The economic and environmental value of the United States crop distribution network

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Abstract

The US crop distribution system transports millions of tons of crops from the Corn Belt to export ports using roads, rail, and rivers. Weather extremes, such as flash floodings, tornadoes, and winter storms, can disrupt this distribution network, raising both economic and environmental costs. This study assesses how extreme weather impacts the cost of transporting corn and soybeans and the associated environmental emissions. Our methodology has three steps. First, the cost of transporting soybeans and corn to export ports is estimated using observed price data and least-cost route mapping. Second, a panel regression analysis evaluates how weather disruptions affect shipping costs, using price gaps (basis spread = local price - export price) as the dependent variable. Key factors such as extreme weather events, transportation costs, and other control variables are included in the model specification. Finally, changes in emissions are calculated when shipments are rerouted due to weather disruptions. In economics terms, during the sample period disasters have caused shocks ranging up to -$0.14 per bushel of corn and -$0.38 per bushel of soybeans. In terms of emissions, disasters along the route have resulted in increases of 159 grams of CO_2 per bushel for corn and 177 grams of CO_2 per bushel for soybeans.

1. Introduction

US crop production is crucial to global food supplies, with the country as a top producer and exporter of grains such as corn and soybeans (Meade et al., 2016). From 2012/13 to 2020/21, the US accounted for an average of 33% of global corn production and 32% of global soybean production (USDA - Foreign Agricultural Service, 2024). Most of this production is concentrated in the Midwest, commonly known as the Corn Belt, with leading states including Illinois, Iowa, Minnesota, Nebraska, Ohio, Indiana, and Missouri (Green et al., 2018). Transporting these crops relies on an integrated, multimodal system of highways, railroads, and waterways, which is crucial for efficiently moving grains from the production regions to processing and export hubs. US competitiveness in global markets, domestic food and fuel supplies, and producer revenues all depend heavily on the effectiveness of this system. Critical coastal, lake, and inland ports serve as vital gateways for international shipments, linking US grains to global food supply chains.

The infrastructure and efficiency of the US transportation system is vulnerable to disruptions caused by weather extremes and natural hazards, such as flash floods, winter storms, tornadoes, mudslides, and hurricanes (Blandford et al., 2016). These disruptions have broader economic and environmental implications. In economic terms, extreme weather can affect transportation planning, network operations, maintenance, and vehicle performance, often resulting in canceled or rerouted shipments (Clarke et al., 2022; Wang et al., 2020). Disruptions in the crop transportation system can limit food availability, increase prices, reduce the global competitiveness of US crops, and threaten farm incomes by reducing crop sales. We use the basis spread as the outcome variable to examine the economic impact of weather extremes on the US crop transportation network. Basis spread is defined as the price differential between interior collection points and export ports. The infrastructure used to transport grains, including road, rail, and river systems, influences the basis spread. Therefore, if one or several transportation system's components do not work efficiently because of extreme weather events, the resulting disruptions may affect the basis spread levels (Mobarok et al., 2023). Also, the commodity basis spread relates to trade and grain flows (Davis & Hill, 1974; McKenzie, 2005; Tilley & Campbell, 1988; Wilson & Dahl, 2011).

In environmental terms, an additional consequence of weather extremes can be increases in emissions from the crop transportation network. Disruptions caused by extreme weather often result in detours and slowdowns (Peterson et al., 2008). Such disruptions can also increase reliance on less efficient routes or transport modes, such as switching from rail to truck, which typically have higher per-mile emissions (Kruse et al., 2021). Furthermore, damaged infrastructure or restricted access to ports may lead to greater fuel consumption as transport vehicles, reroute, or travel longer distances. These changes frequently increase the carbon footprint associated with moving crops from production areas to market or export points.

Evaluating weather extremes' economic and environmental impacts on the crop transportation network is crucial and this area remains underexplored in the literature even as weather extremes become more frequent and intense (Walsh et al., 2020). In economic terms, previous research has examined the effects of weather extremes on agricultural production and prices, often identifying strong links between weather anomalies, crop yields, and commodity prices (Anyamba et al., 2014; Vogel at al., 2019; Ubilava, 2018; Nam, 2021). Additional studies have investigated the impact of weather extremes and climate change on transportation infrastructure in the US (Caldwell et al., 2002; Millerd, 2011; Bundy et al., 2023) and internationally (Chinowsky et al., 2015a; Chinowsky et al., 2015b, Liu et al., 2023). However, these studies overlook the specific effects of extreme weather on agricultural transportation networks. An exception is the study by Attavanich et al. (2013) which examined climate change's broader implications on US grain transportation, considering factors such as shifts in crop production, water levels, and alternative navigation routes. However, none of these studies has examined both the economic and environmental impacts of weather extremes on the crop transportation network system.

In the environmental literature, freight transport is closely linked to greenhouse gas (GHG) emissions (Cristea et al., 2013; Marcilio et al., 2018; Benali & Feki, 2020; Albuquerque et al., 2022), with the transport sector contributing approximately 7% of global GHG emissions (Miklautsch et al., 2022). While extensive research has documented the effects of GHG emissions on climate change and extreme weather events (Kweku et al., 2018; Cassia et al., 2018; Touma et al., 2021; Kabir et al., 2023), there is limited literature examining the reverse impact—namely, how extreme weather events influence GHG emissions. Studies in urban and commuter transport contexts indicate that weather conditions significantly influence travel behavior, with both extreme weather events and warmer climates impacting GHG emissions associated with commuting (Liu et al., 2016; Wang et al., 2022). However, to date, no studies have specifically investigated the impact of extreme weather on emissions through disruptions in the grain transportation network.

This study investigates how weather extremes impacting crop transportation affect corn and soybean basis spread and emissions of transporting these crops to ports of exit. We analyze data from nearly 5,000 US midwestern corn and soybean elevators from 2010 to 2022 and natural disaster declarations to represent weather extremes affecting transportation. To achieve this, we follow a three-step approach. In the first step, a combination of actual price data and mapped least-cost routes is used to estimate the cost of getting soybeans and corn from the interior growing region to the exit ports. We consider the following exit ports in our analysis: New Orleans, LA (Gulf Coast); Vancouver, WA (Pacific Northwest); Toledo, OH, and Duluth, MN (Great Lakes area); Norfolk, VA (Northeastern Seaboard), and Laredo, TX (inland rail port for exports to Mexico).

In the second step, a panel regression analysis is used to estimate the impact of different weather-related disruptions and other factors on the basis spread. Historical data on the basis spread is collected, serving as the dependent variable in the regression analysis. This panel regression approach allows for inferring how extreme weather events affect the US crop distribution network by examining their influence on the crop basis spread.

In the third step, route-specific emissions per bushel of corn and soybeans transported to various export facilities are calculated using the EPA's GHG equivalencies calculator. Additionally, the impact of weather-related disruptions on emissions is assessed by examining how emissions per bushel change when a critical part of the distribution system is taken out of service. In such cases, crop shipments must be rerouted, resulting in altered least-cost routes and emissions compared to the baseline scenario (which assumes no disruptions).

Our findings could improve decision-making by providing insights for policymakers and businesses. Policymakers may reassess the allocation of resources following disasters, while businesses could evaluate whether to store crops to mitigate the effects of disruptions or seek alternative routes. Moreover, emissions associated with a functional distribution system can inform policymaking regarding the value of maintaining or expanding infrastructure. The results may also highlight issues related to the costs of repairing or neglecting crop transportation infrastructure. For instance, what impacts on basis spread and emissions are associated with the maintenance of locks and dams that prompt crop shipments to reroute? Extending this example, if maintenance is postponed or delayed due to budget constraints, what are the associated emissions and basis spread costs, reflecting the increased risk of infrastructure malfunctions?

2. Methodology

To assess the effect of weather extremes on crop basis spread and emissions, we integrate Geographic Information System (GIS) techniques for identifying least-cost transportation routes with econometric modeling to analyze the effects of weather events on basis spread, and emission factor calculations to quantify changes in emissions due to route disruptions. More details about these methods are provided in the following subsections.

