Report to Agricultural Marketing Services
of the United States Department of Agriculture

Inferring impacts of weather extremes on the US crop transportation network

by Theodoros Skevas, Benjamin Brown, and Wyatt Thompson

of the Division of Applied Social Sciences, University of Missouri, Columbia, MO

<u>Final report</u> - Agreement No. 20-TMTSD-MO-0002, Amendment No. 2

January 12, 2024

Acknowledgments
This research was supported by Cooperative Agreement Number 20-TMTSDMO-0002 with the U.S. Department of Agriculture, Agricultural Marketing Service.

The findings and conclusions in this publication are those of the authors and should not be construed to represent any official USDA or U.S. Government determination or policy nor the views of the University of Missouri.

1. Introduction

Basis spread between the prices at collection points in the interior of the United States and the port depends in part on the infrastructure of moving grain from these locations to destinations. This infrastructure can be disrupted by weather extremes and natural hazards. Floods can submerge bridges and railroads that travel in the flood plains, forcing delays and detours on crop transportation. Severe winds, hail, and landslides can slow or halt traffic. Scientists express concerns that weather extremes could become more frequent in the future. If so, this could lead to increased disruptions in the crop transportation network, which could in turn increase food insecurity (e.g., through limiting food availability or raising food prices) and jeopardize farm incomes (e.g., by reducing crop sales). Therefore, gaining a better understanding of the effects of natural hazards on the crop distribution infrastructure is critical as it could allow the development of mechanisms to mitigate these impacts and reduce the associated risks to producers, consumers, and traders.

Despite the importance of assessing the effects of weather extremes on the transportation network that moves crops from production centers to ports of exit, relevant literature is scarce. Past studies have mainly investigated the impact of weather extremes on farm production and prices (Mishra & Cherkauer, 2010; Miao et al., 2016; Haile et al. 2017; Vogel et al., 2019; Ubilava, 2017, 2018; Gutierrez, 2017; Nam, 2021). Most of these studies report significant linkages between weather anomalies and farm production and commodity prices. A few studies have examined the impact of weather extremes on the U.S. transportation infrastructure (Millerd, 2011; Peterson et al., 2006; Caldwell et al., 2002), but not particularly their influence on the U.S. crop distribution network. These studies find that extreme weather events are likely to adversely affect the U.S. transportation infrastructure.

Against this background, the objective of this study is to assess the impact of weather extremes on the U.S. crop export infrastructure. Given that commodity basis determines trade and grain flows (McKenzie, 2005), this study infers impacts on the U.S. crop distribution network by mapping how crop basis spread is affected by extreme weather events. Weather predictions include the risk of more frequent weather extremes. These shocks to the US crop infrastructure could have real effects by driving basis down, meaning the gap between export and farm crop prices widens. These consequences would harm crop producers and sellers. This research could help identify threats to the infrastructure and provide information relevant to planning future investments in this system.

The remainder of this report is organized as follows: section 2 describes the methods used to conduct the analysis. Data are discussed in section 3. Estimation results are detailed in section 4, followed by conclusions in section 5.

2. Overview of the methods

A three-step procedure was used to assess the effect of weather extremes on crop basis spread. In the first step, hypothetical least cost-routes for transporting crops from sample elevators to the port of NOLA were developed. Second, least-cost routes were re-calculated to account for natural disasters blocking the crop transportation pathways. Finally, transportation and natural disaster indicators generated from step two along with control variables were used in an econometric model to determine the effect of weather extremes on crop basis spread. These different steps are described in more detail below.

2.1 Developing hypothetical least-cost routes for transporting crops to NOLA

Least-cost routes for transporting crops to the port of New Orleans were computed using GIS techniques. The first step in this process was to combine the coordinates of sample elevators with geospatial data on roads, railways, and navigable rivers (i.e., Mississippi, Ohio, and Illinois Rivers). These combined data were then used to create a network dataset with roads, railways, and rivers as edges, and grain elevators as nodes. It is common for a bushel of grain to use at least two of these transportation modes before reaching an end user (Gastelle et al., 2017). The following cost levels were associated with each type of edge: 0.1/mile for truck, 0.001/mile for rail, 0.00001/mile for barge. These artificial costs were used to enforce the following hierarchy of transportation modes: 1) rivers, 2) railways, and 3) roads. This hierarchy puts crops on rail instead of road, and on river instead of rail to reflect relative transportation cost as one moves along the hierarchy. This hierarchy reflects the fact that barge is the most cost-effective mode of grain transportation from the upper Mississippi river basin to NOLA (Horn, 2020). At least two thirds of U.S. corn and soybean exports are transported by barge, with inland waterway transport accounting for about half of the U.S. grain exports (Fuller et al, 2004; Gastelle et al., 2017). The base (i.e., disruption free) least cost routes of sample elevators is shown in Figure 1. The artificial costs used to impose the hierarchy of transportation modes is not used to calculate the implied transportation cost for each route. Instead, weekly national average costs of shipping crops are estimated from available historical data and the product of these values and usage of each mode drive the transportation cost variable.

It is important to note here that the generated routes are hypothetical least-cost routes for goods leaving the sample elevators for New Orleans exclusively via the Mississippi River. We acknowledge that the actual routes can differ because (a) costs are not common among all routes of a type, with each span of road, rail, or river probably having at least some difference in cost, (b) not all crops go via the Mississippi River to New Orleans, with any amount moving out of the region in a different direction or even used in the region, although that's not directly relevant to our look into the price spreads relative to the port, and (c) there will always be some error.

