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A Study of Grain and Soybean Export Flows:

Uncovering Their Determinants
and
Implications for Infrastructure Investment[1]

by

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Executive Summary

The Issue

According to the USDA's Foreign Agricultural Service, U.S. farmers export more than 20 percent of what they produce. Since 2000, exports have been rising virtually every year, increasing from $58 billion in 2000 to over $133 billion in 2015. This growth has put pressure on U.S. ports which are vital links to foreign entities and trade. Investment in ports can and do have a significant influence on trade flows. However, there is little research that examines determinants of flows from a port to a foreign country or from the production-rich U.S. interior to the ports en route to foreign countries.

Study Approach

In this study, we provide a comprehensive examination of trade for selected agricultural commodities, namely corn, soybeans, wheat, and grain sorghum. This examination includes a description of the countries that import these commodities and the U.S. ports from which they import, as well as a description of the domestic U.S. suppliers of these commodities and the U.S. ports they use to export over time. A focus of the analysis is on the ports that importers and exporters choose to use.

Two separate econometric analyses are presented: an "importer analysis" and an "exporter analysis." In both cases, the analyses focus on the ports used. In the importer analysis (Section I), we model decisions of 151 foreign countries from 96 U.S. ports from 2003 to 2017, and explain which ports are used and the intensity of trade (quantity) between the foreign country and the U.S. port. In the second, exporter analysis (Section 2), we examine the decisions of 70 different origination points in the Upper Midwest[1] and their choice of ports (i.e., where they send their product) from 2014 to 2018. In both cases, the decisions are framed in terms of shipping rates, port identifiers, and port attributes.

Major Findings

In both the import demand and export supply analyses, we find that the cost of transportation and port attributes are important variables. The results are then used to evaluate the changes in trade to changes in the transportation costs and in port attributes. In the importer model, the results are restricted to sea-going movements. In the exporter model, ports with a barge option (from movements in the study area) are more likely to be chosen than ports without a barge option, and West coast ports are more likely to be chosen than Northeast ports. The results are also used to measure the responsiveness of decisions to changes in rates and port attributes. Finally, we calculate "willingness to pay" for deeper channels and longer berthing lengths, which are key to evaluating the benefits of investments.

In our analysis, the ranking of U.S. ports by total agricultural export tonnage has remained relatively consistent from 2002 to 2017. However, the market share of the top ranked ports has fallen, while the market share of lower ranked ports has grown. The decline in market shares for the top ports and increase in market shares for lower ranked ports indicates that importing countries have diversified the ports used when importing agricultural goods from the United States. More specifically, we find:

- Importers of U.S. agricultural products are less likely to choose ports with high associated shipping costs. As freight rates rise, the probability that a port is chosen falls, while the probability that another port is chosen rises.

[1] These include shippers from Iowa, Illinois, Indiana, Kansas, Minnesota, Missouri, North Dakota, Nebraska, South Dakota, and Wisconsin.

- On the other hand, importers of U.S. agricultural products are more likely to select ports with deeper channels and longer total berthing lengths.

- Exporters of U.S. agricultural products are also more likely to ship goods from ports with deeper channels and longer total berthing lengths. Similarly, as freight rates rise, the probability a port is chosen falls.

- Competition in barge and rail shipping markets influence how exporters of U.S. agricultural products choose to export. As barge rates rise, the probability of selecting to ship goods by barge to U.S. ports falls and the probability of selecting to ship goods by rail rises.

1. Importer Analysis: Port Choice and International Trade in Agricultural Products

1.1 Introduction

Over the last several decades, global trade has grown tremendously. Between 1990 and today, the value of global trade as a fraction of global domestic product has increased by 47 percent. The growth in trade translates into growth in international transportation, which depends critically on coastal ports. To accommodate increased trade levels, there has been massive investment in larger vessels to obtain economies of vessel size (e.g., Fan et al., 2018) and in ports to accommodate larger vessels (Brooks et al., 2014). Thus, analyzing how shippers respond to changes in port attributes is crucial for informing policy decisions. In this section, we provide an analysis of importing country port choices, and an analysis of the intensity of trade between that country and the U.S. port.

We motivate the decisions of port choice using a theoretical framework based on the probabilistic Ricardian model in Eaton and Kortum (2002). Their model is commonly used to analyze country- or industry-level trade flows.[2] In our adaptation of their model, choice probabilities are based on differences in trade costs across U.S. ports instead of differences in costs across countries. Global trade arises as individual buyers in import markets purchase products from the port that offers the highest return.[3] The theoretical framework also allows an analysis of how port-level trade costs influence the intensity of trade using a log-linear gravity

[2] There are several port choice studies that specify a random utility model (Anderson et al. (2009); Veldman et al. (2013); Moya and Feo Valero (2017); Stevens and Corsi (2012)), but these models are not typically developed in a trade model.

[3] As shown in Appendix A, our choice model comes directly from Eaton and Kortum with less aggregation.

relationship. The gravity model is commonly used in the trade literature (e.g., Anderson and Van Wincoop, 2004). It relates trade flows negatively to the distance between two countries and positively to the combined size of the two economies; that is, as distance goes down, trade goes up, and trade increases the larger the trading partners. One benefit of the gravity model is that its structure can be used to calculate tariff equivalence of non-tariff trade barriers (Burlando, Cristea, and Lee, 2015).

We apply the model to trade of agricultural products. In particular, port choice decisions and the volume of trade at the port-level are estimated using data on 151 countries importing from 96 ports in the U.S. between 2003 and 2017. We estimate the port choice model with a fractional logit based on market shares and the intensity between the port and the importing country with a gravity model. The results allow us to evaluate how the choice of port and the level of trade change as prices and attributes (channel depth and berthing length) of the port change.

We find evidence that higher shipping rates reduce the probability a port is chosen. In contrast, deeper ports and ports with longer berthing lengths are more likely to be selected by importers of U.S. agricultural goods. We find that the intensive margin of trade (quantity imported from a port) responds similarly to port attributes and shipping costs. Using the estimates from the log-linear model and the structure of the theoretical gravity model, we estimate that a one-dollar increase in the shipping rate has an equivalent effect on trade intensity as a 2.1 percent tariff. Using the estimation results, the willingness to pay for cost-reducing port attributes suggests that an additional foot of channel depth is worth roughly $0.34 per ton. The average annual cost of dredging between 2003 and 2017 is approximately $1.88 per cubic foot.[4] Thus, the benefit to shippers is roughly 20 percent of the cost. When evaluated at the average annual tonnage, the total willingness to pay for an additional foot of channel depth is equivalent to roughly $1.2 million.[5] Similarly, the willingness to pay for berthing length is worth approximately $10.36 million per 100,000 feet. Finally, the effects are calculated across different commodities and found to be quite heterogenous. For example, we find one additional foot of berthing length, and one additional foot of channel depth is twice as high for shipments of soybeans than for other crops.

The willingness to pay figures shed light on the benefits of potential investments to accommodate larger vessels. For example, the largest bulk vessels require channel depths of 60 feet (Bureau of Transportation Statistics, 2017). For the average port in the sample, with a channel depth of 41 feet, shippers would be willing to pay approximately $22.8 million for channel deepening to accommodate the largest bulk vessels. According to data on dredging costs from the USACE, the total cost of deepening 500-foot-wide channel 19 feet for 1 mile is approximately $94 million.[6]

Own- and cross-price elasticities are calculated to evaluate the responsiveness of quantities across ports from an increase in the cost of shipping and an increase in port depth or berthing length. These actions affect the benefit of using different ports and result in a reallocation of where goods are exchanged. We find that a 1 percent increase in port-specific

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[4] These data are available from USACE Navigation Data Center, "Actual Dredging Cost Data for 1963-2018." For further information on the cost of dredging, see Frittelli (2019).

[5] This is calculated by multiplying the $0.34 per foot per ton by the average annual port-level tonnage, which is approximately 3.5 million tons per year.

[6] This is calculated based on a dredging cost $1.88 per cubic foot from Frittelli (2019) and USACE.

shipping costs is associated with a decrease in quantities at that same port of between 6 percent and 8 percent, depending on the port. Cross-price elasticities, which measure the sensitivity of one port's quantity with respect to the rates attached to another port, range from 0.07 on the low end to 1.4 on the high end.

The analysis provides insights into how shipping costs and port attributes influence the extent (which port to use) and intensity (how much to procure from the chosen port) of trade at U.S. ports. The results of the paper have several important policy implications. First, changes in global trade policy shift where goods are traded, and as a result, which ports are used. Changes in shipping costs influence which ports are the most competitive in serving global markets. As a result, they have significant implications for regional economies that rely on the competitiveness of local ports. For example, a 2014 study found that full- and part-time employment at deep-water ports in Georgia contributed to 8.4 percent of total state-level employment (Humphreys, 2015). Understanding how changes in port attributes and shipping costs influence port use has implications for the day-to-day operations at ports as well. Empirical evidence suggests that port-level infrastructure plays an important role in determining port efficiency (Herrera and Pang, 2008; Munim et al., 2018). Thus, analyzing the trade-offs shippers face when choosing ports can help inform policies aimed at improving efficiency through port-level infrastructure investment.

1.2 Conceptual Framework

We explain importers' port choices and volumes (intensity of trade) with a model developed from a seminal article by Eaton and Kortum (2002) in the international trade literature. In this subsection, we provide a brief description of the empirical implications of the model, with formal development included in Appendix A.

The empirical analysis consists of two elements. First, we estimate a model that explains the choice of port from which the commodities are received. Naturally, this depends on the trade costs from the port. Trade costs are represented by country to port rates, which vary across ports owing to differences in shipping distances and port attributes (e.g., channel depth and berthing length). Second, using the same framework (Appendix A), we estimate trade intensity or volumes using these same factors (country to port rates and port attributes). That is, estimated port-country-commodity shares can be developed to produce a log-linear specification of trade volumes that is similar to the workhorse of international trade modeling, the gravity model (Anderson and Van Wincoop, 2004). Further, this model can be used to calculate the tariff equivalent of a non-trade barrier.

1.3 Data

The data used to estimate the models are readily available and include: (1) trade data from the U.S. Census Trade Online Database, (2) port attributes compiled from the World Port Index, the United States Army Corps of Engineers, and supplemental data from individual port websites, and (3) freight rates provided by USDA from O'Neil Commodity Consulting.

1.3.1 Trade Data

The U.S. Census Trade Online Database is the primary source of data used in this project. The data are the annual quantity of exports of the four agricultural commodities studied (wheat, soybeans, corn, and sorghum) from all U.S. customs ports to all importing countries. We focus specifically on vessel shipments, which account for 98.9 percent of the total shipment value over the sample period. The result is a collection of 111 customs ports. We observe these ports for the years 2003 to 2017.

1.3.2 Port Attributes

We compiled port-level attribute data from a variety of sources. These sources include the World Port Index, the Army Corps of Engineers, and supplemental information from port websites. Our data includes information on the channel depth and total berthing length. The data corresponds to the year 2016. Channel depth is measured in two ways, the minimum and maximum channel depth. In the analysis, the minimum channel depth is used to measure the depth of the port because the shallowest point of a port is a limiting factor in determining the size of vessels that can access the port (Bureau of Transportation Statistics, 2017).[7] In the context of the choice model, these variables influence the probability a port is chosen through the effect on trade costs from a given port. Importers of agricultural products may not directly place importance on the channel depth of a port, for example, but the channel depth factors into the port choice decision through the effect on the port-level price.

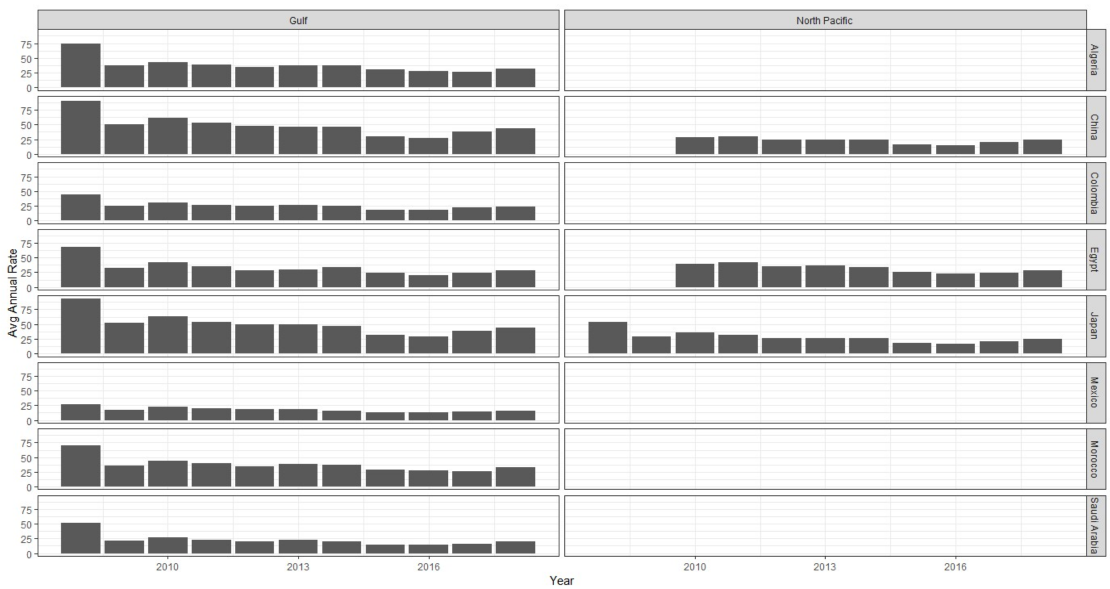
1.3.3 Freight Rates

We use weekly data on freight rates between regions of the United States and destination countries from O'Neil Commodity Consulting to predict annual port-level freight rates for all possible origin-destination pairs. The data are for shipments from the Gulf Coast and Pacific Northwest to several countries. The breadth of the data is displayed in Figure 1.1. We take advantage of detailed distance data to create a measure of port-destination freight rates. Specifically, we use variation in port-destination shipping distances, shipment value, and variables controlling for annual fluctuations in freight rates to predict and impute freight rates at the port-destination-year level.

[7] The results of the empirical analysis are quantitatively and qualitatively similar if maximum channel depth is used.

We measure external shipping distance using data on shipping distances between U.S. ports and importing country ports, which accounts for geographic features, such as the Panama Canal. The distance data come from a database on port-to-port nautical miles. Because our trade data is at the port-country level, we use the average distance to ports in the importing country as a measure of port-country distances.

Figure 1.1: Freight Rate Data Coverage



Note: The figure displays the average annual freight rate from different U.S. regions (Gulf or North Pacific) to importing countries (e.g., China, Egypt, Japan, etc.), 2008-18.

To impute freight rates, we use a log-linear model in which the natural log of the freight rate is predicted based on the natural log of the shipping distance.[8] In Table 1.1 we display four specifications, all of which include the log of the shipping distance between port *k* and country *j*.

[8] We have also used a "random forest" regression model to predict freight rates. The random forest model can flexibly allow for a high dimension of non-linearity in the regressors (or, "attributes of the forest"). The results are qualitatively similar to the results when the OLS mode is used to predict and impute freight rates. Further, we have also estimated rates using additional control variables, such as a port's total annual tonnage. The results are quantitatively very similar.

Columns (2) and (3) of the table include a linear and quadratic time trend, while column (4) includes year fixed effects. The adjusted R^2 of the model is highest when year fixed effects are included, where the model captures 70 percent of the variation in freight rates. Based on fit, we use the specification in column (4) of the table to predict and impute the missing freight rates.[9]

Table 1.1: OLS Model of Freight Rates

	1	2	3	4
log Distance	0.292***	0.295***	0.296***	0.296***
	(0.015)	0.011)	(0.01)	(0.009)
Time Trend		−0.092***	−128.602***	
		(0.002)	(4.551)	
Quadratic Time Trend			27.666***	
			(3.06)	
Constant	0.921***	186.137***	1.248***	1.001***
	(0.131)	(4.172)	(0.093)	(0.079)
N	2086	2086	2086	2086
R^2	0.155	0.566	0.582	0.702
Adjusted R^2	0.155	0.566	0.582	0.701
Year Fixed Effects	No	No	No	Yes

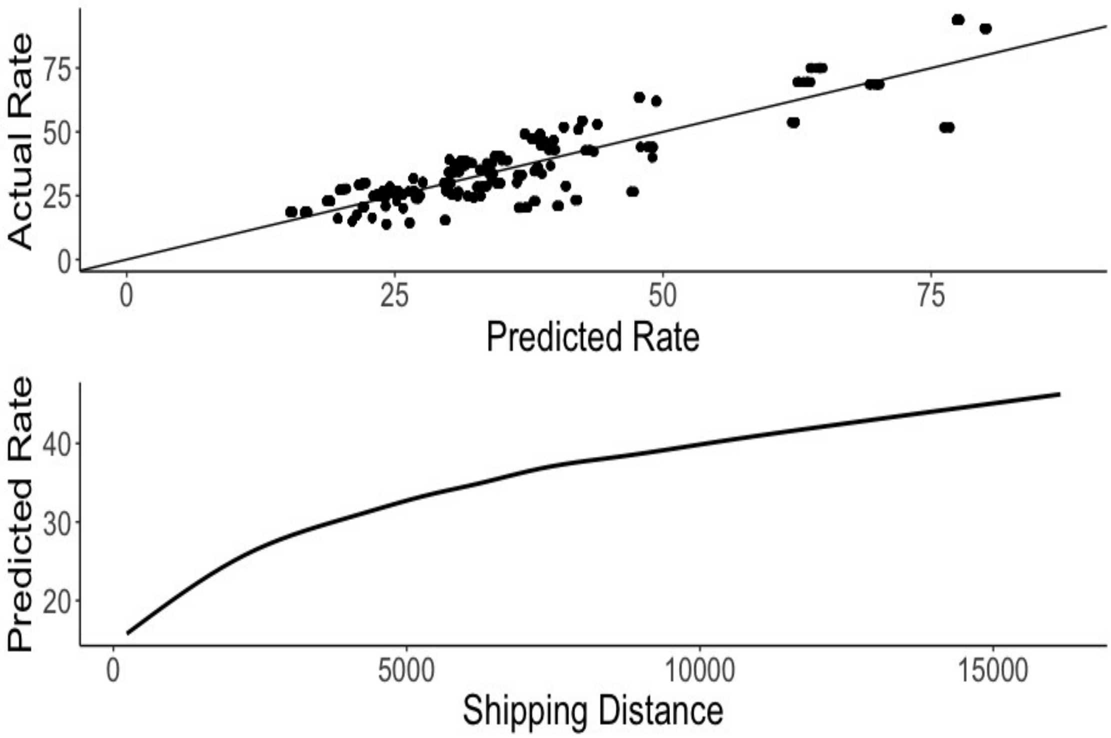
Note: This table presents the results of estimating the OLS regression model used to predict port-destination-year level freight rates. Errors allow for clustering at the importing country level. *p<0.1; **p<0.05; ***p<0.01

In the top panel of Figure 1.2, we display the relationship between actual shipping rates (on the y-axis) and the predicted rates from the model (on the x-axis). These two variables are highly correlated. A regression of actual rates on predicted rates produces a coefficient of 1.09 with an R-squared of 0.79. In the bottom panel of Figure 1.2, we display the relationship between

[9] The empirical results are qualitatively and quantitatively similar if we use the other specifications in Table 1.1.

the average annual predicted port-destination freight rates and the port-destination shipping distances. Freight rates increase with distances at a decreasing rate.[10]

Figure 1.2: Relationship between freight rate and shipping distances



Note: The top panel of the figure displays the relationship between the predicted rates and the actual rates. The black line is a 45^{o} line. The bottom panel of the figure displays the relationship between shipping distances and the predicted rate. The line is calculated with a "lowess-smoother" and represents the average rate at a given distance across years. Some shipping distances are very long—for example shipping from Chicago to Vietnam requires a voyage of 16,000 miles.

