Transportation Disruptions and Corn Basis Volatility along the Mississippi River

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Transportation Disruptions and Corn Basis Volatility along the Mississippi River

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Abstract

This study investigates how river-based transportation costs, particularly barge freight rates, influence corn basis along the Mississippi River. The corn basis (the difference between local cash and futures prices) captures key pricing dynamics affected by both local conditions and broader logistical networks. Using weekly data from 2014 to 2024, we apply a Spatial Durbin Model (SDM) with spatial and time fixed effects to account for both local and spillover effects across markets. Two model specifications are estimated: one assuming directionally constrained spatial spillovers, consistent with downstream trade patterns, and another allowing for unconstrained spatial interactions. The results show that an increase in barge freight rates is associated with a decline in the local corn basis, underscoring the negative impact of rising transportation costs on prices paid at origin. Moreover, significant spillover effects reveal that barge rate changes in one region affect basis values in adjacent markets, indicating that transportation shocks propagate spatially. The analysis also highlights how river navigability and localized energy price variation contribute to basis volatility, depending on how spatial relationships are structured. Overall, the findings emphasize the importance of infrastructure, costs, and spatial connectivity in grain pricing. This research offers important insights for policymakers, producers, and traders seeking to manage transportation risks and improve market efficiency in the agricultural sector.

Keywords: Corn Basis, Barge rates, Spatial Durbin Model, Spillover, Transportation Costs, Mississippi River

JEL Codes: B22, B4; C22; C32; C52; Q18

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1 Background and Relevant Literature

Understanding spatial price relationships in grain markets involves combining classical spatial equilibrium theory with modern empirical insights regarding transportation and spillover effects. The fundamental principle of spatial arbitrage states that, under competitive conditions, price differentials between regions are limited by transportation costs (Takayama and Judge, 1971; Enke, 1951; Samuelson, 1952). Early work by Enke (1951) and Samuelson (1952) drew parallels between commodity flows and electrical networks, establishing the foundation for formal spatial price equilibrium models. Takayama and Judge (1971)'s seminal model further formalized how prices and flows adjust to eliminate arbitrage opportunities, resulting in prices in surplus regions rising and prices in deficit regions falling until the difference equals the cost of transporting the commodity.

In the context of U.S. corn markets, these equilibrium forces are reflected in the basis: the local cash price minus the futures price. The corn basis at a specific location is primarily determined by the cost of transporting corn to the delivery market (or export point) plus local supply and demand factors. In an efficient market, persistent basis differences between two locations should mirror transport costs and constraints; if the price gap exceeds transportation costs, arbitrage through physical grain shipment or storage should occur to restore equilibrium. Consequently, transportation costs are often regarded as the "anchor" of spatial price differentials, and movements in the corn basis frequently correspond to changes in freight rates and infrastructure conditions. For example, a recent panel analysis of U.S. soybean markets found that a \$1 increase in barge shipping costs led to approximately a \$0.19 per bushel decrease in interior soybean basis (Lakkakula and Wilson, 2021), highlighting how higher transport costs weaken local prices (or widen the basis) in producing regions. Although that study focused on soybeans, the behavior of corn basis is similar due to the shared reliance on the Mississippi River for bulk transport.

Numerous empirical studies confirm that Mississippi barge rates are a critical determinant of corn and soybean basis in river markets (McKenzie, 2005; Yu et al., 2006; Haigh and Bessler, 2004). Increases in barge rates tend to widen the inland–export price spread, which weakens the inland basis and/or strengthens the Gulf basis because buyers in interior regions must bid lower to account for the increased cost of transporting grain to the Gulf. Consistent with this, McKenzie (2005) found that shocks to barge freight rates significantly impacted soybean basis at both the Arkansas origin and the Gulf destination, demonstrating that inland and Gulf basis respond together to changes in transportation costs.

Moreover, the volatility of barge freight rates is also an important factor; barge rates are several times more volatile than grain prices (Haigh and Bryant, 2001). Haigh and Bryant (2001) demonstrated that Mississippi barge freight prices exhibit higher volatility than corn prices, which can amplify basis risk for market participants. This persistent volatility in transport costs increases uncertainty in local price relationships, as elevators and traders must navigate rapid fluctuations in the cost of moving grain. Together, these studies highlight that changes in transportation costs, whether gradual or shock-induced, are significant drivers of spatial basis dynamics in U.S. corn markets.

Transportation plays a central role in shaping spatial price relationships, and understanding these effects has evolved. Earlier literature primarily utilized pairwise market integration tests and time-series methods to infer spatial linkages. A common approach was to test for cointegration between prices at different locations, based on the expectation that well-integrated markets should not diverge in the long run. However, McNew and Fackler (1997) warned that using cointegration as a market integration test can be problematic when transportation costs are significant. Using simulated spatial equilibrium examples, they demonstrated that perfectly efficient, arbitraged markets do not necessarily produce cointegrated price series. Price differences can fluctuate within a "band" set by transaction costs, such as transport and handling fees, without establishing a stable long-term relationship. A direct consequence is that standard cointegration tests might falsely indicate market segmentation, even if the Law of One Price holds within certain cost thresholds.

In response to this insight, subsequent research introduced threshold cointegration and parity bound models, which explicitly allow for a neutral band where price gaps up to the transportation cost do not invoke arbitrage (Baulch, 1997; Goodwin and Piggott, 2001; Barrett and Li, 2002). These models recognize that spatial arbitrage only occurs when the price difference exceeds the shipping costs, adding non-linearity to price adjustments. Such threshold-based analyses confirmed that corn and soybean markets are often integrated in a conditional sense, and price disparities lead to trade only when they are large enough to cover transportation fees. For example, Goodwin and Piggott (2001) found that price transmissions in Midwestern corn markets exhibited inaction within a band roughly equivalent to transport costs, alongside rapid adjustments once the prices moved outside that band. These findings reinforce the theory that transportation costs create a buffer for price differences, but also highlight a limitation of purely time-series approaches: the complex network of spatial interactions, characterized by multiple competing routes and modalities, is not easily captured by simply analyzing pairs of markets or assuming static thresholds.

Recently, researchers (Elhorst, 2010; Weng et al., 2023; LeSage and Pace, 2009a; You and Lv, 2018; Wetzstein et al., 2019, 2021) have increasingly adopted spatial econometric techniques to model agricultural markets' interconnectedness more accurately. Spatial econometrics provides a framework that quantifies spillover effects across multiple locations simultaneously, recognizing that shocks in one region can impact others through the network of trade and arbitrage. Unlike traditional time-series or panel regressions, which assume independence among locations, spatial models use a spatial weight matrix to formally define which markets are "neighbors" and the strength of their interactions (Weng et al., 2023; You and Lv, 2018; Wetzstein et al., 2019, 2021). These techniques allow for estimating how much a price change in one area is transmitted to others, beyond what common temporal factors can explain.

The Spatial Durbin Model (SDM) has been particularly favored for such analyses (LeSage and Pace, 2009b). The SDM incorporates both spatially lagged dependent variables and spatially lagged independent variables, enabling researchers to capture direct effects (the impact of local factors on local prices) and indirect effects (the impact of local factors on neighboring prices) within a single model. LeSage and Pace (2009b) suggests that the SDM is often superior for applied work because it encompasses other spatial specifications and reduces bias from omitted spatially correlated covariates. In the context of grain prices, an SDM can model how a shock to corn basis in one location might influence nearby prices and how changes in transportation costs or supply in one area (as an independent variable) can affect prices elsewhere through the trade network. This approach shifts the literature from simply assessing whether two markets move together to quantifying the network multiplier effects of local shocks.

