Natural Disasters and Agricultural Commodity Prices:
Global Evidence

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Abstract

Using the prices of seven agricultural commodities over the period from 1980 to 2019, this study employs both an event study and GARCH modelling to capture whether and how natural disasters occurring in the main production centres of certain agricultural commodities affect their returns and price volatilities.

In a first step, we examine how natural disasters affect the prices and volatilities of the affected commodities. In a second step, we employ a series of ordinary least squares (OLS) regressions to examine what factors (e.g., disaster, commodity, and country characteristics) affect the abnormal return and abnormal volatility. Our study thus provides important insights for traders, hedgers, producers, and purchasers of agricultural commodities who are concerned about the rising risk of climate-induced events and how they may affect the agricultural commodity markets.

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Table of Contents

List of Tables

List of Figure

Introduction

In recent years, we have seen an increase in the frequency and severity of natural disasters all over the world (Rahmstorf & Coumou, 2011; Francis & Vavrus, 2012; Bourdeau-Brien & Kryzanowski, 2017). These natural disasters have caused property and agricultural losses, amounting to an annual average of +18 billion US dollars over the last 25 years (Bourdeau-Brien & Kryzanowski, 2017).

Additionally, the prices and price fluctuations of agricultural commodities have witnessed recently severe changes, with negative economic impacts (Zhang et al., 2020). As the climate continues to change, the number and intensity of natural disasters will increase; leaving agriculture directly exposed to and dependant on environmental natural factors (Mechler et al., 2010).

Like other financial assets, agricultural commodity markets are information-driven (Milonas, 1987). Information is important for capital allocation in markets, and the timely reactions by market participants to information is what makes a market efficient (Fama, 1970). Thus, a speedy and accurate price adjustment to information is the main feature of an efficient market. Quick dissemination of data in markets induce trading, leading to price determination, i.e., a new equilibrium price decided by supply and demand forces.

Information includes the factors that market participants consider as signals carrying pieces of information that is important to them, as buyers and sellers, in reaching the equilibrium price. Many studies have been conducted to determine what financial markets constitute as *signals*, how market participants interpret them, and how they react to them. Studies have also been conducted to measure how different financial markets react to the same signal. Likewise, studies were performed to measure the impact of different events, in terms of magnitude and direction, including regulations (imposing new regulations or changing already existing ones), risk factors, climate change, and natural disasters.

Natural disasters have different effects on different economies. Breiling (2021) discusses the losses and damages caused by natural disasters, including agrarian losses and rural value chains. He finds that the impact of natural disasters on agricultural activity-led economies is particularly pronounced since they are, in effect, *climate-dependent income systems*. Breiling also discusses the heavy toll that natural disasters have imposed in rural areas, particularly in low-income countries, coupled with their poor reporting capacities, which makes quantifying the losses quite difficult. He notes that it remains difficult to gauge the impact of environmental hazards and natural risks, particularly with the expected increase in their frequency and intensity.

This paper adds to this literature by studying the impact of natural disasters on a set of agricultural commodities, by measuring their abnormal price returns and volatility around the occurrence of these natural disasters. Next, this paper investigates whether certain factors exacerbate or mitigate the abnormal returns and variance of these commodities in response to natural disasters.

The findings of this study are meaningful to market participants because it suggests that short-term natural disasters do not impact commodity prices as per the economic intuition. Markets seem to pay more attention to and care more about long-term natural disasters. It may also be the case that disaster information takes longer to be incorporated in prices; or maybe markets have already anticipated these disasters; however, their impact was not as bad as expected. Another explanation is that the agriculture sector has already increased crops production in previous years because of existing demand, thus the reaction is not pronounced when natural disasters occur.

Literature Review

Over the past few decades, regulators and researchers alike have started to gradually recognise the threats of environmental and climate change to the stability of our financial system[1]. The Bank of England identifies these environmental risks as physical risks and transition risks. Physical risks result mainly from weather events (for instance, droughts, floods, and hurricanes, among others). These environmental risks significantly increase the financial value at risk by destroying real assets such as buildings and important infrastructure. At the same time, transition risks are the risks that arise from regulatory environmental policies that eventually

[1] https://www.bankofengland.co.uk/prudential-regulation/publication/2022/june/the-bank-of-englands-climate-related-financial-disclosure-2022

entail a substantial reallocation of capital from the concerned industries (oil and car manufacturing industries, for example). These risks impose significant and systemic threats to financial stability, as well as macroeconomic conditions.

Environmental and climate risks have been linked to human activities. Nordhaus (1977), among the first economists to study climate change as an economic problem, has identified agriculture and energy as the main economic activities that most affect the natural environment. Moreover, some recent natural events are depicted as human-driven, including a number of China's heatwaves and droughts in 2013, as well as the UK's extreme rainfall and flooding in 2014[2].

On the other hand, the economics, finance, and accounting literature includes many recent studies on the role of natural events in these areas, in an effort to better understand and measure their impact. Stroebel and Wurgler (2021) use surveys to identify top climate risks to businesses and investors, showing that regulatory risk is the most impactful climate risk over the next five years, while physical risks take over as the most disconcerting risk factors over the subsequent 25 years. Using 6,759 natural disasters in 104 countries from the International Emergency Events Database (EM-DAT) and the daily stock price returns for 31 major stock indices from 2001 to 2019, Pagnottoni et al. (2022) study the effects of five types of natural disasters (biological, climatological, geophysical, hydrological, and meteorological disasters) on the stock markets. They use event study methodology in their research and document heterogeneous market responses to natural disasters that depend on the type of the disaster.

Studying climate and environmental factors that investors consider in the financial markets, Krueger et al. (2020) show that investors include climate risks in their portfolio decisions because of those risks' implications. When trying to price climate risk, Bolton and Kacperczyk (2021) find that investors ask for a carbon premium. Relatedly, Hsu, Li, and Tsou (2019) show that investors demand a pollution premium for environment carbon risks. Bansal et al. (2016) use capital market data and find that there is a positive risk premium for global warming that -notably- rises with higher temperatures. Conversely, a number of studies support the view that the financial markets misprice environmental and climate risks (see Daniel, Litterman, & Wagner, 2016; Kumar, Xin & Zhang, 2019).

[2] Ibid.

Campiglio et al. (2019) report that environmental physical risks, such as hurricanes and droughts, have a negative impact on financial assets, mainly through lower returns and higher non-performing loans. Weitzman (2013) discusses the degree to which an investment hedges against catastrophic damages arising from bad-tail events, as natural disasters are linked to extreme structural uncertainties. In addition, uncertainty also arises from environment-related regulations that are often coupled with heterogeneous impacts.

Vo et al. (2019) study the impact of oil and agricultural commodity prices, showing that oil prices impact agricultural commodity prices to the extent that oil price movements may explain changes in agricultural commodity prices and volatility. Conversely, Cabrera and Schulz (2016) investigate the linkage between the prices and price volatility of agricultural commodities and oil in Germany and find opposing results. Employing event study methodology, they find that concerns over agricultural commodity price volatility being impacted by energy are *rather unjustified*.

Zhang et al. (2009) also examine price and volatility transmissions and spillover effects between oil prices and a group of commodities including corn and soybean in the USA using a GARCH model. They find no spillover from oil prices to corn and soybean volatility, but they find that volatility transmits from the agricultural sector to the oil sector. On the contrary, Trujillo-Barrera et al. (2011) use a GARCH model and document volatility spillovers from oil to corn in the USA, particularly during times of oil market turbulence. More recently, Hung (2021) finds that there is significant heterogeneity in the response of agriculture commodities to information spillovers from oil prices pre and post the COVID-19 pandemic.

Further, the UN (2020) reports farming activity problems because of COVID-19. Dev (2020) reports that the unavailability of labour in India interrupted the wheat harvest and Ethiopia suffered from the non-availability of agriculture inputs. Likewise, Pu and Zhong (2020) examine the impact that COVID-19 pandemic had on China’s agricultural sector and the impacts of the corresponding policies that were put in place. Among these factors, movement restrictions are documented to have impacted labour inputs, leading to delays in crop planting, which in turn stopped the natural agricultural growth cycle. Such delays in crop planting, beyond the right time for each relevant crop, can result in reduced crops, and harvests and to losses that subsequently cause lower farming investment in the following season.

Developed countries suffered from different problems, like overstocking of agricultural products in the USA and Canada, which required dumping or destroying crops (Weersink et al., 2020). Furthermore, Hadachek et al. (2023) report that the Russia-Ukraine conflict is an extreme shock that is causing disruptions to food supply chains worldwide and is eliciting authorities' reactions and changes in regulations. These reactions and regulations also play a role, exerting an impact on agricultural activities worldwide, as evidenced in the literature.

In addition, Brás, Jägermeyr, and Seixas (2019) discuss the impact of extreme weather disasters on a number of crops, showing substantial effects particularly because of droughts and heat waves. The crops most affected are soybean (due to floods), and cocoa which is affected by both droughts and heat waves. At the same time, coffee prices exhibit gains after cold waves, because of lower supplies, but tend to suffer steady losses in subsequent years. Also, as soybean is a common substitute of both wheat and corn, any variability to its production and hence prices, affects the supply chains of the other agricultural commodities as well.

Most recently, Apergis and Rezitis (2003) study volatility spillovers across the prices of agricultural inputs and outputs using GARCH models. They find that the prices of agricultural outputs fluctuate more than the prices of agricultural inputs. Amann et al. (2013) study the impact of speculation and causal relationships between the spot markets of wheat, corn, rice, and soybean on the one hand and commodity futures on the other. They find no empirical evidence that speculation drives price changes in agricultural commodities.

Studying rationality in commodity markets, Allen et al. (1994) find that *rationality is violated*, as the prices of 15 agricultural commodity seem to reverse in the aftermath of substantial events. They suggest that the non-instantaneous adjustment of prices as new information hits the market may point to violation of rationality in the short term, as traders in commodity markets incline to overreact to substantial events.

Bourdeau-Brien and Kryzanowski (2017) use event study methodology and GARCH models for the conditional variance, and they find that natural disasters have a significant impact on stock returns in areas hit by those disasters and for two to three months after the natural disaster. Similarly, Chen (2021) employs event studies and examines futures prices of seven agricultural commodities during the China-US trade war, documenting a significant impact of this event on China's agricultural commodities.

Chatzopoulos et al. (2020) use *agroclimatic extremes* within a multi-economic simulation scenario analysis, to find that climate extreme events have an economic impact. They add that agricultural commodities show asymmetry in the direction of the agrometeorological shocks. Yang (2008), however, finds that the stronger the storms, the higher the economic damages and the greater the deaths toll. Yang uses EM-DAT database to obtain meteorological, damages and fatalities data from 1970 to 2002.

Some studies match the damage incurred with different asset classes, such as Mechler et al. (2010) that find that droughts and heat shocks mainly impact agricultural commodities. Likewise, Lesk et al. (2016) document that heat-driven natural disasters (namely, droughts and heat waves) have led to losses ranging of 9%-10% of local production (1200-1800 million tonnes) between 1964 and 2007 of wheat, corn, and rice. Hochrainer (2009) assesses the impact of natural disasters on economies, finding that the size of the shock is an important factor in determining the size of the negative impacts of natural disasters. A country's macroeconomic status also plays a part.

Using four natural disasters from EM-DAT, Fomby et al. (2013) find that the impact of natural disasters is greater in developing countries compared to their impact in developed countries, and that the response differs depending on the type of the natural disaster. The stronger impact on developing countries, with smaller economies, compared to developed economies have been documented in the literature (Rasmussen, 2004; Noy, 2009). Likewise, Raddatz (2009) estimates the long-term and short-term impact of climatic disasters, and he finds that small economies are more vulnerable to some types of natural disasters. Cantelmo et al. (2023) echo this finding and add that the frequency and severity of natural disasters impact the growth of *disaster-prone countries*.

Fomby et al. (2013) also find that major drought episodes cause higher volatility of growth of agricultural sectors, as they cause huge drops in the event year, which turn into high growth in the next year. On the other hand, they find that floods have a positive impact on agricultural growth in developing countries in the year following the flood, but not the year of the event itself. This suggests that floods impact land productivity in the event year, so the harvest in the following year (year 1) is positively affected. In addition, moderate storms also show a positive impact on agricultural growth, but only in the second year after the event. Such a delayed effect indicates a supply chain mechanism, similar to the supply chain mechanism of floods. In other words, floods positively impact agriculture through influencing water provision and soil quality in the event year, which takes time to materialize into higher agricultural growth in the following harvests.

