Grain Transport on the Mississippi River and Spatial Corn Basis

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Abstract

This paper analyzes the effects of waterway transportation costs on the spatial distribution of corn prices at U.S. grain markets. Interregional trade theory predicts that in a competitive market price differences between markets are explained by transportation cost. The precise role played by transportation costs can depend on distances that grain needs to travel and also on the extent to which markets are integrated into the transportation system. The Mississippi waterway consists of an efficient barge transportation system that links the Midwest to the largest grain export market, the Gulf of Mexico. In markets with export to the Gulf, I predict that: (1) the magnitude of price differences between two markets increases with an exogenous increase in barge rates; (2) the response of prices to barge rate changes for markets on the river is greater the farther north, or upstream, the market is; (3) the magnitude of the barge-rate effect on prices declines with distance from the market to the river; (4) the barge-rate effect is less pronounced in markets that are less integrated into the river system. I develop theory-based predictions along these lines. I test the predictions and measure the associated effects with a mixture of parametric and nonparametric methods applied to a rich panel data set of corn prices from over one thousand locations.

1 Introduction

Corn is the most widely produced feed grain in the United States, accounting for more than 90 percent of total value and production of feed grains. In 2007, more than 60 percent of U.S. corn was harvested in five midwestern states: Iowa, Illinois, Nebraska, Minnesota, and Indiana. While production is concentrated, demand for corn is geographically diverse, creating areas of deficit throughout the Southeast, Northeast, Texas, and the West. This imbalance of surplus and deficit creates the demand for long-distance transportation. Large quantities of U.S.-grown corn are sent to overseas markets - typically more than 20% of U.S. production. Among all corn exported, over 60% of them are exported through the Gulf of Mexico along the Mississippi waterway system. The importance of the Mississippi River water system largely results from an efficient barge transportation system that links the north central United States and the Cornbelt to the Gulf. As the nation's waterway for grain transportation, the Mississippi River and its tributaries are a critical component linking the nation's grain supply with domestic and export markets. In transporting grains, barges and railroads compete with each other for long haulage. Railroads are also complement to barges when corn produced in the Midwest are moved to an elevator or export terminal on the rivers by rail. Trucking is also a complement to barges and is efficient for short distance shipment.

Transportation cost is an important component in corn prices. Corn is cheapest where it is produced, and its price rises as it makes its way to final end users. The economic problem posed by corn prices variation along with transport is to what extent transportation costs affect prices, and how the effects are related to geographical locations and characteristics of markets.

Ongoing calls for improving the logistical efficiency and hydrologic health of the Mississippi River have attracted attention from policy makers, agricultural producers and consumers groups, and the transportation industry. It is important for policy makers to understand how the river transportation system can influence the agricultural economy and it is important for grain market participants at a more micro level.

In this paper, I derive an equilibrium model of how transportation costs affect the spatial pattern of corn prices and test its implications. I find that the effect of barge rate changes on the Mississippi are geographically diverse, in ways, that can be explained by economic theory.

2 A Theory of Spatial Basis

In this paper, I define the spatial basis of corn at a market as the corn price in the market minus the contemporaneous corn price at New Orleans, Louisana (NOLA). In competitive markets, spatial basis in equilibrium should be explained by transportation costs. To motivate an empirical work I develop a stylized model of spatial price linkages.

Figure 1 illustrates a market for grain (market i) and the destinations to which it ships. An ethanol plant is located to the west of i, at which the equilibrium price of corn is P_E. To the east of i lies the export market. Grain traveling that route is shipped overland to a river market, where the price is P_R. At the river market, grain is loaded onto barges and shipped down the Mississippi to New Orleans, where the price is P_{NO}. From New

Orleans the grain is shipped overseas.

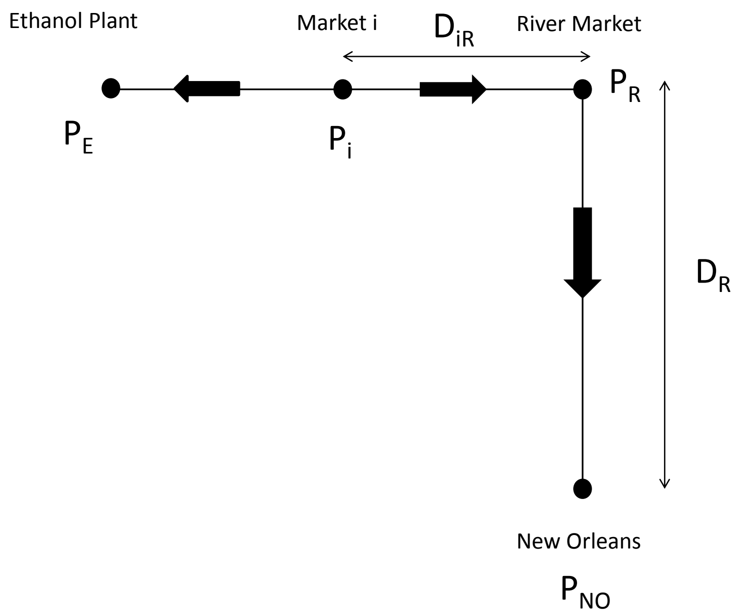

Figure 1: Prices and Grain Flow from Market i

I am interested in how changes in the price of transport by barge along the Mississippi affects prices and basis inland, as well as at buying points along the river. To do so, consider the allocation of a fixed amount of grain, Q_T, harvested near i and to be shipped from there. If grain travels to both inland and export destinations from market i, the price of grain purchased at i for export must equal the price of grain purchased at i for use at the ethanol plant. Further the price at i must account for the transport costs west to the ethanol plant, as well as east to the river market and south to New Orleans. These equilibrium conditions can be represented as:

$$P_E(Q_E) - c_E(Q_E) = P_R - c_R(Q_R) \tag{1}$$

$$P_R = P_{NO} - bD_R \tag{2}$$

$$Q_T = Q_E + Q_R, \tag{3}$$

where Q_E is the quantity of grain shipped from market i to the ethanol plant, $c_E(Q_E)$ is the cost of shipping grain from market i to the ethanol plant, Q_R is the quantity of grain shipped from market i to the river, $c_R(Q_R)$ is the cost of shipping grain from market i to the river, b is the cost per bushel per mile of shipping grain by barge down the Mississippi, and D_R is the river distance from the river market to New Orleans.

In the expressions above P_{NO}-the export price-is assumed to be unaffected by variations in grain flows from market i, while P_E-the price paid by the ethanol plant-is allowed to vary with Q_E: P_E is a non-increasing function of Q_E. The two overland unit transport cost functions, c_E and c_R, are allowed to increase with quantities shipped, reflecting the optimization of shippers who are presumed to use cheaper means of transport before more expensive means.

The price at market i is influenced by the cost of barge transport, b, but is partially insulated from it due to the overland distance to the river and the competing inland demand for corn from the inland ethanol plant source. To understand the influence of barge costs or inland prices, consider the comparative statics of the system resulting from an exogenous change in b, the cost of barge transport along the Mississippi. First, substitute from equations (2) and (3) into (1) to obtain:

$$P_E(Q_T - Q_R) - c_E(Q_T - Q_R) = P_{NO} - bD_R - c_R(Q_R). \tag{4}$$

Totally differentiating (4) with respect to b and Q_R results in:

$$-{P_E}'dQ_R + c'_E dQ_R = -D_R db - c'_R dQ_R. \tag{5}$$

Equation 5 can be solved for the equilibrium response in Q_R to a change in the cost of barge shipping:

$$\frac{dQ_R}{db} = \frac{D_R}{P'_E - c'_E - c'_R} < 0. \tag{6}$$

The change in basis at market i can be deduced from (6) and the following equilibrium relation derived from equations (1)-(3):

$$P_i - P_{NO} = -bD_R - c_R(Q_R). \tag{7}$$

Equations (6) and (7) together imply:

$$\frac{d(P_i - P_{NO})}{db} = -D_R \left(\frac{P'_E - c'_E}{P'_E - c'_E - c'_R} \right). \tag{8}$$

Further noting that $P'_E - c'_E$ is the slope of the inverse demand at market i for grain for shipment to the ethanol plant and that $-c'_R$ is the slope of the inverse demand at market i for grain for export via the river market, expression (8) can be written in terms of the direct elasticities of those demand curves and the shares of market i grain going to each:

$$\frac{d(P_i - P_{NO})}{db} = -D_R \left(\frac{1}{1 + \frac{\eta_E \alpha_E}{\eta_R \alpha_R}} \right) < 0, \tag{9}$$

where α_E and α_R are the shares of Q_T shipped to the ethanol plant and the river, and η_E and η_R are the direct price elasticities of demand, observed at market i, for the two uses of grain. Both elasticities are defined to be negative (non-positive) numbers. Equation (9) yields:

Empirical prediction 1: Basis at market i declines with an exogenous increase in the barge rate.

