33204.pdf

Tomek, W., K Robinson. 1972. Agricultural Product Prices, Ithaca: Cornell University Press.

Volpe, R., E. Roeger, E. Leibtag. 2013. How Transportation Costs Affect Fresh Fruit and Vegetable Prices, ERR-160, Economic Research Service, USDA. http://www.ers.usda.gov/media/1230835/err160.pdf

World Bank. 2015. Commodity Markets Outlook, A World Bank Quarterly Report, World Bank Group. https://www.worldbank.org/content/dam/Worldbank/GEP/GEP2015b/Global-Economic-Prospects-CommodityMarketOutlook_Jan2015.pdf

Yang, S., B. Brorsen. 1992. “Nonlinear Dynamics of Daily Cash Prices,” American Journal of Agricultural Econmics 74(3):706-715.

Yu, TH, D. Bessler, S. Fuller. (2006). “Effect of Lock Delay on grain Barge Rates: Examination of Upper Mississippi and Illinois Rivers.” Ann. Reg. Sci. 40:887-908.

Table A.1. Barge Rate Inverse Distance Based SpVARX Constrained Sample

	River Segment				
	Illinois	Upper Ohio	Lower Ohio	St. Louis	MTCT
Barge Rate, $Y_{n,t-1}$	0.779*	0.667*	1.014*	0.785*	1.086*
	(0.037)	(0.052)	(0.029)	(0.034)	(0.028)
Barge Rate, $Y_{n,t-2}$	−0.196*	−0.341*	−0.341*	−0.228*	−0.311*
	(0.039)	(0.038)	(0.039)	(0.033)	(0.035)
Barge Rate, $Y_{n,t-3}$	0.109*	0.111*	0.107*	0.094*	0.116*
	(0.028)	(0.025)	(0.026)	(0.024)	(0.025)
Barge Rate Interactions, $WY_{n,t-1}$	0.297*	0.568*	0.164*	0.265*	−
	(0.038)	(0.059)	(0.018)	(0.035)	
Draft Depth Interactions, $WD_{n,t-1}$	−0.022	−0.196***	−0.092*	−0.267*	−
	(0.086)	(0.115)	(0.036)	(0.078)	
Draft Depth	0.521*	−0.010	−0.115	−0.099**	−0.306*
	(0.200)	(0.048)	(0.073)	(0.040)	(0.076)
National Corn Stock	−0.138*	−0.191*	−0.174*	−0.193*	−0.205*
	(0.050)	(0.041)	(0.036)	(0.045)	(0.041)
Ten Day Ocean Vessels	0.005	0.011	0.008	0.009	0.008
	(0.009)	(0.008)	(0.007)	(0.009)	(0.008)
Diesel Price	−0.535*	−0.395	−0.342	−0.599**	−0.502**
	(0.305)	(0.247)	(0.221)	(0.280)	(0.252)
Grain Movement	−0.047	−0.060	−0.057	−0.022	0.000
	(0.060)	(0.049)	(0.044)	(0.055)	(0.050)
Constant	0.004	5.648*	5.433*	8.185*	6.858*
	(2.319)	(1.472)	(1.334)	(1.412)	(1.279)

Standard errors are in parentheses with *, **, and *** denoting statistical significance at the 1%, 5% and 10% level, respectively.

Table 1. Expected Signs

Variable	Expected Sign
Lagged Price in Other Segments	+
Own Draft Depth	–
Draft Depth In Other Segments	–
Diesel Price	+
Ocean Vessel Count	+
Grain Movements	–
National Corn Stock	–

Table 2. Definition of Variables

Segment Specific Variables	
Barge Rate ($/ton)	
Draft Depth (feet)	
Conditioning Variables (Non Segment Specific)	
Diesel Price ($)	National Diesel Price
National Corn Stock (bill bu)	Total U.S. National Corn Storage Volume
Grain Movement (mill tons)	Number of Tons of Grain that Traversed Key Locks
Ten Day Ocean Vessel Count	Grain Ocean Vessels to be Loaded in Next Ten Days

