Economic Impact of Mississippi River Drought on U.S. Agriculture: Insights from the Gravity Model

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Abstract

With the increasing severity of weather anomalies, both production and post-production activities in the food supply chain are at stake. This paper examines the economic impact of the Mississippi River drought, an exemplar of extreme weather undermining agricultural production and logistics, employing a structural gravity model. Relying on the interstate commodity flow data, the domestic trade flows from 17 U.S. states adjacent to the Mississippi River system to the 16 U.S. states and 4 country groups during eight non-consecutive years (2007, 2012, 2017-2022) are analyzed. By factoring in the hydrological structure and flow of the river system, the economic costs of river drought reflect the decreasing crop production and increasing transportation costs. The findings show that low water levels in the Mississippi River drive up barge rates, with their effects being more pronounced at downstream. Counterfactual analysis reveals that, without river disruptions, domestic trade flow in the U.S. grain supply chain would have increased by 14.31% during the study period.

Keywords: River Drought, Mississippi Inland Waterways, Gravity Model, Supply Chain Disruption, Agricultural Trade.

1. Introduction

As the severity of weather anomalies increases along with global warming, the economic damage from extreme weather events has been extensively assessed. Agriculture, in particular, by its nature, is regarded as one of the most vulnerable sectors to weather shocks (Deschênes and Greenstone, 2007). The negative impact of warming climate on agricultural production has been proved and established by a myriad of studies, including, *inter alia*, Lee, Moschini, and Perry (2024), Lee, Ji, and Moschini (2022), Ortiz-Bobea and Tack (2018), Schlenker and Roberts (2009), and Lobell and Field (2007). In a broader context, the literature on the economic consequence of warming climate that involves post-production stages, especially in the nexus between adaptation and trade, has evolved into several directions. These include trade adjustments (Dall'Erba, Chen, and Nava, 2021) combined with production reallocation (Costinot et al., 2016), trade creation (Ferguson and Gars, 2020; Reimer and Li, 2010; Randhir and Hertel, 2000).

While most existing literature focuses on the long-term aspects of climate change and its accompanying consequences (Key et al., 2024), few studies have addressed the impacts of a certain type of extreme weather shock (Flores and Janzen, 2023; Steinbach and Zhuang, 2023; Dall'Erba, Chen, and Nava, 2021). Recent weather anomalies, such as drought, storms, or floods, demonstrate the potential for damage in non-conventional forms of the supply chain under a warming climate. Specifically, these weather shocks tend to have immediate and transient impacts on the food supply chain, affecting both crop production and non-production factors, particularly the operations of logistic systems (Chen and Cheng, 2024; Flores and Janzen, 2023; Steinbach and Zhuang, 2023; Arita et al., 2022). To better understand the complex impacts of weather shocks, a comprehensive measure of weather effects on both production and non-production risks is required.

The focus of our study is on the Mississippi River drought, which has become more frequent in recent years. The drought in the major river system has limited barge load capacity (NASA Earth Observatory, 2023), affecting around 50% of U.S. grain transportation (Bureau of Transportation Statistics, 2022). This is of particular concern for the U.S. grain supply chain,

given its high reliance on river transportation and its susceptibility to weather conditions. For example, because of the low levels in the Mississippi River, the monthly average grain barge rate increased from $2,543/ton in October 2021 to $7,835/ton in October 2022 (USDA AMS, 2024). Flores and Janzen (2023) report the rise in barge rate has led to higher crop prices. Steinbach and Zhuang (2023) document diverted wheat export shipments resulting from the 2022 Mississippi River drought, implying a connection between river drought and U.S. grain exports. However, existing studies largely employ the event study approaches, sometimes assuming a homogeneous shock in all locations along the river (Steinbach and Zhuang, 2023), and do not provide welfare measurements.

In this paper, the economic effect of the Mississippi River drought is analyzed by analyzing interstate trade flows for exports using a structural gravity model. The state-level annual commodity trade flow data are drawn from Freight Analysis Framework Version 5 (FAF5), covering the years 2007, 2012, and 2017-2022. To be specific, our focus is on interstate grain flows toward the Gulf Coast states, directly impacted by the condition of the Mississippi River. Thus, the scope of our analysis includes trade flows from 17 origin states adjacent to the Mississippi River or its large tributaries to 16 destination states in the Gulf Coast region and 4 groups of destination countries, over three nonconsecutive 8-year periods.

When implementing the structural gravity model, two primary channels are considered in the analysis through which a river drought influences the economy: transportation costs and crop production in the regions adjacent to the river. Specifically, a low river index is constructed to capture the heterogeneous impact of drought shocks across different hydrological locations in the river system, as highlighted by Henshaw et al. (2013), and map it into barge rates. Utilizing the low river index, this paper tests: (1) whether and to what extent river disruptions along the Mississippi River system affect transportation costs for grain shipping and (2) the degree of drought affects crop production as well as river disruption. Armed with estimated transportation costs and crop production, the effects of Mississippi River drought on the interstate grain flow toward Gulf Coast States and the resulting trade consequence are quantified.

Our findings show that low river levels along the Mississippi River drive up barge rates, with the effect being significant even during minor river disruptions and increasing further as the severity of disruptions rises. The model estimates indicate that a 1% increase in barge rates due to river disruptions leads to a reduction of $1.9 million in export shipments transported by barge, $2.0 million in domestic shipments moved by non-barge modes, and $1.3 million in export shipments carried by non-barge modes. Furthermore, counterfactual analysis suggests that in the absence of river disruptions, total trade flows in the U.S. grain supply chain would have increased by 9.07~14.31% over the eight years of the study period.

Our paper makes a twofold contribution to the literature. First, we evaluate the economic impact of river drought using a gravity model, which allows us to account for its interaction with both agricultural production (Lee, Ji, and Moschini, 2022; Ortiz-Bobea and Tack, 2018; Schlenker and Roberts, 2009; Lobell and Field, 2007) and logistics (Chen and Cheng, 2024; Flores and Janzen, 2023; Steinbach and Zhuang, 2023; Arita et al., 2022). Second, our results provide empirical evidence on how low river levels influence barge freight rates, revealing heterogeneous responses across hydrological locations. In particular, to effectively link barge rates to river conditions on the Mississippi River, we contrive a new river drought measure based on gage-specific river flows across the Mississippi River, which allows us to simulate counterfactual river conditions in the model. These findings can help policymakers assess the economic value of a resilient river transportation system and make more informed infrastructure investment decisions for the Waterway System.

2. Background and Data

2.1. Background: Barge Disruption and its Impact on the U.S. Grain Supply Chain

The U.S. grain supply chain is supported by the inland waterways along the Mississippi River. Flowing southbound for 2,340 miles from northern Minnesota to the Gulf of Mexico (United States Geological Survey, 2009), the Mississippi River and its many tributaries border or pass through the states of Arkansas, Illinois, Indiana, Iowa, Kentucky, Louisiana, Minnesota,

Mississippi, Missouri, Ohio, Tennessee, and Wisconsin (Agribusiness Consulting, 2019). This extensive river system carries large volumes of bulk commodities over long distances at low costs. In 2022, approximately 56% of U.S. agricultural commodities were transported on this system (Bureau of Transportation Statistics, 2022), saving $7-9 billion annually in freight expenses compared to shipping by other modes of transport (Agribusiness Consulting, 2019).

Barge freight rates along the Mississippi River are determined by a volumetric tariff system, where transport expenses increase with the volume of commodities. These rates consist of two components: benchmark prices and tariff rates, both of which vary by location. The tariff system in the barge industry refers to the pricing mechanism used to establish freight rates, in contrast to the taxation system that imposes tariffs on internationally traded products. Previously, the Waterways Freight Bureau (WFB) of the Interstate Commerce Commission (ICC) regulated barge rates in the U.S., but it was dissolved in 1976 (USDA AMS, 2024). Since then, the tariff rates from 1976 have served as benchmark prices, while current rates are determined by market forces. Thus, the benchmark price is a fixed rate for specific routes or commodities, while the tariff rate is a time-varying component influenced by market supply and demand. Barge freight rates for each location are calculated by multiplying the constant benchmark price by the tariff rate for shipping commodities from a lock to a destination at the Gulf of Mexico (Wetzstein et al., 2021).

Despite the reputation of inland barge as a cost-effective and reliable mode of grain transportation, concerns have been raised about the operations of inland barges in recent years. Much of the infrastructure, built in the 1930s, is aging and requires rehabilitation and construction to restore its full capability (USDA AMS, 2016). Increasing weather anomalies have further exacerbated these issues, with droughts being a major threat to barge logistics (Chen et al., 2024; Koetse and Rietveld, 2009). Limited rainfall lowers river levels and impedes vessel movement, causing navigational restrictions and delays that further escalate barge rates.

Starting in the fall of 2022, two consecutive years of droughts combined with prolonged summer heat have parched the Mississippi River, causing water levels to reach historic lows at many gauges. On October 20, 2022, the water level in Memphis, Tennessee, was -10.74 feet, the

lowest level recorded since 1954 (National Weather Service, 2024). These low water levels have limited barge capacity, leading to a significant increase in barge freight rates. The average freight rate at seven locations on the Mississippi River rose from $2,938 per ton in October 2021 to $9,537 per ton in October 2022 (USDA AMS, 2024). Consequently, disruptions to barge movements have reduced domestic trade flows of bulk grains. From October to December 2023, the total number of grain barges passing through Mississippi River Locks 27 near St. Louis was 4,522, a 15% decrease compared to the same period in 2021 (USDA AMS, 2024).

