Environmental Risks and Agricultural Commodities

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As natural disasters are expected to increase both in severity and frequency, their impact on agricultural commodities and the food supply chain is likely to rise in tandem. We use a unique data set of natural disasters that occurred globally between 1970 and 2015 and study their impact on the price and price volatility of eight globally traded agricultural commodities that account for more than 75% of the food supply in the world. Our results show that price and the price volatility of commodities are impacted around the occurrence of a natural disaster in producing countries. In addition, we find that the affected country's production shares, the total damage caused by a natural disaster relative to the affected country's GDP, and the demand pressure for the commodity have an impact on the magnitude of price and price volatility changes of a given commodity around the occurrence of a natural disaster.

Keywords: natural disasters, agricultural commodities, commodity price, price volatility

INTRODUCTION

Environmental risk factors have only recently become an area of intent concern. These risk factors, such as natural disasters, are becoming increasingly prevalent and larger in magnitude and their impact on our daily lives will only become more significant. As climate changes become increasingly severe, the agricultural sector, and by extension the food industry, needs to address the challenges ahead. The long-term success of firms and the long-term effectiveness of their supply chain risk management, especially for firms active in the agricultural and food industry, depend on how well the impact of these emerging risk factors are addressed. This study is an attempt to better identify the impact of these risk factors on individual commodities. We contribute to the literature on food supply chain management and climate change by focusing on agricultural commodities that constitute a significant part of the world's food supply. These commodities are the main part of the food supply chain, and prices are highly dependent on a stable and affordable commodity price. While a single disaster may not significantly impact the supply chain, as extreme weather events become more frequent, instability will spill over to food supply (Rozenweig et al 2001). Natural disasters cannot be prevented but a thorough understanding of their impact and planning for these inevitable disasters will be vital especially for the food industry (Sivakumar et al, 2005).

While the effect of natural disasters on economies and financial markets has been the subject of many studies, few have focused on how commodity prices are affected by natural disasters occurring in producing countries. Our work aims to fill this gap. Our study provides a first-of-its-kind investigation into the immediate impact of emerging environmental risks, such as water- and climate change-related natural disasters, on agricultural commodities' prices and price volatility. Our data includes coffee, wheat, soybeans, rice, cocoa, sugar, maize, and oat. These commodities are chosen as they account for more than 75% of food supply of the world (Lobell et al, 2011). Moreover, to our knowledge, our study is the first to use a comprehensive database of natural disasters around the world. We aim to be a starting point to better assess the impact of emerging environmental disasters on the risk management of the food supply chain.

We focus on the agricultural commodity sector and its whole production process. Natural disasters can cause significant disruptions in the production of an agricultural commodity in the country that produces it. This disruption in production is not limited to the direct impact on crop production. Rather, a natural disaster can affect the producing country's infrastructure, indirectly adversely affecting commodity production (Noy and Nualsri, 2011; Nakamura et al., 2013). The underlying assumption is that a natural disaster that affects a country producing a certain commodity will cause direct or indirect disruption. The direct disruption in production can occur because the disaster affects the actual production of the crop (Haile et al, 2017) and the indirect disruption adversely impacts the infrastructure required in production and distribution (Tembata and Takeuchi, 2019).

The first part of the study focusses on testing whether natural disasters do in fact have an immediate impact on the price and price volatility of commodities. If natural disasters significantly disrupt a commodity's production, directly or indirectly, we expect this disruption to be reflected in its price and price volatility. Our event study results show a significant increase in the price of commodities during and after a natural disaster. Moreover, our results indicate a significant increase in price volatility before, during, and after a natural disaster.

In the second part of our analyses, we explore how various factors may affect the magnitude of price or price volatility changes around the occurrence of a natural disaster. While natural disasters occurring in producer countries can affect the price and price volatility of commodities, the level of impact can vary depending on numerous factors. We include several factors that may have an impact on the magnitude of price and price volatility change in our study. These factors include the global production share of the commodity in the affected country, the damage caused by the natural disaster, and the global demand pressure of the affected commodity.

Our results indicate that various factors can impact the magnitude of a commodity's price and price volatility change. Specifically, we find that the magnitude of the price change of a commodity immediately after the occurrence of a natural disaster is positively related to a country's production share of that commodity, the damage caused by the disaster relative to the affected country's GDP, and the demand pressure of the commodity. Demand pressure is also positively related to the magnitude of price change in the period leading to and during the disaster. Moreover, our results indicate that the price volatility change of a commodity is positively related to a country's production share of that commodity before, during, and after a natural disaster. However, demand pressure is negatively related to the magnitude of price volatility change before, during, and after a natural disaster. Our results mainly remain robust when we control for high and low GDP per capita as a measure of the strength of the infrastructure and when we control how commodity production is spread among producing countries.