Several applications of spatial econometric models to U.S. agricultural markets illustrate the effectiveness of this approach. For instance, Jensen and Miller (2014) applied a spatial error correction model to regional milk prices in the U.S., revealing significant spatial error correlations due to overlapping procurement areas. In the grain sector, Grashuis (2019) explored spatial competition among Iowa corn elevators using a spatial lag and Durbin framework; interestingly, that study found limited spatial dependence in cash bid levels once firm-specific factors were taken into account, suggesting that spatial price spillovers can be diminished in the presence of localized market power or varied buyer behavior. Nonetheless, the general evidence indicates that spatial linkages are economically significant in many agricultural markets, especially those connected by a common infrastructure or flow path.

The Mississippi River corridor is an ideal "natural laboratory" for examining spatial spillovers driven by transportation costs. It operates as a quasi-linear market network where corn from upriver states (such as Illinois, Iowa, and Minnesota) is systematically transported down to the Gulf for export. This setup implies a directed chain of price influences that shapes market dynamics. Numerous studies underscore the critical role of the Mississippi River system in U.S. grain logistics, with over half of U.S. corn exports in certain years originating from the Gulf and predominantly supplied by barges traveling along the Mississippi and Illinois Rivers.

Consequently, interior corn prices in regions adjacent to the river are closely tied to Gulf export prices, adjusted for the barge rate. When barge costs increase, whether due to higher fuel prices, strong demand, or physical constraints on river transport, inland elevators must lower their bids for corn, resulting in a widening basis to maintain their profit margins. Conversely, declines in barge freight prices or expansions in capacity usually strengthen the inland basis relative to the Gulf. Empirical evidence associated with the Mississippi River corridor supports these mechanisms. Li and Thurman (2013) examined the spatial distribution of corn basis across U.S. regions and explicitly included barge rates as a crucial factor in their analysis. They concluded that waterway transport costs account for inter-regional basis differentials and highlighted the critical upstream–downstream price transmission along the river. While Li and Thurman's work was presented as a conference paper, its findings align closely with more recent and systematic analyses. For example, Lakkakula and Wilson (2021) conducted a panel study assessing soybean basis at both interior and export locations, estimating the interdependence among origin basis, Gulf basis, and shipping costs. They reported that a \$1 per ton increase in barge shipping rates typically leads to an approximate \$0.19 per bushel decrease in interior basis, accompanied by a corresponding increase in Gulf basis. This elasticity reflects a straightforward reality: higher barge costs are shared between upward adjustments in farmgate prices in the interior and increased prices or higher basis at the Gulf to maintain competitiveness in exports. Their findings emphasize that fluctuations in transportation costs are effectively transmitted through the market, impacting buyers and sellers in different locations throughout the river system. Additional studies have also explored exogenous disruptions to the river transport network, such as infrastructure failures or extreme weather, to evaluate their effects on spatial price relationships.

Yu et al. (2006) studied the influence of lock delays on the Upper Mississippi and Illinois Rivers on grain barge rates. They discovered that prolonged lock congestion could elevate barge tariffs, albeit modestly. When such cost increases occur, they invariably impact the local basis– if barge delays raise the cost of transporting corn southward, elevators upriver will adjust their bids downward relative to futures to compensate. Moreover, Barrett (2021) illustrated this dynamic through patterns observed in the Mid-South regional basis. During winter months, when the Upper Mississippi is seasonally closed to navigation (Tuthill and Mamone, 1998), southern elevators (in Memphis, Arkansas, and Louisiana) noted a strengthening of their basis compared to northern areas. The inability to ship corn from the Upper Midwest effectively tightened supply in the South, driving up southern cash prices while northern basis weakened due to surplus. This seasonal divergence stands as consistent evidence that transport availability dictates price linkages. Episodic disruptions, like floods or drought-induced low water levels, are even more pronounced. The USDA and various university economists have documented significant events, such as the 2012 drought and the autumn 2022 low water crisis on the Mississippi (Farm Policy News, 2024), both of which resulted in record barge rate spikes and historically wide basis spreads. For instance, in late 2022, the river's low levels forced reductions in barge loads and slowed traffic. Barge tariffs from St. Louis to the Gulf skyrocketed to over 2000% of the benchmark tariff (exceeding $90/ton, multiple times the typical rate). In response, interior cash prices fell sharply: the Illinois corn basis, usually only mildly negative post-harvest, diminished to exceptionally weak levels as elevators discounted prices to offset exorbitant freight costs, while the Gulf export basis soared to unprecedented highs as exporters offered premiums for limited supplies. This resulted in an "extreme divergence," with a nearly $3.00 per bushel gap between Gulf and interior corn prices, directly reflecting the soaring transportation costs and the disruption of regular grain flows. This real-world scenario powerfully illustrates how spatial equilibria can shift in response to changes in transport cost structures. Furthermore, it underscores that spatial spillovers are far from theoretical; a shock in one region (such as low water at a river chokepoint) can ripple through freight markets, ultimately impacting farm prices across a wide area of the Corn Belt.

The literature collectively illustrates that transportation costs and spatial price adjustments are closely connected in grain markets. Transportation infrastructure and rates act as the binding force that integrates regional markets, meaning that changes in this infrastructure can have widespread effects. A prime example of this is the market behavior along the Mississippi River; understanding local corn basis requires consideration of influences from both upstream and downstream conditions.

From a methodological perspective, earlier studies using cointegration or simple regression methods indicated these connections but often faced challenges in accurately pinpointing price movements to spatial factors versus other influences. The introduction of spatial econometric approaches offers a more detailed viewpoint. By implementing an upstream-to-downstream spatial weighting scheme, essentially mapping the river's network into the model, this research can directly test for directed spillover effects. For instance, the study investigates whether price shocks or cost changes in an upstream market significantly impact prices downstream, as theory suggests. It also assesses how far along the river these effects extend.

This approach aligns with the southbound flow of corn and recognizes that spatial dependence may not be symmetrical. Traditional spatial models typically assume mutual influence among neighbors, but upstream locations can exert greater influence on downstream markets in a tree-like transport network. The study refines insights from previous empirical findings within a robust framework that distinguishes local effects from spillover effects by utilizing a Spatial Durbin Model with a customized weighting matrix oriented from upstream to downstream.

In doing so, this study bridges the gap between the substantial theoretical literature on spatial price equilibrium and arbitrage and the contemporary empirical literature focused on network interactions and spatial econometric estimation. The theoretical expectation here is that transportation cost variables will have both direct and indirect impacts on local basis. For example, a rise in barge rates at a specific upriver location might reduce shipments from that point, which could tighten supply downstream and potentially strengthen the basis at downstream locations or induce substitution from nearby areas. The Spatial Durbin framework allows us to incorporate both the local and spatially lagged barge rates of upstream markets as variables, capturing these multiregional dynamics. Previous studies suggest that such spillovers are expected; for instance, Yu et al. (2004) found that changes in barge rates accounted for a modest 2–4% of the variance in grain prices, even in distant markets. A more comprehensive dynamic analysis revealed that shocks to barge, rail, and ocean freight rates could collectively explain as much as 40–65% of the variation in U.S. corn prices over time. Although ocean freight (linked to global demand) was the most significant influence in this study, barge costs also played a notable role. These findings indicate that local price effects from a transportation cost change transmit broadly, meaning a shock at one location on the river can have measurable consequences for prices elsewhere.

In sum, the literature clearly shows that transportation costs are crucial in determining spatial corn basis and spillovers. Foundational theories suggest that price spreads reflect transport charges, and decades of empirical research, from static spatial equilibria to time-series and panel analyses, have confirmed this relationship. The Mississippi River system has been a central focus, with numerous studies (see Haigh and Bryant, 2001; Lakkakula and Wilson, 2021; McKenzie, 2005; Yu and Fuller, 2005, for example) demonstrating how levels and volatility of barge rates influence relative prices between interior and Gulf markets. Furthermore, natural experiments such as river disruptions have dramatically illustrated spatial spillover effects in real time. However, the forms and magnitudes of these spillovers in a multivariate, spatially interactive context have been less explored until recently. By quantifying how changes in one location's basis or transport cost affect other locations throughout the network, the application of a Spatial Durbin Model with an upstream-downstream weighting structure effectively addresses this gap, leveraging spatial econometric techniques to estimate those spillover coefficients. By synthesizing insights from prior research and using this new approach, the present study aims to enhance our understanding of the spatial dynamics of corn basis. Ultimately, this work contributes to both the agricultural economics literature on market integration and the applied econometrics literature on modeling directed network effects, providing a clearer picture of these relationships that can inform transportation infrastructure decisions.