2.1 Hypothetical least-cost routes and basis spread regression

We use GIS techniques to determine the least-cost routes for transporting crops to the ports under a baseline scenario, assuming no route disruptions. The process started by linking the geospatial coordinates of the elevators and port exits (nodes dataset) with the geospatial data that represents a multimodal transportation network of roads, railways, and navigable rivers, including the Mississippi, Ohio, and Illinois Rivers (network dataset). Each type of transportation route was assigned a specific cost per mile: \$0.10/mile for trucks, \$0.001/mile for rail, and \$0.00001/mile for barges. These cost assumptions were applied to establish the following transportation mode hierarchy: (1) rivers, (2) railways, and (3) roads. This structure prioritizes river transport over rail and rail over road, ensuring crops are directed first to the most cost-effective modes, in line with the relative expense of each option. To determine the least-cost routes, we use actual transportation costs, based on weekly national averages for each transportation mode. The total cost for each minimum-cost route is calculated by summing the products of the cost per mile per bushel and the distance traveled for each transportation mode along the route.

We then integrate the minimum-cost route with weekly county-level natural disaster data. Disasters may occur in counties where elevators are located (disasters at collection points) or counties crossed by the minimum-cost route (disasters "along" the route). If a disaster affects the county where a collection point operates, the least-cost route from that point to the port is not used for the affected week, reflecting that collection points typically cannot ship crops to export destinations during such disruptions. If a disaster impacts counties along the route, we create an alternative path that bypasses these affected areas to maintain transportation continuity while avoiding disrupted areas. After drawing the alternative route, we calculate the shipping cost based on the weekly costs and the distance traveled for each transportation mode. The new cost calculation accounts for the disaster impacts, enabling estimation of crop transportation costs for each elevator and capturing the economic effects of the disaster.

Finally, we use a fixed-effect[1] panel regression model to assess the effect of weather extremes on crop basis spread (local price less export price). As described in the next section, we collect historical data on price differences between interior locations and ports (i.e., basis spread) as the dependent variable in the regression model. This approach enables us to assess the effects of extreme weather events on the crop distribution network by analyzing variations in basis spread. Key variables include disaster declaration data for events such as floods, hurricanes, winter storms, tornadoes, and mudslides. Additionally, we incorporate shipping costs based on least-cost route estimates and adjust them for disruptions at collection points and along routes. The model also controls for other factors affecting basis spread. The regression results offer insights into the impact of weather-related disruptions on the basis spread of corn and soybeans. The econometric specification follows the following equation.

$$B_{ip,tw} = \beta_0 + \beta_1 C_{ip,tw} + \beta_2 D_{i,tw} + \beta_3 X_{i,t} + \gamma_i + \epsilon_{ip,tw} \tag{1}$$

where $B_{ip,tw}$ represent the weekly average commodity basis spread for elevator i shipping to destination port p in week w of year t. The variable $C_{ip,tw}$ denote the shipping cost along the hypothetical least-cost route, accounting for natural disasters. Disaster dummies, $D_{i,tw}$, indicate whether a natural disaster occurred in the county where the collecting point is located. We

[1] As discussed in more detail in the data section, the choice of the fixed effects model was guided by the results of a Hausman test, which determined whether a fixed or random effects specification was more appropriate.

initially include an aggregate disaster dummy in the basis spread estimation to test for the overall impact of any natural disaster at collecting points on the basis spread. We further re-estimate the model using separate disaster dummies for each natural event to evaluate the specific effects of different disaster types. $X_{i,t}$ is a vector of control variables, and γ_i captures fixed effects to account for time-invariant differences across elevators. $\varepsilon_{ip,tw}$ is the error term, while the betas are the parameters to be estimated. The model in equation (1) is re-estimated to incorporate an interaction term between the shipping cost which is affected by disaster disruptions, and a dummy variable indicating whether the route was altered due to a disaster ($R_{ip,tw}$).[2]. This term helps assess whether disruptions caused by disasters are more or less severe than suggested by shipping cost estimates.

We assess the expected signs for the main variables of interest in the model to better understand how transportation costs and disasters impact the basis spread. We hypothesize that the cost of transporting a crop ($C_{ip,tw}$) to market negatively affects the basis spread. The collection point price could be the price at an elevator or a facility that processes crops, according to our data source, and our sample only includes collection points with price data. If no price is reported, then the observation is omitted; we do not include cases where we lack evidence of local conditions. Where there are price data, then the price at that facility is seen as an indicator of local supply and demand conditions no matter the type of collection point. For example, higher costs to move crops from the local area to the export port will reduce demand in that local area and tend to drive down the local prices reported at elevators or paid by processing facilities. Thus, increased shipping costs result in lower local prices for a given port price.

The effect of the disasters at collection points ($D_{i,tw}$) on the basis spread is uncertain. A priori, the question is whether the shock affects demand to move crops from the location to export ports or whether the shock affects the supply of crops flowing into the local area from other regions. First, if the marginal flow is from the collection point to export markets, the disaster prevents these crops from being moved out, and there would be an excess supply at the collection point. This excess supply could decrease the local price compared to the export

[2] $R_{ip,tw}$ is not included on its own in the model due to multicollinearity with the disaster dummies. Equation (1) is estimated separately for corn and soybeans.

price, narrowing the basis spread. Second, if the marginal flow is from fields or neighboring collection points to the affected operational point, the disaster could prevent these incoming crops from being delivered to the collection point. In this case there would be a shortage of supply at the collection point in the affected areas. This shortage could increase the local price relative to the export price, widening the basis spread. The effect of the interaction between shipping cost and the route change dummy ($C_{ip,tw} * R_{ip,tw}$) on the basis spread is ambiguous. A positive value of the interaction term indicates that the disruptions are less severe than the shipping cost calculations would imply; for example, shippers may mitigate the costs using storage or redirecting shipments to other ports. A negative value, however, suggests that the disruptions are more severe than the shipping cost suggests. For example, if a disaster forces one trip to reroute, the new route can be less efficient in fuel consumption, leading to higher fuel expenses. Also, shippers may face higher costs when securing transportation options. Furthermore, the rerouted path may require additional planning and coordination, leading to more expenses.

2.2 Assessing changes in emissions due to route disruptions

To calculate the effect of weather extremes on emissions, we use our GIS approach to compare the miles traveled for each transportation mode along the baseline (undisrupted) route with the miles traveled along disrupted routes caused by natural disasters. We then combine the distances for both disrupted and undisrupted routes with emission factors by transportation mode from the Texas A&M Transportation Institute and the Center for Ports and Waterways (Kruse et al., 2021). These emission factors, calculated every five years, are derived from the US Environmental Protection Agency's (EPA) Motor Vehicle Emission Simulator (MOVES).

Table 1 shows the emission factors of the three transportation modes.[3] Notably, truck transportation emits nearly ten times more CO_2 than inland towing, while train emits 1.4 times

[3] For example, the indicators in Table 1 for the truck case in 2019 are interpreted as follows: Trucks emit 140.7 grams of CO_2 per ton-mile. This measurement means a 25-ton capacity truck releases approximately 141 grams of CO_2 for every ton of cargo transported over one mile. Kruse et al. (2021) calculate emissions in the truck scenario using a truck with a 25-ton capacity. The interpretation for other years is analogous.

more CO_2 than inland towing. For our analysis, we assign truck emissions to road miles, railroad emissions to rail miles, and inland towing emissions to river miles. To calculate emissions for each mode of transportation, we use the averages from the last column of Table 1, as these years (2009, 2014, and 2019) closely align with our analysis period (2010–2022).

Table 1. Emissions by transportation mode (grams of CO_2 per ton-mile)

Transportation mode	2009 (1)	2014 (2)	2019 (3)	Average (4)
Truck	171.83	154.08	140.7	155.54
Railroad	21.14	21.19	21.57	21.30
Inland towing	16.41	15.62	15.08	15.70

Source: Kruse, et al., 2021
Note: Kruse et al. (2021) assume all return trips are empty in the truck case. Trucks that transport bulk goods have a limited number of backhaul options. For instance, a grain truck will not return with steel or any liquid product.