Note some limiting cases of equation (9), the equilibrium response of market-i basis to a change in barge rates. First, if $\alpha_E = 0$ and market i ships only to the river, the right-hand side of (9) is equal to $-D_R$. The effect at market i of a change in barge rates is the same at i as it is at the river market. Further, if I consider (9) as describing markets along the river at different distances from New Orleans (and for which $\alpha_E = 0$), the magnitude of the basis response to barge rates is proportional to river distance D_R. This implies:

Empirical prediction 2: The response of basis to barge rate changes for markets on the river is greater for markets farther upstream.

Also note from (9) that the effect of a very elastic river-destination demand is the same as that of a low α_E: if the river-destination demand is highly elastic and serves to nearly fix the price at market i to equal the transportation-cost-adjusted price at the river, then the right-hand-side of (9) is equal to $-D_R$ and the effect of a barge rate change inland is the same as that felt at the river. Because the form of the comparative static result in (9) involves the ratio η_E/η_R, the effect of a barge rate change will be larger in magnitude the more elastic river-destination demand is relative to inland-destination demand. Similarly, the share ratio (α_E/α_R) effect says that the effect of a barge rate change will be larger in magnitude the smaller is the share of market is grain sent inland.

Both the elasticity ratio and share ratio effects are plausibly related to the distance between market i and the river, D_{iR}. For greater distances from the river, markets are more likely to be shipping larger shares of their grain to destinations other than the river; and for those destinations, the elasticity of demand from the inland destination is more likely to be small. For both reasons, I posit a third empirical implication of the model:

$$\frac{d(P_i - P_{NO})}{db} = -D_R f(D_{iR}), \quad where \quad 0 < f(D_{iR}) < 1 \quad and \quad f'(D_{iR}) < 0. \tag{10}$$

In words, I have:

Empirical prediction 3: The magnitude of the barge-rate effect on basis declines with distance from the market to the river.

To restate the second and third empirical predictions: (2) for markets on the river (or shipping all of their grain to the river), $f(D_{iR} = 0) = 1$ and the response of basis to barge rate changes is proportional to D_R, the distance upriver from New Orleans; (3) for markets away from the river, the response of basis to barge rates is smaller than that at the river, and the magnitude of the effect declines with distance to the river. Further, based on equation (9), for markets i and j with the same distance to the river, $D_{iR} = D_{jR}$, if $\frac{\eta_E^i}{\eta_R^i}\frac{\alpha_E^i}{\alpha_R^i} > \frac{\eta_E^j}{\eta_R^j}\frac{\alpha_E^j}{\alpha_R^j}$, market i has smaller barge-rate effect when $D_R^i = D_R^j$, where D_R^i and D_R^j are the river distances for market i and j, respectively. Even if market i is farther up the river, $D_R^i = \alpha D_R^j$ with $\alpha > 1$, if $\frac{\eta_E^i}{\eta_R^i}\frac{\alpha_E^i}{\alpha_R^i} >> \frac{\eta_E^j}{\eta_R^j}\frac{\alpha_E^j}{\alpha_R^j}$, the barge-rate effect on market i can be smaller than on market j. This implies that market i is less integrated into the river transportation system. It may be because more shares of demand of corn at market i comes from the ethonal plant and less corn are supplied to the river market for export. This forms:

Empirical prediction 4: Markets that are more integrated into the river transportation system tend to exhibit more pronounced barge-rate effects.

I test these predictions and measure the sizes of the associated effects with a mixture of parametric and non-parametric methods applied on a rich panel data set of corn prices from over one thousand market locations.

3 Data

GeoGrain is a private firm that provide real-time market information to grain traders and farmers. They collect and maintain a data base of daily observations on bid prices for different grains from over 4,000 buying locations, which I refer to as markets. From their database I have called more than 3.5 million corn observations to form an unbalanced panel of daily corn prices in over 4,000 markets from 2005 to 2010, matched with daily observations on barge rates, quoted as cents per bushel from St. Louis to New Orleans and diesel prices[1], quoted as cents per gallon. Figure 3 plots the universe of markets for which daily corn prices are available. To focus on markets most likely to be integrated into the river transport system, I filtered out markets that are farther than 150 miles from the river system. A market is included in the resulting data set if its straight-line distance to the nearest of the major rivers (Figure 2) is less than 150 miles and if there are more than 45 non-missing observations[2]. Because the stretch of rivers north of McGregor in Minnesota[3] are frozen from December to March every year, markets whose latitude greater than 46.606667 are excluded. There are 1,189 markets that remain and shown in Figure 4.

Figure 2: The Rivers

[1]Diesel price is weekly data from USDA website. The days on which observations are missing were filled with the latest diesel price that is available.

[2]The minimum of 45 observations was chosen to ensure that the degrees of freedom in regression are greater than 30.

[3]Coordinates: lat=46.61, lon=-93.31.

