Port Choice and International Trade in Agricultural Products

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Abstract

Ports are a critical feature in the logistics of international trade. There is considerable research that examines trade between countries, but surprisingly little that examine the choice of ports through which trade occurs. In this paper, we develop and estimate a choice model in which importers of products choose the port(s) from which they receive imports from the US. This choice is made based on port level import prices and port attributes. We estimate the parameters of the model using data on global imports of US agricultural commodities between 2003 and 2017, US port attributes, and shipping costs. We use the results to calculate own- and cross-price elasticities for prices and port attributes as well as the willingness of importers to pay for improvement in port attributes.

JEL codes: R41, F12, L91, Q17
Keywords: Port choice, willingness to pay, agricultural import demand

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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%.[1] The growth in trade translates into growth in international transportation, which depends critically on the 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). However, there is little research that explains the effects of these investments on port selection or intensity of trade from the port.[2]

In this paper, we analyze port choice using a theoretical framework based on the probabilistic Ricardian model in Eaton and Kortum (2002). In our model, choice probabilities are based on differences in trade costs across ports, and global trade arises as individual buyers in import markets purchase products from the port that offers the lowest price. The theoretical framework also allows us to analyze how port-level trade costs influence the intensity of trade using a log-linear gravity relationship commonly estimated in the trade literature (e.g., Anderson and Van Wincoop, 2004). One benefit of the gravity model is that its structure can be exploited to calculate tariff equivalence of non-tariff trade barriers (Burlando, Cristea, and Lee, 2015). The model is then applied to trade of agricultural products, and in particular, the port choice and the level of trade at the port level are estimated using data on 134 countries importing from 85 ports in the US be-

[1]Global trade relative to global GDP has increased from 20 to 30 percent between 1990 and 2017 (https://data.worldbank.org/indicator/NE.EXP.GNFS.ZS).

[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.

tween 2003 and 2017. Port choice and the level of trade are examined in terms of market shares. The result allows us to evaluate how port choice changes as prices and attributes (channel depth, berthing length) of the port change, and also how the volume of trade changes.

We find evidence that higher shipping rates reduce the probability a port is chosen, while deeper ports and ports with longer berthing lengths are more likely to be selected. On the other hand, we find that the intensive margin of trade from a port is not affected by port attributes, but responds strongly to shipping rates. 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 5% tariff. Using the estimation results, the willingness to pay for cost-reducing port attributes yields estimates that suggest that an additional foot of channel depth is worth roughly \$1.34 per ton-mile, and when evaluated at the average tonnage is equivalent to roughly \$36,000. We also find that berthing length is worth roughly \$0.83 per foot using similar methods. There is heterogeneity across commodities in these willingness to pay figures.one foot and one additional foot of channel depth is more twice as high for shipments of soybeans than for other crops.

Next, we calculate the own- and cross-price elasticities across ports from an increase in the cost of shipping. Then, we estimate the own- and cross-price elasticities across ports from an increase in port depth. These actions affect the benefit of using different ports and result in a reallocation of where goods are exchanged. While and an increase in shipping costs has a similar effect across ports, we find there is considerable heterogeneity in response to changes in port-level attributes. For example, a one percent increase in the port of Tacoma's channel depth increases the probability that Tacoma is chosen by 13 percent. In contrast, a one percent increase in the port of New Orleans' channel depth increases the likelihood New Orleans is selected by 2 percent.

The paper provides insights into how shipping costs and port attributes influence the extensive and intensive margins of trade at US ports, and the results of the paper have several important policy implications. First, changes in global trade policy shifts 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, and as a result, 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 the state of Georgia contributed to 8.4% of total employment in the state.[3] Knowing 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, understanding the trade-offs shippers face when choosing ports can help inform policies aimed at improving efficiency through port-level infrastructure investment.

The remainder of the paper is organized as follows. In Section 2, we present the theoretical framework. In Section 3, we discuss the data used in this paper and how it is processed. In Section 4, we present the empirical results. Finally, we conclude in Section 5.

[3] https://www.terry.uga.edu/media/documents/ga$_{p}orts_{2}014_{s}tudy.pdf$

2 Theoretical Framework

In this section, we develop a model that explains trade intensity between a foreign country a specific port, and the choice of the port through which the trade occurs. Generally, the model is developed in the spirit of Eaton and Kortum (2002) (hereafter, EK). The level of trade between the country and the port follows directly from EK. However, as we show below, the model can also be used to explain port choice.[4]

In EK, products are produced in a perfectly competitive market. Exporters 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 $\frac{c_i}{z_i(\omega)}$, where c_i is the cost of inputs. Following EK, country i's productivity is drawn from a Type II extreme value distribution:

$$F_i(z) = Pr\{z_i(\omega) \leq z\} = e^{-T_i z^{-\theta}}$$

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

2.1 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:

[4]Several studies have used the EK framework to examine the choice of trade partner (e.g., Heerman, 2018). To our knowledge, no study has used the framework in the context of port choice.

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

Here, $\tau_{ij}^k > 1$ 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 EK, consumers purchas goods from the lowest priced supplier. More specifically, consumers in country j will purchase good ω from country i using the port with the lowest trade costs. Meaning, conditional on purchasing ω from country i, the price for the good will be:

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

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:

$$p_j(\omega) = \min_{i \in S} p_{ij}(\omega) = \min_{i \in S}(\min_{k \in i} p_{ij}^k(\omega)) = \min_{i \in S}(\min_{k \in i} \frac{c_i}{z_i(\omega)}\tau_{ij}^k) \tag{1}$$

Equation (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 ($z_i(\omega)$). Conditional on i offering the lowest price, country j is more likely to chose 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:

$$G_{ij}^k(p) = Pr\{p_{ij}^k(\omega) \leq p\} \tag{2}$$

and, using the pricing equation, and the Frechete distribution, equation (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:

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

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

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

We use the distribution of prices across ports (equation 3) and the distribution of prices across exporters (equation 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:

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

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:

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

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

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

Equation (7) is the fraction of goods country j purchases from port k located in country i. EK shows that given the properties of the Frechete 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 USA, the i subscript corresponds only to one country. Thus, equation (9) can be simplified as:

$$s_j^k = Prob_{jk} = \frac{\tau_j^{k-\theta}}{\sum_k \tau_j^{k-\theta}} \tag{8}$$

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 USA has been chosen as the exporting country. This share depends solely on port-level trade costs.

Following EK, 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.[5] When we plug trade costs into equation (8) we get the following expression:

$$s_{jk} = \frac{exp[\beta_1 rate_{jk} + \beta_2 Depth_k + \beta_3 Berthing_k + \gamma_k]}{\sum_k exp[\beta_1 rate_{jk} + \beta_2 Depth_k + \beta_3 Berthing_k + \gamma_k]}, \tag{9}$$

which we estimate with a fractional logit model. The parameters on these variables are a composite of the marginal response and the structural parameter θ, which is constant. The model also allows for a gravity-like specification. Taking the natural log of both sides of (9) produces a log-linear gravity-like model. The intensive margin is estimated using OLS with the following specification.

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

(10)

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

where importer fixed effects account for the multi-lateral resistance term in the denominator as in Anderson and Van Wincoop (2003). Given the context of the empirical analysis, which only focuses on the USA, 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. In the next section, we discuss in detail the data used to estimate the model.

3 Data

The data used to estimate equations (9) and (10) comes from several sources. These include 1. Trade data from the US 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; 3. Freight rates were provided to USDA from Drewry Maritime Research.

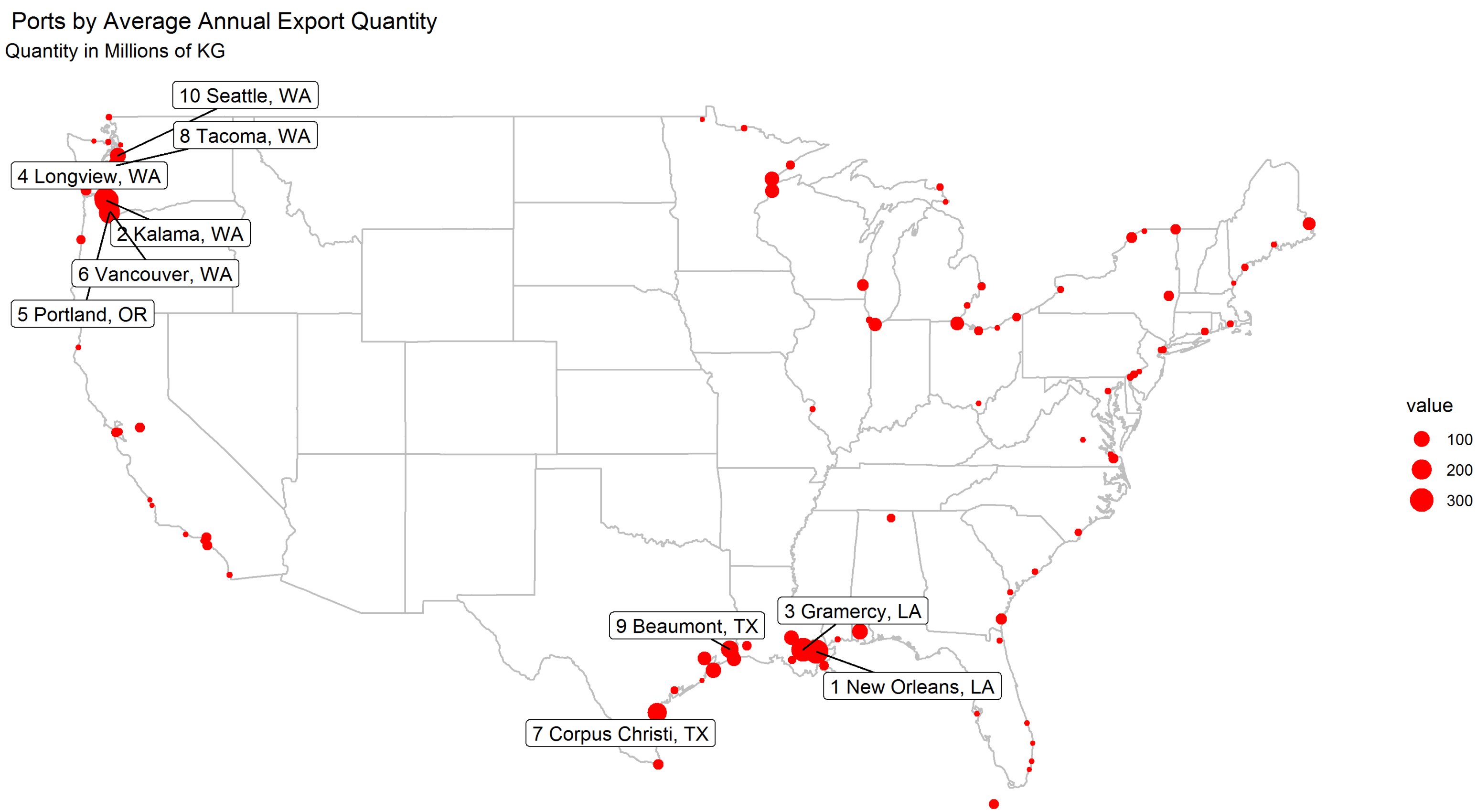
3.1 Trade Data

The US 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 US customs ports to all importing countries. We focus specifically on vessel shipments. Thus we exclude air shipments and rail shipments from the sample. The result is a sample of 120 customs ports. We observe these ports for the years 2003 to 2017. Figure 1 displays the location of all 120 ports as well as information on the average annual export quantity (measured by weight) from each port. The top 10 ports, in terms of average annual export quantity, are labeled in the figure.