Once we have the emissions by transportation mode and the distances in miles (road, rail, and river) for transporting grain from the elevator to the exit port, we calculate the emissions for each route. This is done for both the baseline (unaffected) route and the alternative route impacted by the disaster. To calculate emissions, we sum the product of the miles traveled and the emissions per ton-mile for each transportation mode. We then assess the impact of weather extremes by comparing the emissions of the alternative route to the baseline route during weeks where there is route change ($R_{ip,tw}$ = 1). The analysis focuses on scenarios where disasters affect the transportation route, as these events typically could lead to higher emissions due to the resulting disruptions. Such disruptions often require longer alternative routes or transportation modes with higher emission rates, such as substituting rail with truck transport. We exclude scenarios without route changes ($R_{ip,tw}$ = 0), as no emissions change occurs in these cases. We also exclude scenarios where disasters affect the collection point ($D_{i,tw}$ = 1), as the product not being shipped so the calculated shipping emissions are inapplicable. We use the following formula to evaluate the change in emissions:

$$\Delta Emissions = Emissions_{Rerouted} - Emissions_{Baseline} \quad (3)$$

where $\Delta Emissions$ represents the difference in emissions, $Emisisons_{Rerouted}$ refers to emissions on the disaster-altered route, and $Emissions_{Baseline}$ represents emissions on the unaffected route. The emission difference is measured in grams of CO_2 per ton. To align with the basis spread analysis, we convert the emission (grams/ton) to grams per bushel by dividing the emissions per ton by the number of bushels per ton for each crop. Emissions will vary by product, as a ton equals 39.37 bushels for corn and 36.74 bushels for soybeans (Iowa State University Extension and Outreach, 2024). Changes in emissions are analyzed across crop types, ports of exit, and counties of operation.

3. Data

The data used in the analysis spans from 2010 to 2022 and covers 16 states in the US Corn Belt region (see Table 2 for a list of states). The study focuses on elevators located in these states, with 3,889 corn elevators and 3,561 soybean elevators, from which corn and soybeans are transported to six major export ports, assumed by the researchers, which serve as key export points for U.S. grains and other products. Each elevator in these states can have one or more potential least-cost routes to the exit ports assigned based on spatial proximity (Table 2). Note that we map crops produced in most states to more than one port; we allow for multiple state-port arbitrage relationships to hold to reflect the potential for shipments to go in multiple directions. That said, the key goal is to include ports that appear reliably important and we hesitate to admit possible state-port pairings characterized by intermittent trade and limited arbitrage. These assignments are not subject to sensitivity testing at this time. For each elevator, the key variables in the dataset include the basis spread, transportation costs, and natural disasters, along with control variables such as crop production and total merchandise exports.

Table 2. Potential port of exit according state location of the elevators.

State	Potential port of exit
Arkansas	Laredo (TX), New Orleans (LA)
Colorado	Laredo (TX), Vancouver (WA)
Illinois	Duluth (MN), New Orleans (LA)
Indiana	Toledo (OH), New Orleans (LA)
Iowa	Duluth (MN), Laredo (TX), New Orleans (LA), Vancouver (WA)
Kansas	Laredo (TX), New Orleans (LA)
Kentucky	New Orleans (LA)
Michigan	Toledo (OH)
Minnesota	Duluth (MN), Vancouver (WA)
Missouri	Laredo (TX), New Orleans (LA)
Nebraska	Laredo (TX), Vancouver (WA)
North Dakota	Laredo (TX), Vancouver (WA)
Ohio	New Orleans (LA), Toledo (OH), Norfolk (VA)
Oklahoma	Laredo (TX), New Orleans (LA)
South Dakota	Duluth (MN), Vancouver (WA)
Wisconsin	Duluth (MN)

The basis spread ($B_{i,tw}$) data, sourced from the OCE-USDA (Office of the Chief Economist at the United States Department of Agriculture) database[4], consist of daily observations. For the purposes of this study, these daily values were aggregated into weekly averages. Transportation costs for corn and soybeans ($C_{i,tw}$) are calculated by combining two key variables: the traveled distance from each elevator to the exit port (measured in miles) and the transportation cost per mile per bushel. The shipping cost variable accounts for disruptions at both the collection point and along the transportation route. The GIS analysis provides the mileages across a multimodal transportation network—covering road, rail, and river segments. Transportation costs are drawn from publicly available freight rates (USDA - Agricultural Marketing Service, 2023a; Federal Reserve Economic Data, 2023), rail rates for the Minnesota to St. Louis segment (USDA - Agricultural Marketing Service, 2023a; USDA - Agricultural Marketing Service, 2013), and barge rates from St. Louis (USDA - Agricultural Marketing Service, 2023c). Using ordinary least squares (OLS) regressions, we link transportation rates to diesel prices (U.S. Energy Information Administration, 2023) to estimate the total transportation costs.

[4] Since soybean port prices for Vancouver were unavailable, we predicted them using the methodology outlined in Appendix 1.

The data on natural disasters is collected at the county level and consists of interval data. These intervals are converted to weekly values to align with the analysis's weekly time frame. The data source is the United States Department of Agriculture Farm Service Agency (USDA-FSA), which provides detailed, county-level information on disaster occurrences. The analysis considered several natural disasters that could affect the collection point and disrupt crop transportation, including flash floods, tornadoes, mudslides, winter storms, and hurricanes. For this study, it was found that hurricanes impact only counties along transportation routes rather than those at collection points.[5] The disaster data at the collection points were matched with the locations of crop collection points (counties where elevators are located) to create dummy variables ($D_{i,tw}$) indicating disaster events at these points. These dummy variables represent specific types of natural disasters that affect crop delivery at the collection point. Additionally, disaster data were matched with counties along the minimum-cost transportation route from the operation county to the export port. Dummy variables were also created for disasters occurring along the route, capturing the disruptions caused by these events. Frequency distributions of disaster types along the route for both corn and soybean elevators are presented in Table A1 of Appendix 2. The table shows that flash floods are the predominant type of disaster affecting the minimum cost routes for both crops.

For the control variables ($X_{i,t}$), crop production data consist of county-level annual observations, calculated using acreage and yield data from the USDA Farm Service Agency. Corn and soybean acreage data were drawn from annual acreage reports (USDA - Farm Service Agency, 2023a) and multiplied by the corresponding county-level yields (USDA - Farm Service Agency, 2023b). Monthly data on total merchandise exports were obtained from the United States International Trade Commission (USITC) data web portal. Table 3, presents summary statistics to provide a clear overview of the variables used in the empirical analysis..

[5] The distribution of natural disasters at the county level is presented in Figure A3 of Appendix 3.

Table 3. Summary statistics of the variables used in the empirical analysis (corn = 2,471,184 observations; soybeans = 2,169,755 observations)

Variable	Unit	Corn		Soybeans	
		Mean	Std. Dev.	Mean	Std. Dev.
basis spread	$/bushel	-0.299	0.472	-0.491	0.745
CostPerBushel	$/bushel	1.244	0.823	1.247	0.835
cost_routechange[a]	$/bushel	0.098	0.46	0.103	0.489
disasterdummy[b]	(0/1)	0.015	0.12	0.016	0.125
flashflood	(0/1)	0.014	0.117	0.015	0.121
tornado	(0/1)	0.002	0.043	0.002	0.046
winterstorm	(0/1)	0.004	0.063	0.004	0.061
mudslide	(0/1)	0.001	0.034	0.001	0.035
riveradjct_flashflood[c]	(0/1)	0.001	0.022	0.001	0.023
only_flashflood_rou[d]	(0/1)	0.035	0.183	0.034	0.182
only_tornado_rou[d]	(0/1)	0.003	0.057	0.003	0.057
only_winterstor_rou[d]	(0/1)	0.002	0.044	0.001	0.037
flashflood_other_rou[e]	(0/1)	0.014	0.116	0.013	0.112
production	10 million bushel/county	2.146	1.417	0.974	1.155
export	10 billions $	13.349	1.624	13.365	1.598
Duluth[f]	(0/1)	0.159	0.366	0.147	0.355
Laredo[f]	(0/1)	0.224	0.417	0.218	0.413
New Orleans[f]	(0/1)	0.321	0.467	0.333	0.471
Norfolk[f]	(0/1)	0.026	0.159	0.026	0.159
Toledo[f]	(0/1)	0.056	0.23	0.058	0.233
Vancouver[f]	(0/1)	0.215	0.411	0.218	0.413
RouteChange[g]	(0/1)	0.053	0.225	0.052	0.222
Emissions[h]	CO_2 grams/bushel	637.8	297.7	684.3	319.1