2.2 Hypothetical least-cost solutions accounting for natural disasters

To identify disruptions blocking the crop transportation pathways, the elevator-specific least-cost routes developed in the previous step were overlaid onto maps of county-specific weekly natural disaster data (see the Data section for details on natural disasters). Natural disasters can occur at the county where an elevator is located and/or along its least-cost route (developed in step 1). In the first case, no route is drawn to the elevator the week that the disaster took place, consistent with the possibility that disasters at the collection point tend to disrupt transactions. For disasters occurring along the route, a new route bypassing the affected counties is drawn. This procedure is depicted in Figure 2. The left image in this figure shows the least-cost (undisrupted) routes of three elevators (depicted by circles). The right image shows how the least-cost routes of the same three elevators are affected when the county in red acts as a barrier due a natural disaster occurring in that county in a particular week. No route is drawn to the elevator in the center of the affected county. For the elevator located to the north east of the affected county, a new route (heading south, and then west) bypassing the affected county is drawn. For the elevator located west of the affected county, its route is not impacted by the natural disaster. Once again, weekly national average transportation costs by mode are combined with the transportation path after the disruption to estimate the implied cost effects. The least-cost solution with disaster constraints allows the calculation of elevator-specific crop transportation costs that account for the impact of natural disasters. It further allows identification of the type of disaster affecting crop transportation and whether the disaster occurred at the elevator point or along the route.

2.3 Basis spread regression

The effects of weather extremes on crop basis spread of grain collection points in the central US states were assessed using an econometric panel data model. This model explains changes in basis spread as a function of crop transportation cost, weather extremes (i.e., natural disasters), and control variables. Estimation of basis spread is performed using the equation below:

$$B_{i,tw} = \beta_0 + \beta_1 C_{i,tw} + \beta_2 D_{i,tw} + \beta_3 X_{i,tw} + \gamma_i + \epsilon_{i,tw} \qquad (1)$$

where $B_{i,tw}$ is the weekly average commodity basis spread quoted by elevator i in week w of year t, $C_{i,tw}$ is the shipping cost along the hypothetical least-cost route that accounts for natural disasters, $D_{i,tw}$ are disaster dummies indicating whether a natural disaster occurred at the elevator's county of operation, $X_{i,tw}$ is a vector of control variables, γ_i denotes fixed effects that account for time-invariant differences across elevators, $\varepsilon_{i,tw}$ is an error term, and the betas are parameters to be estimated. Control variables include crop production and ethanol intensity (described in more detail in the Data section). Equation (1) was estimated separately for corn and soybeans. We include an 'aggregate' disaster dummy in the basis spread estimation as an initial test for evidence of the impact of any type of natural disaster on basis spread. We also re-estimate the basis spread model with separate natural disaster dummies to assess the effect of individual disasters on basis spread. Model 1 is also re-estimated by including the interaction term of the recalculated shipping cost and a dummy variable indicating whether the route has changed because of a disaster hitting the route.[1] This variable could help see if disruptions are less or more serious than implied by the shipping cost calculations. For example, a negative value could measure if shippers can mitigate the cost impact implied by the rerouting through other responses, such as storage or selling to a different end user on a different path.

The cost of moving a crop to market is expected to have a negative impact on basis spread. Higher shipping costs lead to lower local price for a given port price. A disaster at the collection point would tend to disrupt transactions, but the effect on basis spread is uncertain. If the marginal flow is from crop stored at the collection point out to broader markets, then inability to move crops out might push down basis. If the marginal flow is from fields or neighboring collection points to the collection point in question, then the inability to move crops in might push up basis. Crop production is an indicator of local supply and demand conditions around the collection point. Higher local supply suggests more supply pushes crops through the system

[1] The route change dummy was not included in estimations because it was found to be almost perfectly correlated with its interaction with the recalculated shipping cost variable.

and is expected to decrease basis. Finally, ethanol production around the collection point should raise basis (i.e., increase local price relative to a given port price) for corn and likely for soybeans, too. More local use of crop means less stress on the system to move the crop to the port for export.

3. Data

Data on corn and soybean basis spread, grain collection points' location, natural disasters, data on transportation costs of corn and soybeans, and data on control variables over the period 2012-2020 were collected for all states of the upper Mississippi river basin.[2] The basis spread data are daily observations (transformed to weekly values) for 2,595 and 2,304 corn and soybean elevators and were retrieved from Refinitiv Thomson Reuters database. The geographic distribution of sample elevators is shown in Figure 1. Natural disaster data are county-specific interval operations (transformed to weekly values) and were retrieved from United States Department of Agriculture Farm Service Agency (USDA-FSA). Disaster declaration data are provided for primary counties and contiguous counties. Only primary counties were used in the analysis. The following types of natural disasters that could potentially disrupt transportation of crops were considered in the analysis: flashfloods, tornados, mudslide, and winter storms.[3] The disaster data were combined with collection points' location (i.e., county of operation) to create dummy variables indicating disaster-specific crop transportation disruptions at the county of operation (i.e., D). Figures 3-6 show

[2] These states include Iowa, Illinois, Indiana, Kansas, Kentucky, Michigan, Minnesota, Missouri, North Dakota, Nebraska, Ohio, South Dakota, and Wisconsin.
[3] Hurricanes were also initially considered but were dropped from further analysis because they were nonexistent in the sample period and counties.