Adding to this literature, Cuaresma et al. (2008) find that studying cross-country and panel regression shows that the level of the natural disasters, or degree of catastrophic risk, has an impact on spillovers between developed (industrialised) and developing economies. Industrialised countries enjoy some benefits from natural disasters, as they upgrade their capital in the aftermath of the natural disasters. Developing countries suffer the consequences, as they lack the capacity for such an upgrade that leads to long-run growth. Skidmore and Toya (2002) also find positive correlation between higher frequency of natural disasters and macroeconomic growth, due to productivity gains and human capital accumulation.

In line with this, Coulibaly et al. (2020) study the impacts of natural disasters on agricultural activities in Africa over 26 years and find that poor African countries are significantly more affected by natural disasters than middle-income countries. Additionally, they find that temperature is the main climatic factor negatively impacting agriculture in African countries studied in both the short and long runs, while droughts are the main natural disaster impacting agrarian production in the short run.

Karali, Ye, and Ramirez (2019) discuss the concept that the relationship between an asset's return and its variance/volatility can be a proxy for that asset's risk, as the direction of this relationship remains controversial in the finance literature due to the conflicting and/or mixed results. To explain this, the time-varying risk premium suggests that there is a positive relationship between return and variance, while both the hypothesis of the volatility feedback and that of leverage effects may explain the negative relationship. However, the volatility feedback hypothesis states that as volatility changes so does expected return, while the leverage hypothesis states that shocks to returns lead to changes in conditional volatility.

Further, these authors conclude that there is a possibility that the causality direction between return and volatility/variance may vary with the nature of the event, which influences the event response in terms of duration and peak. Further, their results show that the market responds to different events differently, as the market absorbs the information and the uncertainty. Market response can take time to evolve, and can last for weeks or months, in the aftermath of the natural disaster.

Iqbal et al. (2022) highlight that high volatility in markets, together with financial contagion, may have caused a hike in shock transmission and connectedness, in different commodity markets. They study the extreme spillovers among the volatility of many commodities, including agricultural, energy and metal commodities, from 2008 to 2020. Volatility exhibited higher intensity during the periods of extreme events compared to non-event periods. In particular, agricultural commodities showed higher volatility connectedness during COVID-19 pandemic time, suggesting that markets had highly speculative expectations while fearing recessions.

Hypothesis Development

This study analyses the impact of natural disasters on top agricultural commodity producing countries, considering the direction and magnitude of both price returns and volatility. Some of the agricultural commodities chosen within the sample data are characterized by being produced in a fewer number of countries. Accordingly, when a natural disaster occurs in this region, it may have an impact on the price returns of the commodity, as well as the price volatility, given the limited spatial range accommodating the related agricultural activities and production.

The global impact of natural disasters leads to disruption in agricultural activities either directly (loss of land or machinery or human capital necessary to perform the labour) or indirectly (losses to general infrastructure or related sectors necessary for any steps of the agricultural process). Accordingly, the natural disasters directly related to agriculture, as identified in the respective literature, are studied herein to measure their impact on the agricultural commodities performance around said natural disasters.

The first part of the study examines the price return and volatility of the specified agricultural commodities around the time the specified natural disasters occur. If natural disasters exert an impact on agricultural production of the said commodities, markets will consider this as *information* or *signal*; and will thus react to this signal. This will translate into a change in prices, which can be captured in both price returns and price volatility or either. This first part of the study hypothesises that natural disasters cause agricultural losses that impact prices upwardly.

Further, due to the uncertainty related to the impact of natural disasters generally and on agriculture in particular, the expectations are that this uncertainty may be translated into price volatility. As market participants assimilate this signal and reflect it into their buy/sell decisions, whether using fundamental or technical analysis, the uncertainty is hypothesised to manifest in volatility. Accordingly, the next step is to measure price volatility of the specified agricultural commodities around the natural disasters' dates in comparison to their historical average performance.

Data

We start by extracting the prices of seven agricultural commodities: cocoa, coffee, corn, rice, soybean, sugar, and wheat from Bloomberg. The historical prices start as of 1960 for cocoa, corn, soybean, and wheat, 1961 for sugar, August 1972 for coffee, and December 1988 for rice, continuing till the present. We compute returns for each of the seven commodities.

As we use the market model in the event study, we choose an agricultural commodity market index. Accordingly, we obtain from Bloomberg the historical prices of Bloomberg Agriculture Subindex Total, which tracks the performance of agricultural commodity prices (coffee, corn, cotton, soybean, soybean oil, sugar, and wheat). The historical data of the index prices also spans from 1960 to 2023. Next, we compute the index returns.

From the FAOSTAT, the database of the FAO (the United Nation's Food and Agriculture Organisation), we obtain the historical data of agricultural production, as value in tonnes, for all countries producing the seven commodities from 1960 till 2023. To identify the main producing countries, we compute each country's annual share of the global production of each respective agricultural commodity over the sample data time horizon as: $country_{it}$_production/aggregate_$production_t$.

Next, we rank countries by annual share in aggregated annual production of each agricultural commodity, identifying the ten largest country-producer of each agricultural commodity separately, per year. Notably, the share of the top ten largest producing countries of each commodity is +75% on average of the world's production of each respective commodity per annum, reaching in some years +95% of the world's production.

The available information about natural disasters varies greatly; in regard to their definitions, types, and coverage in different data sources, with losses reported being unreliable for some time post the natural disaster (Smith & Katz, 2013). However, many studies use the EM-DAT database, as it includes casualties and economic losses as reported by respective countries, to study the impact of environmental natural disasters on economic variables (Dell et al., 2014).

EM-DAT is a global database maintained by the Centre for Research on the Epidemiology of Disasters (CRED) at the School of Public Health of the Université Catholique de Louvain in Brussels. It includes both natural and technological disasters, with data on the occurrence and effects of +21,000 disasters worldwide, from 1900 to the present. The database has geographical, temporal, human and economic information on disasters at the country level. The criteria of including disasters in the EM-DAT is having at least ≥10 dead people, or ≥100 affected people or a country declaring a state of emergency, or a call for international assistance. EM-DAT collects information from various institutions around the world, including UN agencies, governments, the International Federation of Red Cross, and Red Crescent Societies.

EM-DAT initially divides the disasters into two main groups (Disaster Group), natural and technological disasters. Under this classification, the disasters are then distinguished by sub-groups and types, with Disaster Sub-group including 6 sub-groups: biological, geophysical, climatological, hydrological, meteorological, and extra-terrestrial disasters and Disaster Type, the main disaster type, such as drought, flood, and storm.

In line with a number of studies referenced in the Literature Review, we use EM-DAT records for disasters for matching natural disasters for the event study -i.e., the event- per date and country. We obtain from EM-DAT this data for the main countries producing the seven agricultural commodities that we have already identified in the previous step, through their annual share in the respective global production.

EM-DAT has 14,188 natural disasters from 1980 to early 2023, and we identify 8636 natural disasters that have hit the main producing countries over that period. Next, we identify the disasters under natural disasters subgroups of climatological, meteorological, and hydrological. Then, we choose the disasters type that impacts agriculture, namely drought, extreme temperature, flood, landslide, storm, and wildfire. We exclude earthquake, epidemic, insect infestation, mass movement, and volcanic activity, as they are not directly related to environmental disasters impacting agriculture.

Next, we exclude the events that have missing data, in either the dates or the damages. Due to a huge variation in damages, adjusted by inflation (measured by CPI), we next identify the natural disasters with CPI-adjusted damages (in US dollars 000s) above the median. Damages include direct damages, such as losses in infrastructure, housing, and agricultural crops (Cavallo & Noy, 2010). Additionally, we exclude the events that persisted for long periods of time -years in some cases. This follows the event study methodology, which is a short-horizon study showing the responses to a certain event in a short-lived manner (Fama, 1998; Kothari & Warner, 2007). Droughts constitute most long-term disasters in the sample data, in addition to riverine floods, and wildfires (under Disasters Subtype). For example, a drought in Canada lasted from January 1984 until March 1985; Australia saw a three-year drought from 1992 to December 1995; a drought in Spain occurred over 1990-1995; and more recently, the USA suffered a two-year drought from 2000 until 2002. After excluding these long episodes of natural disasters, 686 events remain.

Table 1 summarises the natural disasters' impact on the top producing countries from 190-2019, measured by EM-DAT data of total damages (CPI-adjusted) in US dollars, total death occurrences and total number of affected persons. Total damages grossed US$573.7 billion, while there have been 612.4 million affected persons and almost 52 thousand dead persons over these four decades.

Insert Table 1 about here

Table 2 displays the distribution of natural disasters by type over the four decades from 1980 to 2019. In particular, the years 1993 and 1982 have the highest frequency of events within the sample data, with 31 and 30 natural disasters, respectively. Of the 686 events included in this study, 494 are storms and 149 are floods. Figure 1 depicts the frequency of natural disasters occurrences over the sample period.

Insert Table 2 about here

Insert Figure 1 about here

In addition, Table 3 shows the distribution of the natural disasters by country. The Philippines is the country most suffering of natural disasters, at 124 events over 1980 - 2019, followed by China (117 natural disasters), the USA (112), then at a distance India (36), Viet Nam (34), and Japan and Australia (29 each).

Insert Table 3 about here

Table 4 shows the distribution of the impact of the natural disasters on countries that are the main producers of the selected agricultural commodities. The country most hit by natural disasters as measured by total damages, adjusted by CPI over the study horizon, is the USA with total damages of US$265 billion. In respect to the country suffering the highest number of affected persons, China ranks first with 372 million persons. The Philippines comes first with almost 18 thousand death casualties, followed by China, and India.

Insert Table 4 about here

First, the breakdown of damages by top producing country over the period 1980-2019 shows that the USA suffers from the maximum total damages followed by China, Japan, and India. Geographical breakdown sheds light on the impact of natural disasters and the different responses to them. Because natural disasters are considered as regional geographical natural phenomenon, it is quite crucial to assess their spatial impact (Shibusawa & Matsushima, 2022). It has been suggested in the literature that different weather events cause different impacts, and damages that are economic losses in US dollars (the sum of losses to property and corps) reflect regional vulnerability to those environmental disasters (Zhou et al., 2020).

As per the number of total death occurrences, El Salvador ranks first, followed by the Philippines that is closely followed by Guatemala, India, Bangladesh, Russia, and at almost equal shares, Brazil, China, and Viet Nam. Notably, China comes first by total number of affected persons, followed by the Philippines, then India. This is in line with a number of studies that have shown that natural disasters have a more severe impact on developing countries due to their lack of the capacity to capitalise on any benefits, and as such as only suffer the consequences (see Rasmussen, 2004; Cuaresma et al., 2008; Raddatz, 2009; Noy, 2009; Fomby et al., 2013; & Cantelmo et al., 2023).

Concerning the four decades over which the sample data spans, years 2012 and 1992 witnessed the peak levels of damages in USD caused by natural disasters. The 1990-1999 decade witnessed the highest damages, at US$172.5 billion, followed by the 2010-2019 decade at US$154.5 billion. From 2000-2009, natural disasters caused damages at US$118.3 billion, while the 1980-1989 decade witnessed losses worth US$113.1 billion.

On the other hand, 2013 has witnessed the highest death casualties, while the 1980-1989 decade has the highest rate of death casualties resulting from natural disasters over the study period. In respect to total affected persons, the years 1989 and 1995 have the highest rate.

Storms are shown to have the severest impact as measured by both damages in US dollars and total number of death fatalities, followed at distance by floods. However, in the case of the total affected persons, floods narrowly come first, followed by storms at heel.

It is noteworthy that towards the end of 2019, China started reporting COVID-19 cases before its spread to the rest of the world. Eventually, the World Health Organisation (WHO) declared the Coronavirus a global pandemic on 11 March 2020. The COVID-19 pandemic is an international disruption to agriculture, global food supply chain, and global food security (FAO, 2020). The UN Sustainable Development Group (2020) documents that many countries have suffered from farming activity problems as a result. The unavailability of labour in India has interrupted the harvest of wheat (Dev, 2020), while Ethiopia suffered from the unavailability of agriculture inputs. In contrast, overstocking of agricultural products in the developed countries, such as the USA and Canada, has caused dumping or destroying (Weersink et al., 2020).