Notes:
[a] cost_routechange variable represents the interaction term CostPerBushel*RouteChange.
[b] disasterdummy takes the value of 1 if there are any disasters at the collecting point (i.e., flash flood, tornado, mudslide, winter storm), and 0 otherwise.
[c] riveradjct_flashflood variable takes the value of 1 if an elevator is adjacent to the river and a flash flood occurred in the county that week, and 0 otherwise.
[d] These variables take 1 if there is a specific disaster around the route (only flash flooding, only tornado, only winter storm), and 0 otherwise.
[e] flashflood_other_rou takes 1 if flash flood and other disasters (tornado, winter storm, mudslide, hurricane) are present along the route, and 0 otherwise.
[f] These variables take 1 if the elevator uses the specific port of exit, and 0 otherwise.
[g] Routechange takes 1 if there is one or more disaster along the route, and 0 otherwise.
[h] Greenhouse gas emissions account for disasters at the collection point and along the rout

4. Results

4.1 Basis spread regressions

Tables 4 and 5 represent the regression results for the basis spread. Column (1) presents the estimates based on Equation (1). Column (2) extends this model by incorporating the interaction term between the shipping cost and the route change variable. Column (3) reports Equation (1) estimates, accounting for specific disaster events. Finally, Column (4) extends the model presented in column 2 by considering specific disaster events. The results of the Hausman tests, with test statistics (Chi-squared statistic) ranging from 2,864 to 4,360 for the corn models and 1,430 to 2,476 for the soybean models, and corresponding p-values of zero for both, indicate a preference for the fixed effects specification over the random effects specification in our analysis. The results presented in Tables 4 and 5 are based on the fixed effects models.

The estimates align with the expected signs discussed in the methodology section. The cost per bushel variable (CostPerBushel) has a statistically significant effect across all columns for corn and soybeans. In the case of corn, a one-dollar increase in shipping cost per bushel is associated with a reduction in the basis spread by approximately \$0.393 to \$0.397 for corn and \$0.512 to \$0.546 for soybeans, depending on the model specification. This finding is consistent with expectations, as higher transportation costs decrease the price received by the elevator, given the price received at the port of exit.

As we mentioned, the coefficient for the interaction term between shipping cost and the route change variable (cost_routechange) provides insights into the severity of disruptions caused by disasters beyond what is captured by shipping cost estimates alone (CostPerBushel). In column 2 of Tables 3 and 4, This coefficient is positive and statistically significant (0.007 for corn and 0.0159 for soybeans), suggesting that the disruptions are less severe than indicated by changes in shipping costs. A \$1 increase in shipping costs leads to a change in the basis spread of -\$0.39 for corn (calculated as -0.397 + 0.007) and -\$0.387 for soybeans (calculated as -0.546 + 0.159). These results may reflect effective mitigation strategies against natural disasters that affect shipping costs, such as utilizing storage or redirecting shipments to other ports.

Table 4. Basis spread regression results - Corn

VARIABLES	(1)	(2)	(3)	(4)
CostPerBushel	-0.396***	-0.397***	-0.393***	-0.394***
	(0.000302)	(0.000311)	(0.000302)	(0.000312)
cost_routechange		0.00695***		
		(0.000439)		
disasterdummy	-0.486***	-0.486***		
	(0.00170)	(0.00171)		
cost_roucha_flash				0.0229***
				(0.000570)
cost_roucha_torna				-0.0748***
				(0.00140)
cost_roucha_winte				0.116***
				(0.00395)
cost_roucha_flash_other				0.00392***
				(0.000728)
flashflood			-0.407***	-0.409***
			(0.00198)	(0.00198)
tornado			-0.491***	-0.485***
			(0.00474)	(0.00474)
winterstorm			0.0517***	0.0475***
			(0.00347)	(0.00347)
mudslide			0.0562***	0.0580***
			(0.00596)	(0.00595)
riveradjct_flashflood			0.157***	0.153***
			(0.00913)	(0.00912)
production	-0.106***	-0.106***	-0.104***	-0.103***
	(0.000540)	(0.000540)	(0.000542)	(0.000544)
Export	0.0356***	0.0357***	0.0353***	0.0350***
	(0.000126)	(0.000127)	(0.000127)	(0.000127)
Constant	-0.0484***	-0.0484***	-0.0527***	-0.0498***
	(0.00182)	(0.00182)	(0.00183)	(0.00183)
Observations	2,471,184	2,471,184	2,471,184	2,471,184
R-squared	0.590	0.590	0.588	0.589

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5. Basis spread regression results – Soybeans

Variables	(1)	(2)	(3)	(4)
CostPerBushel	-0.512***	-0.546***	-0.507***	-0.537***
	(0.000570)	(0.000590)	(0.000569)	(0.000583)
cost_routechange		0.159***		
		(0.000791)		
disasterdummy	-0.679***	-0.705***		
	(0.00314)	(0.00312)		
cost_roucha_flash				0.306***
				(0.00101)
cost_roucha_torna				-0.0118***
				(0.00240)
cost_roucha_winte				0.0886***
				(0.00699)
cost_roucha_flash_other				-0.0327***
				(0.00129)
flashflood			-0.584***	-0.618***
			(0.00360)	(0.00353)
tornado			-0.575***	-0.587***
			(0.00834)	(0.00817)
winterstorm			-0.0304***	-0.0190***
			(0.00668)	(0.00654)
mudslide			0.281***	0.302***
			(0.0111)	(0.0109)
riveradjct_flashflood			0.171***	0.128***
			(0.0171)	(0.0167)
production	-0.0141***	-0.00861***	-0.0140***	-0.0126***
	(0.000423)	(0.000420)	(0.000424)	(0.000417)
export	0.0419***	0.0433***	0.0416***	0.0419***
	(0.000267)	(0.000265)	(0.000268)	(0.000263)
Constant	-0.388***	-0.385***	-0.391***	-0.377***
	(0.00338)	(0.00335)	(0.00339)	(0.00332)
Observations	2,169,755	2,169,755	2,169,755	2,169,755
R-squared	0.474	0.484	0.473	0.495

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Column 4 of Tables 3 and 4, we report the coefficients for the interaction terms between shipping costs and specific disasters along the transportation route. The positive and statistically significant coefficients for the interactions between shipping cost and flash floods alone (cost_roucha_flash) and winter storms alone (cost_roucha_winte) suggest that the cost impacts of these events are less severe compared to what is initially indicated by shipping costs for both corn and soybeans. This finding potentially reflects the effectiveness of mitigation strategies implemented to counteract the effects of flash floods and winter storms along transportation routes. In contrast, the negative coefficient for the interaction between shipping cost and tornadoes alone (cost_roucha_torna) for both crops indicates a more severe negative impact on the basis spread, exceeding the effects of shipping costs. This result highlights the challenges of tornadoes, such as trip rerouting, which increases fuel costs due to longer or less fuel-efficient routes. Additionally, rerouting requires more planning and coordination, further elevating expenses. Finally, the interaction term between shipping cost and flash floods combined with other disasters (cost_roucha_flash_other) yields contrasting results: a positive coefficient for corn and a negative coefficient for soybeans. These differences could reflect distinct sensitivities of each crop to disaster impacts, potentially influenced by differences in logistical strategies for mitigating disaster effects and market dynamics. Also, these differences may be partly attributable to the differing sample sizes for soybeans and corn.

The impact of shipping costs on the basis spread is partly attributed to disruptions in the crop distribution network caused by natural disasters. Consequently, we can discern the influence of natural disasters on shipping costs.[6] During the sample period, on average, any disaster increased shipping costs by $0.01 per bushel for corn and $0.20 per bushel for soybeans. The disparity in effects between corn and soybeans arises from differences in how transportation costs (CostPerBushel) affect the basis spread for each crop, with a more pronounced impact on soybeans. Regarding specific disasters, winter storms (only winter storms around the route) have the most important effect on corn, raising shipping costs by $0.15 per bushel. Only flash floods around the route impact soybeans with the most critical effect, increasing shipping costs by $0.38 per bushel.