[10] The finding that rates increase at a decreasing rate is consistent with the so-called "tapering principle" (see, Locklin, 1972). The concave ship is a result of the fixed costs associated with loading and unloading ships is spread out over more miles shipped (Blonigen and Wilson, 2018).

1.4 Results

1.4.1 Descriptive Statistics: Volumes between U.S. Ports and Importing Countries

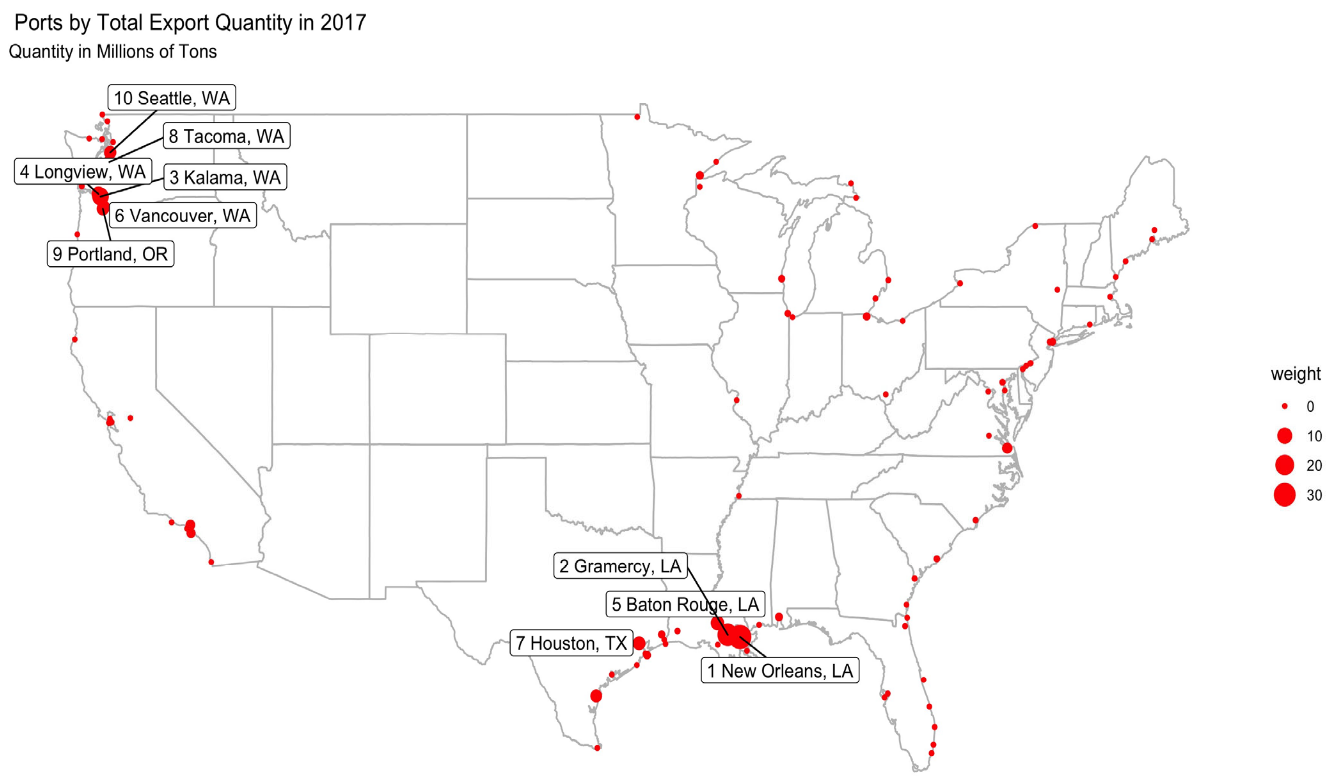
Figure 1.3 displays the location of the ports as well as information on the total export quantity (measured by weight) from each port in 2017. The top 10 ports, in terms of tonnage, are labeled in the figure. This figure highlights several important aspects of the data. First, the Gulf Coast and the Northwest are the two main regions where agricultural exports exit the United States. Ports by the Great Lakes and on the East Coast export less agricultural commodities. Second, the figure highlights how geographically close some of the major ports are to each other. For example, New Orleans is the top-ranked port in terms of export tonnage, and Gramercy is the second. These two ports are located 51 miles apart. We treat each customs port in the data separately, rather than grouping ports into regions, because each port has unique attributes and aggregating trade across ports would make it difficult to determine how these port-specific attributes influence trade flows.

Figure 1.4 plots the quantity by commodity. Sorghum exports are heavily concentrated in the Gulf, while other commodities are exported from a wider range of ports. The general pattern across products remains the same. Ports in the Gulf and Northwest export at higher values than ports on the East Coast and Great Lakes region.

When port-level exports by destination are plotted, several patterns emerge. Figure 1.5 displays tonnage imported across a range of countries. The countries chosen are the top importers by volume in each continent or region of the world. While the Gulf remains a highly used region for most countries, other port regions experience more variation across importers. For example, Germany imports heavily from Gulf and East Coast ports, but very little from the

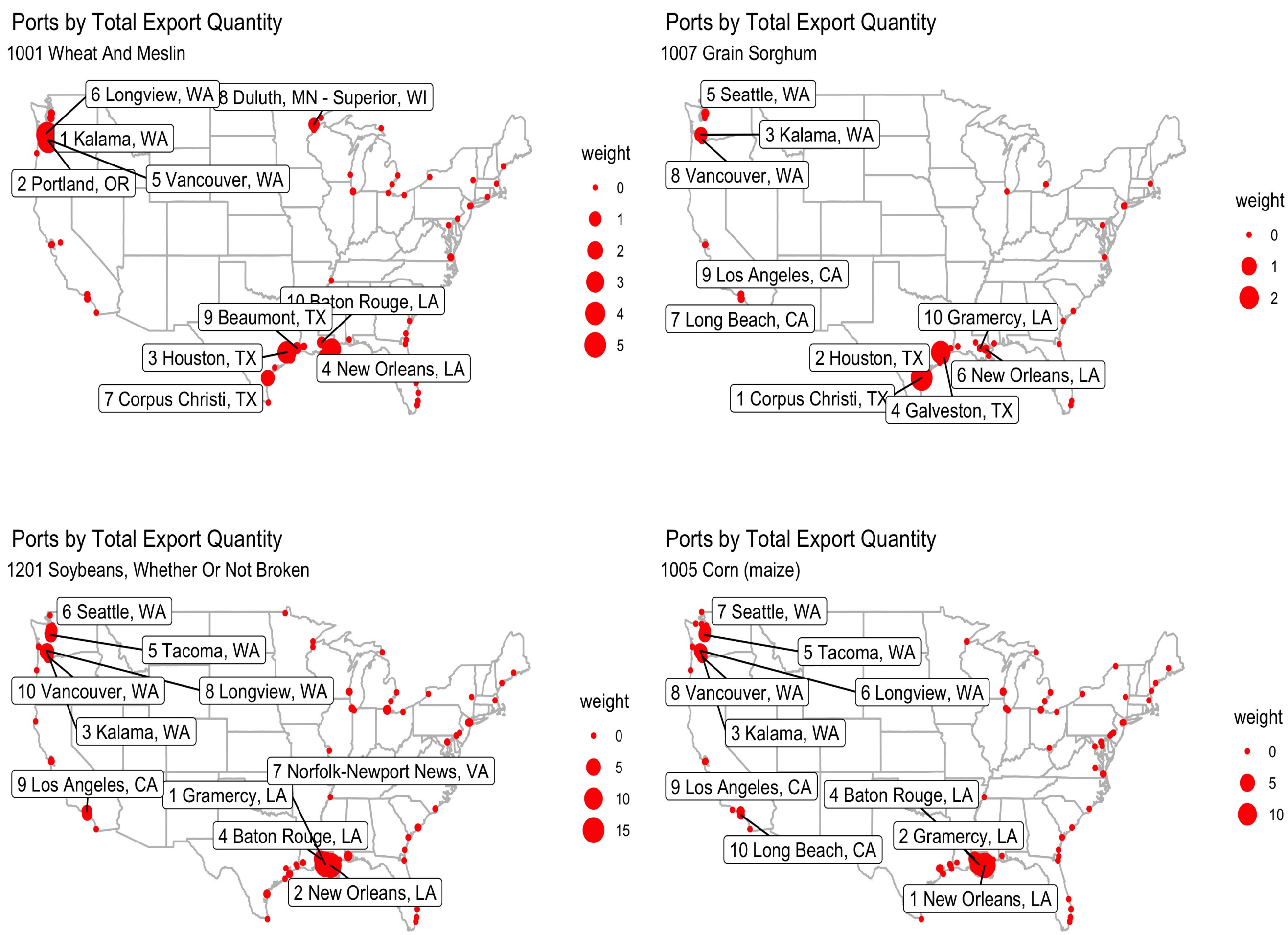
West Coast. The patterns revealed in these figures highlight the importance of the distance between ports and importing countries in port-choice decisions.

Figure 1.3



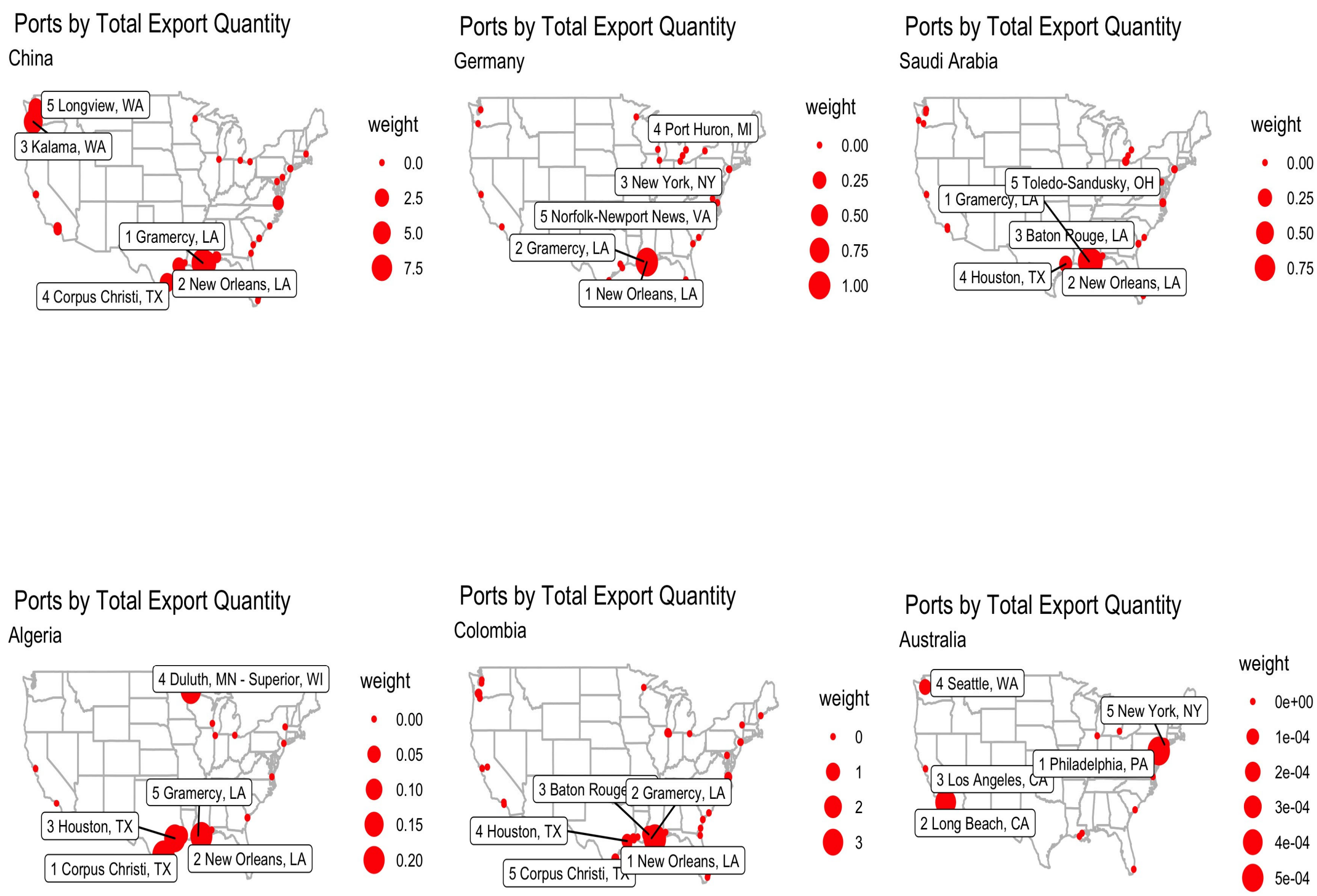
Note: This figure displays the total tonnage (in millions) shipped from each port in 2017. The top ten ports, in terms of total tonnage, are labeled.

Figure 1.4



Note: This figure displays the total tonnage (in millions) shipped from each port in 2017 for each commodity. The top ten ports, in terms of total tonnage, are labeled.

Figure 1.5



Note: This figure displays the total tonnage (in millions) shipped from each port in 2017 for several large importers. The top five ports, in terms of total tonnage, are labeled.

Next, we analyze how the use of ports has changed over the sample period. Table 1.2 displays the top ten ports, in terms of total market share across all commodities and importing countries, in the first and last year of the sample. New Orleans remains the largest source of imports over the sample period. The decline in market shares for the top ports and increase in market shares for lower ranked ports indicates that importing countries have diversified the ports used when importing agricultural goods. Tables 1.3, 1.4, 1.5, and 1.6 display the top ranked ports for soybeans, corn, wheat, and sorghum, respectively.

Table 1.2: Total Market Shares				
Rank	2003		2017	
1	New Orleans, LA	37.65	New Orleans, LA	25.17
2	Gramercy, LA	24.95	Gramercy, LA	19.96
3	Kalama, WA	6.712	Kalama, WA	10.74
4	Portland, OR	6.15	Longview, WA	5.891
5	Tacoma, WA	5.299	Baton Rouge, LA	5.473
6	Houston, TX	3.538	Vancouver, WA	4.557
7	Seattle, WA	3.044	Houston, TX	4.528
8	Vancouver, WA	2.838	Tacoma, WA	4.298
9	Galveston, TX	1.564	Portland, OR	4.11
10	Corpus Christi, TX	1.546	Seattle, WA	3.879

Note: The table displays port-level market shares for 2003 (the first year of the study period) and 2017 (the last year of the study period). Market shares are calculated as the fraction of tonnage from a port across all commodities, relative to total tonnage. The top ten ports in each year are shown.

Table 1.3: Soybeans Market Shares				
Rank	2003		2017	
	Port	share	Port	share
1	New Orleans, LA	43.19	Gramercy, LA	27.33
2	Gramercy, LA	25.21	New Orleans, LA	25.94
3	Kalama, WA	9.578	Kalama, WA	8.312
4	Seattle, WA	6.464	Baton Rouge, LA	7.279
5	Tacoma, WA	6.401	Tacoma, WA	5.133
6	Mobile, AL	4.112	Seattle, WA	5.011
7	Norfolk-Newport News, VA	1.485	Norfolk-Newport News, VA	4.692
8	Brunswick, GA	0.864	Longview, WA	4.201
9	Baton Rouge, LA	0.832	Los Angeles, CA	2.799
10	Superior, Wisconsin	0.584	Vancouver, WA	2.718

Note: The table displays port-level market shares for 2003 (the first year of the study period) and 2017 (the last year of the study period) for soybeans. Market shares are calculated as the fraction of tonnage from a port, relative to total tonnage. The top ten ports in each year are shown.