2 Data

We use weekly data from February 2014 to May 2024 (Table 1). Corn basis and barge freight rate data were obtained from the USDA Agricultural Marketing Service (AMS). Corn is a particularly relevant crop for this analysis due to its high volume of production, significant transportation demand, and large share of exports moving through inland waterways Additionally, corn is a staple U.S. crop with a strong reliance on river-based transport. The Mississippi River system is a central export channel for corn shipments, especially during peak harvest. The data period encompasses a range of economic disruptions and extreme weather events that are expected to influence both freight costs and corn basis. This allows us to explore how transportation constraints shape commodity price behavior over time, providing insights that are especially relevant in today's evolving agricultural markets.

2.1 Corn Basis

We examine corn basis as the primary outcome variable. Basis is defined as the difference between local cash prices and futures prices, and captures localized market conditions that are distinct from broader commodity market trends. By focusing on the basis, we can better assess how changes in transportation costs, particularly those associated with barge freight rates on the Mississippi River, affect regional pricing dynamics. Events such as low river water levels primarily impact

Table 1: Variables, Units of Measurement, and Sources

Variable	Definition	Units	Source
Corn Basis	Difference between the local cash price and futures price for corn	USD/bushel	USDA Grain Transportation Report
Barge Rates	A direct measure of barge transportation costs	USD per bushel	USDA Grain Transportation Report
Gauge Height	The water level recorded at a river gauge station, typically measured relative to a fixed reference point.	Feet (ft)	U.S. Geological Survey (USGS) or Army Corps of Engineers
Diesel Price	Weekly PADD 2 diesel price (USD/gal) × distance (miles) from the basis market to the nearest river terminal.	USD miles per gallon	Energy Information Administration (EIA)

transportation and, consequently, local basis rather than national or global corn price fundamentals. As such, fluctuations in barge rates serve as an important source of basis risk for corn producers who rely heavily on river transport for market access. Basis is computed as:

$$\text{Basis}_{j,t} = \text{Spot Price}_{j,t} - \text{Futures Price}_{j,t} \tag{1}$$

where j is the location, at time t. A positive basis indicates that the spot price is higher than the futures price, often reflecting local supply shortages or high demand. Conversely, a negative basis suggests that the futures price exceeds the spot price, potentially indicating an oversupply or lower demand in the local market.

Basis guides producers who hedge early in the season by informing the expected cash price they can protect through futures or options, despite potential differences between cash and futures prices at the time of sale. Unlike spot or futures prices, which reflect global supply and demand, the basis captures local market conditions, varying by crop, time, and location. It also reflects transportation and storage costs and guides the flow of commodities from surplus to deficit regions.

We focus on fourteen (14) locations along the Mississippi River System with available data on weekly barge rates and grain basis, enabling the analysis of how transportation costs influence grain price dynamics. These sites span the Mississippi River and key tributaries, covering major grain-producing and transit regions from the Upper Mississippi to the Gulf. Figure 1 maps out the markets.

Corn basis data are from 2014 to 2024 USDA reports, which provide weekly cash bid and basis data for the following 14 grain markets: Central Illinois, Chicago, Cincinnati, Gulf, Kansas City, Memphis, Mount Vernon (Ohio), Nebraska, North Peoria, Omaha, South Iowa, South Peoria, St. Louis, and Toledo. Each market is reported using the name of a city, representing a broader grain market rather than an individual elevator or facility. These regional markets reflect prevailing cash bids and local basis conditions, capturing spatial variation in supply, demand, and transportation access. These 14 locations span major grain-producing and export-oriented regions along the Upper, Middle, and Lower Mississippi River, as well as key interior hubs linked to river transport.

2.2 Barge Rates

The barge freight rates[1], collected for the Mississippi River, provide a direct measure of transportation costs, a crucial component influencing commodity prices due to the river's role as a primary route for grain exports. Barge operators utilize a barge percent-of-tariff (BPOT) system to determine transportation costs along the river. Fluctuating spot rates for grain shipments are typically quoted for loadings expected within the next 30 days. The cost per ton to transport commodities is calculated by multiplying the variable BPOT rate by the fixed historical tariff rate for specific locks in each river segment, reflecting the cost from the origin to demand centers, usually export hubs in the Gulf (Wetzstein et al., 2019). For instance, a 289-percent tariff for a St. Louis grain barge, when multiplied by a benchmark rate of \$3.99, results in a rate of \$11.53 per ton. Each river segment has distinct benchmark rates, with northern segments generally higher.

We examine six key locations along the Mississippi River System: Cairo-Memphis, Cincinnati, Lower Illinois, Mid-Mississippi, and St. Louis. Spanning over 2,000 miles of navigable waterways maintained by the Army Corps of Engineers, these locations encompass major grain-producing and transit regions from the Upper Mississippi to the Gulf (See Figure 1).

2.3 Gauge Height

To understand how water levels on the Mississippi River affect corn basis through barge transportation, we use gauge height data from official stream gauges managed by the U.S. Geological Survey (USGS) and the National Weather Service (NWS). These gauges are located at key points along the river, including Chester, IL; Winona, MN; and Belle Chasse, LA, capturing conditions in the upper, middle, and lower sections of the river. Gauge height, measured in feet, represents the

[1] To make the freight rate easier to interpret, we convert the barge rate from a per-ton basis to a per-bushel basis. Since one ton equals 2,000 pounds and one bushel of corn weighs 56 pounds, we calculate the rate per bushel by dividing the rate per ton by 2,000 and then multiplying by 56. This gives us the equivalent cost to ship one bushel of corn by barge, making it easier to compare transportation costs on a per-bushel basis.

vertical distance from a fixed reference point (the river datum) to the water's surface (Lurry, 2010). This measure is location-specific and cannot be directly compared across gauges due to differences in local riverbed elevations (Fahlquist and Hopkins, 2023).

Gauge height is a practical and widely used indicator of navigability, as it forms the basis for flood and drought stage classifications by the NWS. For example, the NWS defines specific threshold values at the Memphis, TN gauge: 28 feet for action stage and 5 feet or below for low-stage conditions (National Weather Service, 2023). A low-stage event indicates river levels are sufficiently shallow to pose risks to navigation, restrict barge traffic, or affect water intake systems. These events, while relatively infrequent, can lead to considerable transportation disruptions and costs.

As the Mississippi River water levels decline, transporting corn by barge becomes more expensive and, in severe cases, barge traffic may be halted altogether. These disruptions influence corn basis, depending on how easily grain elevators can switch to alternative transportation modes such as rail or truck. River-adjacent terminals typically lack viable transportation substitutes, so they face steeper basis declines during low water events. In contrast, grain elevators located farther inland tend to rely more on rail or truck year-round. These elevators can adapt more easily when river shipping is disrupted, leading to smaller changes in basis (Mitchell and Biram, 2025).

2.4 Diesel Price

Diesel fuel prices are a critical component of transportation costs, particularly for barge, truck, and rail freight in agricultural supply chains. In this study, weekly diesel prices from the Petroleum Administration for Defense District (PADD) 2 are used, as all basis markets analyzed fall within this region. PADD 2 includes the Midwest, a core area for U.S. corn production and grain movement The diesel price data were obtained from the U.S. Energy Information Administration (EIA) and represent average wholesale diesel prices within PADD 2, expressed in dollars per gallon.

