The effect of increased weather volatility on agricultural trade

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March 7, 2022

Abstract

We use an econometric gravity model to estimate the effects of weather volatility on international trade flows. To account for variation in weather conditions, we include the standardised precipitation-evapotranspiration index (SPEI). We find that for smaller variation in weather has no impact on trade, but for more extreme events (i.e., more than two standard events from the mean), the trade impacts are substantial, ie, reduced by around 46%. Using the estimation results, we simulate the trade impacts of more widespread weather events. We find that the impact varies by crop, with the largest effect being for wheat and the smallest impact for soybeans.

Keywords: Climate change, Agricultural trade

JEL Codes: Q18

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1 Introduction

Climate change represents one of the largest threats to the future of food security. Rising temperatures and shifting precipitation patterns threaten agricultural yields in many key production regions. Adapting agriculture to these challenges is crucial to securing sufficient access to nutritious food and healthful diets globally. For domestic agricultural systems negatively affected by climate change, agricultural trade represents an important adaptive tool. However, agricultural trade is also likely to respond to projected climate change scenarios and these responses reveal the capacity for international agricultural trade to serve as a climate adaptation strategy. This paper examines the impact of weather volatility on agricultural trade using an econometric gravity model. Specifically, we estimate i) the current impact on extreme weather events on monthly, bilateral trade flows and ii) simulate the impact of more widespread climate events on agricultural trade.

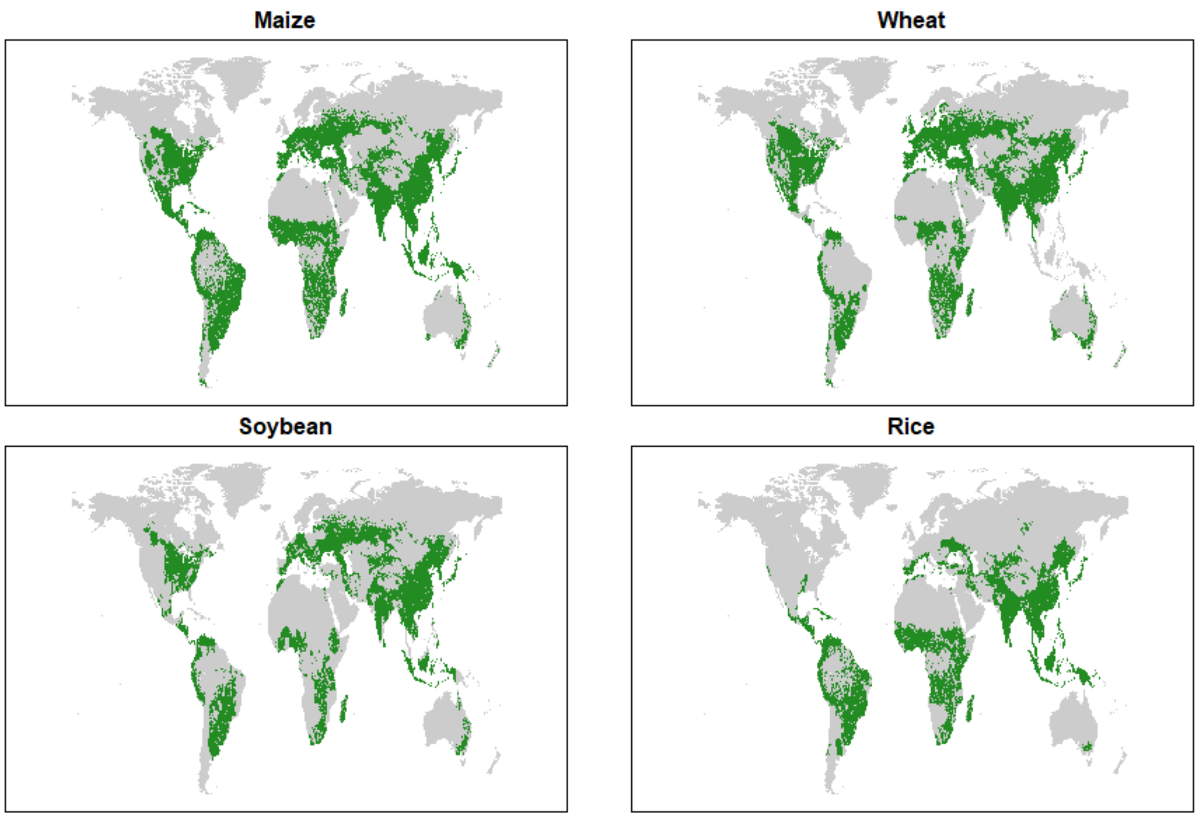
We use an econometric gravity model to estimate the effects of weather volatility on international trade flows. To account for variation in weather conditions, we include the standardised precipitation-evapotranspiration index (SPEI). We find that for smaller variation in weather has no impact on trade, but for more extreme events (i.e., more than two standard events from the mean), the trade impacts are substantial, ie, reduced by around 46%. Using the estimation results, we simulate the trade impacts of more widespread weather events. We find that the impact varies by crop, with the largest effect being for wheat and the smallest impact for soybeans.