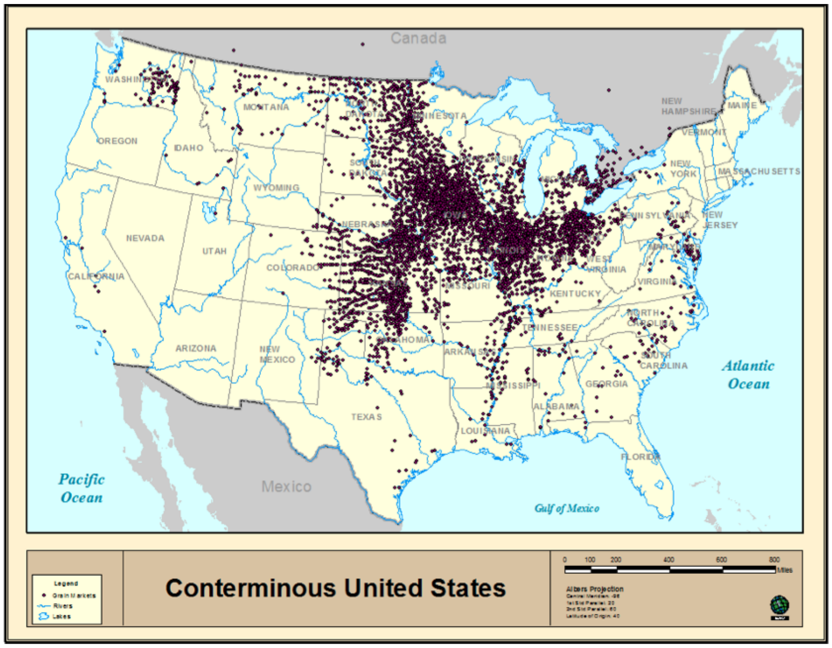

Figure 3: All Markets w/ Price Observations

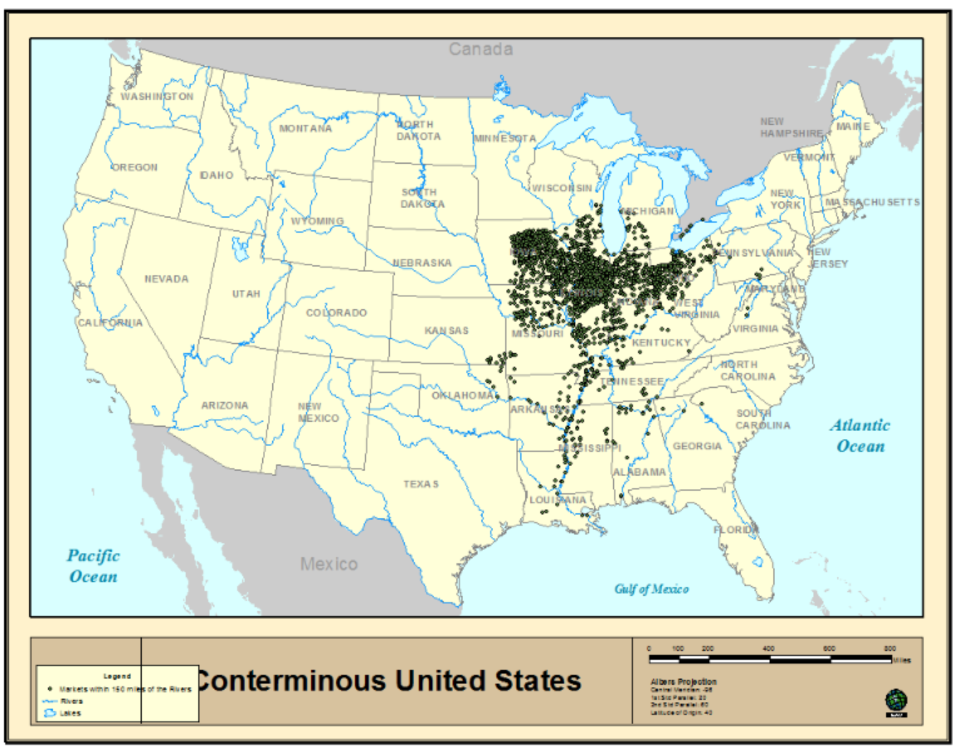

Figure 4: Corn Markets within 150 miles of major navigable rivers and South of Latitude 46.6

4 An Econometric Model of Corn Basis and Transportation Cost

To examine the effect of barge transportation costs on corn prices, I take New Orleans, LA as a reference market. Daily reference market corn prices are subtracted from daily corn prices at market i, which is defined as spatial basis at market i at day t, denoted by $b_{i,t}$. A time series regression model that specifies basis in market *i* on day *t* as a linear function of barge rates and diesel prices on days *t*, *t-1*, and back to *t-j* for j-lagged days, as well as a periodic seasonal term, is represented as:

$$b_{i,t} = \alpha_i + \beta_{i,0} p_t^b + \beta_{i,1} p_{t-1}^b + \beta_{i,2} p_{t-2}^b + ... + \beta_{i,j} p_{t-j}^b + \gamma_{i,0} p_t^d + \theta_i^{'} \psi_{i,t} + \varepsilon_{i,t}, \tag{11}$$

where $i = 1, 2, ..., 1189$ and $t = \{j+1, j+2, ...\}$. $\psi_{i,t}$ comprises four pairs of Fourier components: $\theta_i^{'} \psi_{i,t} = \sum_{s=1}^{4} \left(\lambda_s \cos \frac{2\pi st}{365} + \phi_s \sin \frac{2\pi st}{365} \right)$. p_{t-j}^b are St. Louis-to-NOLA barge rates on day *t-j* in cents/bushel; and p_t^d is contemporaneous diesel price in cents per gallon. Equation (11) represents many linear regressions - one for each of the 1,189 locations shown in figure 4 – with no shared parameters.

To control for possible endogeneity problems, diesel prices are used to represent prices of other transportation modes, such as trucks and railroads. Daily diesel prices are constructed based on weekly diesel prices obtained from USDA. Lagged diesel prices will not explain much of variation in corn prices. Therefore, only contemporaneous diesel price is included in the model. Since seasonality presents in basis across years, a Fourier component, which repeats annually is included in the model to capture the seasonal movement of basis. The question of how many Fourier terms are to be included is an open one. Adding higher frequency terms allows more rapid change during the year.

Another possible source that can cause endogeneity problem is whether barge rates are exogenous. Corn prices can affect barge rates in a way that when export demand for corn are high, barge companies may raise barge rate in response to increased demand for barge services, and vice versa. However, grains are not the major commodities by either tonnage or volumn transported on the rivers. Figure 5[4] shows 2007 barge tonnage by major commodity group on U.S. inland waterways. Coal and petroleum are the major commodities by tonnage shipped on the Mississippi river. Food and Farm products only take 12% of transportation flow. Grains are not the dominant products shipped on the rivers such that they can significantly affect barge rates. Therefore, barge rates will be considered as exogenous.

A big specification issue is the speed with which prices respond to changes in quoted barge rates. I explore this issue with two systematic procedures. The first forward selection starts with a model composed of contemporaneous and one lagged barge rates, contemporaneous diesel price, constant terms and four pairs of Fourier components. I test the addition of each lagged barge rate using a chosen model comparison criterion and add one more lagged barge rate that improves the model until the next one does not. Tables 1 and 2 show the test results. The proportion of regressions with significant F-statistics based on 5% or 10% levels starts decreasing when the number of lagged barge rate $p = 3$ and increases by a small percent when $p = 4$. However, adding fifth

[4]Source: USDA report: Study of Rural Transportation Issues

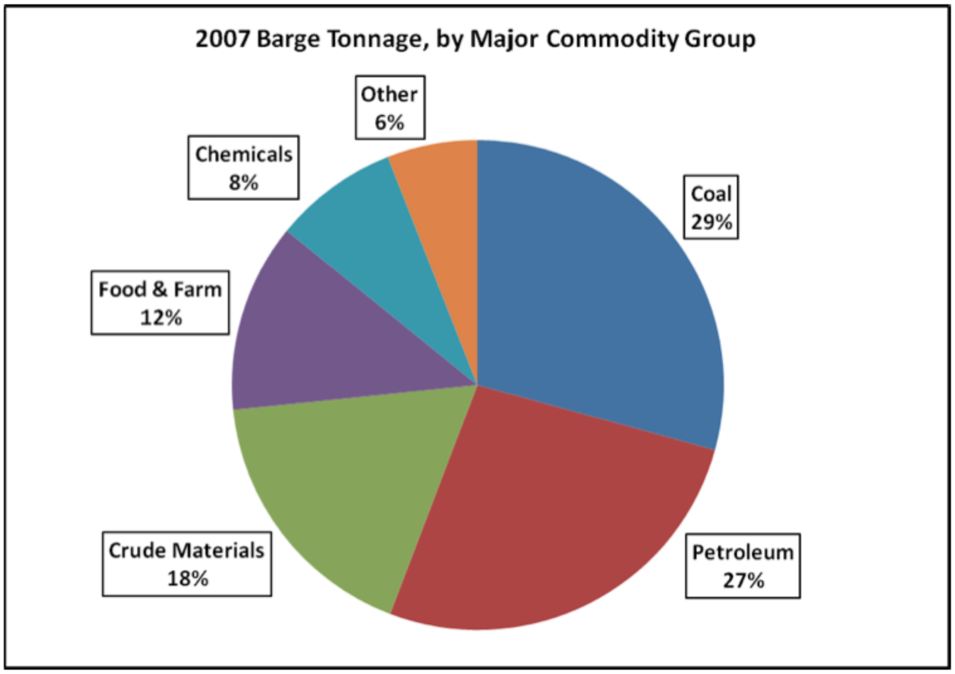

Figure 5: 2007 barge tonnage, by major commodity group

lagged barge rate increases the percentage of significant regressions with respect to F-test by a significant amount. Whether it will be included in the model needs further investigation.