To approximate the cost of transporting grain from local basis markets to river terminals, the PADD 2 diesel price is multiplied by the distance from each market to the nearest barge-loading river location. This distance-weighted fuel cost proxy captures spatial variation in transportation expenses driven by both fuel prices and location-specific access to river infrastructure. Higher diesel prices or greater distances to the river increase the cost of moving grain, which can widen the basis in inland markets. This approach enables a more nuanced understanding of how fuel price dynamics impact regional basis patterns through their influence on transportation costs. This is computed as:

$$\text{Diesel Distance Cost}_{it} = \text{Diesel Price}_t \times \text{Distance to River}_i \tag{2}$$

where t: time index (weekly) and i: basis market location

2.5 Matching the Data

To further analyze the relationship between river conditions and corn basis, we then matched each corn basis market to the nearest barge location based on geographic proximity. This ensures that basis values reflect price dynamics most influenced by transportation conditions at nearby barge loading points. Next, we linked each of these basis markets to the closest river gauge height measurement, allowing us to assess how local river levels may impact barge traffic and, in turn, grain prices. This stepwise matching process, basis-to-barge location, then to river gauge, provides a spatially consistent framework for analyzing the effect of river system variability on corn pricing (See Figure 1)

Each corn market in our dataset was matched to its nearest river gauge to ensure that local water conditions are appropriately reflected. In cases where data were missing, we applied linear interpolation to fill small gaps without distorting trends. Incorporating gauge height adds an important physical dimension to our understanding of how barge freight costs influence corn basis. River depth affects barge draft limits, which in turn shape transportation capacity. For example, while the U.S. Army Corps of Engineers aims to maintain a navigable channel depth of nine feet, river conditions may allow barges to load up to 12.5–13 feet in draft under optimal conditions. Lower water levels reduce barge capacity, raise shipping costs, and ultimately affect local basis (Wetzstein et al., 2019).

3 Empirical Method

Grain movement and export focus on downstream flow, and most upstream barges are either empty or carry non-grain commodities. Downstream interactions form a one-way relationship, where downstream rates affect upstream movements, but not vice versa. This is why we focus on downstream barge rates, because the relationships across river segments are unidirectional. Barge operators are primarily focused on the river levels downstream from their loading point, as these determine navigability for the loaded vessel. Therefore, this analysis focuses on downstream-bound

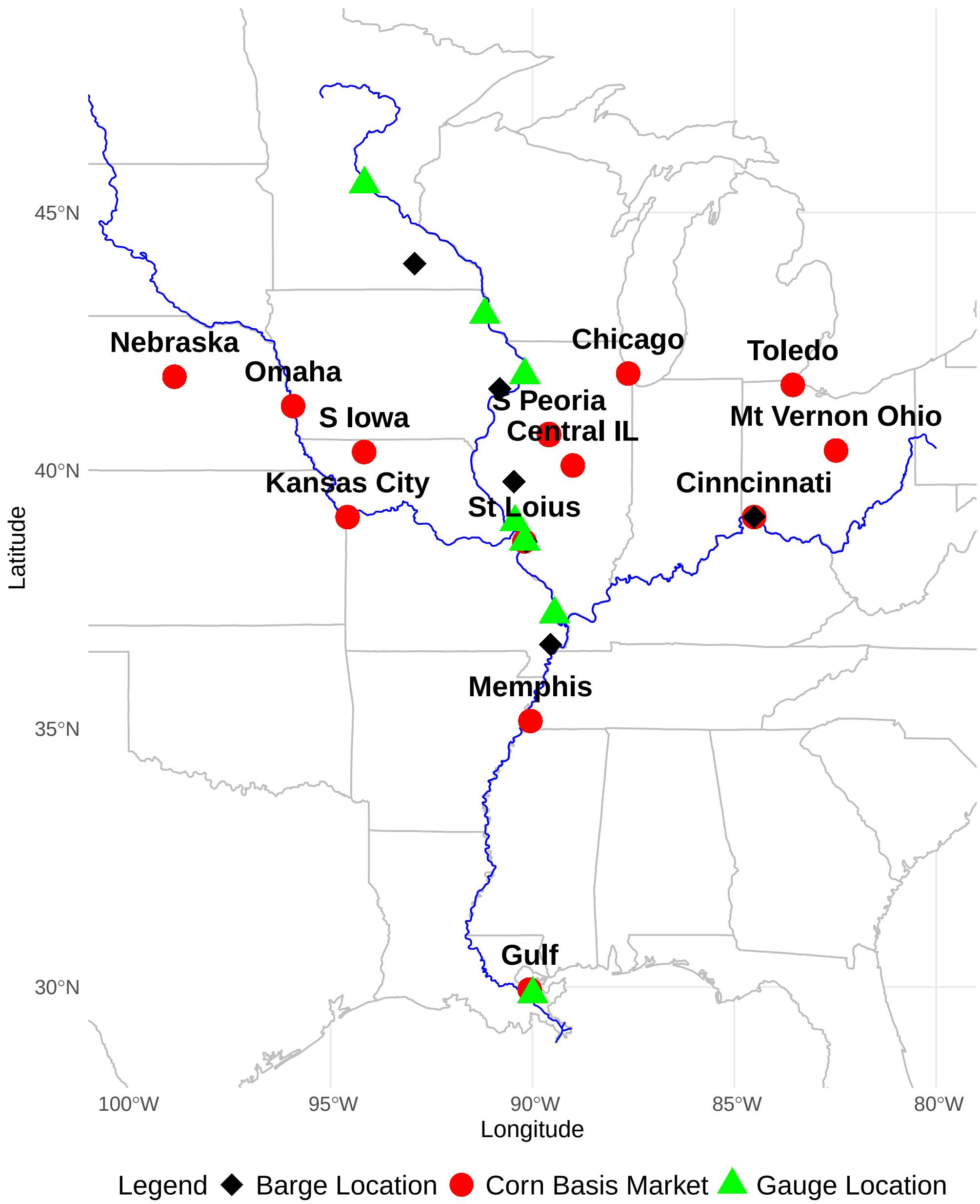

Figure 1: Corn Basis Markets, Barge Locations and Gauge stations along the Mississippi River system

Note: This figure displays the 14 corn basis markets, barge rate reporting locations, and river gauge stations along the Mississippi River system used in this study. The basis markets are represented by city-level locations. Barge locations correspond to points where barge freight rates are reported, while gauge stations indicate monitoring sites for river stage levels. Together, these spatial references capture the transportation and pricing dynamics across key nodes of the grain export network, spanning the Upper, Middle, and Lower Mississippi River regions.

shipments Wetzstein et al. (2021). Further, we focus on fourteen regions (Figure 1) crucial to commodity movement along the Mississippi River and employ a Spatial Durbin Model (SDM) to account for spatial dependencies and dynamic interactions between corn basis and other transportation variables. This approach enables us to capture spatial spillover effects and the evolving impacts of fluctuating barge rates on corn basis, particularly in response to volatile conditions.

3.1 Spatial Model

The Spatial Durbin Model (SDM) is used to analyze the spatial spillover effects, drawing on the methodological framework established by Elhorst (2010). The SDM offers a versatile modeling structure that extends beyond the capabilities of the Spatial Autoregressive (SAR) and Spatial Error Model (SEM) (Weng et al., 2023). Consistent with the approaches outlined by LeSage and Pace (2009a) and further refined by You and Lv (2018), the general form of the SDM in this research is expressed as follows:

$$\begin{aligned}\mathcal{B}_{i,t} = \alpha + \rho \sum_{j=1}^{N} \mathcal{W}_{ij} \mathcal{B}_{j,t} + \beta_1 \mathrm{X}_{i,t} + \sum_{k=2}^{M} \beta_k \mathrm{Z}_{k,i,t} \\ + \gamma_1 \sum_{j=1}^{N} \mathcal{W}_{ij} \mathrm{X}_{j,t} + \sum_{k=2}^{M} \gamma_k \sum_{j=1}^{N} \mathcal{W}_{ij} \mathrm{Z}_{k,j,t} \\ + \mu_i + \eta_t + \epsilon_{i,t}.\end{aligned} \tag{3}$$

where i and j index spatial units, and t represents time period.

