IMPACT OF LOCAL FIRST HANDLER AND AREA TRANSPORTATION INFRASTRUCTUE ON LOCAL CORN AND SOYBEAN BASIS

by

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(Under the Direction of William Secor)

ABSTRACT

This study estimates the impact of local first-handler and area transportation infrastructure on corn and soybean basis during the 2018/19 marketing year. Cross-sectional data on local handlers and transportation infrastructure is aggregated at the county level. Geographical clustering patterns in the aggregated data is controlled through spatial models which provide consistent parameter estimates. Our findings suggest significant impacts from the presence of local corn processors on corn basis. A larger freight rail network and port infrastructure within a county are influential factors in setting corn and soybean basis. The shipping infrastructure of elevators also affects grain basis. The concentration of elevators that can ship through barge and rail improved corn and soybean basis. Lastly, our results show a heterogeneous impact of these variables across seasons within a marketing year.

INDEX WORDS: agricultural transportation, grain basis, transportation infrastructure, spatial econometrics, shipping mode

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BS, Agriculture and Forestry University, Nepal, 2017

A Thesis Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree

MASTER OF SCIENCE

ATHENS, GEORGIA

2021

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August 2021

ACKNOWLEDGEMENTS

I would like to thank Dr. William Secor for his consistent guidance throughout this study. Also, sincere thanks to Dr. Berna Karali and Dr. Michael Adjemian for their time and instructions. Lastly, thanks to my family and friends for supporting me.

TABLE OF CONTENTS

Page

CHAPTER

APPENDIX

LIST OF TABLES

Page

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

In local markets, corn and soybean are traded in basis. Basis is defined as the spot price minus the price of the futures contract closest to expiration. Generally, grain basis is negative in major production areas because of relatively high supply of grain. But high demand of grain makes basis positive in end consumer regions. Strengthening basis refers to a situation when basis becomes less negative or more positive. In contrast, basis weakens when basis becomes more negative or less positive.

Grain transportation is a complementary sector to the U.S. grain industry. Geographically dispersed producers, first-handlers, processors, transportation service providers (e.g., rail, barge, and truck companies), and consumers benefit from efficient grain transportation infrastructure. In 2016, a total of 571 million tons of grain were shipped to domestic and export locations. Rail, barge, and truck shipped 25%, 14%, and 61% of the total U.S. grains shipped in 2016 (Kuo-Liang, Jesse, and Adam, 2019). On average, each year, rail carloads of farm, food, and related products represents around 14% of total U.S. rail carloads (AAR, 2021). Similarly, food and farm products constituted 14% of total barge demand in 2017 (USDA, 2019).

Inefficiency in grain transportation may induce greater welfare losses to producers and consumers relative to the welfare losses generated by inefficiency of the grain handling sector alone (Cakir and Nolan, 2015). Therefore, grain transportation services and the supporting infrastructure is of primary concern. The cost, speed, and reliability of the U.S. grain supply chain is a determining factor for the competitiveness of U.S. grains in the global markets.

Therefore, efficient U.S. grain supply logistics is necessary to maintain the U.S.'s competitive status as a grain exporter.

This study seeks to determine the impact of grain transportation infrastructure on grain basis. The cost to transport grain is an influential factor in grain basis. Inefficiencies in grain transportation increase the cost of shipment and thus weakens local prices for grains as measured by basis. Weaker grain basis lowers the price received by producers. Transportation costs can also influence the price of grains in domestic and export markets (Yu, Bessler, and Fuller, 2007). Different modes of grain transportation infrastructure (railroads, roads, and barge), either independently or in combination, enhance the efficiency of grain supply logistics and provide greater flexibility to U.S. grain shippers. Thus, robust grain transportation infrastructure supports grain basis.

There have been numerous studies on the role of the transportation industry and its impact on grain transportation prices. Bekkerman and Taylor (2020) is conceptually, closely related to the current research. In it, the authors analyze the influence of shuttle loading facilities on wheat basis. Another is Adjemian et al., (2011) which investigates the impact of local market factors, including some elements of the area's transportation infrastructure, on corn basis. These types of study are rare. Other research related to transportation infrastructure and grain basis analyzes the effect of transportation infrastructure disruptions on the grain industry. The present study differs from previous research as it quantifies the impact of existing transportation infrastructure on grain basis for a larger geography, more modes of transportation, transportation infrastructure at different points of the grain transportation process, and additional types of market structure characteristics.

We analyze the impact of local handlers and transportation infrastructure on corn and soybean basis during the 2018/19 marketing year. A spatial econometric approach is applied to address the geographically clustering nature of the aggregated county level data because an ordinary least squares (OLS) regression fails to produce consistent estimates under such conditions. Our modeling with this dataset indicates significant spatial autocorrelation between county basis values and between county unobserved effects.

Our results show that counties with more corn processors have significantly higher corn basis while soybean processor density has an insignificant impact on soybean basis. Freight rail networks and ports supported basis, but the impact of U.S. and state highways did not play a significant role in determining grain basis. The concentration of elevators that can ship via barge and/or by rail in a county improved basis. However, the density of elevators that can ship by truck weakens county basis in some cases. Lastly, we find that the impacts of these different factors often vary by season within the marketing year.

This study provides unique insights to policymakers and may assist them while making decisions related to investment in transportation infrastructure. New entrants in the grain industry must consider both local supply-and-demand factors (e.g., competitors) and the transportation infrastructure (e.g., rail networks) when analyzing site locations. Also, grain handlers, processors, and transportation service providers in the U.S. grain transportation industry benefit from this study.

The remainder of this study is organized into the following sections. Chapter 2 provides a brief background on agricultural transportation and summarizes prior relevant literature. Chapter 3 describes the data and presents summary statistics. Chapter 4 explains the methods used. Results from the spatial regressions and a discussion of the estimates are provided in Chapter 5.

Conclusions drawn from this study are presented in Chapter 6. Finally, results from various spatial models and ordinary least square is presented in Appendices.

CHAPTER 2

BACKGROUND AND LITERATURE REVIEW

The United States is a huge country supported by robust transportation infrastructure. The river transport system and freight rail networks move large volumes of commodities across vast regions of the U.S. in a cost-effective way. Most U.S. grain production occurs in the Midwest region, in many cases, far away from domestic consumers and export terminals. Thus, geographical separation between producers and consumers create demand for transportation services and the need for transportation infrastructure. Grain producers in these regions depend on barge and rail transportation infrastructure to move grains to domestic consumers like soybean processors and to export their grains through ports such as the Texas Gulf or the Pacific Northwest (PNW). In 2019, around 350 thousand carloads of grain are shipped through freight rail while barge transported 29 million tons of grain to various U.S. export terminals (USDA, 2021b).

Truck and rail are the primary shipping modes to transport domestic corn to consumers. Between 2007-2011, these modes shipped 78 percent and 21 percent of domestically used corn respectively (Denicoff, Prater, and Bahizi, 2014a). But barge was a dominant transportation mode shipping 54 percent of export-bound corn in the same period. The different transportation modes have a similar share in soybean transportation during the 2002-2011 period. About 85 percent of domestically consumed soybeans are shipped by trucks. Barge is responsible for the movement of more than half of export-bound soybeans (Denicoff, Prater, and Bahizi, 2014b). Truck is an efficient means for hauling short distance, so it plays an important role in shipping grains from producers to domestic ethanol plants, crushing facilities, and feedlots (Vachal, 2015).

The rail industry went through significant structural and technological changes since the Staggers Rail Act of 1980 (Henrickson and Wilson, 2015). Between 1990 and 2013, consolidation of rail industry reduced the number of Class I carriers from 14 to 7 and unprofitable lines were abandoned. As a result of partial deregulation, many firms merged to improve efficiency in transportation service through adoption of better technology. In the late 1990s, adoption of shuttle trains enhanced shipping efficiency relative to unit trains which exploited economic of scale (Ndembe, 2015).