2 Background

This paper focuses on the major food crops: maize, wheat, soybean and rice. Combined, these crops accounts for two-thirds of human's calorie consumption (Zhao et al., 2017). Production of these crops are concentrated at different part of the world, due to heterogenous growing requirements, as shown in Figure 1. According to FAOSTAT, around 89.9% of

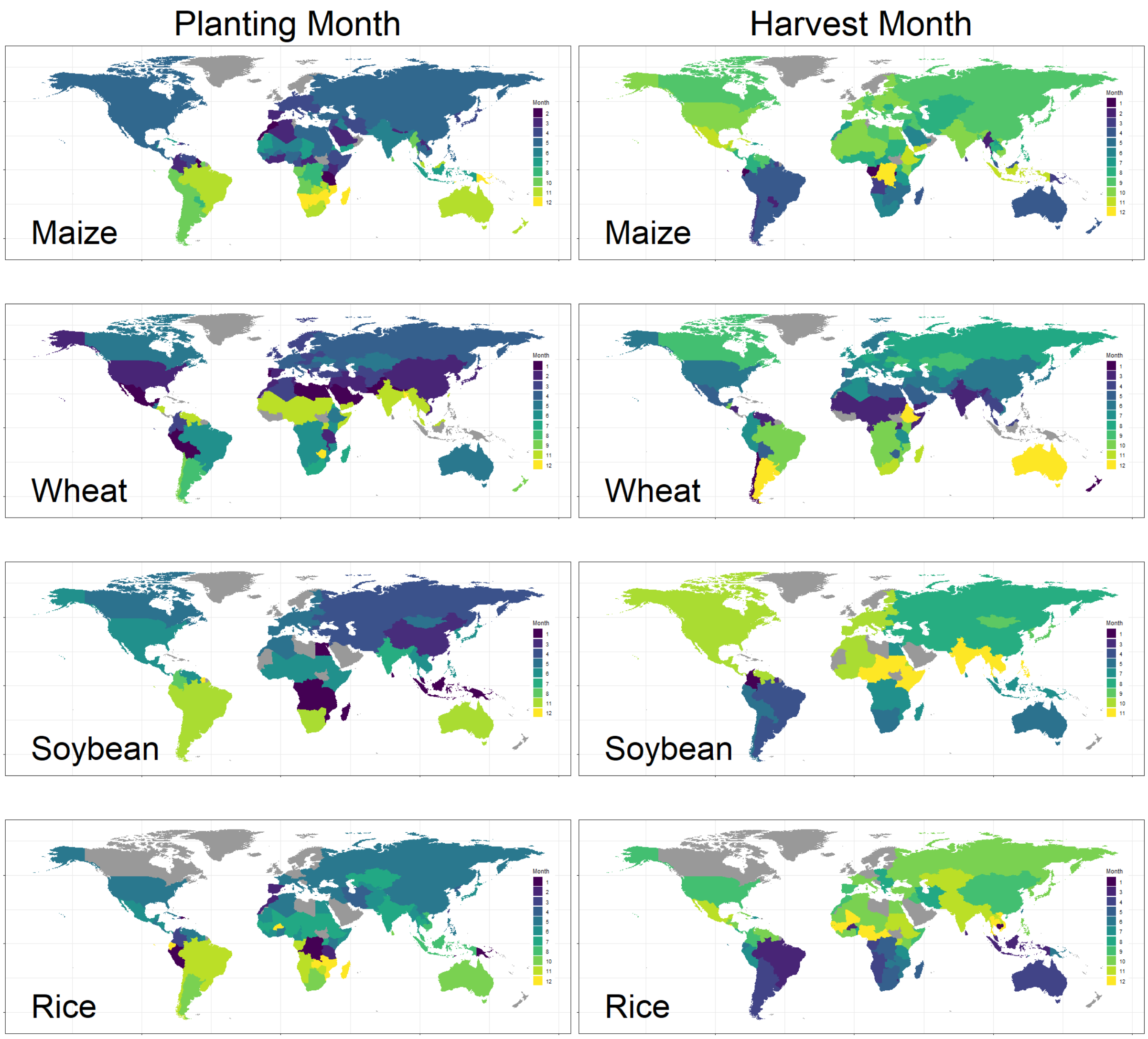
World's rice production is in Asia in 2019, with the leader producer is mainland China, India and Indonesia. Africa and the Americas follow with around 4.9% and 4.6% of the world's rice production, respectively. Asia is a large producer of wheat, with around 44% of the world's wheat being produced in Asia. Europe follows with around one-third of the world's production. The Americas, on the other hand, are large producers of maize and soybean, accounting for around 49.4% and 85.4% of world's production, respectively.