Table 3. Summary Statistics

	Mean	Minimum	Maximum	Standard Deviation	Skewness	Kurtosis
Barge Rates ($/ton)						
Illinois	19.70	8.38	47.81	6.58	0.72	0.65
Upper Ohio	15.86	6.29	43.95	6.77	1.00	1.13
Lower Ohio	13.99	5.51	39.00	6.02	1.06	1.37
St. Louis	13.13	4.80	41.67	5.70	1.28	2.32
MTCT	10.88	4.37	35.27	5.29	1.70	3.86
Draft Depth (feet)						
Illinois	9.47	8.00	10.36	0.29	−0.19	1.43
Upper Ohio	10.43	9.00	11.65	0.66	−0.36	−0.73
Lower Ohio	11.33	9.00	12.60	0.80	−0.94	0.53
St. Louis	10.90	8.60	12.60	1.11	−0.14	−1.23
MTCT	10.39	9.00	11.60	0.61	−0.42	−0.66
Conditioning Variables						
Diesel Price ($)	2.99	1.73	4.10	0.344	0.39	1.20
National. Corn Stock (bill bu)	5.08	0.80	10.90	2.51	0.17	−0.87
Grain Movement (mill tons)	6.39	1.18	13.33	1.96	0.13	0.23
Ten Day Ocean Vessel Count	56.83	18	97	13.32	0.37	−0.24

Table 4 Barge Rate Inverse Distance Weight Based SpVARX

	River Segment				
	Illinois	Upper Ohio	Lower Ohio	St. Louis	MTCT
Barge Rate, $Y_{n,t-1}$	0.813*	0.606*	0.946*	0.845*	1.043*
	(0.033)	(0.043)	(0.025)	(0.029)	(0.026)
Barge Rate, $Y_{n,t-2}$	−0.199*	−0.261*	−0.254*	−0.224*	−0.278*
	(0.035)	(0.033)	(0.034)	(0.030)	(0.033)
Barge Rate, $Y_{n,t-3}$	0.112*	0.096*	0.087*	0.106*	0.121*
	(0.025)	(0.023)	(0.023)	(0.022)	(0.024)
Barge Rate Interactions, $WY_{n,t-1}$	0.256*	0.566*	0.169*	0.188*	–
	(0.032)	(0.050)	(0.016)	(0.026)	
Draft Depth Interactions, $WD_{n,t-1}$	−0.076	−0.183	−0.061**	−0.144**	–
	(0.072)	(0.098)	(0.029)	(0.064)	
Draft Depth	0.365**	−0.028	−0.120**	−0.175*	−0.311*
	(0.159)	(0.043)	(0.062)	(0.041)	(0.067)
National Corn Stock	−0.152*	−0.198*	−0.172*	−0.187*	−0.185*
	(0.039)	(0.034)	(0.031)	(0.035)	(0.033)
Ten Day Ocean Vessels	0.011	0.016**	0.013**	0.011	0.010***
	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)
Diesel Price	−0.514	−0.368	−0.289	−0.512**	−0.345
	(0.273)	(0.236)	(0.211)	(0.250)	(0.236)
Grain Movement	−0.023	−0.047	−0.043	−0.011	−0.006
	(0.049)	(0.042)	(0.038)	(0.045)	(0.042)
Constant	1.378	5.193*	4.486*	7.017*	6.180*
	(1.802)	(1.245)	(1.122)	(1.139)	(1.095)

Standard errors are in parentheses with *, **, and *** denoting statistical significance at the 1%, 5% and 10% level, respectively.

Table 5. SpVARX Forecast Comparison to the Naïve Forecast

	SpVARX	Naïve
One-Week Forecast		
RMSE	1.67	1.79
RMSPE	9.60	10.49
Mean Error	2.79	3.20
Variance	68.61	79.11
Two-Week Forecast		
RMSE	2.44	2.77
RMSPE	15.46	17.75
Mean Error	5.96	7.65
Variance	162.64	266.04
Five-Week Forecast		
RMSE	2.56	3.41
RMSPE	17.89	25.06
Mean Error	6.55	11.60
Variance	169.40	711.23

Table 6. Decision Making Response to Two-Week Forecasts

	Time		
	t	t+1	t+2
Ship If	$\hat{P}_{t+1}\,, \hat{P}_{t+2} > P_t$	$\hat{P}_{t+2}\,, P_t > \hat{P}_{t+1}$	$\hat{P}_{t+1}\,, P_t > \hat{P}_{t+2}$
Store If	$\hat{P}_{t+1}\ or\ \hat{P}_{t+2} < P_t$	$\hat{P}_{t+2} < \hat{P}_{t+1}\,, P_t$	--[a]
Save/Loss	0	$P_{t+1} - P_t$	$P_{t+2} - P_t$

[a] Assumes a trader must ship in one of the three periods.
$\hat{P}_{t+i}$, i = *1*, *2*, is the forecasted barge rate in time $t + i$ and P_t and P_{t+i} are the actual barge rates in time t and $t + i$, respectively.