In addition to rail, many major agricultural production states, including Iowa, Illinois, Minnesota, Missouri, and Wisconsin, also rely on the Upper Mississippi River-Illinois Waterway (UMR-IWW) navigation system to ship corn and soybean to export ports or down-river processing plants. The upper Mississippi River has 28 locks, and the Illinois River has 8 locks. Additionally, a 9-ft shipping channel for barge transportation is maintained. Barges can cheaply ship large volumes of grains, compared to truck and rail, over long distances which gives this mode a competitive shipping advantage. The downfall is its limit to navigable waterways and varying river levels. The disruption of the inland waterway system would affect consumer and producer surplus (Yu, English, and Menard, 2016). The diversity in U.S. grain transportation infrastructure can increase shipping efficiency and provides flexibility to grain shippers.

PREVIOUS STUDIES

In general, grain basis is a measure of the local spot price relative to futures market price. Grain basis provides insights to both buyers and sellers to formulate when purchasing and marketing grain. Grain sellers could use the knowledge of basis to analyze different markets and the timing of grain sales. Grain buyers influence the flow of grain by adjusting basis bids (McKissick and Shumaker, 1991). Grain terminals might strengthen their basis bid to ensure sufficient inflow of grain to meet their demand and prevent demurrage cost. A good understanding of the determinants of basis and its historical patterns is essential to profitably participating in physical grain markets.

There are several studies on the factors affecting variations in grain basis. Bullock and Wilson (2019) find that local and international supply-and-demand factors significantly influence Gulf and Pacific Northwest (PNW) soybean export basis during the 2004-2017 marketing period. Also, the level of export activity, logistical condition (cost of secondary railcars, barge and ocean freight rates), marketing response of farmers' and differences in transportation costs between ports were primary factors for seasonal variation in soybean export basis.

The relationship between export and origin basis for soybean is studied by Lakkakula and Wilson (2021). They find that the PNW basis and origin basis are jointly determined which provide evidence that these markets are interlinked. They estimate that an increase in shipping costs by $1 would increase export basis by $0.82/bushel while the origin basis would decrease by $0.19 per bushel.

In addition to these studies, earlier empirical studies that examine factors affecting grain basis include Garcia and Good (1983), Garcia and Hauser (1986), Naik and Leuthold (1991). In general, local supply and demand, transportation costs, and production relative to storage capacity significantly influence corn basis. Basis also gives information about local supply and demand conditions. Basis is weaker in major grain production areas because of the relatively high supply of grain. The relative high demand of grain at export locations strengthens basis.

O'Brien (2009) studies the influence of micro-market structure on spatial grain price differentials among Kansas grain elevators. Local demand, elevator storage capacity, size of competitors, and grain handling facilities' access to railroads have a significant impact on spatial corn price differentials between Kansas grain elevators. In a similar study, Wenzel, Hill, and Garcia (2000) find that the efficiency of the firm, the nature of firm (cooperative or privately owned), the final market destination of the grain, and the period of the marketing year also created price differentials among geographically separated corn elevators in Illinois.

Numerous studies investigate the impact of the transportation sector on local grain markets. Yu, Besssler, and Fuller (2004) analyze the impact of the cost of transportation on corn and soybean prices. Their study shows Illinois processors' prices are a significant factor for both corn and soybean prices during 1992-2001. Also, rail rates explained relatively more (10-12%) variation in corn and soybean prices than barge rates (2-4%). Likewise, shipping costs, shipping industry concentration, availability of rail cars, the ratio of stock to storage capacity, outstanding export sales have also been found to be major factors for changes in grain basis (Wilson and Dahl 2011).

In a study of barge disruptions, domestic corn prices are influenced by grain barge rates on the upper Mississippi / Illinois river (Yu, Bessler, and Fuller, 2007). Shocks in transportation rates are found to considerably affect the corn price relative to other grains. In other research, Haigh and Bryant (2000) find that barge rate volatility produced a greater impact on grain prices and marketing margins compared to ocean rate volatility. Because barge transportation is an economical means of transportation, any disruption could influence grain prices considerably. The impact of barge rates was not significant in a market which is less integrated in the river system, and it declined as distance away from the river increased (Li and Thurman, 2013). Hart and Olson (2017) analyze the impact of transportation disruptions on weekly grain prices. The context is a hurricane and winter closure of upper Mississippi river impacting port operations in Midwest grain markets from 2003 to 2013. They find that transportation disruptions raised shipping costs either by delaying shipment or compelling shippers to use costly alternative routes.

Fuller et al. (2003) estimate the impact of improving transportation infrastructure on competitiveness in world grain markets. This study considers the following infrastructure improvement in South American countries: a reduction in South American port facility costs by $4/ton, an improvement in barge rate by $5/ton in Parana River Ports, and a decrease in transportation costs for west central Mato Grosso. These resulted in efficiency gains of $1 billion/year and annual exports increased by 3.28 million tons in South America.

Ndembe and Bitzan (2018) analyze the impact of freight elevator consolidation, transportation demand, and the growth of the shuttle facilities. The savings in transportation costs are higher in shuttle shippers compared to non-shuttle shippers.

Two final studies are similar to the current study and deserve special note. The first is research by Bekkerman and Taylor (2020) that measures the effect of transportation infrastructure on grain pricing behavior. They estimate the impact of the adoption of shuttle loading facilities on prices offered by Kansas and Montana wheat elevators from 2005-2013. The shuttle-loading facilities increase basis bids by $0.13 per bushel compared to conventional grain elevators in Kansas. However, our research differs from this study by focusing on a large cross section of the U.S., diverse transportation infrastructure (road, rail, and water), and local handlers' shipping characteristics.

The second is a study by Adjemian et al. (2011) that uses a spatial model to assess corn basis determinants at the county-level using data from 785 counties in the U.S. in August 2007. They find that local supply-and-demand factors in a particular county influenced basis in that county. Additionally, they find that basis has spatial spillover effects on neighboring counties' basis. This study is similar to our study because it also estimates how some county-level transportation infrastructure factors influence corn basis. We differ from this study as we use spatial variation in transportation infrastructure density to explain variation in county-level basis, estimate models across seasons within a given marketing year, and include estimates for soybean basis in addition to corn basis.

CHAPTER 3

DATA

The weekly mean county basis of corn, from September 2018 to May 2019, for 600 counties are collected from the USDA-ERS. Likewise, the weekly mean county soybean basis for 600 counties from September 2018 to June 2019 are gathered from the USDA-ERS. This county-level basis data represent the average corn and soybean basis bids offered to producers based off the nearby futures contract (not the harvest contract). The corn and soybean basis from week 33 to 35 of 2019 is missing from our data. Therefore, we could not include all seasons of the 2018/19 marketing year in our analysis.

We grouped the 2018/2019 corn and soybean basis into harvest, post-harvest, and planting seasons. The corn harvest season starts on September 1, 2018 and ends on November 30, 2018. The post-harvest season runs from December 1, 2018 to March 31, 2019. Finally, the planting season begins on April 1, 2019 and ends on May 31, 2019. For soybean, the harvest season starts on September 1, 2018 until October 31, 2018, the post-harvest season runs from November 1, 2018 to April 31, 2019, and the planting season is from May 1, 2019 to June 30, 2019. The timeline for each season of corn and soybean coincides with the crop calendar for the United States published by USDA (USDA, 2021a). The average basis during each season for a given county is computed by taking the average of that county's basis values across the weeks that fall in that particular season.

The average county corn and soybean production in 2018 is collected from USDA-ERS. We use county production data to capture the local supply of grains in that marketing year.

Data on grain processors and local handlers along with their available shipping modes are drawn from the Grain Directory published by the Grain Journal (2019). This represents a large cross-section of U.S. grain processors and local handlers. The address of each grain processor and local handler is coded using the ggmap package in R. Their respective county code is derived from this geocoding that provides their latitude and longitude. Finally, grain processors and local handlers are aggregated at the county-level based on their county code. Our study includes 3,592 elevators, 172 ethanol plants, 35 bio-diesel plants, 56 soybean processors, 1,145 feed mills, and 67 other mill dry corn processors spatially distributed.