Table 1.4: Corn Market Shares				
Rank	2003		2017	
	Port	share	Port	share
1	New Orleans, LA	46.54	New Orleans, LA	35.44
2	Gramercy, LA	35.81	Gramercy, LA	24.88
3	Tacoma, WA	7.978	Kalama, WA	8.321
4	Kalama, WA	4.625	Baton Rouge, LA	6.3
5	Seattle, WA	2.415	Tacoma, WA	6.288
6	Baton Rouge, LA	1.166	Longview, WA	6.098
7	Toledo-Sandusky, OH	0.316	Seattle, WA	5.012
8	Lake Charles, LA	0.226	Vancouver, WA	3.52
9	Albany, NY	0.18	Los Angeles, CA	1.036
10	Mobile, AL	0.107	Long Beach, CA	0.681

Note: The table displays port-level market shares for 2003 (the first year of the study period) and 2017 (the last year of the study period) for corn. Market shares are calculated as the fraction of tonnage from a port, relative to total tonnage. The top ten ports in each year are shown.

Table 1.5: Wheat Market Shares				
Rank	2003		2017	
	Port	share	Port	share
1	Portland, OR	23.95	Kalama, WA	20.01
2	New Orleans, LA	15.69	Portland, OR	18.63
3	Houston, TX	13.25	Houston, TX	13.66
4	Vancouver, WA	10.89	New Orleans, LA	12.42
5	Kalama, WA	7.097	Vancouver, WA	11.17
6	Gramercy, LA	6.971	Longview, WA	10.59
7	Galveston, TX	5.875	Corpus Christi, TX	5.346
8	Corpus Christi, TX	4.758	Duluth, MN - Superior, WI	2.612
9	Superior, Wisconsin	4.298	Beaumont, TX	1.552
10	Beaumont, TX	3.902	Baton Rouge, LA	1.437

Note: The table displays port-level market shares for 2003 (the first year of the study period) and 2017 (the last year of the study period) for wheat. Market shares are calculated as the fraction of tonnage from a port, relative to total tonnage. The top ten ports in each year are shown.

Table 1.6: Sorghum Market Share				
Rank	2003		2017	
	Port	share	Port	share
1	New Orleans, LA	47.71	Corpus Christi, TX	47.19
2	Gramercy, LA	27.83	Houston, TX	35.19
3	Corpus Christi, TX	12.97	Kalama, WA	10.34
4	Houston, TX	5.622	Galveston, TX	2.906
5	Tacoma, WA	1.521	Seattle, WA	1.189
6	Seattle, WA	1.256	New Orleans, LA	0.991
7	Kalama, WA	0.843	Long Beach, CA	0.542
8	Baton Rouge, LA	0.807	Vancouver, WA	0.504
9	Galveston, TX	0.76	Los Angeles, CA	0.454
10	Los Angeles, CA	0.311	Gramercy, LA	0.384

Note: The table displays port-level market shares for 2003 (the first year of the study period) and 2017 (the last year of the study period) for sorghum. Market shares are calculated as the fraction of tonnage from a port, relative to total tonnage. The top ten ports in each year are shown.

In general, the rank ordering across ports remains relatively constant. However, by 2017, Longview and Baton Rouge replaced Galveston and Corpus Christi in the top ten. In general, the top ports are consistent across commodities. Port competition is stronger in some commodities than in others. For example, the top port in wheat has a market share of roughly 20 percent, while the top port in sorghum has a market share of nearly 50 percent. In general, the top-ranked ports remain constant over the sample period, but there is more movement lower in port rankings. Across commodities, the ports that climb in the rankings tend to be located on the West Coast, while East and Gulf Coast ports tend to fall out of the top ten. The rise of West Coast ports can be attributed to the shift in U.S. trade partners and is consistent with the results in Blonigen and Wilson (2013).

1.4.2 Summary Statistics

Table 1.7 presents the summary statistics of the main variables, along with information on the data source. In the average year, port-level shipping weights are roughly 36,376 tons, and freight rates are roughly $35 per ton. The number of observations falls for the port-attributes—berthing length and channel depth—because information is not available for all ports in the dataset. However, the ports for which we do have data on port attributes cover 97 percent of the total export tonnage. Thus, we analyze how these characteristics influence shipments from the major U.S. agricultural ports.

Table 1.7: Summary Statistics

Variable	Description	Source	Mean	Std. Dev.	N
Weight	Tons	U.S. Census	36,376	272,270	44,579
Distance	Shipping Distances (miles)	Army Corps	6944.9	3636.2	44,579
Rate	Freight Rate (per ton)	O'Neil Commodity Consulting	$34.74	$11.99	44,579
Berthing	Total Berthing Length (in 100,000 ft)	Multiple Sources	1.05	1.07	38,941
Depth	Minimum Channel Depth (ft)	Multiple Sources	41	14.8	39,150

Note: N is the number of observations.

Table 1.8 breaks down the data by crop. Average annual shipments of soybeans are larger than the other commodities, travel further, and have higher average freight rates. Sorghum shipments, while the smallest in terms of weight, tend to exit through ports with deeper channels and longer total berthing lengths.

Table 1.8: Summary Statistics by Crop

Commodity	Tons	Rate ($/ton)	Berthing (100,000 ft)	Depth (ft)	Dist (mi)
Wheat	33, 730	34.84	1.00	41	6818.1
Corn	26,041	34.21	1.05	41	6642.8
Sorghum	15,211	34.64	1.15	43	6751.2
Soybeans	57,540	35.70	1.05	41	7755.4

1.4.3 Empirical Results

The results of multiple empirical models are presented in the first three columns of Table 1.9. All columns include destination commodity-year fixed effects. In columns (2) and (3) we include dummy variables that account for the region in which a given port lies (the omitted category is Great Lakes). In the column labeled Trade Intensity, we estimate a log-linear model with the log of export quantity as the dependent variable.

The results in Table 1.9 highlight the relevant trade-offs importing countries make when choosing a port. Higher freight rates reduce the probability a port is selected across all models, while deeper ports and ports with longer berthing lengths are more likely to be chosen. From the model in column (4), we estimate that a one dollar increases in the freight rate (an additional dollar per ton) reduces the intensity of trade from the port by 8.5 percent.

As noted earlier, one benefit of the gravity trade model is its structure can be used to convert marginal effects of non-tariff barriers into tariff equivalents (Burlando, Cristea, and Lee (2015)). In our context, the marginal effect of a one dollar increase in the freight rate can be translated into a tariff equivalent by scaling it by the trade elasticity from Eaton and Kortum (2002). More detail on how this parameter enters the empirical specifications can be found in

Appendix A. Following Simonovska and Waugh (2014), we use a scaling value of 4.12. The tariff-equivalent of a one-dollar increase in the freight rates is roughly 2.1 percent.[11]

Table 1.9: Estimation Results

Variable	Port Choice			Trade Intensity
	(1)	(2)	(3)	(4)
Rate	−0.11∗∗∗	−0.18∗∗∗	−0.20∗∗∗	−0.085∗∗∗
	(0.007)	(0.010)	(0.012)	(0.008)
Depth			0.068∗∗∗	0.026∗∗∗
			(0.005)	(0.006)
Berthing			0.591∗∗∗	0.062∗∗
			(0.030)	(0.030)
Gulf		1.15∗∗∗	0.49∗∗∗	2.38∗∗∗
		(0.082)	(0.11)	(0.15)
North Atlantic		0.02	−1.58∗∗∗	−0.75∗∗∗
		(0.084)	(0.144)	(0.167)
North Pacific		0.45∗∗∗	0.38∗∗∗	1.17∗∗∗
		(0.095)	(0.121)	(0.152)
South Atlantic		−1.15∗∗∗	−0.96∗∗∗	−1.37∗∗∗
		(0.110)	(0.129)	(0.150)
South Pacific		−0.051	−0.039	−0.209
		(0.098)	(0.121)	(0.152)
Observations	44473	44473	37871	13321

Note: This table presents the results of estimating the fractional logit model. All columns include destination-commodity-year fixed effects. Columns (1) through (3) display the results of the choice model. The column labeled Trade Intensity presents the results of a gravity model specification, with the log of port level export value as the dependent variable. To account for the fact that our freight rate variable is generated, errors in the table are calculated using a bootstrap over both the imputation of freight rates and the estimation of the fractional logit or the intensity equation (see Appendix A). This is known as a two-stage bootstrap procedure. ∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01.

[11] The tariff equivalent is calculated from $\widehat{\beta_1}=-\theta*\alpha_1$, where these parameters come from the theoretical model. In the context of the model, α_1 is the tariff equivalent. Thus, with $\theta=4.12$, and $\widehat{\beta_1}=8.5\%$, the tariff equivalent is roughly 2.1%.

Choice models allow the calculation of a “willingness to pay" of importers for a change in an attribute.[12] To calculate willingness to pay, we divide the marginal effect on utility associated with deepening or widening the port by the coefficient on rates, which is the marginal effect of a higher price on utility. For example, using the results in column (3), the shipper’s willingness to pay for an additional foot of channel depth at a port is $0.34 per ton (0.068/$0.20 per ton = $0.34 per ton). Given that the average shipment weighs roughly 36,400 tons (from Table 1.3), this comes to a total of $12,376 per foot. We use a similar method to calculate the willingness to pay for added berthing length, and we produce an estimate of roughly $2.96 per ton (0.591/$0.20 per ton) per 100,000 feet of total berthing feet. When evaluated at the average total port-level tonnage, the willingness to pay in total for an additional foot of channel depth comes to $1.2 million (0.34*3.5 million tons), and the willingness to pay for an additional foot of berthing length comes to $10.36 million per 100,000 feet (2.96*3.5 million tons).

We also simulate choice probabilities to graphically display demand for ports. For example, Figure 1.6 displays the likelihood that the port of New Orleans is chosen at different freight rates. The predicted probabilities are generated based on the estimates from column (3) of Table 1.9. The x-axis plots freight rates from the port of New Orleans, and the y-axis plots the choice probability based on the estimated parameters. The solid line corresponds to the choice probability of New Orleans, and the dashed line corresponds to the choice probability for any port other than New Orleans. As the freight rates from New Orleans increases, the probability

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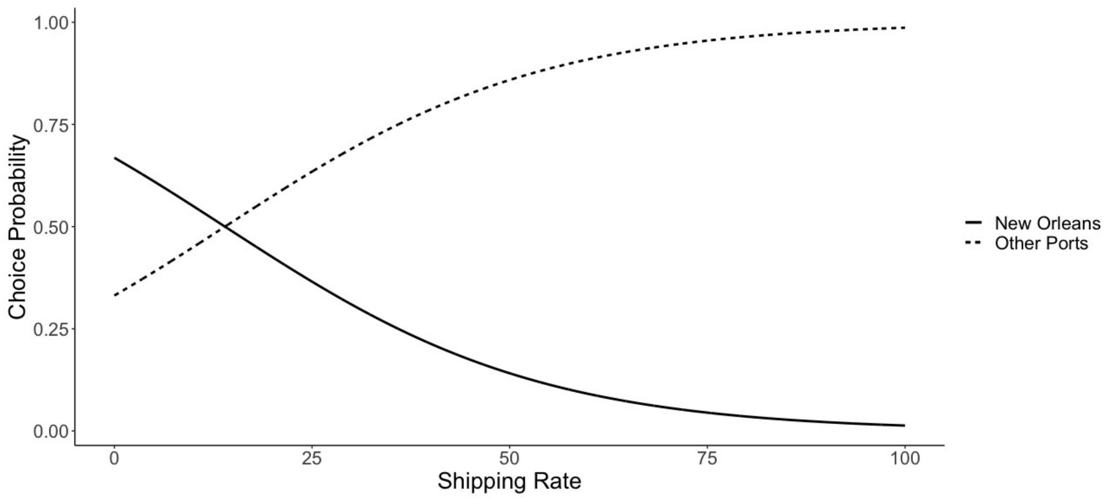
[12] The willingness to pay is generated from the parameter estimates. Technically, if depth increases by one unit, it is the amount price can rise to keep utility the same as before the depth was increased. Details can be found in McCarthy (2001).

that New Orleans is chosen falls while the probability that an importer chooses a different port rises.

Figure 1.6: Choice Probability for New Orleans



Note: The figure displays the simulated choice probabilities for the port of New Orleans based on the results in column (3) of Table 1.9. The choice probabilities are simulated over different freight rates from New Orleans, which are displayed on the x-axis. Choice probabilities for other ports are shown with the dashed lines.

1.4.4 Differences Among Commodities

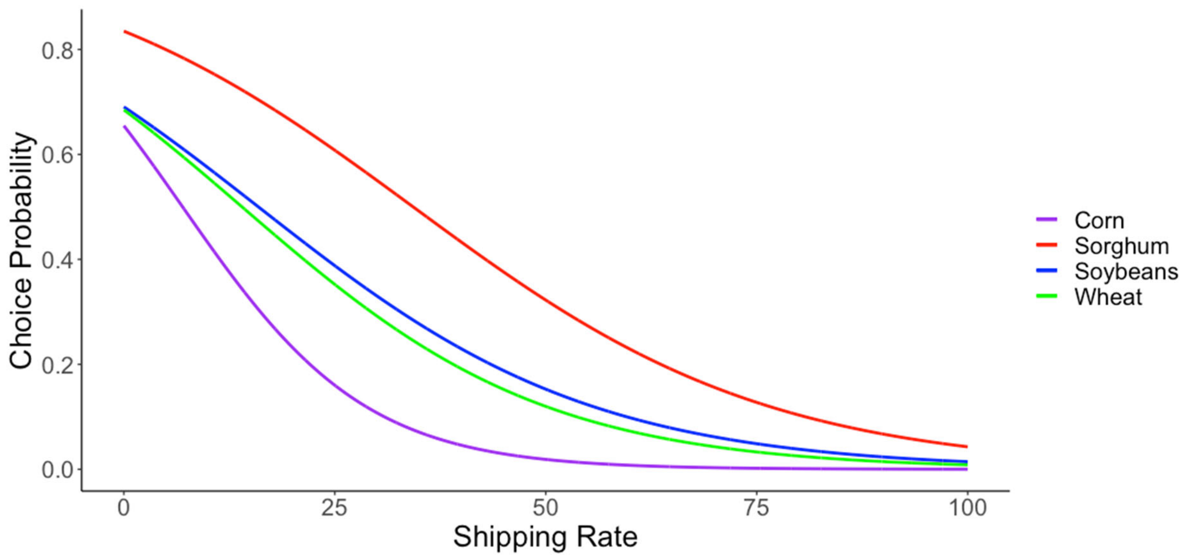
To consider heterogeneity—or differences across commodities—we run the fractional logit model for each crop separately. Table 1.10 presents the results. The results are generally similar to the pooled results in Table 1.9. However, it is clear the marginal effects differ across commodities. Sorghum is the least price-sensitive of all commodities, while corn is the most price sensitive. We also find that channel depth does not have a statistically significant effect on port choice for wheat shipments.

Table 1.10: Results by Crop				
	Wheat	Corn	Sorghum	Soybeans
Rate	-0.222***	-0.378***	-0.189***	-0.201***
	(0.034)	(0.0400)	(0.027)	(0.026)
Berthing	0.689***	0.749***	0.982***	0.480***
	(0.049)	(0.042)	(0.103)	(0.085)
Depth	-0.011	0.106***	0.151***	0.095***
	(0.009)	(0.008)	(0.020)	(0.011)
Gulf	1.610***	-0.443***	2.209	-0.892***
	(0.594)	(0.143)	(2.276)	(0.248)
North Atlantic	-1.062	-2.377***	-2.278	-1.439***
	(0.671)	(0.187)	(2.357)	(0.374)
North Pacific	2.834***	-1.552***	0.592	-0.451
	(0.593)	(0.220)	(2.308)	(0.314)
South Atlantic	-0.860	-1.765***	1.142	-0.373
	(0.702)	(0.174)	(2.285)	(0.276)
South Pacific	0.585	-0.840***	1.619	0.163
	(0.638)	(0.185)	(2.285)	(0.280)
Observations	9889	16399	3177	8406

Note: This table presents the results of estimating the fractional logit model for each crop separately. All columns include destination-year fixed effects. Errors in the table are bootstrapped. *p<0.1; **p<0.05; ***p<0.01.

To consider the effects of rates on the probability a specific port is chosen, Figure 1.7 plots the probability New Orleans is selected against various freight rate levels for each crop. The figure highlights the differences in price sensitivity across crops shown in Table 1.10. As freight rates rise, the probability the port is chosen falls quickly for shipments of corn. The probability the port is chosen for sorghum shipments declines more slowly with freight rates.

Figure 1.7: Choice Probability for New Orleans for Each Commodity



Note: The figure displays the simulated choice probabilities for the port of New Orleans for each crop. The choice probabilities are based on estimates from Table 6 and are simulated over freight rates from New Orleans, shown on the x-axis.

As noted earlier, willingness to pay for changes in attributes can be made using the results. Using data on the average tonnage from Table 1.10, we calculate the total willingness to pay for a change in port attributes across commodities. Soybean shippers have the highest willingness to pay for cost-reducing port attributes. For example, shippers would be willing to pay roughly \$2.38 for an additional foot of berthing length for soybean shipments, but only \$1.98 for an additional foot of berthing length for corn shipments. Soybean shipments also have the highest willingness to pay (0.4723) for an additional foot of channel depth at roughly \$29,000 per foot.

