

# DIGITALES ARCHIV

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**Working Paper**

## Feedstock Transportation Demand in the Biofuel Supply Chain

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*Feedstock Transportation Demand in the Biofuel Supply Chain*

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***Abstract***

*We employ a derived demand model to estimate modal input demand elasticities for feedstock transportation logistics using a pooled cross section of corn shipments to large-scale ethanol plants from 95 grain elevators. As expected, results indicate that truck dominates feedstock traffic based on modal input demand elasticities. Despite truck dominance, rail's share of total transportation cost increases with increasing output pointing to rail's contribution to efficient feedstock logistics than previously known. Rail share increases by 87% while truck share reduces by 26% from the smallest to the largest output. Interestingly, seasonality was not significant. This could stem from the fact that grain elevators store and provide a continuous year around flow of grain or feedstock. Results point to modal usage mix and competitiveness as supply chain participants strive for efficiency in feedstock transportation.*

**Keyword:** Transportation Demand, Elasticity, Biofuel Supply Chain, Bioenergy Policy

## **Introduction**

The dynamics of feedstock transportation logistics associated with fluctuations in flow, need, usage, and seasonality create major challenges for biofuel supply chains, BSC. These transportation logistics challenges adversely affect the efficiency and reliability of BSC systems (Liu et al. 2017). BSC activities range from feedstock production, feedstock transportation logistics, biofuel production, biofuel distribution, and biofuel end use. BSC participants are often disparate entities with decisions made at each stage important for efficiency. Efficient feedstock transportation logistics contribute to enhancing U.S corn-based ethanol competitiveness. Corn represents about 95% of the feedstock in first generation ethanol with the remaining 5% consisting of grain sorghum, barley, wheat, cheese whey, and potatoes (Yacobucci 2008).

Transportation logistics is a significant part of tactical medium-term sourcing decisions for BSC (Ayodele et al. 2020). Feedstock constitutes a major share of the total production cost for corn-based ethanol (Ayodele et al. 2020; Yacobucci 2008). This higher cost places emphasis on the need for low-cost feedstock transportation logistics options. Higher transportation cost is one of the main drivers behind shifts in supply chain sourcing strategies (Russell et al. 2014). Changes in sourcing strategy are an effort to lessen the number of miles of hauling freight tonnage (Russell et al. 2014). Locating closer to the source of feedstock enables biofuel producers to minimize sourcing cost by reducing feedstock travel distance or ton-mile. Most ethanol plants are found in major grain producing states in the U.S. Great Plains and Midwest.

The use of agricultural crops to produce bioenergy introduces volatility into the BSC. For example, fluctuations in grain flow due to the seasonal nature of production has a direct impact on biofuel producers' use of transportation logistics services reflected in the responsiveness of modal input demand or elasticities. The demand for transportation is a derived demand; changes in grain flow associated with need for feedstock will alter the demand for transportation. Hence,

an understanding of the nature of transportation demand is central to improving feedstock sourcing and procurement decisions that enhances the competitiveness of U.S. bioenergy.

The aim of this paper is to examine modal input demand for feedstock transportation with a derived transportation demand model. We use a unique dataset representing a sample of monthly corn shipment from 95 individual grain elevators to large-scale ethanol plants in the U.S. Great Plains between 2009 and 2016. Grain elevators are used for grain storage providing year-round source of feedstock compared to shipments originating from farms or farmgate.

Trucks can access farm locations directly, compared to other modes including rail that require an access point or terminals. This gives trucking a cost advantage and exclusivity for farmgate shipments. Moreover, the nature of grain production suggests that truck shipments with farm origins are likely more sensitive to seasonality. Using feedstock shipments with grain elevator origin facilitates examination of input demand for both rail and truck as well as determine the role of seasonality for an alternative source to farmgate.

Although trucks are the preferred mode, the advent of newer larger capacity ethanol plants requiring significantly more feedstocks has a potential to increase the use of rail for inbound corn shipments (Denicoff et al. 2014). According to data from the Alternative Fuel Data Center of the U.S. Department of Energy, the average capacity of a U.S. ethanol plant rose by 148% from 33.3 million to 82.7 million gallons on average between 2000 and 2018. Moreover, higher commodity prices paid by ethanol producers has increased the volume of corn transported to large-scale ethanol plants (USDA 2014). Rail benefits from economies of shipment size, consequently, has a cost advantage in moving larger volumes in a single train whereas a 40-ton weight limit is placed on trucks. Grain represents a sizeable share of the railroad revenues.

Specifically, corn traffic constitutes close to 45% of all class I railroad gross revenue from grain (AAR 2020).