Table 7. Five-Week Inverse Distance SpVARX Forecast Savings

Future Time Period	River Segment				
	Illinois	Upper Ohio	Lower Ohio	St. Louis	Lower Miss
t + 1					
Predicted Profit Tally	13	17	10	21	16
Actual Profit Tally	6	7	8	8	4
Average Loss ($/ton)	−2.05	−2.84	−3.66	−1.36	−1.55
Average Gain ($/ton)	3.31	1.46	1.17	1.33	3.32
Average Overall ($/ton)	0.58	−0.90	0.21	−0.14	0.04
Average Percent Saved (%)	3	−6	1	−1	0
t+2					
Predicted Profit Tally	8	12	7	12	12
Actual Profit Tally	6	11	6	10	7
Average Loss ($/ton)	−1.19	−3.06	−0.72	−0.61	−0.17
Average Gain ($/ton)	1.12	1.05	0.62	0.63	2.13
Average Overall ($/ton)	0.69	0.71	0.43	0.48	1.22
Average Percent Saved (%)	4	4	3	4	11
t+3					
Predicted Profit Tally	12	13	9	11	12
Actual Profit Tally	10	11	7	9	6
Average Loss ($/ton)	−0.94	−1.25	−4.67	−0.50	−0.94
Average Gain ($/ton)	2.14	2.02	1.67	0.92	1.78
Average Overall ($/ton)	1.63	1.52	0.26	0.66	0.42
Average Percent Saved (%)	8	10	2	5	4
t+4					
Predicted Profit Tally	13	10	9	11	11
Actual Profit Tally	11	8	8	9	5
Average Loss ($/ton)	−2.12	−2.96	−3.69	−2.39	−1.24
Average Gain ($/ton)	1.60	4.15	2.72	2.00	1.42
Average Overall ($/ton)	1.03	2.73	2.01	1.20	0.08
Average Percent Saved (%)	5	17	14	9	1
t+5					
Predicted Profit Tally	31	26	27	34	35
Actual Profit Tally	25	23	23	27	28
Average Loss ($/ton)	−1.26	−2.15	−2.62	−2.04	−2.70
Average Gain ($/ton)	4.35	5.41	5.26	4.05	3.42
Average Overall ($/ton)	3.27	4.54	4.09	2.80	2.27
Average Percent Saved (%)	17	29	29	21	21