In China as well, Pu and Zhong (2020) identify the impact that the COVID-19 pandemic and the policies implemented as a result had on the country's agriculture sector. They show that movements and traffic restrictions to have impacted labour inputs, which have led to a delay in crop plantation, which in turn have slowed nature's growth cycle of agriculture. Such a delay in crop plantation can result in reduced crops, while such harvest losses can lead to lower farming investment in the following season.

In addition, Hadachek et al. (2023) state that the Russia-Ukraine conflict is acting as an extreme shock, disrupting food supply chains worldwide and eliciting authorities' reactions and influencing changes in regulations. These reactions and regulations also play a role, exerting an impact on agricultural activities worldwide, as evidenced in the literature.

Accordingly, and to ensure that this study does not coincide with the COVID-19 pandemic or any later major events such as the Russia-Ukraine war, and that the results are not impacted by them, this study covers till the end of 2019. Accordingly, 600 natural disasters remain in the sample data, ranging between the years 1980 and 2019.

Lastly, for the control variables in the ordinary least squares (OLS) regression, we obtain country level data of GDP per capita and foreign exchange rate of domestic currency vis-à-vis the US dollar from the IMF databases of WEO (International Monetary Fund's World Economic Outlook, 2013a) and IFS (International Monetary Fund's International Financial

Statistics), in order. We compute the percentage change in the exchange rate of each top producer-country's respective national currency per the US dollar.

Methodology

To study agricultural commodity performance, in terms of returns and return volatility, we follow Bourdeau-Brien and Kryzanowski (2017), employing the event study methodology for abnormal returns and GARCH (generalized autoregressive conditional heteroskedastic) model for the conditional variance. Next, we employ the ordinary least squares (OLS) regression, to study the nature of the abnormal return and abnormal volatility to identify the factors behind fluctuations in returns and volatility of agricultural commodities in their respective main producer countries around the time of the natural disasters. Likewise, this follows Karali et al. (2018), who study the changes in oil returns and volatilities around groups of events, employing the GARCH model for volatility estimates, then the OLS regression for further inspection.

Event Study Methodology

We follow the event study procedure, as described by MacKinlay (1997), to identify the events of interest and the period over which the prices concerned are examined, i.e., the event window(s). MacKinlay's work builds on the 1969 study by Fama, Fisher, Jensen, and Roll, who introduced the event study methodology to measure market reaction to information (Fama, 1998). As per the literature, this methodology is for short-term studies (Kothari and Warner, 2007), as it measures asset returns' direct reaction to a certain event, which is in line with market efficiency hypothesis (Fama, 1998).

Fama (1970) stipulates that for a market to be informationally efficient, it necessitates that assets prices would reflect all available information at all times. In other words, the market interprets any given event as information and reacts to it in a timely manner. Hence, assets prices move, with prices signalling to investors resource allocation opportunities, because the competition among market participants leads naturally to informational efficiency. Information is treated as a signal, and market act and react to this signal; otherwise, market prices will be mispriced, leading the market to consequently trade this asset till prices reach an equilibrium where the mispricing disappears. Thus, market efficiency results from competition forces that push forward, till the signal is fully incorporated in prices.

Binder (1998) adds that a variety of events can be employed in event studies, extending the understanding of the event beyond a corporate announcement. Binder asserts that an event study is a standard method to measure price reaction to some announcement or event. This supports Kothari and Warner (2007) who describe the event as clustered at a particular date, no matter what its nature is. Recent studies have used environmental and climatic events to measure economic and financial variables' reaction to them, in an effort to understand the magnitude, direction and causality between them.

In addition, MacKinlay (1997) explains measuring the impact of an event requires measuring the abnormal return (AR). The abnormal return is the actual ex-post return during the event window minus the normal return during time of the event window. Further, the normal return is defined as the expected return without conditioning on the event. He describes the statistical expression as: for a firm *i* and an event date *t*, the abnormal return is:

$AR_{it} = R_{it,} - E(R_{it}|X_t)$;

where AR_{it}, $R_{it,}$, and $E(R_{it}|X_t)$ are the abnormal, actual, and normal returns, respectively over the time period *t*. X_t is the conditioning information for the normal return model.

Following MacKinlay (1997), we employ the market model, with X*t* as the market return (the constant mean model is also another common method used). The market model assumes a stable linear relation between the market return and the security return. Further, Kothari and Warner (2007) show that the event study focuses on mean of abnormal returns' distribution, to studying whether asset prices have responded to a certain event and if the alternative hypothesis predict the sign of the average effect.

The specifications of the market model to measure the expected excess normal return R_{it} of an asset *i* at a certain day *t* are:

$$R_{it} = \propto \; + \beta_i R_{mt} + \varepsilon_{it} \tag{1}$$

where: b_i is the slope coefficient linking returns for each commodity i to the returns for the market index, and R_{mt} is the market index returns at time t (event time).

The abnormal return (AR_{it}) is statistically the amount deducted from the estimated normal return and the actual observed return. The abnormal return of an asset at a given event window, following Kothari and Warner (2007) is:

$$AR_{it} = \sum_{i=1} e_{it} \qquad (2)$$

where, t is the event day and e is the residual or excess return. e_{it} is calculated as:

$$AR_{it} = R_{it} - (\beta_0 + \beta_1 * R_{mt}) \qquad (3)$$

where, AR_{it} is the abnormal return of an agricultural commodity i at the day t when the natural disaster hit, $b_0 + b_i$ are the estimated coefficients, and R_{mt} is the market return, which is the Bloomberg Agriculture Subindex Total for agricultural commodities.

Further, we calculate the average abnormal returns (AARs) for commodity i impacted by the all the natural disaster events within the sample data that hit all the identified top producing countries of that one commodity:

$$AAR_t = \frac{1}{N} \sum_{i=1}^{N} AR_{it} \qquad (4)$$

where, N is the number of commodity returns, t is the event day.

Next, we calculate the cumulative abnormal returns (CARs), which is the summation of the abnormal returns over the period of time studied. Following Kothari and Warner (2007) definition of the statistical model for CAR calculation:

$$CAR_{it} = \sum_{t_2}^{t_1} AR_{it} \qquad (5)$$

(where, the event window is $\in t_1, t_2$)

Likewise, we compute the cumulative average abnormal returns (CAARs), which is the sum of average abnormal returns.

$$CAAR_t = \frac{1}{N} \sum_{i=1}^{N} CAR_{it} \tag{6}$$

The CAR method tests the null hypothesis that abnormal performance is equal to zero (Kothari & Warner, 2007), whereas the event study test is a joint test of whether abnormal returns are zero and whether the assumed model of expected returns is correct.

Following MacKinlay (1997), we define the estimation window, which is the period prior to the event. Day 0 is the event day, i.e., it is the day on which the natural disaster occurred, and it is excluded from the estimation period. This is to avoid the impact of the event itself on the model parameter estimates of the commodities' normal performance, measured by their returns. Accordingly, the event itself was divided into an estimation window of 250 days ending 30 days before the event.

Following Obi et al. (2023), we choose the total event window to be [-15,+15], with several other event windows to measure the impact of natural disasters on agricultural commodity returns over different time periods. The event windows are [-10,+10], [-7,+7], [-3, +3], [-1, +1], [-3, -1], [-1, 0], [0, +1], and [0, +3].

GARCH Model

Following Obi et al. (2023) and Truong and Friday (2021), who argue for including a volatility model to the conventional event study methodology, to account for volatility and asymmetries in asset returns around the event day, we employ also the GARCH model to calculate the abnormal variance of returns within the event window time, with day 0 being the event day of the natural disaster occurrence.

Some studies define volatility as *the variation (in both amplitude and frequency) of changes in commodity price around their means* (Huchet-Bourdon, 2011). The volatility of agricultural commodity prices has been studied in the literature, with causes including oil prices fluctuations, inflation levels worldwide, exchange rate of the US dollar, and climate change, among others. However, volatility remains one important factor impacting agricultural commodity prices.

Milonas (1987) states that commodity cash markets adequately reflect all existing information, while the prices do not show the same volatility as futures contracts do because of nearing maturity or daily trading limits. In addition, he argues for agricultural commodity markets to have non-stationary volatilities He discusses the *year effect*, which is a specific year variability in prices that reflects crops shortage or abundance that may result from exogenous shocks, leading to new price equilibrium as the market reacts to this year-specific variability. Due to their non-consistent nature, markets cannot predict these shocks; however, they recognize the higher prices volatility as these events occur.

Bollerslev (1986) introduces the generalized autoregressive conditional heteroskedasticity or GARCH model, as a natural generalization of the autoregressive conditional heteroskedastic (ARCH) model introduced by Engle (1982). The GARCH model computes the current conditional variance, taking into consideration past conditional variances. The model allows for more flexible lag structure (Bollerslev, 1986) and conditional variance changes over time (being a function of prior errors). Accordingly, we use GARCH (1,1) to estimate the conditional variance of each commodity returns, and following the GARCH model assumptions, returns variance is expected to change over time, and so does volatility. We use the prices of the same commodities employed in the event study, with daily frequency in US dollars, obtained from Bloomberg.

Figure 2 shows the computed conditional volatilities of the seven agricultural commodities, as per GARCH model:

$$\sigma^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{7}$$

each separately, over the span of the study. Sugar demonstrates the highest one-year volatility in 1983, followed by wheat in 1996 (highest volatility spikes). Cocoa, coffee, and soybean show, however, the utmost fluctuations over the span from 1980 to 2019.

Insert Figure 2 about here

After estimating the conditional volatility for each agricultural commodity over the sample time horizon, we measure abnormal variance, using 16,539 observations (simply as $Y_t = \mu + \varepsilon_t$), and employing the mean-adjusted model (following Brown & Warner, 1980):

$$AV_{it} = CV_{it} - \frac{1}{31} \sum_{t=-60}^{-30} CV_{it} \tag{8}$$

where, AV_{it} is the abnormal volatility of returns, for each commodity in the sample data impacted by the natural disaster *i* at time *t*, whereas CV_{it} is the estimated conditional volatility by the GARCH model for each commodity in the sample data impacted by the natural disaster *i* at time *t*.

Next, to compute the cumulative abnormal variance (CAV), we follow the same statistical method used to compute CARs:

$$CAV_{it} = \sum_{t=1}^{t} AV_{it} \tag{9}$$

To compute the average cumulative abnormal variance (CAV):

$$CAAV_t = \frac{1}{N} \sum_{i=1}^{N} CAV_{it} \tag{10}$$

It is worth noting that we perform the tests of event study and the GARCH model *separately* for each agricultural commodity. Given the nature of the different natural disasters studied herein this study, it is expected that the agricultural commodities may have different reactions in terms of returns and returns volatility to these events. Accordingly, separate tests were conducted for the total event window [-15,+15], and the other event windows to measure the impact of natural disasters on agricultural commodity performance around the event date. The event windows are [-10,+10], [-7,+7], [-3,+3], [-1,+1], [-3,-1], [-1,0], [0,+1], and [0,+3] as performed to compute CARs.

OLS Regression

In the next part of this research, we study the factors underlying the cumulative abnormal returns and cumulative abnormal variance, in terms of direction and magnitude. To achieve this, we employ a series of ordinary least squares regressions, as:

$$CAR_{t1,t2,ij} = \propto + \beta_1\, Price.Increase_i + \beta_2\, Tot.Damages_j + \beta_3\, Deaths_j + \beta_4\, Tot.Affected_j + \beta_5\, Prod.Share_i + \beta_6\, GDP.Capita_k + \beta_7\, FX.Rate.Change_k + \sum_{h=1}^{6} \beta_{7+h}\, Ag.Commodity_h + \sum_{m=1}^{3} \beta_{13+m}\, Nat.Disaster.Type_m + \varepsilon_{ijt1,t2} \tag{11}$$

where:

$CAR_{t1,t2,ij}$ is the cumulative abnormal return over the event window (through day *t1* and day *t2*), using the return of Bloomberg Agriculture Subindex Total as the index market return, for commodity *i* and disaster *j*.

$Price.Increase_i$ is a measure of demand pressure for an agricultural commodity, assumed as a factor that may have driven abnormal returns, and as such included as factor to be tested. It is computed as:

$$Price.Increase_i = \frac{\frac{1}{30}\sum_{j=t-60}^{t=-31} Price_{it} - \frac{1}{500}\sum_{j=t-560}^{t-61} Price_{it}}{\frac{1}{500}\sum_{j=t-560}^{t-61} Price_{it}} \tag{12}$$

where, $Price_{it}$ is the price of commodity *i* at time *t*, as it measures the change in each commodity price over the past two years of trading, i.e., before the event occurrence at time *t*. Economically, higher demand on a certain commodity equates to higher prices of that commodity. Natural disasters may disrupt farming and agriculture; accordingly, demand may play a part in higher abnormal returns.