The focus of this study is to determine transportation infrastructure's impact on grain basis. To do this, we control for the impact of corn and soybean buying entities in a county. A corn processor variable is created by counting the number of ethanol plants, feed mills, and other corn processors in a county. Similarly, a soybean processor variable is created by counting the number of bio-diesel plants, soybean processors, and feed mills in the county.

Figure 1 shows that most processors and local handlers of corn and soybean in our dataset are clustered in the Midwest. At a state-level the spatial distribution of processors might be clustered to one or more region(s) within a state. At a county level, we assume that processors are evenly distributed within a county. Based on this assumption we normalize corn and soybean processor counts per 100 square miles of the county's area. This can be thought of as a density, the number of corn (soybean) processors per 100 square miles of county area. Similarly, the density of elevators shipping via a particular transportation mode is calculated per 100 square miles of the county's area.

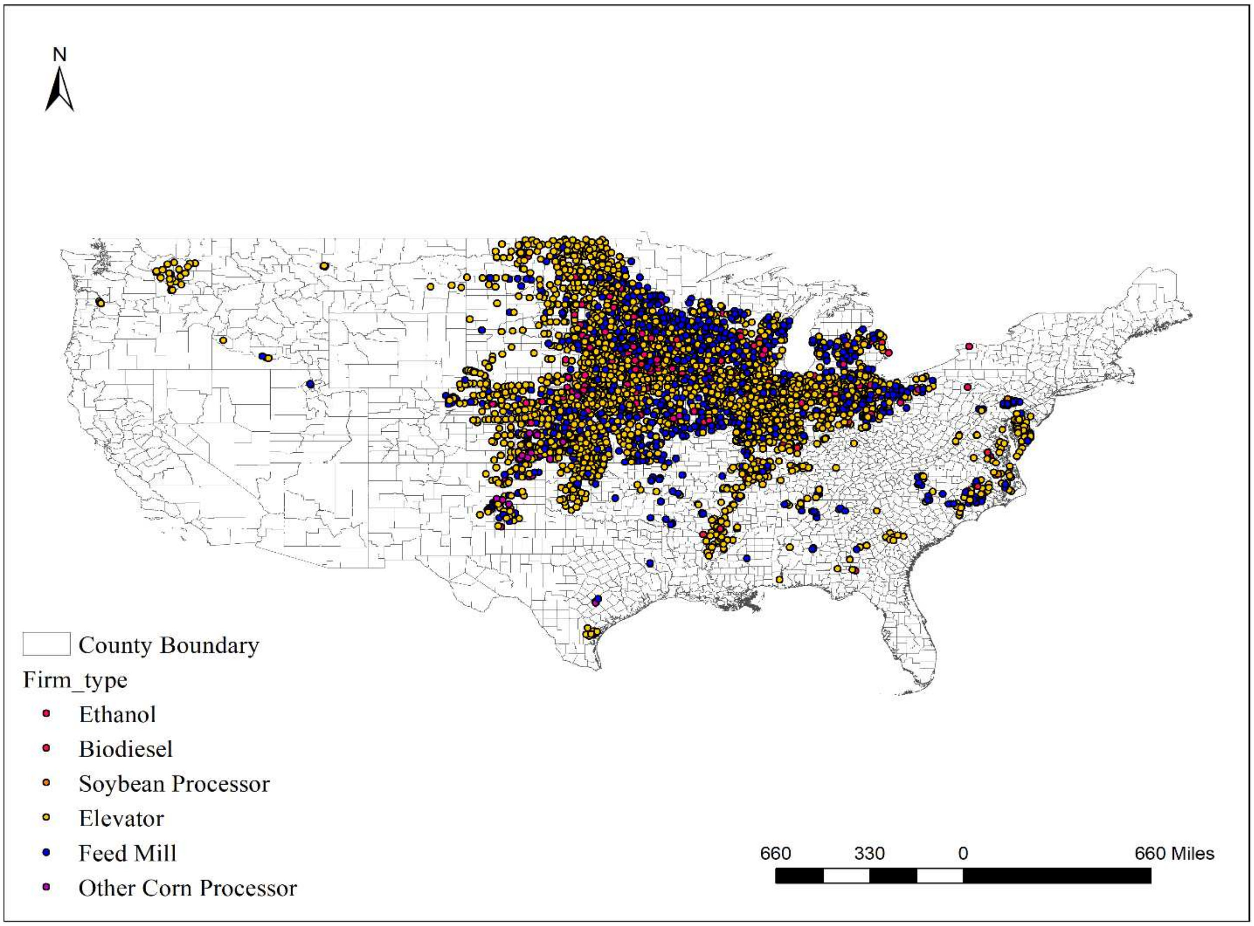

Figure 1: Spatial distribution of U.S. processors and local handlers of corn and soybean, 2018/2019

Data on port infrastructure within a county is gathered from Department of Homeland Security infrastructure foundation-level data available on the ArcGIS platform (HIFLD, 2020). We apply text analysis to identify ports that handled corn and soybean from the pool of all U.S. ports. Due to the limited number of ports in general, and within a particular county, the port variable enters as a dummy variable.

Data on the county freight rail network is pulled from the Bureau of Transportation Statistics (BTS), U.S. Department of Transportation (BTS, 2020). The information on U.S. and state highways in each county is extracted from ArcGIS hub (ArcGIS, 2020). All freight rail and highway variables are normalized per 100 square miles of the county's area to estimate their density in a given county.

We exclude states with less than ten counties that had basis observations to remove potential outlier counties. The final list of states included in the analysis is: Illinois, Indiana, Iowa, Kansas, Kentucky, Michigan, Minnesota, Missouri, Nebraska, North Carolina, North Dakota, Ohio, South Dakota, Wisconsin.

Based on the county code, the dataset of seasonal basis, grain production, processors and local-handlers, and transportation infrastructure are merged to create a final county-level aggregated dataset for each season to be used in the regression analysis.

DESCRIPTIVE STATISTICS

Table 1 shows the mean, standard deviation, minimum, and maximum of the variables used in the study from our final dataset. The mean county-level basis, from September 2018-May 2019, for corn is -24.83 cents per bushel. The mean county-level basis, from September 2018-June 2019, for soybean is -88.08 cents per bushel. The average corn and soybean basis for the above time periods are shown in figure 2 and figure 3, respectively. Corn and soybean basis strengthens considerably throughout the year indicating that capturing heterogeneity within the marketing year may be important. The average county corn production measured in the logarithm of bushel of corn produced per square mile of county area is 9.82. Similarly, the average county soybean production is 8.80 bushels per square mile of the county.

Table 1: County data summary for the 2018/19 corn and soybean marketing years

Variables (Units)	Mean	Std.Dev.	Max.	Min.
Corn Basis (cents per bushel)	-24.83	31.45	111.72	-99.54
Soybean Basis (cents per bushel)	-88.08	37.74	71.34	-198.71
Corn Production (ln of the corn production in bushel per square mile of county area)	9.82	1.13	11.81	5.21
Soybean Production (ln of the soybean production in bushel per square mile of country area)	8.80	0.91	10.54	4.19
Corn Processor (No. of corn processors per 100 square miles of county area)	0.27	0.30	2.37	0.00
Soybean Processor (No. of soybean processors per 100 square miles of county area)	0.25	0.30	2.37	0.00
U.S. Highway (miles of U.S. highway per 100 square miles of county area)	6.45	4.7	46.58	0.00
State Highway (miles of state highway per 100 square miles of county area)	8.78	6.33	48.13	0.00
Freight Rail (route miles of freight rail per 100 square miles of county area)	9.13	6.58	53.63	0.07
Port (dummy =1 if county has a port)	0.09	0.28	1.00	0.00
Elevator Truck (No. of elevators with Truck option per 100 square miles of county area)	0.63	0.47	4.05	0.00
Elevator Rail (No. of elevators with Rail option per 100 square miles of county area)	0.28	0.29	2.52	0.00
Elevator Barge (No. of elevators with Barge option per 100 square miles of county area)	0.04	0.13	1.31	0.00
County area (Square miles)	652.60	386.85	6247	160

The mean county corn processor density is 0.27 corn processors per 100 square miles of a county, and the mean county soybean processor density is 0.25 soybean processors per 100 square miles of a county. The mean U.S. highway density in a county is 6.45 miles of roadway per 100 square miles of a county, and the mean state highway density in a county is 8.78 miles of roadway per 100 square miles of a county. The mean county freight rail density is 9.13 miles of track per 100 square miles of a county. Only 9% of the counties has a port. The mean density of elevators that can ship by truck, rail, and barge are 0.63, 0.28, and 0.04 elevators per 100 square miles of a county, respectively.