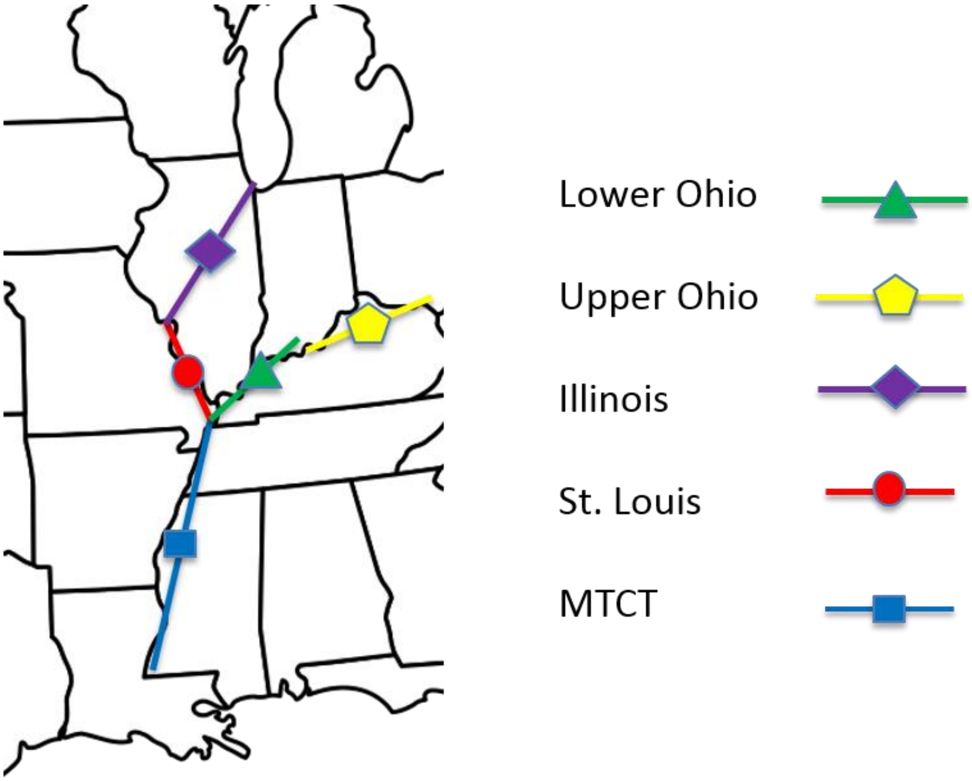


Figure 1. Mississippi River Segments

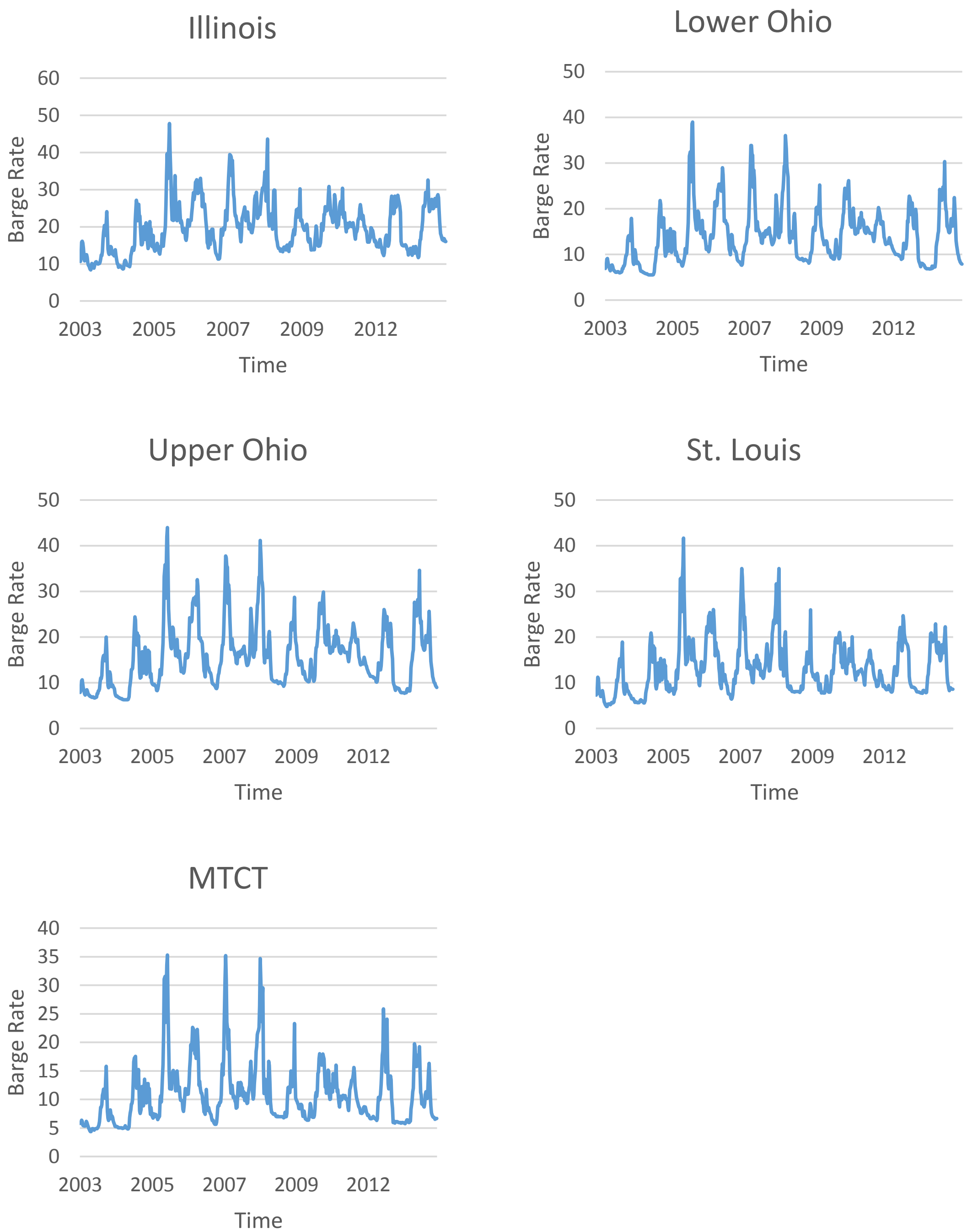