1.4.5 Elasticities

Elasticities measure how responsive a given variable is to another variable. Here, we define elasticities for the responsiveness of shippers to changes in the rates to a specific port and for changes in a port's attributes. This allows us to analyze substitution across ports under counterfactual scenarios. We begin by analyzing the response to a 1 percent increase in freight rate for a given port. This increase in port-specific freight rates makes the given port less attractive to shippers and may result in shippers substituting to another port to mitigate the increased trade costs. To estimate the own- and cross-price elasticities with respect to the increase in freight rates, we first use the estimated model to predict port choices based on the baseline data. Then, we increase the freight rate for a single port by 1 percent, leaving the freight rates of other ports unchanged, and then we predict port choices using the new data and the estimates of the model parameters. Elasticities are then calculated based on the differences from the baseline and simulated port-level shipment quantities.

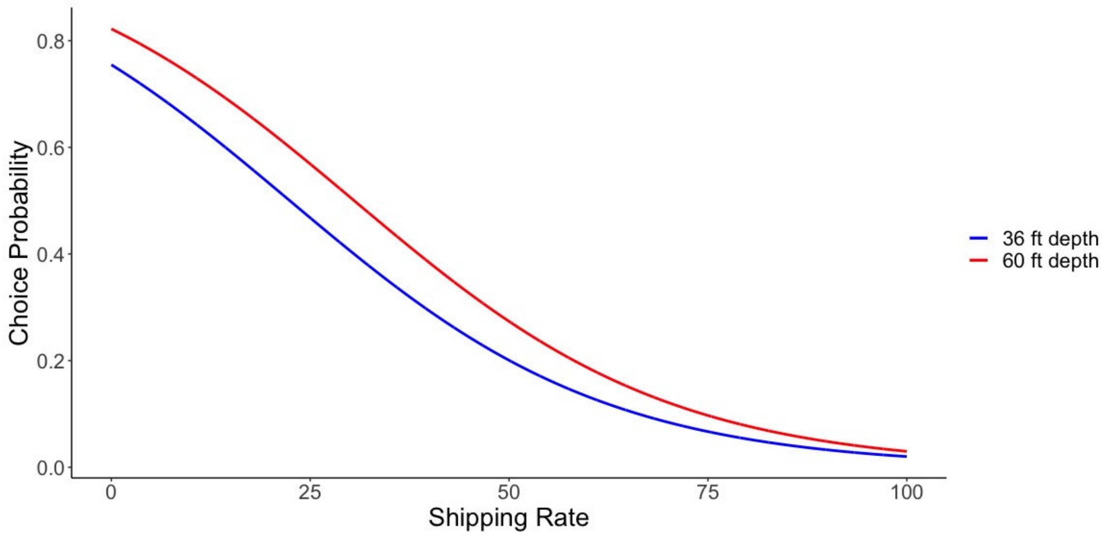
Given the large number of ports in the data, we present the results for the top ten largest ports and the results for the largest market—soybean shipments to China. The results are presented in Table 1.11. Each port's own-price elasticity shows the percent decline in predicted use after a 1 percent increase in port-specific freight rates. The cross-price elasticity is the percent increase in the use of other ports. The results are relatively consistent across ports. A 1 percent increase in the port-specific freight rate results in the port losing roughly 6 percent of their business, while other ports gain approximately 0.3 percent in market share. The second and third part of Table 1.11 displays the own- and cross-price elasticities with respect to a 1 percent increase in port-specific channel depth or berthing length. We find own- and cross-price elasticities are smaller in magnitude. For example, a 1 percent increase in channel depth results in a port gaining roughly 1 percent more business, while other ports lose roughly 0.05 percent of their market share.

Table 1.11: Elasticities						
	1% increase in rate		1% increase in Depth		1% increase in Berthing	
Port	Own Price	Cross-Price	Own Price	Cross-Price	Own Price	Cross-Price
New Orleans	-8.15	0.256	1.10	-0.04	1.56	-0.05
Kalama	-6.73	0.316	1.10	-0.05	0.03	-0.001
Longview	-6.71	0.344	1.10	-0.05	0.11	-0.006
Portland, OR	-6.59	0.484	1.05	-0.07	0.43	-0.03
Vancouver	-6.68	0.380	1.21	-0.07	0.07	-0.004
Houston	-8.18	0.260	1.38	-0.05	1.31	-0.04
Tacoma	-5.71	1.40	1.92	-0.05	0.21	-0.05
Baton Rouge	-8.27	0.14	1.30	-0.02	0.88	-0.02
Seattle	-6.44	0.62	0.88	-0.08	0.80	-0.07
Gramercy	-8.19	0.22	2.50	-0.07	0.02	$-5.7e^{-6}$

Note: This table presents the own and cross-price elasticities from a one percent change in either the port-destination specific freight rates, port channel depth, or total berthing length. The results for the top ten ports, in terms of average annual export quantity, are displayed in the table.

Figure 1.8 summarizes the choice probability at different rates for the port of New Orleans. As the freight rate at the port increases, the choice probability falls. The blue line displays the results for New Orleans using the actual channel depth of the port (36 feet), while the red line displays the choice probabilities for New Orleans as if it were 60 feet deep. The demand for the port of New Orleans does not change dramatically with channel depth.

Figure 1.8: Channel Depth at Port of New Orleans



1.5 Summary of Importer Analysis

In summary, this section provides an analysis of the decisions importers make on the ports that they use to procure commodities and the level of trade between the country and a port. These decisions are framed in terms of shipping costs and port attributes. We provide estimates of the probability a port is used and the level of trade between a country and the port chosen. The models also provide a mechanism to estimate of willingness to pay for cost-reducing port attributes as well as elasticities with respect to changes in the characteristics of a port or of the costs of shipping from a port.

Understanding how port attributes and shipping costs influence port choice is highly relevant for policymakers. Specifically, the results can be used to estimate the effects of alternative port projects—for example, how demand changes as a port is deepened as well as the effect of how demand changes for one port as the attributes of another port change. Relatedly, the results of the study offer insights into how much shippers would be willing to pay for such infrastructure investments. Finally, the results of this study offer insights into how the demand for ports change as shipping costs vary. Changes to global trade policy may influence shipping costs between trading partners, and as a result, influence demand for ports. Given the importance of ports to regional economies, changes in demand driven by trade policy are relevant at a local level as well.

2. Exporter Analysis: Agricultural Supply to Ports

2.1 Introduction

Most of the production of agricultural commodities occurs in the interior of the U.S. and then flows through ports to foreign countries. In Section 1, we provided an analysis of importing countries' choice of ports. In this section, we examine the supply of commodities from locations in the interior U.S. to U.S. ports. The amount of commodities sent to a port is an economic decision made by suppliers (e.g., interior grain elevators). Shippers consider the prices of the goods offered at different locations, the availability and cost of transport by different modes, distance, and other factors when determining where and how to ship goods to ports. This section provides an analysis of shipper port choices using summaries of volumes, transportation costs, and significant destinations and origins.

We consider movements of agricultural commodities from 10 states in the Upper Midwest and shipments of corn, wheat, and soybeans to different exporting U.S. ports. Two primary but different separate sources of data are used—waybill data from the Surface Transportation Board and waterborne commerce data from the U.S. Army Corps of Engineers. The waybill statistics contain the location of both the origin and destination of rail movements within the United States. The waterborne commerce data includes the location of origin and destination for barge movements along major waterways. We use these two data sources to frame the analysis. Rail and barge are quite sufficient for studying these flows; trucks are not typically used due to the long distances over which they cannot effectively compete.[13]

[13] For grain shipments destined to export markets (ports), truck handles only about 10 percent of traffic, while barge and rail dominate. See https://agtransport.usda.gov/stories/s/n6aq-hd3y and Anderson and Wilson (2008).

There is a long history of research that examines transport demand. This literature uses a wide array of different techniques, and there have been a number of significant innovations over the past several decades.[14] Conventional techniques used to model shipper choice behavior range from the use of aggregated data with classical techniques—both with and without behavioral underpinnings—to methods involving the application of McFadden's (1973) random utility model to disaggregate models of shipper choices. The latter is particularly important because the choice is typically made based on rates, shipper attributes, and shipment attributes.

The application of choice models to freight transport is complicated because information must be obtained on individual shipments, which typically involves survey data. Survey-based approaches have been used by Train and Wilson (2006, 2007, 2008, 2019) to empirically analyze the shipment of agricultural commodities. Other approaches must be used when survey data is unavailable. Modern methods allow for the use of aggregated data based on a choice modeling framework (e.g., see Berry et al. (1995), Nevo (2000)). However, a difficulty in applying this approach is that it requires a well-defined market (e.g., automobile purchases in the U.S.). In transportation sectors, most markets are relatively local, overlap, and depend critically on prices. This complicates the use of modern empirical methods to estimate choices in transportation markets.

In this analysis, we develop and apply an approach that defines market shares from aggregated shipping data, which are then used to estimate a model of shipper demands. Further, unlike the bulk of the literature, we model not only the mode choice but also the choice of where to travel. Specifically, we model the shares with a logit specification that reflects shipper

[14] Winston (1981, 1983, 1985) and Chris Clark et al. (2005) provide reviews of this extensive literature.

decisions. These decisions are taken as a function of the rates, port attributes, and/or port fixed effects. The final data considers 10 origination zones and 12 termination zones, and we consider an array of different catchment areas.

In the next section, we provide an overview of the standard choice model, which we use to frame the empirical results. In Section 2.3 and Appendix C, we provide a discussion of the data and its development. This discussion includes our definitions of port zones, origination zones, and shipment characteristics including rates and port attributes. In Section 2.4, we provide the estimation results for three different commodities including corn, wheat, and soybeans, while Section 2.5 summarizes the primary findings.

2.2 Modeling Shipper Decisions

The random utility model offers a useful framework to view how shippers choose ports. Given a set of alternatives, individuals select the option that provides them with the highest utility (or payoff). In the context of this study, the set of alternatives are the port zones (for a visual of these zones, see Figure C.2 in Appendix C). The individuals are shippers (grouped into origination zones), and utility corresponds to expected profit attached to each port zone. More specifically, we model each shipper's choice as a function of observable (measurable) attributes and unobservable attributes.[15] The shipper makes choices over port zones and mode, and associated with each port zone and mode is a random utility for each shipper.

The random utility function consists of a deterministic component and a random component. The deterministic component is a function of known variables and a set of unknown

[15] More technically, unobservable attributes are unobservable to the analyst or econometrician; they are observable to the shipper.

parameters that are estimated. We assume the unobservable terms are drawn from an independent and identically distributed extreme value distribution which yields the well-known logit model wherein the probability shipper *i* chooses port *p* (P_{pi}) can be estimated with a logit model:

$$P_{pi} = \frac{e^{V_{pi}}}{\sum_j e^{V_{ji}}}$$

where V_{pi} is the measurable component of shipper utility. We express the measurable component as a function of freight rates and port attributes and estimate multiple versions of the following:

$$V_{pit} = \beta_1 Barge_p + \beta_2 Rate_{pit} + \delta_p + \Gamma_t$$

Where:

$Barge_p$ is a dummy variable that corresponds to port *p* providing a barge option;

$Rate_{pit}$ is the rate to port p from port origination zone in time period t,

δ_p is a set of port zone fixed effects, which control for berthing length and channel depth,

and Γ_t includes other time-invariant factors that may influence shipper decisions.

In the estimation, we provide specifications without the fixed effects but include measures of berthing length and channel depth.

2.3 Data Sources and Zone Development

The primary sources of data used in this study are the U.S. Army Corps of Engineers' Waterborne Commerce Statistics (WBC) and the Surface Transportation Board's confidential Carload Waybill Sample (CWS). The WBC data includes dock to dock movements by commodity. The CWS includes data from shipper origin to shipper destination by product. We use these data to examine export flows of corn, wheat, and soybeans from the interior to U.S. ports from 2004 to 2018.

We take several steps to process the data. First, we identify all barge and rail shipments that originate within primary agriculture-producing states and terminate around major US ports. We create "origin zones" by aggregating shipments that originate in specific geographic regions. These regions are defined vertically by segments of the Mississippi, Illinois, and Ohio rivers, and horizontally by the distance from the shipment origin to the river. We define "port zones" by aggregating shipments that terminate in the vicinity of major ports. Port zones differ across commodities. The result is a panel data set that captures freight movements by origin zone to each port zone by year and commodity. The data work is extensive and detailed in Appendix C.

2.4 Results

Tables 2.1, 2.2, and 2.3 display the empirical results for corn, soybean, and wheat shipments, respectively. In our preferred specifications, shown in columns 4 and 5 of each table, the results are broadly similar across commodities. For corn and soybeans, a barge option increases the conditional log-odds that a port zone is chosen, but for wheat shipments a barge option does not have a statistically significant effect on the conditional log-odds a port zone is selected.[16] Essentially this means, if barge is present, the probability a given port is chosen goes up for corn and soybeans. This result makes sense, because the inland waterways are only available in limited regions, and grain shipments by barge are primarily corn and soybeans. Whether port

[16] That is, the interpretation of the coefficients is the effect on the change in the log odds ratio. The relative odds are the probability of an event occurs divided by the probability the event does not occur: $\frac{p}{1-p}$. Thus, logged odds are of the form: $\log(\frac{p}{1-p})$.

zone attributes or port zone fixed effects are used, higher shipping rates reduce the log odds a port zone is chosen across all commodities. We also find relatively consistent effects of channel depth. That is, port zones with deeper channels have higher conditional log-odds of being selected. We find mixed evidence of the effect of berthing lengths. The results are similar if other distance bands are used. For example, Table B.1 of Appendix B displays the results using a 200-mile and 300-mile distance band rather than the 100-mile distance band used in Tables 2.1, 2.2, and 2.3.

Table 2.1: Corn Model Estimates

	(1)	(2)	(3)	(4)	(5)
Barge	4.234***	4.564***	3.589***	4.383***	3.670***
	(0.763)	(0.943)	(0.520)	(0.557)	(0.551)
Rate	0.151***	0.164***	-0.097***	-0.077***	-0.290***
	(0.026)	(0.036)	(0.025)	(0.026)	(0.036)
Berthing		0.005		0.023***	
		(0.005)		(0.005)	
Channel Depth			0.321***	0.315***	
			(0.033)	(0.023)	
East					-11.128*** (0.882)
LA					-8.623*** (0.636)
Lakes					-11.369*** (1.051)
PNW-2					-1.962*** (0.288)
TX-1					-7.574*** (0.513)
TX-2					-9.571*** (0.672)
Constant	-7.761***	-8.409***	-17.027***	-18.224***	9.054***
	(1.655)	(2.044)	(1.568)	(1.299)	(1.287)
Log-Likelihood	-797	-795	-616	-595	-495

Note: This table displays the results for corn shipments. The omitted port zone is PNW1. See Appendix C (Table C.1) for variable definitions.

Table 2.2: Soybean Model Estimates

	(1)	(2)	(3)	(4)	(5)
Barge	9.645***	9.996***	6.848***	7.331***	4.956***
	(0.599)	(0.620)	(0.411)	(0.457)	(0.410)
Rate	0.215***	0.210***	-0.012	-0.039**	-0.172***
	(0.012)	(0.011)	(0.018)	(0.015)	(0.020)
Berthing		-0.003**		-0.006	
		(0.001)		(0.004)	
Channel Depth			0.208***	0.224***	
			(0.015)	(0.013)	
AL					-8.025*** (0.544)
LA					-4.443*** (0.268)
Lakes-1					-11.120*** (0.867)
Lakes-2					-11.819*** (0.717)
PNW-1					-0.376** (0.148)
TX-1					-7.319*** (0.507)
TX-2					-5.973*** (0.398)
Constant	-13.738***	-13.173***	-16.036***	-15.172***	2.646***
	(3.013)	(2.910)	(0.915)	(0.824)	(0.849)
Log-Likelihood	-693	-689	-603	-594	-523

Note: This table displays the results for corn shipments. The omitted port zone is PNW2. See Appendix C (Table C.1) for variable definitions. There were no observations on the Florida destinations.

Table 2.3: Wheat Model Estimates

	(1)	(2)	(3)	(4)	(5)
Barge	-2.860***	-1.882***	-2.944***	-2.342***	-0.465
	(0.431)	(0.458)	(0.430)	(0.464)	(0.566)
Rate	-0.066***	-0.027***	-0.071***	-0.071***	-0.073***
	(0.006)	(0.007)	(0.010)	(0.013)	(0.017)
Berthing		0.015***		0.020***	
		(0.001)		(0.001)	
Channel Depth			0.008	0.094***	
			(0.012)	(0.015)	
FL-1					-0.637 (0.520)
FL-2					-0.846 (0.645)
LA					-3.686*** (0.384)
Lakes-1					-2.385*** (0.210)
Lakes-2					-3.468*** (0.347)
PNW-2					-0.612** (0.282)
TX-1					-2.117*** (0.311)
TX-2					-3.486*** (0.377)
Constant	-0.339	-2.458***	-0.511	-5.269***	1.073
	(0.955)	(0.755)	(0.983)	(0.809)	(0.734)
Log-Likelihood	-629	-560	-628	-536	-485

Note: This table displays the results for wheat shipments. The omitted port zone is Lakes. See Appendix C (Table C.1) for variable definitions.

Across commodities, we find consistent evidence that shippers have a strong preference for ports with deeper channels. Using the estimates in Tables 2.1, 2.2, and 2.3, we calculate the willingness to pay for channel depth.[17] Table 2.4 summarizes the results. The second column of the table displays the willingness to pay for one foot of channel depth in USD per foot per ton. The last column of the table converts the second column to USD per foot by multiplying by the average annual tonnage.[18] Across all commodities, shippers would be willing to pay millions of dollars for additional channel depth. Such information can be used by planners to assess the benefits of port investments.