the spatial distribution of weekly counts of the examined natural disasters during the study period. The transportation cost data for corn and soybeans are based on information publicly available sources for freight rates (BTS, 2017; FRED, 2023), rail rates based on the average on the Minnesota to St. Louis segment (USDA AMS, 2023), and St. Louis barge rates (USDA AMS 2023). All transportation mode rates are per mile. In each case, data were partial, omitting some weeks or even failing to overlap the full period of our basis data, so rates were related to diesel prices (EIA, 2023) using OLS regressions and these relationships were used to estimate the transportation rates. These data were combined with the least-cost route information from step 2 to calculate crop transportation costs that account for natural disasters. More specifically, using calculated miles and costs for each mode of transportation, a total transportation cost per bushel variable was created as the sum of the products of transportation mode-specific miles and costs (i.e., C).[4] The control variables (i.e., X) include data on historic ethanol intensity measures linked to the corn and soybeans buyers in our dataset, and corn and soybean production. Ethanol intensity is a kernel density function-based estimate that uses the nameplate capacity of ethanol plant located near the sample elevators[5]. Production data are county-specific annual observations that were calculated using acreage and yield data retrieved from USDA Farm Service Agency. Corn and soybean acreage was taken from annual acreage reporting reports (USDA FSA, 2023) and multiplied by the respective commodity yield for the county (USDA FSA, 2023). FSA yields are calculated using area-based revenue crop insurance products offered through the Risk Management Agency, survey yields reported by the National

[4] Due to data limitations, we have not been able to retrieve cost per mile data for rail. Consequently, the rail cost used in the total transportation cost calculation is the per bushel cost of the crop on a car for a period of time.
[5] This variable is estimated by Vince Breneman, Office of the Chief Economist, United States Department of Agriculture.

Agricultural Statistics Service, or the State FSA Committee. Table 1 presents summary statistics of the variables used in the basis spread estimations.

4. Results

Tables 2 and 3 present the results of basis spread estimations. The results in columns 1 and 2 differ in the level of detail at which the natural disasters are accounted for in the estimation, and columns 3 and 4 incorporate the cross effect of the shipping cost variable and the route change dummy variable.

Results show that the coefficients of transportation cost per bushel are statistically significant for both corn and soybean models. More specifically higher cost per bushel decreases basis spread. In the soybean models, basis spread decreases by about \$1.65 to \$2.61 for each dollar per bushel increase in shipping costs, ceteris paribus, while in the corn models the decrease in basis spread as a result of higher shipping costs is in the range of \$1.64 to \$2.77. The direction of these results is expected given that higher shipping costs can lower local price for a given port price. The indicators of cost by route are based on indicator values or broad averages, and will not reflect the actual prices of shipping crops. In addition, even if the price indicators were very close to true values, an increase in these prices might not map perfectly to a change in basis. Rising transportation costs might have diminishing effects on the crop prices in any particular collection point if the crop is rerouted to a different export market, local use, or storage. In the well-functioning crop distribution system, one response to higher costs of moving a crop in one direction might be to look for other options.

The coefficients of the interaction term between shipping cost and the route change dummy are estimated to be positive and statistically significant on both the soybean and corn models. These results – when combined with the shipping cost results above – imply that our average weekly recalculated shipping cost rates tend to overstate the basis spread impact. For instance, in the soybean model (Table 2, column 3), a $1 increase in the shipping costs associated with rerouting causes -1.18 (i.e., -2.612+1.432) basis spread change (as opposed to -2.612). One possible reason is that some disasters do not disrupt the transportation network as fully as we assume. Also, the fact that the estimated basis-spread models do not account for all possible steps that elevators can take to mitigate transportation cost shocks of a disaster along the route could explain why the employed shipping cost variable overstates the basis impact.

The natural disaster dummy is shown to have a significant effect on both corn and soybean basis spread. More specifically, basis spread weakens when a natural disaster occurs at the collection point level. Natural disasters may hamper an elevator's ability to move stored crops to ports of exit thus leading to a lower local price relative to a given port price. Separating the natural disaster dummy into its four component categories (i.e., flashflood, tornado, mudslide, and winter storm) results in similar negative effects on basis spread (except for winter storms in the corn model). Flashfloods and winter storms show the largest negative effect on basis spread, in the corn and soybean model, respectively. In the corn model, winter storm shows a positive effect on basis spread. Each outcome reflects one of the possibilities expected, namely that the local disaster makes it difficult to send crops out of the area towards NOLA and drives down basis. The other possibility is that the local disaster makes it difficult to bring in more of the crops flowing through the collection point to NOLA, consequently driving up basis for the crops that remain available in the area of the disruption. The ‘riveradjct-flood’ dummy shows a positive effect on basis spread on both corn and soybean models. This result could reflect the inability of collection points to move crops to the elevator from fields or neighboring collection points, thus leading to higher local price relative to a given port price.

Among the control variables, crop production negatively affects both corn and soybean basis spread. Higher production reflects a higher crop supply which can in turn strain the crop distribution network leading to lower local price for a given port price. The ethanol intensity measure positively affects both corn and soybean basis spread. More local use of crops means less stress on the system to move the crop to the port for export. The increased demand for nearby cash sales of crops can raise local price relative to a given port price.

5. Conclusions

This study examines the effect of weather extremes that could disrupt crop transportation on the margins between buyer and seller prices for corn and soybean. A three-step procedure is employed to assess the links between weather extremes and basis spread. First, we estimate hypothetical least cost-routes for transporting crops from sample elevators to the port of NOLA. In the second step, least-cost routes are re-calculated to account for weather extremes blocking the crop transportation pathways. Third, crop transportation-related variables and indicators of extreme weather events generated from the previous step along with control variables are introduced into an econometric model that is used to evaluate the effect of weather extremes on crop basis spread.

Results show that, in most cases, weather extremes (as modelled using natural disaster indicators) impact negatively crop basis spread in the U.S. Midwest (measured here as local price less port price). The highest negative effect is shown by flash floods and by winter storms in the corn and soybean models, respectively, and these two disasters had the highest mean frequency of occurrence in the sample with a combined average of about 3% in the soybean model and 1.2% in the corn model (Table 1). This result could be attributed to elevators facing difficulties in moving crops to ports of exit when natural disasters occur in the county of operation. Results also show that winter storms affect corn basis positively, possibly reflecting the inability of collection points to move crops in, which in turn pushes up basis. We further find that the cost impact of natural disasters along the base least-cost route of sample elevators lowers basis spread. Given that lower basis spread could hurt commodity producers' income and increase food insecurity (through limiting food availability), increased focus could be directed to mitigating the negative effects of natural disasters on the transportation network that moves crops from the U.S. Midwest to ports of exit. Results at this time suggest that improvements in transportation infrastructure that improve resilience to flooding and winter storm might be more likely to reduce the potential for natural disasters to disrupt this network.