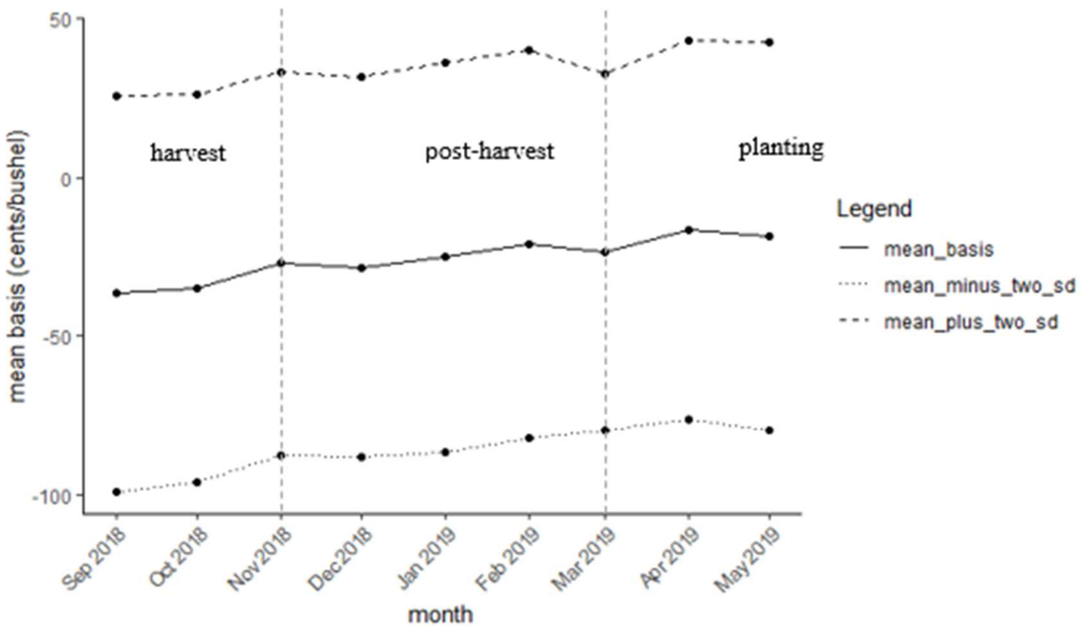

Figure 2: Mean county corn basis during the 2018/19 marketing year

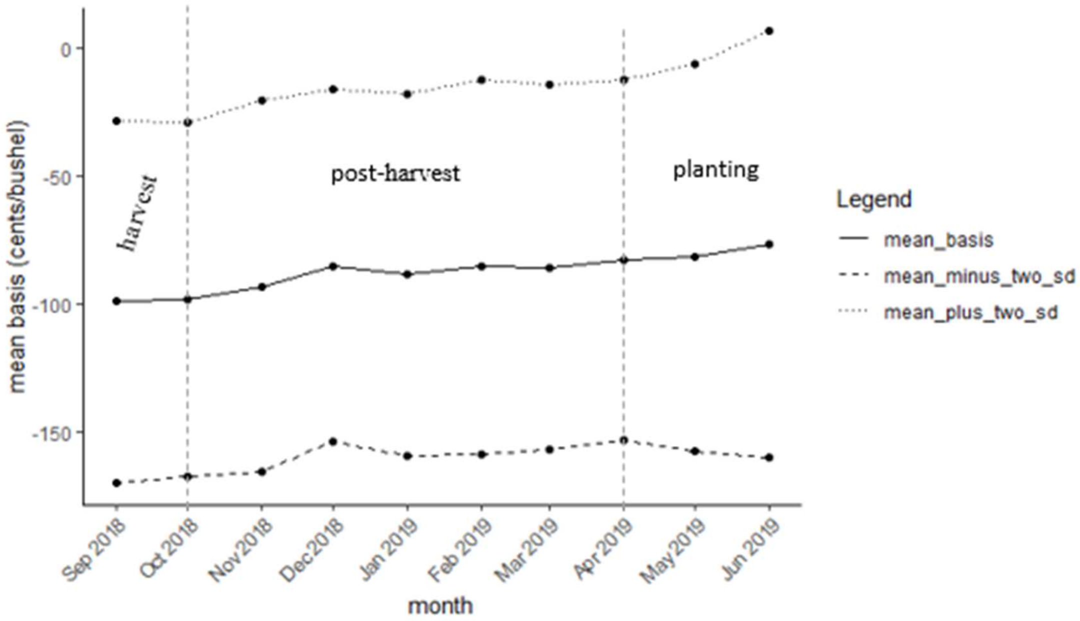

Figure 3: Mean county soybean basis during the 2018/19 marketing year

CHAPTER 4

METHODOLOGY

The basis at county i, b_i, is influenced by local supply and demand factors as well as other transportation and handling costs. Spatially separated U.S. corn and soybean markets are linked together through transaction costs which represents all shipping and management costs to move grains from one market to another market (Bekkerman et al., 2009). If corn and soybean basis follow the law of one price at a given time, then the equilibrium relationship between the basis in two different locations is:

$$b_i = b_j + M_{ji}, \qquad (1)$$

where,

M_{ji} = transaction costs to ship grains from county j to county i separated by distance (d)

b_j = basis at county j

Any shock in the factors determining basis at county j that causes a difference in basis between county i and j greater than the transaction cost would incentivize the movement of grain from county j to i. This movement of grain would then change the local supply and demand conditions at county i until a new equilibrium is reached, where the difference in basis no longer offsets their transaction cost. We can say that basis at county i is influenced by its own factors and by basis at county j and vice versa. Therefore, basis at these two counties is simultaneously determined.

In case of multiple counties, the basis at a particular county is the function of its local factors affecting basis and the basis at neighboring counties.

Mathematically,

$$b_i = \int (X_i , b_j, b_k, \ldots.., b_n) \qquad (2)$$

where,

b_j, b_k,….., b_n = basis at nearby counties that affects basis at county *i*

X_i = Local factors that influence basis at county *i*

The ordinary least square (OLS) regression does not consider the spatially weighted lag of nearby counties basis which is important in explaining variations in basis of a particular county. Because our cross-sectional data are aggregated at the county level, it is likely to suffer from clustering and other spillover effects (Anselin and Griffith, 1988). To detect these issues in our dataset, we carry out the global Moran's I test for spatial autocorrelation of OLS residuals. The OLS regression that is run to obtain the OLS residuals is of the following form:

$$Y_i = \alpha + \sum_{k=1}^{K} \beta_k X_{ik} + \varepsilon_i \qquad (3)$$

where,

Y_i = grain (corn or soybean) basis in county *i*

X_{ik} = a vector of explanatory variables.

This regression creates residuals, U_i. These residuals are measured as the actual grain basis in the county minus the predicted grain basis in the county. Note, the vector of explanatory variables contains the same variables that are also used in the spatial models. The specific variables included in this study are discussed below.

The residual Moran's I test considers both basis of a county and its spatial characteristics to detect clustering patterns in data (Andy, 2005). Thus, clustering patterns in the data confirms spatial dependency of residuals. Mathematically, the residual Moran's I test can be written as:

$$I = n\frac{\left(\sum_{i=1}^{n}\sum_{j=1}^{n} W_{i,j}\, A_i\, A_j\right)}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n} W_{i,j}\right)\left(\sum_{i=1}^{n} {A_i}^2\right)} \qquad (4)$$

where,

A_i = the deviation in OLS residuals in county *i* from the mean residual $\left(U_i - \overline{U}\right)$

A_j = the deviation in OLS residuals in county *j* from the mean residual $\left(U_j - \overline{U}\right)$

$W_{i,j}$ = Spatial weight between county *i* and county *j*

n = total number of counties

In equation (4), the spatial weight matrix represents the relative proximity of counties with respect to a particular county. We assume that a particular county has a spatial effect within the twenty nearest counties. This is an ad hoc choice. However, other previous literature make similar ad hoc decisions. For example, Adjemian et.al. (2011) assume local corn basis of a given county is spatially correlated with its nearest twenty counties.