Figure 1: Growing area of major crops



The impact of weather events are more likely to have a sever, negative impact on production if it occurs in the growing season; i.e. in the months between planting and harvesting. Due to differences in climate zones and growing requirements, both the harvesting and planting months vary by country and crop. The left side of Figure 2 shows the planting months while the right side shows the harvesting month, by crop.

Figure 2: The planting and harvesting months by country and crop



3 Methods

The analysis is conducted in two parts: we first estimate the effect of extreme weather events on trade and using the coefficient estimated, we simulate the effect on trade on increased weather volatility.

3.1 The effect of extreme weather events on trade

We use an econometric gravity model to estimate the effects of weather volatility on international trade flows. We combine data on planting and harvesting months for rice, wheat, soybean, and corn with monthly trade flows for the years 2010-2019. We then estimate a standard gravity equation using the following equation:

$$V_{iept} = \alpha Y_{it}^{\beta 1} Y_{et}^{\beta 2} exp[SPS_{high,epg} + SPS_{low,epg} + \mathbf{Z}'\theta]\varepsilon_{iept} \tag{1}$$

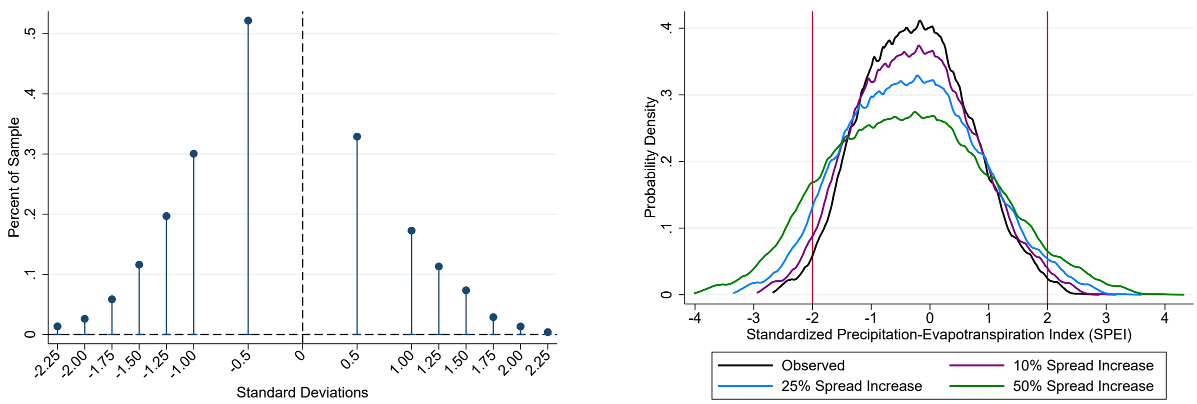
Consistent with the gravity equation, V_{iept} is the bilateral trade flow from exporter e to importer i for product p, at time t. Y_{it} and Y_{et} are the GDP for the importer and exporter, respectivly, accounting for economic "mass" of the countries.