Table 2.4: Willingness to Pay for Channel Depth

Commodity	**WTP ($ per foot per ton)**	**Total WTP ($ per foot)**
Corn (for PNW1)	4.1	41 million
Wheat (for Lakes)	1.3	6.7 million
Soybeans (for PNW2)	5.6	15.8 million

Note: This table displays the willingness to pay (WTP) for additional feet of channel depth. The first column displays the WTP in USD per foot per ton. This is calculated as the marginal effect of channel depth divided by the marginal effect of rates (given in column 4 of Tables 2.1, 2.22, 2.3). The second column evaluates the WTP at the average annual tonnage for each commodity. The average annual tonnage is calculated across all shippers to each port zone. It represents the annual benefit of an added change in depth. As noted earlier in Footnote 12, the willingness to pay is generated from the parameter estimates. Technically, if depth increases by one unit, it is the amount price can rise to keep utility the same as before the depth was increased. Details can be found in McCarthy (2001).

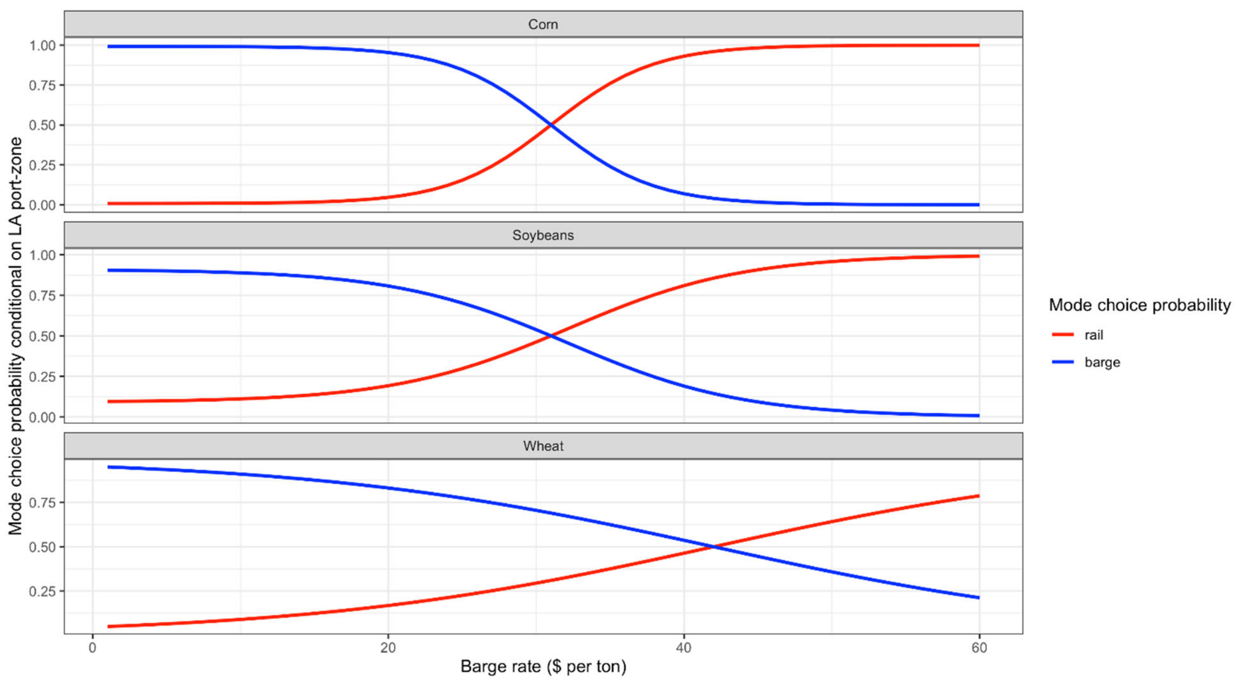
The results in Tables 2.1, 2.2, and 2.3 can also be used to calculate conditional choice probabilities, which are easier to interpret than log-odds. For example, Figure 2.1 displays the probability a shipper chooses barge, conditional on selecting the LA (Louisiana) port zone in 2017.

[17] This is calculated as the marginal effect of channel depth relative to the marginal effect of rates.

[18] For example, for Corn, the average annual tonnage is approximately 1 million. Thus, the total WTP is given by $4.1 per foot per ton *1 million tons=$41 million per foot.

The y-axis displays that predicted choice probability, and the x-axis displays the barge shipping rate. Rail shipping rates are held constant at the commodity-specific average for the LA port zone. The figure shows that as the barge shipping rate rises, the probability of choosing to ship to the LA port zone by barge falls, while the probability of choosing to ship to the LA port zone by rail rises. The response to changes in the barge rate is consistent across commodities.

Figure 2.1: Mode Choice Probabilities



Note: This figure displays the conditional mode choice probabilities for the LA port zone. The blue line represents the probability of choosing to ship by barge, and the red line displays the probability of choosing to ship by rail. The barge rate varies along the x-axis and the rail rate is held constant at the commodity specific average.

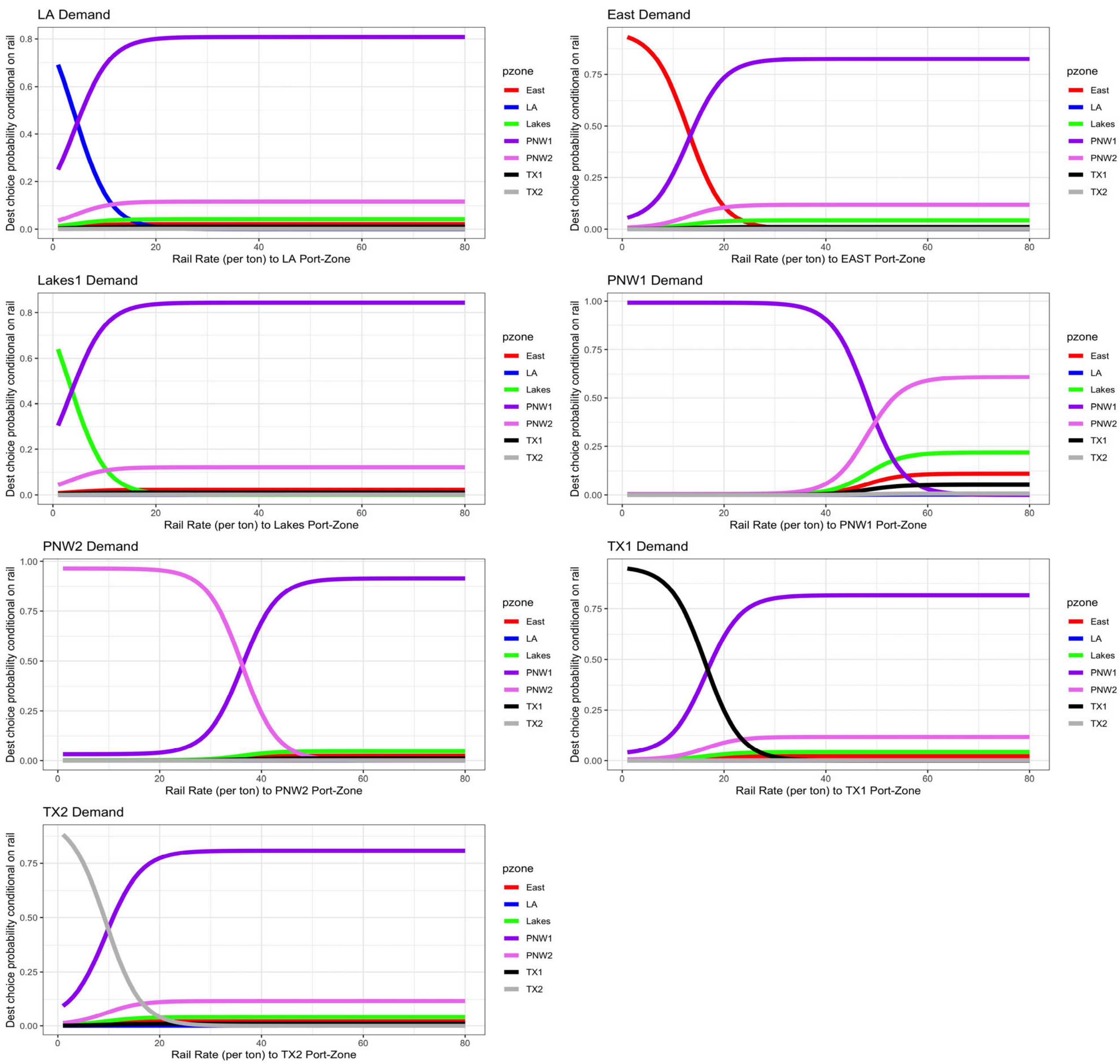
We can also use the results in Tables 2.1, 2.2, and 2.3 to display the conditional choice probabilities for each destination. For example, Figures 2.2, 2.3, and 2.4 show how the conditional choice probabilities change for each port zone in 2017 for corn, soybeans, and wheat, respectively. In these figures, the y-axis displays that port zone choice probability, conditional on choosing to ship by rail, and the x-axis displays the rail shipping rate for that port (given the rates in other ports). In each panel of the graph, we present how an increase in the cost of shipping to a port zone impacts the probability the port zone is selected, as well as the probability other port zones are chosen. For example, the top left panel of Figure 2.2 shows that as the cost of shipping corn (by rail) to the LA port zone rises, the probability that a shipper selects the LA port zone falls (as expected). As the cost of shipping to the LA port zone increases, the probability that the shipper picks another port zone rises, which bears directly on the substitutability between ports. The amount of switching from one port to anther depends on prices. For example, in Figure 2.2, the share of corn that flows through the PNW2 port falls dramatically as rates increase from $25 to $45 per ton, and the alternative port—PNW1—has dramatic increases. This points to considerable substitution when the rate changes between $25 and $45 per ton and suggests significant switching from PNW2 to PNW1 as the rate in PNW2 increases. Of course, it depends on the level of rates in each port, but the probabilities can easily accommodate a wide range of different rates.

Finally, the Pacific Northwest port zones are dominant for corn and soybeans, while the Lakes port zone is dominant for wheat.[19] The lakes region has milling locations and is also a major transshipment point. As illustrated in Figures 2.2, 2.3, and 2.4, the dominance of these locations does depend on the rates attached and, over some ranges of rates, further increases can and do affect the dominance of the port. For example, the Lakes zone receives about one-half of the wheat tonnages in the study frame. However, the tonnages received depend critically on the

[19] See Figure C.9 in Appendix C.

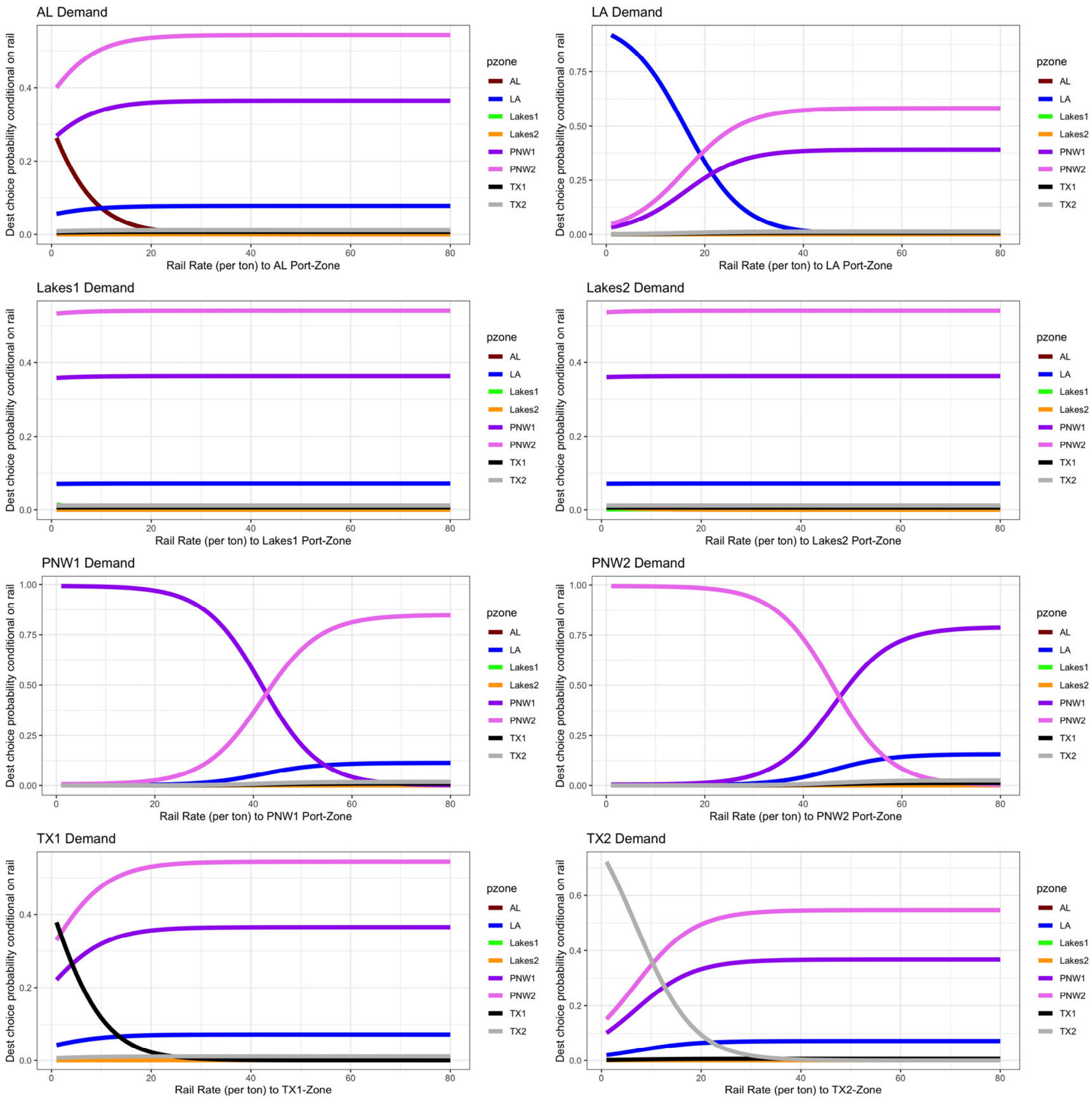
rates to the Lakes zone as well as the rates to alternative zones, which, together, point to the importance of rates in the destination choice of shippers.

Figure 2.2: Destination Choice for Corn



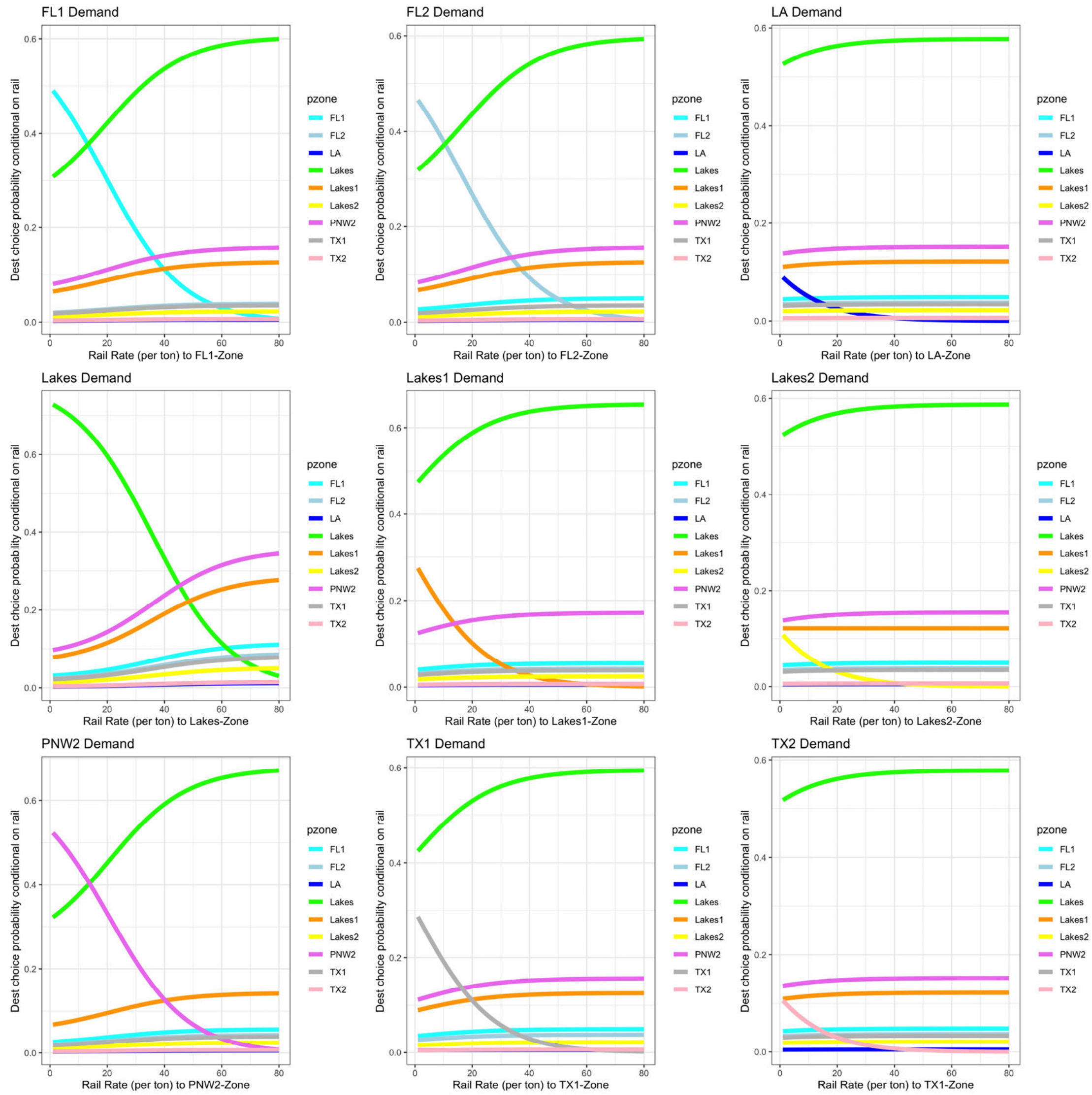
Note: This figure displays the probability of choosing each port zone, conditional on choosing to ship by rail, for corn shipments. Each panel corresponds to one port zone, with the rail rate to the port zone varying on the x-axis.