The weight matrix is estimated using a hybrid step process. First, the nearest twenty counties of a given county are selected as neighbors. Second, we assume that the spatial effect of a given county decreases as we move away from that county. So, specific weights are assigned as the inverse of the distance between a county and its selected neighbors. Third, the weight matrix is then row standardized. Each row is standardized by dividing all non-diagonal elements in a row of the weight matrix by the sum of that row. The diagonal element of the weight matrix is zero because a county cannot be neighbor to itself. The sum of all elements in each row of the weight matrix is equal to one.

The Moran's Index calculates the cross products, A_i A_j in the above equation, based on the deviation in OLS residuals of a county from all neighboring counties' residuals and their distance. If A_i and A_j have the same sign, then the value of the cross product will be positive. The positive value of Moran's Index indicates spatial clustering. That is, high values cluster near other high values and low values cluster near other low values. The Moran's I test results using the specification below suggest significant spatial dependence of residuals in our dataset. Including a spatial lag of the dependent variable, which is a relevant variable in our case, will cause simultaneity bias in a typical OLS regression. Accordingly, we prefer spatial models over traditional OLS regressions.

Following Anselin et al. (1996), we perform a robust Lagrange Multiplier (LM) test to choose the best-fitting spatial model specification. It compares robustness of simultaneous autoregressive model (SAR), spatial error model (SEM), and simultaneous autoregressive and autoregressive residual (SARAR) based on their fitness in the model. We prefer the SARAR model over other spatial models because the SARMA test has the lowest p-value in the LM test. The SARMA test, in the series of LM tests discussed above, evaluates whether adding a spatial lag and a autoregressive residual is a better fit for the spatial model. The SAR model is transformed into the SARAR model, as in Anselin (1988), by adding an autoregressive residual. A lag term of both basis and residuals is added to the classical linear model to capture the spatial dependence of basis and unobserved effects across counties. The general SARAR regression equation can be written as follows:

$$Y_i = \rho \sum_{j=1}^{J} W_{i,j} Y_j + \sum_{k=1}^{K} \beta_k X_{ik} + \lambda \sum_{j=1}^{J} W_{i,j} U_j + \varepsilon_i \qquad (5)$$

$$W_{i,j} = \frac{1}{d_{ij}} \times \frac{c_{ij}}{\sum_{j=1}^{J} c_{ij}}$$

where,

$$C_{ij} = \begin{cases} 1 \; if \; j \; is \; a \; neighbor \; to \; i \\ \quad 0 \; otherwise \end{cases}$$

d_{ij} is the distance between centroids of counties *i* and *j*.

X_{ik} = a vector of explanatory variables.

In equation (5), Y_i is grain (corn or soybean) basis in county *i*. *J* is the number of nearby counties to county *i*. Y_j is grain (corn or soybean) basis in nearby county *j*. λ is the spatial correlation between unobserved effects in county *i* and the unobserved effects in selected nearby counties. U_j is a vector of SARAR model residuals. ρ is a coefficient representing the spatial correlation between the basis in county *i* and the basis in selected nearby counties. W is a weight matrix created in the same way as in Moran's I test discussed above.

β_k is a vector of coefficient estimates, and X_{ik} is a vector of explanatory variables. For the corn basis regression, X_{ik} contains variables for corn production, corn processor density, U.S. highway density, state highway density, freight rail density, corn port presence, density of elevators that can ship by truck, density of elevators that can ship by rail, and density of elevators that can ship by barge. For the soybean basis regressions, X_{ik} contains variables for soybean production, soybean processor density, U.S. highway density, state highway density, freight rail density, soybean port presence, density of elevators that can ship by truck, density of elevators that can ship by rail, and density of elevators that can ship by barge. Lastly, we assume ε_i is a noise term with zero mean and a constant variance.

We present the results from the SARAR model that estimates the impact of local handlers and transportation infrastructure on corn and soybean basis across different seasons. The regression results of the OLS model and other spatial models are presented in the appendix.

CHAPTER 5

RESULTS

CORN

The estimates from the SARAR regressions of corn basis across different seasons is shown in table 2. The sign of the coefficient for corn processor density (Corn Processor) is positive and statistically significant (1% level) in all three seasons. An increase in the concentration of corn processor density increases demand for corn which strengthens basis. The estimated coefficient for corn processor density is highest in the planting season (4.81 cents/bushel) compared to the post-harvest (4.66 cents/bushel) and harvest seasons (3.54 cents/bushel). This may reflect the importance of the convenience yield for processors. During the planting season, if the density of corn processors in the county increases by one per 100 square miles, corn basis increases by 4.81 cents/bushel.

The coefficient of freight rail density (Freight Rail) is positive and statistically significant during the post-harvest and planting seasons. The estimates range from 0.02 cents/bushel during the harvest season to 0.15 cents/bushel during the planting season. This result suggests that a one-mile increase in the total miles freight rail per 100 square miles of a county increases corn basis during the planting season by 0.15 cents/bushel.

The sign of the estimates for both U.S. highway (U.S. Highway) and state highway (State Highway) density are inconsistent across seasons, and none are statistically significant in any season. This statistical insignificance may be driven by the fact that the density of road infrastructure is similar across counties.

As expected, the impact of having a port within a county (Corn Port) was positive in all three seasons but is significant only in the harvest season. The coefficient of port on corn basis is higher during the harvest season relative to other seasons. During the harvest season, a county with port infrastructure has higher basis bids by 2.35 cents/bushel.

The estimated coefficient for the density of elevators that can ship by truck (Elevator Truck) is negative in all three seasons and ranged from -0.36 cents/bushel during the harvest season to -2.41 cents/bushel during the planting season. This suggests that if the number of elevators that ship by truck in a county increases by one per 100 square miles, corn basis decreases by 2.41 cents/bushel during the planting season. Trucks are less economical means of transportation than rail and barge. Therefore, using trucks for shipping increases transportation costs, and hence, weakens the basis. As the season progresses the corn basis strengthens and reaches a maximum in the planting season because of low supply of corn in this period. Therefore, in the planting season elevators are motivated to ship all of their old corn and be prepared for new corn which may be the reason for a larger impact during planting season.

In contrast, the estimated coefficient of the density of elevators that can ship by rail (Elevator Rail) and/or ship by barge (Elevator Barge) is positive in all three seasons. The coefficient of Ship Barge is significant in all seasons, while the coefficient of Ship Rail is not significant in any season. The coefficient of Ship Barge is greater during the planting season (9.97 cents/bushel) relative to harvest (6.76 cents/bushel) and post-harvest seasons (6.50 cents/bushel). If the number of elevators that can ship by barge increase by one per 100 square miles of the county area, corn basis increases by 9.97 cents/bushel in the planting season.

The lower portion of table 2 shows several specification tests for the spatial regression models. The Moran's I test for spatial dependence of OLS residuals is statistically significant for all seasons. This indicates that a spatial regression model should be used. The coefficient for the spatially lagged basis term and spatially lagged error term ranged from 0.79 to 0.82 and are statistically significant in all seasons. This means there is significant spatial correlation in basis and unobserved effects (residuals).