Figure 2. $/Ton Barge Rates by River Segment

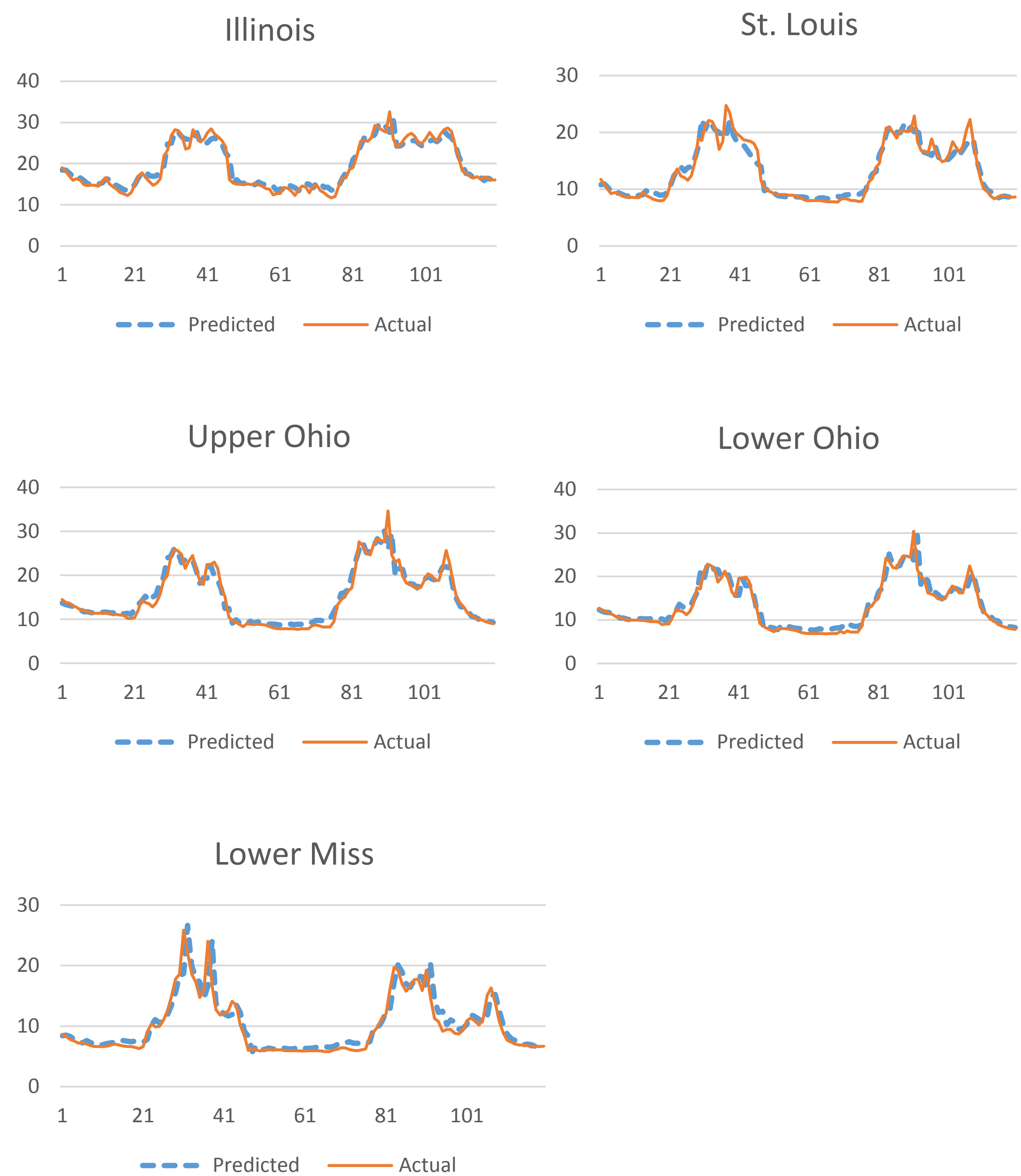