This paper is organized in the following order. In the next section, we present the literature review. Next, we present the data used in our study. Then, a summary of our methodology is presented while a full description is included in the appendix. Next, we present our results and robustness measures, followed by our conclusion.

LITERATURE REVIEW

Both private and institutional investors are increasingly aware that their portfolio firms are subject to emerging risk factors such as water and climate change risks (Chang et al., 2014; Ranger, 2012), particularly if those firms operate in the agricultural and resource extraction sector or if their supply chains are based on the associated agricultural and natural resource commodities (Michel-Kerjan, 2010). There is also ample evidence that climate change will in fact increase the frequency and magnitude of natural disasters

(Rahmstorf and Coumou, 2011) and extreme weather events in the future (Michel-Kerjan, 2010; Ranger, 2012; Francis and Vavrus, 2012).

Natural disasters' adverse effects can go beyond the impacted area and can affect the entire economy of the affected country (Strobl, 2012; Tembata and Takeuchi, 2019), causing riskier business environments for a variety of sectors, including the food industry (Chang et al., 2014; Ranger, 2012). In addition, natural disasters can significantly impact a country's infrastructure and labor force, adversely impacting areas beyond the affected areas (Noy, 2009, Noy and Vu, 2010). As climate change related events and natural disasters become more frequent and more severe, these studies magnify the necessity of research to identify the possible impacts of natural disasters and how to be prepared for them.

Few studies also investigate the impact of weather-related events on agricultural commodities. Extreme weather events can affect agricultural production and prices significantly as they are likely to have a negative impact on crop production (Haile et al, 2017). Existing studies have established that heat waves and droughts (Ciais et al., 2005; Verheijen et al., 2010), hailstorms (Sanchez et al., 1996), excessive cold and precipitation (Rosenzweig et al. 2002) have all shown to have adverse effects on crop production which are likely to affect crop prices. Roll (1984) studied the impact of weather and weather-related events on the price of orange juice concentrate. Gebregewergs and Hadush (2017) study the impact of weather conditions on potato and onion prices in Ethiopia. Spencer and Polacheck (2015) studied the impact of hurricanes and consequent damage on local crop production and prices in Jamaica. Lara-Chavez and Alexander (2006) studied the impact of Hurricane Katrina on Corn, Wheat, and Soybean Prices as Katrina caused severe damage to crop production and transportation and grain export infrastructure. These studies use a limited number of agricultural commodities. Our study builds on the existing literature by including eight agricultural commodities that account for more than 75% of the world's food supply.

Most of these studies have examined the long-term impacts of extreme weather events on the agricultural sector. For instance, Griggs et al., (2013) study the losses in agricultural production due to adverse weather conditions, alongside the potential for high volatility in food prices. However, the immediate impact of natural disasters on the price movements of agricultural commodities has yet to be studied thoroughly.

DATA

Our data comes from four separate sources. The study includes eight commodities: coffee, wheat, rice, soybeans, sugar, cocoa, maize, and oat. We use Bloomberg to access the historical prices of each commodity.

We also use the International Disaster Database from the Center for Research on the Epidemiology of Disasters (CRED) to compile our natural disaster dataset. In our sample, we include all available agricultural natural disasters listed in the CRED database—namely landslides, wildfires, floods, storms, and droughts—that caused at least $5 million in damage. We use different cut-off values for damages caused by natural disasters (for example, $10 million and $20 million), and our results remain materially unchanged. All damage values are adjusted for inflation. This results in 731 unique natural disasters. Since a single disaster can affect a country that produces more than one of the commodities in our study, we included separate observations for the impact on each commodity, for a total of 1,658 observations. For every agricultural disaster listed in CRED, we manually extract the start date of the disaster, the country affected, the total damages in US dollars caused, and the total number of deaths.

Our sample also includes 30 countries. Each country's production share of a given commodity is collected from historical data and statistics provided by the Food and Agriculture Organization of the United Nations (FAOSTAT). For every commodity, we gather historical data on the production levels of individual countries, we then use the annual global individual production figures to calculate the historical production share of each country for every commodity.

Finally, we use the World Bank and the Organization for Economic Co-operation and Development (OECD) national accounts to retrieve information on each country's historical GDP per capita.