Table 2: Corn – Spatial lag and spatial error (SARAR)

	Parameter estimate		
Explanatory Variable	Harvest Season	Post-Harvest Season	Planting Season
Intercept	- 4.33	-9.41	-6.66
	(13.09)	(12.40)	(8.97)
Corn Production	-0.48	0.18	-0.03
	(0.52)	(0.53)	(0.58)
Corn Processor	3.95***	4.66***	4.81***
	(1.52)	(1.28)	(1.60)
U.S. Highway	0.008	-0.05	0.03
	(0.08)	(0.08)	(0.09)
State Highway	0.04	-0.02	-0.02
	(0.07)	((0.07)	(0.08)
Freight Rail	0.02	0.12*	0.15**
	(0.06)	(0.07)	(0.07)
Corn Port	2.35*	1.69	1.26
	(1.39)	(1.54)	(1.60)
Elevator Truck	-0.36	-1.48	-2.41**
	(1.07)	(1.24)	(1.26)
Elevator Rail	1.47	1.76	2.24
	(1.53)	(1.67)	(1.72)
Elevator Barge	6.76*	6.50*	9.97**
	(3.64)	(3.55)	(4.06)
Lagged Basis	0.82**	0.79**	0.79**
	(0.33)	(0.36)	(0.31)
Lagged Error	0.82**	0.82**	0.80***
	(0.33)	(0.33)	(0.30)
Observations	569	570	567
Residual Moran's I	0.66***	0.66***	0.66***
Log Likelihood	-1916.97	-1982.75	-1982.77

Notes: Standard errors in parentheses. * 10% significance, ** 5% significance, and *** 1% significance.

SOYBEAN

Table 3 reports the parameter estimate of the SARAR regressions of soybean basis across different seasons. The impact of soybean production is positive in all seasons but is statistically significant during the post-harvest and planting season. If soybean production increases by 1 percent, then local basis increases by 0.02 cents per bushel in the planting season. However, the estimates for soybean production are in contrast with economic theory as higher soybean production increases the supply of soybean in an area and should decrease the local basis. The 2018/19 marketing year is affected by the U.S.- China trade dispute which may be the reason for the unexpected sign of soybean production.

The sign of the estimated coefficient of soybean processor density (Soybean Processor) is positive during the harvest and post-harvest seasons and is negative during the plating season. All estimates of soybean processor density for different seasons are statistically insignificant. This may be different than our result for corn processors because soybean processors are fewer, and many are located close to end users (away from producers) which increases the cost of transportation. As a result, they may not pass back savings in transportation costs like corn processors.

Our analysis shows a positive impact of U.S. highways (U.S. Highway) on soybean basis in all seasons. The impact of state highways (State Highway) is negative for all seasons. But, the coefficients of U.S. Highway and State Highway are not statistically significant in any season.

As expected, the coefficient estimates of freight rail density (Freight Rail) are positive and statistically significant during the harvest and planting seasons but not during the post-harvest season. The coefficient of freight rail during the harvest, post-harvest, and planting seasons were 0.15 cents/bushel, 0.14 cents/bushel, and 0.23 cents/bushel, respectively. This result suggests that an increase of 1 mile of freight rail per 100 square miles of a county increases soybean basis in a county by 0.23 cents/bushel during the planting season. Rail is important for soybean in harvesting and planting season because, on average, about a quarter of all soybean are shipped from the Midwest via rail to ports located in the PNW region (Denicoff , Prater, and Bahizi, 2014a).

The impact of having a port that handles soybean (Soybean Port) within a county is positive across all seasons. Barge shipment is a relatively economical means for shipping soybean. Accordingly, soybean (and corn) buyers in counties with ports may pass savings in transportation costs to farmers that would be reflected in stronger basis. The impact of having a port in the county that handles soybean is highest during the planting season (8.6 cents/bushel) compared to the post-harvest (5.16 cents/bushel) and harvest (2.33 cents/bushel) seasons. These estimates are statistically significant during the post-harvest and planting seasons but insignificant during the harvest season. Our analysis shows that having a port that handles soybean in a county increases soybean basis by 8.6 cents/bushel during the planting season.

The impact of elevators that can ship via truck (Elevator Truck) is negative during the post-harvest and planting seasons but positive during the harvest season. However, the coefficient estimates are statistically insignificant in all three seasons.

The density of elevators that can ship through rail (Elevator Rail) has a positive effect on basis but not statistically significant in all seasons. The estimate is higher during the post-harvest season (3.12 cents/bushel) relative to other seasons.

Similarly, the impact of the density of elevators that can ship by barge (Elevator Barge) is positive in all three seasons. The coefficient of Elevator Barge increases from 8.80 cents/bushel to 18.49 cents/bushel as it progresses from harvest to planting season. This suggests that an additional elevator per 100 square miles in a county that can ship via barge increases basis by 18.49 cents/bushel in the planting season.

The coefficient on the spatially lagged basis term is positive and statistically significant in all seasons. Likewise, the coefficient on the spatially lagged error term is positive and statistically insignificant only during the planting season. This indicates significant spatial correlation in basis and unobserved factors (residuals). Also, the Moran's I test indicates significant spatial dependence of residuals in all seasons.

Table 3: Soybean – Spatial lag and spatial error (SARAR)

	Parameter estimates		
Explanatory Variable	Harvest Season	Post-Harvest Season	Planting Season
Intercept	-14.81**	-23.83***	-24.44***
	(5.88)	(5.68)	(6.09)
Soybean Production	0.92	2.04*	2.24***
	(0.77)	(0.67)	(0.71)
Soybean Processor	1.38	0.10	-0.44
	(1.91)	(1.33)	(1.56)
U.S. Highway	0.08	0.20	0.12
	(0.12)	(0.09)	(0.11)
State Highway	-0.08	-0.06	-0.08
	(0.12)	(0.08)	(0.09)
Freight Rail	0.15**	0.14	0.23**
	(0.09)	(0.08)	(0.08)
Soybean Port	2.33	5.16*	8.60***
	(2.34)	(1.77)	(2.00)
Elevator Truck	0.07	-1.06	-1.90
	(1.71)	(1.24)	(1.37)
Elevator Rail	2.27	3.12	1.70
	(1.74)	(1.69)	(1.89)
Elevator Barge	8.80**	15.11*	18.49***
	(5.62)	(4.15)	(5.00)
Spatially Lagged Basis	0.94***	0.93***	0.93***
	(0.02)	(0.02)	(0.02)
Spatially Lagged Error	0.60***	0.52***	0.45
	(0.11)	(0.11)	(0.45)
Observation	546	548	533
Residual Moran's I	0.75***	0.73***	0.67***
Log Likelihood	-1855.18	-1863	-1889.41

Notes: Standard errors in parentheses. * 10% significance, ** 5% significance, and *** 1% significance.

DISCUSSION

The impact of corn processor density is positive and significant during the 2018/19 marketing year. A previous study by Behnke and Fortenbery (2011) finds a similar positive impact of ethanol plants on local corn basis. They use a spatial panel approach and estimate that an ethanol plant with 50 million gallons of capacity within 50 mi of a county centroid improved basis by 0.40 cents/bushel. Unlike this study, we focus on aggregated impacts of the density of all ethanol plants, as well as other corn processors, per 100 square miles of a given county. Combined with the use of more recent data, these factors may help explain the difference in magnitude of the estimates.

In contrast, soybean processors have an insignificant impact on local basis in all seasons. Most of the processed soybean products (oil and meal) are consumed domestically (Goldsmith, 2008). To increase market access, soybean processors might locate their plant close to end-users, far from producers, which may affect soybean basis's relationship with transportation variables in a way that is different compared to corn basis and corn processors.

The density of road infrastructure (U.S. and state highways) in a county has an insignificant impact on local corn and soybean basis. In corn and soybean, roadways are responsible for short distance movements of grain (between producers, local handlers, and processors) in a non-metropolitan area where traffic congestion might not be a major issue. Also, the distribution of roadways across U.S. counties is relatively even and might be responsible for the insignificant effect on local basis. Similar insignificant impact of road infrastructure on local corn basis is estimated by Adjemian et al. (2011). However, they used the mean county distance to a highway instead of road infrastructure density in their spatial analysis.

The robustness of the significant, positive effect of freight rail infrastructure on local corn and soybean basis during the planting season is notable. A county with robust freight rail might be able to ship large volume of grains in an economical way domestically during a low supply period locally (e.g., the planting season) or internationally during a high supply period locally (e.g., harvest or post-harvest) which increases basis.