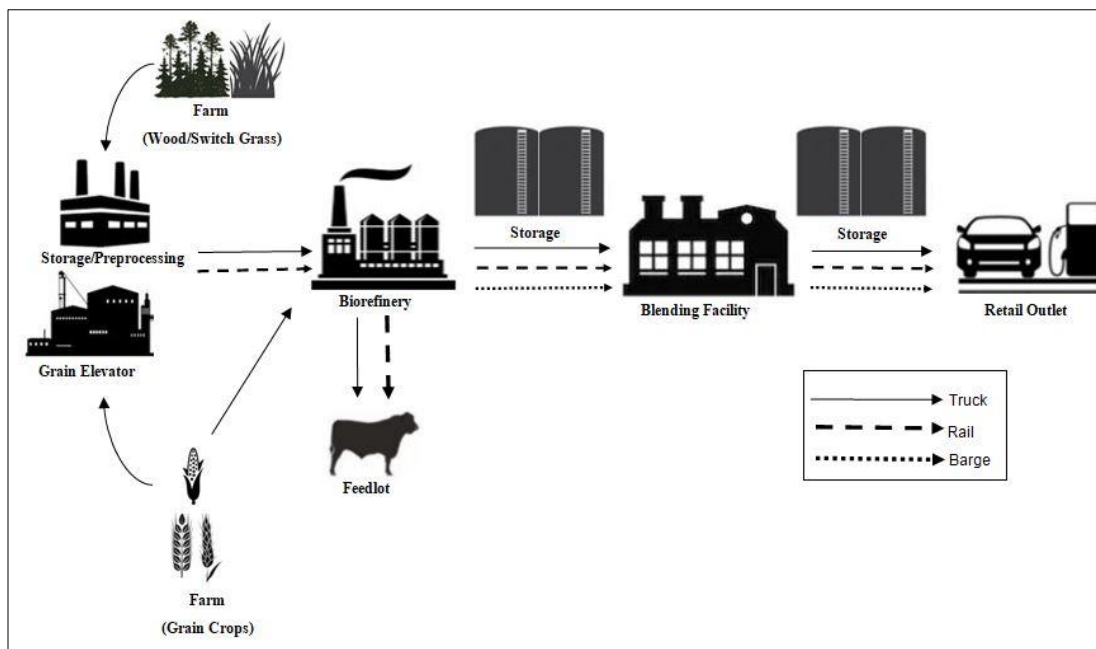
Despite the derived nature of transportation and its potential role in generating efficiencies for the biofuel supply chain, no study to our knowledge has empirically evaluated the nature of modal input demand for feedstock transportation in the BSC as well as underlying issues such as seasonality. Seasonality in feedstock transportation logistics is often assumed owing to the seasonal nature of grain production. Furthermore, empirical research on feedstock transportation logistics in this study contributes and provides vital insights to bioenergy producers, transportation carriers, and policy making. Bioenergy producers are interested in using the most cost-effective modal mix in feedstock procurement while information embedded in transportation demand provides marketing signal to transportation carriers. Policy makers on the other hand are interested in addressing market power in freight transportation.

This paper proceeds as follows. The next two sections describe the growth and expansion of the BSC and the link between corn-ethanol and the local U.S. freight transportation system. The theoretical underpinning follows next, then a description of the empirical model. After describing the data and econometric details, we present results. We conclude with discussion, implication, and suggest future transportation research related to the bioenergy industry.

### **Biofuel Supply Chain Growth and Expansion**

Energy security, environmental concerns, and regional economic development have led governments and authorities to enact policies promoting the production and use of renewable energy. Biofuel is energy derived from naturally renewable energy sources or feedstock including food crops, lignocellulose, and cellulosic biomass used as additive and substitute for transportation fuel. Energy policies enacted in the United States including the 1978 Energy Tax

Act, 1990 Clean Air Act, 2007 Energy Independence and Security Act, EISA have partly played a role in the emergence and growth in the industry and have spurred interest in the BSC. Figure 1 depicts the disparate entities that make up the BSC adapted from Lim and Ouyang (2016).



**Figure 1:** General Depiction of Biofuel Supply Chain

While volume requirements in the Renewable Fuel Standards (RFS) from the 2007 EISA emphasize production of second, third, and fourth generation biofuels from cellulosic and lignocellulose biomass, first generation or conventional biofuel using food crops as feedstock still constitute the single largest share of biofuel production in the U.S. According to data from the Alternative Fuel Data Center ethanol used about 39% or 5.4 billion bushels out of 13.7 billion bushels of all corn produced in the U.S in 2019 up from about 6% in 2000. Although this paper focusses on first generation biofuel feedstock, transportation logistics is central to planning bioenergy production systems for advanced BSC as well (Malladi and Sowlati, 2018). Hence, results are applicable to feedstock transportation logistics for advanced biofuels.

The BSC illustrated in Figure 1 is like most supply chains. It involves various stages and actors including farmers and distributors and related entities like farms and biorefineries (Lim and Ouyang, 2016). Transportation logistics facilitated by rail, truck, and barge help link all activities comprising the BSC. Feedstock production is the first stage of the biofuel supply chain. It involves activities undertaken by farmers culminating in harvest from farmland. Individual farmers that cooperate with the biorefinery through yearly contracts are the main feedstock growers (Lim and Ouyang, 2016). Farmer cooperatives also engage in contractual agreements with biorefineries.