The presence of natural disasters at collection points, as captured by the disaster dummy variable, significantly affects the basis spread. Elevators located in disaster-affected areas experience a basis spread reduction of $0.49 for corn and $0.68 to $0.71 for soybeans compared to those in unaffected areas. Natural disasters disrupt elevators' ability to transport crops to ports of exit, increasing local supply and lowering local prices relative to export prices. Considering specific disasters at the collecting point (i.e., flash flood, tornado, mudslide, and winter storm dummy variables), we observe the same negative effect associated

[6] See Appendix 4 for details on calculating the effect of natural disasters on shipping costs.

with flash floods and tornadoes for corn and soybeans. Also, the soybean model reveals a negative effect associated with the winter storm dummy variable. These findings align with the notion that natural disasters hinder elevators' ability to transport grain to ports of departure, leading to an increase in local supply and a decrease in local prices relative to export prices. Conversely, mudslides in corn and soybean models and winter storms in the corn model show a positive effect. This outcome might reflect how disasters at collection points can prevent the inflow of crops from neighboring regions, reducing local supply in the affected area, increasing local prices relative to export prices, and consequently widening the basis spread. Additionally, the dummy variable for river-adjacent flash floods shows a positive effect, possibly due to natural barriers restricting crop inflows from surrounding regions, further decreasing local supply and increasing local price compared to export price.

Finally, concerning the control variables, we observe the expected signs for production and export. The production variable consistently shows a negative coefficient in all crop regressions. Increasing crop supply may pressure the distribution system as production rises, leading to lower local prices than port prices, thereby decreasing the basis spread. The export variable displays a positive coefficient in all regressions for both crops. Increased demand for commodities like corn and soybeans can lead to higher local prices relative to port prices, thus raising the basis spread.

4.2 Changes in emissions due to route disruptions

We analyze emissions, measured in CO_2 per bushel transported by comparing emissions from disrupted routes taken due to disasters along the route with those from the baseline route, as described in Equation (3). Table 6 presents the emissions (measured in grams of CO_2 per bushel) by port of exit for corn (panel A) and soybeans (panel B). The table provides the mean emissions for the rerouted route (Column 1), the baseline route (Column 3), and the change in emissions per unit transported, calculated as the difference between the rerouted and baseline routes (Column 5). Vancouver consistently exhibits the highest emissions per unit transported among all ports of exit across both the baseline and rerouted scenarios for corn and soybeans. This is the case because Vancouver, on average, is the longest potential transportation route from collection points to the port, associated with a heavy reliance on rail transport—the second most emission-intensive mode of transport after road. The average distance from the elevators to Vancouver is 1,805 miles under baseline, with approximately 97% of the route covered by rail, 1.9% by river, and 1.1% by road transportation. Conversely, Toledo consistently demonstrates the lowest emissions per unit transported for both crops and rerouted and baseline routes. This port benefits from the shortest distance between collection points and exit port, averaging 190 miles under the baseline scenario, with 89% of transportation by rail, 6.8% by river, and 3.5% by road.

Table 6. Average emissions (CO_2 Grams per Bushel) for rerouted and baseline routes, and emission changes

Port of exit	Rerouted		Baseline		Change = Rerouted - Baseline	
	Mean (1)	Std. Dev. (2)	Mean (3)	Std. Dev. (4)	Mean (5)	Std. Dev. (6)
A. Corn						
Duluth	435.32	257.04	293.31	98.06	142.01	243.20
Laredo	881.40	206.57	661.48	137.47	219.92	187.58
New Orleans	759.40	135.50	662.27	97.25	97.14	105.67
Norfolk	599.57	190.03	437.54	46.63	162.02	179.21
Toledo	268.97	167.39	128.43	61.41	140.54	143.45
Vancouver	1,171.44	198.81	1,039.85	123.05	131.59	213.08
Total	883.27	321.59	724.05	285.95	159.22	194.11
B. Soybeans						
Duluth	535.95	389.45	307.72	103.84	228.23	379.04
Laredo	941.79	225.22	701.65	151.98	240.15	204.42
New Orleans	808.66	142.14	704.46	103.46	104.21	110.21
Norfolk	640.48	205.69	467.12	48.08	173.36	195.10
Toledo	277.58	175.32	132.73	62.77	144.85	152.02
Vancouver	1,263.92	225.00	1,115.37	131.36	148.55	245.80
Total	958.93	348.01	781.36	306.42	177.57	222.60

Note: The calculation considers only observations with route change (RouteChange = 1)

In terms of changing emissions per unit transported, Laredo stands out as the port of exit most impacted by disruptions (rerouted minus baseline). On average, route disruptions increased transportation emissions by 220 grams of CO_2 per bushel for corn and 240 grams per bushel for soybeans. This outcome is primarily driven by the high frequency of flash flooding events along the routes connecting collection points to Laredo. Flash flooding is the sample's most common type of disaster, occurring in 3.5% of the weeks in this study. Notably, routes to Laredo are affected by flash flooding in 8.5% of weeks in this study, accounting for 55% of all such events across the six analyzed ports. Also, for Laredo, disrupted routes rely more on transportation modes associated with higher emissions than the baseline route. For example, in the case of corn , under the baseline scenario, the average distance traveled by road—the most pollutive mode of transportation—is 14.7 miles. However, in the rerouted scenario, the average road distance increased to 38.1 miles, reflecting a significant shift from the baseline. A similar trend is observed for corn shipments to Norfolk and soybean shipments to Duluth, the second most affected ports in emission changes for corn and soybeans, respectively. Under the baseline condition, the average road distance to Norfolk is 9.3 miles, which increases to 33.5 miles in the rerouted scenario. Duluth's average road distance rises from 16.5 miles under baseline conditions to 63.9 miles when rerouted. In contrast, New Orleans port experiences the least change in emissions, as transportation to this port primarily relies on river transport, which is the least polluting mode. On average, approximately 79% of the distance from the elevator to this port is traveled via river under both rerouted and baseline scenarios. Disruptions along the route increase reliance on river transport, with an average of 1,209 miles traveled in the rerouted scenario compared to 1,140 miles in the baseline in the corn case. However, disrupted routes also require greater use of road transport — a more polluting mode — than under baseline conditions.

Table 7 presents the changes in transportation emissions (grams of CO_2 per bushel) across types of disasters and crops. Flash flooding alone results in the highest average increase in transportation emissions for corn (185.35 grams CO_2/bushel) and soybeans (201.63 grams CO_2/bushel). This result can be attributed to the disrupted route's increased reliance on transportation modes with higher emissions, such as road transport, which is the most polluting. For instance, in the case of corn under scenarios with only flash flooding, the average road miles for the disrupted route were 525.7 miles, compared to just 194.5 miles for the baseline route. This substantial shift to road transportation significantly amplifies emissions per unit shipped.

Table 7. Change in emissions (rerouted – baseline) CO_2 grams per bushel by disaster type

	Corn		Soybeans	
Type of disaster	Mean (1)	Std. Dev. (2)	Mean (3)	Std. Dev. (4)
Only flash flooding	185.35	199.29	201.63	223.95
Only tornado	115.53	93.57	133.39	144.26
Only winter storm	112.25	253.23	175.13	364.72
Flash flooding and other disasters	110.29	175.36	124.3	203.2