Figure 1 highlights several important aspects of the data. First, the Gulf Coast and the Northwest are the two main regions where agricultural exports exit the USA. Ports by the Great Lakes and on the East Coast export agricultural commodities at lower values. 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 third. 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 and as the empirical results indicate there are important differences across the ports in the data. Figures 7, 8, 9, and 10 plot 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 interesting patterns emerge. Figure 11 displays export values shipped to European countries. While the Gulf remains a highly used region, the Northwest is much less used to send goods to Europe. Ports in the Great Lakes region ship higher export values than most of the ports in the Northwest. Figure 12 displays exports shipped to Latin American countries. Unsurprisingly, exports are highly concentrated among Gulf Coast ports. The patterns revealed in these figures highlight the importance of the distance between ports and importing countries in port-choice decisions.

Figure 1


Ports by Average Annual Export Quantity
Quantity in Millions of KG
10 Seattle, WA
8 Tacoma, WA
4 Longview, WA
2 Kalama, WA
6 Vancouver, WA
5 Portland, OR
9 Beaumont, TX
3 Gramercy, LA
1 New Orleans, LA
7 Corpus Christi, TX
value
100
200
300

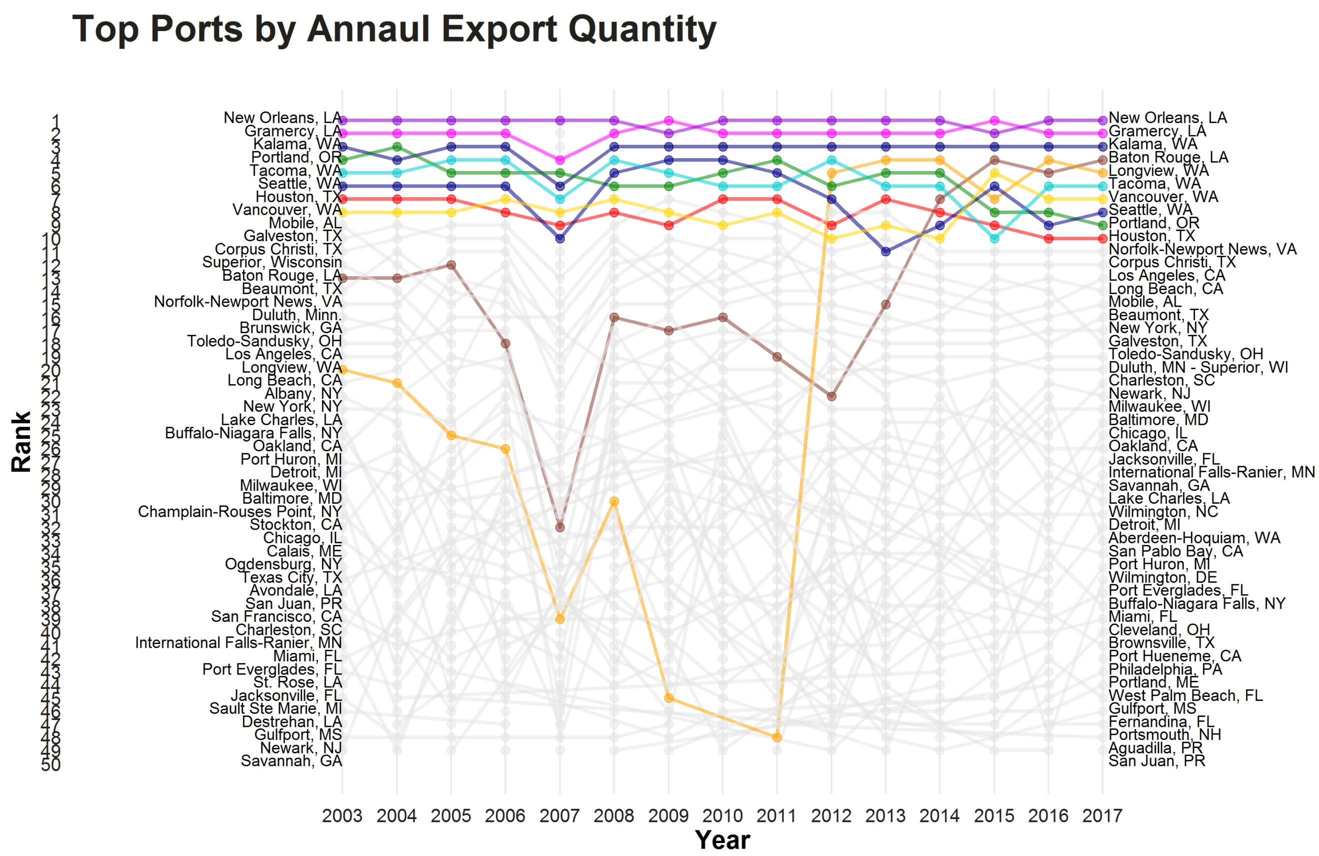
Next, we analyze how the use of ports has changed over the sample period. We present this information in Figure 2, which displays the ranking of ports for all commodities in each year of the sample. From the figure, it is clear that there is not much year-to-year variation in the top-ranked ports. Both Baton Rouge, and Longview saw dramatic increases in use over the sample period. Figures 13, 14, 15, and 16 present the port rankings for corn, soy, wheat, and sorghum, respectively.[6] In these figures, a similar pattern emerges. 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 the ranking of US trade partners and is consistent with the results in Blonigen and Wilson (2013).

3.2 Port Attributes

Through a variety of sources, we compile port-level attribute data for 2016. These data come from the World Port Index, Army Corps of Engineers, as well as supplemental information from port websites. Our data includes information on the channel depth and total berthing length. 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, still, the channel depth factors into the port choice decision through the effect on the port-level price.

[6]Fewer than fifty ports export soybeans, wheat, and sorghum. This is why these figures present the rankings for fewer ports.

Figure 2


Top Ports by Annaul Export Quantity
Rank
Year
2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50
New Orleans, LA
Gramercy, LA
Kalama, WA
Portland, OR
Tacoma, WA
Seattle, WA
Houston, TX
Vancouver, WA
Mobile, AL
Galveston, TX
Corpus Christi, TX
Superior, Wisconsin
Baton Rouge, LA
Beaumont, TX
Norfolk-Newport News, VA
Duluth, Minn.
Brunswick, GA
Toledo-Sandusky, OH
Los Angeles, CA
Longview, WA
Long Beach, CA
Albany, NY
New York, NY
Lake Charles, LA
Buffalo-Niagara Falls, NY
Oakland, CA
Port Huron, MI
Detroit, MI
Milwaukee, WI
Baltimore, MD
Champlain-Rouses Point, NY
Stockton, CA
Chicago, IL
Calais, ME
Ogdensburg, NY
Texas City, TX
Avondale, LA
San Juan, PR
San Francisco, CA
Charleston, SC
International Falls-Ranier, MN
Miami, FL
Port Everglades, FL
St. Rose, LA
Jacksonville, FL
Sault Ste Marie, MI
Destrehan, LA
Gulfport, MS
Newark, NJ
Savannah, GA
New Orleans, LA
Gramercy, LA
Kalama, WA
Baton Rouge, LA
Longview, WA
Tacoma, WA
Vancouver, WA
Seattle, WA
Portland, OR
Houston, TX
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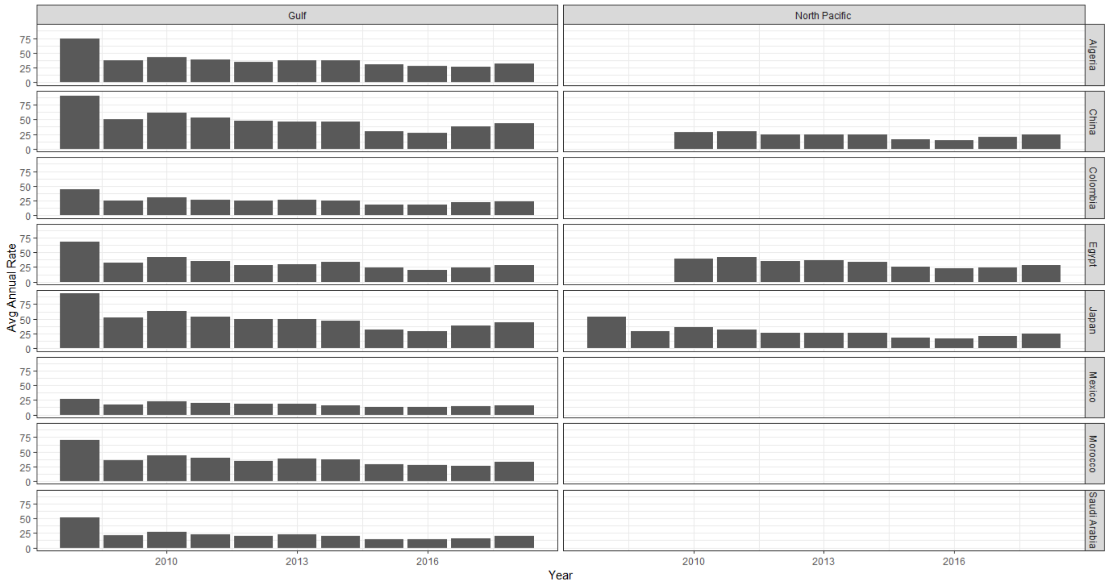
Mobile, AL
Beaumont, TX
New York, NY
Galveston, TX
Toledo-Sandusky, OH
Duluth, MN - Superior, WI
Charleston, SC
Newark, NJ
Milwaukee, WI
Baltimore, MD
Chicago, IL
Oakland, CA
Jacksonville, FL
International Falls-Ranier, MN
Savannah, GA
Lake Charles, LA
Wilmington, NC
Detroit, MI
Aberdeen-Hoquiam, WA
San Pablo Bay, CA
Port Huron, MI
Wilmington, DE
Port Everglades, FL
Buffalo-Niagara Falls, NY
Miami, FL
Cleveland, OH
Brownsville, TX
Port Hueneme, CA
Philadelphia, PA
Portland, ME
West Palm Beach, FL
Gulfport, MS
Fernandina, FL
Portsmouth, NH
Aguadilla, PR
San Juan, PR

Figure 3: Freight Rate Data Coverage



3.3 Freight Rates

We use weekly data on freight rates between regions of the USA and destination countries from Drewry Maritime Research to predict annual port-level freight rates that are used in the estimating equation. The data are for shipments from the Gulf Coast and Pacific Northwest to several countries. The breadth of the data is displayed in Figure 3. We take advantage of the 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.

We measure external shipping distance using data on shipping distances between US ports and importing country ports, which takes into account geographic features like the Panama Canal. The data come from the Army Corps of Engineers database on port-to-port nautical miles. Of the 120 ports used to export agricultural commodities, the database contains distance measures for 84. However, these 84 ports comprise the vast majority of annual export tonnage. 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.