METHODOLOGY

In the first part of our empirical analyses, we employ a standard event study methodology to measure abnormal returns and abnormal volatilities around the occurrence of natural disasters. Our use of an event study analysis is inspired by Kothari and Warner (2008) and Brown and Warner (1980). The event study methodology is based on the efficient market hypothesis developed by Fama et al. (1969) who state that asset prices reflect all available information and that markets establish a new equilibrium as soon as new information becomes available. This methodology has been widely used to measure the impact of natural disasters and other disasters on economies and financial markets (Walker, Thiengtham, and Lin, 2005; Hochrainer, 2009; Nakamura et al., 2013).

The first part of our event study analysis focuses on commodity prices and their possible abnormal returns around the occurrence of natural disasters. For this, we first estimate the commodity prices because the event did not happen. For this purpose, the commodities' expected returns are estimated using model (1):

$$R_{i,t} = \beta_0 + \beta_1 * R_{m,t} + \epsilon_{i,t} \tag{1}$$

where $R_{i,t}$ is the return on each commodity impacted by disaster *i* at time *t*, $R_{m,t}$ is the return on market index *m* at time *t*, and $\epsilon_{i,t}$ is the random error term. β_0 and β_1 are estimated coefficients. Our event study uses the S&P 500 Goldman Sachs Commodity Index (GSCI). In our estimation of β_0 and β_1, the event date is marked at *t* = 0. The β_0 and β_1 coefficients are estimated using a prior-to-the-event-date estimation window of [–60, –30]. Our results remain unchanged when we also use longer estimation periods, such as an estimation window of [–250, –30].

The abnormal returns of commodities are then calculated using model (2):

$$AR_{i,t} = R_{i,t} - (\beta_0 + \beta_1 * R_{m,t}) \tag{2}$$

where AR_{it} denotes the abnormal return of each commodity impacted by natural disaster *i* at time *t*. Our model assumes that the abnormal return is the result of an occurrence of a natural disaster in a production center.

We use model (3) to calculate cumulative abnormal returns (CARs) for a period of τ days:

$$CAR_{it} = \sum_{t=1}^{\tau} AR_{i,t} \tag{3}$$

Similarly, the variance of CARs is calculated using model (4).

$$var(CAR_{i\tau}) = \sum_{t=1}^{\tau} var(AR_{i,t}) \tag{4}$$

An average of the CARs and of the variance of CARs across all natural disasters impacting the production centers of each commodity are calculated using models (5) and (6):

$$\overline{CAR_\tau} = \frac{1}{N} \sum_{i=1}^{N} CAR_{i,t} \tag{5}$$

$$var(\overline{CAR_\tau}) = \frac{1}{N^2} \sum_{i=1}^{N} var(CAR_{i,t}) \tag{6}$$

We use a Student's *t*-tests to test for the null hypothesis of mean excess returns during an event window being equal to zero.

To calculate the abnormal variance of returns around the occurrence of natural disasters in production centers, we use an Exponential Generalized Autoregressive Conditional Heteroskedastic (EGARCH) model

(Nelson, 1991; Nelson and Cao, 1992) to estimate conditional volatility. Specifically, we use the EGARCH model to allow the return sign (positive or negative) to have a separate effect from the return magnitude.

Once we estimate the conditional volatility of a given commodity, we use a similar approach as that for mean-adjusted abnormal returns (Brown and Warner, 1980) to measure abnormal return variance using model (7):

$$AV_{i,t} = CV_{i,t} - \frac{1}{31}\sum_{t=-60}^{-30} CV_{i,t} \tag{7}$$

where AV_{it} denotes the abnormal volatility of returns for each commodity affected by natural disaster *i* at time *t*. $CV_{i,t}$ is the conditional volatility estimated by the EGARCH model for each commodity affected by natural disaster *i* at time *t*.

We then measure the cumulative abnormal variance (CAV) and the relevant *t*-statistic using an approach similar to the one we used to estimate abnormal returns.

We use model (8) to calculate the cumulative abnormal variance for a period of τ days:

$$CAV_{i\tau} = \sum_{t=1}^{\tau} AV_{i,t} \tag{8}$$

In addition, we use model (10) to measure the variance of cumulative abnormal returns:

$$var(CAV_{i\tau}) = \sum_{t=1}^{\tau} var(AV_{i,t}) \tag{9}$$

We estimate the average CAVs and the variance of the CAVs across all-natural disasters affecting the production centers of each commodity using models (10) and (11):

$$\overline{CAV_{\tau}} = \frac{1}{N}\sum_{i=1}^{N} CAV_{i,t} \tag{10}$$

$$var(\overline{CAV_{\tau}}) = \frac{1}{N^2}\sum_{i=1}^{N} var(CAV_{i,t}) \tag{11}$$

Finally, we perform a Student's *t*-test to test for the null hypothesis in which the mean excess variance is equal to zero in any given event window.