To account for variation in weather conditions, we include the standardised precipitation-evapotranspiration index (SPEI). The SPEI index is used to determine the onset, duration and magnitude of drought conditions compared to normal years. We define a growing season and a trading season and we assume that a weather event has most impact of production if it occurs during a growing season, which we define as the months between planting and harvesting of the product. The trading season is when this product is traded. We define this season as the months between harvesting months. We create dummy variables using this index for weather events in the growing seasons of the products (i.e., the months between planting and harvesting). These weather dummies are then used to estimate the impact of weather events on trade in the trading season (i.e., the months following the harvest month).

[1] These weather and climate variables augment the standard gravity model of trade and it is seen in the equation as $SPS_{high,epg}$ and $SPS_{low,epg}$.

Controls include fixed effects for country-pair-crop-month-of-year, to control for typical seasonal levels of trade, and crop-month-year, to control for global crop-specific shocks to trade. The gravity model is estimated using a Pseudo-Poisson Maximum Likelihood (PPML) Regression Model.

Figure 3: The SPEI distribution and distribution of mean-preserving simulations



(a) Summarize

(b) Mean-Preserving Spread Simulations

3.2 Impacts of more widespread weather volatility

To simulate the potential effects of more volatile weather patterns induced by climate change, we use the results estimated in the first stage of the analysis to simulate an increase in occurrence of weather events. In particular, we use a mean preserving spread simulation to simulate trade effects of various increases in the spread of the SPEI distribution. This is described in Figure 3. In panel (a) of the Figure, it shows the current distribution of the SPEI variable with mean at 0, and the horizontal axis is the standard deviation. Panel (b) of the Figure shows this distribution under various mean-preserving simulations; specifically,

[1]Suppose Norway grows soybean between April 2011 and August 2011, then April-August would be the growing season, and August 2011 to July 2012 would be the trading season. Any weather event in the growing season April-August 2011, would be coded as 1 in the months August 2011 to July 2012.

considering a 10, 25, 50% spread increase. The intersection between the vertical line at -2 and 2 shows the increase in extreme weather events at 2 standard deviations under the various simulations.

3.3 Data and Summary Statistics

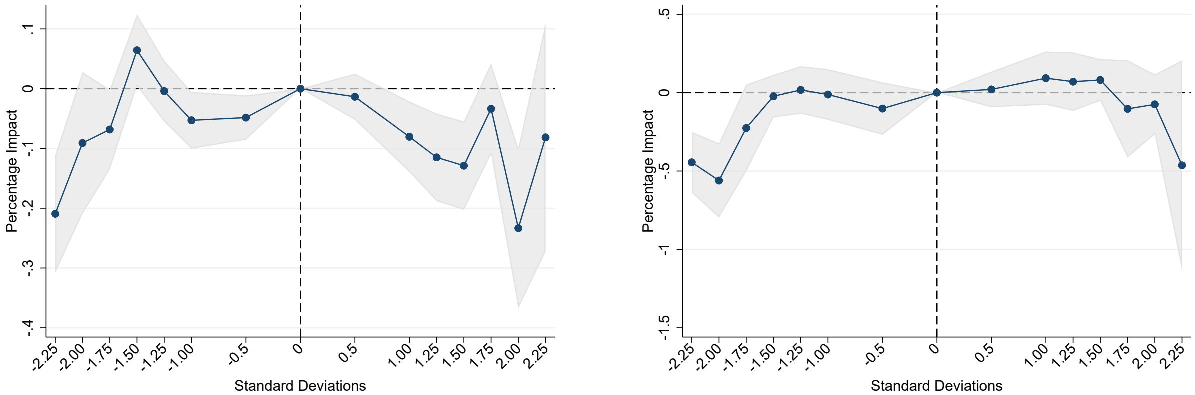
We combine bilateral monthly trade data from 2010-2019 obtained from COMTRADE with data on growing season and growing areas from FAO. The data on the SPEI index is from the Global SPEI database and the data on GDP are from the World Bank.