Figure 3. One-Week Forecasts and Actual Barge Rates

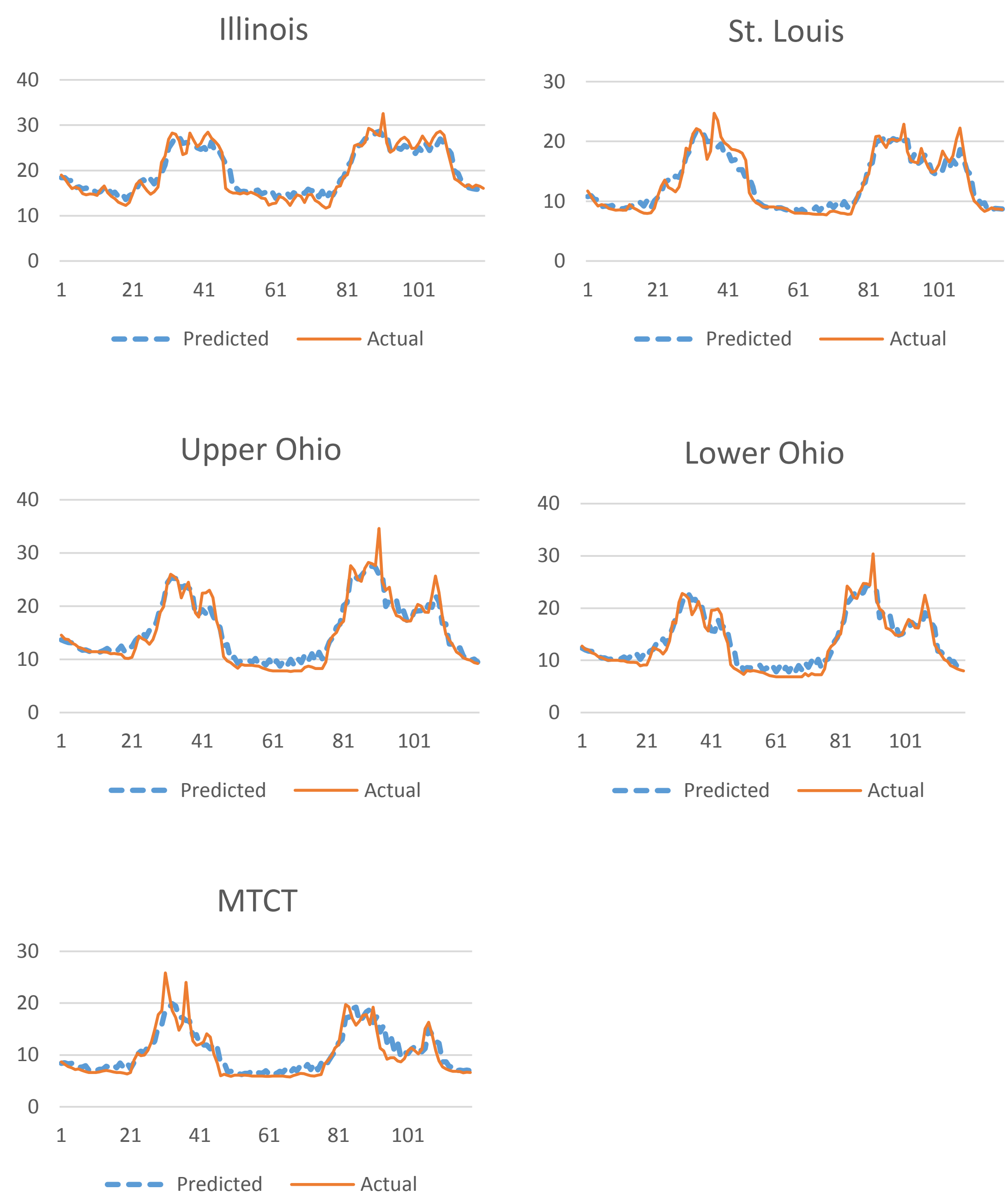


Figure 4. Two-Week Forecasts