In the second part of our empirical analysis, we study the possible impact of various factors on the magnitude of abnormal return and abnormal variance.

$$CAR.GSCI_{t1,t2,i,j} = \alpha + \beta_1 * Production\,Share_i + \beta_2 * Total\,Damage_j/GDP_j + \beta_3 * Deaths_j/Population_j + \beta_4 * Demand.Pressure_i + \beta_5 * GDPPerCapita_j + \sum_{h=1}^{7} \beta_i * Commodity_h + \sum_{m=1}^{4} \beta_m * Disaster.type_m + \varepsilon_{i,j,t_1,t_2} \tag{12}$$

where $CAR.GSCI_{i,j,t_1,t_2}$ is the cumulative abnormal return using the Goldman Sachs Commodity Index (GSCI) as the bench mark for the event window of $[t1, t2]$ for commodity *i* and disaster *j*.

$Production\,Share$ is a country's production share of a certain commodity in the year prior to the occurrence of a natural disaster. We use the previous year's information because a disaster can affect the commodity's production in the current year.

$Total\,Damage_j/GDP_j$ is the total damage in US dollars caused by a natural disaster as reported by CRED divided by the affected country's Gross Domestic Product (GDP) in the prior year multiplied by 1000.

$Deaths_j/Population_j$ is the number of casualties caused by a natural disaster divided by affected country's population multiplied by 1000. This information is also reported by CRED. While we use the

Total Damage/GDP as a measure of significance of a natural disaster, Total Deaths/Population may provide additional information on the severity of a natural disaster.

$Demand.Pressure$ is a proxy of the demand pressure for a given commodity (Trostle, 2010). We define this measure as

$$Demand.Pressure_{i,t} = \frac{1/30\sum_{j=t-60}^{t-31} Price_{i,t} - 1/500\sum_{j=t-560}^{t-61} Price_{i,t}}{1/30\sum_{j=t-60}^{t-31} Price_{i,t}} \quad (13)$$

where $Price_{i,t}$ is the price of commodity *i* at time *t*. This variable simply measures the price increase of commodity *i* prior to the natural disaster occurring at time *t*. We conjecture that commodities that are in high demand have experienced a relatively recent increase in price. Consequently, a disruption in their production caused by a natural disaster affecting a production center may significantly impact their price and price volatility.

$Commodity_i$ is a dummy variable that identifies our sample's commodities: cocoa, coffee, rice, soybeans, wheat, maize, and oats (with sugar as the excluded category).

Similarly, $Disaster_j$ is a dummy variable that identifies the disasters: storms, droughts, wildfires, and landslides (with floods as the excluded category).

We also use an extension of model (1) to test the possible impact of various factors on the cumulative abnormal price volatility of a given commodity by replacing $CAR.GSCI_{t1,t2,i,j}$ with $CAV.EGARCH_{i,j,t1,t2}$in the regression model where $CAV.EGARCH_{i,j,t1,t2}$ is the cumulative abnormal variance for commodity *i* affected by disaster *j* using the conditional variance calculated by a EGARCH(1,1) model for the event window of $[t1, t2]$.

EMPIRICAL RESULTS

Event Studies

Table 1 shows the impact of natural disasters on the price and price volatility of commodities before, during, and after natural disasters.

To study the impact of a natural disaster on commodity price and price volatility before a natural disaster, we use two event windows: (-7,0) and (-5,-1). As presented in table 1, we do not observe a meaningful change in the abnormal return of commodity prices. In other words, in days immediately preceding a natural disaster, we do not observe a meaningful change in commodity prices. Our results show a significant increase in commodity price volatility for the same event windows. In other words, during the immediate period he occurrence of a natural disaster, commodity prices show a significant increase in volatility.

In summary, while we do not observe a significant change in commodity prices before a natural disaster, we observe an increase in commodity price volatility during the same period. We conjecture that this is because the natural disasters in our sample include landslides, wildfires, floods, storms, and droughts, the occurrence or declaration of which can be forecasted with a certain level of confidence. For example, landslides and floods are preceded by intense rainfall, and weather forecasts can relatively accurately forecast storms. Moreover, droughts are preceded by low precipitation, and wildfires are the product of dry and hot weather and start as smaller fires. These indications that a natural disaster may be looming cause an increase in price volatility. However, these indications do not provide an accurate indication of the magnitude of the disaster and the damage it may cause; consequently, commodity prices do not show a significant change before the occurrence of the natural disaster.

To study the change in commodity price and price volatility surrounding the occurrence of natural disaster, we use one event window: (-1,+1). Our results indicate a significant increase in both the price and price volatility of commodities during the occurrence of a natural disaster. In the days immediately preceding the disaster and immediately after its occurrence, better estimates of its magnitude and the damage it caused are available. As a result, both price and price volatility significantly increase during this period.