Figure 2.3: Destination Choice for Soybeans



Note: This figure displays the probability of choosing each port zone, conditional on choosing to ship by rail, for soybean shipments. Each panel corresponds to one port zone, with the rail rate to the port zone varying on the x-axis.

Figure 2.4: Destination Choice for Wheat



Note: This figure displays the probability of choosing each port zone, conditional on choosing to ship by rail, for wheat shipments. Each panel corresponds to one port zone, with the rail rate to the port zone varying on the x-axis.

Finally, the results in Tables 2.1, 2.2, and 2.3 can be used to calculate elasticities with respect to rail rates. Table 2.5 displays the percent change in each port zone's choice probability given a 1 percent increase in the rail shipping rate to the port zone, with all rail rates to other port zones held constant. These elasticities are calculated from the model in column 5, our preferred specification with port zone fixed effects. We find that demand for port zones is highly elastic with respect to rail rates. However, there is variance across crops. Corn and soybeans have particularly high own-price elasticities, while wheat elasticities are relatively smaller in magnitude. This implies corn and soybean shipments are more responsive to changes in rail rates, likely due to the presence of other transportation options (e.g., barge). The Northwest port zones have the highest elasticities for corn and soybeans. The Florida port zones have the highest elasticities for wheat. The two Texas port zones also have relatively high elasticities across all three commodities.

Table 2.5: Elasticities w.r.t Rail Rates

	Corn	Soybeans	Wheat
AL		-4.3	
East	-7		
LA	-6	-5.4	-3.5
Lakes	-3.4		-1.7
Lakes-1		-2.7	-1.4
Lakes-2		-4.5	-2.1
PNW-1	-8.2	-7.3	
PNW-2	-9.2	-7.4	-2.9
TX-1	-7.1	-4.6	-2.9
TX-2	-7	-5.4	-3.4
FL-1			-4
FL-2			-4

Note: This table displays the own-price elasticity's with respect to rail rates. These elasticities correspond to a 1 percent increase in rail rates.

2.5 Summary of Exporter Analysis

International trade involves many different decisions by suppliers. In this section, we developed and estimated a model of the choices made by suppliers of agricultural products (corn, soybeans, and wheat) as they decide which port to ship goods to and the mode used (if multiple modes are available). The model itself is based on a standard random utility framework, and shipper choices are based on transportation costs, port attributes, and modal dummies. The results illustrate the impact of each of these variables on the port choice and the modal choice.

Our approach uses the Surface Transportation Board's Carload Waybill Statistics and the Army Corps of Engineers' Waterborne Commerce data to estimate the parameters in a random utility model. The waybill data provide highly precise location identifiers for the rail shipments, while the waterborne commerce data provide very precise location identifiers for barge shipments. These data are used to define port zones and origination zones, as well as the share that is shipped from each zone. These shares are the dependent variable in our analysis, which we explain with measures of rail and barge rates, port attributes, or port zone dummy variables.

The construction of origination zones depends on distances to the water, and there is not a well-defined distance to use in this context. We, therefore, examined a variety of distances in defining the origination zones. The results are remarkably stable across different distances. In all cases, we find rates have a strong effect on port/mode choices, as do the port attributes or port fixed effects.

The results allow choice probabilities and elasticities to be calculated and used to illustrate the shippers' response to rates and port attributes. The effects of changes in rail rates can and do have impacts on both mode choice and on port choice. The estimated elasticities point to highly elastic substitutions as rates change.

This section provides a unique approach to modeling freight transportation and allows modern approaches to be used to estimate supplier demands. The empirical techniques in this study are highly flexible in several critical ways. First, it allows suppliers of agricultural goods to choose the mode and the destination of shipments. Allowing for choices over multiple dimensions helps provide a more detailed analysis of shipper decisions. Second, the methods used in this study allow for different market definitions and catchment areas, both of which are needed to model demand for barge and rail services. These methods are broadly applicable to other industries characterized by markets that are relatively local, overlap, and depend critically on prices. Finally, the results in this section can be used to analyze a broad range of economic and policy changes. For example, the model can be used to study how port infrastructure projects influence demand for ports among suppliers of agricultural products, or how freight rates influence how and where products are shipped within the United States.

3. Summary and Conclusions

In this study, we provide a comprehensive examination of trade for selected agricultural commodities. The analysis includes a description of the domestic U.S. suppliers of exported agricultural commodities, the ports used to export, and the foreign countries that import these products. The descriptive analysis is conducted by commodity, and describes primary importers, ports used, and supply locations using summaries of volumes, transportation costs, and major destinations and origins.

The focus of the analysis is on the ports that importers and exporters choose to use and the mode used (if applicable). Specifically, we study how port attributes and shipping route characteristics influence how ports are selected from the perspective of foreign importers of U.S. goods and domestic suppliers of U.S. goods. The results of both the importer and the exporter models indicate that ports with deeper channels and longer total berthing lengths are more likely to be selected by importers and exporters. We also find that port choice decisions are influenced by shipping costs. For example, as the cost of importing goods from a particular U.S. port increases, the probability that a foreign consumer selects the port to facilitate a transaction declines. Similarly, as the cost of shipping agricultural products from the U.S. interior to a coastal port increases, U.S. shippers are less likely to use the port to facilitate export shipments. The results of the study have several important policy implications. First, competition among U.S. ports for agricultural exports depends strongly on shipping costs. We estimate that demand for ports by foreign consumers and domestic producers are highly elastic with respect to shipping costs. For example, a 1 percent increase in the freight rate associated with shipping goods from a U.S. port to a foreign country reduces the probability the port is chosen by between 6 percent and 8 percent. We find a similar response among domestic shippers: a 1 percent increase in the shipping rate to U.S. ports from domestic production markets reduces the probability a port is chosen by between 6 percent and 9 percent. Intermodal competition also impacts shipper decisions. As barge rates rise, the probability of using barge to ship goods from the interior of the U.S. to a port falls, and the likelihood of using rail to ship goods rises. The results also have important policy implications for investments in port infrastructure. Increased vessel size requires deeper channels and larger berthing lengths at ports, and these investments can be costly. For example, according to data from the USACE, the cost of dredging the average U.S. port, with a 41-foot-deep channel, to the 60-foot depth needed to accommodate large bulk vessels amounts to approximately $94 million.[20] Using the estimates from the empirical models in this paper, we find that importers of U.S. agricultural products would be willing to pay $22.8 million for this type of project. In comparison, domestic suppliers of U.S. agriculture would be willing to pay between $6.7 million to $41 million for this type of project, depending on the commodity. Given the importance of ports to local economies, additional stakeholders would benefit from this type of port investment.

[20] This is based on dredging a 500-foot-wide channel 19 feet for 1 mile at a rate of $1.88 per cubic foot.

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Appendix A: Trade Model Development

In Eaton and Kortum (2002), products are produced in a perfectly competitive market. Countries are differentiated by their productivity. For example, country *i*'s productivity at producing good ω is denoted by $z_i(\omega)$. Given perfect competition, the cost of producing one unit of good ω in country *i* is given by $\frac{c_i}{z\_i(\omega_i)}$, where c_i is the cost of inputs. Following Eaton and Kortum, country *i*'s productivity is drawn from a Type II extreme value distribution:

$$F(z_i) = \Pr\left\{z_{i(\omega)} \leq z\right\} = e^{-T_i z^{-\theta}}$$

where $T_i > 0$ represents the aggregate productivity (stock of technology), and ϑ is a shape parameter that is common across all countries, and corresponds to the elasticity of trade.

Next, in terms of prices, the price of shipping good ω from country *i* to country *j*, through port *k* (which is located in country *i*) is given by the following relationship:

$$p_{ij}^{k}(\omega) = \frac{c_i}{z\_i(\omega)} \tau_{ij}^{k}$$

In this equation, $\tau_{ij}^k > 1$ represents trade costs associated with this trade flow. These trade costs include factors like the internal shipping costs, external shipping costs, and port infrastructure, as well as international policy variables like the tariff rates applied to commodity ω by destination *j*. As in Eaton and Kortum, consumers purchase goods from the lowest priced supplier. More specifically, consumers in country *j* purchase good ω from country *i* using the port with the lowest trade costs. This means that, conditional on purchasing ω from country *i*, the price for the good is:

$$p_{ij}(\omega) = \min_{k \in i} p_{ij}^{k}(\omega).$$

Furthermore, country *j* only purchases good ω from country *i* if country *i* can offer the lowest price. Thus, the price of good ω paid by country *j* is given by:

$$p_{j(\omega)} \min_{i \in S} p\_ij(\omega) = \min_{i \in S}(\min_{k \in i} p_{ij}^{k}(\omega)) = \min_{i \in S}(\min_{k \in i} \frac{c_i}{z_i(\omega)} \tau_{ij}^{k}) \qquad (\mathrm{A}.1)$$

Equation (A.1) is the basis for a model of port choice. Country *j* will be more likely to purchase a good from country *i* if *i* has a low cost of producing the good (c_i) or high productivity ($z_i(\omega)$). Trade costs vary by port, based on factors like shipping distances and port attributes. Thus, conditional on *i* offering the lowest price, country *j* is more likely to choose port *k* if port *k* offers the lowest trade costs.

The distribution of productivity implies prices also have a distribution and, conditional on country *i* being chosen by country *j*, the probability that port $k \in i$ can offer a price less than *p* is given by:

$$G_{ij}^{k}(p) = Pr\{p_{ij}^{k}(\omega) \leq p\} \qquad (\mathrm{A.2})$$

and, using the pricing equation, and the Fréchet distribution, equation (A.2) can be rewritten as:

$$G_{ij}^{k}(p) = 1 - F_i(\frac{c_i}{p}\tau_{ij}^{k})$$

The distribution of port-level prices faced by country *j* when importing good ω from country *i* can be expressed as:

$$G_{ij}(p) = 1 - e^{-T_i(\frac{c_i}{p})^{-\theta}\sum_k(\tau_{ij}^{k})^{-\theta}} \qquad (\mathrm{A.3})$$

Finally, the distribution of prices faced by country *j* across all exporters is can be shown to be:

$$G_j(p) = (1 - e^{-\sum_i T_i(\frac{c_i}{p})^{-\theta}\sum_k(\tau_{ij}^{k})^{-\theta}})(1 - e^{-T_i(\frac{c_i}{p})^{-\theta}\sum_k(\tau_{ij}^{k})^{-\theta}}) \qquad (\mathrm{A.4})$$

We use the distribution of prices across ports (equation A.3) and the distribution of prices across exporters (equation A.4), to define the overall probability of choosing port *k*, which is the joint probability of choosing country *i* and port *k* within *i*. This is is given by:

$$s_{ij}^{k} = Pr\{p_{ij}^{k}(\omega) \leq \min_{m \neq k \in i} p_{ij}^{m}(\omega)\} * Pr\{p_{ij}(\omega) \leq \min_{n \neq i \in S} p_{nj}(\omega)\} \qquad \text{(A.5)}$$

where the first probability is the probability of choosing port *k* out of all potential ports conditional on choosing country *i*, and the second is the probability of choosing country *i* out of all potential exporters. This equation can be rearranged into:

$$\int_0^\infty \Pi_m(1 - G_{ij}^{m}(p))dG_{ij}^{k}(p) \int_0^\infty \Pi_n(1 - G_{nj}(p))dG_{ij}(p)) \qquad \text{(A.6)}$$

and, after substituting in for the price distributions given by equations (A.3) and (A.4), equation (A.6) yields the following expression:

$$s_{ij}^{k} = \frac{T_i(c_i\tau_{ij}^{k})^{-\theta}}{\sum_i \sum_k T_i(c_i\tau_{ij}^{k})^{-\theta}}. \qquad \text{(A.7)}$$

Equation (A.7) is the fraction of goods country *j* purchases from port *k* located in country *i*. Eaton and Kortum show that given the properties of the Fréchet Distribution, the fraction of goods purchased is equivalent to the fraction of country *j*'s expenditures on goods from port *k* in country *i*. We interpret this market share as the probability that a port is chosen.

Given the focus of this project is on exports from the United States, the *i* subscript corresponds only to one country. Thus, equation (A.7) can be simplified as:

$$s_{j}^{k} = Prob_{jk} = \frac{(\tau_j^k)^{-\theta}}{\sum_k (\tau_j^k)^{-\theta}} \qquad \text{(A.1.8)}$$

where technological stock and unit production costs (which are both specific to *i*) have canceled out. The left-hand side is the share of exports to country *j* through port *k*, given that the U.S. has been chosen as the exporting country. This share depends solely on port-level trade costs.

We also use an alternative approach, which also is derived from Eaton and Kortum. Specifically, following Waugh (2010), and Heerman (2018), we model trade costs as a function of bilateral factors, exporter specific factors, and importer specific factors. In particular, our specification is:

$$ln(\tau_j^k) = \alpha_1 rate_{jk} + \alpha_2 Depth_k + \alpha_3 Berthing_k + \gamma_j$$

where, $rate_{jk}$ is the shipping rate between port k and importer j. The variables $Depth_k$ and $Berthing_k$ are the channel depth and total berthing length of port k, and γ_j is a destination-specific fixed effect that accounts for factors like GDP.[21] Substitution of trade costs into equation (8) yields:

$$s_{jk} = \frac{exp[\beta_1 rate_{jk} + \beta_2 Depth_k + \beta_3 Berthing_k + \gamma_k]}{\sum_k exp[\beta_1 rate_{jk} + \beta_2 Depth_k + \beta_3 Berthing_k + \gamma_k]}, \qquad \text{(A.1.9)}$$

which forms the basis for our fractional logit model. The parameters on these variables are a composite of the marginal response and the structural parameter ϑ, which is constant.

Following the empirical international trade literature, we also estimate how the intensity of trade responds to port and route attributes. To do this, we take the natural log of both sides of the share equation, above, to produce a log-linear gravity-like specification. This results in equation that models the volume of trade (x_{jk}) as a function of port and route attributes. In the log-linear specification, the coefficients on port freight rates correspond to the percentage

[21] The actual empirical specification includes time subscripts as well. Thus we can flexibly control for time-varying destination-specific factors with a destination-commodity-year fixed effect.

change in trade intensity from the port, rather than the probability that the port is selected by the shipper. Specifically, the log-linear model of trade intensity is given by:

$$\ln(x_{jk}) = \beta_1 rate_{jk} + \beta_2 Depth_k + \beta_3 Berthing_k + \gamma_j + \epsilon_{jk}$$

where importer fixed effects account for the multi-lateral resistance term in the denominator as in Anderson and Van Wincoop (2003), as well as the total volume of imports in country j (i.e., the denominator of the share). Given the context of the empirical analysis, which only focuses on the United States; exporter fixed effects are not needed. Further, port-level fixed effects are collinear with port attributes. Thus, port-level fixed effects are excluded from the intensive margin specification as well.

Appendix B: Exporter Results for Alternative Distance Bands

Table B. 1: Other Distance Bands

	Corn		Soybeans		Wheat	
	200 miles	300 miles	200 miles	300 miles	200 miles	300 miles
Rate	-0.150***	-0.321***	-0.157***	-0.121***	-0.0798***	-0.0788***
	(0.0296)	(0.0378)	(0.0165)	(0.0222)	(0.0206)	(0.0209)
Barge	3.399***	3.949***	1.634***	1.503***	-0.375	-0.720
	(0.484)	(0.752)	(0.319)	(0.436)	(0.564)	(0.553)
AL	NA	NA	-7.285***	-7.661***	NA	NA
			(0.426)	(0.626)		
East	-8.867***	-11.49***	NA	NA	NA	NA
	(0.601)	(0.954)				
LA	-8.464***	-11.82***	-4.640***	-5.961***	-3.636***	-3.588***
	(0.733)	(1.015)	(0.282)	(0.638)	(0.456)	(0.500)
Lakes1	-8.785***	-12.75***	-10.79***	-10.62***	-2.345***	-2.238***
	(1.074)	(1.192)	(0.849)	(0.994)	(0.203)	(0.192)
Lakes2	NA	NA	-11.57***	-11.55***	-3.500***	-3.538***
			(0.704)	(0.809)	(0.361)	(0.373)
PNW1	NA	NA	-0.381**	-0.689***	NA	NA
			(0.159)	(0.195)		
PNW2	-1.481***	-1.872***	NA	NA	-0.538*	-0.475
	(0.306)	(0.358)			(0.324)	(0.309)
TX1	-6.113***	-7.955***	-6.889***	-7.388***	-1.972***	-2.046***
	(0.503)	(0.647)	(0.467)	(0.633)	(0.365)	(0.346)
TX2	-8.579***	-10.20***	-5.959***	-6.359***	-3.248***	-3.436***
	(0.662)	(0.730)	(0.433)	(0.567)	(0.458)	(0.449)
FL1	NA	NA	NA	NA	-0.456	-0.496
					(0.605)	(0.633)
FL2	NA	NA	NA	NA	-0.629	-0.649
					(0.745)	(0.763)
Constant	5.389***	10.74***	4.413***	4.291***	1.471***	1.689***
	(1.092)	(1.314)	(0.721)	(0.981)	(0.473)	(0.513)
N	1,771	1,526	1,924	1,540	1,802	1,502

Note: This table displays the results from estimating equation (4) using either a 200-mile or 300-mile distance band to define shippers.