It is worthy to note that another measure has also been employed in untabulated tests and results. The other proxy was the moving average of a commodity price returns over the past three years. However, as $Price.Increase_i$ is a better proxy as a measure of changes in prices over time, the moving average factor was not used.

Extracted from the EM-Dat database, the next three variables are included as proxy to the severity of natural disasters impacting the prices of the agricultural commodities:

$Tot.Damages_j$ is the natural log of the total damages, adjusted by CPI inflation, in 000s US dollar in producing countries hit by natural disasters.

$Deaths_j$ is the number of death casualties resulting from the natural disasters.

$Tot.Affected_j$ is the natural log of the number of affected persons, impacted by the natural disasters.

$Production.Share_i$ is each producing country lag share (in %) of a given agricultural product, i.e., of the year before the event, as it is documented that current's year agricultural production is impacted by the level of last year activity.

$GDPCapita_k$ is the natural log of each affected country *k* GDP per capita (gross domestic product), as a measure of purchasing power that impact results.

$FX.Rate.Change_k$ is the foreign exchange rate of domestic currency -of affected country *k*- against the US dollar.

The results of Nazlioglu and Soytas (2012) support that a weaker dollar positively affects agricultural commodity prices, contradictory to some previous studies. Likewise, Abbott et al. (2008) find that because commodities are priced in the US dollar though countries purchase them in local currencies, higher oil prices feed into current account deficit, leading to a lower local currency value. Accordingly, we add the change in foreign exchange rate of domestic currency against the US dollar as an explanatory variable in the OLS regression.

$Ag.Commodity_h$ is a dummy variable for the agricultural commodities within the sample data, namely, coffee, corn, rice, soybean, sugar, and wheat, with cocoa being excluded.

$Nat.Disaster.Type_m$ is a dummy variable for the natural disaster by type that are included in the study, namely, storm, extreme temperature, landslide and, wildfire, with flood being excluded. In addition to being an excluded category, flood is colinear with storm type.

Next, we extend model (11) to examine the factors that may have impacted the cumulative abnormal return volatility of the agriculture commodities included in the sample data. We run the OLS regression with return volatility as the dependent variable:

$$CAV_{t1,t2,ij} = \propto + \beta_1\, Price.Increase_i + \beta_2\, Tot.Damages_j + \beta_3\, Deaths_j + \beta_4\, Tot.Affected_j + \beta_5\, Prod.Share_i + \beta_6\, GDP.Capita_k + \beta_7\, FX.Rate.Change_k + \sum_{h=1}^{6} \beta_{7+h}\, Ag.Commodity_h + \sum_{m=1}^{3} \beta_{13+m}\, Nat.Disaster.Type_m + \varepsilon_{ijt1,t2} \tag{13}$$

where:

$CAV_{t1,t2,ij}$ is the cumulative abnormal volatility over the event window (through day *t1* and day *t2*), using CARCH conditional volatility, for commodity *i* and disaster *j*.

All independent variables are the same as specified and defined in the OLS regression test for the CARs.

Results

Table 5 exhibits the main producing countries within the sample data. Of the 46 countries, four countries produce six out of the seven agricultural commodities covered in this study: Russia, Brazil, India, and Indonesia. Mexico and China produce five agricultural commodities each, while the USA and Argentina produce four agricultural commodities each. Five countries produce three agricultural commodities each: Canada, the Philippines, Pakistan, Colombia and Ukraine. Eight countries produce two agricultural commodities each, while twenty-four countries produce only one agricultural commodity each.

Insert Table 5 about here

This geographical concentration of agricultural production per producing country enhances production efficiency as regions play to their comparative advantages, which generates the efficiency gains (Sexton, 2009; Hadachek et al., 2023). Table 4 shows the main producing countries of each agricultural commodity studied herein, whose shares have demonstrated some variation over years, albeit remaining as a main producer of the respective commodity (or commodities in case of a multiple-commodity producer country). Notably, this historical concentration is expected to continue, as technology and the use of big data further progress worldwide. Technology-based precision farming, which is currently widespread in developed economies, is projected to extend to other economies (Senthilvadivu et al., 2016).

In addition, this geographical concentration may inevitably mean that once a natural disaster occurs in an agricultural country, there may be repercussions on the performance of the number of commodities this country is producing. Furthermore, given that the majority of these countries are emerging or developing countries as per the IMF classification (IMF WEO database, 2023b), data dissemination and information processing are still developing (Mtega, 2012; Msoffe & Ngulube, 2016). This may feed into the international commodity markets as well, leading to information asymmetry, and may explain agricultural commodities' uneven performance and behaviour in reaction to external shocks, including natural disasters.

Further, Table 6 shows the top producing countries for each agricultural commodity, based on the FAO statistics. The data shows the geographical distribution of agricultural production, highlighting specific concentrations, namely that, only Asian countries are top producers of rice. Wheat, on the other hand, is produced almost on all continents, with a wide global geographical distribution.

Insert Table 6 about here

The results of the event study, showing the impact of the natural disasters on the agricultural commodities in the sample data, are displayed in Tables 6 to 12. Each table shows the estimated CARs (%) and abnormal variance, along with the p-values showing significance, for each commodity separately, over several event windows.

Table 7 displays the analysis of the impact of natural disasters on cocoa prices, with no statistically significant results for any of the CARs (%) in any event window. This may be attributed to the fact that most producing countries are heavily impacted by drought. However, since most drought episodes largely persist over multiple days and up to several years, 58 drought incidents were excluded from the sample data.

Insert Table 7 about here

Table 8 reports the CARs (%) of coffee, with no statistically significant results at any significance level. Boarding towards significance is the event window of [-15, +15], with CAR of 0.123 or 12.3%. However, untabulated results show significant results in the 14^{th}, 13^{th}, 12^{th}, 11^{th}, and 9^{th} day before the events, along with 12^{th}, 13^{th}, and 14^{th} day after the event, at 0.1 significance level. This may suggest that the dominating type of natural disaster plays a role in shaping the market's reaction. Storms constitute 81% of the natural disasters hitting the coffee-producing countries. Particularly, scientist consider storms to be the most devastating natural disaster (Sanyal & Lu, 2004), along with being predictable as scientists use satellite images in the post-disaster assessment and can produce highly predictive maps of vulnerable areas to floods (Gillespie et al., 2007). In addition, their level of devastation may explain the market's reaction almost two weeks after the storm, as damages are estimated, and impact is quantified.

Insert Table 8 about here

Table 9 covers the results of the event study on corn prices, which also shows no significant results in any tabulated results. Untabulated results show only two days, -9 and -7, with significant results, at 0.1 significance level. As it is the case with coffee, corn-producing countries within the sample data are mostly hit by storms (at 75% of total events).

Insert Table 9 about here

Table 10 displays statistically significant cumulative abnormal returns for rice, namely, during the [-3, +3] event window, at 1% significance level (specifically a p-value of 0.008), with a positive coefficient of 0.884. Likewise, the event window [-1, +1] shows significant CARs of 0.656% at 1% significance level. CARs of the event window [-3, -1] are significant at 5%, with coefficient of 0.5%, while CARs of the event window [-1, 0] are statistically significant at 10%. Finally, the event window [0, +1] shows significant results, at 1% level, with CAR of 0.6%. These results may suggest that spatial and geographical characteristics of producing countries play a part in explaining the statistically significant results at different event windows. Given that rice is strictly produced in Asian countries that are predominantly hit by storms and floods (97.5% within the sample data), information asymmetry and the type of natural disasters may be substantial underlying factors.

Insert Table 10 about here

The CARs of soybean are reported in Table 11. Window [0, +1] has the only statistically significant results at 5%, suggesting that corn's main producing countries suffer from significant and negative repercussions a day after being hit by natural disasters, with a cumulative market-model estimated abnormal return of -0.4%. This result may show that market participants react to natural disasters hitting soybean producing countries one day after the occurrence of the events. Soybean main producing countries are geographically varied, and therefore, experience a number of different natural disasters. A number of developed countries are among the top producers of soybean, including the USA and Canada, and that maybe behind the market's post-event reaction, as the market reacts to losses reported and not the uncertainty prior the event due to the availability of better meteorological models and weather stations.

Insert Table 11 about here

Table 12 shows the CARs (%) for sugar, without any statistically significant results at any reported event window (nor in the untabulated results). Like soybean, sugar producing countries are geographically widespread throughout Asia, Australia, Latin America, and North America, with storms and floods being the main environmental disasters type affecting these countries, with wildfires also playing a role (with substantial total damages in some events, such as the case of the 1983 Australia wildfire reaching US$1.175 billion). This spatial heterogeneity alleviates the impact of natural disasters, as markets have substitute production centres. Thus, markets may not consider natural disasters hitting this production centres as *signals* or information to react to or they may react to them but not in a collective or panicking manner.

Insert Table 12 about here

Lastly, wheat CARs are reported in Table 13, where no statistically significant results are reported at any significance level. Also, these results may reflect the spatial heterogeneity of top producing countries, along with the developed economy status of half of them allowing better information transfer channels permitting markets to react normally being well-informed and in a timely framework.

Insert Table 13 about here

As for GARCH-estimated price volatilities, Table 7 displays the analysis of the impact of natural disasters on the volatility of cocoa prices, showing statistically significant cumulative abnormal variance (CAVs) at 0.1 significance level with 0.053, on the 15th day after the natural disasters hit the main producing countries. This result suggests that price volatility of cocoa peaks in the aftermath of natural disasters hitting its main country producers, with a cumulative mean-adjusted abnormal variance of 0.006 or 0.6%.

Coffee, on the other hand, exhibits statistically significant results across all reported windows for cumulative abnormal variance; all at 1% significance level, as seen in Table 8. Cumulative abnormal variance reported 0.022 with p-value of 0.000 for the event window [-15, +15], 0.017 with p-value of 0.000 for the event window [-10, +10], 0.013 with p-value of 0.000 for event window [-7, +7], 0.007 with p-value of 0.000 for event window [-3, +3], 0.003 with p-value of 0.000 for event window [-1, +1], and 0.002 with p-value 0.002 for event window [-3, -1]. On the event day itself, cumulative abnormal variance reports 0.002, with p-value of 0.002, remaining at the same level in the day after the event with a p-value of 0.001, doubling to 0.004 with a p-value of 0.000 three days after the event.

Notably, these results may suggest that the market reacts to new arriving information -natural disasters in this case- in line with the efficient market hypothesis (EMH), and these reactions lead to higher volatility due to increased frequency of reactions as more pieces of news arrive. This is in line with the results of Serrão (2015), who uses ARCH model to measure investors' decisions on agricultural commodities price volatility. However, Serrão explains that these results show leverage effect (volatility is more impacted by negative information), and he attributes this to the Prospect Theory, where negative information leads to higher volatility.

Table 9 exhibits cumulative abnormal variance of corn, with statistically significant results for all event windows except the event day (day 0). Cumulative abnormal variance reported 0.019 with p-value of 0.000 for day +15, 0.012 with p-value of 0.000 for day +10, 0.008 with p-value of 0.000 for day +7, 0.004 with p-value of 0.000 for day +3, 0.001 with p-value of 0.041 for day +1, and 0.001 with p-value 0.014 for day -1, 0.001 with p-value of 0.080 for day +1 and 0.002 with p-value of 0.000 for day +3.

Such volatility around the event day for corn prices is in line with Diffenbaugh et al. (2012), who show that corn prices in the USA exhibit higher volatility in reaction to near environmental shocks more than they do towards other factors. However, Wright (2011) mentions the storability and substitutability of grains as other factors that highly impact corn price volatility, as demand increase on corn to produce biofuels. Thus, oil prices are also considered as a factor impacting corn price volatility, as oil prices feed into the demand on corn to produce biofuels. Accordingly, corn prices are vulnerable to environmental hazards, due to the numerous factors impacting its demand and supply.

Cumulative abnormal variance of rice is reported in Table 10, with statistically significant results for all event windows, all at 1% significance level. With p-value of 0.000: the volatility coefficient is 0.044 for day +15, 0.029 for day +10, 0.021 for day +7, 0.010 for day +3, 0.004

for day +1, 0.004 for day -1, 0.003 for day 0, 0.003 for day +1 and 0.006 for day +3. These results suggest higher volatility of rice prices across all days around the natural disaster occurrence.