Table 1: Forward Selection: Proportion of regressions with significant coefficients at the 10% level.
(p = number of lagged barge rates, q = number of lagged of diesel prices)

Models	T-tests								F-tests
p=1, q=0	$\alpha = 0$	$\beta_0 = 0$	$\beta_1 = 0$					$\gamma_0 = 0$	$\beta_0 = \beta_1 = 0$
	0.898	0.584	0.415					0.737	0.710
p=2, q=0	$\alpha = 0$	$\beta_0 = 0$	$\beta_1 = 0$	$\beta_2 = 0$				$\gamma_0 = 0$	$\beta_0 = ... = \beta_2 = 0$
	0.899	0.729	0.210	0.278				0.702	0.766
p=3, q=0	$\alpha = 0$	$\beta_0 = 0$	$\beta_1 = 0$	$\beta_2 = 0$	$\beta_3 = 0$			$\gamma_0 = 0$	$\beta_0 = ... = \beta_3 = 0$
	0.891	0.656	0.186	0.153	0.266			0.673	0.748
p=4, q=0	$\alpha = 0$	$\beta_0 = 0$	$\beta_1 = 0$	$\beta_2 = 0$	$\beta_3 = 0$	$\beta_4 = 0$		$\gamma_0 = 0$	$\beta_0 = ... = \beta_4 = 0$
	0.877	0.590	0.174	0.175	0.130	0.359		0.642	0.771
p=5, q=0	$\alpha = 0$	$\beta_0 = 0$	$\beta_1 = 0$	$\beta_2 = 0$	$\beta_3 = 0$	$\beta_4 = 0$	$\beta_5 = 0$	$\gamma_0 = 0$	$\beta_0 = ... = \beta_5 = 0$
	0.860	0.650	0.2050	0.140	0.1440	0.1250	0.469	0.475	0.853

Table 2: Forward Selection: Proportion of regressions that are significant at 5% level

(p = number of lagged barge rates, q = number of lagged of diesel prices)

Models	T-tests								F-tests
p=1, q=0	$\alpha = 0$	$\beta_0 = 0$	$\beta_1 = 0$					$\gamma_0 = 0$	$\beta_0 = \beta_1 = 0$
	0.880	0.501	0.346					0.681	0.649
p=2, q=0	$\alpha = 0$	$\beta_0 = 0$	$\beta_1 = 0$	$\beta_2 = 0$				$\gamma_0 = 0$	$\beta_0 = ... = \beta_2 = 0$
	0.879	0.645	0.138	0.200				0.630	0.713
p=3, q=0	$\alpha = 0$	$\beta_0 = 0$	$\beta_1 = 0$	$\beta_2 = 0$	$\beta_3 = 0$			$\gamma_0 = 0$	$\beta_0 = ... = \beta_3 = 0$
	0.874	0.541	0.144	0.103	0.180			0.600	0.693
p=4, q=0	$\alpha = 0$	$\beta_0 = 0$	$\beta_1 = 0$	$\beta_2 = 0$	$\beta_3 = 0$	$\beta_4 = 0$		$\gamma_0 = 0$	$\beta_0 = ... = \beta_4 = 0$
	0.851	0.509	0.120	0.115	0.092	0.265		0.579	0.708
p=5, q=0	$\alpha = 0$	$\beta_0 = 0$	$\beta_1 = 0$	$\beta_2 = 0$	$\beta_3 = 0$	$\beta_4 = 0$	$\beta_5 = 0$	$\gamma_0 = 0$	$\beta_0 = ... = \beta_5 = 0$
	0.825	0.568	0.121	0.083	0.077	0.070	0.404	0.414	0.805

The second procedure starts with a model composed of all candidate lagged barge rates: contemporaneous and the maximum considered number, which is seven. Proportions of significant regressions of joint tests on subsets of barge rate coefficients are compared. Tables 3 and 4 show the t-tests and F-tests at 10% and 5% significance levels, respectively. T-tests on each coefficients illustrate that contemporaneous, 1-lagged and 2-lagged barge rates are significant in 63%, 31%, and 33% of regressions, which are far more than other lagged barge rates[5]. Besides, joint tests on the subsets of coefficients of barge rates show that in more than 50% of the regressions, the null hypothesis of $\beta_2 = .. = \beta_7 = 0$ is rejected at the 10% significance level. Therefore, two lagged barge rates are chosen based on a selection criteria that at least 50% of regressions suggest the null should be rejected at the 10% significance level. Based on forward and backward testing procedures, a model with up to two-lagged barge rates and a contemporaneous diesel price are chosen. This being said, as we shall see, most of the power in the relationship between barge rates and spatial basis is concentrated on the contemporaneous effect.

[5] β_7 is exceptional. However, β_7 is not selected if lagged barge rates before are not chosen.

Table 3: Backward Selection: Proportion of regressions that are significant at 10% level (p = number of lagged barge rates, q = number of lagged of diesel prices)

Model:	p=7, q=0			T-tests					
$\alpha = 0$	$\beta_0 = 0$	$\beta_1 = 0$	$\beta_2 = 0$	$\beta_3 = 0$	$\beta_4 = 0$	$\beta_5 = 0$	$\beta_6 = 0$	$\beta_7 = 0$	$\gamma_0 = 0$
0.818	0.630	0.314	0.331	0.131	0.185	0.114	0.110	0.320	0.430
				F-tests					
$\beta_6 = \beta_7 = 0$	$\beta_5 = ... = \beta_7 = 0$	$\beta_4 = ... = \beta_7 = 0$	$\beta_3 = ... = \beta_7 = 0$	$\beta_2 = ... = \beta_7 = 0$	$\beta_1 = ... = \beta_7 = 0$	$\beta_0 = ... = \beta_7 = 0$			
0.328	0.359	0.447	0.498	0.574	0.680	0.865			

Table 4: Backward Selection: Proportion of regressions that are significant at 5% level (p = number of lagged barge rates, q = number of lagged of diesel prices)

Model:	p=7, q=0			T-tests					
$\alpha = 0$	$\beta_0 = 0$	$\beta_1 = 0$	$\beta_2 = 0$	$\beta_3 = 0$	$\beta_4 = 0$	$\beta_5 = 0$	$\beta_6 = 0$	$\beta_7 = 0$	$\gamma_0 = 0$
0.787	0.531	0.225	0.235	0.081	0.106	0.064	0.063	0.223	0.351
				F-tests					
$\beta_6 = \beta_7 = 0$	$\beta_5 = ... = \beta_7 = 0$	$\beta_4 = ... = \beta_7 = 0$	$\beta_3 = ... = \beta_7 = 0$	$\beta_2 = ... = \beta_7 = 0$	$\beta_1 = ... = \beta_7 = 0$	$\beta_0 = ... = \beta_7 = 0$			
0.237	0.280	0.360	0.391	0.472	0.583	0.832			

Both test procedures mentioned above and model estimations are performed based on quasi-differenced variables to account for serial correlation, as OLS estimates show serial correlation in the residuals. Therefore, an estimate of $\hat{\rho}$ from an OLS regression on the residual model $\varepsilon_{i,t} = \rho\varepsilon_{i,t-1} + u_{i,t}$ is used to transform variables:

$$b^*_{i,t} = b_{i,t} - \hat{\rho}b_{i,t-1},$$

$$X^*_t = X_t - \hat{\rho}X_{t-1},$$

$$\alpha^*_i = \alpha_i\left(1 - \hat{\rho}\right), and$$

$$\varepsilon^*_{i,t} = \varepsilon_{i,t} - \hat{\rho}\varepsilon_{i,t-1},$$

where $X^{*'}_t = \begin{bmatrix} p^{b^*}_t & {p^b_{t-1}}^* & {p^b_{t-2}}^* & p^{d^*}_t \end{bmatrix}$ for all $t \geq 3$.

The sum of barge-rate effects in three time periods *t*, *t-1* and *t-2* will be referenced to as a "long-run" barge-rate effect. The interpretation of long-run effect is if, for example, barge rates were to use and then be sustained for a long period (three days in my model), the ultimate effect on spatial basis for market i would be $\beta_{i,0} + \beta_{i,1} + \beta_{i,2}$.

5 Regression Results

Seasonal Components

Of 1,189 markets that satisfy the distance-to-the-river and degrees-of-freedom criteria, 83% have seasonal components significant at the 10% significance level. Across the estimates, the median difference between seasonal peak and seasonal trough is approximately 7 cents/bushel. Figure 6 displays the estimated seasonal factors for five markets whose seasonal ranges were close to this median value. Their locations are displayed on the map in Figure 7.

Although there are variations in seasonal pattern for the five displayed markets, seasonal components tend to peak in April, May or June and fall to troughs around August, September and October, which is harvest or post-harvest season.