TABLE 1
PRICE AND VOLATILITY IMPACT OF NATURAL DISASTERS ON COMMODITIES

Event Window	Abnormal Return CAR.GSCI (*p*-value)	Abnormal Variance CAV.EGARCH (*p*-value)
(-7,0)	1.4656	**0.3033*** **
	0.4589	0.0000
(-5,-1)	1.6894	**0.2564*** **
	0.1503	0.0000
(-1,+1)	**3.1684** **	**0.5029*** **
	0.0380	0.0000
(+1,+5)	**1.9930** **	**0.2215*** **
	0.0400	0.0000
(0,+7)	**0.3007***	**0.0004*** **
	0.0912	0.0000

This table shows the impact of a natural disaster on the price and price volatility of various commodities for various event windows. *P*-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. Significant results are in bold. Sample size is 1658.

Finally, our results show a significant increase in both the price and price volatility of commodities during natural disasters. We used two event windows to examine this: (0,+7) and (+1,+5). This seems intuitive as in the days after a natural disaster, better estimates regarding the damage to crop production and infrastructure are available. As a result, both the commodity price and price volatility show a significant increase after a natural disaster.

OLS REGRESSIONS

Table 2 provides OLS regression results for various factors affecting the price and price volatility change of commodities during a natural disaster. We observe that demand pressure positively impacts abnormal return, CAR.GSCI, across all event windows (Models 1, 2, and 3). This means the price of commodities that have experienced a recent demand pressure show more sensitivity to natural disasters, resulting in a higher price increase around the time of a natural disaster.

In addition, the *Damage-to-GDP* variable has a positive impact on abnormal returns during and after the occurrence of a natural disaster. As damage can only be accurately assessed once a disaster occurs, damage doesn't seem to impact the abnormal return before the occurrence of the disaster. However, once the disaster occurs and the magnitude of its damages is clear, we note that natural disasters with higher damages result in a higher price increase for commodities.

TABLE 2
OLS REGRESSIONS OF CUMULATIVE ABNORMAL RETURN AND CUMULATIVE ABNORMAL VARIANCE

	(1)	(2)	(3)	(4)	(5)	(6)
	Abnormal Return CAR.GSCI			Abnormal Variance CAV.EGARCH		
Event Window	(–5, –1)	(–1, +1)	(+1, +5)	(–5, –1)	(–1, +1)	(+1, +5)
Production Share	-0.0210	0.0001	**0.0215***	**0.0017*****	**0.0010*****	**0.0016*****
	(0.2634)	(0.9951)	**(0.0720)**	**(0.0036)**	**(0.0025)**	**(0.0032)**
Total Damage/GDP$_{t-1}$	0.0003	**0.0005****	**0.0007****	0.0000	0.0000	0.0000
	(0.3173)	**(0.0390)**	**(0.0106)**	(0.4827)	(0.3625)	(0.2282)
Total Deaths/Population	0.0113	-0.0119	**-0.0783****	-0.0003	0.0002	-0.0004
	(0.7216)	(0.6278)	**(0.0108)**	(0.7227)	(0.7837)	(0.6694)
Demand Pressure	**0.0513*****	**0.0199*****	**0.0359*****	**-0.0004****	**-0.0002***	**-0.0005*****
	(0.0000)	**(0.0002)**	**(0.0000)**	**(0.0336)**	**(0.0889)**	**(0.0087)**
Commodity Control	Yes	Yes	Yes	Yes	Yes	Yes
Disaster Control	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.0022	-0.0015	-0.0039	-0.0002	**-0.0001***	-0.0002
	(0.5109)	(0.5456)	(0.2298)	(0.1117)	**(0.0568)**	(0.1079)
Observations	1658	1658	1658	1658	1658	1658
Adjusted R-squared	0.0319	0.0139	0.0168	0.0076	0.0084	0.0117

This table provides OLS regression results for the impact of various factors on cumulative abnormal returns and cumulative abnormal variances prior, during, and after the occurrence of a natural disaster. The dependent variable in models (1) through (3), CAR.GSCI, is the cumulative abnormal return using the Goldman Sachs Commodity Index as the bench mark for the event window [t1, t2]. The dependent variable in models (4) through (6), CAV.EGARCH, is the cumulative abnormal variance using the EGARCH(1,1) as the bench mark for the event window [t1, t2]. All other variables are as defined earlier. The event windows used to calculate the cumulative abnormal returns before, during, and after the event (day 0) are shown in the first row. Robust *p*-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. Significant results are in bold.