To predict and 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 distance and shipment characteristics.[7] The fit of the model is shown in Table 1. In each column of the table, we alter the specification slightly. All columns include the log of the shipping distance between port k and country j, and columns (2) through (5) include the log annual tonnage as well. Columns (3) and (4) of the table include a linear and quadratic time trend, while column (5) include year fixed effects. The adjusted R^2 of the model is highest when year fixed effects are included, where the model captures 73% of the variation in freight rates. We use the specification in column (5) of the table to predict and impute the missing freight rates. In Figure 4 we display the relationship between the predicted port-destination freight rates and the port-destination shipping distances. Freight rates increase with distances at a decreasing rate.[8]

[7]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 regessors (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.

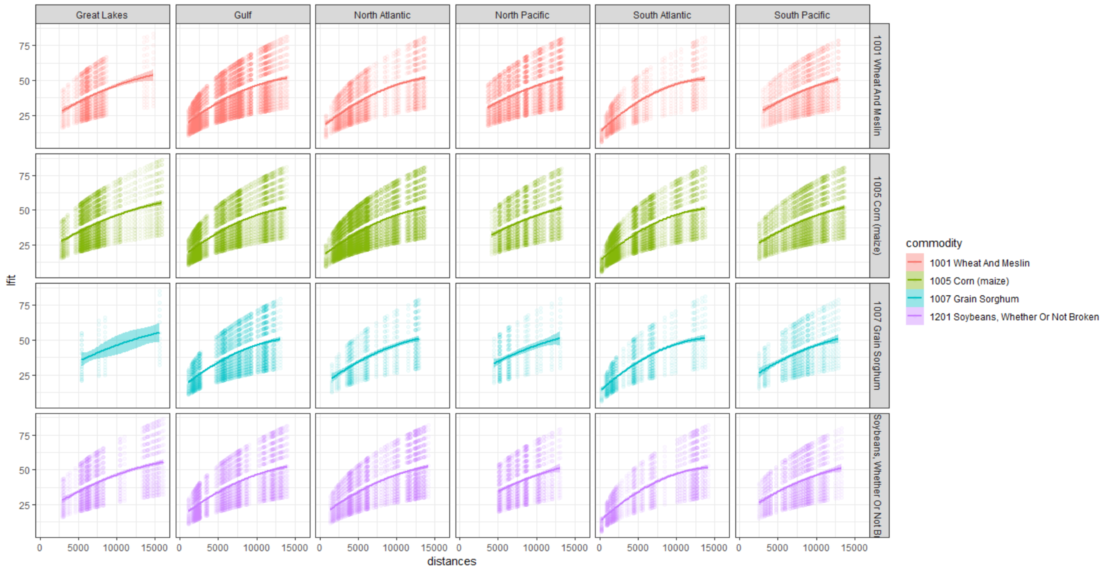
[8]The finding that rates increase at a decreasing rate is consistent with the so-called "tapering principle" (see, Locklin, 1972). The concave ship is a result of the fixed costs associated with loading and unloading ships is spread out over more miles shipped (Blonigen and Wilson, 2018)

Table 1: OLS Model of Freight Rates

	Dependent variable:				
	$ln(rate_{jkt})$				
	(1)	(2)	(3)	(4)	(5)
$ln(dist_{jk})$	0.410^{***}	0.408^{***}	0.415^{***}	0.416^{***}	0.415^{***}
	(0.132)	(0.131)	(0.130)	(0.130)	(0.130)
$ln(weight_{jkt})$		-0.003	-0.003^{**}	-0.003^{**}	-0.003^{***}
		(0.002)	(0.001)	(0.001)	(0.001)
Time Trend			-0.087^{***}	-111.670***	
			(0.007)	(12.815)	
Quadratic Time Trend				21.744^{***}	
				(5.158)	
Constant	-0.159	-0.118	175.355^{***}	0.142	
	(1.152)	(1.145)	(14.230)	(1.150)	
Observations	2,198	2,198	2,198	2,198	2,198
R^2	0.307	0.311	0.628	0.637	0.731
Adjusted R^2	0.307	0.311	0.627	0.637	0.730
Year Fixed Effects	No	No	No	No	Yes

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

Figure 4: Relationship between freight rate and shipping distances (linear model)



3.4 Summary Statistics

Table 2 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 25 million kg, and freight rates are roughly $39. The number of observations falls for the port-attributes because we have data on port-attributes for 2016, and we do not have this information for all of the ports in the data set. However, the ports for which we do have data on port attributes cover 97% of the total export tonnage in 2016.

Table 2: Summary Statistics

Variable	Meaning	Source	Mean	SD	N
Weight	Trade Quantity	US Census	24.5m kg	188m kg	47,565
Dist	Shipping Distances (miles)	Army Corps	6577.9	3480.9	47,565
Rate	Freight Rate (linear impute)	Drewery	$39.12	$16.40	47,565
Berthing	Total Berthing Length (in 100,000 ft)	Multiple Sources	1.15	1.06	2,738
Depth	Minimum Channel Depth (ft)	Multiple Sources	11.9	3.32	2,738

Table 3: Summary Statistics by Crop

Commodity	Weight	Rate	Berthing	Depth	Dist
Wheat	27.5	37.99	1.11	11.95	6552.50
Corn	19.2	37.34	1.15	11.79	5948.70
Sorghum	19.0	37.45	1.27	12.78	6537.43
Soy	36.7	39.46	1.16	11.79	7884.03

Table 3 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.

4 Empirical Results

4.1 Estimation Results

We begin by estimating equation (9) using a fractional logit model. The results are presented in Table 4. Columns (3) and (4) of the table are estimated only for the year 2016, and only with the ports for which we have data on port attributes (which account for roughly 97% of total tonnage in 2016). In the column labeled Intensity, we estimate a log-linear model with the log of export quantity 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.[9]

[9] We bootstrap over both stages of estimation, and allow the bootstrap errors to cluster at the importing country level. This allows for correlation in the unobservables across port-level trade flows entering a given country.

Table 4

outcome: $Prob_{jkt}$	(1)	(2)	(3)	(4)	Intensity
$Rate_{jkt}$	-0.113***	-0.113***	-0.203***	-0.217***	-0.186***
	(0.0105)	(0.0108)	(0.0221)	(0.0253)	(0.051)
Total Berthing $Length_k$			0.431***	0.666***	-0.085
			(0.0562)	(0.0837)	(0.011)
Channel $Depth_k$			0.0500***	0.0681***	-0.002
			(0.0152)	(0.0204)	(0.029)
Gulf		0.614***		-0.822***	2.79***
		(0.104)		(0.232)	(0.515)
North Atlantic		0.446***		-1.618***	-1.945 ***
		(0.0928)		(0.278)	(0.637)
North Pacific		0.518***		-0.314	0.432
		(0.110)		(0.237)	(0.601)
South Atlantic		-0.307***		-0.764***	-2.561***
		(0.115)		(0.183)	(0.567)
South Pacific		0.420***		-0.334	-1.657 **
		(0.108)		(0.259)	(0.583)
Observations	40,482	40,482	2,255	2,255	754

This table presents the results of estimating the fractional logit model. All columns include destination, commodity, and year fixed effects. Columns (4) of both panels displays the results when port attributes are included. The sample is restricted to only 2016 in columns (3) and (4) due to data availability issues. The column labeled Intensity presents the results of a gravity model specification, with the log of port level export value as the dependent variable. Errors in the table are cluster bootstrapped at the importing country level. *p<0.1; **p<0.05; ***p<0.01

The results in Table 4 highlight the relevant trade-offs shippers make when choosing a port. Higher freight rates reduce the probability a port is selected across all specifications. In column (2), we find that relative to ports on the Great Lakes (the omitted category), ports in other regions are more desirable choices for shippers. This relationship changes in column (4) once we control for port level attributes. Port attributes do not have a statistically significant effect on the intensity of trade from a port, conditional on the port being chosen. However, we estimate that a one-dollar increase in the freight rate (an additional dollar per ton) reduces the quantity of trade from the port by nearly 19%. One benefit of the gravity trade model is its structure can be exploited 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 θ. Following Simonovska and Waugh (2014), we use a value of $\theta = 4.12$. The tariff-equivalent of a one-dollar increase in the freight rates is roughly 5%.[10]

We calculate a shippers' willingness to pay for a change in port attributes using the results in column (4). To calculate willingness to pay, we use the marginal effect associated with the attribute divided by the marginal effect of money, which in this case, is represented by freight rates. For example, the shipper's willingness to pay for an additional foot of channel depth at a port is (0.0556 per foot)/(-\$0.0416 per mile)= -\$1.34 per foot per ton. Given that the shipments weights roughly 27,000 tons (from Table 2), this comes to a total of \$36,188 per foot. We use a similar

[10]The tariff equivalent is calculated from $\hat{\beta_1} = -\theta * \alpha_1$, 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 $\hat{\beta_1} = 19\%$, the tariff equivalent is roughly 5%. Similar methods are used in

method to calculate the willingness to pay for each additional foot of berthing length, and we produce an estimate of roughly \$0.83.

We can also use the estimates to simulate choice probabilities. For example, Figure 5 displays the likelihood that the port of New Orleans is chose based on different freight rates. The predicted probabilities are generated based on the estimates from column (4) of Table 5. 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 red line corresponds to the choice probability of New Orleans, and the blue line corresponds to the choice probability for any port other than New Orleans. As the freight rates from New Orleans increases, the probability that New Orleans is chosen falls while the probability that an importer chooses a different port rises.

4.2 Heterogeneity

Next, we estimate equation (9) using the fractional logit model for each crop separately. Table 5 presents the results. The results are generally similar to the pooled results in Table 4. Using data on the average tonnage, we calculate the total willingness to pay for a change in port attributes across commodities. We show the willingness to pay for port attributes in the table. We estimate that willingness to pay for berthing length and channel depth is highest for soybeans.