Given that there are concerns about the possibility of a higher frequency of extreme weather events due to climate change, an interesting direction for future research could be to investigate the climate change cost of natural disasters on the U.S. crop transportation network. However, such research is currently hampered by the lack of natural disaster predictions. Such predictions would also need to be spatially and temporally explicit enough to provide accurate estimates of the climate change cost on the crop transportation network. Second-order approximations could be developed. For example, the average annual impacts of a disaster type (winter storm, flood) during the historical period could be calculated and paired with more general predictions about the future frequency of these events in this region to scale up or down those annual effects. Such options fall short in some way, such as by losing location-specific impact estimates that the system currently can provide. Given impacts on extreme weather likelihood by county and by week, this system could estimate collection point basis spread effects.

References

Caldwell, H., Quinn, K.H., Meunier, J., Suhrbier, J., & Grenzeback, L. (2002). The Potential Impacts of Climate Change on Transportation Potential Impacts of Climate Change on Freight Transport. US Department of Transportation, Center for Climate Change and Environmental Forecasting.

Bureau of Transportation Statistics (BTS), U.S. Department of Transportation (2017). Average Freight Revenue Per Ton-mile. https://www.bts.gov/archive/publications/national_transportation_statistics/table_03_21.

Energy Information Administration (EIA), US Department of Energy (2023). Weekly U.S. No 2 Diesel Ultra Low Sulfur (0-15 ppm) Retail Prices. www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=EMD_EPD2DXL0_PTE_NUS_DPG&f=W.Federal Reserve Economic Data (FRED), Federal Reserve Bank of St. Louis (2023). Producer Price Index by Industry: General Freight Trucking, Long-Distance Truckload, Index Dec 2003=100, Monthly, Not Seasonally Adjusted.

FRED, Federal Reserve Economic Data, Federal Reserve Bank of St. Louis. Producer Price Index by Industry: General Freight Trucking, Long-Distance Truckload. https://fred.stlouisfed.org.

Fuller, S.W., & Yu, T.H. (2004). Briefing paper on the upper Mississippi and Illinois Rivers transportation corridors: Grain transportation rates and associated market area. Food and Agricultural Policy Research Institute (FAPRI) at the University of Missouri-Columbia.

Gastelle, J., Caffarelli, P., Chang, K., and Marathon, N. (2017). Transportation of U.S. Grains: A Modal Share Analysis. https://www.ams.usda.gov/sites/default/files/media/ModalOctober2017.pdf.

Gutierrez, L. (2017). Impacts of El Niño-Southern Oscillation on the wheat market: A global dynamic analysis. *PLOS ONE*, *12*(6), e0179086. https://doi.org/10.1371/journal.pone.0179086.

Haile, M.G., Wossen, T., Tesfaye, K., & von Braun, J. (2017). Impact of Climate Change, Weather Extremes, and Price Risk on Global Food Supply. *Economics of Disasters and Climate Change*, *1*(1), 55-75. https://doi.org/10.1007/s41885-017-0005-2.

Horn, K. (2020). *A financial feasibility study: Constructing unit train capabilities to access the Pacific Northwest export market* (Doctoral dissertation).

Miao, R., Khanna, M., & Huang, H. (2016). Responsiveness of Crop Yield and Acreage to Prices and Climate. *American Journal of Agricultural Economics*, *98*(1), 191–211. https://doi.org/10.1093/ajae/aav025.

Millerd, F. (2011). The potential impact of climate change on Great Lakes international shipping. *Climatic Change*, *104*(3), 629-652. https://doi.org/10.1007/s10584-010-9872-z.

Mishra, V., & Cherkauer, K.A. (2010). Retrospective droughts in the crop growing season: Implications to corn and soybean yield in the Midwestern United States. *Agricultural and Forest Meteorology*, *150*(7), 1030-1045. https://doi.org/10.1016/j.agrformet.2010.04.002.

Nam, K. (2021). Investigating the effect of climate uncertainty on global commodity markets. *Energy Economics*, *96*, 105123. https://doi.org/10.1016/j.eneco.2021.105123.

Peterson, T.C., McGuirk, M., Houston, T.G., & Horvitz, A.H. (2006). Climate Variability and Change with Implications for Transportation (p. 146). NOAA National Climatic Data Center.

Ubilava, D. (2017). The ENSO Effect and Asymmetries in Wheat Price Dynamics. World Development, 96, 490-502. https://doi.org/10.1016/j.worlddev.2017.03.031.

Ubilava, D. (2018). The Role of El Niño Southern Oscillation in Commodity Price Movement and Predictability. *American Journal of Agricultural Economics*, *100*(1), 239-263. https://doi.org/10.1093/ajae/aax060.

US Department of Agriculture, Agricultural Marketing Service (USDA AMS). (2023). Weekly barge freight rates. Barge Dashboard | Open Ag Transport Data: https://agtransport.usda.gov/stories/s/Barge-Dashboard/965a-yzgy/.

US Department of Agriculture, Farm Service Agency (USDA FSA). (2023). ARC/PLC Program Data ARC/PLC Program Data: https://www.fsa.usda.gov/programs-and-services/arcplc_program/arcplc-program-data/index.

US Department of Agriculture, Farm Service Agency (USDA FSA). (2023). Acreage Reports. Crop Acreage Data: https://www.fsa.usda.gov/news-room/efoia/electronic-reading-room/frequently-requested-information/crop-acreage-data/index.