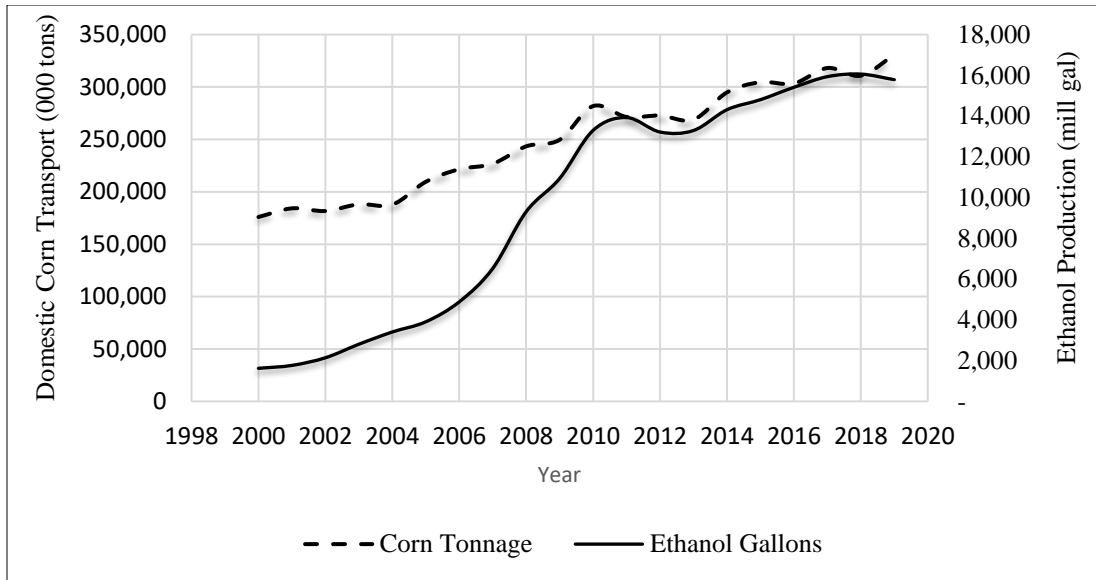
Grain elevators and preprocessing/storage enable gathering of food crops (grains) and biomass hauled by trucks from different farms to fewer locations. Grain elevators provide a year-round source of feedstock especially during the non-growing season. Trucks are exclusively used to ship from farms. Truck and rail subsequently haul grain and biomass to the biorefinery. The biorefinery uses a chemical process (e.g., fermentation) to transform feedstock to liquid form of energy or biofuel. The chemical process using food crops produces a byproduct called distillers dried grains (DDGs) used as animal feed.

Rail and truck transport DDGs from the biorefinery to feedlots. Expansion of ethanol production has led to the development and growth of the transportation logistics market for DDGs. Rail, truck, and barge transport ethanol from the biorefinery to storage locations and blending facilities where the mixture with gasoline occurs to produce different fuel grades used by automobiles. Presently, most automobiles can run on E10 grade, which includes 10% ethanol and 90% gasoline with ongoing development for E15 and E20. Rail, truck, and barge transport distribute different grades of blended fuel from storage to retail outlets.

## **U.S. Ethanol and Corn Transportation**

Environmental concerns leading to passage of the 1990 Clean Air Act (CAA) gave U.S. ethanol a major boost (Newes et al. 2020). In addition to federal legislation, state and local policies have fostered the recent ethanol boom (Newes et al. 2020). The increasing use of corn to produce ethanol has spurred growth in the ethanol industry with consequent increased flow and corn transportation. The trend in number and size of ethanol plants and ethanol production reflects growth in the ethanol industry over time. Although the number of ethanol plants rise and fall from year to year, close to 200 ethanol plants were operational in the United States in 2018 up from 54 plants in 2000 according to the Alternative Fuel Data Center. Larger capacity ethanol plants draw grain from a wider area with considerable impact on grain transportation logistics. Ethanol plants are in grain producing states providing a readily available source of feedstock.

Growth in ethanol demand has contributed to the rapid rise in production and changes in the volume of corn flowing domestically. The rise in volume of corn in tons shipped domestically mimics U.S. ethanol production as illustrated in Figure 2 based on data from the Alternative Fuel Data Center and USDA (2019). Domestic corn transportation represents all shipments made by truck, rail, and barge modes. In general, freight transportation relies on rail, truck, and barge transportation to haul commodities from production sites often located in rural areas to domestic consumption centers and ports for exports. According to USDA (2019) data, trucks have led rail and barge in tonnage of corn transported domestically; with a noticeable increase in truck share the last couple of decades. During 2000 and 2019, trucks hauled about 76% of domestic corn while rail and barge were respectively responsible for 23% and 1% on average. This contrasts with truck, rail, and barge respectively representing 61%, 37%, and 2% of domestic movement between 1985 and 1999. This change reflects increasing production and domestic corn usage.