4.3 Elasticities

The port choice model estimated in this paper predicts which port is chosen based on attributes of the port, characteristics of the shipping route, and characteristics

Figure 5: Choice Probability for New Orleans

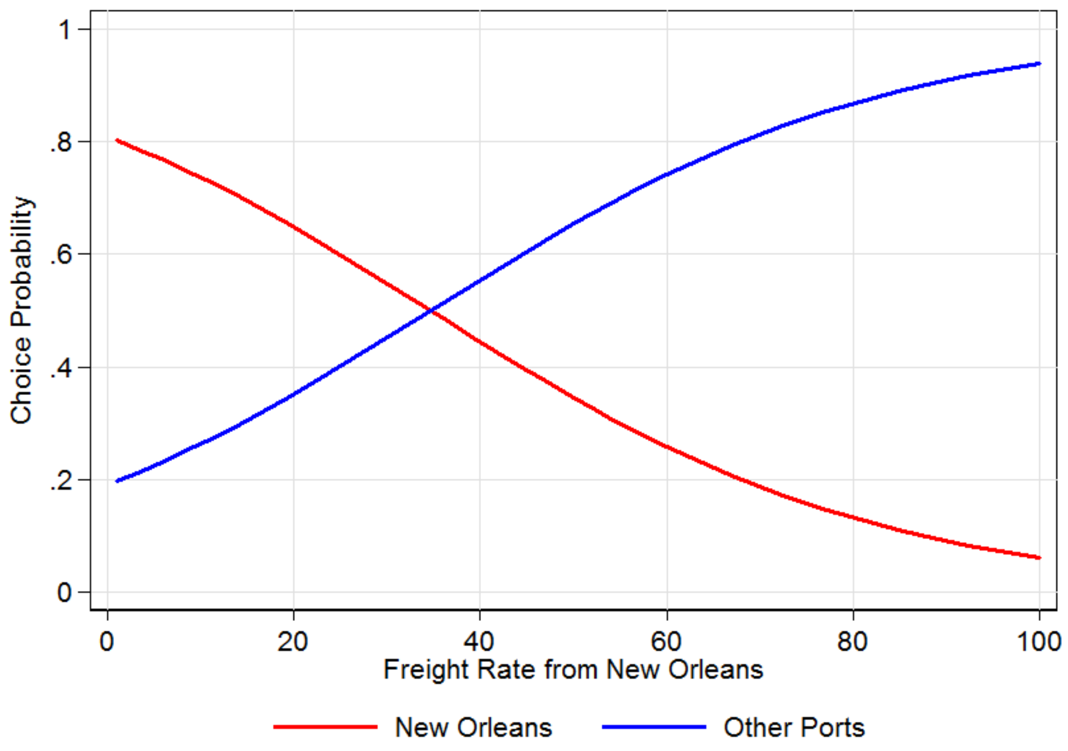


Table 5: Results by Crop

	Wheat	Corn	Sorghum	Soy
Rate_{jkt}	-0.270***	-0.324***	-0.372***	-0.219***
	(0.0514)	(0.0414)	(0.0923)	(0.0501)
Berthing_k	0.557***	0.749***	0.521*	1.056***
	(0.154)	(0.0982)	(0.267)	(0.152)
Depth_k	0.0512	0.0569**	0.193*	0.147***
	(0.0397)	(0.0269)	(0.117)	(0.0390)
Gulf	0.942	-1.272***	13.76***	-1.858***
	(1.092)	(0.320)	(1.242)	(0.490)
North Atlantic	-1.290	-1.531***	11.05***	-3.225***
	(1.197)	(0.328)	(1.973)	(0.626)
North Pacific	2.615**	-0.748*	9.391***	-2.028***
	(1.212)	(0.421)	(2.213)	(0.617)
South Atlantic	0.470	-1.279***	12.52***	-0.474
	(0.986)	(0.332)	(1.141)	(0.497)
South Pacific	1.034	-0.202	12.62***	-1.136**
	(1.024)	(0.364)	(1.187)	(0.575)
WTP for 1 ft of Berthing	\$0.62	\$0.49	\$0.29	\$1.94
WTP for 1 ft of Depth	\$5,748	\$3,716	\$10,865	\$27,154
Observations	528	1,003	199	525

This table presents the results of estimating the fractional logit model for each crop separately. The linear regression predicted freight rates are used in all columns. All columns include destination fixed effects. Willingness to pay is calculated based on the coefficients in the table Errors in the table and evaluated at the sample means. Errors are cluster bootstrapped at the importing country level. *p<0.1; **p<0.05; ***p<0.01

of alternative ports and routes. Using the structure of the model, we calculate the response of shippers to changes in a specific port or route attributes. This allows us to analyze substitution across ports under counterfactual scenarios.

We begin by analyzing the response to a 1% 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%, 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 6. Each port's own-price elasticity shows the percent decline in predicted use after a 1% 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% increase in the port-specific freight rate results in the port losing roughly 5% of their business, while other ports gain approximately 0.3% in market share.

The second half of Table 6 displays the own- and cross-price elasticities with respect to a 1% increase in port-specific channel depth. Here, there appears to be more variation in responses. For example, a 1% increase in the channel depth at New Orleans increases the probability New Orleans is chosen by only 2% percent.

Table 6: Elasticities

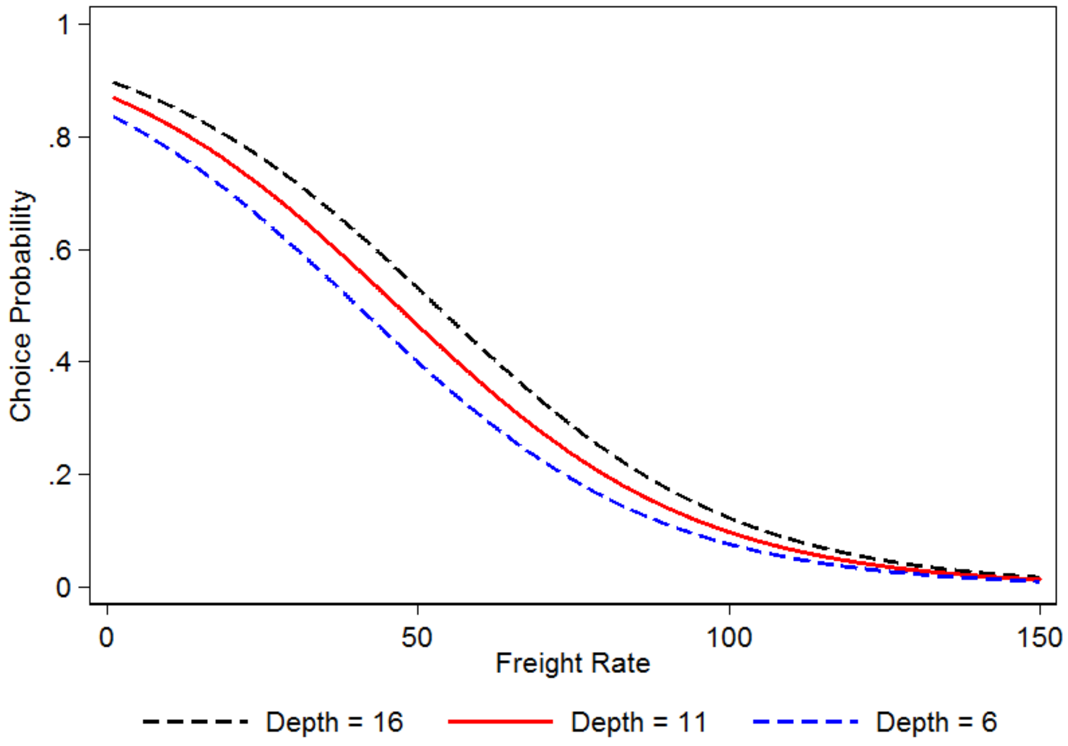
	1% increase in rate		1% increase in Depth	
Port	Own Price	Cross-Price	Own Price	Cross-Price
New Orleans	-6.5%	0.12%	2%	-0.3%
Kalama	-5.0%	0.28%	7%	-0.4%
Longview	-5.0%	0.31%	7%	-0.4%
Portland, OR	-5.0%	0.45%	7%	-0.6%
Vancouver	-5.0%	0.33%	8%	-0.5%
Corpus Christi	-7.0%	0.08%	9%	-0.1%
Tacoma	-4.5%	0.81%	13%	-0.07%
Beaumont, TX	-6.8%	0.06%	7%	-0.07%
Seattle	-4.7%	0.62%	5%	-0.07%
Mobile	-6.7%	0.09%	7%	-0.1%

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

However, a 1% increase in the channel depth at Tacoma increases the likelihood Tacoma is selected by 13% percent. Cross-price elasticities are small across all ports.

We display the information in Table 6 in another way in Figure 6. This figure presents the choice probability for the port of New Orleans at different freight rates. As the freight rate at the port increases, the choice probability falls. The red line displays the results for New Orleans using the actual channel depth of the port (11 feet), while the two dashed lines show the results if the port was five feet deeper and five feet shallower. The demand for the port of New Orleans does not change dramatically with channel depth.

Figure 6: Channel Depth at Port of New Orleans



5 Conclusion

In this paper, we analyze the trade-offs that shippers of agricultural goods make when selecting ports for their shipments. Using data on port-level agricultural imports, port attributes, and shipping costs, we estimate a choice model that allows us to measure the utility shippers receive from using different ports. We use the model to back out an estimate of willingness to pay for cost-reducing port attributes. We also use the model to predict how port choices change when critical characteristics of the port or shipping route change.

We find that shipping costs reduce the probability a port is chosen. At the same time, deeper channels, and longer berths increase the likelihood. We also analyze how these characteristics influence the intensity of trade from a port. We that shipping costs reduce trade intensity, but port attributes do not have a statistically significant effect on trade intensity. Using the estimates of the choice model, we find that shippers are willing to pay roughly \$8,000 for an additional foot of channel depth at a port and that shippers are willing to pay approximately \$21,000 for an increase in total berthing length of 100,000 feet. We also find that there is heterogeneity in willingness to pay for these attributes across crops. Shippers are willing to pay more for port attributes for shipments of soybeans than for other crops.

Understanding how port attributes and shipping costs influence port choice is highly relevant for policymakers. We contribute to the literature on port choice and international trade by deriving a fractional logit empirical model from the probabilistic Ricardian trade model in Eaton and Kortum (2002). This framework allows us to estimate a choice model as well as analyze trade intensity. The results of the paper provide an estimate of how demand for ports changes under potential infrastructure projects. For example, policymakers may be interested in increased channel depth to accommodate larger ships. The results of this study offer insights into how demand for ports will change when channels are deepened, and provide estimates of how demand for competing ports will change.

Similarly, the results of the study offer insights into how much shippers would be willing to pay for such infrastructure investments. This information is useful for cost-benefit analysis. Finally, the results of this study offer insights into how demand for ports changes with 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.