Timmer (2008) mentions that among the drivers behind high variance of supply of and demand for rice, as per the drivers' predictability, are weather factors on the supply side and exchange rates on the demand side. Given that rice is mostly produced in Asia, environmental hazards highly shocks prices. Timmer also mentions that since the rice market is concentrated, and since it does not have direct substitutions and due to its importance for Asian consumption, rice prices are complicated. In particular, due to rice importance in Asian dietary system, rice witnesses price panics, leading to higher sensitivity of its prices and higher volatility.

Likewise, soybean cumulative abnormal variance, as shown in Table 11, display statistically significant results for all event windows, at 1% significance level. Similar to rice, with p-value of 0.000 across all windows, the volatility coefficient of soybean reports 0.039 for day +15, 0.026 for day +10, 0.018 for day +7, 0.009 for day +3, 0.003 for day +1, 0.004 for day -1, 0.002 for day 0, 0.002 for day +1 and 0.005 for day +3. The results show high volatility of soybean prices throughout all event windows around the occurrence of natural disasters.

Gilbert and Morgan (2010) associate high grain prices with higher volatility. Haile et al. (2016) display that specifically soybean, along with corn, have the largest production reactions in response to changes in its domestic prices. This research has also found a negative correlation between wheat prices and soybean production, which leads soybean prices to change reflecting supply changes, as well as its price volatility to increase. This study finds that increasing international wheat prices cause farmers to decrease land for soybean planting and production, inducing price and price volatility responses. Timmer (2008) specifies droughts to have caused wheat prices to soar, leading farmers to shift acreage of soybean and corn, leading to higher price sensitivity and increasing volatility of soybean prices.

Table 12 shows cumulative abnormal variance of sugar prices. Day +15 exhibits statistically significant result of 0.008, at 1% significance level, while days +10 and +7 show significant result with a coefficient of 0.005 each at 5% significance level. Lastly, day +3 reports a significant result of 0.002 at a significance level of 5%. This volatility in days prior and post natural disasters in sugar producing countries may suggest that markets take time to measure the expected impacts of natural disasters on sugar and in relation to its substitutes. Sugar prices are highly volatile, particularly resulting from climatic events (Carpio, 2019). Exchange rates also highly impact sugar prices.

Cumulative abnormal variance of wheat is demonstrated in Table 13, showing no statistically significant results for any reported event windows, at any level of significance. Although wheat has shown some volatility spikes, having no significant results may suggest that markets pay a great attention to information about wheat, due to its global importance, and this scrutiny does not allow much space for huge price fluctuations around the event dates. Volatility spillovers, from international to local markets and vice versa, is documented to increase on disruptions of wheat supply, while wheat self-sufficiency cools price volatility spillover from international markets to local markets (Tanaka, 2019).

Next, to analyse the factors impacting the cumulative abnormal returns and cumulative abnormal variance of the seven agricultural commodities studied herein, Table 14 presents the descriptive statistics of the variables (dependant and independent) employed in the OLS regression. CARs show a minimum of -25.8% and a maximum of 16.5% over 1066 observations, with a mean of -0.059%.

Insert Table 14 about here

Table 15 shows the correlation matrix, displaying Pearson correlation coefficients and significance levels. All variables included in the OLS regression are not highly correlated, with the exception of storms and floods (-87.2%). Thus, the flood variable was excluded from the OLS regression, as the fifth dummy variable of natural disaster types (the excluded category), to prevent multicollinearity and ill-fit model.

Insert Table 15 about here

Table 16 presents the OLS regression results, with CARs (%) as the dependant variable, to identify the factors impacting CARs across different event windows. As shown, price increase that is the proxy for demand pressure, is statistically significant following a natural disaster in a producing country. This is true for the [-1,+1] and [+1,+3] windows[3].

However, the sign of this coefficient is negative, indicating that demand pressure mitigates abnormal returns caused by a natural disaster. This negative sign is quite unexpected, as it contradicts common economic intuition. We expected demand pressure to exacerbate the abnormal returns upon the occurrence of a natural disaster, given the economic dynamic of demand and supply.

On the level of the agricultural commodities themselves, only the coefficient of the dummy variable of coffee is significant and negative, in the day before the event hits. As per the type of natural disasters, storm's coefficient on the event day was statistically significant at 5% significance level. With a negative coefficient, it suggests that the stronger the impact of storm, the lower the CARs. GDP per capita is also a statistically significant factor behind CARs movements, on the day after the event and three days after the event; albeit having a negative coefficient, indicating a negative relationship between the CARs and the GDP per capita. This may suggest that as the purchasing power grows, demand on grains decline while demand on other higher-end food commodities increases, such as livestock and processed food. This finding is in line with previous research, such as Hawkes et al. (2017).

Insert Table 16 about here

The results of the OLS regression including cumulative abnormal variance as the dependent variable are exhibited in Table 17. Price increase is positive and significant on the day after the event, meaning higher demand on the agricultural commodities. This exerts pressures on prices, and hence volatility increases. As price increase variable is a proxy for demand pressure on the

[3] In untabulated results, we exclude the USA and Japan from the sample data as they are the two countries mostly impacted by natural disasters in terms of damages. This may have allowed a bias in the OLS regression of CARs and CAVs. However, we find that Price.Increase variable is statistically significant at some event windows, namely [+1,+3], at 1% significant level, when we regress CARs. In case of CAVs, the main independent variable is not statistically significant at any event window, while Wildfire (control variable) remain statistically significant across all event windows.
It is worthy mentioning that the USA and Japan do not produce both cocoa and coffee, while the USA is not rice-producing country. As such, results are not much impacted by excluding the two countries.

agricultural commodities, this suggests that demand on these commodities add to their price volatility, given the pressure it exerts as prices fluctuate to finally reach the new price equilibria in response to natural disasters hitting the producing countries.

Insert Table 17 about here

In addition, the dummy variable for wildfire is statistically significant across all event windows, at 5% significance level. With negative coefficients, the results may suggest that the more frequent and the stronger the wildfire events, the lower the CAVs. This may be explained by the fact that wildfires are not that impactful to agriculture, as natural wildfires that are the outcome of natural environmental cycles, of rainfall, dryness, and lightning, are mostly common in forests, for example in Canada. On the other hand, human-driven fires, whether accidental or intentional, are common in areas, such as Africa, Asia, and South America, where humans use controlled fires to manage and clear farmlands and natural vegetation to enable agriculture activities.[4]

Furthermore, the change in foreign exchange rate of domestic currencies vis-à-vis the US dollar is statistically significant at 5% significance level, in the day before the event. The negative sign suggests that foreign exchange of domestic currency against the US dollar increases, the abnormal volatility declines. Agricultural commodities are traded in the US dollar, thus stronger local currencies would mean lower exports of these commodities.

[4] NASA Earth Observatory: https://earthobservatory.nasa.gov/global-maps/MOD14A1_M_FIRE

Conclusion

This study examines how natural disasters, impact the prices and price volatilities of seven agricultural commodities when they occur in their respective main agricultural production centres: cocoa, coffee, corn, rice, soybean, sugar, and wheat. Natural disasters spanning over a period from 1980 to 2019 were employed to measure their impact, in terms of abnormal return and abnormal variance.

This study uses event study and GARCH modelling, followed by series of ordinary least squares (OLS) regressions to examine the underlying factors impacting agricultural commodities' abnormal return and abnormal volatility.

We find statistically significant results in our event studies on rice and soybeans, when examining abnormal returns. Similarly, cumulative abnormal variances are statistically significant for cocoa, coffee, corn, rice, sugar, and soybean in different event windows. Wheat does not display any statistically significant results across any event window, neither for cumulative abnormal returns nor for cumulative abnormal variance. This suggests that markets react to the news about different agriculture commodities differently, because of the commodity importance to certain nations, substitutability, storability, and geographical concentration of production.

Furthermore, we find that demand pressure feeds into agricultural commodities price abnormal returns and volatility across some event windows. However, the direction of the contribution to abnormal returns of this variable is unexpected. It may be explained that short-term natural disasters do not impact commodity prices as per the economic intuition. Markets seem to care more about long-term natural disasters, or maybe disaster information takes longer to be incorporated in prices. Or markets may have already anticipated these disasters; however, their impact was not as bad as expected.

These results may follow the economic intuition, because as commodity prices increase, substitutes consumption increases as well, alleviating the demand pressure on the initial commodity. Further, prices revert to their mean (mean-reversion theory), accordingly, prices move but do not generate demand pressure, as commodity price returns and price volatility eventually revert to their historical mean.

Finally, there are a number of limitations to this study. The commodity literature regarding variable causality and direction of causality reports some mixed results. Thus, this study may be exposed to some omitted variables or reverse causality effects. In addition, some natural disaster events included in the event study may have raised the noise level in the analysis of both cumulative abnormal returns and cumulative abnormal variance. Adding a threshold (above-median damages) was employed to reduce the number of events to address this weakness.

Also, given the nature and specifications of the event study methodology as introduced and described by Fama, Fisher, Jensen, and Roll (1969), Fama (1970 and 1998), and detailed by MacKinlay (1997), Binder (1998) and Kothari and Warner (2007), one important natural disaster type, droughts, was excluded from this study. Drought incidents generally last over long periods of time and, thus, cannot be measured in short-window event studies. Accordingly, further research needs to study these weather episodes given their importance to and impact on agriculture. In addition, some countries impose policies and regulations to protect their agriculture sector and industries (some developed countries for instance), accordingly, that impacts crops production and market reactions. As such, these results cannot be generalised, as markets are not only impacted by demand and supply forces.

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Table 1: Natural Disasters Distribution by Impact, 1980-2019

Year	Type of Disaster	Total Deaths	Total Affected (million persons)	Total Damages, CPI-Adjusted (billion US$)
1980	Flood	246	0.739	1.467
	Storm	155	1.608	3.819
1981	Storm	905	1.073	3.439
	Flood	2,584	17.533	4.388
1982	Storm	1,754	6.528	7.523
	Flood	1,486	0.121	1.700
	Landslide	0	0.004	2.123
1983	Flood	271	0.052	0.606
	Storm	798	1.684	13.429
	Wildfire	75	0.011	1.763
1984	Storm	3,319	5.850	8.259
	Flood	36	0.754	1.140
1985	Flood	372	1.014	0.703
	Storm	270	2.604	10.378
	Extreme temperature	225	0	0.392
1986	Flood	145	0.368	1.212
	Storm	430	8.549	10.825
1987	Flood	2,297	29.735	1.664
	Storm	1,382	3.266	12.098
	Wildfire	0	0.153	0.258
1988	Storm	1,156	6.725	2.108
	Flood	640	10.601	5.163
1989	Storm	2,710	39.610	21.184
	Landslide	6	0.012	0.001
	Flood	2,044	100.270	6.598
1990	Storm	1,675	8.589	11.953
	Flood	8	0	1.735
	Extreme temperature	0	0	0.090
1991	Landslide	50	0	0.001
	Storm	628	5.606	23.847
	Flood	24	0.437	4.477
1992	Storm	227	0.343	58.057
	Landslide	124	0.039	0.851
	Flood	232	0.002	1.978
	Wildfire		0.001	0.365
1993	Storm	1,033	12.720	12.808
	Flood	48	0.688	1.235
	Landslide	56	0.000	0.425
1994	Flood	121	0.943	0.668
	Storm	443	10.010	2.339
	Wildfire	4	0.026	0.300
	Extreme temperature	0	0	0.938
1995	Flood	1,559	114.574	13.103
	Storm	2,213	3.740	2.988
	Landslide	40	0.014	0.009
1996	Storm	692	1.400	1.807
	Flood	700	1.478	2.109
1997	Storm	40	0.000	1.827
	Wildfire	2	0.001	0.017
	Extreme temperature	87	0	0.007
	Flood	110	0.900	2.049
1998	Wildfire	2	0.013	0.074
	Flood	755	1.982	2.569
	Storm	1,280	17.371	12.637
1999	Flood	87	0.049	0.651
	Storm	376	1.584	14.234