**Figure 2:** Corn Transportation and Ethanol Production, 2000-2019

### Theoretical Model

Construction of the total transportation cost function follows Oum (1979), where estimation of a firms' demand for freight transportation assumes transportation costs are separable from other production costs. The total transportation cost is a function of rail and truck price and ton-mile which represents the movement of a ton of freight for a mile. These variables are the principal determinants of transportation cost. The general total transportation cost function for large-scale ethanol plants is shown in equation 1:

$$tc = f(p_r, p_t, tm) \tag{1}$$

Where,  $tc$  is total transportation costs,  $p_r$  and  $p_t$  are prices for truck and rail transportation and  $tm$  is total ton-mile. Shephard's Lemma (Shephard 1973) enables derivation of conditional modal input demand functions from large-scale ethanol producers' total transportation cost as shown in equation 2.

$$\frac{\partial tc}{\partial p_i} = x_i, \quad i = t, r \tag{2}$$

Where, the variable  $x_i$  is the quantity of rail or truck transportation employed. The cost function involves a sample of corn shipments from individual grain elevators representing a pooled cross section to large-scale ethanol production plants. Equation 3 represents the general form of the transportation cost model.

$$tc = f(p_i, tm, ti, q_i) \quad (3)$$

Where,  $tc$  is the total rail and truck transportation costs for shipment from a given grain elevator,  $p_i$  is vector of prices of  $i$  modes,  $tm$  is output in ton-mile from a given elevator,  $ti$  is time trend while  $q_{iS}$  are quarterly seasonal dummy variables. Using individual elevators as in Equation (3) closely represents supply chain marketing and distribution processes.

### Model Specification

We estimate total transportation cost with the translog functional form. Developed originally by Christensen et al., (1971), the translog functional form is “flexible” enough to provide a valid second order estimation to an arbitrary differentiable function (Oum 1979). Equation 4 shows the estimable transportation cost function. Where,  $tc$  is total transportation cost,  $rr$  and  $tr$  are rail and truck rate in dollars per ton-mile;  $tm$  is output in ton-mile, while  $q_1$ ,  $q_2$ , and  $q_3$  are first, second and third quarterly seasonal dummy variables with fourth quarter as base.

$$\begin{aligned} (Intc = & \alpha_0 + \alpha_1 \ln(rr) + \alpha_2 \ln(tr) + \rho_2 \ln(tm) + \rho_3 ti + q_1 + q_2 + q_3 \\ & + \tau_{11} \frac{1}{2} (\ln rr)^2 + \tau_{22} \frac{1}{2} (\ln tr)^2 + \beta_{22} \frac{1}{2} (\ln tm)^2 + \beta_{33} \frac{1}{2} ti^2 \\ & + \tau_{12} \ln(rr) \cdot \ln(tr) + \chi_{12} \ln(rr) \cdot \ln(tm) + \chi_{13} \ln(rr) \cdot ti + \chi_{14} \ln(rr) \cdot q_1 + \chi_{15} \ln(rr) \cdot q_2 \\ & + \chi_{16} \ln(RR) \cdot q_3 + \chi_{22} \ln(tr) \cdot \ln(tm) + \chi_{23} \ln(tr) \cdot ti + \chi_{24} \ln(tr) \cdot q_1 \\ & + \chi_{25} \ln(tr) \cdot q_2 + \chi_{26} \ln(tr) \cdot q_3 + \beta_{23} \ln(tm) \cdot ti + \beta_{24} \ln(tm) \cdot q_1 \\ & + \beta_{25} \ln(tm) \cdot q_2 + \beta_{26} \ln(tm) \cdot q_3 + \varepsilon_i \end{aligned} \quad (4)$$

The translog cost is homogeneous of degree one in input prices. A proportional change in rates of all transportation modes used in shipping would alter total transportation cost

proportionately. Linear homogeneity in shipping rates imposes the following restrictions on the estimable cost function in equation 4:

$$\alpha_1 + \alpha_2 = 1; \tau_{11} + \tau_{12} = 0; \tau_{22} + \tau_{12} = 0; \chi_{12} + \chi_{22} = 0; \chi_{13} + \chi_{23} = 0; \chi_{14} + \chi_{24} = 0 \\ \chi_{15} + \chi_{25} = 0; \chi_{16} + \chi_{26} = 0$$

Input share equations for rail and truck are obtainable from the translog cost function using Shephard's Lemma (Shephard 1973) in equation 2, with share equation as:

$$\frac{\partial tc}{\partial p_l} = x_{il} \quad (5)$$

Equation (5) generates factor share equations as follows:

$$s_i = \alpha_i + \tau_{ii} \ln(\text{rate}_i) + \tau_{ij} \ln(\text{rate}_j) + \chi_{i2} \ln(tm) + \chi_{i3} ti + \chi_{i4} q_1 + \chi_{i5} q_2 + \chi_{i6} q_3 + \varepsilon_i \quad (6)$$

Where,  $s_i$  is the expenditure factor share for rail or truck transportation. The rail factor share is jointly estimated with total cost function using Zellner's Seemingly Unrelated Regression (SURE). To facilitate the interpretation of estimated parameters and given the Taylor series expansion feature of the transcendental function, all independent variables except time are normalized by dividing by their means. Estimated coefficients for rail ( $\alpha_1$ ), and truck ( $\alpha_2$ ) rates depict each mode's share of total transportation cost at the means of all variables except time. Modal own-price input demand elasticities for rail and truck at the means of all variables when time is at first period and by ton-mile are respectively shown in Equation 7 and 8 below:

$$\varepsilon_{ii} = \left( \frac{\tau_{ii}}{s_i} \right) - 1 + s_i \quad (7)$$

$$\varepsilon_{ii} = \left( \frac{\tau_{ii}}{s_i + \chi_{ii}} \right) - 1 + (s_i + \chi_{ii}) \quad (8)$$

Calculated modal input demand elasticities above are conditional demand elasticities that do not take changes in the quantity demanded of the final product in response to changes in freight rates into account. However, these modal demand elasticities could be used to reflect usage and

dominance of a given mode over another. When one mode dominates another, the dominated mode is likely to have a higher modal input demand elasticity (Oum, 1979).