Barge disruptions caused by droughts could thus hinder the timely delivery of grain to consumption areas, leading to higher food prices and potentially harming food security for U.S. consumers. On top of that, since about half of U.S. grain exports are transported to the export locations at the Gulf via the Mississippi River, increased uncertainty from droughts could negatively affect the competitive position of U.S. farmers in the international market, further exacerbating challenges in U.S. export performance in the global supply chain.

2.2. Variable Construction: River Disruption Index

Recent research has frequently used event study frameworks to examine the impact of river droughts on U.S. crop prices, focusing on spatial and temporal variations. In contrast, this study takes a broader approach by investigating the economic costs of river droughts through changes in both production and transportation costs. It is thus essential to define the impact of river disruptions on transportation costs for the remaining analysis — a relationship often assumed but seldom empirically tested in existing literature. Consequently, this study aims to assess disruption status along the entire transportation network between trading partner states along the Mississippi River, rather than focusing solely on localized disruptions (Flores and Janzen, 2023; Steinbach and Zhuang, 2023).

A major challenge in assessing river droughts and their impact on transportation costs is the lack of comprehensive metrics for low water status across the river system. The National Weather Service (NWS) provides low-flow statistics like 7Q10 (the lowest average flow for

seven consecutive days expected to occur once every ten years) for selected gages on the Mississippi River.[1] However, only a few of these gages have updated estimates with recent data.[2] On the top of that, 7Q10 reflects conditions at individual gages rather than providing a comprehensive view along entire barge routes. Therefore, this study devises an alternative measure to identify the occurrence and severity of river disruptions, consisting of the following four steps:

First, data on grain barge rates are collected. Multiplying the constant benchmark price for each location by the barge tariff rates at a given time yields the dollar-per-ton freight rates for transporting grains to the Gulf states (USDA AMS, 2024). Accordingly, barge rates for delivering grain from origin i to destination j along the route r at time t can be expressed as $f^B_{r[ij]t} = p^0_r(\tau^B_{r[ij]t}/100)$, where $f^B_{r[ij]t}$ is barge freight rate, p^0_r is benchmark price for route r, and $\tau^B_{r[ij]t} \geq 0$ is the average tariff rate for route r connecting two states i and j at time t.[3] When limited rainfall decreases barge load capacity in route r at time t, the time-varying tariff rate, $\tau^B_{r[ij]t}$, increases, thus driving up barge freight rate, $f^B_{r[ij]t}$ for route r at time t. USDA Agricultural Marketing Service (USDA AMS) provides data on benchmark price and weekly tariff rates for grain shipments along seven major routes on the Mississippi River System. These routes originate from specific locations – *Twin Cities* (TWC), *Mid-Mississippi* (MM), *Illinois River* (IL), *St. Louis* (STLOUIS), *Cincinnati* (CINC), *Lower Ohio* (LOHIO), *and Cairo-Memphis* (CAIROMEM) – and are destined for the Gulf of Mexico.

Second, a hydrological network is established for each barge route by identifying gages where river levels are regularly monitored. The analysis includes routes with corresponding barge rate data from USDA AMS, spanning the Mississippi River and its major tributaries. Using data from the NWS River Forecast Center, gages located along barge routes with corresponding USDA AMS barge rate data were listed, and their upstream-downstream

[1] NOAA uses 7Q10 as a threshold of "low water stage" to discern river disruption in each gage. While NOAA provides the relevant data upon request, the number of gages with the updated 7Q10 values is limited.

[2] USGS provides data on minimum operating level for gages, indicating when river is entirely out of operation, which differs from common low-flow statistics. In our investigation, no gages fell below the minimum operating level during the study period. This necessitates the development of an alternative measure for further analysis.

[3] It is assumed that one unit of shipping service is needed to transport one unit of grain-related commodities, and transportation cost exhibits unit elasticity with respect to product prices.

relationships were determined. Gages upstream from the USDA barge rate data collection points are excluded. Figure 1 illustrates the geographic locations where barge rate and gage height data are collected.

Third, river disruptions at each gage are identified daily based on water level data, or "gage height data," obtained from the USGS and USACE over 16 years (2007-2022).[4] Gages without complete data are excluded from the analysis, leaving 55 gages with a total of 1,520,930 observations. River disruption is defined as significant declines in river flow, with the low water threshold calculated as the lower 10% of the 16-year average river heights. Gages with heights below this threshold are considered to be in disruption on a particular day.

Lastly, the severity of disruptions at the route level is measured by calculating the proportion of disrupted gages out of the total gages for each route, creating a river disruption index from 0 to 1, with values closer to 1 indicating higher disruptions. The index is constructed at weekly intervals to align with the frequency of barge rate data, enabling an empirical assessment of how low water levels in the Mississippi River impact grain transportation costs.

Figure 2 presents a visual presentation of the relationship between river disruption and barge rates for each route over time. The river disruption index appears to have a positive correlation with tariff rates, moving in the same direction. Barge rates tend to soar up when the river disruption index increases. In particular, barge rates hit historic high in 2022, coinciding with river disruption index reaching around 1 in most routes.[5] Moreover, it is revealed barge disruption followed by soaring barge rate is not a new phenomenon in the U.S. All routes experienced declines in river level in 2007, 2012, and 2022. Finally, barge rates and river levels exhibit seasonality, with barge rates increasing and river levels decreasing during the winter.

4 Gauge height measurements can be negative because they indicate relative water levels measured from a chosen reference point.

[5] Figure 2 shows that, compared to 2012, 2022 had fewer days of river disruption. However, the barge rate was higher in 2022. This might be because the river disruption index accounts for the severity of disruptions at the route-level rather than at the gage level. It could be that there were more disruption days rather than the most severe disruptions in 2012.

Figure 2 shows apparent correlations between barge freight rates and low river levels, enabling the identification of how drought conditions might affect the cost of transporting grain in the U.S. Despite these observed correlations, establishing their causal relationship requires controlling for other factors, such as seasonality.[6] Once this relationship is established, it will feed into the final gravity model to measure how changes in transport costs due to droughts affect the grain trade flow between states. A detailed discussion of this process and its implications will be provided later in the document, referred to as Section 3.2.1. and 3.2.2.

2.3. Domestic Trade Flow for U.S. Agricultural Commodities

This paper focuses on U.S. domestic grain flow among U.S. states. We draw data on interstate trade flow of agricultural commodities from the Freight Analysis Framework Version 5 (FAF5). Developed by the National Transportation Research Center at Oak Ridge National Laboratory, with support from the Bureau of Transportation Statistics and the Federal Highway Administration, FAF5 offers annual estimates of trade flow in both tonnage and dollar value across the U.S. The dataset integrates information from various sources, including the Commodity Flow Survey (CFS) and the Agricultural Census (Hwang et al., 2021). Historically published every five years until 2012, FAF5 has been released annually from 2018 to 2022. Therefore, data for eight non-consecutive years—covering 2007, 2012, and 2017-2022—are used in this study. Our study period begins in 2007 to align with FAF5 availability and the barge rate data which are going to be discussed later starts from 2004.

The FAF5 dataset uniquely identifies each observation by year, origin state, export status of shipment, destination, domestic transportation mode, and commodity type. For shipment destinations, domestic shipments are recorded as destined for a specific U.S. state, whereas international shipments are recorded as destined for a specific country.[7] Additionally, for export

[6] For example, the high barge rate during the winter might be due to increased demand for barge shipments during the soybean harvest season. This intertwined relationship calls for the econometric analysis to establish the relationship between river disruption and barge rates.

[7] The FAF5 dataset reports export destinations primarily at the continental level, with the exception of Canada and Mexico. As a result, shipments to key trade partners such as China are grouped under broader regions like "East

shipments, the intermediate U.S. destination state representing the point of physical export movement is also reported.[8] Our dataset captures commodity movements both domestically and internationally. This unique feature allows us to scale the analysis down to the state level, enabling the evaluation of how both domestic and international trade flows are affected by barge disruptions, specifically through the spillover effects of barge rate shocks on other transportation modes.

While FAF5 provides detailed information on commodity movements, it does not include data on freight expenses. To address this, we impute barge freight rates using origin-destination state pairs (or origin-intermediate state pairs for export shipments) to estimate the unobserved unit freight rates. Specifically, for each origin-destination state pair (origin-intermediate state pairs for export shipments), we assign barge freight rates corresponding to the longest available routes. For example, for shipments originating in Minnesota and destined for Louisiana, we apply barge rates from the "TWC" route, as "TWC" is the only route whose barge rates are collected on the state border of Minnesota. Similarly, for shipments from Wisconsin to Louisiana, although both "TWC" and "MM" rates are collected at the Wisconsin border, we use the "TWC" route rates, as "TWC" represents the longest routes connecting Wisconsin and Louisiana. [9]

As briefly discussed in Section 2.2, the barge rate data are specific to routes originating in states adjacent to the Upper and Mid-Mississippi River, but not the Low-Mississippi River, and

Asia," limiting the ability to observe country-specific trade flows. To address this, we augment FAF5 data with the Census State Export dataset, which provides annual export values by country, commodity type (based on HS codes), and the state of outbound movement, corresponding to the intermediate state in FAF5. Using this alignment, we estimate the share of each FAF5 observation attributable to China by calculating the proportion of exports from a given intermediate state to China relative to that state's total exports to East Asia. This share is then applied to the relevant FAF5 observations to disaggregate East Asia-bound shipments into those going to China and to other countries in East-Asia.