	Landslide	11	0.0003	0.019
	Wildfire	0	0.0001	0.162
2000	Storm	188	1.935	2.510
	Flood	93	1.114	0.563
	Landslide	14	0.000	0.004
2001	Storm	465	22.302	5.594
	Flood	301	9.050	1.777
	Landslide	19	0.010	0.099
2002	Storm	195	1.246	7.954
	Flood	165	6.341	0.883
	Wildfire	0	0.003	0.369
2003	Flood	87	0.218	0.231
	Storm	114	9.652	1.446
2004	Storm	384	6.441	43.486
	Flood	1	0.000	0.007
2005	Storm	312	28.385	30.503
	Flood	0	0	0.004
	Landslide	143	0	0.007
2006	Landslide	1,126	0.006	0.003
	Storm	13	0.001	0.145
2007	Storm	90	1.011	10.940
2008	Storm	359	4.418	12.479
	Flood	121	4.611	0.199
2009	Storm	184	2.351	0.874
2010	Landslide	74	0.078	0.695
	Storm	220	3.365	4.959
	Flood	285	9.146	0.764
2011	Storm	167	4.194	2.940
	Flood	273	3.744	1.976
2012	Storm	2,142	13.454	71.140
	Flood	183	0.036	0.767
2013	Storm	7,463	16.988	15.129
	Flood	5	0.004	0.003
2014	Storm	206	9.745	10.163
	Landslide	125	0	0.072
	Wildfire	2	0	0.031
	Flood	0	0.007	0.159
2015	Storm	202	2.402	10.096
	Flood	19	0.048	1.484
2016	Storm	262	1.929	7.445
	Flood	268	1.929	7.567
2017	Storm	76	0.124	8.056
	Landslide	63	0.001	0.016
	Flood	61	0.022	0.486
2018	Landslide	12	0	0.00004
	Storm	300	6.510	4.347
2019	Storm	85	20.168	13.429
	Flood	27	0.001	0.052
	Total	51,920	612.421	573.687

Natural disasters data is obtained from EM-DAT database, over the period 1980-2019 for the natural disasters impacting agriculture. **Total Deaths** is the total number of deaths is the number of casualties resulting from the natural disasters per year in top agricultural commodity producing countries. **Total Affected** is the number of people, in million, affected by the natural disasters per year in top agricultural commodity producing countries. **Total Damages, CPI-Adjusted** is the total damage in billion US dollar resulting from natural disasters per year for all top agricultural commodity producing countries.

Table 2: Natural Disasters Distribution by Type, 1980-2019

Year	Disaster Type					Total
	Extreme temperature	Flood	Landslide	Storm	Wildfire	
1980	0	3	0	8	0	11
1981	0	5	0	10	0	15
1982	0	6	1	23	0	30
1983	0	4	0	7	2	13
1984	0	3	0	13	0	16
1985	1	6	0	9	0	16
1986	0	8	0	14	0	22
1987	0	7	1	16	1	25
1988	0	5	0	10	0	15
1989	0	2	1	14	0	17
1990	1	2	0	15	0	18
1991	0	4	1	15	0	20
1992	0	4	3	10	2	19
1993	0	6	1	24	0	31
1994	1	9	0	14	2	26
1995	0	7	1	11	0	19
1996	0	2	0	7	0	9
1997	1	4	0	7	2	14
1998	0	7	0	14	3	24
1999	0	5	1	14	1	21
2000	0	8	1	19	0	28
2001	0	7	1	18	0	26
2002	0	2	0	19	3	24
2003	0	5	0	9	0	14
2004	0	2	0	14	0	16
2005	0	1	1	12	0	14
2006	0	0	1	2	0	3
2007	0	0	0	7	0	7
2008	0	6	0	15	0	21
2009	0	0	0	8	0	8
2010	0	3	3	12	0	18
2011	0	4	0	8	0	12
2012	0	2	0	20	0	22
2013	0	1	0	13	0	14
2014	0	1	2	6	1	10
2015	0	2	0	15	0	17
2016	0	1	0	10	0	11
2017	0	3	2	12	0	17
2018	0	1	1	14	0	16
2019	0	1	0	6	0	7
Total	4	149	22	494	17	686

Natural disasters data is obtained from EM-DAT database, over the period 1980-2019 for the natural disasters impacting agriculture, and hence agricultural commodities.

Table 3: Distribution of Natural Disasters by Country, 1980-2019

Country	Disaster Type	Number	Total
Argentina	Flood	3	8
	Storm	4	
	Wildfire	1	
Australia	Flood	5	29
	Storm	20	
	Wildfire	4	
Bangladesh	Flood	2	8
	Storm	6	
Bolivia	Flood	3	4
	Landslide	1	
Brazil	Extreme temperature	1	7
	Flood	3	
	Storm	2	
	Wildfire	1	
Canada	Flood	7	15
	Storm	8	
China	Flood	20	117
	Landslide	3	
	Storm	94	
Colombia	Flood	1	3
	Landslide	1	
	Storm	1	
Costa Rica	Flood	1	3
	Storm	2	
Cuba	Storm	7	7
Dominican Republic	Flood	1	7
	Storm	6	
Ecuador	Flood	1	1
El Salvador	Flood	1	2
	Storm	1	
Ethiopia	Landslide	1	1
France	Flood	2	8
	Landslide	1	
	Storm	5	
Germany	Flood	1	10
	Storm	8	
	Storm	1	
Guatemala	Flood	2	4
	Landslide	1	
	Storm	1	
Honduras	Flood	2	4
	Storm	2	
India	Extreme temperature	1	36
	Flood	9	
	Landslide	1	
	Storm	25	
Indonesia	Flood	9	14
	Landslide	4	
	Storm	1	
Italy	Flood	6	9
	Landslide	2	
	Storm	1	
Japan	Flood	2	29
	Landslide	2	
	Storm	25	
Kazakhstan	Storm	1	1
Malaysia	Flood	1	1

Mexico	Extreme temperature Flood Storm	1 3 14	18
Myanmar	Flood Storm	1 3	4
Nigeria	Flood Storm	2 1	3
Pakistan	Landslide	1	1
Papua New Guinea	Flood Storm	2 1	3
Peru	Flood	1	1
Philippines	Flood Landslide Storm	14 2 108	124
Romania	Storm	1	1
Russia	Flood Landslide Storm	5 1 7	13
South Africa	Flood Storm	2 6	8
Thailand	Flood Storm	14 5	19
Turkey	Flood Storm	2 1	3
Ukraine	Flood Storm	1 2	3
UK	Flood Storm	3 5	8
USA	Extreme temperature Flood Landslide Storm Wildfire	1 13 1 87 10	112
Uruguay	Storm	1	1
Viet Nam	Flood Storm	3 31	34
Yugoslavia	Flood Wildfire	1 1	2
		Grand Total	686

Natural disasters data is obtained from EM-DAT database, over the period 1980-2019 for the natural disasters impacting agriculture, and hence agricultural commodities. Data of main countries producing the selected agricultural commodities and their production share are obtained from FAOSTAT database. The FAOSTAT reports the annual production of agricultural commodities in tonnes, for each country. Production is over the period from 1980 to 2019.

Table 4: Distribution of Natural Disasters Impact by Country

1980-2019

Country	Total Deaths	Total Affected (million persons)	Total Damages, CPI-Adjusted (billion US$)
Argentina	51	6.003	3.336
Australia	122	0.312	9.116
Bangladesh	762	4.827	2.932
Bolivia	49	0.001	0.834
Brazil	385	3.043	3.775
Canada	29	0.008	4.699
China	9,187	372.352	82.112
Colombia	26	0.100	0.124
Costa Rica	79	0.628	0.522
Cuba	44	6.621	7.589
Dominican Republic	31	0.150	0.038
El Salvador	500	0.068	0.849
France	73	0.002	7.216
Germany	44	0.000	17.146
Guatemala	1,057	0.177	2.317
Honduras	194	0.187	0.602
India	5,349	63.715	29.546
Indonesia	127	0.017	0.177
Italy	78	0.008	7.487
Japan	246	0.313	53.887
Malaysia	11	0.025	0.031
Mexico	673	0.768	8.635
Myanmar	68	0.620	0.248
Papua New Guinea	2	0.038	0.076
Philippines	17,961	77.307	24.651
Russia	172	0.071	5.062
South Africa	20	0.000	1.176
Thailand	317	10.271	1.408
Turkey	0	0.000	0.716
UK	67	0.048	8.904
Ukraine	4	0.006	0.204
USA	790	8.612	265.041
Viet Nam	1,851	2.982	5.259

Natural disasters data is obtained from EM-DAT database, over the period 1980-2019 for the natural disasters impacting agriculture. **Total Deaths** is the total number of deaths is the number of casualties resulting from the natural disasters per year in top agricultural commodity producing countries. **Total Affected** is the number of people, in million, affected by the natural disasters per year in top agricultural commodity producing countries. **Total Damages, CPI-Adjusted** is the total damage in billion US dollar resulting from natural disasters per year for all top agricultural commodity producing countries. Data of main countries producing the selected agricultural commodities and their production share are obtained from FAOSTAT database. The FAOSTAT reports the annual production of agricultural commodities in tonnes, for each country. Production is over the period from 1980 to 2019.

Table 5: Countries Producing Multiple Agriculture Commodities

Country of Production	Number of produced Commodities
Russia	6
Brazil	6
India	6
Indonesia	6
China	5
Mexico	5
USA	4
Argentina	4
Ukraine	3
Philippines	3
Pakistan	3
Colombia	3
Canada	3
Ethiopia	2
Thailand	2
Peru	2
Guatemala	2
France	2
Côte d'Ivoire	2
Australia	2
Viet Nam	2

Data of agricultural commodities production is obtained from FAOSTAT database. The FAOSTAT reports the annual production of agricultural commodities in tonnes, for each country. Production is over the period from 1980 to 2019.

Table 6: Agriculture Commodities Production per Country

Cocoa	Coffee	Corn	Rice	Soybean	Sugar Cane	Wheat
Brazil	Brazil	Argentina	Bangladesh	Argentina	Argentina	Argentina
Cameron	Burundi	Brazil	Brazil	Bolivia	Australia	Australia
Colombia	Cameroon	Canada	China	Brazil	Brazil	Canada
Côte d'Ivoire	Colombia	China	India	Canada	China	China
Dominican Republic	Costa Rica	France	Indonesia	China	Colombia	France
Ecuador	Côte d'Ivoire	India	Japan	India	Cuba	Germany
Ghana	Ecuador	Indonesia	Myanmar	Indonesia	Guatemala	India
Indonesia	El Salvador	Italy	Pakistan	Italy	India	Kazakhstan
Malaysia	Ethiopia	Mexico	Philippines	Mexico	Indonesia	Pakistan
Mexico	Guatemala	Romania	Thailand	Paraguay	Mexico	Russia
Nigeria	Honduras	Russia	Viet Nam	Russia	Pakistan	Turkey
Papua New Guinea	India	South Africa		Ukraine	Philippines	Ukraine
Peru	Indonesia	Ukraine		Uruguay	Thailand	UK
Togo	Mexico	USA		USA	USA	USA
	Peru	Former Yugoslavia				
	Philippines					
	Uganda					
	Viet Nam					

Data of agricultural commodities production is obtained from FAOSTAT database. The FAOSTAT reports the annual production of agricultural commodities in tonnes, for each country. Production is over the period from 1980 to 2019. Russia data includes the data of the former USSR, up till its dissolution in on 31st December 1991. Germany data includes Eastern Germany data, up till Germany reunification at the end of 1990.

Table 7: Impact of Natural Disasters on Cocoa Prices

Event Windows	CAR % *(p-value)*	Abnormal Variance *(p-value)*
[-15, +15]	2.087 (0.271)	**0.006 *** (0.053)
[-10, +10]	0.949 (0.544)	0.001 (0.718)
[-7, +7]	0.247 (0.852)	0.001 (0.755)
[-3, +3]	0.082 (0.928)	0.001 (0.505)
[-1, +1]	-0.219 (0.713)	0.001 (0.571)
[-3, -1]	0.100 (0.819)	0.000 (0.987)
[-1, 0]	0.100 (0.917)	0.000 (0.654)
[0, +1]	0.600 (0.266)	0.000 (0.605)
[0, +3]	0.100 (0.929)	0.001 (0.411)

The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. P-values are presented in parentheses. Significant results are set in bold. The table shows the impact of agriculture-related natural disasters hitting main top country producers on the price of rice for event windows: before, during, and after the event (day 0). Day 0 is the day of the event listed in EM-DAT database. CAR (%) is the cumulative abnormal return at the end of the event window (the summation of abnormal return from the first day in event window to the end day). Events included are the natural disasters in the top country-producers, with total damages are > Median, and N = 29 (natural disasters). Abnormal variance is cumulative abnormal GARCH volatility at the end of the event window (the summation of abnormal volatility from the first day in the event window to the end day).