The final dataset includes 1,457,064 monthly observations for the crops maize, wheat, soybean, and rice from 2010 to 2019 .The summary statistics are shown in Table 1.

Table 1: Summary Statistics (n = 1,457,064)

Variable	Description	Mean	Std. Dev.	Min	Max
Dependent Variable					
Trade	Value of Trade (US$1M)	0.42	11	0	3540
Ln Trade	Ln(Trade+1)	1.87	4.26	0	22
Extreme Weather Variables					
Extreme Low	SPEI <-2	0.03	0.16	0	1
Extreme High	SPEI >2	0.01	0.11	0	1
Third Low					
Indicator		0.84	0.36	0	1
Continuous		0.01	0.07	0	1
Third High					
Indicator		0.75	0.43	0	1
Continuous		0.01	0.07	0	1
Control Variables					
FX_p		2.22	2.69	-1.29	10
FX_r		1.88	2.37	-1.29	10
FTA		0.40	0.49	0	1
GDP_p		26.92	1.93	20.71	31
GDP_r		25.83	2.10	19.08	31

Figure 4: The effect of variation in the SPEI on trade flows



(a) OLS (b) PPML

4 Results

4.1 Estimating the effect of weather events on trade

We examine the impact of various weather conditions on trade flows. Figure 4 summarises the results from the PPML and OLS estimations for various thresholds of extreme weather events. These thresholds are created based on the standard deviations of the SPEI variable. For instance, consider the trade effect of standard deviation at 1 and -1 in the Figure. The point estimate in the graph refer to the coefficient on the weather event dummy in the PPML and OLS estimations using the cut-off for a weather event in the growing season as one standard deviation lower (ie, -1) or higher (i.e., 1) than normal.

The Figure shows that trade flows are not affected for smaller variation in weather conditions (i.e, using cut-offs of less than 2 standard deviations for weather events). However, for greater variation in weather conditions during the growing season — i.e., if the SPEI is lower than -2 — it reduces trade by 46.7%.

As the Figure shows that the weather events only affected trade if it was more extreme, Table 2 shows the regression results when the SPEI threshold is defined as 2 standard deviations from the mean.The Table shows that, for the PPML estimates, the magnitudes of the effects are quite consistent for various specifications. For instance, the Table shows