[8] There are few other datasets covering domestic trade activities in the U.S. While the Commodity Flow Survey (CFS), published by the Bureau of Transportation Statistics (BTS) and the Federal Highway Administration (FHWA), is commonly used, it lacks clarity on whether shipments are ultimately exported or consumed domestically (Dall'Erba, Chen, and Nava, 2021). Thus, here FAF5 is chosen over CFS.

[9] Since we match viable barge routes for each observation based on origin-destination state information for domestic shipments and origin-intermediate state information for export shipments, domestic observations with the same destination state as the intermediate state of export observations are assigned the same barge rate. For example, domestic shipments originating from Minnesota and delivered to Louisiana are mapped to the "MM" route barge rate, and export shipments traveling the same route are also assigned the "MM" rate.

destined for Gulf Coast states. This limitation stems from the nature of river transportation. Although river transport offers low unit freight costs, it is relatively slow, making it unsuitable for short-distance shipments. Moreover, it is constrained by the hydrological structure of the river system. Both the origin and destination must have direct access to navigable rivers with appropriate port infrastructure for river transport to be a viable option for grain shipping. In cases where shipments are headed to nearby states, for short distances within the same state, or are destined for states lacking river access, truck or rail is typically preferred over barge. Additionally, river transport is constrained by the natural flow of the river. Since the Mississippi River flows south, grain shipments typically move in that direction, and as a result, barge rate data primarily cover southbound flows.

As a result, barge rate data are not applicable to all observations in the FAF5 dataset. To ensure consistency with the USDA barge rate data, we apply the following filtering criteria: (1) trade flows must originate from states adjacent to the Mississippi River system or its major tributaries, with at least one time history of moving commodities of our interest via river transport between those state pairs;[10] and (2) shipments must move southbound when crossing state boundaries. These filtering steps ensure that the remaining observations accurately represent freight expenses based on the available barge rate information. As shown in Figure 1, this filtering process results in a dataset that captures trade flows from 17 origin states to 16 destination states in the Gulf Coast region and 4 destination country group.[11]

[10] We use the Census Commodity Flow Survey (CFS) for the years 2012 and 2017 to identify origin–destination state pairs with a history of transporting the commodities of our interest via inland barges. The FAF5 dataset classifies domestic transportation modes as "rail", "truck", "water", "mixed", etc., where the "water" category includes inland barges along with other waterborne modes such as ocean shipping and Great Lakes shipping. The "mixed" category includes various combinations of transportation modes, but it does not specify which modes are combined. In contrast, the Census CFS uses the same structural format as FAF5 (year – origin state – destination state (or country) – intermediate state (for export shipments) – export status – commodity type – domestic transportation mode), but provides more detailed information on transportation modes. Specifically, the "water" category in FAF5 is further broken down in CFS into "inland barges," "deep sea shipping," and "mixed waterways." Likewise, the "mixed" category in FAF5 is more detailed in CFS to indicate specific combinations, such as "rail and water" or "truck and water." Using the CFS data, we identify state pairs that have at least one recorded instance of transporting the selected commodities using inland barges, either partially or exclusively. This approach allows us to include some observations where the origin states are not directly adjacent to the mainstem of the Mississippi River or its major tributaries, such as shipments moving from North Dakota to Louisiana or from Oklahoma to Gulf states.

[11] To obtain consistent estimates, intrastate trade observations are included in our analysis (Piermartini and Yotov, 2016). In our context, these reflect the amount of commodities traded or stored within the country during the

While USDA barge rates represent freight rates for shipments destined for Gulf states, the FAF5 dataset includes many observations moving shorter distance along the inland waterway system. For these cases, we employ a distance-based imputation method. Specifically, we apply barge rate to the distance share of the observed route to the full route on which that rate is based [12]. For example, consider a shipment from Iowa to Illinois. We identify the longest relevant barge route connecting this pair (namely, the "MM" route), and set the distance between the uppermost gauge where barge rates for this route are recorded (Dubuque, IL) and the port of New Orleans (1,477 nautical miles) as the reference distance. We then find the actual (longest) distance of the segment relevant to this shipment (in this case, the distance from Dubuque, IL to Keokuk, IA; 216 nautical miles). The ratio of these distances ($0.146 \approx 216/1{,}477$) is multiplied with the full-route barge rate to impute freight expenses for Iowa-Illinois observations.[13]

The FAF5 dataset categorizes transportation modes into several types: water, air, rail, truck, mixed modes, mail, pipeline, other, and unknown. The "water" category includes a broad range of waterborne transportation methods, such as river shipping, maritime routes, and Great Lakes shipping. Similarly, the "mixed modes" category does not specify the exact combination of transportation modes used. However, as noted in footnote 9, we have verified, using an external dataset, that our sample includes only state pairs with a documented history of shipping the commodities of interest either partly or exclusively via inland waterways. As a result of this filtering process, the origin states in our analysis are all located inland and are connected to the Gulf of Mexico via the mainstem of the Mississippi River or its major tributaries, all of which

transportation bottleneck. For intrastate trade flows, we impute zero values for barge rates assuming that intrastate trade costs are the same across states.

[12] Bilateral distances are proxied using information on distances between major river ports, as provided by NOAA (2019), to approximate travel distances along the Inland Waterways.

[13] For observations originating from states not directly adjacent to the mainstem of the Mississippi or Ohio Rivers—and therefore lacking corresponding barge rate data—we impute rates based on the confluence point between a major tributary river that passes through or borders the origin state and the mainstem of the Mississippi River. For example, for shipments from North Dakota to Louisiana, we use barge rates associated with the "STLOUIS" route (originating in St. Louis, MO), as the Missouri River flows through North Dakota and merges with the Mississippi River at St. Louis. Similarly, for shipments from Oklahoma to Gulf states, we apply barge rates from the "LM" route (originating in Yellowbend, AR), which is the nearest gauge to the confluence of the Arkansas River—a major tributary passing through Oklahoma—with the Mississippi River.

support suitable navigation conditions. Therefore, it is reasonable to infer that shipments from these states to the Gulf are transported primarily by inland barges rather than by Great Lakes or ocean vessels. Accordingly, in this analysis, the "water" category is interpreted specifically as inland barge transportation, and "mixed modes" are treated as including inland barge use as part of the shipment route. Except for water, rail, truck, and mixed modes, the remaining categories represent only a small portion of our sample and are therefore aggregated into the "others" category. Note that shipments not carried by barge are also included to test the spillover effects of barge rates on domestic trade flows carried by other transport options.[14]

In addition, the FAF5 dataset provides commodity classification similar to the two-digit Harmonized System, facilitating sectoral analysis. Since USDA barge rate data are specific to the bulk grain and related products, our study focuses on the sectors relevant to those rates: "Cereal Grains," "Oilseed", "Animal Feed," and "Milled Grain Products."

Figure 3 shows the percentage changes in total annual domestic trade values (in million dollars) by route during the three years of severe river drought (2007, 2012, 2022; average low water index = 0.149) compared to the rest of the years representing period with less severe river drought (2017-2021, average low water index = 0.009), categorized by whether shipments are carried by barge. The classification of these years is based on the river disruption index. The figure only considers changes in trade values of grains and oilseeds, as trade flows for animal feeds and grain milling products are missing in some years. Intrastate trade flows are included in the "non-barge" group. The color intensity represents the degree of changes in trade value, with darker red indicating higher drops on a given route.

In the "barge group" (left panel), most routes have witnessed decreased trade flows during the drought years. For example, the annual average trade value from Indiana to Mexico by 78% in the drought years compared to the less severe drought years. Yet, few routes have shown increased trade flows, potentially driven by the increase in production at origin states. Comparing with the "non-barge" group (right panel), trade flows carried by barge are generally

[14] However, the mechanism of barge rate affecting freight rates of other transport modes is not explicitly modeled in this study.

more negatively affected by river drought in terms of the magnitude of percentage change in trade flows.

In the "non-barge" group (right panel), the pattern varies across routes. For instance, trade from Oklahoma to China saw a significant increase of trade flows by 206%, while trade from Wisconsin to China decreased by 33%. The increase in trade flows along certain routes may be attributed to mode substitution away from barge transport, or to shifts in origin states that replaced trade flows previously routed through longer, southern paths. Conversely, the decrease in trade flows along other routes may reflect spillover effects of rising barge rates onto other freight rates. Overall, these findings suggest that while barge shipments are generally more adversely affected by river droughts, non-barge shipments also experience notable changes. These variations in trade values across state pair and time serve as a key source of identification in the model estimation.