With respect to waterborne transportation, counties with ports have strong corn basis during the harvest season relative to other seasons. However, the impact is not large. For soybean basis, counties with a port offered significantly higher basis during the post-harvest and planting seasons. The majority of the local handlers in Midwest region, shipping by barge, may collect and store soybean during harvest season (when basis is weak) and start exporting during post-harvest and planting season when basis gradually increases. The winter closure of the upper Mississippi river on numerous locks in the upper Midwest region might affect the flow of soybean in the months following soybean harvest (see for example AgFax (2018)). However, the 2018/19 marketing year was also marked by the U.S.-China trade dispute. Accordingly, this may have contributed to seasonal and regional changes in soybean basis.

If more elevators in a county are shipping through truck, then it significantly weakens local corn basis during the planting season. The concentration of elevators shipping via truck has a negative but insignificant impact on soybean basis during the 2018/19 marketing year. A significant share of the soybean crop is exported. Accordingly, truck may be less important in soybean supply logistics, compared to rail and barge, as it is an inefficient way of transporting large volumes of bulk commodities (e.g., grain) to distant markets. The negative basis impact on corn may also reflect local elevators that are trying to empty grain bins prior to the next harvest.

The concentration of elevators that can ship through rail has a positive effect on corn and soybean basis. However, the impact is statistically significant only in the post-harvest season for corn basis. This may be insignificant for a number of reasons. One may be limited variation in this variable across counties. Another may be that elevators with rail shipping capabilities may be larger and may exhibit market power, countering transportation cost savings with market power effects.

The concentration of elevators in a county that can ship via barge has a significant, positive impact on local corn and soybean basis in all seasons except the harvest season for soybean basis. Elevators shipping through barge might increase their basis bids to fulfill large grain demand without delay and thus avoid demurrage cost which strengthens local basis.

CHAPTER 6

CONCLUSIONS

This study examines the impact of local handlers, processors, and transportation infrastructure on local corn and soybean basis. Cross-sectional data of corn and soybean basis aggregated at the county level is analyzed across different seasons for the 2018/19 marketing year. We choose a spatial approach to address the geographically clustering nature of the basis data.

Our results suggest that local supply and demand conditions are influencing factors of local basis, similar to previous literature and as theory would suggest. Additionally, the results indicate that rail and port infrastructure supported basis, but U.S. and state highway density does not provide significant basis support. Local first handler (i.e., elevator) shipping infrastructure also plays a significant role in determining basis, especially rail and barge shipping capabilities. Finally, our findings suggest that the impact of these factors vary across the marketing year with some being more important during harvest (e.g., elevators shipping via truck), while other factors support basis later in the marketing year (e.g., the density of corn processors or the density of elevators with barge shipping infrastructure).

Some care should be taken while considering the results of this study. This study focuses on the aggregate impact of local handlers, processors and transportation infrastructure on grain basis. Accordingly, one cannot tie these estimates to individual entities. For example, the impact of increasing the density of elevators shipping through barge in a county by 1 per 100 square miles, increased corn basis by 9.97 cents/bushel during the planting season. One cannot say that shipping through barge, in a nearby location would strengthen the basis by 9.97 cents per bushel at a given elevator.

Additionally, this study analyzes only a single cross-section of corn and soybean basis because of limited data. As a result, the estimates obtained in this marketing year might not be consistent in other marketing years. In particular, the U.S.-China trade dispute that arose in 2018 may factor into the data and affect the regression results. Due to data limitation for this study, the 2018/19 marketing year was the only marketing year available to study.

Finally, these aggregated data have limitations in themselves. For example, the grain processor variables do not capture production capacity, but just counts the number of processors in a county. Because of this, the actual demand in a county may be different and not proportional to the number of processors in a county.

Further research should seek to build on these results using more detailed data (e.g., basis bids at the firm-level with capacity figures). Future researchers might also explore the impact of elevators that have multi-modal transportation capabilities (e.g., rail and barge).

Our study might assist policymakers in analyzing the decisions regarding investment in transportation infrastructure. For example, policymakers concerned about supporting farm-level prices (as measured by basis) may seek to facilitate rail infrastructure developments over highway infrastructure. New entrants in the grain handling industry might benefit by locating near to freight rail or port infrastructure to take benefit of transportation cost advantages. However, our results suggest that both transportation infrastructure and local supply-and-demand factors need to be considered.

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APPENDIX

In the following tables, regression result from ordinary least squares regressions (OLS) is presented in the first column. The SEM column shows results from the spatial error model. This is a spatial model that considers spatial autocorrelation of residuals only. There is no direct lag specified for the dependent or independent variables. The SAR column presents results from the spatial lag model or spatial autoregressive model. This model only includes a lag between the dependent variables, assuming that there is no spatial lag in the error term and/or explanatory variables.

Table A.1: Corn regression results across different specifications for the harvest season, 2018.

Explanatory Variable	Parameter estimate (Harvest Season)			
	OLS	Spatial Error	SAR	SARAR
Intercept	-5.29	-7.53	7.75***	- 4.33
	(7.24)	(33.95)	(2.92)	(13.09)
Corn Production	-4.02***	-0.13	-1.50*	-0.48
	(0.77)	(0.49)	(0.61)	(0.52)
Corn Processor	0.75	3.51***	4.83***	3.95***
	(2.41)	(1.06)	(1.90)	(1.52)
US highway	0.33*	0.008	0.05	0.008
	(0.17)	(0.07)	(0.14)	(0.08)
State Highway	-0.36*	0.04	-0.09	0.04
	(0.14)	(0.06)	(0.09)	(0.07)
Freight Rail	0.14	0.01	-0.01	0.02
	(0.14)	(0.06)	(0.10)	(0.06)
Port Corn	4.36	2.19*	2.20	2.35*
	(3.02)	(1.31)	(2.10)	(1.39)
Elevator Truck	6.60**	-0.38	0.93	-0.36
	(2.24)	(1.03)	(1.58)	(1.07)
Elevator Rail	-4.05	1.27	1.77	1.47
	(3.23)	(1.37)	(2.25)	(1.53)
Elevator Barge	14.75	5.75*	11.81**	6.76*
	(7.16)	(2.98)	(5.79)	(3.64)
Spatially Lagged Basis			0.98***	0.82**
			(0.05)	(0.33)
Spatially Lagged Error		0.99**		0.82**
		(0.04)		(0.33)
Observation	569	569	569	569
Residual Moran's I	0.66***	0.66***	0.66***	0.66***
Log Likelihood		-1941.61	-1937.42	-1916.97

Notes: Standard errors in parentheses. * 10% significance, ** 5% significance, and *** 1% significance.

Table A.2: Corn regression results across different specifications for the post-harvest season, 2018/19

	Parameter estimate (Post-harvest Season)			
Explanatory Variable	OLS	Spatial Error	SAR	SARAR
Intercept	-14.66*	-27.28	2.72	-9.41
	(7.64)	(24.49)	(3.28)	(12.40)
Corn Production	-2.15***	0.50	-0.57	0.18
	(0.82)	(0.55)	(1.44)	(0.53)
Corn Processor	1.15	4.20***	5.19	4.66***
	(2.54)	(1.18)	(4.76)	(1.28)
US highway	0.32*	-0.04	-0.04	-0.05
	(0.18)	(0.08)	(0.14)	(0.08)
State Highway	-0.47***	-0.005	-0.20	-0.02
	(0.14)	(0.06)	(0.20)	((0.07)
Freight Rail	0.43***	0.10*	0.09	0.12*
	(0.15)	(0.06)	(0.13)	(0.07)
Port Corn	3.60	1.60	2.09	1.69
	(3.18)	(1.46)	(4.54)	(1.54)
Elevator Truck	3.42	-1.42**	-0.72	-1.48
	(2.36)	(1.14)	(1.92)	(1.24)
Elevator Rail	-2.91	1.56	1.88	1.76
	(3.41)	(1.53)	(3.29)	(1.67)
Elevator Barge	16.44**	5.51*	11.13	6.50*
	(7.54)	(3.32)	(8.17)	(3.55)
Spatially Lagged Basis			0.98***	0.79**
			(0.07)	(0.36)
Spatially Lagged Error		0.98***		0.82**
		(0.005)		(0.33)
Observation	570	570	570	570
Residual Moran's I	0.66***	0.66***	0.66***	0.66***
Log Likelihood		-2005.49	-2004.53	-1982.75

Notes: Standard errors in parentheses. * 10% significance, ** 5% significance, and *** 1% significance.