The dependent variable in Equation (3), $\mathcal{B}_{i,t}$, represents corn basis in market $i.\mathcal{B}_{j,t}$ is the corn basis at location j while the main explanatory variable is the barge freight rate ($X_{i,t}$, $X_{j,t}$) in locations i and j respectively. Additional controls (diesel price, gauge height, Fourier terms) account for broader factors, represented by the vector $\{Z_k\}_{i,t}$ and $\{Z_k\}_{j,t}$ for locations i and j respectively.. The spatial weights matrix, $\mathcal{W}$, quantifies spatial relationships between regions, with $\mathcal{W}_{ij}$ representing the spatial weight between regions i and j. This specification allows us to isolate the effects of transportation-related shocks on localized corn price dynamics.

The key model parameters include ρ, which measures the spatial autoregressive effect, or the influence of neighboring regions' corn basis values on region i. Fixed effects, μ_i and η_t, control for unobserved region-specific and time-specific heterogeneity, respectively. Finally, the error term $\epsilon_{i,t}$ is assumed to be independently and identically distributed with zero mean and constant variance, ensuring robustness of the model's statistical properties.

3.1.1 Disentangling Direct and Indirect Effects

In contrast to the coefficients from non-spatial models, the parameter estimates of the Spatial Durbin Model (SDM) cannot be directly interpreted as marginal effects because spatial dependence introduces feedback effects (LeSage and Pace, 2009a). To address this, the coefficients are typically separated into direct and indirect effects. Drawing from Elhorst (2010), the SDM equation (3) can be expressed as:

$$\mathbf{Y}_t = (\mathbf{I}_N - \rho\mathbf{W})^{-1}(\mathbf{X}_t\boldsymbol{\beta} + \mathbf{W}\mathbf{X}_t\boldsymbol{\gamma}) + \mathbf{R}_t, \tag{4}$$

where $\mathbf{Y}_t$ is the dependent variable, $\mathbf{X}_t$ includes the independent variables, and $\mathbf{R}_t$ encompasses additional terms such as the constant and error.

To determine the impact of the k-th independent variable on the dependent variable across all units at time t, the matrix of partial derivatives is given by:

$$\begin{aligned}\left[\frac{\partial E(\mathbf{Y})}{\partial x_{1k}} \cdots \frac{\partial E(\mathbf{Y})}{\partial x_{Nk}}\right]_t &= (\mathbf{I}_N - \rho\mathbf{W})^{-1} \begin{bmatrix} \beta_k & w_{12}\gamma_k & \cdots & w_{1N}\gamma_k \\ w_{21}\gamma_k & \beta_k & \cdots & w_{2N}\gamma_k \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1}\gamma_k & w_{N2}\gamma_k & \cdots & \beta_k \end{bmatrix} \\ &= (\mathbf{I}_N - \rho\mathbf{W})^{-1}(\beta_k\mathbf{I}_N + \gamma_k\mathbf{W})\end{aligned} \tag{5}$$

The **direct effect** is obtained by averaging the diagonal elements of the matrix $(\mathbf{I}_N - \rho\mathbf{W})^{-1}(\beta_k\mathbf{I}_N + \gamma_k\mathbf{W})$. This represents the mean effect of a one-unit change in an independent variable on the dependent variable within the same unit. The **indirect effect**, also referred to as the spillover effect, is calculated by averaging the row sums of the off-diagonal elements in the same matrix. This captures the influence on a unit's dependent variable resulting from a one-unit change in the independent variable in other units. The **total effect** is the sum of the direct and indirect effects.

It is important to highlight that the direct effect differs from the estimated coefficient $\hat{\beta}$ in the original model equation (3) due to feedback effects. These effects occur because changes propagate through neighboring units and may circle back to the originating unit (e.g., passing from unit $i \rightarrow j \rightarrow i$ or through more complex routes such as $i \rightarrow j \rightarrow k \rightarrow j \rightarrow i$).

3.2 Spatial Weights Matrix

We define a spatial weight matrix[2] to capture potential spatial interactions among river segments. This nonnegative matrix, denoted as $\mathcal{W}_{ij}$,[3] quantifies the spatial influence of segment i on segment j (Bhattacharjee and Jensen-Butler, 2013; Wetzstein et al., 2021). A distance-based spatial weight matrix assigns weights to neighboring segments inversely proportional to their distances, with elements normalized by the sums of the rows to ensure comparability.

The choice of an appropriate spatial weights matrix is critical, as different weighting schemes can reveal distinct spillover effects (LeSage and Pace, 2009a). For our baseline, we use geographical distance. According to Tobler (1970), spatial correlations typically decrease as the geographical distance between locations increases. To account for this, we employ an inverse distance matrix, which captures spatial correlations that decay with distance (see, for example, (Weng et al., 2023; You and Lv, 2018)). The elements of the spatial weights matrix are defined as:

$$w_{ij} = \begin{cases} \frac{1}{d_{ij}} & \text{if } i \neq j, \\ 0 & \text{if } i = j, \end{cases} \tag{6}$$

where d_{ij} represents the geographical distance between regions i and j. Following standard practice, we apply row-sum normalization so that the sum of the elements in each row equals one.

Specifically, $\mathcal{W}$ measures the relationships between the corn basis in one segment and both current and historical values of the corn basis in adjacent segments, with distances calculated in river miles between the midpoints of these segments. This approach is consistent with (Ollier et al., 2003; Adjemian et al., 2011; Wetzstein et al., 2019), who used a spatial weight matrix to explore interactions among segments with a common endpoint. In our model, the spatial weight matrix captures one-way interactions where only downstream segments influence those upstream.

The spatial weight matrix $\mathcal{W}$ establishes lagged interactions among the corn basis of different river segments, imposing spatially determined constraints on the cross-lag parameters. The normalized inverse distance spatial weight matrix used in our analysis is shown in Table 2.

[2] Spatial weights define how "neighbors" are identified in spatial analysis. Based on Tobler (1970)'s First Law of Geography (1970) — "near things are more related than distant things" — this principle supports methods like spatial autocorrelation

[3] See Table 2

3.2.1 Measuring Distances

To accurately capture the spatial structure of inter-market relationships, we compute geodesic distances between all corn basis market locations. Each market is georeferenced using its latitude and longitude coordinates, and the pairwise distances are calculated as the shortest path between two points on the Earth's surface (i.e., great-circle distances). These geodesic distances provide a precise and realistic measure of physical proximity, which serves as the foundation for constructing the spatial weight matrix used in the Spatial Durbin Model (SDM) (See Tables 2) The weight matrix reflects how strongly each market is connected to others based on geographic closeness, enabling the model to account for spatial spillovers in corn basis behavior. Incorporating distances ensures that the analysis of spatial dependence is grounded in the actual transportation and trade geography of the U.S. corn market.