2.4. Supply and Demand Potential of Individual States

In the FAF5 dataset, each observation of unilateral trade flow is classified into one of four sectors: grain, oilseed, animal feed, and grain milling. To accurately model the supply and demand terms within these sectors, it is essential to approximate these terms with variables representing each state's capacity to export or import the relevant commodities. This is particularly important when estimating the trade of intermediate goods like grains using the gravity model. The ability of a given state to import intermediate goods from another state is determined not by its capacity to consume the goods directly, but by the extent to which these goods are required to produce final products using the intermediate goods. For example, if an observation in the FAF5 dataset concerns the trade flow of grains from Ohio to Louisiana, the supply in the origin state ("exporter") Ohio should be approximated by variables related to grain production. However, the demand in the destination state ("importer") Louisiana should be approximated by variables related to the production of manufactured foods that use grains. To account for this characteristic, production data needs to be broken down by state, year, state

attribute (whether a state is an origin or destination state), and sector. Thus, data on production value, categorized into state, year, state attribute, and sector, are obtained from three different sources: USDA National Agricultural Statistics Service (NASS), Annual Survey of Manufacturers, and the Economic Census.[15]

The supply of crop items in origin states are approximated by annual state-level production value for corn, soybean, and wheat – the primary agricultural commodities shipped by inland barge – obtained from NASS. State-level production value of corn and wheat is used to approximate each of the origin state's supply in the grain sector, while that of soybean is used to represent origin state's supply in the oilseed sector.

The demand for crop items in destination states is approximated by annual state-level production values for food manufacturing, sourced from the Annual Survey of Manufacturers and the Economic Census. These surveys are conducted nationally and provide detailed financial information at the firm level, focusing on the value of production from all firms with one or more employees in the U.S. The value of production is defined as the FOB (Free on Board) plant selling value of all products made during the survey year, including those sold, transferred, added to inventory, or used in further processing. For NAICS 3-digit code 311 observations (indicating "food manufacturing"), this firm-level data on production value is aggregated at the year and state level to derive the annual state-level production value in food manufacturing.

In a similar manner, the supply and demand for non-crop items are constructed by aggregating firm-level production data at the state and 6-digit NAICS subsector level. Specifically, in the animal feed sector, supply in origin states is represented by total production from “animal food manufacturing” (NAICS Code: 3111), while the demand at destination states is represented by the total production from “dairy product manufacturing” (NAICS Code: 3115) and “animal slaughtering and processing” (NAICS Code: 3116). In the grain milling sector,

[15] The Annual Survey of Manufacturers is not published during Census year (years ending in 2 or 7). In those years, the Economic Census is published, instead, while the two sources have same data structure, identified by year, region (narrower than state), and NAICS 8-digit codes sector. Thus, both of the data sources are used to construct the annual series of production value.

supply in origin states is represented by total production from "grain milling" (NAICS Code: 3112), while demand in destination states is represented by total production from "food manufacturing" (NAICS Code: 311) for each state.

The resulting supply and demand data are deflated using the U.S. GDP deflator from Federal Reserve Economic Data (FRED) and then mapped to the FAF5 dataset by year, sector, and origin-destination state pair.

2.5. Summary Statistics

Table 1 reports summary statistics for key variables for the analysis, including annual totals for trade value and means for other variables. The dataset comprises 16,302 observations spanning eight non-consecutive years (2007, 2012, 2017, 2018, 2019, 2020, 2021, and 2022).

The average annual total trade value is $271.7 billion. On average, $23.0 billion worth of trade is transported annually by inland barge, accounting for 8.5% of total trade and 31.8% of non-intrastate trade. This alludes to the comparative advantage of barge transportation in long-distance grain shipping. Because river transport is slow and cost-inefficient for short hauls, it is rarely used for intrastate shipments. Instead, barges are a vital mode for long-distance movement of grain across states, making them a key component of the U.S. grain supply chain (Vortex Global, n.d.).

Interestingly, trade flows of interstate shipments move in the opposite direction with barge freight rates. Interstate shipments carried by barge rose from $8.8 billion in 2007–2012 to $16.6 billion in 2017–2018, then declined slightly to $15.5 billion by 2022. This trend contrasts with the movement of barge rates, which fell from $2,143/ton in 2007–2012 to $1,728/ton in 2017–2018, and then reaching a record $3,599/ton in 2022. The inverse relationship is consistent to our hypothesis that increased barge rate would negatively affect trade flows. On the top of that, interstate shipments not carried by barge show a decline in trade flows from $16.6 billion in 2017-18 to $15.5 billion in 2022, indicating potential spillover effects from rising barge rates onto other transport modes. Also, the statistics indicate that export trade flows considerably

increased from 2007-12 to 2022, despite rising barge rates. However, Figure 3 shows that barge shipments declined during drought years on most routes. This suggests that the overall upward trend reflects increased demand potential along certain routes, coinciding with greater commodity supply from origin states during the same period. Thes patterns underscore the importance of accounting for external shocks when estimating gravity models

3. Model and Estimation Strategy

This section lays out the theoretical foundation of the structural gravity system and details the derivation of the empirical model utilized in this study. The primary objective of this study is to assess the impact of droughts on trade flows by examining changes in crop production and transportation costs. To link the input markets – crop production and transportation – with the trade flow for grains and related products, the structural gravity framework is used, as it is a widely-used empirical model in the general equilibrium analysis. The section starts with the theoretical foundations of the Armington-CES structural gravity system of the interstate trade flows in the U.S. and concludes with the derivation of the empirical model for the estimation.

3.1. Structural Gravity Framework

The basic assumption of the Armington-CES type structural gravity model is that each product is differentiated by its state of origin. Consumers are assumed to have identical CES preferences with a common elasticity σ for all variety of goods differentiated across origin states (Anderson, 1979). Let i be the origin state (or "exporter"), j be the destination (or "importer"), k be the type of commodity (or "sector"), t be the year, τ be trade type, and m be the domestic transportation mode, where $i \in I\{1,2,\dots,n\}$, $j \in J\{1,2,\dots,m\}$, $k \in K\{1,2,\dots,K\}$ (Anderson and van Wincoop, 2003, 2004), $\tau \in \{\text{domestic}, \text{export}\}$, and $m \in \{\text{barge}, \text{truck}, \text{rail}, \text{and mixed}\}$. Based on these assumptions, the structural gravity model of interstate trade is derived as: [16]

[16] Anderson and van Wincoop (2003) provide detailed explanations on the derivation of the Armington-CES structural gravity model.

$$X_{ijkt}^{\tau,m} = \left(\frac{T_{ijt}}{\Pi_{it} \mathrm{P}_{jt}}\right)^{1-\sigma} \frac{Y_{it} E_{jt}}{Y_t} \tag{1}$$

$$\Pi_{it}^{1-\sigma} = \sum_j \left(\frac{T_{ijt}}{P_{jt}}\right)^{1-\sigma} \frac{E_{jt}}{Y_t} \tag{2}$$

$$P_{jt}^{1-\sigma} = \sum_i \left(\frac{T_{ijt}}{\Pi_{it}}\right)^{1-\sigma} \frac{Y_{it}}{Y_t} \tag{3}$$

where X_{ijt} is the unilateral trade flows from state i to state j at time t, and T_{ijt} represents unilateral trade costs associated with shipping commodities from state i to state j, $Y_{it} = \sum_j X_{ijt}$ is total supply from the state i, and $Y_{jt} = \sum_i X_{ijt}$ is total expenditure by the state j at each point of time t. The parameter σ is the elasticity of substitution between commodities procured by different exporters. Both Y_{it} and E_{jt} include intrastate sales, where $i = j$. Y_t is the market clearing term, which corresponds to the total output by all origin states i as well as the total consumption from all destination states j, denoted as $Y_t = \sum_i Y_{it} = \sum_j E_{jt}$.

T_{ijt} is a function of trade cost for moving commodities from origin state i to destination state j at time t. While trade costs are unobserved in the data, the gravity equation can infer them from the observed variables. Thus, the trade cost function can be specified as a function of both time-varying factors (e.g., barge freight rate) and time-invariant factors (e.g., distance, contiguity, and border) that influence the unilateral trade costs between state i and state j.

P_{jt} and Π_{it} are the multilateral resistance terms, which differentiate the structural gravity model with the traditional gravity equation. P_{jt} is an inward multilateral resistance (IMR), derived as the weighted average trade frictions for consumers in state j. Π_{it} is an outward multilateral resistance (OMR), derived as the weighted average trade frictions faced by producers in state i (Anderson and van Wincoop, 2004, 2010). IMR is equivalent to the CES price index in the demand system. OMR accounts for the relative size of the outward trade costs compared to the destination price indexes. Thus, MRTs capture indirect trade flow changes arising from shifts in all other trading relationships between states resulting from the changes in barge freight rates (Anderson and van Wincoop, 2003, 2004, 2010).

The reduced-form empirical model for the structural gravity equations (1)-(3) is derived by specifying each term as a function of observable variables and plugging equations (2) and (3) into equation (1). The following subsection will discuss the specification of each term based on observable factors.

3.2. Empirical Model

3.2.1. Barge Rate and River Drought

Prior to estimating the gravity model specified in equation (1)-(3), it is useful to identify the impact of river disruption on transport costs. To do so, we regress barge rates on the weather indicators and disruption index specific to each route using the following specification:

$$lnf_{rt}^{B} = \beta_0 + f_1(low_{rt}) + \sum_{h=1}^{4} \gamma_h N_{h,rt}^{\mathrm{PPT}} + \sum_{h=1}^{4} \delta_h N_{h,rt}^{\mathrm{TEMP}} + v_r + u_{\mathrm{rt}}\,, \tag{4}$$

where lnf_{rt}^{B} is the log of barge rate specific to route r at time t. low_{rt} is river disruption index for route r at time t, and $f_1(low_{rt})$ is a piecewise linear spline function with knots at the 25th, 50th, 75th, and 100th percentiles. $N_{h,rt}^{W}$ represent the share of counties along route r that fall into weather condition group h in year t, constructed based on the county-level daily precipitation (PPT) and temperature (TEMP) data. v_r denotes the geographic fixed effect for each route r, and u_{rt} is the idiosyncratic error term.