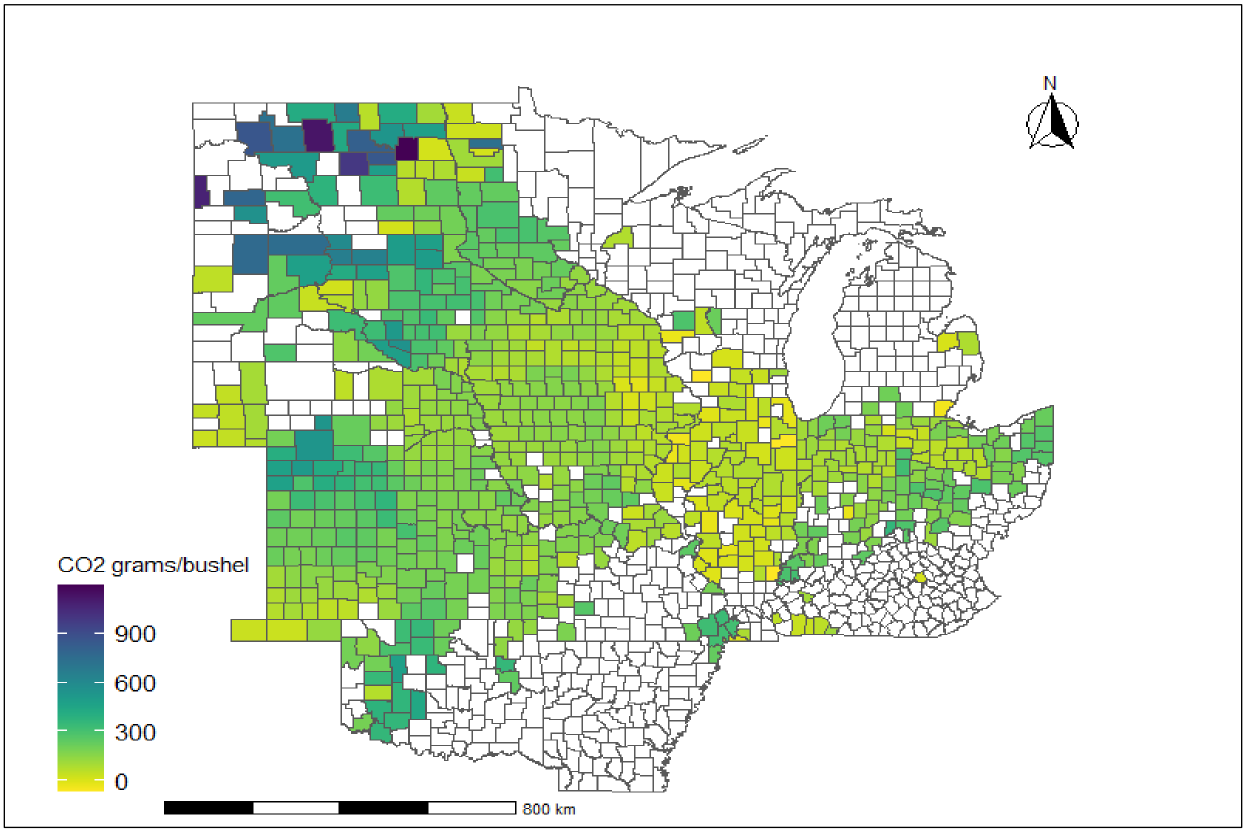
Note: The calculation considers only observations with route change (RouteChange = 1)

4.2.1 Change in emissions from transportation by county of origin

Figure 1 illustrates the change in emissions per unit transported to export ports at the county level for corn. North Dakota exhibits the largest change, with 53 counties reporting an average increase of 456.2 CO_2 grams per bushel transported during the sample period. This substantial change in transportation emissions can be attributed to the longer transportation distances to potential exit ports, such as Vancouver and Laredo, compared to elevators in other states. Additionally, the shift to more pollutive transportation modes due to disasters along the route plays a meaningful role in increasing transportation emissions. South Dakota follows with a notable emission change, averaging 315.3 CO_2 grams per bushel across 66 counties experiencing emission changes. Other states include Oklahoma (77 counties), Nebraska (93 counties), Kansas (105 counties), and Minnesota (87 counties). The counties in these states show important emission changes, with county-level averages exceeding the overall county-level average of 174.91 CO_2 grams per bushel transported.

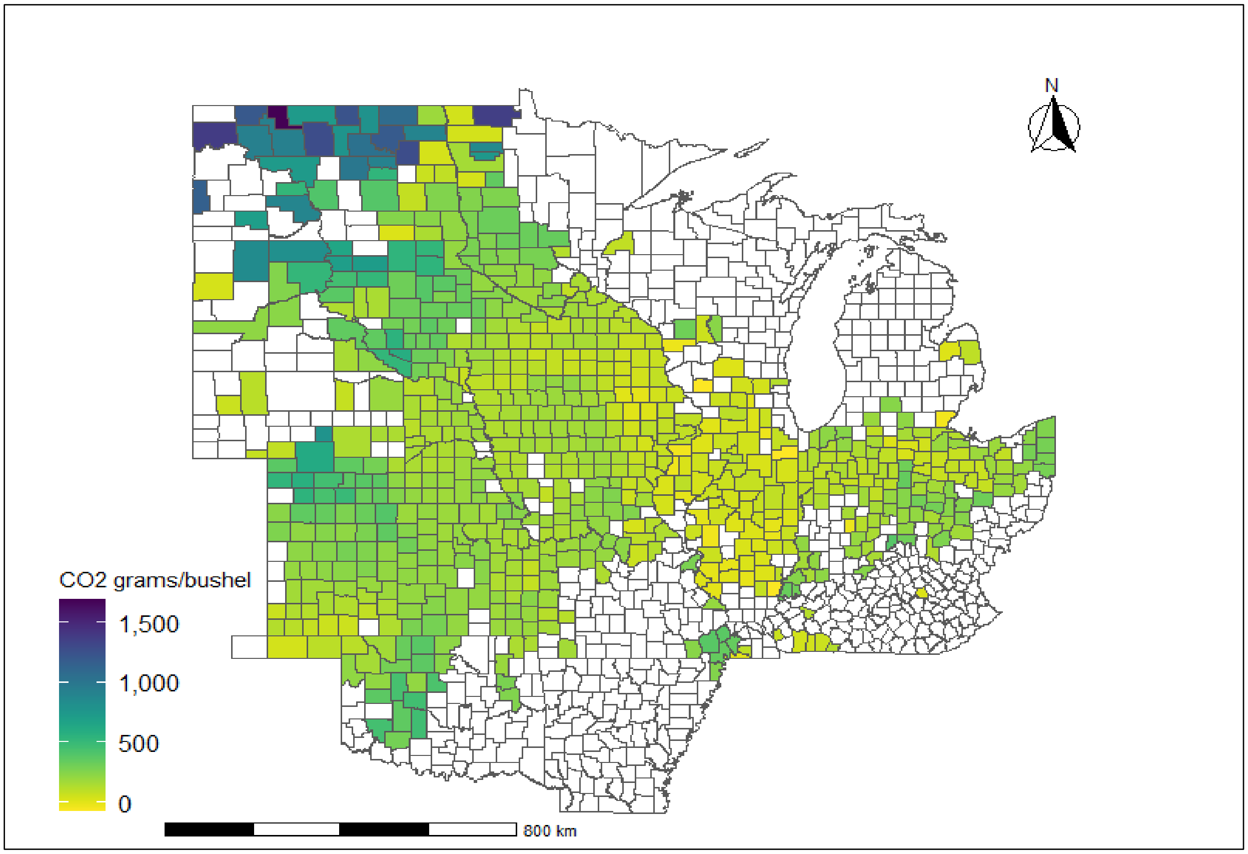
In Figure 2, we conduct a similar analysis for soybeans, and the results are comparable to those for corn. The states of North Dakota, South Dakota, Oklahoma, Nebraska, Minnesota, and Kansas emerge as the regions with the largest number of counties and average transportation emission changes. The changes in transportation emissions for soybeans are more pronounced than for corn, primarily because soybeans have lower bushels per ton than corn, resulting in higher emissions per ton transported.

Figure 1. Average change (rerouted – baseline) in emissions from transportation (CO_2 grams per bushel) due to disasters along the route by county of origin - Corn



Notes: Mean = 174.91, Min = -66.75, Max = 1,196.24. The calculation considers only observations with route change (RouteChange = 1). The emission change can be negative because the rerouted route may generate less emission than the baseline scenario. Top 25 counties with the highest emission changes: Nelson (ND), McHenry (ND), Golden Valley (ND), Wells (ND), Mountrail (ND), Eddy (ND), Benson (ND), Stark (ND), Perkins (SD), Corson (SD), Pennington (MN), Ward (ND), Rolette (ND), Walworth (SD), Edmunds (SD), Campbell (SD), Hettinger (ND), Douglas (SD), Lincoln (NE), Logan (NE), Ramsey (ND), Aurora (SD), Hayes (NE), McLean (ND), Day (SD).