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Figure 7

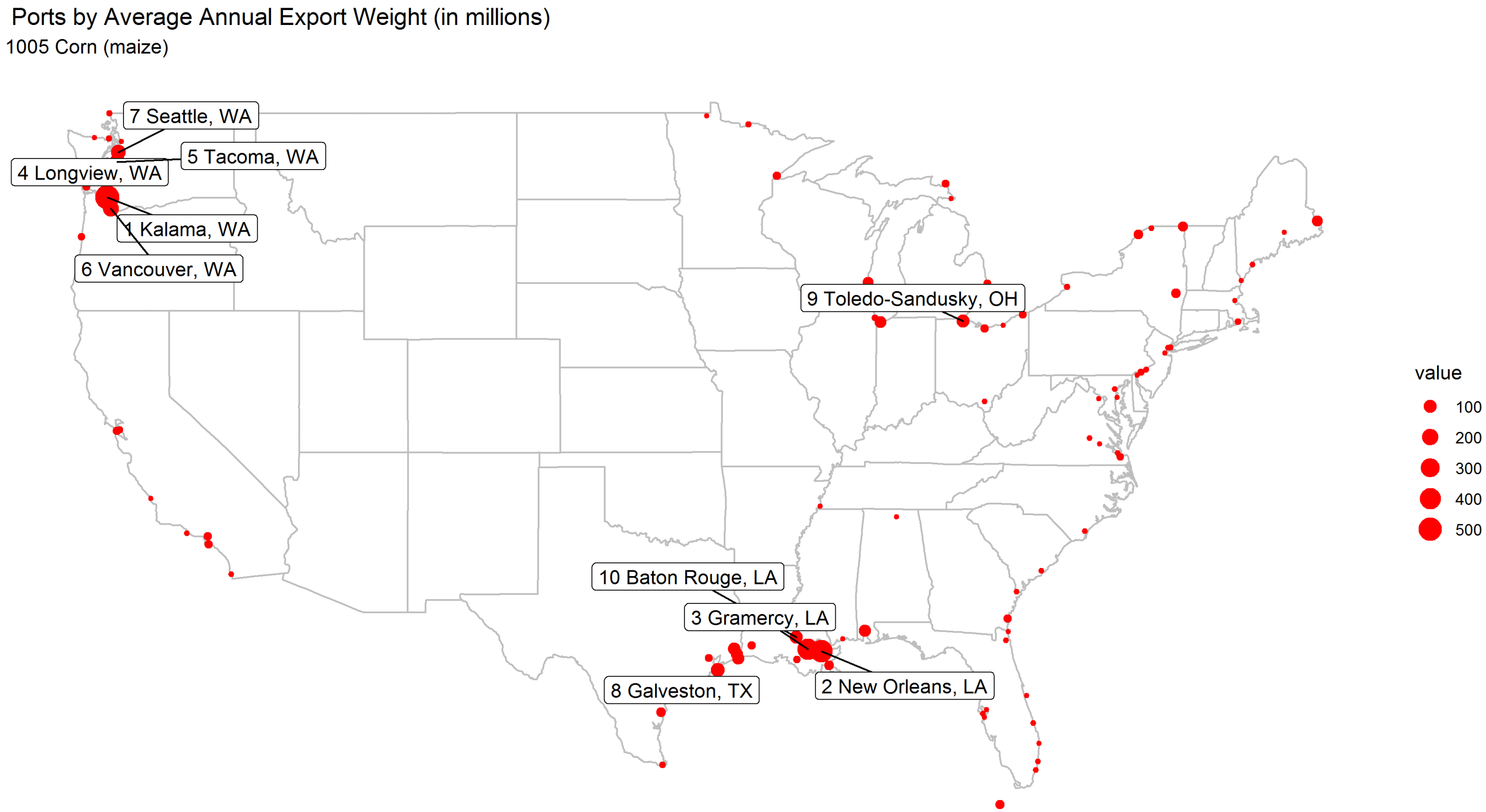
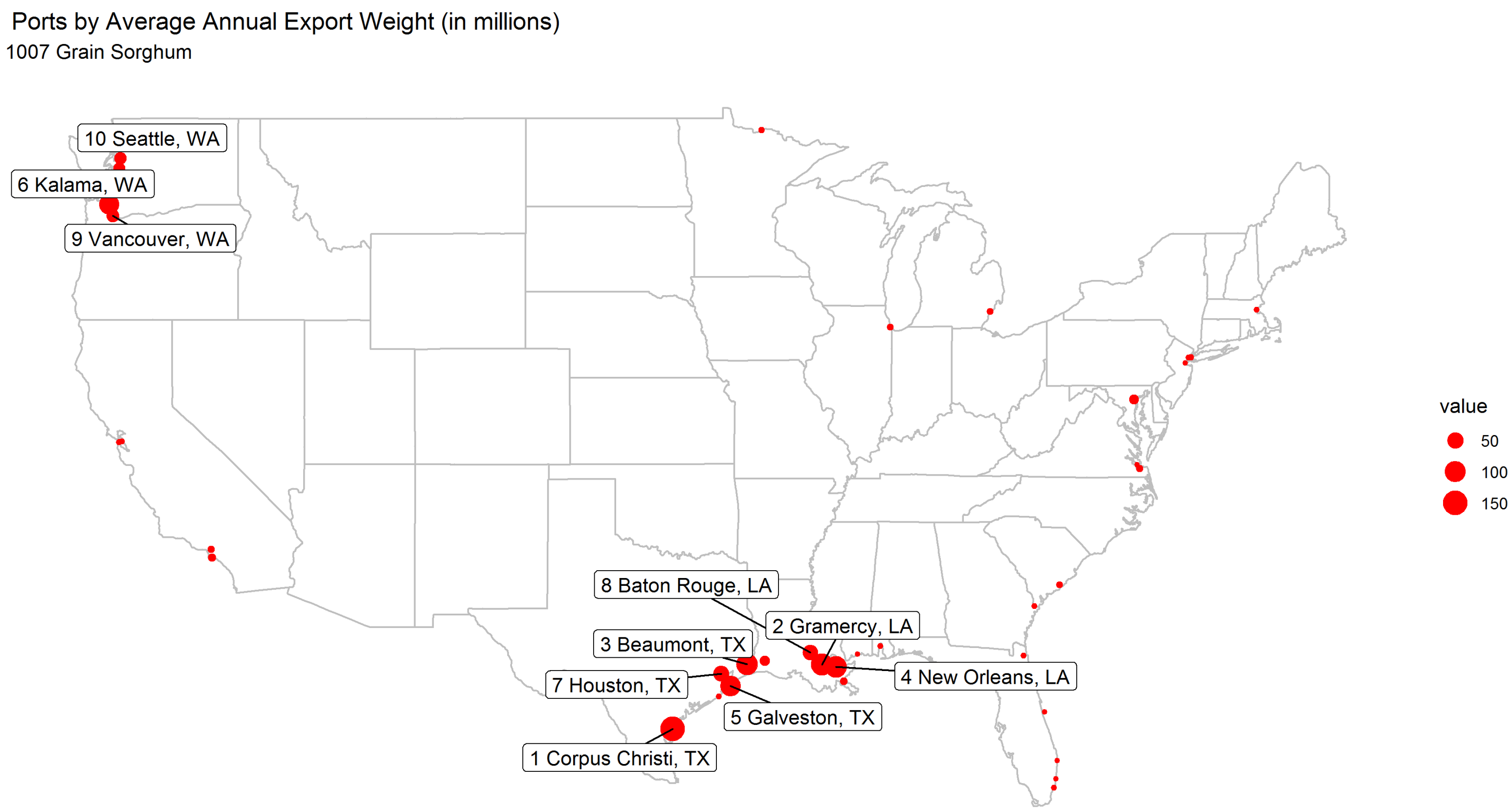

Ports by Average Annual Export Weight (in millions)
1005 Corn (maize)
7 Seattle, WA
5 Tacoma, WA
4 Longview, WA
1 Kalama, WA
6 Vancouver, WA
9 Toledo-Sandusky, OH
10 Baton Rouge, LA
3 Gramercy, LA
8 Galveston, TX
2 New Orleans, LA
value
100
200
300
400
500

Figure 8



Ports by Average Annual Export Weight (in millions)
1007 Grain Sorghum
10 Seattle, WA
6 Kalama, WA
9 Vancouver, WA
8 Baton Rouge, LA
2 Gramercy, LA
3 Beaumont, TX
7 Houston, TX
4 New Orleans, LA
5 Galveston, TX
1 Corpus Christi, TX
value
50
100
150

Figure 9

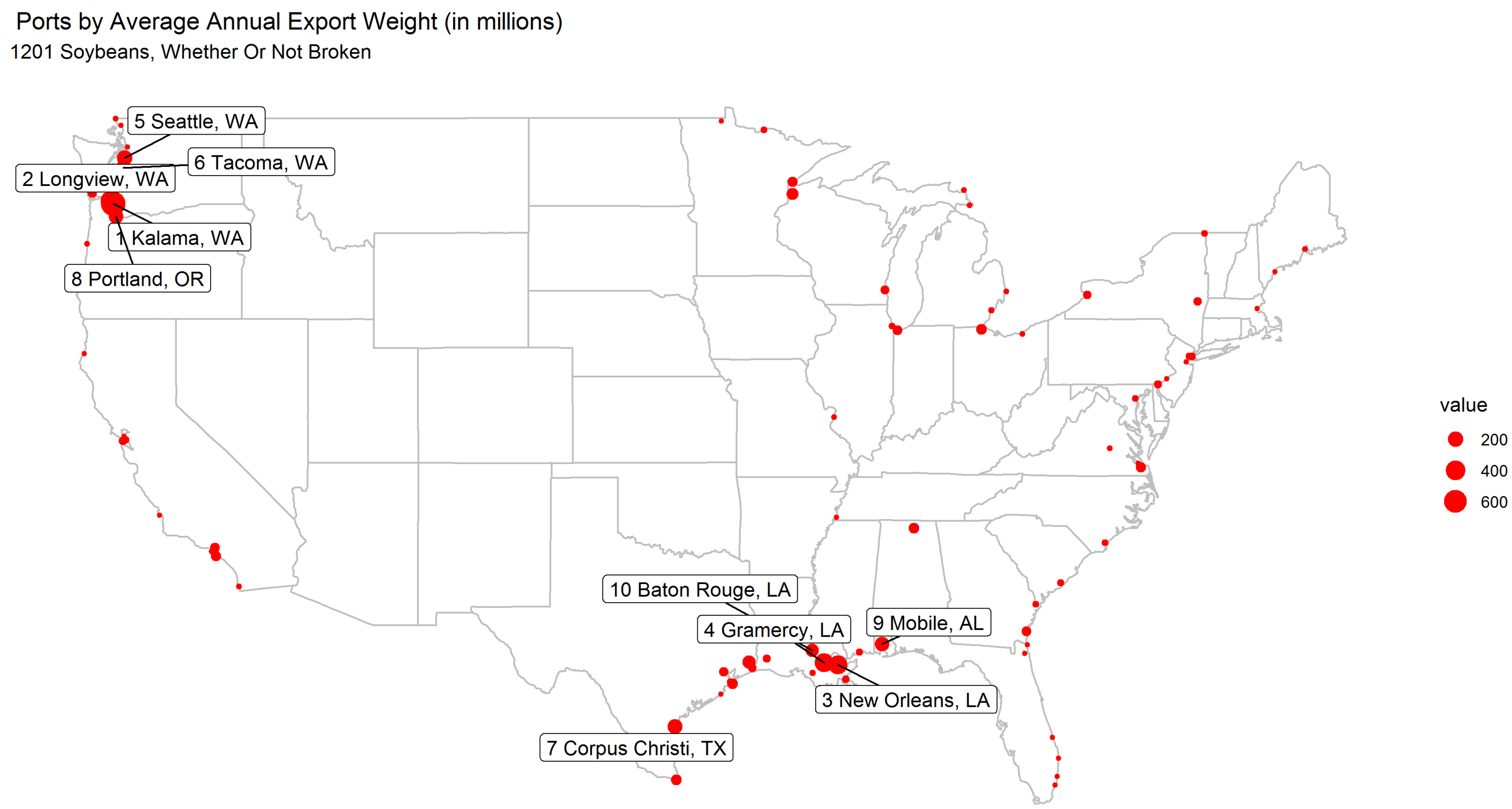

Ports by Average Annual Export Weight (in millions)
1201 Soybeans, Whether Or Not Broken
5 Seattle, WA
6 Tacoma, WA
2 Longview, WA
1 Kalama, WA
8 Portland, OR
10 Baton Rouge, LA
4 Gramercy, LA
9 Mobile, AL
3 New Orleans, LA
7 Corpus Christi, TX
value
200
400
600