Table 2: Normalized inverse distance spatial-weight matrix

	Central IL	Chicago	Cinncinnati	Gulf	Kansas City	Memphis	Mt Vernon Ohio	Nebraska	N Peoria	Omaha	S Iowa	S Peoria	St Loius	Toledo
Central IL	0.00	0.12	0.00	0.00	0.00	0.00	0.05	0.00	0.33	0.05	0.06	0.34	0.00	0.06
Chicago	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Cinncinnati	0.11	0.11	0.00	0.00	0.00	0.00	0.20	0.11	0.10	0.05	0.05	0.10	0.00	0.16
Gulf	0.08	0.06	0.07	0.00	0.08	0.15	0.06	0.08	0.07	0.06	0.07	0.07	0.09	0.06
Kansas City	0.09	0.07	0.00	0.00	0.00	0.00	0.04	0.09	0.10	0.17	0.31	0.10	0.00	0.05
Memphis	0.10	0.07	0.08	0.00	0.09	0.00	0.06	0.10	0.09	0.06	0.08	0.09	0.14	0.06
Mt Vernon Ohio	0.00	0.15	0.00	0.00	0.00	0.00	0.00	0.13	0.12	0.06	0.00	0.12	0.00	0.42
Nebraska	0.00	0.22	0.00	0.00	0.00	0.00	0.00	0.00	0.60	0.08	0.00	0.00	0.00	0.10
N Peoria	0.00	0.71	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.29
Omaha	0.00	0.34	0.00	0.00	0.00	0.00	0.00	0.00	0.44	0.00	0.00	0.00	0.00	0.23
S Iowa	0.00	0.10	0.00	0.00	0.00	0.00	0.06	0.13	0.15	0.33	0.00	0.15	0.00	0.07
S Peoria	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.03	0.96	0.00	0.00	0.00	0.00	0.00
St Loius	0.16	0.07	0.06	0.00	0.08	0.00	0.04	0.16	0.13	0.05	0.08	0.13	0.00	0.05
Toledo	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: This displays the corresponding spatial-weight matrix, where non-zero upstream relationships are weighted by the normalized inverse geodesic distance between market pairs. This matrix is row-standardized so that the weights for each row sum to one, ensuring comparability across markets within the Spatial Durbin Model framework.

3.3 Spatial Autocorrelation

Spatial autocorrelation analysis provides a framework for understanding the mechanisms of spatial clustering and heterogeneity among research variables by describing the spatial distribution patterns of observed phenomena (Anselin, 2001). It is typically divided into global and local spatial autocorrelation measures. Global spatial autocorrelation evaluates the overall similarity of observed values, such as corn basis, across adjacent regions, identifying whether a spatial pattern exists across the entire study area. However, when the study area covers a broad geographic range, global measures may overlook localized variations or spatial heterogeneity, failing to reflect the specific spatial relationships within smaller units. To address this limitation, local spatial autocorrelation can reveal fine-grained patterns, identifying high- or low-value clusters within and between neighboring regions (Anselin and Rey, 1997).

This study applies local spatial autocorrelation to investigate whether spatial clustering exists in corn basis across regions along the Mississippi River system. The Moran scatterplot and Local Indicators of Spatial Association (LISA) cluster maps are then utilized to analyze the extent of high-value or low-value spatial clustering of corn basis between river-adjacent regions. The corresponding formulas for these measures are as follows:

The Global Moran's I is calculated as:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \cdot \sum_{i=1}^{n} (x_i - \bar{x})^2}$$

The Local Moran's I is given by:

$$I_i = \frac{(x_i - \bar{x}) \cdot \sum_{j=1}^{n} w_{ij}(x_j - \bar{x})}{\sum_{i=1}^{n} (x_i - \bar{x})^2}$$

Here, x_i and x_j represent the observed corn basis in regions i and j, $\bar{x}$ denotes the mean corn basis across all regions, and w_{ij} is a binary spatial weight matrix where $w_{ij} = 1$ if regions i and j are spatially adjacent, and $w_{ij} = 0$ otherwise.

The Moran's I index ranges from -1 to 1. A positive Moran's I ($I > 0$) indicates spatial clustering, where high (or low) corn basis values are located near other high (or low) values. A negative Moran's I ($I < 0$) suggests spatial dispersion, where high values are adjacent to low values, and vice versa. An index close to zero ($I \approx 0$) reflects no discernible spatial pattern, implying that corn basis is randomly distributed across the study area (Li et al., 2020).

4 Results

This section presents the main empirical findings from our analysis of corn basis dynamics. We estimate four model specifications: (1) a Spatial Durbin Model (SDM) with directionally constrained spatial interactions, (2) an unconstrained SDM, (3) a directionally constrained SDM excluding winter months, and (4) an unconstrained SDM excluding winter months. Each model is estimated with three types of fixed effects: spatial, time, and two-way (spatial and time). For brevity, we report results from the first two specifications, which use the full sample with and without directional constraints, in the main text. Results from the additional specifications that exclude winter months are presented in the Appendix (available on request).

Before interpreting results, recall that the dependent variable is corn basis, defined as the difference between the local cash price and the futures price. A negative basis implies that local cash prices are below futures prices, while a positive basis indicates local prices exceed futures prices. Basis is said to weaken or widen as it becomes more negative and to strengthen or narrow as it becomes more positive. Accordingly, a negative coefficient on a covariate reflects a weakening (widening) of the corn basis, while a positive coefficient indicates a strengthening (narrowing) of the basis.

Our results are organized as follows. First, we discuss estimates from the constrained and unconstrained SDMs, highlighting the effects of river conditions and barge freight rates on regional corn basis. We also discuss the implications of spatial spillovers using the average direct and indirect effects from the model. Next, we assess robustness across specifications and model variations. Finally, we contextualize the magnitude of the estimated impacts, translating key coefficients into economic losses or gains for corn producers along the Mississippi River system.

4.1 Model Selection & Validation

To evaluate the suitability of the Spatial Durbin Model (SDM), we follow the model selection procedures outlined by Elhorst (2014). The test results are summarized in Table 3. We begin by assessing whether a spatial model is appropriate using a series of Lagrange Multiplier (LM) and Robust LM tests for spatial lag and spatial error dependence (Anselin et al., 2008; Debarsy and Ertur, 2010). As shown in rows one through four of Table 3, all LM and Robust LM test statistics are large and statistically significant at the 1% level.This provides strong evidence of spatial dependence in the data and justifies the use of a spatial econometric model over a non-spatial panel specification.

We then assess whether a simpler model, such as a Spatial Autoregressive (SAR) or Spatial Error Model (SEM), is sufficient, or if the more general SDM is needed. Likelihood ratio (LR) and Wald tests for spatial lag and spatial error (rows five through eight) all reject the null hypotheses at the 1% significance level.These results support the SDM as the preferred specification, indicating that neither the SAR nor SEM models alone adequately capture the spatial relationships in the data.

Finally, to determine whether a fixed-effects or random-effects model is more appropriate, we conduct the Hausman (1978) test (row nine). The test yields a p-value of 0.000, indicating rejection of the null hypothesis that the random-effects estimator is consistent. Therefore, the fixed effects

Table 3: Test Results of Model Selection

Test Statistic	**Test Statistic Value**	**P Value**
LM spatial lag	810.646	0.000
LM spatial error	1118.556	0.000
Robust LM spatial lag	133.413	0.000
Robust LM spatial error	441.323	0.000
LR spatial lag	80.98	0.000
LR spatial error	88.38	0.000
Wald spatial lag	10.31	0.016
Wald spatial error	11.81	0.008
Hausman test		0.000

Note: This table summarizes the results of various diagnostic tests used for spatial model selection. The LM, robust LM, and LR tests all yield statistically significant results ($p < 0.01$), indicating the presence of spatial dependence in the data. Among the robust LM tests, the spatial error model shows stronger significance than the spatial lag model, suggesting that a Spatial Error Model (SEM) may be more appropriate. This is also supported by the Wald tests, where the spatial error component is more significant ($p = 0.008$) than the spatial lag component ($p = 0.016$). The Hausman test yields a p-value of 0.000, indicating a statistically significant difference between fixed and random effects estimators and supporting the use of a fixed effects specification in a spatial panel context.

model is preferred. Since the coefficients in the SDM cannot be directly interpreted as marginal effects, we compute and report the average direct and indirect effects in Table 5.