Table 8: Impact of Natural Disasters on Coffee Prices

Event Windows	CAR % *(p-value)*	Abnormal Variance *(p-value)*
[-15, +15]	1.673 (0.123)	**0.022** *** (0.000)
[-10, +10]	0.283 (0.752)	**0.017** *** (0.000)
[-7, +7]	-0.009 (0.990)	**0.013** *** (0.000)
[-3, +3]	0.175 (0.734)	**0.007** *** (0.000)
[-1, +1]	-0.282 (0.403)	**0.003** *** (0.000)
[-3, -1]	-0.300 (0.365)	**0.002** *** (0.002)
[-1, 0]	-0.300 (0.239)	**0.002** *** (0.002)
[0, +1]	-0.200 (0.502)	**0.002** *** (0.001)
[0, +3]	0.500 (0.228)	**0.004** *** (0.000)

The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. P-values are presented in parentheses. Significant results are set in bold. The table shows the impact of agriculture-related natural disasters hitting main top country producers on the price of rice for event windows: before, during, and after the event (day 0). Day 0 is the day of the event listed in EM-DAT database. CAR (%) is the cumulative abnormal return at the end of the event window (the summation of abnormal return from first day in event window to the end day). Events included are the natural disasters in the top country-producers, with total damages are > Median, and N = 126 (natural disasters). Abnormal variance is cumulative abnormal GARCH volatility at the end of the event window (the summation of abnormal volatility from the first day in the event window to the end day).

Table 9: Impact of Natural Disasters on Corn Prices

Event Windows	CAR % *(p-value)*	Abnormal Variance *(p-value)*
[-15, +15]	0.330 (0.596)	**0.019** *** (0.000)
[-10, +10]	0.200 (0.696)	**0.012** *** (0.000)
[-7, +7]	0.283 (0.510)	**0.008** *** (0.000)
[-3, +3]	-0.070 (0.811)	**0.004** *** (0.000)
[-1, +1]	-0.179 (0.352)	**0.001** ** (0.041)
[-3, -1]	0.100 (0.466)	**0.001** ** (0.014)
[-1, 0]	-0.100 (0.378)	0.001 (0.207)
[0, +1]	-0.200 (0.132)	**0.001** * (0.080)
[0, +3]	-0.200 (0.344)	**0.002** *** (0.000)

The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. P-values are presented in parentheses. Significant results are set in bold. The table shows the impact of agriculture-related natural disasters hitting main top country producers on the price of rice for event windows: before, during, and after the event (day 0). Day 0 is the day of the event listed in EM-DAT database. CAR (%) is the cumulative abnormal return at the end of the event window (the summation of abnormal return from first day in event window to the end day). Events included are the natural disasters in the top country-producers, with total damages are > Median, and N = 186 (natural disasters). Abnormal variance is cumulative abnormal GARCH volatility at the end of the event window (the summation of abnormal volatility from the first day in the event window to the end day).

Table 10: Impact of Natural Disasters on Rice Prices

Event Windows	CAR % *(p-value)*	Abnormal Variance *(p-value)*
[-15, +15]	0.813 (0.243)	**0.044** *** (0.000)
[-10, +10]	0.499 (0.386)	**0.029** *** (0.000)
[-7, +7]	0.289 (0.551)	**0.021** *** (0.000)
[-3, +3]	**0.884** *** (0.008)	**0.010** *** (0.000)
[-1, +1]	**0.656** *** (0.002)	**0.004** *** (0.000)
[-3, -1]	**0.500** ** (0.011)	**0.004** *** (0.000)
[-1, 0]	**0.300** * (0.072)	**0.003** *** (0.000)
[0, +1]	**0.600** *** (0.001)	**0.003** *** (0.000)
[0, +3]	0.300 (0.200)	**0.006** *** (0.000)

The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. P-values are presented in parentheses. Significant results are set in bold. The table shows the impact of agriculture-related natural disasters hitting main top country producers on the price of rice for event windows: before, during, and after the event (day 0). Day 0 is the day of the event listed in EM-DAT database. CAR (%) is the cumulative abnormal return at the end of the event window (the summation of abnormal return from first day in event window to the end day). Events included are the natural disasters in the top country-producers, with total damages are > Median, and N = 196 (natural disasters). Abnormal variance is cumulative abnormal GARCH volatility at the end of the event window (the summation of abnormal volatility from the first day in the event window to the end day).

Table 11: Impact of Natural Disasters on Soybean Prices

Event Windows	CAR % *(p-value)*	Abnormal Variance *(p-value)*
[-15, +15]	-0.012 (0.983)	**0.039** *** (0.000)
[-10, +10]	0.154 (0.743)	**0.026** *** (0.000)
[-7, +7]	-0.093 (0.815)	**0.018** *** (0.000)
[-3, +3]	0.002 (0.993)	**0.009** *** (0.000)
[-1, +1]	-0.180 (0.312)	**0.003** *** (0.000)
[-3, -1]	0.200 (0.336)	**0.004** *** (0.000)
[-1, 0]	0.000 (0.948)	**0.002** *** (0.000)
[0, +1]	**-0.400** ** **(**0.011)	**0.002** *** (0.000)
[0, +3]	-0.200 (0.410)	**0.005** *** (0.000)

The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. P-values are presented in parentheses. Significant results are set in bold. The table shows the impact of agriculture-related natural disasters hitting main top country producers on the price of rice for event windows: before, during, and after the event (day 0). Day 0 is the day of the event listed in EM-DAT database. CAR (%) is the cumulative abnormal return at the end of the event window (the summation of abnormal return from first day in event window to the end day). Events included are the natural disasters in the top country-producers, with total damages are > Median, and N = 180 (natural disasters). Abnormal variance is cumulative abnormal GARCH volatility at the end of the event window (the summation of abnormal volatility from the first day in the event window to the end day).

Table 12: Impact of Natural Disasters on Sugar Prices

Event Windows	CAR % *(p-value)*	Abnormal Variance *(p-value)*
[-15, +15]	0.874 (0.338)	**0.008** *** (0.003)
[-10, +10]	0.846 (0.260)	**0.005** ** (0.014)
[-7, +7]	0.42 (0.509)	**0.005** ** (0.013)
[-3, +3]	0.542 (0.211)	0.002 (0.117)
[-1, +1]	0.015 (0.957)	0.001 (0.139)
[-3, -1]	0.100 (0.689)	0.000 (0.956)
[-1, 0]	-0.100 (0.668)	0.001 (0.272)
[0, +1]	-0.100 (0.638	0.001 (0.161)
[0, +3]	0.300 (0.374)	**0.002** ** (0.034)

The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. P-values are presented in parentheses. Significant results are set in bold. The table shows the impact of agriculture-related natural disasters hitting main top country producers on the price of rice for event windows: before, during, and after the event (day 0). Day 0 is the day of the event listed in EM-DAT database. CAR (%) is the cumulative abnormal return at the end of the event window (the summation of abnormal return from first day in event window to the end day). Events included are the natural disasters in the top country-producers, with total damages are > Median, and N = 240 (natural disasters). Abnormal variance is cumulative abnormal GARCH volatility at the end of the event window (the summation of abnormal volatility from the first day in the event window to the end day).

Table 13: Impact of Natural Disasters on Wheat Prices

Event Windows	**CAR %** *(p-value)*	**Abnormal Variance** *(p-value)*
[-15, +15]	1.055 (0.343)	-0.002 (0.410)
[-10, +10]	0.584 (0.522)	-0.001 (0.528)
[-7, +7]	0.262 (0.734)	-0.001 (0.476)
[-3, +3]	-0.180 (0.735)	-0.001 (0.489)
[-1, +1]	-0.148 (0.670)	0.000 (0.516)
[-3, -1]	-0.300 (0.458)	0.000 (0.741)
[-1, 0]	-0.100 (0.735)	0.000 (0.791)
[0, +1]	0.100 (0.732)	0.000 (0.458)
[0, +3]	0.200 (0.540)	-0.001 (0.252)

The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. P-values are presented in parentheses. Significant results are set in bold. The table shows the impact of agriculture-related natural disasters hitting main top country producers on the price of rice for event windows: before, during, and after the event (day 0). Day 0 is the day of the event listed in EM-DAT database. CAR (%) is the cumulative abnormal return at the end of the event window (the summation of abnormal return from first day in event window to the end day). Events included are the natural disasters in the top country-producers, with total damages are > Median, and N = 182 (natural disasters). Abnormal variance is cumulative abnormal GARCH volatility at the end of the event window (the summation of abnormal volatility from the first day in the event window to the end day).

Table 14: Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
CARs (%)	1066	-25.801	16.517	-0.059	3.019
Price.Increase	1089	-0.625	1.925	0.022	0.246
Tot.Deaths	913	1	7,354	139	491.954
Tot.Affected (Ln)	801	0	18.556	11.436	3.349
Tot.Damages (Ln)	1089	10.029	17.970	13.214	1.310
GDP.Capita (Ln)	1079	4.815	10.943	8.231	1.651
Prod.Share	1084	0.005	10.873	1.790	3.332
FX.Rate.Change	1089	-0.245	9.592	0.207	0.983

CAR (%) is the cumulative abnormal return at the end of the event window and is the summation of abnormal returns at day 0. **Price.Increase** measures demand pressure on the agriculture commodities in the two years prior to the natural disaster**. Tot.Damages (Ln)** is the natural log of the net CPI-adjusted value of damages caused by a natural disaster in US$. **Tot.Deaths** is number of the people that passed away because of a natural disaster. **Tot.Affected (Ln)** is the natural log of the of the number of people affected by a natural disaster in a country. All three control variables are downloaded from EM-DAT database. **GDP.Capita (Ln)** is the natural log of the gross domestic product per capita of the affected country; GDP per capita is downloaded from the IMF WEO database. **Prod.Share** is the production share of a producing country of a certain commodity in the year before the natural disaster. **FX.Rate.Change** is the change in the foreign exchange rate of the domestic currency of a producing country against the US$ over the year of the occurrence of the nature disaster and the year before; FX rates are downloaded from the IMF IFS database.

Table 15: Correlation Matrix

	CARs%	Price. Increase	Tot.Deaths	Tot. Affected	Tot. Damages	Cocoa	Coffee	Corn	Rice	Soybean	Sugar	Wheat	Storm	Flood	Wildfire	Landslide	GDP. Capita	Prod. Share	FX.Rate. Change
CARs%	1																		
Price.Increase	-0.012	1																	
Tot.Deaths	0.059	-.0340	1																
Tot.Affected (Ln)	0.049	0.017	0.285**	1															
Tot.Damages (Ln)	-0.006	0.047	0.199**	.0246**	1														
Cocoa	0.006	-0.038	-0.032	-0.053	-0.129**	1													
Coffee	-0.032	-0.048	0.072*	0.065	-0.240**	-0.060*	1												
Corn	-0.013	0.029	-0.033	-0.029	0.110**	-0.075*	-0.164**	1											
Rice	0.055	0.025	0.015	0.044	-0.086**	-0.066*	-0.143**	-0.180**	1										
Soybean	0.011	0.039	-0.028	-0.020	0.107**	-0.073*	-0.160**	-0.201**	-0.175**	1									
Sugar	-0.011	-0.032	0.031	0.004	-0.009	-0.088**	-0.192**	-0.241**	-0.211**	-0.235**	1								
Wheat	-0.011	0.001	-0.041	-0.043	0.134**	-0.074*	-0.162**	-0.203**	-0.178**	-0.198**	-0.238**	1							
Storm	-0.084**	0.009	-0.070*	0.060	0.043	-0.050	0.025	-0.036	0.048	-0.036	0.025	0.000	1						
Flood	0.083**	-0.001	0.079*	0.027	-0.013	0.043	-0.017	0.027	-0.036	0.024	-0.025	0.006	-0.872**	1					
Wildfire	0.024	-0.024	-0.021	-0.153**	-0.106**	0.010	-0.039	0.022	-0.046	0.009	0.015	0.024	-0.301**	-0.074*	1				
Landslide	0.025	-0.025	-0.017	-0.104**	0.029	-0.015	-0.001	0.012	0.023	0.042	-0.024	-0.041	-0.172**	-0.042	-0.015	1			
GDP.Capita (Ln)	-0.053	0.072*	-0.186**	-0.485**	0.177**	-0.007	-0.256**	0.086**	-0.117**	0.069*	0.036	0.135**	0.057	-0.105**	0.141**	0.018	1		
Prod.Share	0.015	-0.015	0.117**	-0.040	-0.148**	0.052	0.140**	-0.076*	-0.015	-0.107**	0.139**	-0.102**	-0.040	-0.014	0.106**	0.080**	0.087**	1	
FX.Rate. Change	0.027	0.024	0.030	0.034	0.004	0.162**	0.046	0.001	-0.042	0.002	-0.009	-0.064*	-0.243**	0.176**	0.021	-0.020	-0.063*	-0.046	1