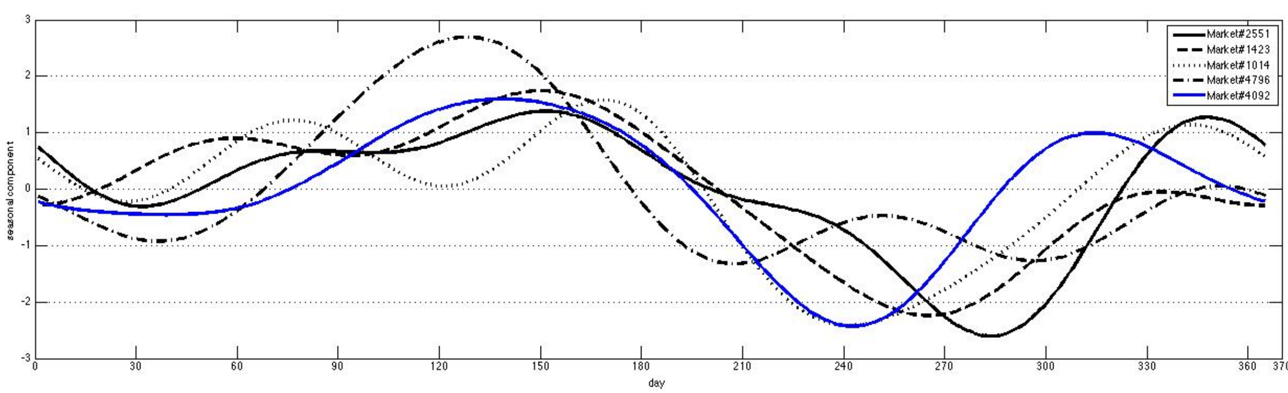

Figure 6: Estimated Seasonal Factor for Markets #2551, #1423, #1014, #4796 and #4092

Figure 7: Markets #4796, #2551, #4092, #1423 and #1014 from North to South

Barge Rate Coefficients

The coefficient β_0 reflects the contemporaneous effects of barge rate on basis. Table 5 is the summary of tests on three barge rate coefficients. T-tests from the 1,189 regressions show that the contemporaneous effect $\hat{\beta}_0$ is statistically significant in explaining the variations in corn prices and 99% of the significant ones are negative. Fewer $\hat{\beta}_1$ and $\hat{\beta}_2$ coefficients are significant, most of which are negative. Compared to contemporaneous effect, one-day and two-day lagged barge rates have mild effects on corn prices. From the distribution of estimated barge rate effects shown in Figures 8, 9 and 10, contemporaneous and lagged barge rates effects are negative, which is consistent with my empirical prediction 1 that basis declines with an exogenous increase in the barge rate.

F-tests show that 77% of the $\hat{\beta}_i^{'}$ s are jointly significant, which verifes that barge-rate changes explain part of changes in spatial basis. To test the long-run (three-day) effect of barge rates, F-tests of the hypothesis that the sum of all $\hat{\beta}_i^{'}$ s equal to zero, for each market, indicates that the sum is significant in 78% of regressions. Figure 11 shows the frequency distribution of the long-run effect. The mean of the sum is -0.34, and the median is -0.32, which means that a one cent per bushel increase in the barge rate at St. Louis from shipping corn to NOLA will induce a 0.34 cents per bushel drop, on average, in corn price in the Midwest relative to the corn price at NOLA. The effect is economically significant considering that the price of corn is around 600 cents per bushel and barge rates are volatile with a possible change of 100 cents per bushel. Price can change as much as 34 cents caused by barge rates for a bushel of corn.

Table 5: Statistics and tests on barge rates coefficients

	T-test	(Significance level = 10%)		
Coefficients	% significant	% of negative among significant ones	Mean	Median
β_0	72%	99%	-0.25	-0.23
β_1	20%	74%	-0.04	-0.02
β_2	29%	87%	-0.04	-0.05
F-tests	H_0: $\beta_0 = \beta_1 = \beta_2 = 0$	H_0: $\beta_0 + \beta_1 + \beta_2 = 0$	Mean of sum	Median of sum
	77% reject	78% reject	-0.34	-0.32