Figure 10

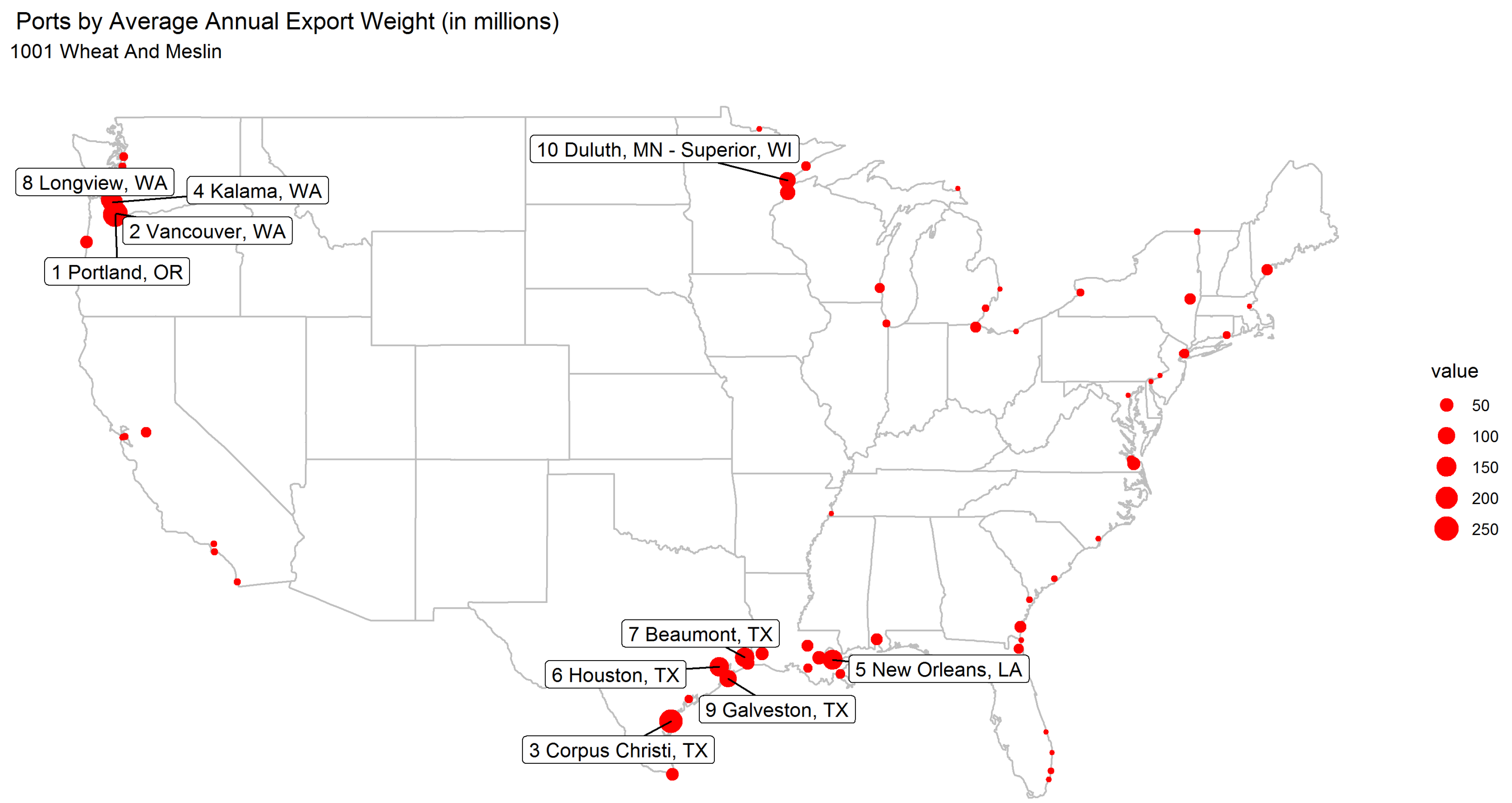

Ports by Average Annual Export Weight (in millions)
1001 Wheat And Meslin
8 Longview, WA
4 Kalama, WA
2 Vancouver, WA
1 Portland, OR
10 Duluth, MN - Superior, WI
7 Beaumont, TX
6 Houston, TX
9 Galveston, TX
3 Corpus Christi, TX
5 New Orleans, LA
value
50
100
150
200
250

Figure 11

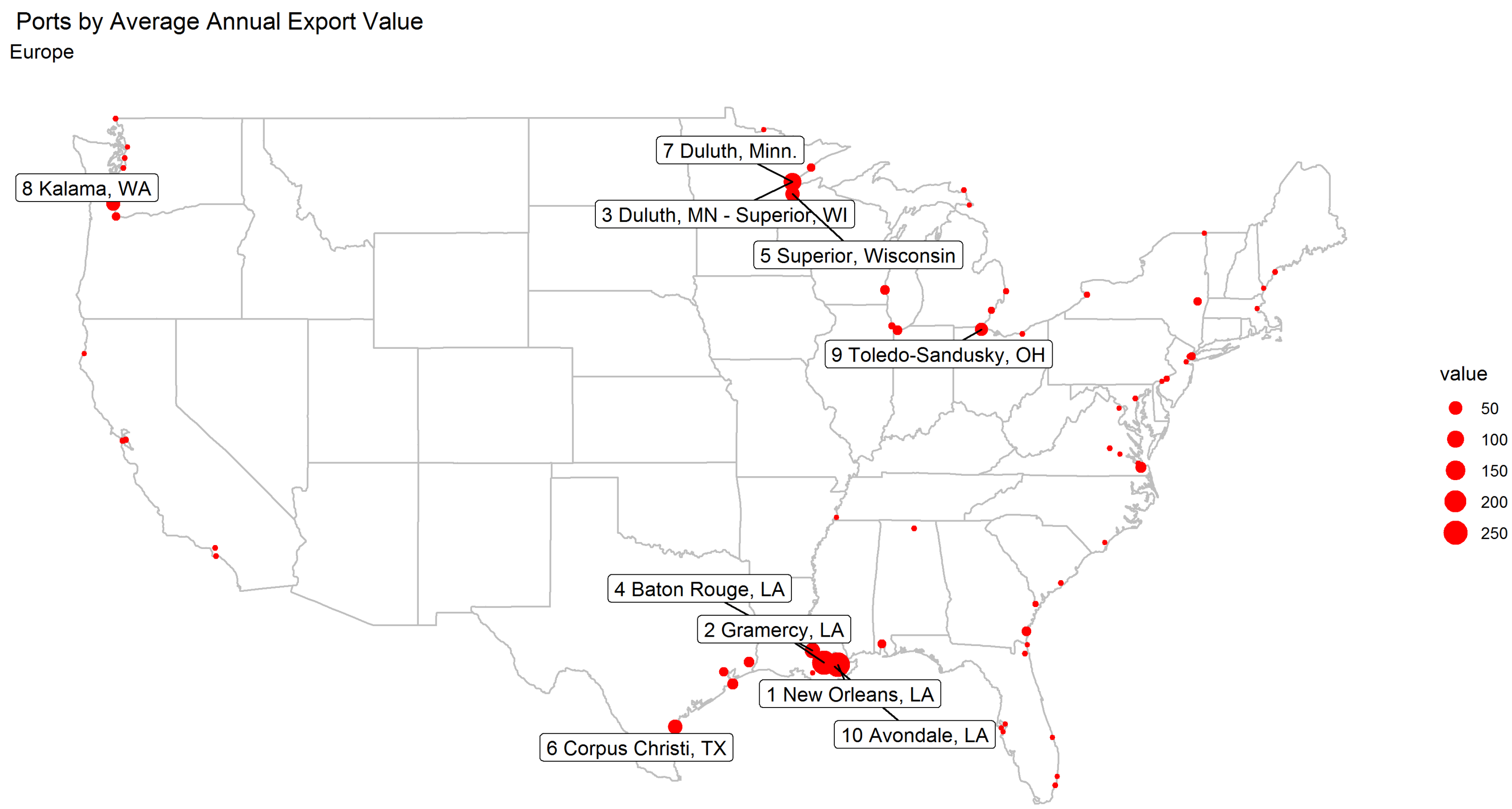

Ports by Average Annual Export Value
Europe
7 Duluth, Minn.
8 Kalama, WA
3 Duluth, MN - Superior, WI
5 Superior, Wisconsin
9 Toledo-Sandusky, OH
4 Baton Rouge, LA
2 Gramercy, LA
1 New Orleans, LA
10 Avondale, LA
6 Corpus Christi, TX
value
50
100
150
200
250