Finally, our results show a price increase for countries with a higher production share after the occurrence of the natural disaster as a more significant global production share of the commodity is disrupted.

Table 2 (Models 4, 5, and 6) presents the impact of various factors on the cumulative abnormal variance of commodity prices (CAV.EGARCH) surrounding the occurrence of natural disasters. Specifically, we observe significant negative coefficients for the demand pressure variable. This result is expected given that commodities that have undergone recent turmoil (as measured by recent price increases) are likely to be less affected than commodities whose prices were more stable. In other words, the price volatility increases of commodities that had stable prices before a disaster is higher during a natural disaster when compared to commodities that have experienced recent price increases.

Moreover, we notice that the production share variable is significantly positive across all regression models, suggesting that when a natural disaster affects a country with a higher production share, the agricultural commodities produced by that country will experience a significant increase in price volatility and this increase in price volatility is observed before, during, and after the occurrence of natural disaster.

ADDITIONAL TESTS

We continue our data analysis by studying whether other factors may impact abnormal returns and abnormal variance when natural disasters occur. The first factor that may have an impact is the strength of a country's infrastructure. We use GDP per Capita as a proxy for the strength of infrastructure and divide our sample to two sub samples: countries with High GDP per Capita and countries with Low GDP per Capita. We define a High GDP per Capita (Low GDP per Capita) country as a country with higher (lower) than median GDP per Capita in our sample.

Countries with High GDP per Capita are likely to have stronger infrastructure and may be better prepared for natural disasters and hence sustain less damage, the opposite being true for countries with a Low GDP per Capita.

Table 3 shows our results using sub-samples of our data based on producing countries' GDP per Capita. Models 1, 3, 5, and 7 include countries with Low GDP per Capita and models 2, 4, 6, and 8 include countries with High GDP per Capita as defined before.

Our abnormal return results remain consistent with those presented in table 2 for the period after the disaster in both High and Low GDP per Capita countries (models 3 and 4). Production Share, Damage-to-GDP, and Demand Pressure have positive and significant relation with abnormal return.

For the period leading to the disaster (models 1 and 2), similarly to the results in table 2, Demand Pressure remains positive and significant. However, for the same period (Model 1), we also observe that both Production Share and Damage-to-GDP have a positive and significant relation with abnormal return only in the Low GDP per Capita countries subsample. In other words, during the period leading to the natural disaster and in countries with weaker infrastructure, production share is also positively and significantly related to the price increase of the commodity. Moreover, anticipation of a stronger natural disaster and consequently higher Damage-to-GDP in countries with weaker infrastructure will generate a significant price increase for the commodities produced in those countries.

Table 3 shows that our results for abnormal variance remain consistent with those depicted in table 2 (models 5 through 8). Production share is positively related to abnormal variance before and after a natural disaster. Moreover, demand pressure is negatively related to abnormal variance before and after a natural disaster.

Another factor that can affect the abnormal return and abnormal variance around the occurrence of natural disaster is the degree to which production of a commodity is concentrated in various countries. To measure this, we use the Herfindahl index. We calculate the Herfindahl Index for commodity k for year t as the $HI_{kt} = \sqrt{\sum_{i=1}^{n} P_{ikt}{}^{2}}$. Where HI_{kt} is the Herfindahl Index for commodity k in year t and P_{ikt} is the production share of country i for commodity k in year t.

TABLE 3
OLS REGRESSIONS OF CUMULATIVE ABNORMAL RETURN AND CUMULATIVE ABNORMAL VARIANCE USING SAMPLES BASED ON AFFECTED COUNTRIES WITH HIGH OR LOW GDP PER CAPITA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GDP per Capita	Low	High	Low	High	Low	High	Low	High
Event Window	(–5, –1)	(–5, –1)	(+1, +5)	(+1, +5)	(–5, –1)	(–5, –1)	(+1, +5)	(+1, +5)
	CAR.GSCI	CAR.GSCI	CAR.GSCI	CAR.GSCI	CAV.EGARCH	CAV.EGARCH	CAV.EGARCH	CAV.EGARCH
Production Share	**0.0653***	-0.0018	**0.0285***	**0.0665****	**0.0019*****	**0.0020*****	**0.0016***	**0.0023*****
	(0.0754)	(0.9475)	**(0.0971)**	**(0.0178)**	**(0.0012)**	**(0.0019)**	**(0.0923)**	**(0.0006)**
Total Damage/GDP_{t-1}	**0.0004****	0.0002	**0.0003****	**0.0020*****	-0.0000	0.0000	0.0000	0.0000
	(0.0144)	(0.8087)	**(0.0268)**	**(0.0055)**	(0.9735)	(0.4454)	(0.5867)	(0.3006)
Total Deaths/ Population	-0.0165	0.0838	-0.0309	**-0.1932*****	-0.0002	0.0016	-0.0005	0.0019
	(0.6547)	(0.2428)	(0.3585)	**(0.0075)**	(0.8534)	(0.3298)	(0.6684)	(0.2715)
Demand Pressure	**0.0643*****	**0.0423*****	**0.0431*****	**0.0235****	**-0.0005*****	**-0.0005****	**-0.0008****	**-0.0003*****
	(0.0000)	**(0.0000)**	**(0.0000)**	**(0.0226)**	**(0.0051)**	**(0.0488)**	**(0.0283)**	**(0.0012)**
Commodity Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Disaster Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.0031	-0.0009	0.0072	**-0.0094****	-0.0001	**-0.0003*****	-0.0001	**-0.0003*****
	(0.6505)	(0.8414)	(0.2469)	**(0.0340)**	(0.6845)	**(0.0027)**	(0.8215)	**(0.0072)**
Observations	829	829	829	829	829	829	829	829
Adjusted R-squared	0.0551	0.0194	0.0231	0.0225	-0.0003	0.0256	0.0066	0.0234