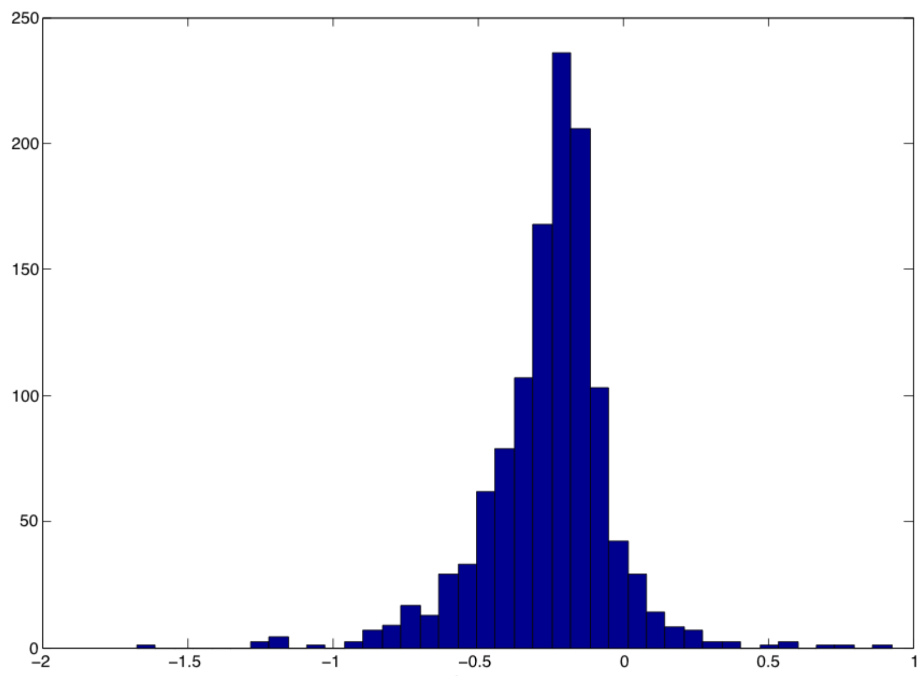

Figure 8: Histogram of $\hat{\beta}_0$

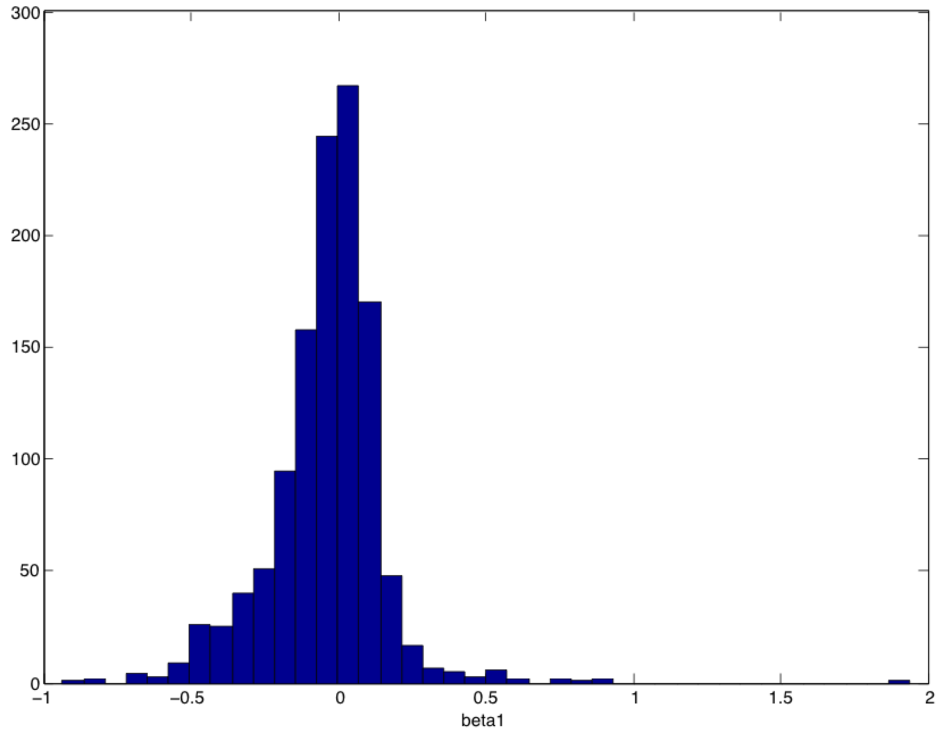

Figure 9: Histogram of $\hat{\beta}_1$

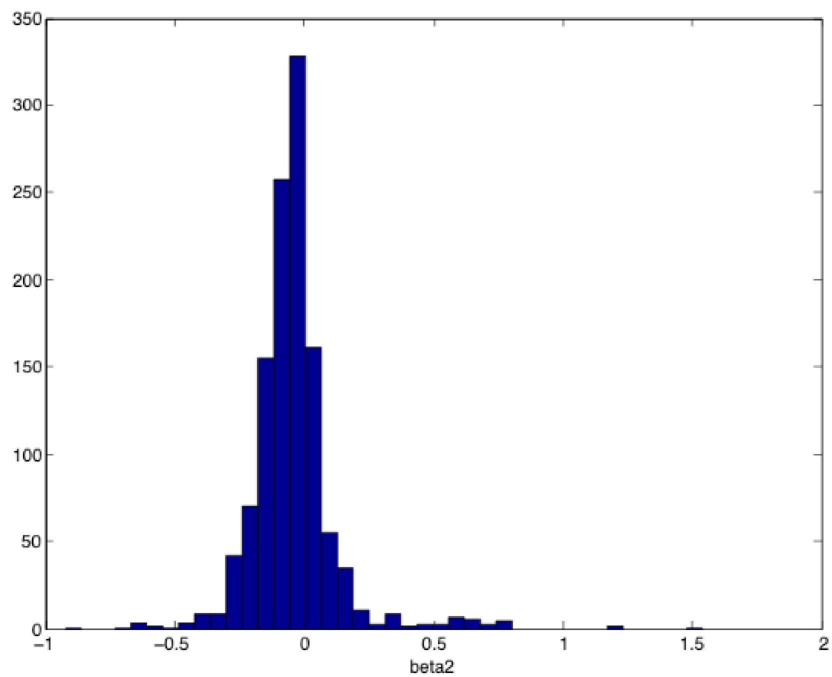

Figure 10: Histogram of $\hat{\beta}_2$

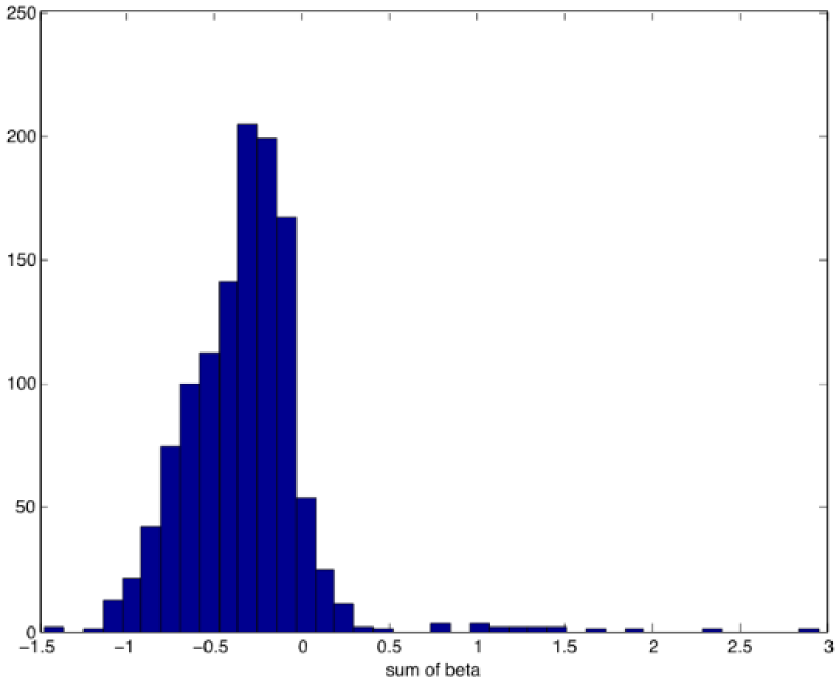

Figure 11: Histogram of long-run effect: sum of $\hat{\beta}_i^{'}$s

Diesel Price Coefficients

As to diesel price, across markets only 15% of the estimates of γ_0 are significant at the 10% level, and 75% of these are negative. Compared with barge rates, diesel prices are less statistically significant in explaining corn prices since fewer regressions show a significant diesel price, which might partially be due to the collinearity between barge rates and diesel prices, and might also be due to the fact that daily diesel prices are imputed from weekly observations.

5.1 Smoothing and Mapping

What is left unexamined in the discussion of barge rate and diesel price effects so far is the spatial variation in the estimated effects. Nonparametric smoothing techniques provide a graphical method for us to uncover such spatial behavior of the equilibrium basis surface. Visual information on barge rate and diesel price effects on basis in markets can be shown by applying those methods. Kernel smoothing and robust locally weighted regression (LOESS) techniques are applied to long-run barge rate and diesel price effects to estimate a smoothed surface so that spatial pattern of barge rate effects and diesel price effects can be visually observed.

Kernel smoothing

The first smoothing method applied is kernel smoothing. The spatial surface of long-run barge effects is smoothed based on a 60-by-60 grid evenly spaced betwen the minimum and maximum of latitude and longitude of obser-

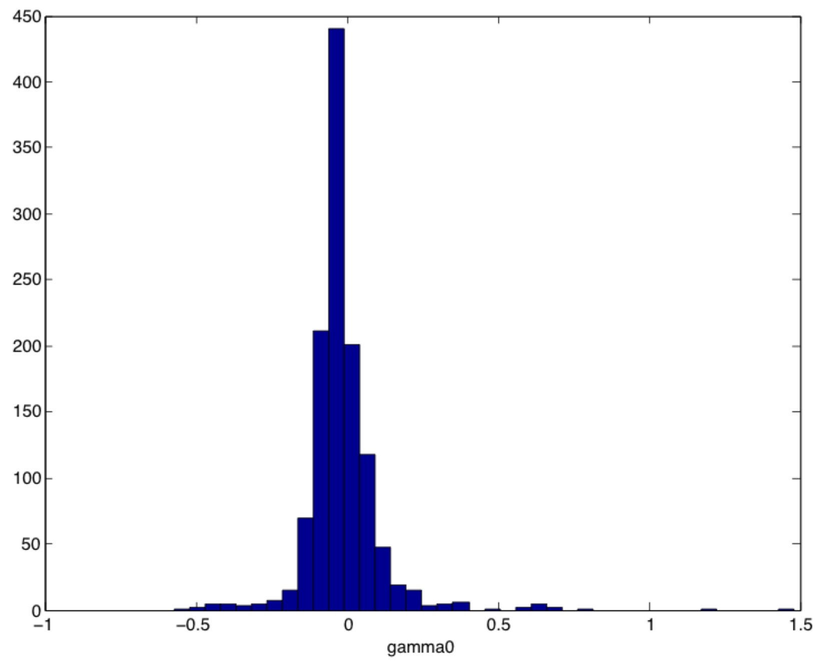

Figure 12: Histogram of $\hat{\gamma_0}$

vations. The length of a degree of latitude is approximately 69 miles. A degree of longitude varies in size. At the equator, it is approximately the same size as a degree of latitude, 69 miles. The size gradually decreases to zero as the meridians converge at the poles. Most of our data are located near 45 degree of latitude, where one degree of longitude is approximately 53 miles. Our data span approximately 14 degrees in latitude and 17 degrees in longitude. Therefore, each cell in the 60-by-60 grid is approximately 16 miles (in latitude) by 15 miles (in longitude).

Data points that do not fall on nodes of the grid are "moved" to their closest node. The smoothed estimate at each node is a weighted average of all observations on the grid. The weights of the average are determined by the bivariate normal p.d.f. centered at the node in question. I use a bivariate normal density with equal variances (scaled in miles) and zero covariance. The common standard deviation of the distribution controls the smoothness of the surface. Larger standard deviation creates a smoother surface, creating a trade-off with bias.

Figure 13 shows the estimated surface of barge rate effects using kernel smoothing with standard deviation of 50 miles. The surface has its low points in St. Louis region, which support my prediction #4 that markets that are well integrated into the river system exhibits more pronounced effects. St. Louis is a well-known port with the largest capacity for loading or unloading grains on the Mississippi river waterway system. The majority of corn in St. Louis is loaded for shipment to the Gulf. In terms of the model, this implies that $\frac{\alpha_E}{\alpha_R}$ in equation (9) is small and the magnitude of the barge-rate effect is large at St. Louis. Further, markets close to the rivers have large barge rate effects and the surface rises as one moves toward east and west of the rivers[6]

Specific effects can also be observed from its corresponding contour plots which are shown in figures 14 and

[6]New Orleans is at the south point of the river.