US Department of Agriculture, National Agricultural Statistics Service (USDA NASS). (2023) Quick Stats. Crop Production Report USDA/NASS QuickStats Ad-hoc Query Tool: https://quickstats.nass.usda.gov/.

Vogel, E., Donat, M.G., Alexander, L.V., Meinshausen, M., Ray, D.K., Karoly, D., Meinshausen, N., & Frieler, K. (2019). The effects of climate extremes on global agricultural yields. *Environmental Research Letters*, *14*(5), 054010. https://doi.org/10.1088/1748-9326/ab154b.

Tables

Table 1. Summary statistics of the variables used in the empirical analysis.

	Unit	Soybeans		Corn	
		Mean	St.dev	Mean	St.dev
Basis spread	$/bushel	-1.154	0.373	-0.804	0.241
CostPerBushel	$/bushel	0.115	0.09	0.118	0.088
production	million bushel/county	6.544	6.744	22.387	14.033
ethanol	million gallons/km^2	0.017	0.014	0.017	0.014
disaster[a]	(0/1)	0.026	0.160	0.012	0.111
flashflood	(0/1)	0.018	0.134	0.010	0.100
tornado	(0/1)	0.005	0.068	0.002	0.046
mudslide	(0/1)	0.002	0.040	0.000	0.000
winter storm	(0/1)	0.010	0.100	0.002	0.038
riveradjct-flood[b]	(0/1)	2.45e-4	0.016	8.82e-5	0.009
Routechange[c]	(0/1)	0.033	0.179	0.053	0.225

[a] The 'disaster' dummy takes the value of 1 if any of the five disasters (i.e., flashflood, tornado, mudslide, winter storm) occurs in the county where an elevator is located for a given week, and 0 otherwise. For the individual disaster dummies, if any of those single disasters occurred in each week, it's given a 1, else a 0. Mudslides did not affect the sample corn elevators' routes during the study period (i.e., its mean and standard deviation are both zero).

[b] The 'riveradjct-flood' variable takes the value of 1 if an elevator is adjacent to the river and a flashflood occurred in the county that week, and 0 otherwise.

[c] The 'Routechange' dummy takes the value of 1 if route changed as a result of a disaster hitting the route, and 0 otherwise.

Table 2. Basis spread regression results - Soybeans

VARIABLES	(1)	(2)	(3)	(4)
CostPerBushel	-1.696***	-1.648***	-2.612***	-2.472***
	(0.0108)	(0.0106)	(0.0131)	(0.0126)
cost_routechange			1.432***	1.355***
			(0.0117)	(0.0116)
disaster	-0.142***		-0.255***	
	(0.00283)		(0.00294)	
flashflood		-0.0795***		-0.148***
		(0.00347)		(0.00347)
tornado		0.0101*		-0.0529***
		(0.00603)		(0.00597)
mudslide		-0.0414***		-0.0497***
		(0.0100)		(0.00989)
winterstorm		-0.147***		-0.213***
		(0.00448)		(0.00445)
riveradjct_flood		0.108***		0.153***
		(0.0258)		(0.0255)
production	-0.000605***	-0.000574***	-0.000727***	-0.000658***
	(7.29e-05)	(7.29e-05)	(7.18e-05)	(7.19e-05)
ethanol	9.986***	9.867***	7.847***	7.818***
	(0.151)	(0.151)	(0.150)	(0.150)
Constant	-1.124***	-1.129***	-0.986***	-1.003***
	(0.00300)	(0.00299)	(0.00317)	(0.00314)
Observations	479,674	479,674	479,674	479,674
R-squared	0.065	0.065	0.093	0.091
Number of elevators	2,304	2,304	2,304	2,304

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 3. Basis spread regression results - Corn

VARIABLES	(1)	(2)	(3)	(4)
CostPerBushel	-1.653***	-1.636***	-2.773***	-2.753***
	(0.0114)	(0.0114)	(0.0137)	(0.0137)
cost_routechange			1.668***	1.661***
			(0.0121)	(0.0121)
disaster	-0.0942***		-0.220***	
	(0.00351)		(0.00351)	
flashflood		-0.137***		-0.252***
		(0.00399)		(0.00395)
tornado		-0.00420		-0.159***
		(0.00807)		(0.00788)
winterstorm		0.194***		0.149***
		(0.0101)		(0.00981)
riveradjct_flood		0.222***		0.327***
		(0.0395)		(0.0382)
production	-0.0101***	-0.0102***	-0.0115***	-0.0116***
	(9.61e-05)	(9.63e-05)	(9.34e-05)	(9.36e-05)
ethanol	8.477***	8.609***	5.532***	5.648***
	(0.138)	(0.138)	(0.135)	(0.135)
Constant	-0.531***	-0.532***	-0.332***	-0.334***
	(0.00338)	(0.00337)	(0.00357)	(0.00356)
Observations	269,819	269,819	269,819	269,819
R-squared	0.109	0.111	0.169	0.170
Number of elevators	2,593	2,593	2,593	2,593