Figure 2. Average change (rerouted – baseline) in emissions from transportation (CO_2 grams per bushel) due to disasters along the route by county of origin - Soybeans



Notes: Mean = 203.74, Min = -75.99, Max = 1,690.92. The calculation considers only observations with route change (RouteChange = 1). The emission change can be negative because the rerouted route may generate less emission than the baseline scenario. Top 25 counties with highest emission change: Renville (ND), Williams (ND), Roseau (MN), Nelson (ND), McHenry (ND), Rolette (ND), Burke (ND), Ramsey (ND), Golden Valley (ND), Cavalier (ND), Benson (ND), Wells (ND), Ward (ND), Mountrail (ND), Eddy (ND), Walsh (ND), Morton (ND), Pennington (MN), Perkins (SD), Corson (SD), Towner (ND), Logan (NE), Pierce (ND), Red Lake (MN), McLean (ND).

5. Conclusions

This study investigates the economic and environmental impacts of weather extremes on the US crop transportation network, focusing on corn and soybeans. More specifically, we assess how weather-induced disruptions to transportation routes influence basis spreads and transportation emissions. Weather extremes, such as flash floods that submerge railways and winter storms that freeze roadways, can seriously hinder crop movement, affecting both economic efficiency and environmental outcomes. By quantifying the dual impact of weather extremes on crop transportation, this research fills a critical gap in the literature. While a limited number of previous studies have explored the economic consequences of crop transportation disruptions, our study uniquely incorporates an assessment of their environmental implications, particularly CO_2 emissions, providing new and valuable insights into this underexplored area.

Our findings demonstrate that weather extremes at collection points, such as flash floods and tornadoes, negatively affect the basis spread for both corn and soybeans. This outcome can be attributed to barriers these events impose on collection points, hindering the movement of crops to exit ports. As a result, local supply increases, driving down local prices relative to port export prices. In contrast, mudslides have a positive impact on the basis spread. Disruptions at operational points can prevent the inflow of crops from surrounding areas into the affected region, thereby reducing local supply and raising local prices relative to the port price. Furthermore, our analysis highlights the significant role of disasters occurring along transportation routes, which influence the basis spread through their impact on transportation costs. Natural disasters along the route lead to higher shipping costs. Over the sample period, the basis spread shocks up to -\$0.40 per bushel for corn and -\$0.53 per bushel for soybeans for every dollar increase in shipping costs, with part of this effect linked to disruptions in the crop distribution network. When disaggregating the impact of specific disasters on transportation costs, we find that flash floods have the largest impact on soybean shipping costs, increasing them by \$0.38 per bushel, while winter storms have the largest impact on corn shipping costs, increasing them by \$0.15 per bushel.

In addition to the economic consequences, this study highlights the environmental implications of weather-induced disruptions in the transportation network. Our analysis shows that extreme weather events, particularly flash floods, tornadoes, and winter storms, result in higher emissions due to increased travel distances using more pollutant transportation modes. Forced detours and the increase of reliance on less fuel-efficient routes or transportation modes contribute to elevated emissions levels. The results reveal that, on average, emissions increase by 156 grams of CO_2 per bushel for corn transported and 177 grams of CO_2 per bushel for soybeans shipped for export during weather-related disruptions. Our results reveal that the most affected routes are those with final destination of Laredo and Norfolk for corn, and Laredo and Duluth for soybeans. The result is attributed to the fact that disasters along the route increase significantly the traveled distance for the most pollutant transportation mode, that is road transportation.

These findings have implications for policymakers aiming to enhance the efficiency of the U.S. crop transportation network. The results emphasize the potential value of targeted investments in resilient infrastructure at critical collection points and along transportation routes to mitigate the economic disruptions caused by weather extremes. Strengthening transportation networks to withstand events such as flash floods and winter storms can help stabilize basis spreads, ensuring a more predictable distribution of economic impacts across regions. Additionally, policies promoting the adoption of cleaner, more fuel-efficient transportation means and optimizing detour routes during disruptions could reduce the emissions associated with crop transportation. Identifying and prioritizing high-risk routes, such as those leading to Laredo, Norfolk, and Duluth, for interventions could yield the most significant benefits in minimizing the adverse effects of weather-induced disruptions.

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Appendices

Appendix 1. Prediction of Vancouver port price for soybeans

We present a method for predicting soybean port prices in Vancouver. To validate the approach, we first test it using the corn crop, for which actual port prices in Vancouver are available, enabling an assessment of its accuracy. After validation, we apply the method to estimate soybean port prices in Vancouver. These are the main steps for predicting and comparing our predictions.

1. Select the elevator located in North Dakota to predict the Vancouver Port. North Dakota is the closet state to Vancouver Port. We have 167 elevators and for each elevator we have 663 weeks between 2010 and 2022. In total we have 75,074 observations or week where the elevator is located in North Dakota and the port of exit is Vancouver.

2. To calculate the predicted port price in Vancouver. We calculate a variable that is the sum of the local price (we have the local price for every elevator) plus the cost per bushel to transport a bushel from the elevator to Vancouver port (in our data set, we have the number of miles and the cost per bushel for every mode of transportation). We call this variable LocalPrice&TransportCost. To calculate the cost, we only use the routes towards Vancouver, and we use the baseline route with no disruptions. Therefore, the LocalPrice&TransportCost is defined as follows:

   $$LocalPrice\&TransportCost = LocalPrice + TransportCost \qquad \text{(A1)}$$

   Where $LocalPrice$ refers to the local price, price received at collection point. The transportation cost is defined as:

$$TransportCost = Road\_Miles \cdot Cost\_Bushel\_Mile\_Raod\_Corn + Rail\_Miles \cdot Cost\_Bushel\_Mile\_Rail\_Corn + River\_Miles \cdot Cost\_Bushel\_Mile\_River\_Corn \quad \text{(A2)}$$

Where $Road\_Miles$, $Rail\_Miles$, and $River\_Miles$ are the distance of road, rail, and rivel miles, respectively. $Cost\_Bushel\_Mile\_Raod\_Corn$, $Cost\_Bushel\_Mile\_Rail\_Corn$, and $Cost\_Bushel\_Mile\_River\_Corn$ are the cost per bushel per mile for road, rail and river, respectively.

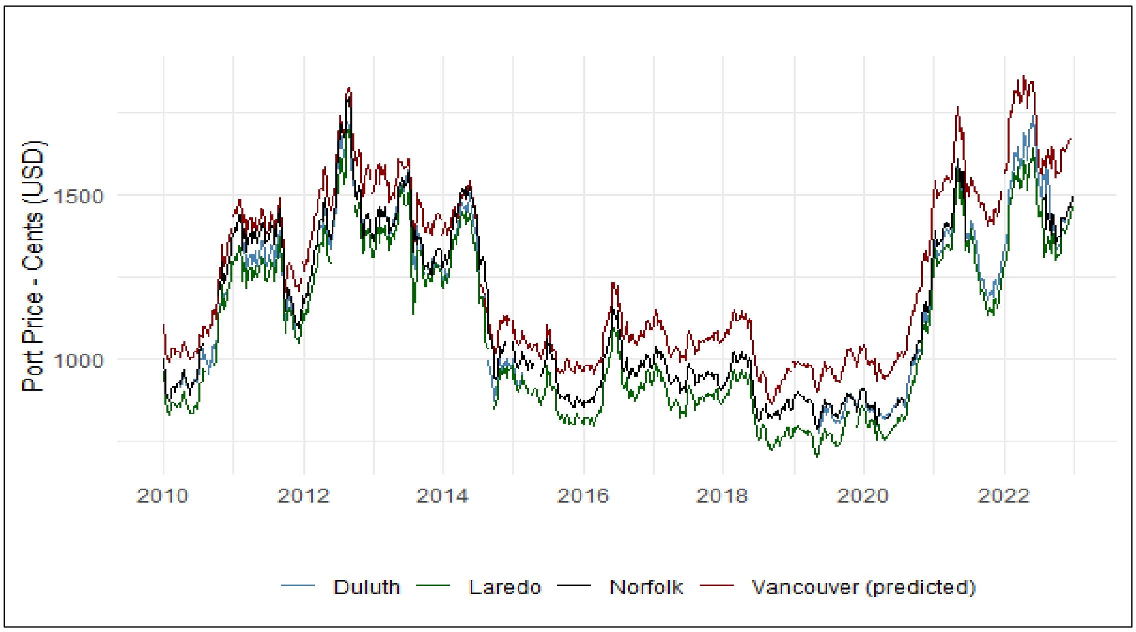
3. Once we have the LocalPrice&TransportCost variable for every week, we calculate the average at the weekly level of this variable. In each week, we calculate the average using the 167 elevators in North Dakota. This average will be our predicted port price in Vancouver.