This dominated mode cannot increase or decrease shipping rates because it would result in a reduction in revenue since its pricing is likely close to marginal cost. Based on this logic, in the case of truck transport, Oum (1979) classifies markets that are dominated by truck as those that have own rail price elasticities greater than one in absolute value and own rail price elasticities greater than twice the magnitude of truck own price elasticities. Equations 9 and 10 show criteria for truck and rail dominance with subscripts for rail ( $i = 1$ ) and truck ( $i = 2$ ).

$$\text{Truck Dominance: } |\varepsilon_{11}| > 1 \text{ and } |\varepsilon_{11}| > 2|\varepsilon_{22}| \quad (9)$$

$$\text{Rail Dominance: } |\varepsilon_{22}| > 1 \text{ and } |\varepsilon_{22}| > 2|\varepsilon_{11}| \quad (10)$$

We use these dominance criteria to evaluate modal competition and use in feedstock transportation logistics. This will provide insights into the relative usage as well as determine mode dominance for different output or ton-mile range. A relationship exists between modal share and modal input demand elasticities. The mode with a larger share of traffic often has the lowest modal input demand elasticities in absolute terms.

### **Data and Variable Construction**

The primary data used in the econometric analysis in this paper are from the Upper Great Plains Transportation Institute, UGPTI; the Surface Transportation Board, STB, and USDA's, Agricultural Marketing Service, USDA-AMS. Modal corn shipment data from UGPTI and truck rate from USDA-AMS entered directly into analysis while rail rates for individual elevators were constructed using primary data from the STB. The grain movement database provided the sample of corn shipments from 95 individual grain elevators shipped to large-scale ethanol plants. The

grain movement database contains grain elevator and shipment related information including location, volume hauled, destination, mode, and rail service type.

Due to the proprietary nature of shipping rates, rail rates in the STB's waybill sample are published at the aggregate level representing shipments from one Bureau of Economic Analysis region, BEA to another. Rail rates for individual elevators disaggregate rates are therefore estimated in a two-step process using shipment aggregate data containing information on revenue, tonnage, distance, type of service, and time shipment was made.<sup>1</sup>

The first step uses STB rail waybill data to estimate a railroad-pricing model with rail rates per ton-mile estimated as a function of; shipment distance or short miles; tons per railcar or load; rail service type; quarterly dummies; and time trend. Railroad service type include single railcar or 1 to 5 railcar and multicar services or 6 to 52 railcar trains. In the second step of the rail rate estimation, we use regression parameter estimates from the first step to estimate real rail rates in dollars per ton-mile).

USDA-AMS Grain Truck and Ocean Rate Advisory (GTOR) publishes average quarterly grain truck rates. Rates are from national surveys of grain shippers. Truck rates per loaded mile reflect 40-ton statutory weight limit for commercial trucks on highways with payload of 26.6 tons. Rates per loaded mile from USDA-AMS are converted to rates per ton-mile by dividing by payload. The trucking industry, as opposed to the rail industry, is a perfectly competitive industry, which includes trucking operators with no single firm able to control prices for the entire industry. All grain elevators therefore face similar truck rates.

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<sup>1</sup> **Step 1:**  $\ln(rrptm) = \beta_0 + \beta_d \ln(\text{distance}) + \beta_l \ln(\text{load}) + \beta_s \text{multicar} + \delta \sum \text{quarters} + \beta_t \text{time} + \varepsilon$

**Step 2:**  $rrptm = \exp[\beta_0 + \beta_d \ln(\text{distance}) + \beta_l \ln(\text{load}) + \beta_s \text{multicar} + \delta \sum \text{quarters} + \beta_t \text{time}]$

We are confident that these estimated rates reflect actual rates paid. Estimating separate rate equations by BEA region and controlling for shipment characteristics means that rates reflect the actual competitive characteristics faced by grain elevators in the sample. Ndembe and Bitzan (2018, 2022) use rates estimated in a similar manner in the absence of actual rates paid by grain elevator that confirmed a priori expectation about modal demand by grain elevator type and in examining modal shadow prices.

## Descriptive Statistics

Table 1 shows summary statistics for variables used to estimate the total transportation cost function. There are 1,360 total observations. Trucking represents a larger share, 0.85 of total transportation cost compared to 0.15 for rail on average. Average rail rates are 34% higher than average truck rates. This reflects the higher share of truck share. Moreover, this means rail is likely unable to take advantage of economies of shipment size given the relatively smaller output in ton-mile relative to export bound shipments to major ports hauled longer distances and larger volumes, dominated by rail.