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Figures

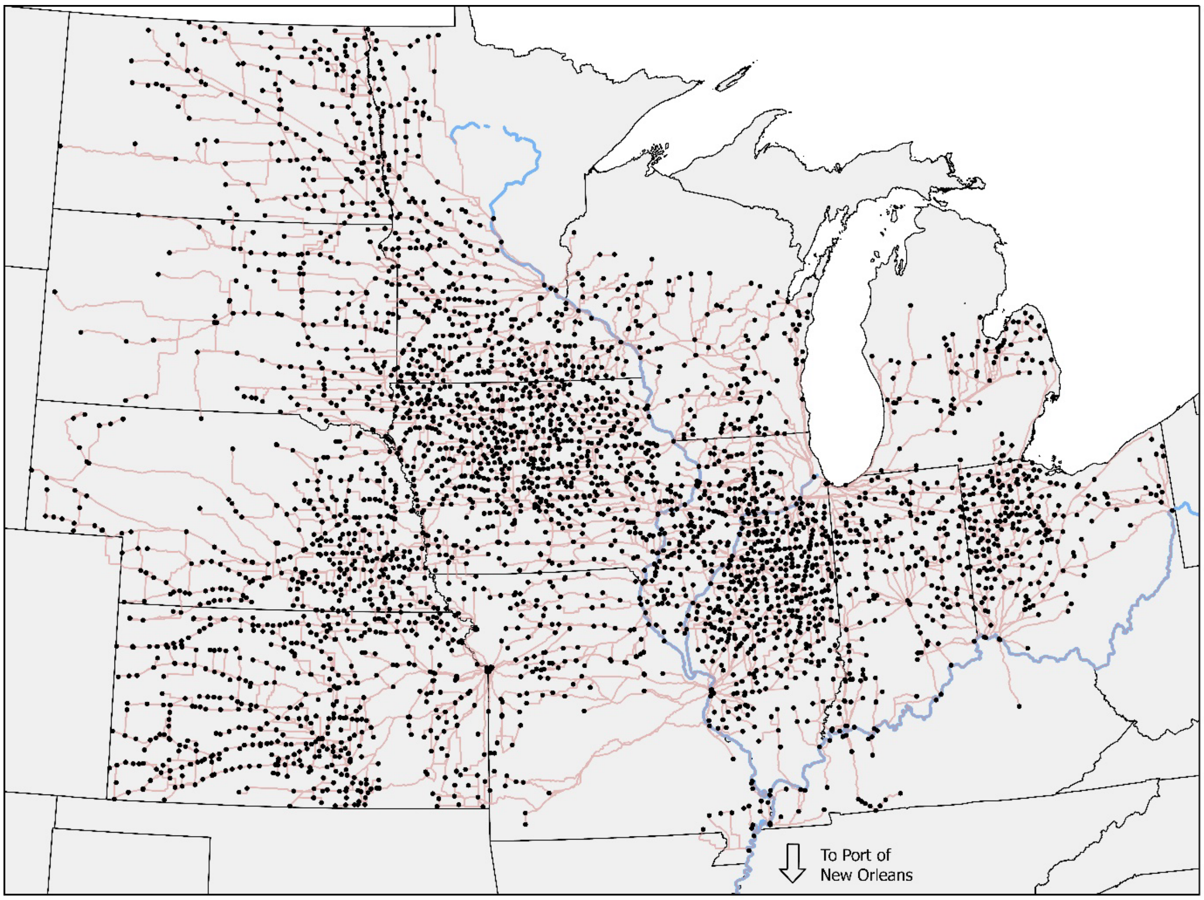

Figure 1. Least-cost routes of sample elevators (without disaster constraints).

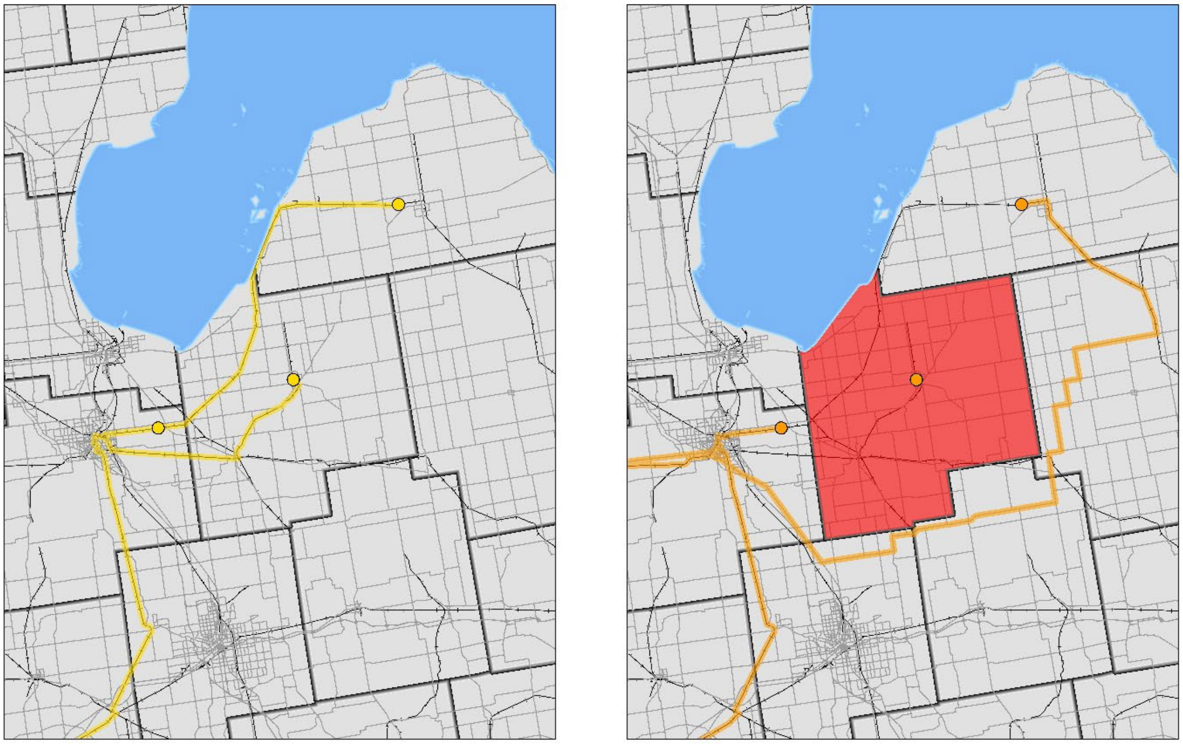

Figure 2. Example of a natural disaster occurring at the elevator's county of operation.
Note: Elevators are shown with circles. Yellow and gold lines show least-cost routes for scenarios with (right panel) and without (left panel) disruptions. The county in red acts as a barrier due a natural disaster occurring in that county in a particular week.