Since the spline function $f_1(\cdot)$ is constructed using the marginal option, the cumulative marginal effect of river disruptions on barge rates is interpreted as:

$$\frac{dlnf_{rt}^{B}}{dlow_{rt}} = \begin{cases} a_1 & \text{if } low_{rt} < P_{25} \\ a_1 + a_2 & \text{if } P_{25} \le low_{rt} < P_{50} \\ a_1 + a_2 + a_3 & \text{if } P_{50} \le low_{rt} < P_{75} \\ a_1 + a_2 + a_3 + a_4 & \text{if } low_{rt} \ge P_{50} \end{cases}, \tag{5}$$

where P_n denotes the nth percentiles of low_{rt}. This structure captures the nonlinear and increasing marginal impact of river disruptions on barge transportation costs.

To construct the weather condition indicators, $N_{h,rt}^{W}$, we use the county-level daily data on precipitation and temperature from the PRISM dataset. For each weather variable $W \in \{\mathrm{PPT}, \mathrm{TEMP}\}$, given a pair of county c, and day m, we compute the county-level annual average as

$$\mu_c = \frac{1}{M}\sum W_{cm}\,, \tag{6}$$

, and the county-level daily standard deviation as

$$\sigma_c = \sqrt{\frac{1}{M}\sum (W_{cm} - \mu_c)^2} \tag{7}$$

Based on these statistics, daily weather observations, W_{cm}, are categorized into four mutually exclusive groups via binary indicators $G_{h,ct}^{W}$:

$$\begin{aligned} G_{1,ct}^{W} &= 1\{\mathrm{W_{cm}} < \mu_\mathrm{c} - \sigma_\mathrm{c}\} \\ G_{1,ct}^{W} &= 1\{\mu_\mathrm{c} - \sigma_\mathrm{c} \le W_{cm} < \mu_c\} \\ G_{1,ct}^{W} &= 1\{\mu_\mathrm{c} \le W_{cm} < \mu_c + \sigma_\mathrm{c}\} \\ G_{1,ct}^{W} &= 1\{\mu_c + \sigma_\mathrm{c} < W_c\} \end{aligned} \tag{8}$$

Each indicator identifies whether a county's daily weather falls within a specific range relative to its daily average from 2007 to 2022. The share of counties in each group h on day t is then given by:

$$N_{h,rt}^{W} = \frac{\Sigma_{c\in r} G_{h,ct}^{W}}{n_r(G_{h,ct}^{W})}, \quad \text{for } h = 1, \dots, 4 \; and \; c \in r \tag{9}$$

where $n_r(G_{h,ct}^{W})$ is the number of county-level observations where the gauge to construct low_{rt} for route r are located. Note that for each route r, $N_{h,rt}^{W}$ is constructed using weather data from the counties where the gauges are located whose river level data are used to construct low_{rt}.

Table 2 presents the OLS estimation result for Equation (4). The coefficients for the first two bins of the river disruption index are positive and statistically significant, indicating that the

occurrence of river disruptions even with less severity leads to immediate and sharp increases in barge rates. Temperature and precipitation also show statistically significant and mostly positive effects across several bins, though the impact of the river disruption index appears to be outstanding overall. The results provide strong evidence that drought-induced river disruptions and weather conditions significantly affect barge rates, posing a significant risk to the agricultural supply chain in the United States.

3.2.2. Trade Cost

The unilateral trade costs for delivering commodity from producers in state i to final consumers in state j are defined as a function of time-varying and time-invariant factors to capture the diverse aspects of trade cost:

$$T_{ijt} = \exp\left(\gamma_1' \log f^B_{r[ij]t} + \theta_{ij}\right), \tag{10}$$

where $f^B_{r[ij]t}$ represent the unit barge freight rate specific to barge route r, used to deliver commodities from state i to state j at time t. θ_{ij} represents the bilateral country-pair fixed effect to strip out the impact of any unobservable factors affecting trade costs. γ_1' is a parameter for log of barge rates.

While the majority of gravity literature has treated transport costs as exogenous to the trade flow under the iceberg cost assumption since Samuelson (1954), the presence of endogenous trade costs is well-documented in both theoretical and empirical dimensions (Bosker and Bruingh, 2020; Brancaccio, Kalouptsidi, and Papageorgiou, 2020; Hummels and Schaur, 2013; Hummels, Lugovskyy, and Skiba, 2009; Hummels and Skiba, 2004). This concern is critical in the current context, as barge rates could have reverse causality with trade value. If the trade flow decreases in response to changes in barge rates, it may decrease demand for barge shipments and lower the unit barge rate. If the endogeneity of transport cost is not addressed, its trade effects would be underestimated (Wong 2022; and Baier and Bergstrand, 2007).

The solution to this identification challenge is to replace the endogenous tariff rate with its predicted value. A major challenge is finding exogenous shocks that are correlated with the tariff rate and indirectly affecting trade flow (Angrist and Krueger, 1994). The identification

strategy is to borrow the insights from "river disruption index", which has been discussed earlier in Section 2. Specifically, the anomalous declines in river height is used as an instrument for barge tariff rates. River disruption is an exogenous event occurred by weather conditions, and potentially has an indirect effect over trade flow through tariffs. If river heights drop below the desirable level, the capacity of river transportation may decrease, consequently driving up tariffs.

Based on the results shown in Table 2, predicted residual is obtained. This predicted residual is henceforth defined as "control function (CF)", and we incorporate it into the barge rate function to explicitly incorporate the hydrological structure of the river system in the model. Weekly barge rates are adjusted with the quarterly GDP deflator, and averaged at the annual level to match the frequency with FAF5 data. The resulting trade cost function is as follow:

$$T_{ijt} = \exp\left(\gamma_1 \log f^{B}_{r[ij]t} + CF + \theta_{ij}\right) \tag{11}$$

3.2.3. Supply and Demand for Trade Potentials

In equations (1)-(3), for commodity k and year t, Y_{ikt} represents the total supply in state i, and E_{jkt} is the total demand at destination j. These terms reflect a state's capacity to export to and import from other states, respectively. Traditionally, supply and demand values are approximated by Gross Domestic Product (GDP). However, using GDP complicates the understanding of the relationship between climate shocks and production because GDP includes various components beyond production. Therefore, for domestic shipment, we approximate supply and demand for origin state i and destination state j using state-level production values of the relevant sector for each commodity. For export shipments, demand at destination country j is imputed using country-level food production values for each year, measured in U.S. dollars. Note that those data represent the value of products, measured at the Free on Board (FOB) plant price which exclude freight expenses. This aggregated production data provides a precise representation of economic activity in terms of agricultural and food

production and trade potential, independent of barge rates. Thus, the supply and demand are defined as:

$$Y_{ikt} = \exp(\gamma_2 \log Q^s_{ikt}) \tag{12}$$

$$E_{jkt} = \exp\left(\gamma_3 \log Q^d_{jkt}\right), \tag{13}$$

where Q^s_{it} represents the total production of commodity k in origin state i in year t, and Q^d_{ikt} represents the total production of final processed food (made up of k) in destination state j in year t.

3.2.4. Multilateral Resistance Terms

In this context, the multilateral resistance terms (MRTs) capture how droughts affect trade flow through changes in all other trading relationships between the states in the economy. Studies highlight that the estimation of gravity model without MRTs would lead to the overestimated estimates (Paniagua, 2016). Despite their practical and empirical advantages in the general equilibrium analysis (Anderson and van Wincoop, 2004, 2010), the estimation of MRTs has long been a significant empirical challenge due to complex calculation. However, a recent trend simplifies this process by calculating MRTs based on origin state (or "exporter") and destination state (or "importer") fixed effects estimated from the gravity model (Feenstra, 2015). Nevertheless, fixed effects at the individual state-level may absorb regional variations in climate shocks, which are of interest in this study, as they typically have a regional expression (Xie et al., 2015). A similar concern has been acknowledged by Dall'Erba, Chen, and Nava (2021), where the fixed effects for estimating multilateral resistance terms are constructed based on the U.S. climatic zone to identify the trade effect of drought in the U.S. In this study, the fixed effects are set based on U.S. Census Division Classification, with each category covering 1-4 states in the dataset[17].

3.2.5. Estimating Equation

[17] The division classification is chosen over climatic zone classification to generate exporter-by-year and importer-by-year fixed effects as division system represents more granular classifications. Yet, the estimation results are robust to using fixed effects constructed using U.S. Climatic Zones.

By plugging equations (11), (12), and (13), along with fixed effects to estimate multilateral resistance terms, into equations (1)-(3), the final estimating equation is obtained:

$$X_{ijkt}^{\tau,m} = \exp\left(\alpha_0 + \alpha_1 \log f_{r[ij]t}^{B} + \alpha_3 \log Q_{it}^{s} + \alpha_4 \log Q_{jt}^{d} + \alpha_5 CF + \theta_{ij} + \mu^{m} + \mu^{\tau}\right) + \varepsilon_{ijt} \qquad (14)$$

where α_0 is an intercept, $\alpha_1 = (1-\sigma)$ is the trade elasticity of barge rate which recovers the estimates for σ. $\alpha_3 = \gamma_2(1-\sigma)$ is the trade effect of supply (or "export potential"), $\alpha_4 = \gamma_3(1-\sigma)$ is the trade effect of demand (or "import potential"), and α_5 is the coefficient for control function. The bilateral fixed effects θ_{ij} constructed for each origin-destination pair are included in the model to capture pair-specific effects and control for unobserved heterogeneity between each bilateral relationship. Equation (14) includes additional fixed effects, μ^m and μ^τ, for domestic transport mode m and trade type τ, respectively. [18]

An increase in barge rates may elevate freight costs across other transport modes, potentially reducing domestic trade flows for non-barge shipments. To examine these spillover effects, we estimate the model on subsamples defined by export status and barge use in domestic shipping, assessing whether the negative impact of rising barge rates on trade flows persists for non-barge shipments.