Table 1: Descriptive Statistics for Variables Used in Estimation

<i>Dependent Variable</i>	<i>Mean</i>	<i>Standard Deviation</i>
<i>Total Transportation Cost (\$000)</i>	<i>24.6</i>	<i>39.3</i>
<i>Rail share</i>	<i>0.14</i>	<i>0.33</i>
<i>Truck share</i>	<i>0.86</i>	<i>0.33</i>
<i>Explanatory Variables</i>		
<i>Rail Rate (\$/ton-mile)</i>	<i>0.165</i>	<i>0.159</i>
<i>Truck Rate (\$/ton-mile)</i>	<i>0.109</i>	<i>0.029</i>
<i>Ton-mile (000)</i>	<i>255.8</i>	<i>439.8</i>
<i>rail ton-mile</i>	<i>70.7</i>	<i>259.5</i>
<i>truck ton-mile</i>	<i>185.1</i>	<i>375.5</i>
<i>Number of Observations</i>	<i>1,360</i>	

Average truck output is more than double rail ton-mile. However, truck ton-mile also varies more widely than rail ton-mile as shown by the difference in standard deviation. This likely stems from the flexibility involved in using truck. Smaller volumes can be shipped at irregular intervals whereas using rail entails larger volumes in a single shipment.

## Results and Discussions

Table 2 shows results of parameter estimates from the SURE estimation. The system weighted R-Squared ( $R^2 = 0.9880$ ) shows that variables included in the estimation of equation 4 account for much of the variation in ethanol feedstock transportation logistics for our sample data. Parameter estimates for shipping rates modal input prices reflect each mode's share of total

transportation cost according to Shephard's lemma. At the point of means, the average truck share is 0.855 while average rail share is 0.145. The parameter estimate on ton-mile shows the expected positive relationship with real total transportation cost. Real total transportation cost increases with output. This variable is significant at the 1% level of significance. The time variable suggests that total transportation cost is declining and is statistically significant at the 5% level of significance, suggesting decline total transportation cost over time.

All three quarterly seasonal variables are insignificant at conventional levels of statistical significance, suggesting that there is no difference or variability in total transportation cost between the first three quarters and the fourth quarter which serves as the base. These results were unexpected. It is widely viewed that the use of food crops planted and harvested during different seasons as principal feedstock would introduce seasonality in feedstock transportation logistics. Based on this fact, total transportation cost was expected to statistically different from one quarter to the next reflecting planting, harvest, and post-harvest seasons. Corn harvest traditionally takes place in the fourth quarter from October to December. It is expected that the availability of a large volume of feedstock should lead to a higher need and use of transportation services with comparatively higher total transportation cost compared to the first, second or third quarters which represent post-harvest, storage, and planting seasons.

Table 2: Seemingly Unrelated Regression Parameter Estimates

<i>Name</i>	<i>Coefficient</i>	<i>Standard Error</i>
<i>Intercept</i>	<i>10.321***</i>	<i>0.0164</i>
<i>In(rail rate)</i>	<i>0.145***</i>	<i>0.0155</i>
<i>In(truck rate)</i>	<i>0.855***</i>	<i>0.0155</i>
<i>In(ton-mile)</i>	<i>0.981***</i>	<i>0.0077</i>
<i>time</i>	<i>-0.017**</i>	<i>0.0080</i>
<i>first quarter</i>	<i>-0.016</i>	<i>0.0169</i>
<i>second quarter</i>	<i>-0.004</i>	<i>0.0174</i>
<i>third quarter</i>	<i>-0.001</i>	<i>0.0170</i>
$\frac{1}{2}(\ln \text{ rail rate})^2$	<i>-0.071***</i>	<i>0.0119</i>
$\frac{1}{2}(\ln \text{ truck rate})^2$	<i>-0.071***</i>	<i>0.0119</i>

$\frac{1}{2}(\ln \text{ ton-mile})^2$	-0.015***	0.0024
$\frac{1}{2}(\text{time})^2$	-0.001	0.0023
$\ln(\text{rail rate}) * \ln(\text{truck rate})$	0.071***	0.0119
$\ln(\text{rail rate}) * \ln(\text{ton-mile})$	0.043***	0.0035
$\ln(\text{rail rate}) * \text{time}$	0.018***	0.0028
$\ln(\text{rail rate}) * \text{first quarter}$	-0.033**	0.0168
$\ln(\text{rail rate}) * \text{second quarter}$	-0.012	0.0171
$\ln(\text{rail rate}) * \text{third quarter}$	-0.021	0.0169
$\ln(\text{truck rate}) * \ln(\text{ton-mile})$	-0.043***	0.0035
$\ln(\text{truck rate}) * \text{time}$	-0.018***	0.0028
$\ln(\text{truck rate}) * \text{first quarter}$	0.033**	0.0168
$\ln(\text{truck rate}) * \text{second quarter}$	0.012	0.0171
$\ln(\text{truck rate}) * \text{third quarter}$	0.021	0.0169
$\ln(\text{ton-mile}) * \text{time}$	-0.006***	0.0013
$\ln(\text{ton-mile}) * \text{first quarter}$	0.005	0.0081
$\ln(\text{ton-mile}) * \text{second quarter}$	0.004	0.0084
$\ln(\text{ton-mile}) * \text{third quarter}$	0.0004	0.0081
Weighted R <sup>2</sup>		0.9880
RMSE		0.1819