Table 2: The results from the gravity estimation

VARIABLES	(1) PPML	(2) OLS	(3) PPML	(4) OLS	(5) PPML	(6) OLS
Extreme Low	-0.436***	-0.126***	-0.427***	-0.106***	-0.467***	-0.130***
	(0.0757)	(0.0390)	(0.0770)	(0.0406)	(0.0716)	(0.0390)
Extreme High	-0.193*	-0.149**	-0.0642	-0.153**	-0.178	-0.151**
	(0.102)	(0.0586)	(0.0842)	(0.0626)	(0.111)	(0.0586)
Third Low						
Indicator			0.308	0.223*		
			(0.252)	(0.125)		
Continuous					0.315*	0.133*
					(0.163)	(0.0762)
Third High						
Indicator			0.448	-0.0214		
			(0.274)	(0.115)		
Continuous					0.115	-0.0635
					(0.227)	(0.0941)
FTA_{iet}	0.205	0.0801	0.205	0.0809	0.207	0.0802
	(0.221)	(0.114)	(0.222)	(0.114)	(0.222)	(0.114)
GDP_{et}	-0.155	-0.117	-0.150	-0.122	-0.162	-0.118
	(0.238)	(0.114)	(0.237)	(0.114)	(0.239)	(0.114)
GDP_{it}	0.314	-0.445***	0.302	-0.445***	0.315	-0.446***
	(0.241)	(0.103)	(0.246)	(0.103)	(0.241)	(0.103)
FX_{et}	0.0158	-0.0127	0.0128	-0.0137	0.0139	-0.0131
	(0.113)	(0.0601)	(0.112)	(0.0601)	(0.113)	(0.0601)
FX_{it}	-0.0333	-0.154***	-0.0165	-0.153***	-0.0392	-0.155***
	(0.241)	(0.0484)	(0.243)	(0.0484)	(0.241)	(0.0485)
MRT Terms	Yes	Yes	Yes	Yes	Yes	Yes
Panel Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-HS-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Importer-HS-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
HS-Month-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,297,713	1,457,064	1,297,713	1,457,064	1,297,713	1,457,064
R-squared		0.555		0.555		0.555

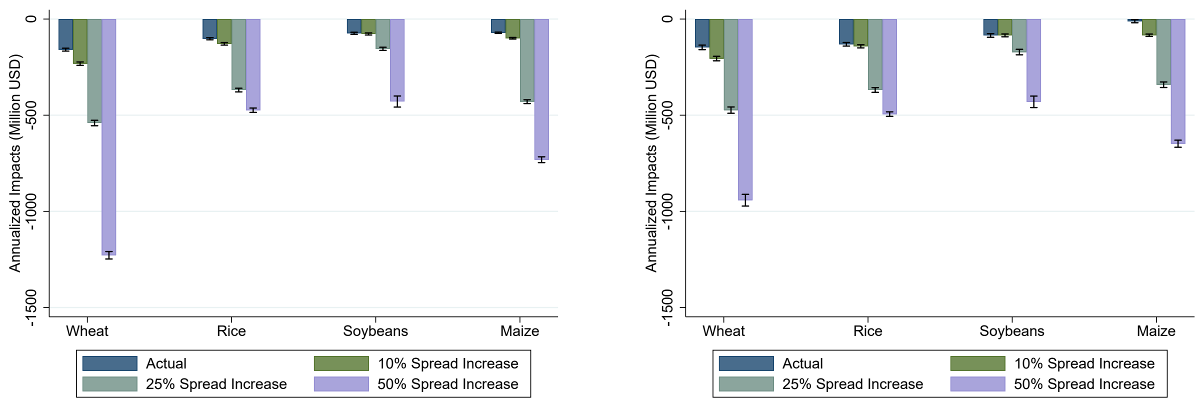
Standard errors in parentheses are clustered by importer-exporter pair.
*** p<0.01, ** p<0.05, * p<0.1

that an extreme weather events based on negative numbers of the SPEI variable — ie, low level of precipitation combined with high temperature — reduces trade more than a extreme weather event based on positive numbers of the SPEI.

4.2 Simulate the impact of more widespread weather events on agricultural trade

Figure 5 shows that trade is only affected for weather events that are more extreme. We use the cut-off of SPEI greater than 2 standard deviation from the mean, and simulate the effect of greater volatility of weather events (ie, "fatter" tail of the SPEI distribution) on trade. Figure 2 shows the trade impact of under various scenarios by crop. As seen in the graph, we find that the impact varies by crop, with the largest effect being for wheat and the smallest impact for soybeans.

Figure 5: Mean Preserving Impacts



(a) Exporter Impacts (b) Importer Impacts

5 Conclusion

This research creates new knowledge about climatic change and the impact on international agricultural trade flows. It measures how international agricultural trade flows respond to changes weather events. Based on this assessment, predictions of trade responses to projected climate change scenarios reveals the capacity for international agricultural trade to serve as a climate adaptation strategy. Further, the scenario analyses assess how more widespread weather events may diminish international trade's ability to act as a buffer in mitigating climate impacts on food availability.

References

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