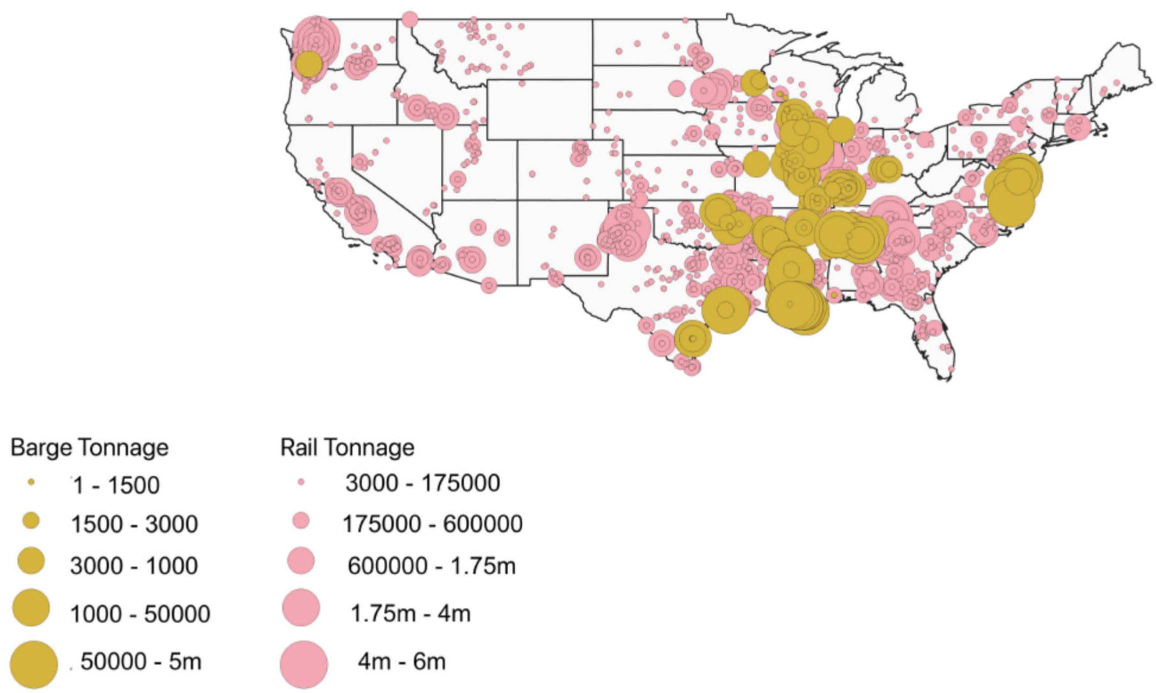
Appendix C: Exporter Analysis – Port Zones and Data Summaries

In this appendix, we discuss the data in detail, using corn shipments as an example. The process is similar for other commodities, and any significant differences are noted.

C.1 Port Zone Definitions

Figure C.1 displays the point of termination for all rail and barge shipments of corn. As illustrated, rail shipments are sent to many destinations throughout the U.S., while barge shipments mainly terminate in Louisiana. It is not possible to directly ship corn by barge to ports other than those at the mouth of the Mississippi in Louisiana. Thus, barge shipments reported at ports in the Pacific Northwest or East coast require multi-modal transportation.

Figure C.1: Shipment Destinations by Rail and Barge for Corn

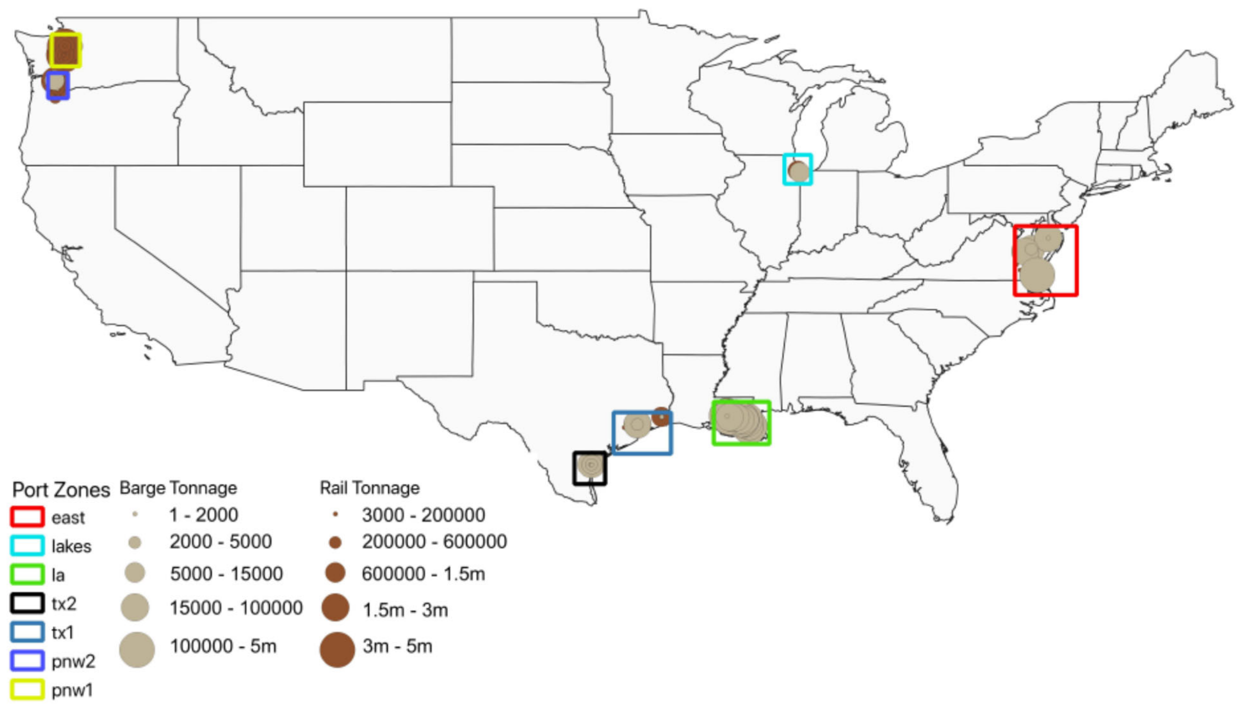


Note: This figure shows the total tonnage shipped by barge or rail to all termination points in the US.

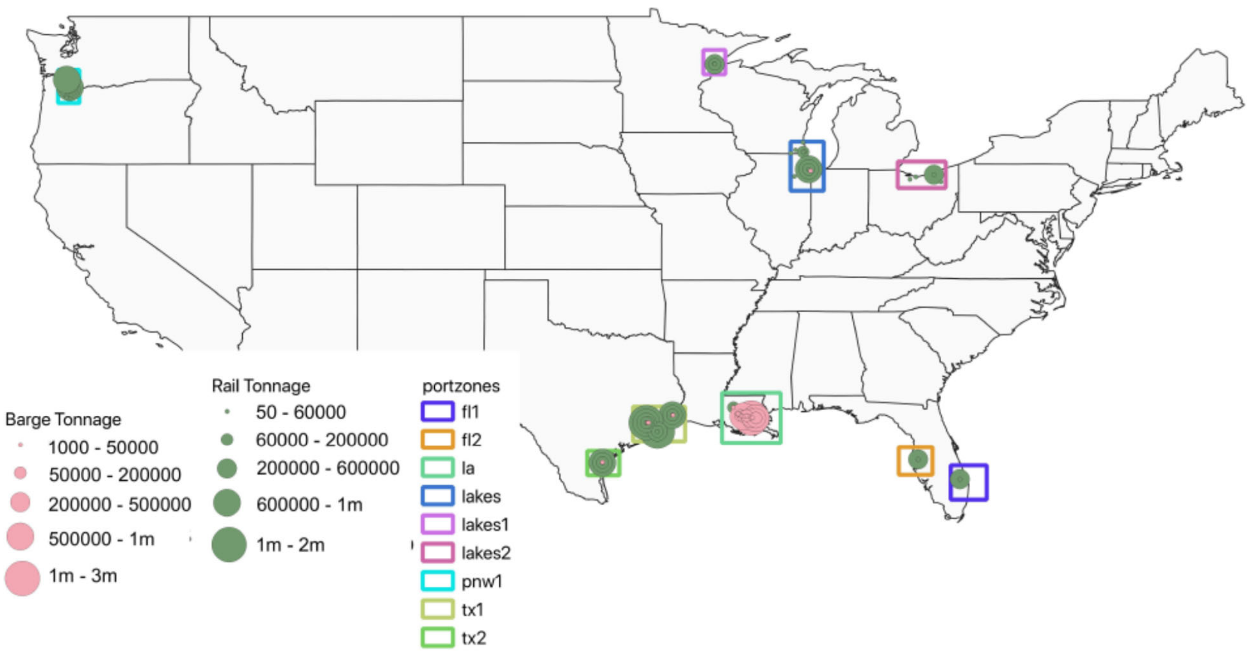
We define US port zones based on the shipment termination points in Figure C.1. These port zones are based on geographical clusters of shipments around primary coastal ports. Port zones vary by commodity, which arises due to differences in where each commodity is typically exported. Figure C.2 displays the port zones for corn, wheat, and soybeans.

Figure C.2: Port Zones for each commodity

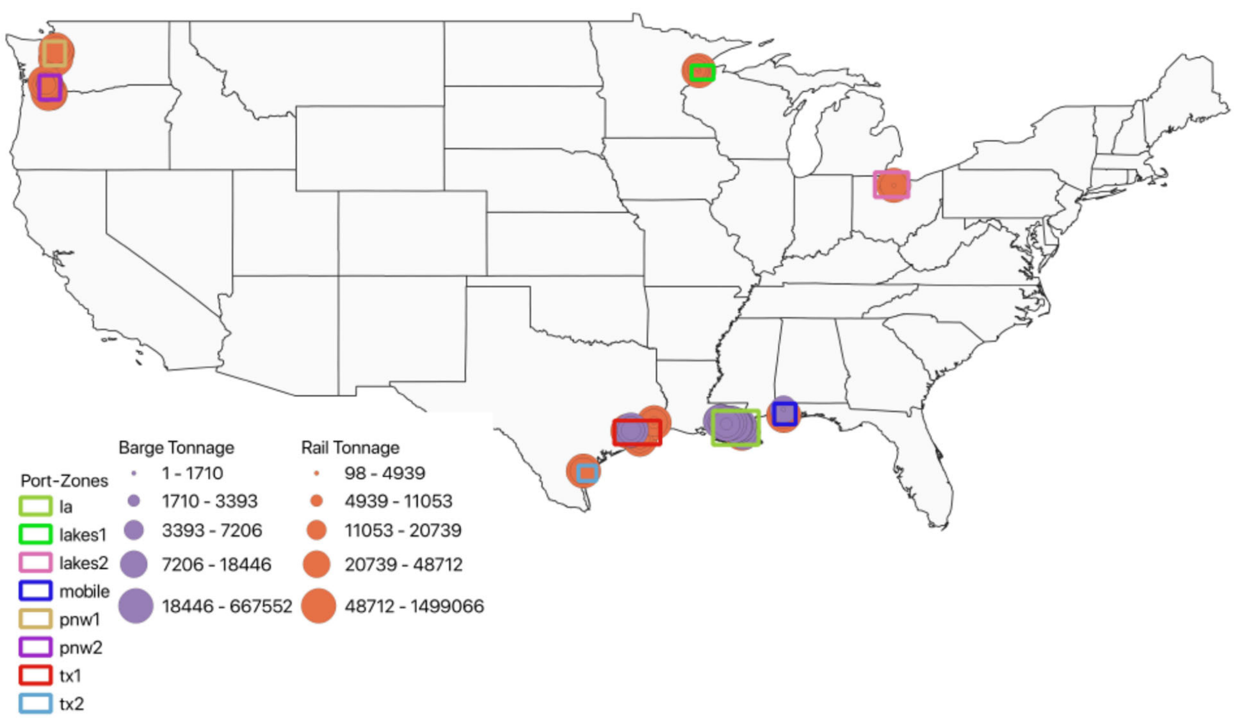
Corn



Wheat



Soybeans



There is a significant amount of overlap in port zones across commodities. For example, the port zone "PNW 2," which contains shipments to Oregon and Washington ports on the Columbia River, is present for all commodities. New Orleans is also a major port for all commodities. Table C.1 shows the major ports within each port zone. These port zones are taken to represent the options available to shippers in the Upper Midwest.

Table C.1: Ports within Port Zones

Port Zone	**Individual Ports**
PNW 1	Seattle, Tacoma
PNW 2	Portland, Kalama, Longview
LA	New Orleans, Southern Louisiana, Baton Rouge
TX 1	Houston, Galveston
TX 2	Corpus Christi
Lakes	Chicago
Lakes 1	Duluth, Superior
Lakes 2	Cleveland, Sandusky, Toledo
East	Norfolk, Elizabeth River, Baltimore
AL	Mobile
FL 1	Miami, Port Everglades

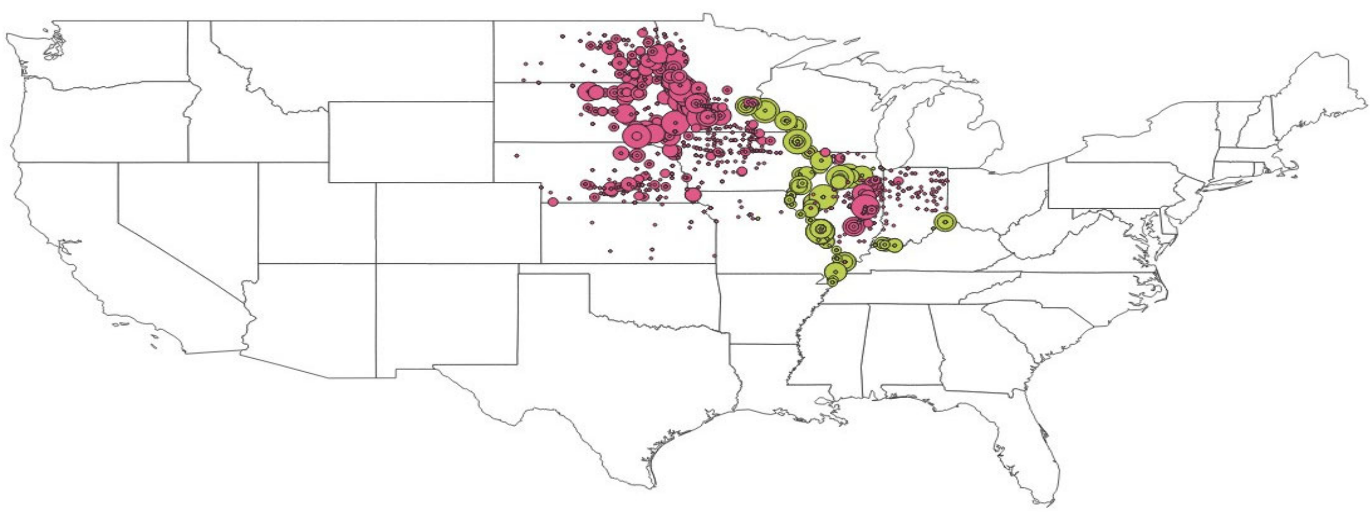
FL 2	Tampa, St Petersburg, Port Manatee

Note: This table displays the individual ports included within each port zone.

C.2 Origination Zone Definitions

As shown, barge origins are limited to the waterways (Mississippi, Illinois, and Ohio Rivers), while sources for rail shipments exist throughout the study region. Figure C.3 summarizes tonnages by origin for corn (for both rail and barge). Shipment origins for wheat and soybeans are not included but are quite similar in terms of geographic location as shipments of corn.

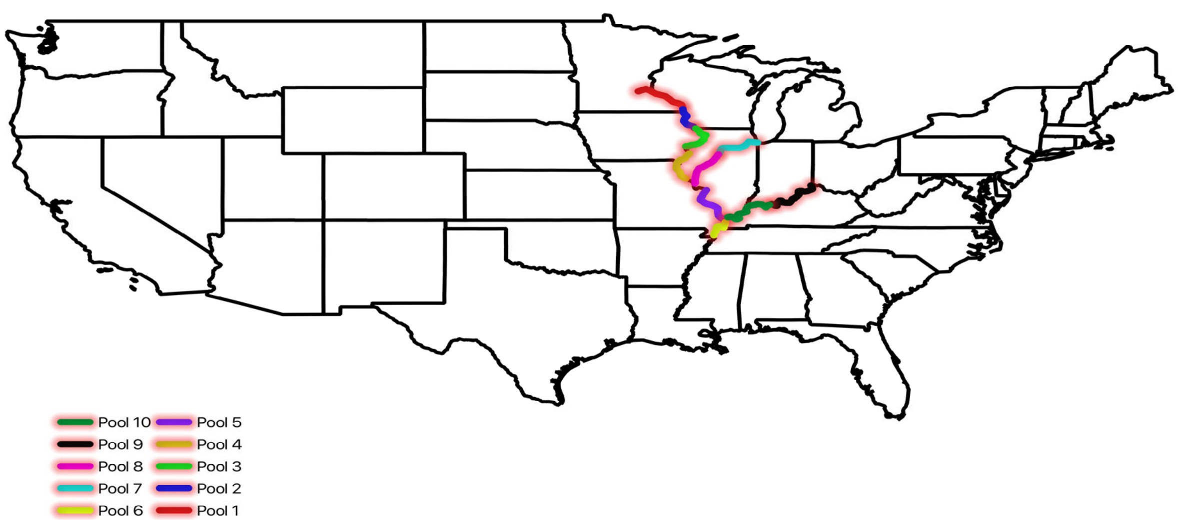
Figure C.3: Shipment Origins by Rail and Barge



One limitation of the WBC data is that the original origin of the waterway movements is not observable. Instead, only the origin of the waterway leg is observed in the data. As is evident from Figure C.3, there is little rail traffic that originates near the waterways. As the distance to the waterway increases, the frequency and size of rail shipments are higher. If the "original" origin of waterway traffic were observed, each movement could be modeled. We overcome this limitation by creating origin zones based on segments of the waterway. We then aggregate rail and water movements into these zones based on the distance to the waterway. The origin zones are the same for each commodity.