The final estimating equation, (14), is estimated as a unidirectional model, because the barge rate data represent southbound movement only. Our sample includes observations with zero trade flows. Following Silva and Tenreyro (2010), we use PPML (Poisson pseudo-maximum-likelihood) to estimate equation (14) to account for zero trade flows and heteroskedasticity.

4. Gravity Model Estimation

Table 3 presents the estimation results of the gravity model, specified in the Equation (14), with fixed effects for exporter-importer pairs, year, sector, domestic transport mode [19], and trade

[18] Domestic transportation mode includes barge, truck, rail, and mixed mode. Trade type includes domestically traded shipments (including intrastate trade observation) and exported shipments.

[19] In the final dataset, observations are categorized into three different groups in terms of transport mode: 1) shipped by barge (interstate trade), 2) shipped by mixed modes, 3) shipped by other modes (interstate trade), and 3) intrastate trade. Interstate trade flows are grouped by whether they are shipped by barge, mixed modes, or others to

type. Column 1 presents the PPML result without using control function. Columns 2 through 8 display PPML results with control function, yet on different subsamples. Specifically, Column 2 shows the results in the full sample. Column 3 presents results for shipments transported domestically by barge, while Column 4 focuses on those not moved by barge. Columns (3a) through (4b) show the estimation results for subsamples further disaggregated by export status and barge use (for domestic shipping) of the observation. Specifically, Column (3a) includes domestic shipments moved from origin to destination by barge; Column (3b) focuses on export shipments moved from origin to intermediate state by barge; Column (4a) focuses on domestic shipments that are moved from origin to destination state by non-barge modes; and Column (4b) includes export shipments moved from origin to intermediate state by non-barge modes. [20]

The first consistent finding is the negative effect of river disruptions on trade flows across most specifications. In Column 1, a 1% increase in barge rates (measured in dollars per ton) is associated with a $1.74 million decrease in trade flows. However, this estimate reflects only the direct correlation between barge freight rates and trade flows, without accounting for the role of river levels. When the control function is introduced into the gravity model (Column 2), the estimated effect of barge rates on trade flows becomes positive and larger in magnitude: a 1% increase in barge rates is associated with a $1.80 million increase in trade. Moreover, a positive and significant coefficient of the control function (2.191) indicates the presence of unobserved source of endogeneity in barge rates, supporting the validity of using control function in our analysis. It should be noted that this finding is consistent with previous findings in the literature where the effects of trade costs increase with the endogeneity of trade costs taken into account (Wong 2022; and Baier and Bergstrand, 2007).

Another key finding is that while barge rates significantly decrease trade flows in most subsamples, domestic shipments appear to be less sensitive to barge rates. Column 3 shows an insignificant effect of barge rates on domestic trade flows, whereas Column 4 shows a

evaluate the spillover effects of barge rate into trade flow of other modes. Intrastate observations are not broken down in detail by transport mode as structural gravity model is derived, assuming that domestic transport cost is zero.

[20] Intrastate trade observations are grouped as shipments not shipped by barge.

significant impact of barge rates on export flows: a 1% increase in barge rates is associated with a $1.92 million decline in trade. This underscores the limited role of barge transport in domestic trade, where end-users, such as food processing plants and feedlots, are often located away from navigable waterways. In contrast, barge shipping remains cost-effective for exports due to the concentration of export terminals along the Gulf Coast (Burton, 2019).

A comparison between the results in Column 5 through Column 8 further highlights the importance of barge shipping in export trade flows. For domestic shipments moved by barge (in Column 5), barge rates do not have significant impact on trade flows. This is partly consistent with our findings from the Column 3. For export shipments that are carried from origin to intermediate state by barge (in Column 6), a 1% increase in barge rates decreases trade flows by $1.87 million, supporting the negative trade effects of barge rates. Results in Column 7-8 provide evidence for the spillover effects of barge rates onto other transportation modes. Column 7 shows that a 1% increase in barge rates decreases trade flow of domestic shipments that are moved from origin to destination state by non-barge modes by $1.96 million and that of export shipments that are moved from origin to intermediate state by non-barge modes by $1.34 million. Additionally, throughout all specifications, a 1% increase in commodity demand at destination states captured by the value of food production is found to increase trade flows by $0.07-0.11 million, with the effects being insignificant only for domestic barge shipments. Yet, the trade effects of supply are insignificant.[21] [22] Our results indicate that river disruptions significantly affect the grain supply chain by influencing barge rates in most cases. We could not find evidence that barge rates impact domestic barge trade flows which is consistent with the less prominent role of barge shipping in domestic grain trade.

5. Counterfactual Implications for Barge Disruption

[21] The results are robust to: (1) varying low water stage thresholds set as 5%, 15%, and 20%; (2) using data on crop quantities produced expressed in BU as proxy for crop export potential in origin; and (3) using (implicit) quantities produced as a proxy for trade potentials, derived from dividing aggregate production value by sector-specific producer price index.

[22] The effect of distance is insignificant, consistent with findings in the most recent gravity literature.

Table 4 displays trade predictions for interstate shipments under three river disruption scenarios, based on the river disruption index and the estimation results presented in Columns 5-8 of Table 3. Specifically, the value of the river disruption index has been adjusted under three different scenarios, which yield new predicted barge rates. The scenarios are: (i) no disruption, where the low water index for each route in all years is set to 0 implying 100% mitigation of river disruption for each route; and (ii) 50% mitigation of river disruption where the low water index for each route at a given time is reduced by half.

Under a full mitigation scenario (100% reduction in river disruption), total interstate trade is estimated to have increased by 14.31% over the eight-year study period. The counterfactual effects are heterogeneous across shipment types. Domestic shipments would have exhibited only a negligible change, whereas export shipments show substantial gains. Specifically, export barge shipments are predicted to have increased by 32.45%, representing the largest effect, while non-barge export shipments would have risen by 3.82%. These results are consistent with the presence of spillover effects from barge rate shocks to other transport modes via modal substitution. Under a 50% reduction scenario, we observe similar patterns. Total trade flows would have increased by 9.07% over the eight-year period. Domestic shipments would have remained relatively stable, while export barge shipments would have increased by 20.93% and non-barge shipments by 2.14%.

Temporal disaggregation reveals that the effects are most pronounced in 2022, a year characterized by historically low water levels on the Mississippi River. Under the full mitigation scenario, trade flows in that year would have increased by 79.50%, compared with 68.88% under partial mitigation.

It should be highlighted that the counterfactual changes in trade flows are specific to domestic trade flows for grain and related products between selected states and only during the eight-year study period. Moreover, the model presented in this study does not account for the welfare impact from the loss of exports attributable to river disruption, which should be considerable. Thus, the counterfactual analysis requires a strong assumption that international trade, especially exports in this context, is independent of domestic trade volume. This implies

the reported values can be seen as the lower bound, and calls for future research to examine how changes in barge rates and the associated changes in domestic trade costs affect trade flows originating from the U.S.

Nevertheless, the trade predictions provide crucial insights for evaluating the benefits of policies aimed at controlling river levels when compared to the costs associated with improving the river system. The Corps of Engineers (2010) estimates renovation costs for aging locks to reach working status at $3 billion. IADOT (2019) estimates that rehabilitating all locks and dams in the Upper Mississippi River for improved transportation would cost about $1.22 billion, with each lock costing around $45 million. Given that the annual average trade value in our sample is estimated at $271.7 billion (see Table 1), and that even a conservative 50% reduction scenario projects a 9.07% increase in total trade flows over the eight-year period, the potential benefits of such policies would likely outweigh their costs, underscoring the substantial returns from infrastructure investments for mitigating river disruptions.

6. Conclusion

When measuring the impact of extreme weather on agricultural markets, previous literature has predominantly focused on changes in agricultural production. In reality, however, extreme weather can also affect post-production stages, particularly logistics operations, resulting in substantial economic costs by reducing trade flows and disrupting the food supply chain. This is especially critical in the context of U.S. agriculture, which heavily relies on barge transportation that is highly sensitive to river conditions. Namely, when river levels are reduced due to droughts and extreme heat, the capacity of river transportation would be reduced. Thus, it would result in the surge in barge freight rate, affecting trade flows in the country. In this respect, this paper diverges from the traditional strand of literature by focusing on how drought affects not only production but also transport costs in the U.S. grain supply chain.

To measure the degree of logistical disruption caused by droughts, barge freight rates are modeled to capture abnormal declines in river heights. This approach allows for the heterogeneity in the magnitude of river shocks across locations. In doing so, transportation cost function is specified to reflect the hydrological structure and flow of the river system. Furthermore, the structural gravity model is estimated, which incorporates both production and transport cost components, to measure the changes in domestic trade flow resulting from climate shocks from an overarching perspective.