Table A.3: Corn regression results across different specifications for the planting season, 2019

Explanatory Variable	Parameter estimate (Planting Season)			
	OLS	Spatial Error	SAR	SARAR
Intercept	-12.78*	-26.62	2.24	-6.66
	(7.57)	(22.32)	(3.34)	(8.97)
Corn Production	-1.54*	0.27	-0.59	-0.03
	(0.81)	(0.56)	(0.55)	(0.58)
Corn Processor	3.06	4.32***	5.47***	4.81***
	(2.51)	(1.20)	(1.98)	(1.60)
US highway	0.41**	0.03	0.06	0.03
	(0.18)	(0.08)	(0.13)	(0.09)
State Highway	-0.46***	-0.005	-0.17*	-0.02
	(0.14)	(0.06)	(0.10)	(0.08)
Freight Rail	0.40***	0.12*	0.13	0.15**
	(0.14)	(0.07)	(0.09)	(0.07)
Port Corn	1.34	1.32	1.38	1.26
	(3.17)	(1.50)	(2.24)	(1.60)
Elevator Truck	2.52	-2.30**	-1.50	-2.41**
	(2.33)	(1.17)	(1.58)	(1.26)
Elevator Rail	-3.07	2.02	2.12	2.24
	(3.37)	(1.55)	(2.37)	(1.72)
Elevator Barge	19.77***	8.67***	14.36**	9.97**
	(7.48)	(3.40)	(6.39)	(4.06)
Spatially Lagged			0.97***	0.79**
Basis			(0.07)	(0.31)
Spatially Lagged		0.98***		0.80***
Error		(0.04)		(0.30)
Observation	567	567	567	567
Residual Moran's I	0.66***	0.66***	0.66***	0.66***
Log Likelihood		-2003.10	-2002.35	-1982.77

Notes: Standard errors in parentheses. * 10% significance, ** 5% significance, and *** 1% significance.

Table A.4: Soybean regression results across different specifications for the harvest season, 2018/19

Explanatory Variable	Parameter estimate (harvest Season)			
	OLS	Spatial Error	SAR	SARAR
Intercept	-206.98***	-159.24	-9.30**	-14.81**
	(13.55)	(45.34)	(3.64)	(5.88)
Soy Production	9.93***	1.18*	0.97	0.92
	(1.58)	(0.66)	(0.68)	(0.77)
Soy Processor	9.99**	0.87	1.93	1.38
	(3.88)	(1.08)	(1.93)	(1.91)
US highway	0.91***	0.04	0.11	0.08
	(0.28)	(0.07)	(0.11)	(0.12)
State Highway	0.11	-0.005	-0.19	-0.08
	(0.23)	(0.06)	(0.15)	(0.12)
Freight Rail	1.02***	0.11*	0.14	0.15**
	(0.23)	(0.06)	(0.14)	(0.09)
Port Soybean	8.12	1.80	2.24	2.33
	(5.04)	(1.41)	(4.54)	(2.34)
Elevator Truck	3.81	-0.15	0.86	0.07
	(3.62)	(1.06)	(1.49)	(1.71)
Elevator Rail	-10.48**	1.99	1.99	2.27
	(5.27)	(1.42)	(2.56)	(1.74)
Elevator Barge	16.14**	7.36**	14.17	8.80**
	(12.59)	(3.38)	(10.60)	(5.62)
Spatially Lagged Basis			0.98***	0.94***
			(0.005)	(0.02)
Spatially Lagged Error		0.99***		0.60***
		(0.003)		(0.11)
Observation	546	546	546	546
Residual Moran's I	0.75***	0.75***	0.75***	0.75***
Log Likelihood		-1875.15	-1866.93	-1855.18

Notes: Standard errors in parentheses. * 10% significance, ** 5% significance, and *** 1% significance.

Table A.5: Soybean regression results across different specifications for the post-harvest season, 2018/19

	Parameter estimate (Post-harvest Season)			
Explanatory Variable	OLS	Spatial Error	SAR	SARAR
Intercept	-218.99***	-152.98***	-20.73***	-23.83***
	(12.18)	(33.66)	(3.88)	(5.68)
Soy Production	13.54***	2.02***	2.34***	2.04*
	(1.42)	(0.67)	(0.55)	(0.67)
Soy Processor	3.40	-0.22	0.28	0.10
	(3.49)	(1.09)	(1.30)	(1.33)
US highway	0.71***	0.14*	0.22**	0.20
	(0.25)	(0.07)	(0.09)	(0.09)
State Highway	0.11	-0.04	-0.12*	-0.06
	(0.20)	(0.06)	(0.07)	(0.08)
Freight Rail	1.01***	0.11*	0.11	0.14
	(0.20)	(0.06)	(0.07)	(0.08)
Port Soybean	13.12***	4.17***	5.13***	5.16*
	(4.54)	(1.42)	(1.62)	(1.77)
Elevator Truck	-2.55	-1.01	-1.23	-1.06
	(3.25)	(1.07)	(1.25)	(1.24)
Elevator Rail	-8.29*	2.70*	2.76	3.12
	(4.74)	(1.43)	(1.77)	(1.69)
Elevator Barge	30.34***	12.35***	19.45***	15.11*
	(11.34)	(3.40)	(4.44)	(4.15)
Spatially Lagged Basis			0.96***	0.93***
			(0.008)	(0.02)
Spatially Lagged Error		0.99***		0.52***
		(0.004)		(0.11)
Observation	533	533	533	548
Residual Moran's I	0.73***	0.67***	0.67***	0.73***
Log Likelihood		-1916.69	-1871.92	-1863

Notes: Standard errors in parentheses. * 10% significance, ** 5% significance, and *** 1% significance.

Table A.6: Soybean regression results across different specifications for the planting season, 2019.

Explanatory Variable	Parameter estimate (Planting Season)			
	OLS	SEM	SAR	SARAR
Intercept	-235.15***	-145.77***	-25.32***	-24.44***
	(13.02)	(37.32)	(4.65)	(6.09)
Soy Production	16.26***	1.56*	2.86***	2.24***
	(1.51)	(0.80)	(0.59)	(0.71)
Soy Processor	2.03	-0.67	-0.33	-0.44
	(3.65)	(1.29)	(1.53)	(1.56)
US highway	0.56**	0.09	0.14	0.12
	(0.26)	(0.09)	(0.10)	(0.11)
State Highway	0.24	-0.06	-0.11	-0.08
	(0.21)	(0.08)	(0.09)	(0.09)
Freight Rail	1.10***	0.18**	0.21**	0.23**
	(0.21)	(0.07)	(0.09)	(0.08)
Port Soybean	18.10***	6.90***	8.30***	8.60***
	(4.74)	(1.68)	(1.93)	(2.00)
Elevator Truck	-4.24	-1.61	-2.13	-1.90
	(3.40)	(1.26)	(1.37)	(1.37)
Elevator Rail	-9.31*	1.45	1.27	1.70
	(4.94)	(1.68)	(2.01)	(1.89)
Elevator Barge	37.65***	14.93***	22.73***	18.49***
	(11.81)	(4.01)	(5.00)	(5.00)
Spatially Lagged Basis			0.95***	0.93***
			(0.009)	(0.02)
Spatially Lagged Error		0.99***		0.45
		(0.004)		(0.45)
Observation	533	533	533	533
Residual Moran's I	0.67***	0.67***	0.67***	0.67***
Log Likelihood		-1916.69	-1895.42	-1889.41

Notes: Standard errors in parentheses. * 10% significance, ** 5% significance, and *** 1% significance.