15. Figure 15 is identical to figure 14 but also shows market locations. Contour lines are at -0.5, -0.4, -0.2, -0.1 and 0. Markets east of the Upper Mississippi River, which are located in Iowa present smaller barge rate effects since much of corn also rely on the railway lines in those regions to be shipped to PNW for export. In contrast, for markets with the same latitudes as Iowa markets, the effects in those markets are larger, which can be attributed to their convenient locations close to both the Mississippi and Illinois Rivers. In general, contour lines stretch out along the Mississippi River, which implies that markets that are closer to the Mississippi River have more negative effects. As markets get farther away to the west and the east of the Mississippi river, effects eventually fade to zero. This feature is consistent with my empirical prediction #3. It can also be seen from Figure 14 that barge rate effects are not symmetric with respect to the Mississippi River. West of the Mississippi barge rate effects fade out more rapidly than east of the river. This makes sense because there is little barge traffic on the Missouri river. The Illinois and Ohio rivers, to the east of the Mississippi, are also major transportation waterways. As noted from the surface, the most negative effects are around St. Louis, where the surface level is lower than -0.5.

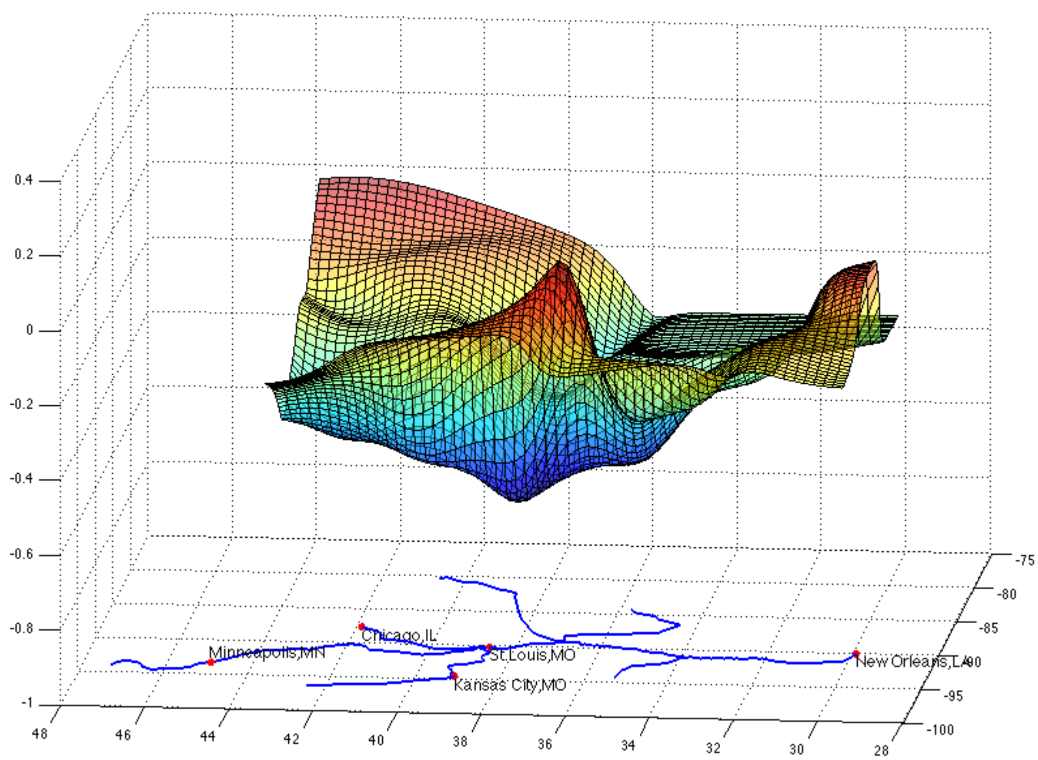

Figure 13: Surface of Barge Rate Effects Using Kernel Smoothing (SD = 50 miles)

Figures 16 and 17 show contour plots with smoother standard deviations of 30 and 70, respectively. The contour lines for Figure 16 are -0.6, -0.4, -0.2 and 0. The contour maps present similar spatial patterns of barge rates effects on basis, but with different degrees of spatial smoothness.

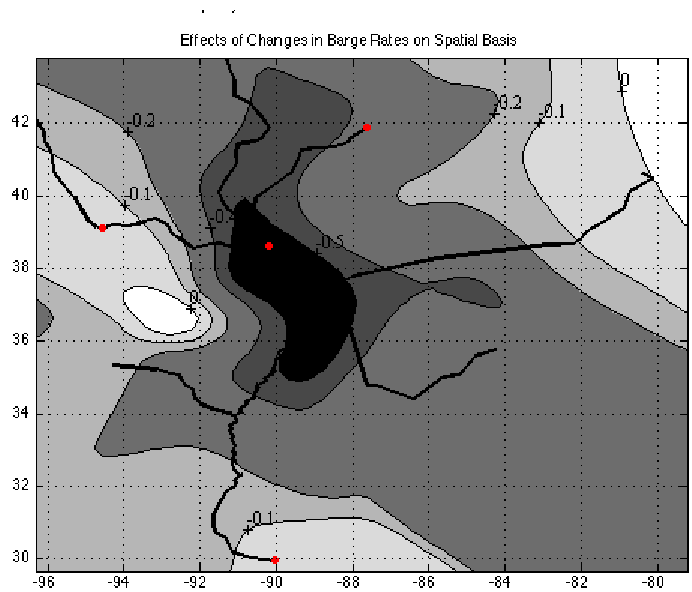

Figure 14: Contour Map of Barge Rate Effects Using Kernel Smoothing (SD = 50 miles)

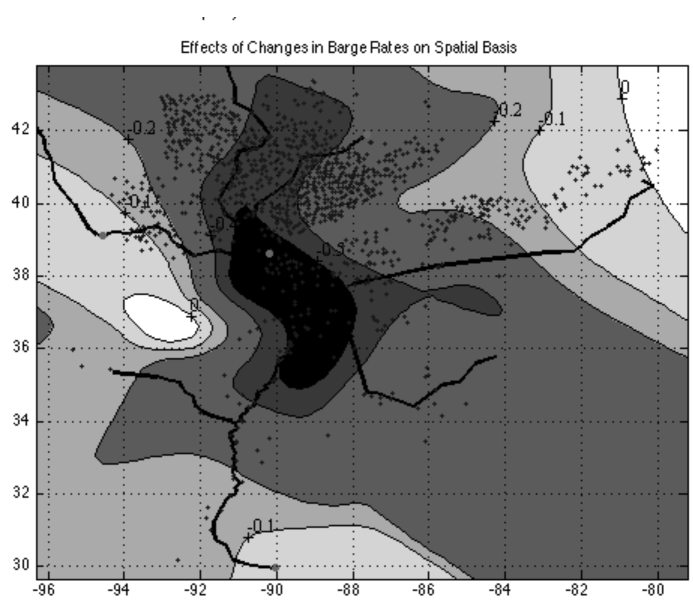

Figure 15: Contour Map of Barge Rate Effects Using Kernel Smoothing (SD = 50 miles)

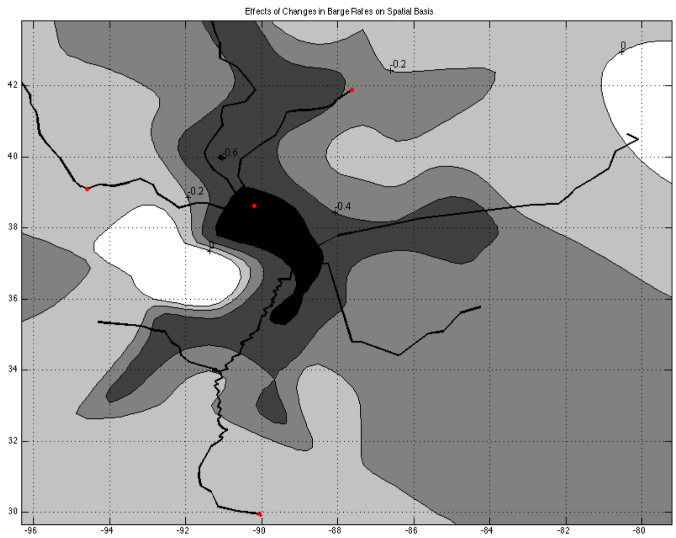

Figure 16: Contour Map of Barge Rate Effects Using Kernel Smoothing (SD = 30 miles)