4.2 Directionally Constrained SDM

4.2.1 Spatial dependence test

We begin by testing for spatial dependence in the corn basis data using the global Moran's I-statistic introduced by Moran (1950). Table 4 reports the results of this spatial autocorrelation analysis. Using a row-standardized, non-binary spatial weights matrix (W), we calculate Moran's I for corn basis over the period from 2014 to 2024. The average Moran's I value for basis is 0.260, with an expected value under the null hypothesis of no spatial autocorrelation of approximately 0, and a standard deviation of 0.007. The corresponding z-score of 36.715 and p-value less than 0.001 strongly indicate statistically significant positive spatial autocorrelation. This result implies that regions with similar corn basis values tend to be geographically clustered, validating the use of spatial econometric techniques in further analysis.

To provide a visual representation of local spatial dependence in the vicinity of each observation, Figure 2 displays Moran's I scatter plots for the corn basis and barge rates, using the specified spatial weights matrix. The first and third quadrants of the scatter plots represent clusters of similar values (i.e., high–high and low–low groupings), whereas the second and fourth quadrants

Table 4: Moran's I Statistics for Corn Basis

Variable	I	E(I)	sd(I)	z	p-value
Corn Basis	0.260	-0.000	0.007	36.715	0.000

Note: This table reports the results of the global Moran's I-statistic for corn basis using a row-standardized, non-binary spatial weights matrix. The expected value $E(I)$, standard deviation $sd(I)$, and resulting z-score and p-value are used to test the null hypothesis of no spatial autocorrelation. A statistically significant positive Moran's I indicates strong evidence of spatial clustering in corn basis across regions.

indicate concentrations of dissimilar values (i.e., high–low and low–high groupings). As Figure 2 illustrates, most observations exhibit positive spatial correlation.

4.2.2 Estimation Results

The Spatial Durbin Model (SDM) results presented in Table 5 analyze the determinants of the corn basis while explicitly accounting for spatial dependence across markets. The SDM framework is particularly well-suited for this analysis as it allows us to capture both the direct effects of explanatory variables within a given market and the indirect (spillover) effects from neighboring markets. The model specification includes spatial fixed effects, which control for time-invariant unobserved heterogeneity across the 14 geographic markets in our sample, and time fixed effects, which account for temporal shocks or macroeconomic conditions that influence all markets simultaneously.

While alternative model specifications are explored, including those with only spatial only time fixed effects our preferred specification includes both (Table 5). As detailed in the Appendix, we report the results for all specifications for completeness. However, for the sake of brevity and clarity, we focus our discussion on the model with both spatial and time fixed effects, as this specification yields the lowest Bayesian Information Criterion (BIC) among the alternatives, indicating superior model fit. This preferred model more accurately isolates the impact of barge rates and spatial interactions on the corn basis while appropriately controlling for both cross-sectional and temporal heterogeneity.

The findings from this study carry several important economic implications for grain markets, particularly in how transportation conditions influence corn basis formation across space and time. The strong and negative relationship between barge freight rates and corn basis suggests that increases in transportation costs reduce the price that grain buyers and elevators are willing to pay at origin markets. A one-dollar increase in barge rates per bushel is associated with a decline in the local basis by approximately 4.2 cents, reflecting the direct cost pressure passed on to

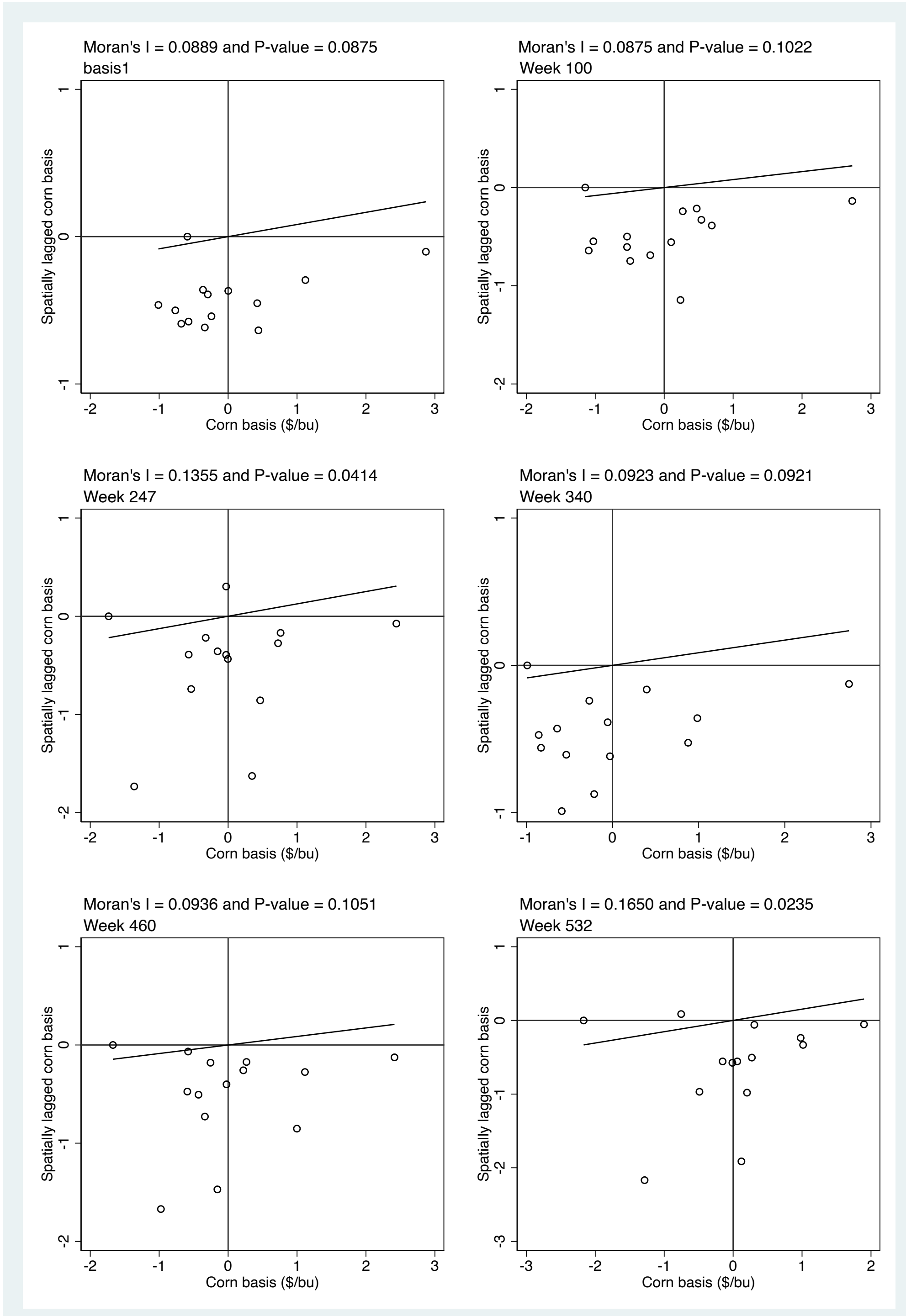

Figure 2: Moran's I scatter plots of the Corn Basis (Directionally Constrained)

Note: Moran's I scatter plots for corn basis and barge rates highlight local spatial dependence using the spatial weights matrix. The first and third quadrants depict clusters of similar values (high–high and low–low), while the second and fourth quadrants show clusters of dissimilar values (high–low and low–high). Positive spatial correlation is evident in most cases, supporting the presence of spatial dependence.

producers. This result highlights the sensitivity of local cash prices to upstream logistical costs and underscores the importance of efficient and affordable transportation infrastructure in supporting producer returns.

Beyond the direct effects, the model also identifies negative spillover effects from barge rates across space. This means that higher freight rates in one location not only reduce the basis locally but also depress basis in neighboring markets. Such spatial transmission of transportation costs reflects the interconnected nature of grain marketing systems along the river network. For traders and policymakers, this finding emphasizes that disruptions or cost increases in one region can cascade downstream, affecting pricing and competitiveness throughout the system.