This table provides OLS regression results for the impact of various factors on cumulative abnormal returns and cumulative abnormal variances prior and after the occurrence of a natural disaster. The dependent variable in models (1) through (4), CAR.GSCI, is the cumulative abnormal return using the Goldman Sachs Commodity Index as the bench mark for the event window [t1, t2]. The dependent variable in models (4) through (8), CAV.EGARCH, is the cumulative abnormal variance using the EGARCH(1,1) as the bench mark for the event window [t1, t2]. All other variables are as defined earlier. The event windows used to calculate the cumulative abnormal returns before, during, and after the event (day 0) are shown in the first row. Robust *p*-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. Significant results are in bold.

A higher Herfindahl Index means a commodity's global production is concentrated in fewer countries, and thus a natural disaster affecting one of these major producers is more likely to affect a larger global production share. In our sample, we define a High Production Share Herfindahl (Low Production Share Herfindahl) commodity as a commodity with higher (lower) than median Production Share Herfindahl. Similar to Table 3, we divide our sample into two sub-samples: commodities with High Production Share Herfindahl and commodities with Low Production Share Herfindahl.

Table 4 shows our regression results for subsamples of countries with Low Production Share Herfindahl (models 1, 3, 5, and 7) and High Production Share Herfindahl (models 2, 4, 6, and 8).

Our results for abnormal variance remain consistent with those in table 2 (models 5 through 8). We also observe similar results for abnormal returns to those depicted in Table 2 for the period after a natural disaster (models 3 and 4). Interestingly, for the period leading up to a natural disaster, we observe a difference between Low and High Production Share Herfindahl commodities (models 1 and 2). Specifically, for High Production Share Herfindahl commodities (commodities whose global production is concentrated in fewer countries), production share is positively and significantly related to abnormal returns for the period immediately before a natural disaster (model 2). In other words, for commodities whose global production is concentrated in fewer countries, production share is positively and significantly related to abnormal return when there is an anticipation of a natural disaster, as the disaster is likely to disrupt a larger portion of the global production of the commodity.

CONCLUSION

We use a unique, hand-collected sample of large-scale natural disasters around the globe to study the immediate impact of natural disasters on the price and price volatility of agricultural commodities when a producing country is affected by a natural disaster. The eight agricultural commodities used in our sample account for more than 75% of the food supply in the world. Natural disasters cause damage not only to crops but also to production infrastructure, consequently disrupting the supply chain of the commodity. We test if these disruptions in the supply chain are reflected in the market via price changes and price volatility changes. Our empirical study also examines which factors drive the magnitude of price and price volatility changes when a natural disaster occurs.

Our event study results indicate that a natural disaster impacts the price and price volatility of agricultural commodities when natural disasters occur. Specifically, we observe an increase in price volatility during the period leading to a disaster, around the time of the disaster, and immediately after the occurrence of a natural disaster. Moreover, we observe an increase in price around the occurrence of a natural disaster immediately after a natural disaster.

Our results also indicate that the production share of an affected country is positively related to the magnitude of price volatility changes before, during, and after a natural disaster. Moreover, production share and damage caused by the natural disaster relative to the affected country's GDP are positively related to the magnitude of price changes immediately after a disaster. Our results also indicate that demand pressure is positively related to price increase and negatively related to price volatility increase before, during, and after the occurrence of a natural disaster. In other words, commodities under demand pressure, measured by recent price increases, experience a larger price increase and a smaller price volatility increase around a natural disaster.