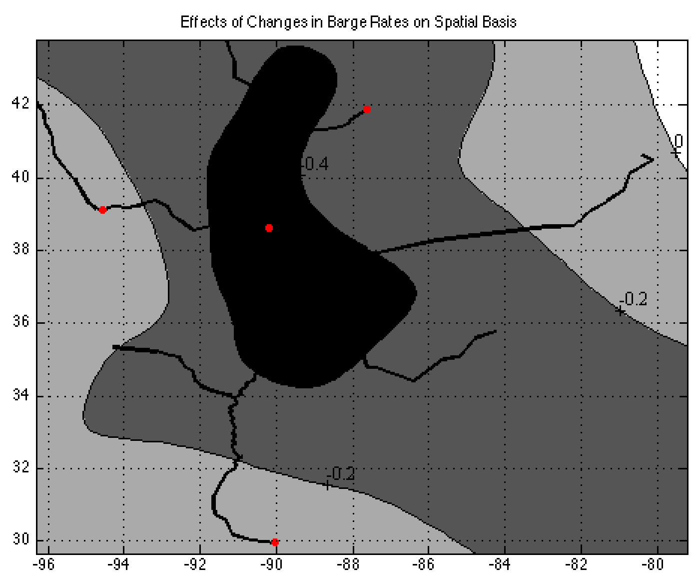

Figure 17: Contour Map of Barge Rate Effects Using Kernel Smoothing (SD = 70 miles)

With regard to the contemporaneous diesel price, no spatial pattern appears[7]. Consistent with the histogram of diesel price effect shown earlier, diesel price effects are near zero for most markets. As noted earlier, this may be due to imputed daily data from weekly diesel price and multicollinearity with barge rates.

Locally weighted regression

To examine the robustness of my inference, I smooth the same estimated long-run large effects using a different non-parametric smoother. Locally weighted regression, or LOESS, which was first discussed by Cleveland (1979), is an alternative method for smoothing a scatterplot. In my context, a scatterplot $(\mathbf{x_i}, y_i), i = 1, ...n$, in which $\mathbf{x_i}$ is a vector represent latitude and longitude of market i, and y_i represents barge effect at market i. The fitted value at $\mathbf{x_k}$ is the value of a polynomial fit to the data using weighted least squares, where the weight for $(\mathbf{x_i}, y_i)$ is large if $\mathbf{x_i}$ is close to $\mathbf{x_k}$ and small if it is not. A robust fitting procedure is used that guards against deviant points distorting the smoothed points. In my context, an estimate of the regression surface at any value $\mathbf{x}$, is the value of a polynomial fit of latitudes and longitudes of markets in a neighborhood. Each point in the neighborhood is weighted according to its Euclidean distance from $\mathbf{x_k}$.

Contour plots of smoothed barge rate effects on spatial basis in 1,189 markets based on bivariate locally weighted regression smoothing are shown in Figure 18 and Figure 19. Figure 19 is identical to Figure 18 but also shows market locations. The parameters that control the smoothness and biasedness of estimates are proportion of data used in local regressions and degree of regression. More proportion of data used in local regression and smaller degree of regression will produce smoothed surface. Proportions of data commonly used are from 0.2 to 0.5, and linear or quadratic regressions are common in practice. Contour plot in my case is a local linear regression (degree = 1) with 20% of data in regression. Contour lines are at -0.6, -0.4, -0.2 and 0. A similar spatial pattern is shown using LOESS. Similar LOESS smoothing with the same parameter selections are applied to diesel price effects. No particular spatial pattern is observed[8].

From contour plots by kernel and LOESS smoothing techniques, it can be observed that kernel and LOESS methods give similar results.

6 Concluding Remarks

This paper studies how the costs of transporting grain down the Mississippi influence the prices across the United States. Unrestricted linear regressions using feasible generalized least square for each market based on daily data from 2005 to 2011 generate market-specific barge-rate effects while controling for endogeneity of barge rates. Of 1,189 regressions, the majority of them show that three-day barge rates are both individually and jointly significant at the 10% level, but less so for the contemporaneous diesel price. The long-run effects of barge rates, which are the sums of three-day coefficients, are significant for over 70% of regressions, which indicates that barge rates are

[7] Contour plot is omitted.

[8] Figure is omitted.

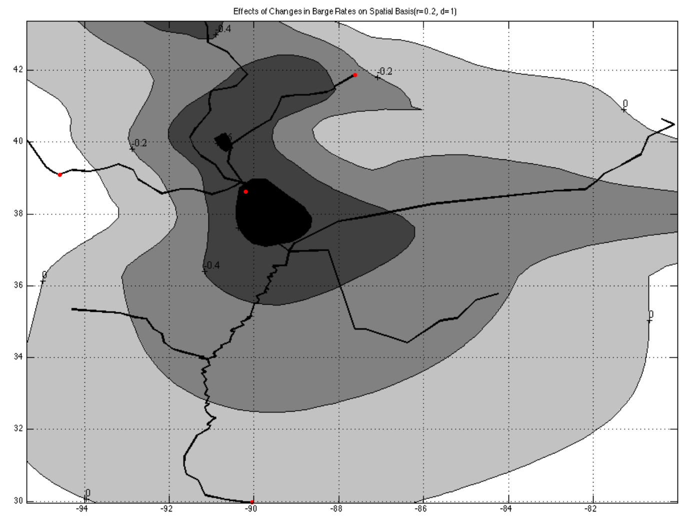

Figure 18: Contour Map of Barge Rate Effects Using loess Smoother

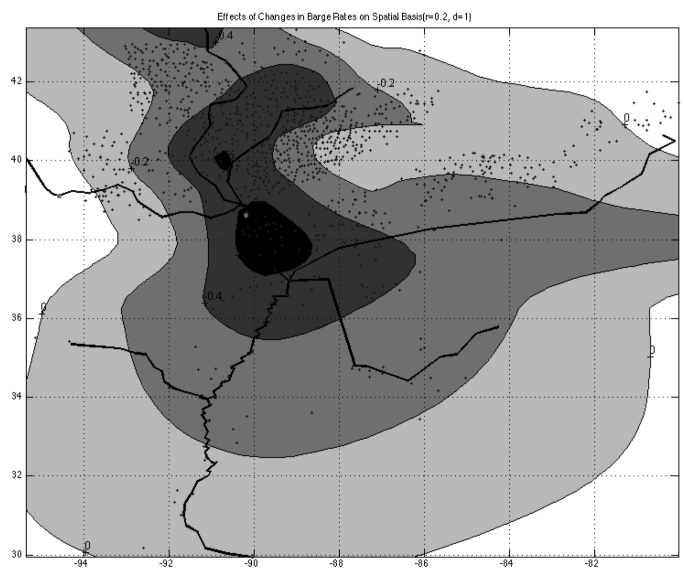

Figure 19: Contour Map of Barge Rate Effects Using loess Smoother w/ Markets

an important factor in influencing corn prices across domestic markets. On average, one cent increase in barge rate can induce 34 cents drop in spatial basis in markets in the Midwest. The size of the effects is economically significant considering volatile barge rates with a maximum change of 100 cents per bushel from 2005 to 2011. Changes in barge rate can cause approximate 34 cents-per-bushel change in corn spatial basis, which is significant considering a typical corn price level of 600 cents per bushel.

To obtain a surface that shows how markets are integrated into the river transportation system, I apply non-parametric smoothing algorithms – kernel and LOESS – to the long-run coefficients of barge rates and contemporaneous diesel price. Contour maps show that corn prices in markets that are close to St. Louis and close to the Mississippi River and Illinois River, are negatively affected by barge rates. The effects are less pronounced in markets that are farther away from the rivers, which shows the importance of the Mississippi waterway system in transporting corn for export. Those markets, such as markets near St. Louis, which has large proportation of grains loaded onto barges on the rivers for export, tend to show more negative effects. For markets in Iowa, which have more supplying regions beside the Gulf of Mexico, such as PNW and other markets in Texas and elsewhere, the barge-rate effects on basis are smaller compared to the effects in markets in Illinois, which have the same latitudes but own convenient and easier access to the rivers. These markets that are well integrated into the river system exhibit more pronounced effects. With respect to diesel prices, the effects of diesel prices are much smaller, almost zero. No particular spatial patterns present themselves in the smoothed plots, which may be due to multicollinearity between barge rates and diesel prices and the nature of the weekly data used.