River gauge height, a proxy for navigability, has a more nuanced impact. In the directionally constrained model, higher water levels are associated with a local increase in the basis but a decline in neighboring markets. This pattern suggests that while improved navigability enhances competitiveness in one region, it may do so at the expense of others by shifting market advantage. However, when spatial spillovers are modeled in the unconstrained higher river levels yield a net positive impact on the system-wide basis. This contrast illustrates that river conditions benefit the grain transportation network as a whole, but the distribution of those benefits depends on the direction and structure of market flows. The results imply that sustained investment in waterway infrastructure can generate widespread gains but may also create regional disparities if access or benefits are unevenly distributed.

The diesel price also plays a significant role in determining the corn basis. Regions experiencing higher variability in diesel prices, due to differences in local supply chains or access to fuel infrastructure, tend to see reduced basis values. The effect is statistically and economically significant, with more than 20 cents per bushel decline in the basis in areas with high diesel prices. Interestingly, these effects appear to be largely localized, as no substantial indirect effects are observed. This suggests that energy-related transportation frictions are more contained geographically and do not transmit broadly across space, unlike barge rates or river conditions.

Lastly, the negative and significant spatial lag coefficients in both models confirm the presence of spatial interdependence in corn basis pricing. A higher basis in one market tends to reduce the basis in neighboring locations, consistent with arbitrage behavior and competitive pricing. This finding reinforces the importance of accounting for spatial relationships when evaluating pricing mechanisms in agricultural markets. It also supports the notion that basis values are not determined in isolation, but rather as part of a broader, interconnected pricing system.

Table 5: SDM with Spatial and Time Fixed Effects (Directionally Constrained)

Variable	Direct Effect	Indirect Effect	Total Effect
Dependent Variable: Corn Basis ($/bu)			
Main Variables			
Barge Rates	-0.042***	-0.006**	-0.049***
	(0.002)	(0.002)	(0.003)
River Gauge Height	0.185***	-0.635***	-0.449***
	(0.058)	(0.157)	(0.155)
Diesel Price	-0.202***	0.051***	-0.151***
	(0.011)	(0.016)	(0.019)
Seasonal Controls			
Sine 1	1.472	1.075*	2.547**
	(1.031)	(0.651)	(1.266)
Sine 2	-8.997***	4.424***	-4.574***
	(1.038)	(0.680)	(1.318)
Sine 3	-3.116***	0.404	-2.712***
	(0.672)	(0.529)	(0.911)
Sine 4	4.093***	-1.573***	2.520***
	(0.712)	(0.529)	(0.948)
Cosine 1	1.589**	-0.009	1.581*
	(0.631)	(0.506)	(0.860)
Cosine 2	-0.750	1.192**	0.442
	(0.644)	(0.512)	(0.870)
Cosine 3	0.160	0.090	0.250
	(0.705)	(0.515)	(0.924)
Cosine 4	0.854	-0.113	0.741
	(0.689)	(0.489)	(0.917)
Corn basis (Spatial lag)		-0.096***	
		(0.024)	
Diagnostics			
Number of observations		7,518	
Number of markets		14	
Number of weeks		537	
Log-likelihood		-31259.06	
AIC		62566.11	
BIC		62732.31	
Sigma_e^2		239.351	

Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Notes: This table presents direct, indirect, and total effects from a Spatial Durbin Model with spatial and time fixed effects, assuming downstream-constrained spillovers. The dependent variable is the corn basis ($/bu). Barge rates and diesel prices have significant negative effects, indicating that higher transport costs reduce local basis values. River gauge height shows mixed effects, positive locally but negative across space, suggesting reallocation of trade flows. Seasonal variation is captured using Fourier terms. The negative spatial lag coefficient confirms competitive pricing across markets.

The key takeaway: the results demonstrate that transportation-related factors such as freight rates, river conditions, and fuel prices are central to understanding corn basis behavior. They influence not only local prices but also exert pressure across regions. These dynamics have critical implications for policy design, investment decisions, and risk management strategies in grain markets. A spatially informed approach that considers regional interactions can better support infrastructure planning and ensure more stable and efficient market outcomes.

5 Conclusion

This study examines the impact of river-based transportation variables, specifically barge freight rates, river gauge height, and diesel prices, on corn basis across space and time. Using a Spatial Durbin Model (SDM) with both spatial and time fixed effects, the analysis accounts for directional and symmetric spatial spillovers to better understand the mechanisms through which transportation frictions impact regional grain pricing.

The findings consistently show that barge freight rates exert a significant and negative effect on the corn basis. A $1.00 increase in barge rates (in dollars per bushel) is associated with a 4.2-cent decline in local basis values. This confirms that rising transportation costs reduce the price that elevators and grain buyers are willing to pay at the origin. Additionally, the directionally constrained model reveals statistically significant negative spillover effects, indicating that higher freight costs in one region also depress basis in adjacent markets. This suggests that logistical constraints are not contained locally but ripple through interconnected markets, reinforcing the systemic nature of transportation shocks.

River gauge height, which reflects navigability, presents differentiated impacts based on spatial assumptions. In the constrained model, higher river levels increase basis values by 18.5 cents locally but reduce them in neighboring regions by 63.5 cents, resulting in a net total effect of –44.9 cents. This implies a reallocation of competitive advantage rather than a net system-wide gain. These contrasting results underscore the importance of modeling spatial structure explicitly when evaluating infrastructure impacts.

Diesel price has a large and statistically significant negative effect on the basis. Regions with higher variability in fuel costs, owing to factors such as refinery access, local taxation, or distribution bottlenecks, see basis reductions of 20.2 cents locally, partially offset by 5.1 cent positive spillovers, for a total impact of –15.1 cents. Notably, the indirect effects, though significant, are modest, reinforcing that energy-related shocks are largely geographically contained.

The spatial lag coefficients are negative and significant, with a magnitude of –0.096, indicating that higher basis values in neighboring markets reduce the local basis. This is consistent with spatial arbitrage theory, where buyers factor in relative pricing across locations, leading to interdependent price formation.

Overall, this study demonstrates that transportation infrastructure, energy costs, and navigability have economically meaningful and spatially diffuse effects on corn basis formation. These dynamics are sensitive to how spatial relationships are modeled, affecting both the magnitude and distribution of estimated impacts. The results have important implications for infrastructure investment, grain procurement strategies, and price risk management, highlighting the need for spatially informed policies that recognize the interconnected nature of commodity markets.

5.1 Policy Implications and Future Work

The aging infrastructure of the Mississippi River system presents a growing risk to maintaining reliable and stable-cost transportation for bulk agricultural commodities. As highlighted by Farm Policy News (2024), outdated locks and dams cause congestion and delay, which lead to higher barge rates and ultimately suppress the corn basis. The spatial spillovers observed in this study suggest that such effects extend beyond localized regions, threatening the competitiveness of U.S. grain exports in global markets. Investments aimed at modernizing riverine infrastructure, such as dredging, lock replacement, and climate-resilient engineering, could yield measurable improvements in market access and farm-level profitability.

The positive impacts of higher river gauge levels on basis outcomes, particularly when spatial trade is unconstrained, further underscore the value of infrastructure improvements that maintain or raise navigability, such as sediment management and adaptive water-level regulation. Similarly, regional coordination in addressing diesel price through targeted subsidies, regulatory harmonization, or logistical upgrades may help to mitigate location-specific disadvantages in fuel-intensive grain shipping corridors.

Several promising avenues emerge for future study. First, this framework can be extended to other commodities, such as soybeans or wheat, to assess whether similar spatial and infrastructural dynamics shape their basis behavior. Second, integrating rail and trucking cost measures would allow for a more comprehensive multimodal assessment of transportation's effect on pricing. Third, introducing nonlinear components, such as thresholds for minimum navigable depths, could help capture regime-switching behavior during periods of extreme river conditions. Lastly, climate variability may differentially impact transportation modes and merit integration into future modeling efforts.

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