Figure 12

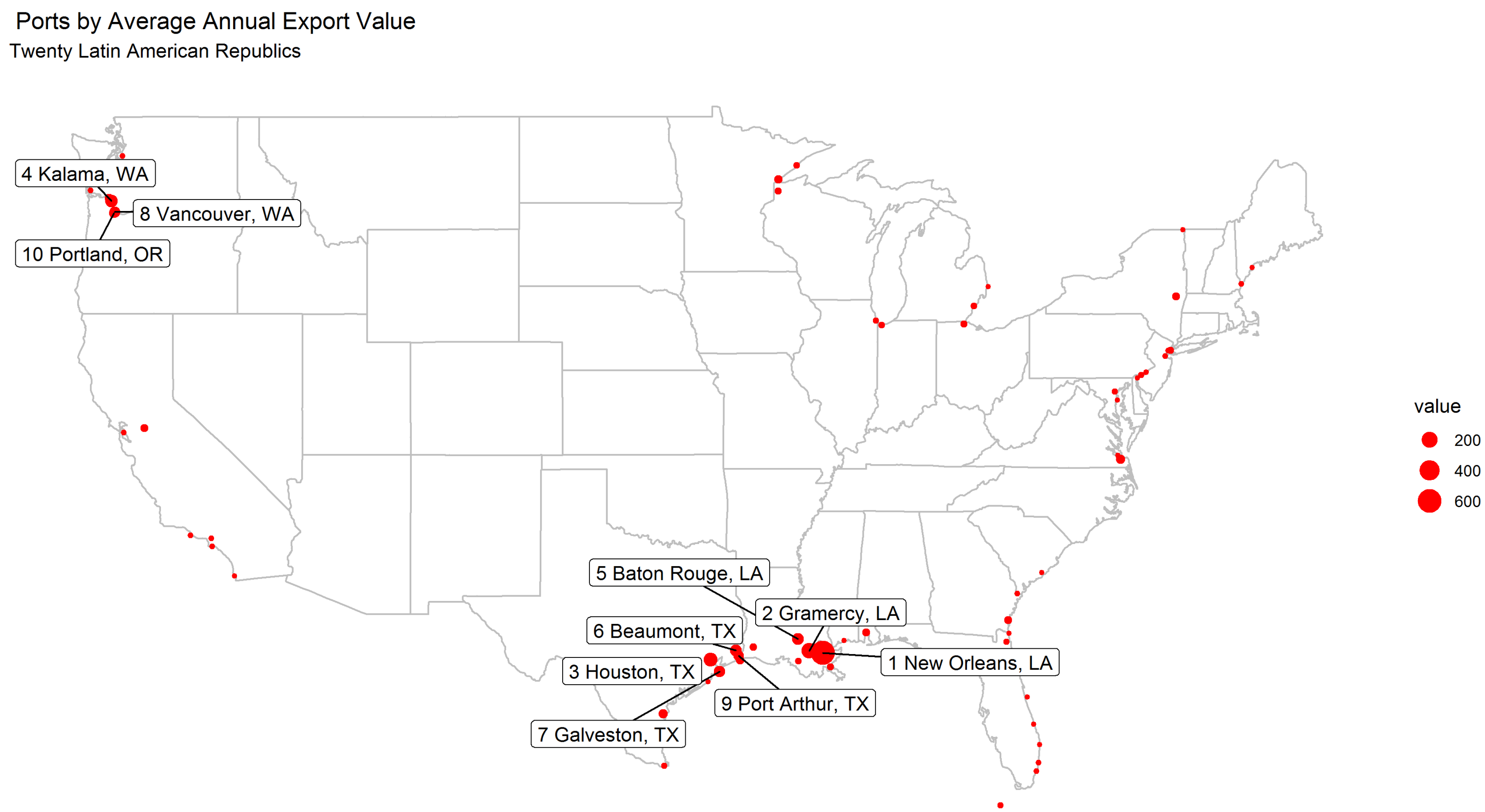
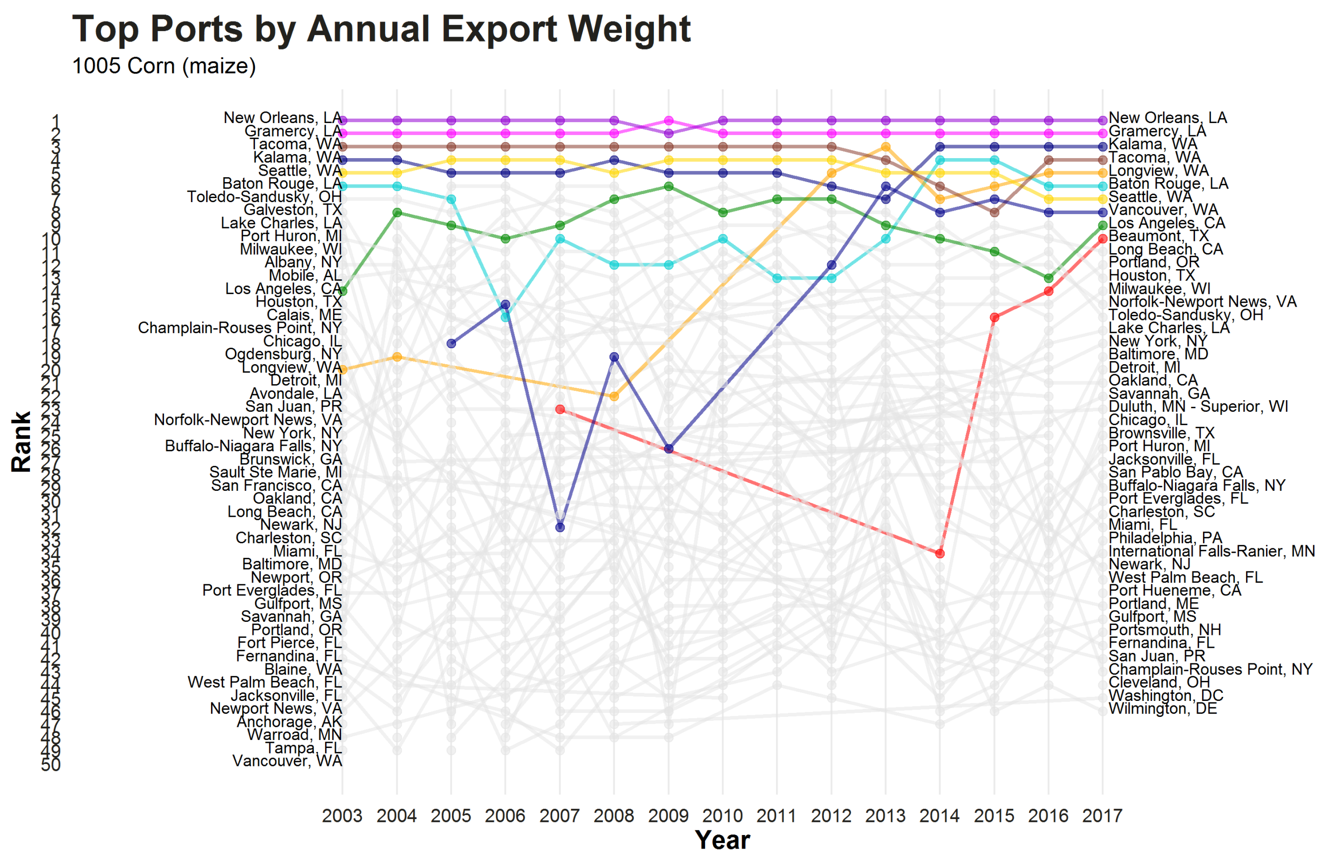
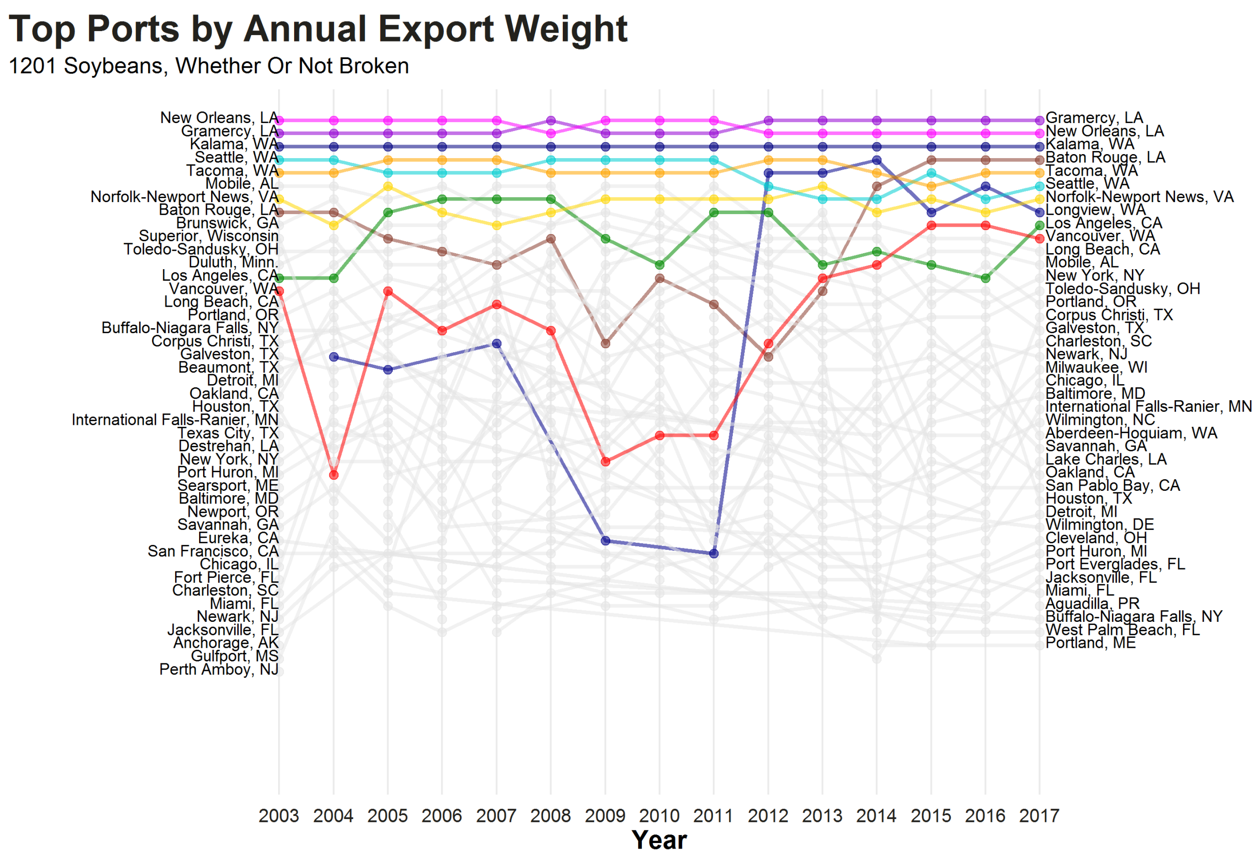

Ports by Average Annual Export Value
Twenty Latin American Republics
4 Kalama, WA
8 Vancouver, WA
10 Portland, OR
5 Baton Rouge, LA
2 Gramercy, LA
6 Beaumont, TX
3 Houston, TX
1 New Orleans, LA
9 Port Arthur, TX
7 Galveston, TX
value
200
400
600

Figure 13



Top Ports by Annual Export Weight
1005 Corn (maize)
Rank
Year
2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017
New Orleans, LA
Gramercy, LA
Tacoma, WA
Kalama, WA
Seattle, WA
Baton Rouge, LA
Toledo-Sandusky, OH
Galveston, TX
Lake Charles, LA
Port Huron, MI
Milwaukee, WI
Albany, NY
Mobile, AL
Los Angeles, CA
Houston, TX
Calais, ME
Champlain-Rouses Point, NY
Chicago, IL
Ogdensburg, NY
Longview, WA
Detroit, MI
Avondale, LA
San Juan, PR
Norfolk-Newport News, VA
New York, NY
Buffalo-Niagara Falls, NY
Brunswick, GA
Sault Ste Marie, MI
San Francisco, CA
Oakland, CA
Long Beach, CA
Newark, NJ
Charleston, SC
Miami, FL
Baltimore, MD
Newport, OR
Port Everglades, FL
Gulfport, MS
Savannah, GA
Portland, OR
Fort Pierce, FL
Fernandina, FL
Blaine, WA
West Palm Beach, FL
Jacksonville, FL
Newport News, VA
Anchorage, AK
Warroad, MN
Tampa, FL
Vancouver, WA
New Orleans, LA
Gramercy, LA
Kalama, WA
Tacoma, WA
Longview, WA
Baton Rouge, LA
Seattle, WA
Vancouver, WA
Los Angeles, CA
Beaumont, TX
Long Beach, CA
Portland, OR
Houston, TX
Milwaukee, WI
Norfolk-Newport News, VA
Toledo-Sandusky, OH
Lake Charles, LA
New York, NY
Baltimore, MD
Detroit, MI
Oakland, CA
Savannah, GA
Duluth, MN - Superior, WI
Chicago, IL
Brownsville, TX
Port Huron, MI
Jacksonville, FL
San Pablo Bay, CA
Buffalo-Niagara Falls, NY
Port Everglades, FL
Charleston, SC
Miami, FL
Philadelphia, PA
International Falls-Ranier, MN
Newark, NJ
West Palm Beach, FL
Port Hueneme, CA
Portland, ME
Gulfport, MS
Portsmouth, NH
Fernandina, FL
San Juan, PR
Champlain-Rouses Point, NY
Cleveland, OH
Washington, DC
Wilmington, DE