4. We compare the predicted port price in Vancouver with the actual port price for the corn crop. We observe that both series, actual and predicted, follow the same trend, although the predicted (red line) overestimates the actual port price (blue line) in most cases, see Figure A1.

Figure A1. Predicted Vs. actual corn price in Vancouver

5. We estimate the prediction for the port price of soybeans in Vancouver following the previous steps used to predict the port price of corn and using the sample related to soybeans elevators with the cost per bushel per mil of soybeans as well. In Figure A2, as we cannot compare with the actual soybean price in Vancouver, we show the prediction for soybeans and compare it with the actual port price of soybeans in other ports (Duluth, Laredo, and Norfolk). We observe that the port price in Vancouver is the highest compared to the other ports. We also observe the same pattern in the corn case, Vancouver has the highest port price.

Figure A2. Predicted soybeans port price in Vancouver Vs. current port price in other ports



Appendix 2. Disasters along the route

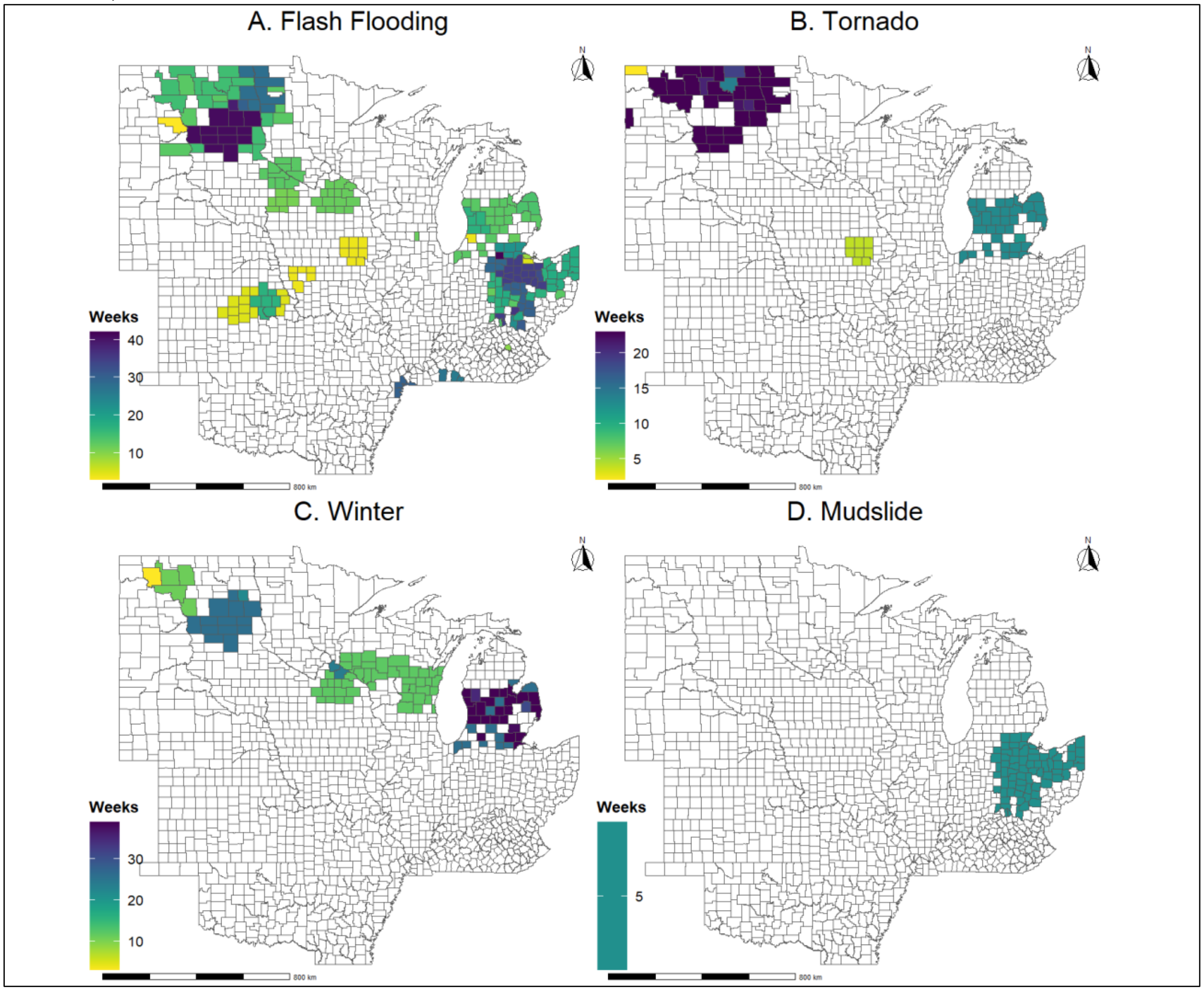
Table A1. Distribution of disasters along the route

Disaster along the route	Corn		Soybeans	
	Freq.	Percent	Freq.	Percent
only flash flood	85,306	3.45%	74,571	3.44%
only tornado	7,941	0.32%	7,173	0.33%
only winter storm	4,762	0.19%	3,044	0.14%
flash flood, hurricane	4,049	0.16%	3,634	0.17%
flash flood, hurricane, tornado	748	0.03%	698	0.03%
flash flood, landslide	68	0.00%	45	0.00%
flash flood, landslide, winter storm	10	0.00%	10	0.00%
flash flood, winter storm	27,123	1.10%	21,486	0.99%
flash flood, tornado	558	0.02%	507	0.02%
flash flood, tornado, winter storm	1,331	0.05%	1,203	0.06%
No disaster	2,339,288	94.66%	2,057,384	94.82%
Total	2,471,184	100.00%	2,169,755	100.00%

Note: A minimum cost route can be affected by three disasters in the same week.

Appendix 3. Distribution of natural disasters at county level

Figure A3. Distribution of natural disasters at county level between 2010 – 2022 (number of weeks)



Appendix 4. Effect of natural disasters on shipping cost

To estimate the impact of natural disasters on shipping costs, we utilize Equation A3, incorporating the coefficients from Column 2 of Tables 4 and 5. When the disaster variable is considered in aggregate terms.

$$EDC = [(\beta_{CostPerBushel} + \beta_{cost\_routechange}) \cdot CostPerBushel_{rerouted}] - [\beta_{CostPerBushel} \cdot CostPerBushel_{base}] \quad \text{(A3)}$$

Where EDC represents the effect of the disaster on shipping costs. $\beta_{CostPerBushel}$ is the coefficient for the CostPerBushel variable, while $\beta_{cost\_routechange}$ is the coefficient for the interaction term between cost per bushel (CostPerBushel) and the route change (RouteChange) variables. $CostPerBushel_{rerouted}$ denotes the shipping cost per bushel under a disrupted route, and $CostPerBushel_{base}$ represents the shipping cost per bushel under baseline route. Also, we can calculate the effect for every specific disaster considering the column 4 of Tables 4 and 5. Under the specific disaster, we change the $\beta_{cost\_routechange}$ coefficient in the equation (A3) with the corresponding coefficient associated with the interaction term between the cost per bushel variable and the specific disaster dummy variable ($\beta_{cost\_roucha\_flash}$ for only flash floodings, $\beta_{cost\_roucha\_torna}$ for only tornadoes, $\beta_{cost\_roucha\_winte}$ for only winter storms, and $\beta_{cost\_roucha\_flash\_other}$ for flash flooding and other disaster). We apply Equation (A3) to the entire sample to compute the average effect of the disaster on shipping costs. The results are presented in Table A2, with the first row showing the effect of the aggregated disaster along the route and rows 2 through 5 displaying the effects of the specific disasters.

Table A2. Effect of natural disaster on shipping cost ($ per bushel)

Effect	Corn		Soybeans	
	Mean	Std. Dev.	Mean	Std. Dev.
Any disaster	0.0105	0.0697	0.198	0.1492
Only flash flood	0.0304	0.0687	0.3818	0.2509
Only tornado	-0.0912	0.1024	-0.015	0.1109
Only winter storm	0.1467	0.1064	0.1102	0.1143
Flash flood and other	0.029	0.2722	0.0302	0.2896