The key findings of this study are as follows. First, low water levels in the Mississippi River are found to significantly increase barge rates, while the effects are more pronounced at downstream. Second, transportation costs have a more substantial impact on interstate trade flows compared to agricultural production. Third, modeling barge transportation costs as exogenous rather than considering their endogeneity resulted in an underestimation of the trade effect of barge rates by approximately 5.66%. Finally, counterfactual analysis reveals that, if river disruption is 100% mitigated in all river segments, total trade flows would have increased by 14.31%, where the increase is more pronounced for export shipments.

Future research should consider international trade flows in addition to domestic ones. This analysis focuses solely on domestic trade flows, based on the assumption that international trade represents a negligible share of the total trade in the U.S. grain market and can thus be disregarded. In other words, the majority of trade occurs domestically, leading to the conclusion that international trade has a minimal impact on overall trade. While this assumption may sound restrictive at first, our data justify it. In our dataset, which considers trade directions from the Upper/Mid-Mississippi states to the Gulf, 96% of the total trade value is traded domestically, and 4% is exported.[23] When excluding intrastate trade observations, which

[23] The portion of domestic trade in the grain supply chain appears to be larger in our dataset compared to what is generally known. For example, around 11% of corn, 44% of soybeans, and 33% of wheat in the total supply in the United States are exported in 2022/2023 (USDA, 2024), where approximately 50% of corn exports (about 11% × 50% = 5.5% of the total domestic supply) and 60% of soybean exports (about 44% × 60% = 26.4% of the total domestic supply) are transported via the Mississippi River to reach the Gulf of Mexico (USDA AMS, 2024). This discrepancy may arise because the sectoral classifications in the FAF5 dataset encompass a broader array of crops. Consequently, the higher domestic trade proportion observed in our dataset may result from the inclusion of other crops within this sector that have higher domestic trade proportions compared to corn and wheat specifically.

constitute the majority of the trade observed in our dataset, the share of interstate trade decreases to 80% while the share of international trade increases to 20%. Despite the relatively large share of domestic trade compared to exports, ignoring international trade could still lead to an underestimation of the effects of trade disruption if river droughts significantly impact exports.

The findings from this study highlight the significant impact of climate-induced logistical disruptions and provide valuable insights for policymakers to improve the resilience of the river transportation system.[24]

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[24] Remaining challenges include handling (i) dropped observations, (ii) international trade flow, and (iii) the impact of weather conditions on low river levels. First, some state pairs were excluded due to missing barge rate data; future research should use imputation methods to avoid sacrificing these observations. Second, future studies should include international export data. Although over 50% of the grain shipped via the Mississippi River is for export, this study only focuses on domestic flows due to data limitations. Including export data could significantly alter the results, especially the counterfactual trade predictions. Third, it is necessary to establish the relationship between low river levels and weather conditions to test which regions' grain supply chains are more affected by drought. For example, if drought occurs in counties along the Mississippi River, the combined impact of production damage and transportation issues could be substantial. Identifying these regions can help determine where to install effective drought mitigation infrastructure.

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Figures and Tables

Figure 1. Geographic Illustration of Barge Rates and Gage Points

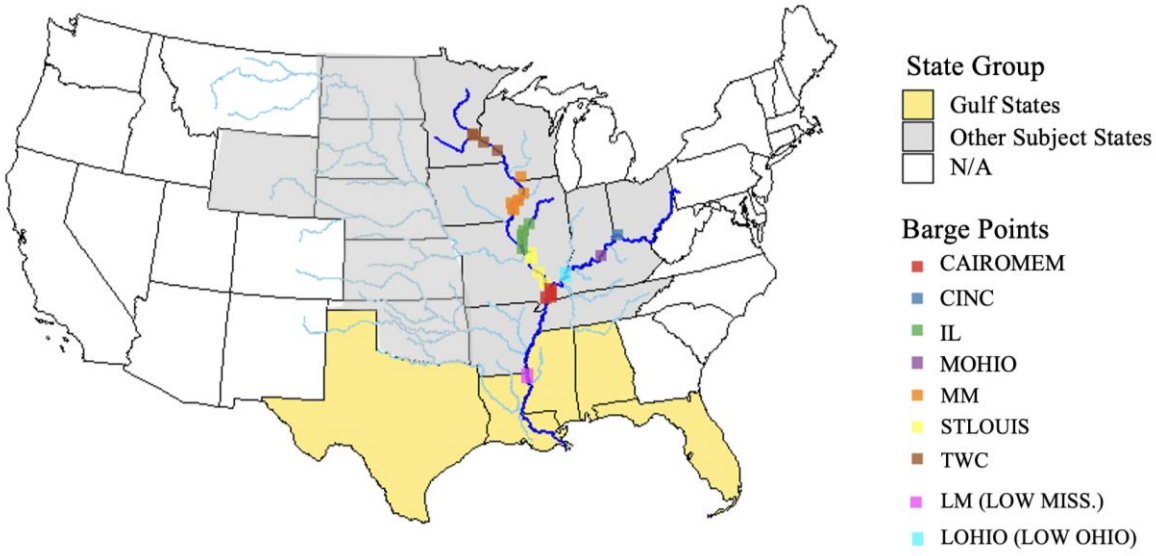
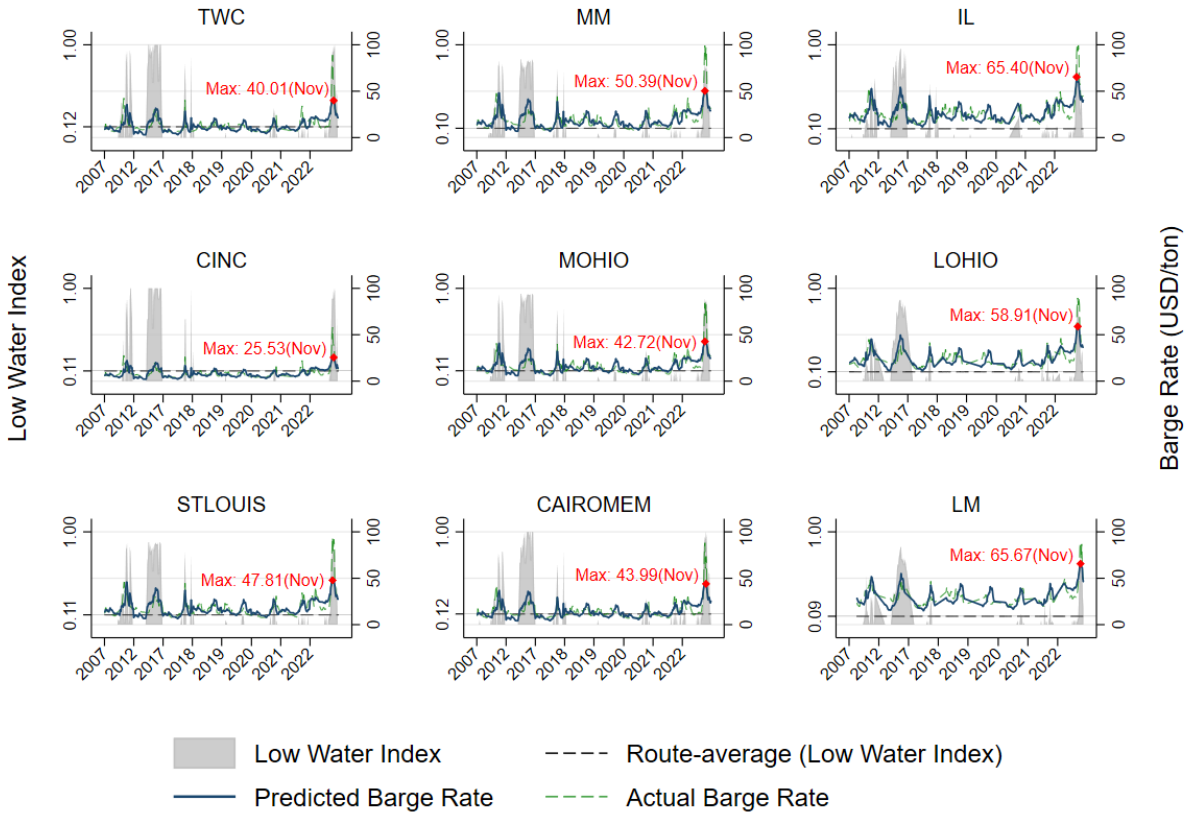
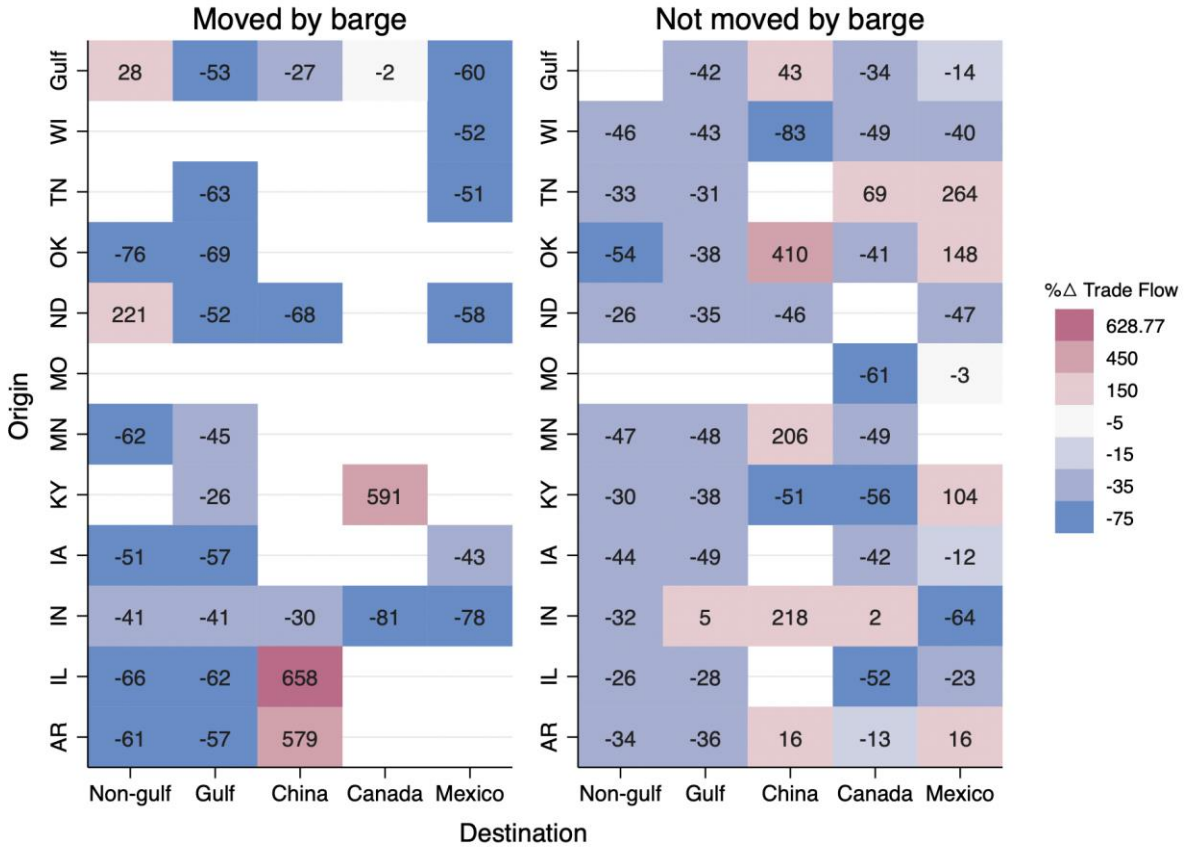