Figure 14


Top Ports by Annual Export Weight
1201 Soybeans, Whether Or Not Broken
Rank
Year
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
New Orleans, LA
Gramercy, LA
Kalama, WA
Seattle, WA
Tacoma, WA
Mobile, AL
Norfolk-Newport News, VA
Baton Rouge, LA
Brunswick, GA
Superior, Wisconsin
Toledo-Sandusky, OH
Duluth, Minn.
Los Angeles, CA
Vancouver, WA
Long Beach, CA
Portland, OR
Buffalo-Niagara Falls, NY
Corpus Christi, TX
Galveston, TX
Beaumont, TX
Detroit, MI
Oakland, CA
Houston, TX
International Falls-Ranier, MN
Texas City, TX
Destrehan, LA
New York, NY
Port Huron, MI
Searsport, ME
Baltimore, MD
Newport, OR
Savannah, GA
Eureka, CA
San Francisco, CA
Chicago, IL
Fort Pierce, FL
Charleston, SC
Miami, FL
Newark, NJ
Jacksonville, FL
Anchorage, AK
Gulfport, MS
Perth Amboy, NJ
Gramercy, LA
New Orleans, LA
Kalama, WA
Baton Rouge, LA
Tacoma, WA
Seattle, WA
Norfolk-Newport News, VA
Longview, WA
Los Angeles, CA
Vancouver, WA
Long Beach, CA
Mobile, AL
New York, NY
Toledo-Sandusky, OH
Portland, OR
Corpus Christi, TX
Galveston, TX
Charleston, SC
Newark, NJ
Milwaukee, WI
Chicago, IL
Baltimore, MD
International Falls-Ranier, MN
Wilmington, NC
Aberdeen-Hoquiam, WA
Savannah, GA
Lake Charles, LA
Oakland, CA
San Pablo Bay, CA
Houston, TX
Detroit, MI
Wilmington, DE
Cleveland, OH
Port Huron, MI
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Jacksonville, FL
Miami, FL
Aguadilla, PR
Buffalo-Niagara Falls, NY
West Palm Beach, FL
Portland, ME

Figure 15

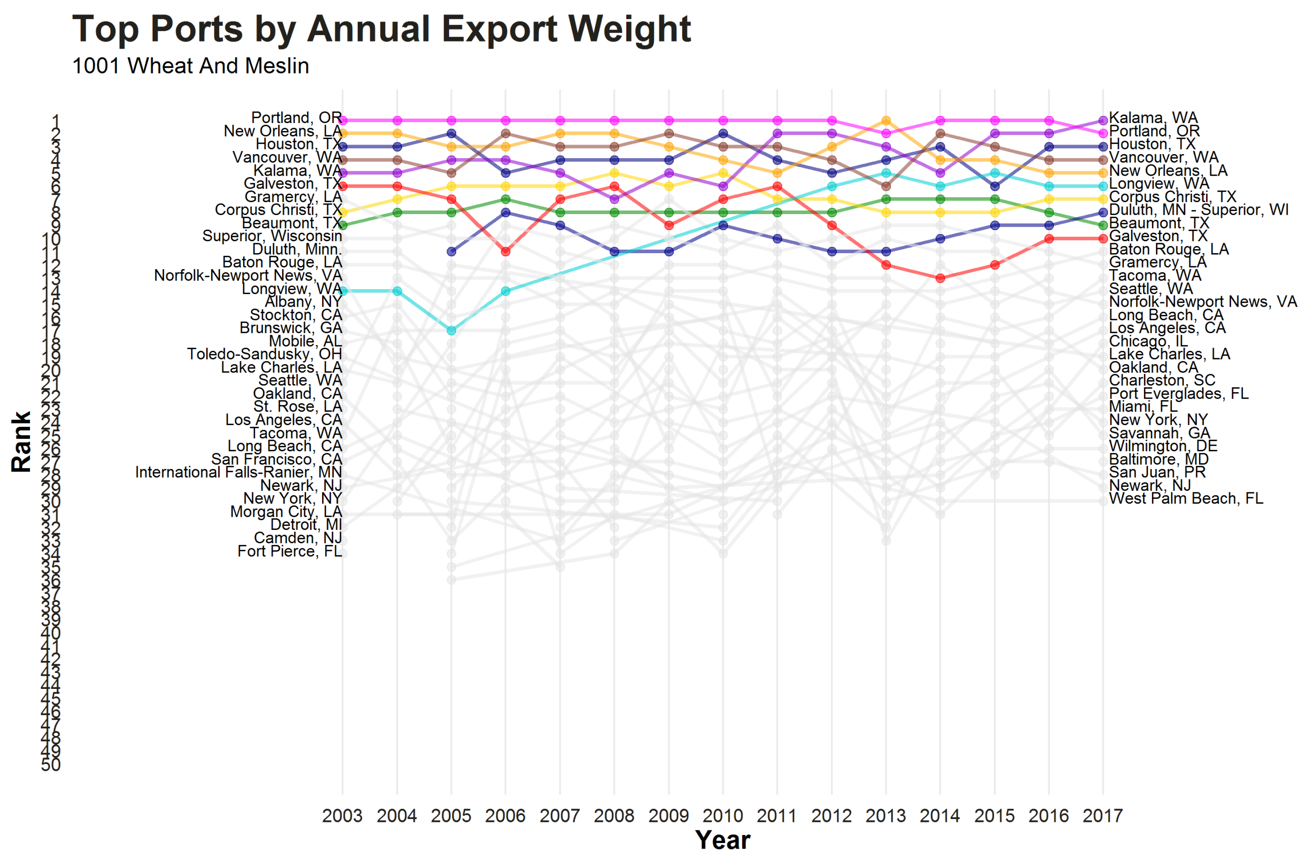
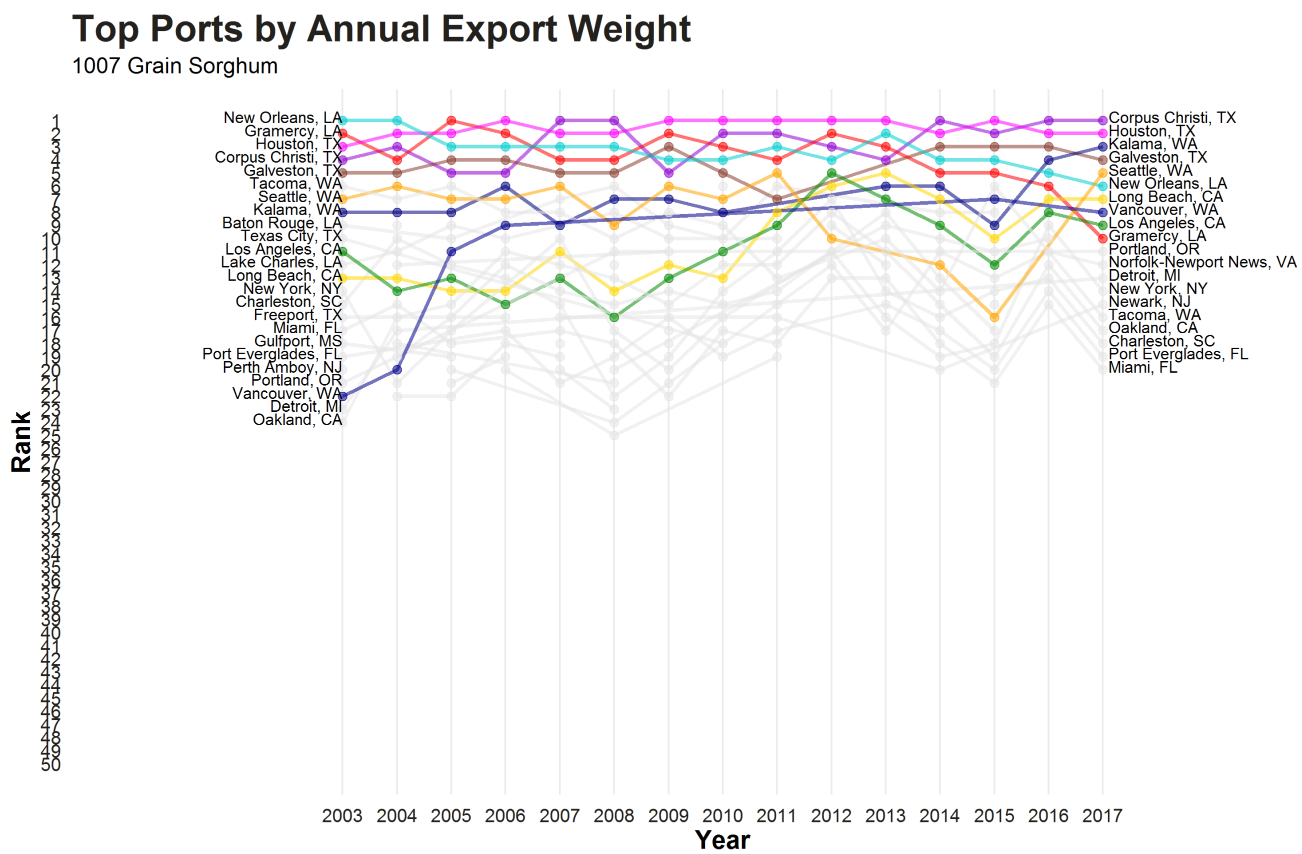

Top Ports by Annual Export Weight
1001 Wheat And Meslin
Rank
Year
2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017
Portland, OR
New Orleans, LA
Houston, TX
Vancouver, WA
Kalama, WA
Galveston, TX
Gramercy, LA
Corpus Christi, TX
Beaumont, TX
Superior, Wisconsin
Duluth, Minn.
Baton Rouge, LA
Norfolk-Newport News, VA
Longview, WA
Albany, NY
Stockton, CA
Brunswick, GA
Mobile, AL
Toledo-Sandusky, OH
Lake Charles, LA
Seattle, WA
Oakland, CA
St. Rose, LA
Los Angeles, CA
Tacoma, WA
Long Beach, CA
San Francisco, CA
International Falls-Ranier, MN
Newark, NJ
New York, NY
Morgan City, LA
Detroit, MI
Camden, NJ
Fort Pierce, FL
Kalama, WA
Portland, OR
Houston, TX
Vancouver, WA
New Orleans, LA
Longview, WA
Corpus Christi, TX
Duluth, MN - Superior, WI
Beaumont, TX
Galveston, TX
Baton Rouge, LA
Gramercy, LA
Tacoma, WA
Seattle, WA
Norfolk-Newport News, VA
Long Beach, CA
Los Angeles, CA
Chicago, IL
Lake Charles, LA
Oakland, CA
Charleston, SC
Port Everglades, FL
Miami, FL
New York, NY
Savannah, GA
Wilmington, DE
Baltimore, MD
San Juan, PR
Newark, NJ
West Palm Beach, FL

Figure 16


Top Ports by Annual Export Weight
1007 Grain Sorghum
Rank
Year
2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017
New Orleans, LA
Gramercy, LA
Houston, TX
Corpus Christi, TX
Galveston, TX
Tacoma, WA
Seattle, WA
Kalama, WA
Baton Rouge, LA
Texas City, TX
Los Angeles, CA
Lake Charles, LA
Long Beach, CA
New York, NY
Charleston, SC
Freeport, TX
Miami, FL
Gulfport, MS
Port Everglades, FL
Perth Amboy, NJ
Portland, OR
Vancouver, WA
Detroit, MI
Oakland, CA
Corpus Christi, TX
Houston, TX
Kalama, WA
Galveston, TX
Seattle, WA
New Orleans, LA
Long Beach, CA
Vancouver, WA
Los Angeles, CA
Gramercy, LA
Portland, OR
Norfolk-Newport News, VA
Detroit, MI
New York, NY
Newark, NJ
Tacoma, WA
Oakland, CA
Charleston, SC
Port Everglades, FL
Miami, FL