\*\*\*, \*\*, \* Significance at the 1%, 5% and 10% respectively

Another unexpected result from Table 2 is the sign for the interaction between ton-mile and input prices. Rail rates and ton-mile interaction is expected to have a negative sign and that between truck rate and ton-mile a positive sign. Total transportation cost is supposed to decline with increasing output for rail. This unexpected result is likely a partial reflection of truck dominance or a freight market in which rail rates are increasing at an increasing rate rather than at a decreasing rate in a “rate taper” as described by Koo and Uhm (1984). Rail rates increasing at an increasing rate, means railroads are unable to fully benefit from economies of shipping size.

The parameter estimates in Table 2 enable calculation of modal input demand elasticities. Modal input elasticities are from a conditional demand function, assuming constant outputs. That is, the impact of a price change of the commodity on output is not considered. Given that modal conditional demand elasticities sum to zero in the two-mode case, the cross-price elasticity of a given mode with respect to the other mode is equal to the absolute value of the own price

elasticity of the first mode (i.e.,  $\varepsilon_{12} = |\varepsilon_{11}|$  and  $\varepsilon_{21} = |\varepsilon_{22}|$ ). Table 3 shows calculated average modal shares and input demand elasticities at the means of all variables.

Table 3: Modal Shares and Calculated Modal Input Demand Elasticities

	Modal Input Share at Means of All Variables [Std. Error]
Truck Share ( $S_{2l}$ )	0.855 [0.0155]
Rail Share ( $S_{1l}$ )	0.145 [0.0155]
	Mean Modal Input Demand Elasticity [Std. Error]
Truck Input Demand Elasticity $\varepsilon_{22} = -\varepsilon_{21}$	-0.228 [0.0190]
Rail Input Demand Elasticity $\varepsilon_{11} = -\varepsilon_{12}$	-1.347 [0.1198]

Results for calculated modal input demand elasticities in Table 3 show that truck dominates local corn-ethanol traffic originating from grain elevators based on the modal dominance rule used in this paper. The absolute value of modal input demand elasticity for rail, 1.347 is greater than 1 and greater than twice the absolute value of the input price elasticity for truck 0.456 ( $2 \times 0.228$ ). Truck dominance means rail carriers are unable to increase rates without losing a more than proportional level of traffic. Alternatively, trucks can increase prices without losing traffic.

This observation is confirmed with results from the cross-price elasticity. The relatively high cross price input demand elasticity of rail with respect to truck ( $\varepsilon_{12}$ ) suggests that at the means of all variables, a reduction in truck rate will decrease rail traffic more than truck rate reduction as rail is the dominated mode. On the other hand, the comparatively low cross price elasticity of truck with respect to rail rate ( $\varepsilon_{21}$ ) suggests that a reduction in rail rate will decrease truck traffic less than rail rate reduction as truck is the dominant mode. For example, if rail reduces prices by 10%, truck traffic will fall by about 2.3%. We examine the nature of modal input demand elasticity with changing output to determine the potential for rail to compete with larger outputs.

Table 4 shows estimated average modal share and input demand elasticity for different outputs up to the maximum for both rail and truck.

Table 4 Average Modal Share and Input Demand Elasticity by Ton-mile

Ton-mile Interval (000)	Rail Share $\alpha_1$	Rail Input Demand Elasticity $ \varepsilon_{11} $	Truck Share $\alpha_2$	Truck Input Demand Elasticity $ \varepsilon_{22} $	Modal Dominance
0-75	0.030	1.58	0.970	0.10	Truck $ \varepsilon_{11}  > 1$ and $ \varepsilon_{11}  > 2 \varepsilon_{22} $
75-150	0.108	1.55	0.892	0.19	
150-225	0.130	1.42	0.870	0.21	
225-300	0.145	1.35	0.855	0.23	
300-375	0.156	1.30	0.844	0.24	
375-450	0.165	1.27	0.835	0.25	
450-525	0.172	1.24	0.828	0.26	
525-600	0.178	1.22	0.822	0.27	
600-675	0.184	1.20	0.816	0.27	
675-750	0.188	1.19	0.812	0.28	
750-825	0.192	1.18	0.808	0.28	
825-900	0.197	1.17	0.804	0.29	
900-975	0.200	1.16	0.800	0.29	
975-1,250	0.206	1.14	0.794	0.30	
1,250-7,500	0.231	1.08	0.769	0.32	

Table 4 confirms truck traffic dominance based on the modal dominance rule. Truck share decreases by 26% from 0.97 to 0.77, while that for rail increases by 87% from 0.03 to 0.23 from the smallest to the largest output respectively. Rail modal input demand elasticity in absolute terms decreases with increasing output (1.583 to 1.079) but does not fall below 1 while truck input demand elasticity increases from 0.103 to 0.323 but remains below 1. Results suggest that the large-scale ethanol plants use truck services more intensely to haul feedstock corroborating the traditional notion that truck has a cost advantage for such shipments. Large-scale ethanol plants minimize their feedstock sourcing cost by using trucks intensely.