Figure 2. Barge Tariff Rate and Low Water Index by Route



Note: Barge rate is calculated by multiplying baseline price by tariff rates and dividing by 100, which has been further adjusted using the quarterly GDP deflator obtained from Federal Reserve Economic Data (FRED).

Figure 3. Percentage Changes in Trade Flows During River Drought Years



Note: This figure displays the percentage changes in annual average trade flow by route during three years of severe river droughts (2007, 2012, 2022; annual mean low water index ≥ 0.077) compared to other five years referred to as less drought years. The observation is further categorized by whether shipments are domestically carried by barge. Mixed mode observations included in "not moved by barge" group. The classification of these years is based on the river drought index detailed in Section 2.2. Note that Figure 3 only includes data from grain and oilseed shipments due to missing observations for animal feed and grain milling products in some years.

Table 1. Summary Statistics

Description	Entire Period	Period			
		2007-12	2017-18	2019-21	2022
Total number of obs.	**16,302**	**5,564**	**3,611**	**3,563**	**3,564**
Annual total trade value* (1B $)	**271.7**	**226.4**	**292.5**	**285.5**	**279.1**
- *Export Shipment**	29.0	24.3	29.4	30.2	34.4
- Shipped by barge*	8.8	5.2	9.7	9.7	11.4
- Otherwise*	20.2	19.0	19.7	20.5	23.0
- *Interstate Shipment**	43.3	36.5	46.6	45.5	44.0
- Shipped by barge*	14.2	8.8	16.6	15.9	15.5
- Otherwise*	29.1	27.7	30.0	29.6	28.5
- *Intrastate trade**	199.3	165.7	216.4	209.9	200.8
Shipped by Barge	0.12	0.13	0.11	0.11	0.11
Barge freight rate ($/ton)	2,287	2,143	1,728	1,777	3,599
Supply at origin (1B $)	3.5	3.6	3.4	3.5	3.6
Demand at destination (1B $)	368.7	281.7	398.4	426.4	416.5

Note: All monetary values are adjusted for inflation using the U.S. annual GDP deflator. To minimize information loss, however, bi-weekly barge rates are first aggregated to a quarterly level, adjusted using the quarterly GDP deflator, and then converted to an annual frequency. Both GDP deflator series are sourced from Federal Reserve Economic Data (FRED). The *Total number of observations* shows the aggregate number of observations for each period. An asterisk (*) indicates that the annual average of aggregate trade values for the specified period and category is displayed.

Table 2. First Stage Regression Results

	(1)	
Dep. Var: ln f_{rt}^{B}	OLS	
Low Water Index (Bin 1)	1.001***	(0.06)
Low Water Index (Bin 2)	0.645***	(0.11)
Low Water Index (Bin 3)	-3.138***	(0.15)
Low Water Index (Bin 4)	1.683***	(0.11)
Temperature (Indicator 1)	2.327***	(0.07)
Temperature (Indicator 2)	0.063***	(0.01)
Temperature (Indicator 3)	0.285***	(0.00)
Temperature (Indicator 4)	0.000	(.)
Precipitation (Indicator 1)	0.238***	(0.01)
Precipitation (Indicator 2)	0.203***	(0.01)
Precipitation (Indicator 3)	-0.017	(0.01)
Precipitation (Indicator 4)	0.000	(.)
Linear Time Trend	0.013***	(0.00)
Route FE	8	
Adjusted R-squared	0.832	
N	16,294	

Note: Robust standard errors are displayed in the parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 3. Gravity Model Estimation Results

	PPML	PPML with Control Function						
	(1)	(2)	(3)	(4)	(3a)	(3b)	(4a)	(4b)
Dep. Var: X_{ij}	All	All	Barge	Non-barge	Domestic Barge	Export Barge	Domestic Non-barge	Export Non-barge
log (barge rate)	-1.738***	-1.798***	0.205	-1.915***	-0.274	-1.865**	-1.964***	-1.335**
	(0.52)	(0.50)	(1.09)	(0.41)	(1.05)	(0.86)	(0.41)	(0.63)
log (supply)	0.022	0.022	0.088**	0.020	0.792	0.041	0.033	0.009
	(0.02)	(0.02)	(0.04)	(0.01)	(0.54)	(0.03)	(0.03)	(0.02)
log (demand)	0.064***	0.064***	0.070**	0.078***	-0.719***	0.110***	0.631***	0.077***
	(0.001)	(0.01)	(0.03)	(0.01)	(0.27)	(0.02)	(0.08)	(0.01)
Control Function		2.191***	0.262	1.850***	0.647	2.600	1.573***	2.272*
		(0.54)	(0.84)	(0.40)	(1.00)	(2.16)	(0.45)	(1.28)
Exp-Imp FE	40	40	30	40	13	17	20	20
Year FE	8	8	8	8	8	8	8	8
Sector FE	4	4	4	4	4	4	4	4
Domestic Mode FE	5	5	N	5	N	N	5	5
Trade Type FE	2	2	2	2	N	N	N	N
N	16,294	16,294	1,879	14,373	643	1,236	6,274	8,099

Note: Standard errors are clustered by year displayed in parentheses. All values are converted into million USD and prices into thousand USD for the analysis. Monetary values are deflated using the annual GDP deflator from FRED, except for barge rates which are adjusted by the quarterly GDP deflator. Results include intrastate trade observations, * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 4. Projected Changes in Trade Flow Under Counterfactual River Scenarios (%)

Category		Year 2007	2012	2017	2018	2019	2020	2021	2022	**Total**
Scenario 1: No Disruption (100% Mitigation)										
Domestic	Barge	0.02	0.02	-0.01	-0.01	-0.01	-0.01	0.01	0.05	**0.01**
	Non-barge	-0.56	-0.79	0.72	0.72	0.66	0.51	-0.22	-2.20	**-0.15**
Export	Barge	40.76	58.08	-11.13	-15.81	-19.09	-12.94	9.60	180.55	**32.45**
	Non-barge	7.87	11.11	-5.75	-6.24	-6.20	-4.75	2.64	28.77	**3.82**
Total		**21.09**	**30.04**	**-6.93**	**-8.89**	**-10.05**	**-7.12**	**4.83**	**79.50**	**14.31**
Scenario 2: 50% Mitigation										
Domestic	Barge	0.01	0.02	-0.01	-0.01	-0.01	-0.01	0.00	0.04	**0.01**
	Non-barge	-0.37	-0.57	0.78	0.73	0.66	0.54	-0.20	-1.97	**-0.05**
Export	Barge	23.47	32.38	-15.21	-16.36	-19.16	-14.72	8.21	156.55	**20.93**
	Non-barge	4.97	7.19	-6.62	-6.37	-6.22	-5.14	2.35	24.85	**2.14**
Total		**12.33**	**17.19**	**-8.82**	**-9.16**	**-10.08**	**-7.96**	**4.17**	**68.88**	**9.07**

Note: The trade predictions vary upon the threshold of the river level set in formulating river disruption index, which has been described in Section 2.1. Table 5 is the results based on threshold for low water status as a lower 10% of 16 years average from 2007 to 2022.