Weeks of Flood and Flash Flooding
2012-2020; Max- 468

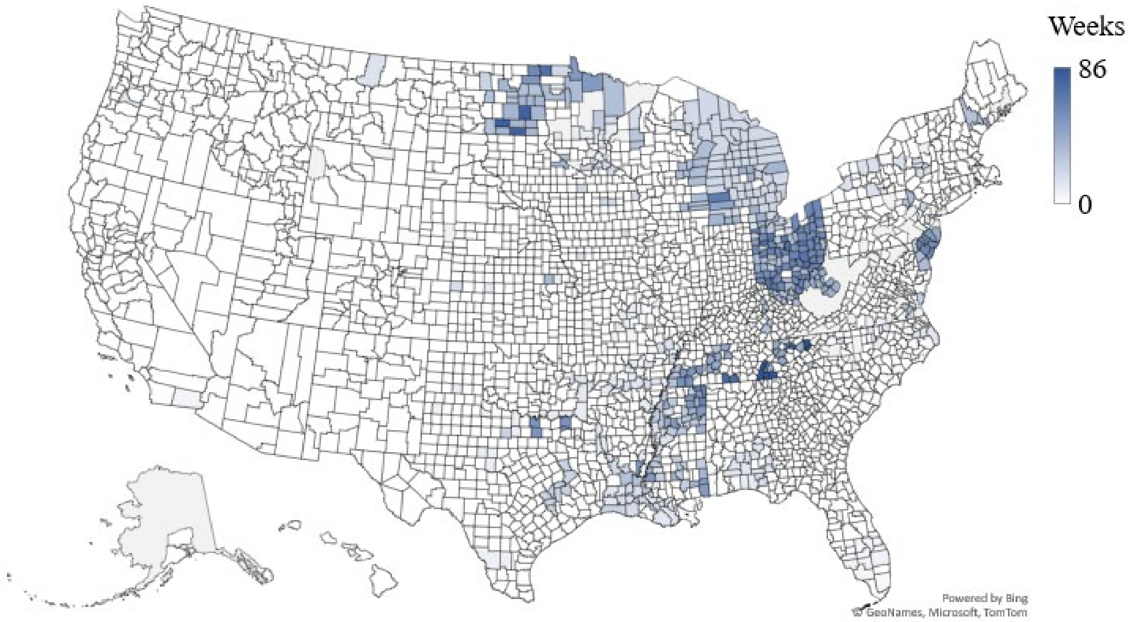

Figure 3. Weeks of flooding and flash flooding disaster declaration 2012-2022.