Origin zones are defined based on two factors: (1) distance from a major river, and (2) natural breaks in the location of shipments on the river.[22] With the latter factor, we define river pools or catchment areas for water shipments. Figure C.4, below, displays the river pools. We define ten unique pools along the major rivers.

Figure C.4: River Pools

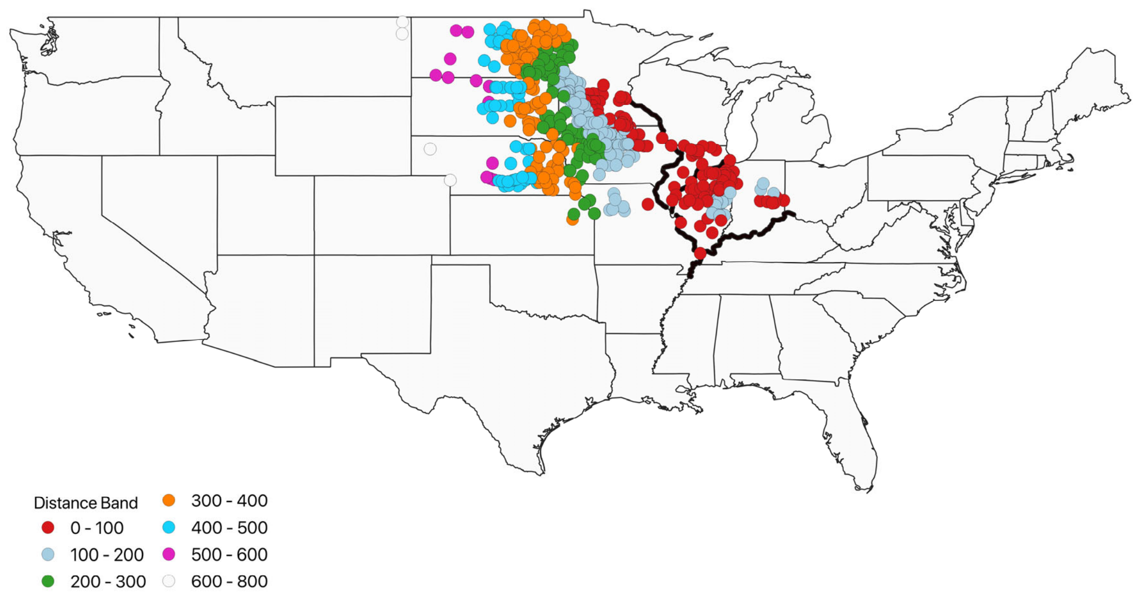


Note: This figure displays the river pools defined based on natural breaks in the geographic clusters of barge shipments, USACE district zones, and major geographic landmarks.

[22] The natural breaks are determined by inspection of the barge origins. USACE districts and significant landmarks (i.e., major cities and river tributaries) are also taken into account when defining the breaks along the river.

Within each river pool, rail shipment locations are classified into distance bands based on the miles to the nearest barge facility. We then aggregate movements to a port zone for each origin zone based on a given distance buffer around each river pool. For example, shippers within 100 miles of the waterway have the option of shipping by rail or barge. In contrast, shippers outside the 100-mile band only have rail as an option. In the empirical analysis, we vary the distance band from 100 to 300 miles by increments of 50 miles. Figure C.5, displays the distance to the river for each rail origin broken down into 100-mile segments for corn.[23] Thus, an individual shipper in the analysis consists of a river pool-distance band group. With 100-mile distance bands, there are 700 different shippers (10 river pools by seven distance bands).

Figure C.5: Distance to River Bands



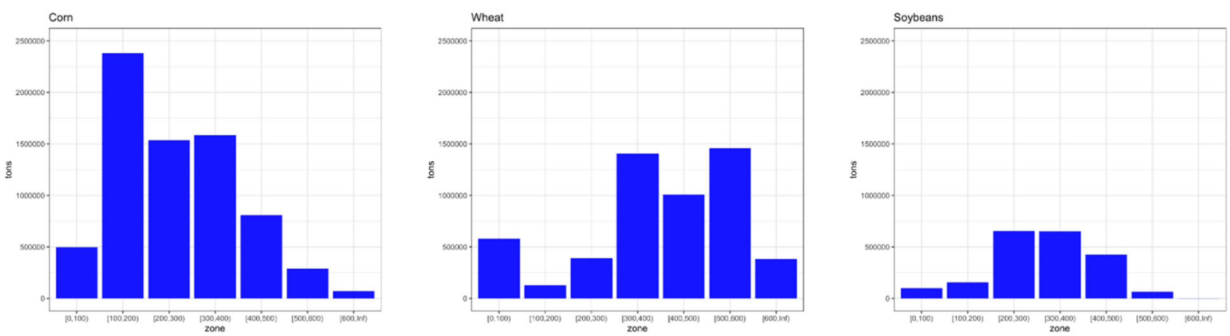
Note: This figure displays the river pools defined based on natural breaks in the geographic clusters of barge shipments, USACE district zones, and major geographic landmarks.

[23] We do not have data on the distance to the nearest barge location for several rail shipment locations. The missing origins account for approximately 10% of total tonnage.

C.3 Volumes, Rates, and Port Attributes

Figure C-6 displays the average annual tonnage by distance band for each commodity. The same general pattern holds across all commodities. However, the distribution of tonnage is more left-skewed for corn shipments. Shipments originating over 600 miles from the river have relatively low average annual tonnages, while shipments that originate between 100 and 500 miles from the river have the highest yearly tonnages.

Figure C.6: Average annual tonnage by distance band for corn, wheat, and soybeans

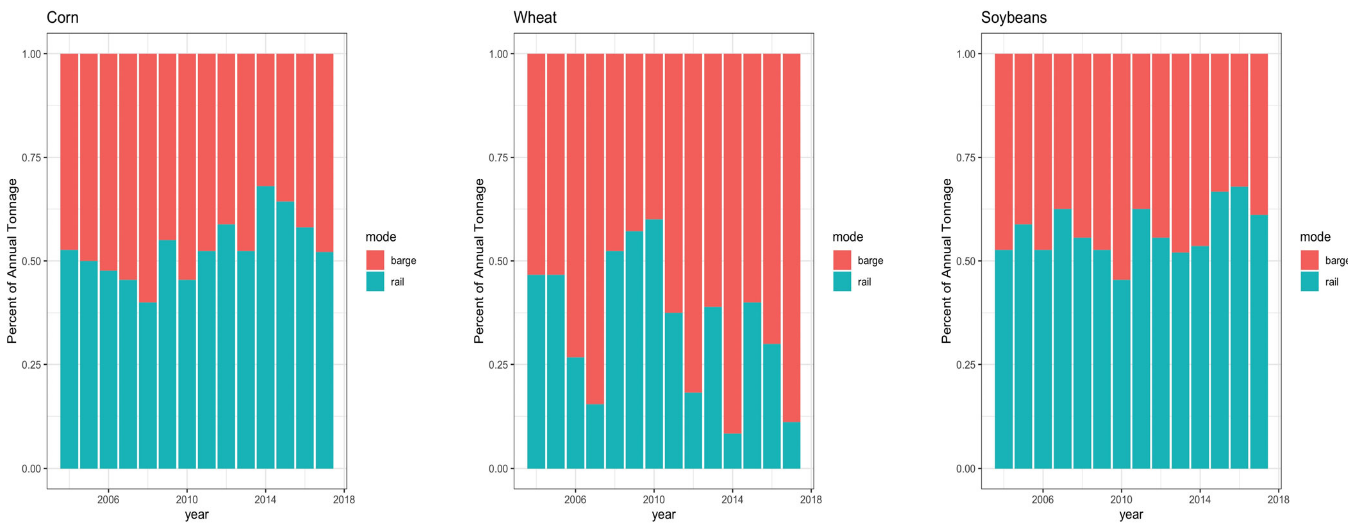


Note: This figure displays the average annual tonnage by commodity and distance band from the river.

Shipments that originate within 100 miles of the waterway are defined as a barge or rail catchment area. Meaning, shippers in the distance band “[0,100)” (inclusive of 0 but not inclusive of 100) have the option to ship by rail or barge. Figure C.7 displays the average annual share of total tonnage shipped by each mode for this catchment area over the sample period. For corn and soybean shipments, barge and rail are utilized relatively evenly. For wheat shipments, barge shipments comprise a larger share to total tonnage.

We estimate how shipping route and port zone specific characteristics influence port choice using data on shipping rates and port attributes. For barge rates, we use data from the USDA on pool-specific barge rates per ton-mile. For each river pool, we calculate the barge rate for shipments to New Orleans. Rail rates come from the CWS data. We aggregate to the origin zone-port zone level using a weighted mean that takes into account how frequently shippers are surveyed in the CWS data.

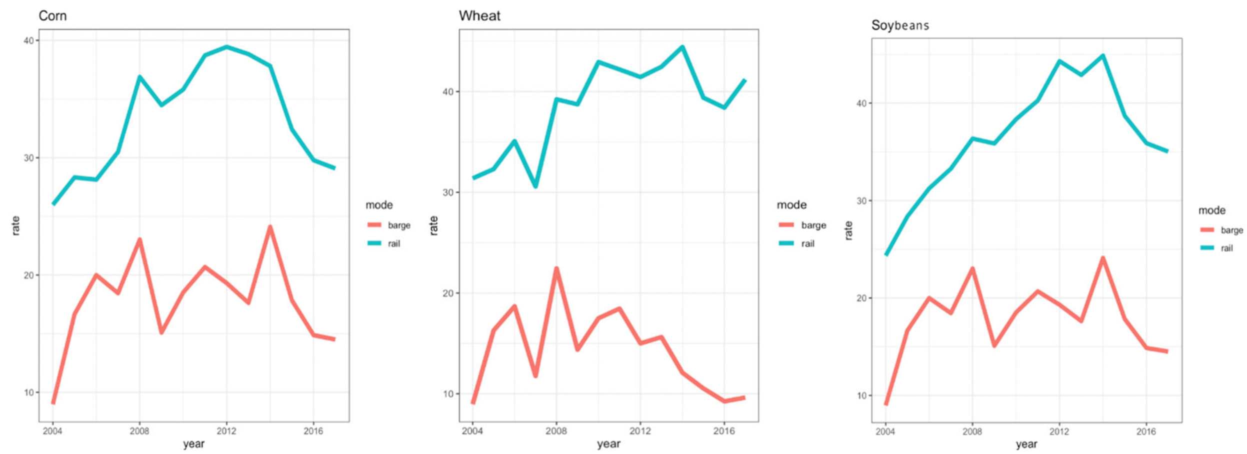
Figure C.7: Average annual share of tonnage by mode



Note: This figure displays the average annual share of tonnage by mode.

Figure C.8 displays the average annual freight rate by mode from 2004 to 2018. Rail rates increased from 2004 to 2012 and then declined from 2012 to 2018. Barge rates remained relatively constant for all commodities over the sample period. On the other hand, rail rates increase for all commodities; however, for corn and soybeans, there was a sharp decline in rail rates after 2014.

Figure C.8: Average annual freight rates by commodity and mode



Note: This figure displays the average annual freight rates by mode for each commodity.

Data on port attributes come from the U.S. Army Corps of Engineers. We collect information on the total berthing length and channel depth for each port within each port zone. We aggregate to the port zone level using the maximum berthing length and channel depth across the individual ports. Table C.2 shows that the LA and TX2 port zones have the largest berthing lengths, while the Pacific Northwest port zones have the deepest channels.

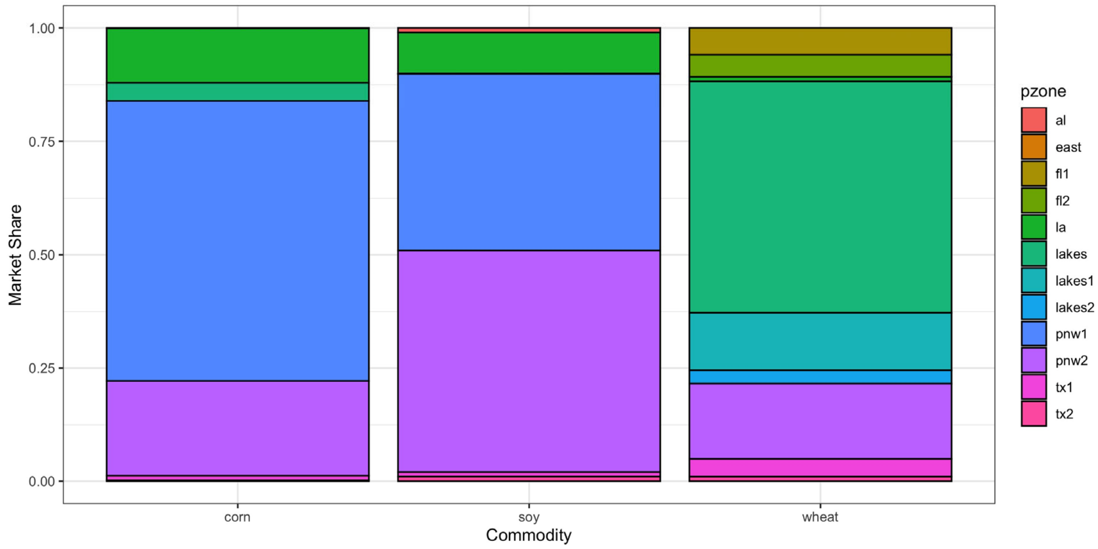
Table C.2: Port Attributes by Port

Port Zone	**Berthing Length (in 1,000 ft)**	**Depth** (in ft)
East	117.7	50
LA	266.3	45
Lakes	180.6	27
Lakes1	66.2	27
Lakes2	44.6	28
PNW1	138.5	60

PNW2	77.7	55
TX1	222.5	40
TX2	64.6	45
AL	120.1	40
FL1	41.4	43
FL2	25.4	32
Overall Average	**113.8**	**41**

Figure C.9 displays the market share for each port zone for rail shipments. Market shares are determined based on the total tonnage over the sample period. Only rail shipments are displayed as the LA port zone (Louisiana) is the only port zone with a barge option, which implies that the LA port zone has 100 percent of the barge market share. For rail shipments of corn and soybeans, the Northwest port zones have the largest market shares. For corn shipments, the PNW1 port zone is particularly dominant with a 60 percent market share. Wheat shipments are predominately shipped to the Lakes port zone.

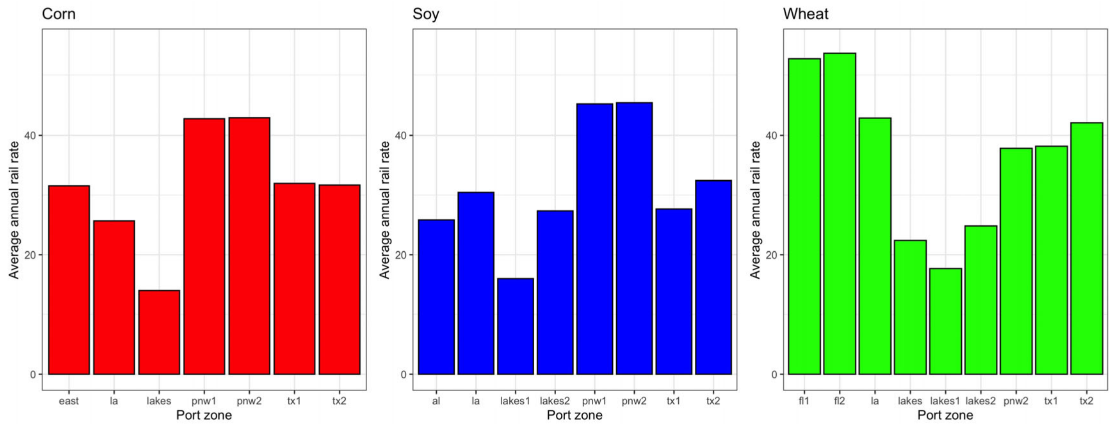
Figure C.9: Port zone market share



Note: This figure displays the market share for each port zone across commodities.

Figure C.10 displays the average annual rail rates for shipments to each port zone by commodity. For corn and soybean shipments, the Northwest port zones have the highest average annual rates. The lakes port zones have the lowest average annual rail rates, due in part to their proximity to major agricultural producing regions. The highest average annual rail rates are those corresponding to the Florida port zones for wheat.

Figure C.10: Average rail rates by port zone



Note: This figure displays the average annual rail rates to each port zone by commodity.

Table C.3 displays the overall summary statistics for the variables in the data. The table is broken down by transport mode and commodity. Across all commodities, freight rates for rail shipments are higher than freight rates for barge shipments. The average share of tonnage shipped by barge varies considerably by commodity. For shippers with a barge option, barge shipments make up 50 percent of total tonnage for soybeans, 70 percent for wheat, and 36 percent for corn.

Table C.3: Summary Statistics

	Tons	Rate per ton ($)
	Corn	
Barge	65,655.7	19.8
Rail	781,416.9	33.6
Barge Share	0.363	
	Wheat	
Barge	12,768.7	18.6
Rail	443,126.1	39.9
Barge Share	0.68	
	Soybeans	
Barge	167,242.2	18.2
Rail	102,499.7	33.9
Barge Share	0.5	