## **Management and Policy Implications**

Policies promoting biofuel have fostered the growth in and spurred interest in issues surrounding the BSC. The BSC encompasses activities that transform feedstock including food crops and biomass like switchgrass to liquid energy blended with fossil fuels used by automobiles. These activities, amongst which includes feedstock transportation and logistics involve different entities with decisions made at each stage contributing to BSC efficiency.

In addition to being used as food source and animal feed, agricultural commodities and grains used to produce first generation biofuels are affected by seasonality in cultivation and harvest with direct effect on ethanol producers' sourcing cost and demand for feedstock transportation logistics reflected in modal input demand. Although seasonality is reasonably assumed in feedstock sourcing, little empirical evidence exists to ascertain this assumption and the nature of feedstock transportation demand. An understanding of the nature and magnitude of feedstock transportation demand is central to improvements in feedstock sourcing and procurement decisions and development of supply chain strategies that enhances the competitiveness of the U.S. bioenergy industry.

The aim of this paper is to examine modal input demand for feedstock transportation with a derived transportation demand model. We use a unique dataset representing a sample of monthly corn shipment from 95 individual grain elevators to large-scale ethanol production plants in the U.S. Great Plains between 2009 and 2016. Farmgate, which represents shipments originating from farms, is exclusively truck dominated given truck's ability to access most areas without an access point or terminal. Using grain elevator origination provides an avenue to examine the nature of modal input demand for transporting renewable energy resources. The large volume of grain required suggests the potential for rail to compete for traffic. Moreover, the biofuel

feedstock transportation market is attractive with potential to grow into the future given increasing environmental concerns and frequent energy shortages.

This study provides evidence suggesting that large-scale ethanol producers employ a dynamic flexible strategy that involves a mix of transportation services albeit a more intensive use of truck in sourcing feedstock from grain elevators. Results contrast with farmgate sourcing which is exclusively truck. This flexible strategy could also mean large-scale ethanol producers use transportation to counterbalance inventory-carrying cost as widely suggested in the supply chain literature. For example, during periods of increasing or decreasing input or inventory cost, trucking provides the flexibility for frequent shipments whereas rail usage could facilitate less frequent larger volume shipments. Ethanol producers face tight margins; hence, cost reduction associated with feedstock sourcing enhances profitability and favorable prices for ethanol, an energy mainstay.

Another important finding in this paper is the lack of seasonality. All three seasonal variables representing the first, second, and third quarter were insignificant at conventional levels. It was expected that modal input demand for feedstock would fluctuate with quarters representing the growing and harvesting seasons. Demand for trucking, the dominant mode, was expected to be more inelastic during harvest, which occurs in the fourth quarter and becomes less inelastic during post-harvest. Alternatively, the transportation share for rail, the dominated mode, was expected to decline during the harvest season. This lack of seasonality likely stems from the fact that grain elevators that serve as storage for grain are a continuous source of feedstock which limits the effect of seasonality. These results add to knowledge on feedstock transportation logistics and sourcing strategy in the BSC. By using grain elevators for feedstock sourcing, ethanol producers are likely to mitigate the effect of seasonality associated with grain production.

Apart from ethanol producers sourcing strategy, calculated modal input demand elasticity also provides marketing signals to transportation carriers and regulatory insights to policy makers. The complexities associated with railroad operation for makes an understanding of the usage of transportation services by high traffic generators an important consideration for demand forecasting, investment planning, and position of moving stock including railcars and locomotives. For trucking, dominance in feedstock transportation provides information to potential trucking market entrants. Operating a trucking business only requires a truck and related documentation.

Policy makers are interested in maintaining competitiveness of the freight transportation industry by mitigating unintended consequences of policy outcomes. It appears the restructured railroad industry following deregulation by the 1980 Staggers Rail Act, SRA has provided rail with an opportunity to handle more local traffic than previously thought. Even though trucks are the preferred mode for local shipments, the comparatively higher than expected rail share especially with increasing output shipment portends an evolving dynamic environment surrounding local freight transportation. Effective and efficient feedstock transportation aided by the freight transportation system enhances the competitiveness of the U.S bioenergy industry.

### **Limitations and Future Research**

As with most research endeavors, one of the principal limitations with this paper is the lack of data. First is the use of total transportation cost rather than total logistics. Using total logistics cost which includes other costs like inventory carrying cost will provide a more comprehensive picture of large-scale ethanol producers' sourcing strategy.

Second, estimated modal input demand elasticities are compensated for input demand elasticities which do not account for changes in the quantity demanded of corn in response to

changes in freight rates. Suggested future research could evaluate the impact of increases in truck size and weight on modal competition in feedstock transportation logistics. This is an important consideration, especially given projected future increases in advanced biofuel production and associated transportation demand for biomass.

Large-scale ethanol plants have begun appearing in non-traditional corn producing states. Is there a movement of corn-ethanol longer distances from traditional states in the Midwest and Great Plains to these non-traditional regions? If so, what are the transportation implications on feedstock sourcing. Does rail transportation play a bigger role? These are some of the other questions that could be answered with further research.

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