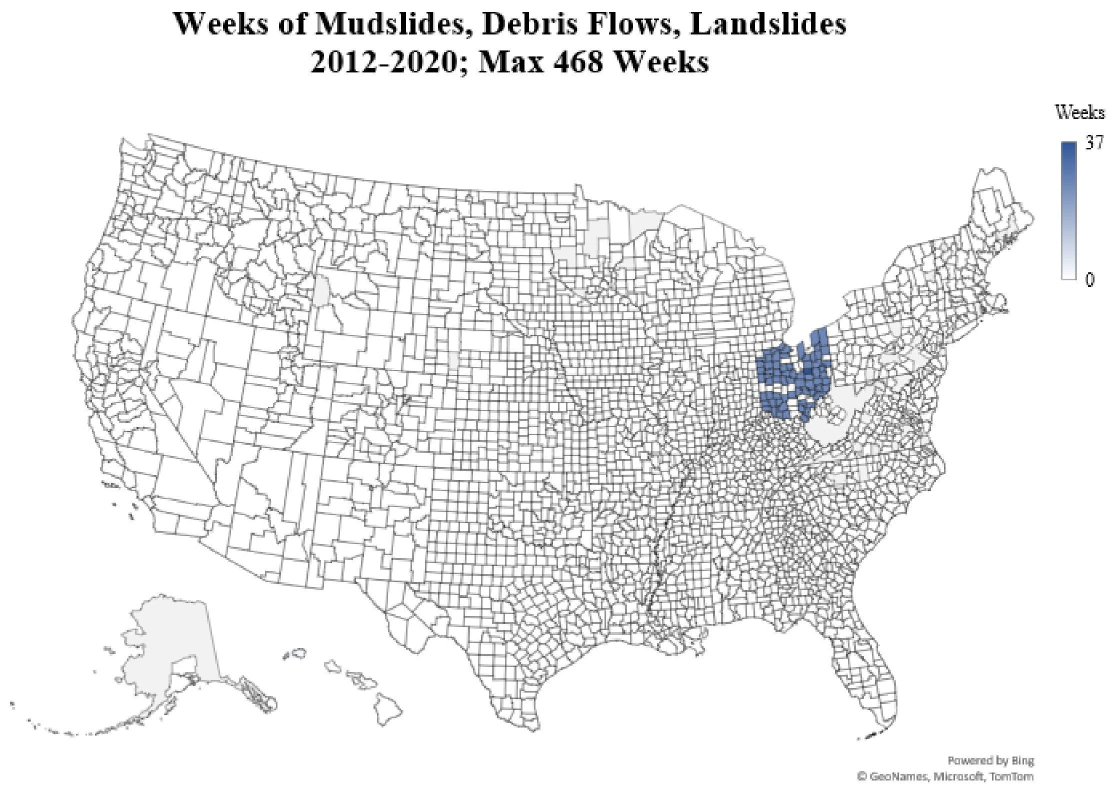

Figure 4. Weeks of mudslides, debris flows, or landslides 2012-2022

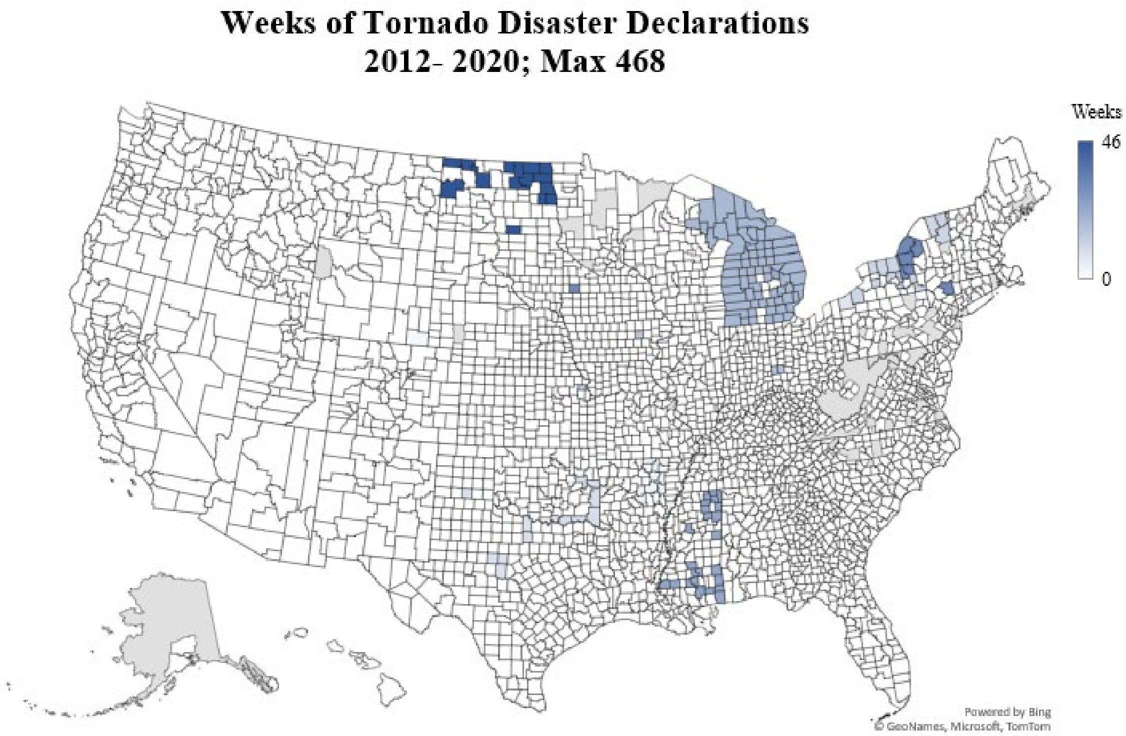

Figure 5. Weeks of tornadoes, 2012-2022.

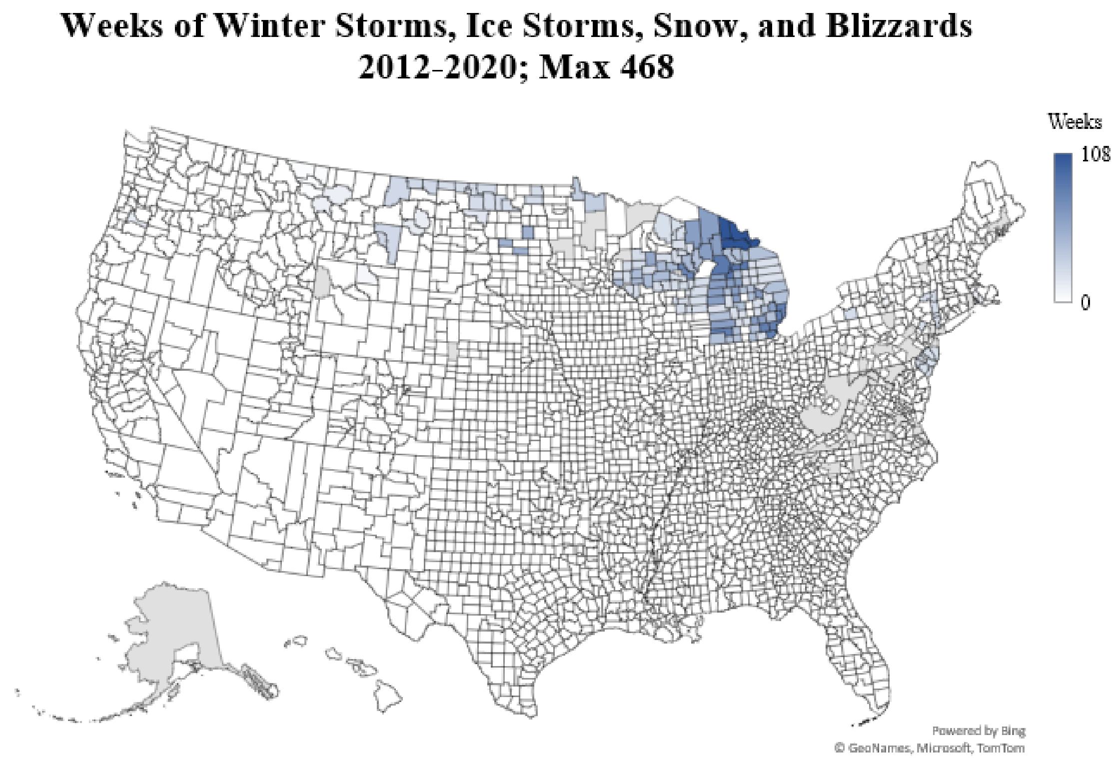

Figure 6. Weeks of winter storms, ice storms, snow, and blizzards, 2012-2022.