and Actual Barge Rates

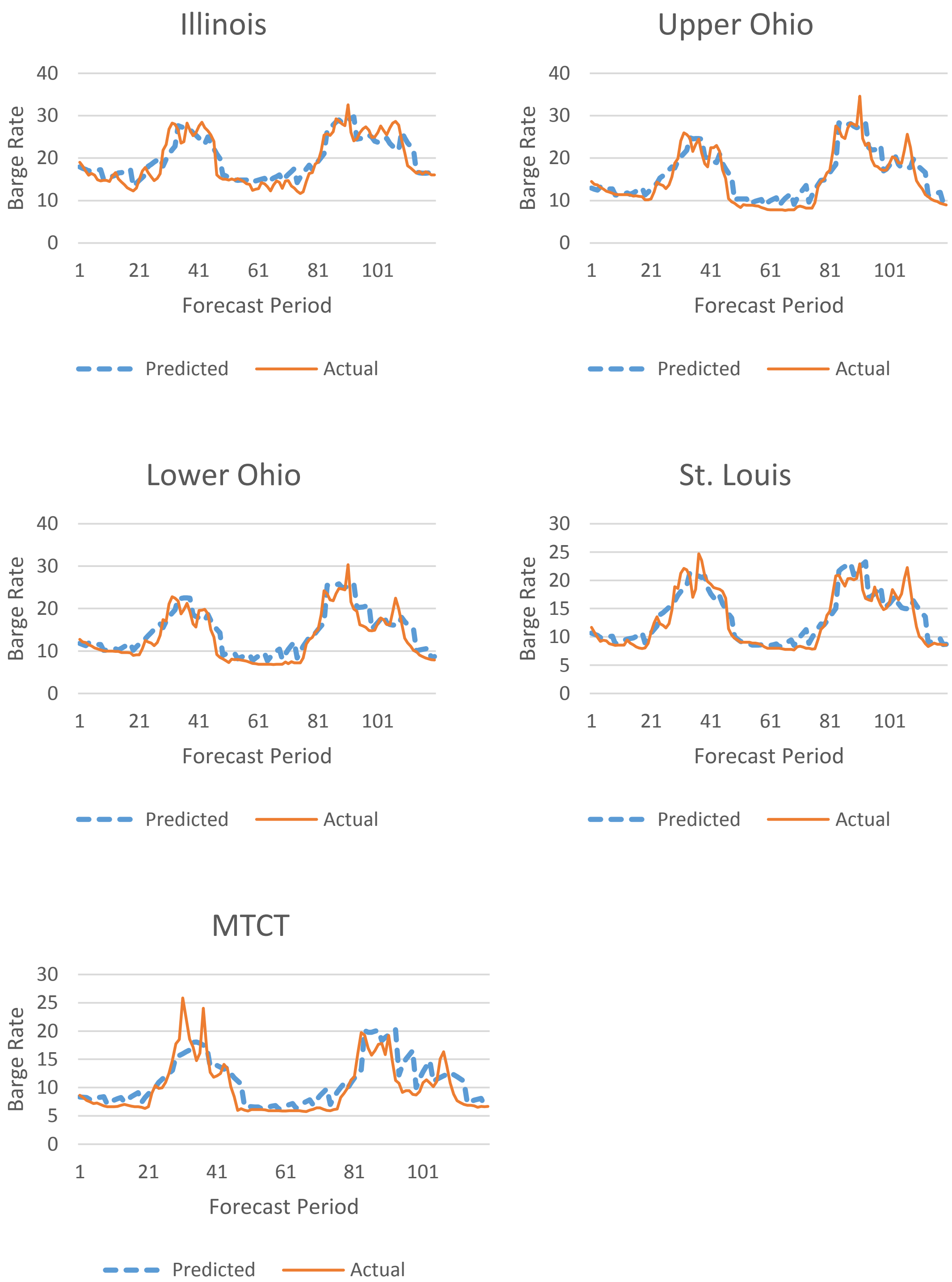
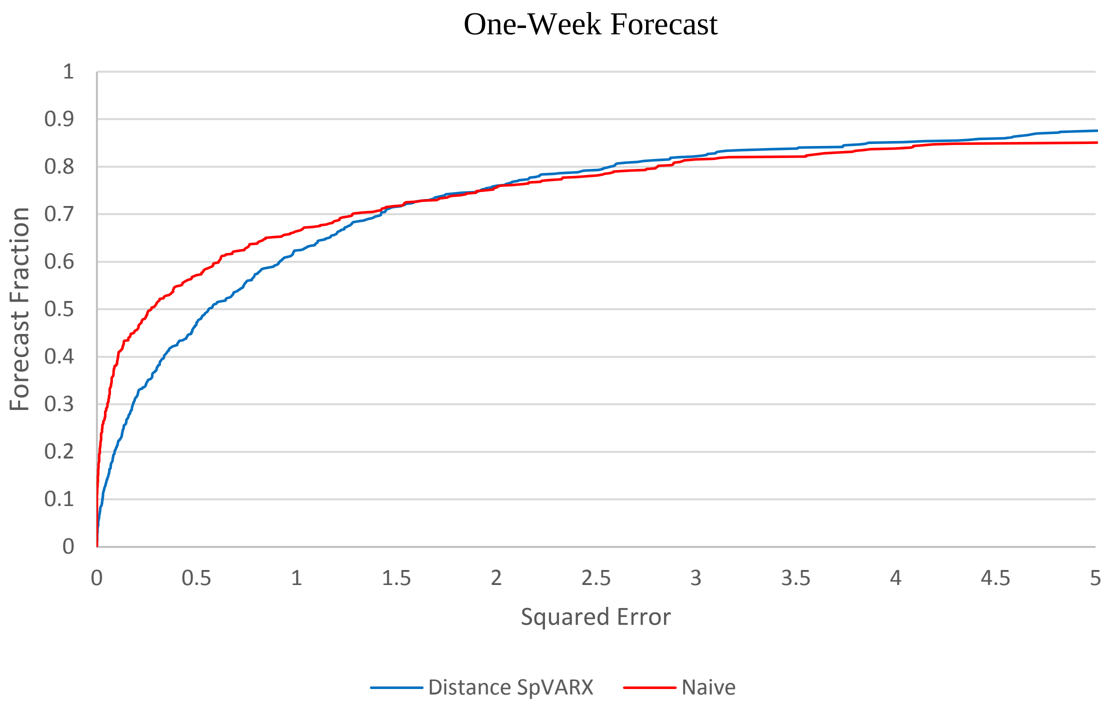