We also control for countries' infrastructure strength and how commodity production is spread among countries across the globe. Our results indicate that the production share of the countries with weaker infrastructure is positively and significantly related to price increases even during the period leading to the natural disaster. Moreover, the anticipation of a stronger natural disaster and consequently higher Damage to GDP in countries with weaker infrastructure will generate a significant price increase during the period leading to the occurrence of the natural disaster. Furthermore, for commodities whose global production is concentrated in fewer countries, production share is positively and significantly related to abnormal returns even during a natural disaster.

TABLE 4
OLS REGRESSIONS OF CUMULATIVE ABNORMAL RETURN AND CUMULATIVE ABNORMAL VARIANCE USING SAMPLES BASED ON PRODUCTION SHARE HERFINDAHL OF COMMODITIES

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Production Share Herfindahl	Low Herfindahl	High Herfindahl	Low Herfindahl	High Herfindahl	Low Herfindahl	High Herfindahl	Low Herfindahl	High Herfindahl
Event Window	(–5, –1)	(–5, –1)	(+1, +5)	(+1, +5)	(–5, –1)	(–5, –1)	(+1, +5)	(+1, +5)
	CAR.GSCI	CAR.GSCI	CAR.GSCI	CAR.GSCI	CAV.EGARCH	CAV.EGARCH	CAV.EGARCH	CAV.EGARCH
Production Share	-0.0425	**0.0067*** **	**0.0575***	**0.0034****	**0.0023****	**0.0011***	**0.0024****	**0.0011****
	(0.2328)	**(0.0070)**	**(0.0821)**	**(0.0331)**	**(0.0493)**	**(0.0711)**	**(0.0465)**	**(0.0420)**
Total Damage/GDP_{t-1}	0.0010	0.0000	**0.0014****	**0.0004****	0.0000	0.0000	0.0000	0.0000
	(0.1063)	(0.9096)	**(0.0115)**	**(0.0282)**	(0.8196)	(0.3871)	(0.2966)	(0.3790)
Total Deaths/Population	0.0149	0.0215	-0.0870	**-0.0625***	0.0050	-0.0010	0.0054	-0.0009
	(0.8878)	(0.5095)	(0.3763)	**(0.0547)**	(0.1483)	(0.2759)	(0.1297)	(0.2790)
Demand Pressure	**0.0676*****	**0.0400*****	**0.0320*****	**0.0396*****	**-0.0004****	**-0.0005****	**-0.0003*****	**-0.0007*****
	(0.0000)	**(0.0000)**	**(0.0030)**	**(0.0000)**	**(0.0339)**	**(0.0471)**	**(0.0011)**	**(0.0006)**
Commodity Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Disaster Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.0020	-0.0052	**-0.0074***	-0.0084	-0.0002	-0.0001	-0.0003	-0.0002
	(0.6700)	(0.3979)	**(0.0924)**	(0.1645)	(0.1762)	(0.3875)	(0.1027)	(0.2903)
Observations	829	829	829	829	829	829	829	829
Adjusted R-squared	0.0508	0.0181	0.0224	0.0139	-0.0006	0.0092	0.0077	0.0204

This table provides OLS regression results for the impact of various factors on cumulative abnormal returns and cumulative abnormal variances prior and after the occurrence of a natural disaster. The dependent variable in models (1) through (4), CAR.GSCI, is the cumulative abnormal return using the Goldman Sachs Commodity Index as the bench mark for the event window [t1, t2]. The dependent variable in models (4) through (8), CAV.EGARCH, is the cumulative abnormal variance using the EGARCH(1,1) as the bench mark for the event window [t1, t2]. All other variables are as defined earlier. The event windows used to calculate the cumulative abnormal returns before, during, and after the event (day 0) are shown in the first row. Robust *p*-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. Significant results are in bold.

As natural disasters become more common and severe globally, likely because of climate change, their impact on our lives becomes more significant. As climate change and its associated risks become increasingly urgent, the incentive to identify and address their impact on the supply chain of leading firms also becomes increasingly urgent. Agricultural commodities are used in the supply chain of many companies, and any impact on their price can significantly affect global food production. Firms' long-term success in the food industry is highly dependent on their comprehensive understanding of the emerging risk factors in their supply chain. To our knowledge, this study is the first to use a comprehensive database of global natural disasters to study the immediate impact of natural disasters on price and price volatility of agricultural commodities. We contribute to the literature by studying the impact of these emerging risk factors on agricultural commodities that constitute most of the world's food supply. Our study aims to be a starting point contributing to this pressing issue which will require further research to ensure better food security and food supply chain risk management around the globe.

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