Figure 5. Five-Week Forecasts and Actual Barge Rates



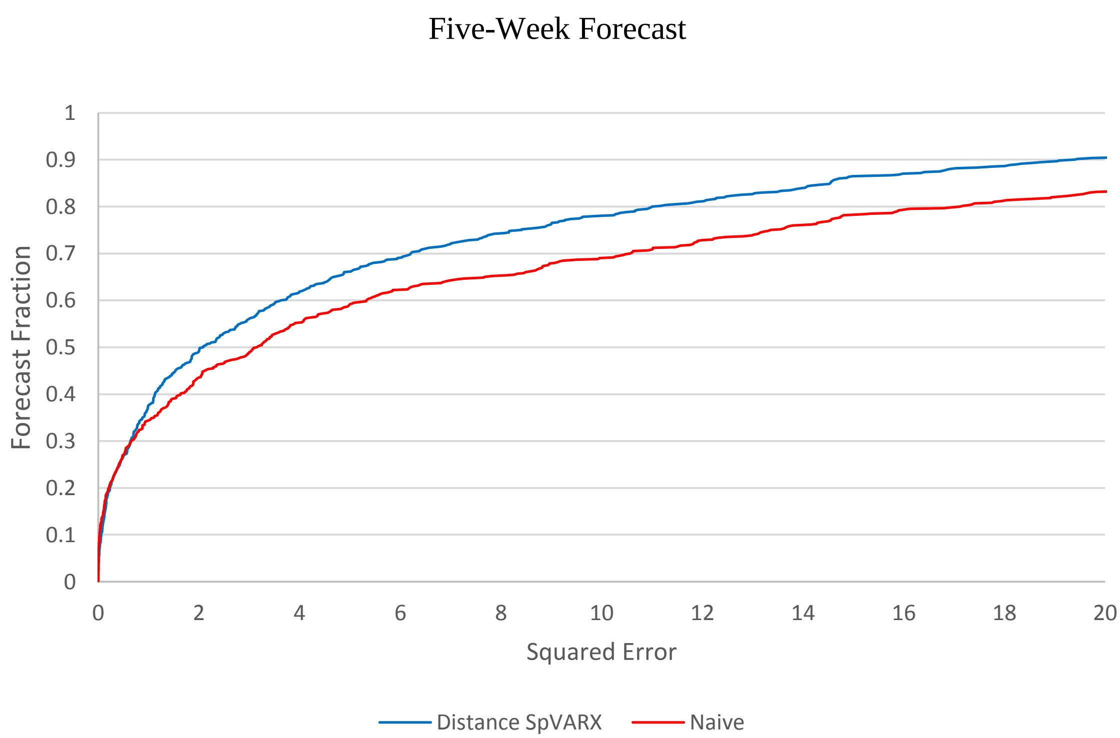


Figure 6 Stochastic Dominant RMSE Comparisons