The table reports Pearson correlation coefficients between the variables used in the OLS regressions. The symbols *, **, and *** denote statistical significance at the 0.1, 0.05, and 0.01 level, respectively. P-values are reported below the correlation coefficients. **CAR (%)** is the cumulative abnormal return at the end of the event window and is the summation of abnormal returns, at day 0. **Price Increase** measures demand pressure on the agriculture commodities in the two years prior to the natural disaster**. Tot.Damage** is the natural log of the net CPI-adjusted value of damages caused by a natural disaster in US$. **Tot.Deaths** is number of the people that passed away because of a natural disaster. T**ot.Affected** is the natural log of the of the of number of people affected by a natural disaster in a country. All three control variables are downloaded from EM-DAT database. **Cocoa, Coffee, Corn, Rice, Soybean, Sugar,** and **Wheat** are dummy variables for the agriculture commodities included, with values downloaded from Bloomberg. **Storm, Flood, Extreme Temperature and Wildfire** are dummy variables for natural disasters included, as reported by EM-DAT. **GDPCapita** is the natural log of the gross domestic product per capita of the affected country; GDP per capita is downloaded from the IMF WEO database. **Prod.Share** is the production share of a producing country of a certain commodity in the year before the natural disaster. **FX.Rate.Change** is the change in the foreign exchange rate of the domestic currency of a producing country against the US$ over the year of the occurrence of the nature disaster and the year before; FX rates are downloaded from the IMF IFS database.

Table 16: OLS Regression of Cumulative Abnormal Return (CAR)

Event Window	CAR% [-3, -1]	CAR% [-1, +1]	CAR% [-1,0]	CAR% [0, +1]	CAR% [+1, +3]
Price.Increase	-0.586 (0.318)	**-1.115** ** (0.035)	-0.138 (0.764)	-0.417 (0.216)	**-2.331** *** (0.000)
Tot.Deaths	0.0001 (0.764)	0.0001 (0.698)	0.0002 (0.300)	-0.000003 (0.985)	-0.0001 (0.644)
Tot.Affected (Ln)	-0.015 (0.782)	0.042 (0.389)	0.035 (0.408)	0.014 (0.652)	-0.032 (0.505)
Tot.Damages (Ln)	-0.142 (0.276)	0.075 (0.525)	0.005 (0.964)	0.087 (0.245)	-0.093 (0. 417)
Coffee	**-1.631** * (0.096)	-0.908 (0.302)	-0.748 (0.329)	-0.126 (0.822)	-0.276 (0.749)
Corn	-0.734 (0.460)	-0.320 (0.720)	-0.531 (0.496)	-0.189 (0.740)	0.154 (0.861)
Rice	-0.462 (0.638)	0.476 (0.590)	0.016 (0.983)	0.441 (0.435)	-0.142 (0.870)
Soybean	-0.751 (0.451)	-0.460 (0.607)	-0.431 (0.580)	-0.196 (0.731)	-0.078 (0.929)
Sugar	-0.669 (0.487)	-0.322 (0.710)	-0.545 (0.471)	-0.243 (0.661)	-0.015 (0.986)
Wheat	-0.856 (0.394)	-0.037 (0.967)	-0.303 (0.700)	0.141 (0.807)	0.210 (0.812)
Storm	-0.274 (0.482)	-0.563 (0.109)	**-0.603** ** (0.049)	-0.057 (0.800)	-0.187 (0.586)
Wildfire	-0.990 (0.519)	-0.613 (0.657)	-0.102 (0.933)	-0.312 (0.724)	-1.612 (0.233)
Landslide	1.143 (0.452)	1.869 (0.171)	0.882 (0.459)	**1.454** * (0.096)	0.573 (0.668)
GDP.Capita (Ln)	-0.080 (0.502)	**-0.224** ** (0.037)	-0.125 (0.183)	**-0.150** ** (0.028)	**-0.192** * (0.069)
Prod.Share	-0.037 (0.447)	-0.025 (0.569)	-0.017 (0.656)	0.013 (0.634)	-0.068 (0.115)
FX.Rate.Change	0.243 (0.127)	-0.059 (0.678)	-0.127 (0.309)	-0.054 (0.622)	0.074 (0.595)
(Constant)	3.621 (0.048)	3.040 (0.660)	1.383 (0.335)	0.224 (0.831)	3.398 (0.035)

The symbols *, **, and *** denote statistical significance at the 0.1, 0.05, and 0.01 level, respectively. P-values are reported below the correlation coefficients. **CAR (%)** is the cumulative abnormal return at the end of the event window and is the summation of abnormal returns. **Price.Increase (%)** measures demand pressure on the agriculture commodities in the two years prior to the natural disaster**. Tot.Damage (Ln)** is the natural log of the net CPI-adjusted value of damages caused by a natural disaster in US$. **Tot.Deaths** is number of the people that passed away because of a natural disaster. **Tot.Affected (Ln)** is the natural log of the of the number of people affected by a natural disaster in a country. All three control variables are downloaded from EM-DAT database. **Cocoa, Coffee, Corn, Rice, Soybean, Sugar,** and **Wheat** are dummy variables for the agriculture commodities included, with values downloaded from Bloomberg. **Storm, Flood, Extreme Temperature and Wildfire** are dummy variables for natural disasters included, as reported by EM-DAT. **GDPCapita (Ln)** is the natural log of the gross domestic product per capita of the affected country; GDP per capita is downloaded from the IMF WEO database. **Prod.Share** is the production share of a producing country of a certain commodity in the year before the natural disaster. **FX.Rate.Change** is the change in the foreign exchange rate of the domestic currency of a producing country against the US$ over the year of the occurrence of the nature disaster and the year before; FX rates are downloaded from the IMF IFS database.

Table 17: OLS Regression of Cumulative Abnormal Variance (CAV)

Event Window	CAV% [-3, -1]	CAV% [-1, +1]	CAV% [-1,0]	CAV% [0, +1]	CAV% [+1, +3]
Price.Increase	0.094 (0.230)	**0.392 *** (0.095)	0.254 (0.105)	**0.273 *** (0.089)	0.340 (0.190)
Tot.Deaths	-0.0001 (0.184)	-0.0002 (0.169)	-0.0001 (0.185)	-0.0001 (0.165)	-0.0001 (0.238)
Tot.Affected (Ln)	0.007 (0.354)	0.014 (0.516)	0.006 (0.690)	0.012 (0.412)	0.028 (0.248)
Tot.Damages (Ln)	0.016 (0.363)	0.069 (0.184)	0.054 (0.123)	0.046 (0.195)	0.037 (0.522)
Coffee	-0.030 (0.820)	0.045 (0.909)	0.016 (0.950)	0.023 (0.932)	0.123 (0.776)
Corn	-0.049 (0.709)	-0.217 (0.585)	-0.179 (0.500)	-0.134 (0.623	0.002 (0.997)
Rice	-0.072 (0.581)	-0.214 (0.586)	-0.156 (0.552)	-0.145 (0.588)	-0.139 (0.749)
Soybean	0.031 (0.816)	0.049 (0.903)	0.004 (0.989)	0.039 (0.886)	0.187 (0.670)
Sugar	-0.092 (0.474)	-0.167 (0.666)	-0.123 (0.632)	-0.112 (0.670)	-0.115 (0.786)
Wheat	-0.065 (0.625)	-0.226 (0.574)	-0.161 (0.547)	-0.155 (0.572)	-0.169 (0.703)
Storm	-0.008 (0.879)	-0.006 (0.969)	-0.003 (0.980)	-0.006 (0.952)	0.034 (0.844)
Wildfire	**-0.501**** (0.014)	**-1.451 **** (0.019)	**-0.959 **** (0.019)	**-0.974 **** (0.020)	**-1.447 **** (0.033)
Landslide	0.107 (0.596)	0.042 (0.945)	0.091 (0.822)	-0.027 (0.948)	0.038 (0.954)
GDP.Capita (Ln)	0.002 (0.921)	-0.020 (0.680)	-0.024 (0.448)	-0.010 (0.757)	0.044 (0.403)
Prod.Share	-0.009 (0.177)	-0.013 (0.503)	-0.011 (0.382)	0.008 (528)	-0.004 (0.854)
FX.Rate.Change	**-0.050 **** (0.018)	-0.082 (0.198)	-0.062 (0.141)	-0.044 (0.307)	-0.006 (0.934)
(Constant)	-0.200 (0.412)	-0.615 (0.402)	-0.376 (0.441)	-0.459 (0.359)	-0.923 (0.253)

The symbols *, **, and *** denote statistical significance at the 0.1, 0.05, and 0.01 level, respectively. P-values are reported below the correlation coefficients. **CAV (%)** is the cumulative abnormal volatility at the end of the event window and is the summation of abnormal returns. **Price.Increase (%)** measures demand pressure on the agriculture commodities in the two years prior to the natural disaster**. Tot.Damage (Ln)** is the natural log of the net CPI-adjusted value of damages caused by a natural disaster in US$. **Tot.Deaths** is number of the people that passed away because of a natural disaster. **Tot.Affected (Ln)** is the natural log of the of the number of people affected by a natural disaster in a country. All three control variables are downloaded from EM-DAT database. **Cocoa, Coffee, Corn, Rice, Soybean, Sugar,** and **Wheat** are dummy variables for the agriculture commodities included, with values downloaded from Bloomberg. **Storm, Flood, Extreme Temperature and Wildfire** are dummy variables for natural disasters included, as reported by EM-DAT. **GDPCapita (Ln)** is the natural log of the gross domestic product per capita of the affected country; GDP per capita is downloaded from the IMF WEO database. **Prod.Share** is the production share of a producing country of a certain commodity in the year before the natural disaster. **FX.Rate.Change** is the change in the foreign exchange rate of the domestic currency of a producing country against the US$ over the year of the occurrence of the nature disaster and the year before; FX rates are downloaded from the IMF IFS database.

Figure 1: Selected Natural Disasters Frequency, 1980 - 2019

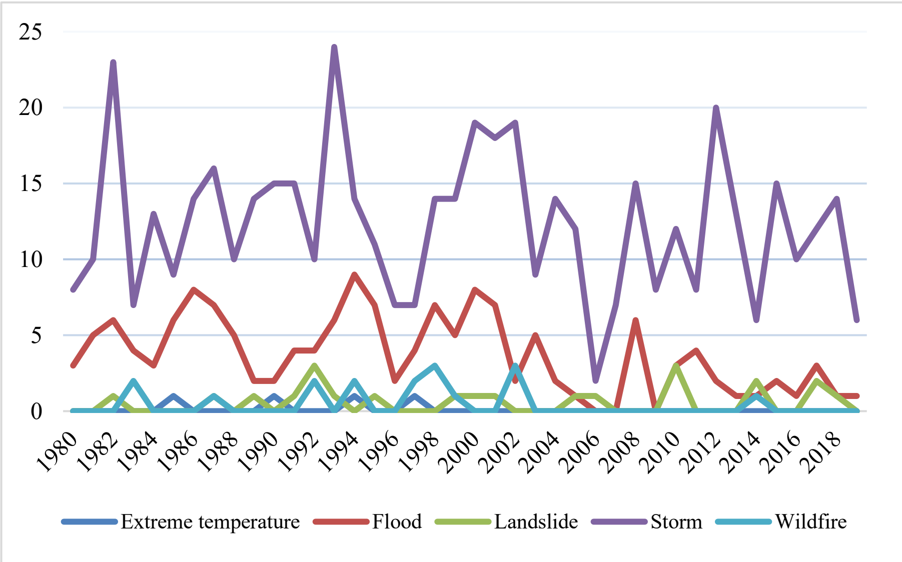
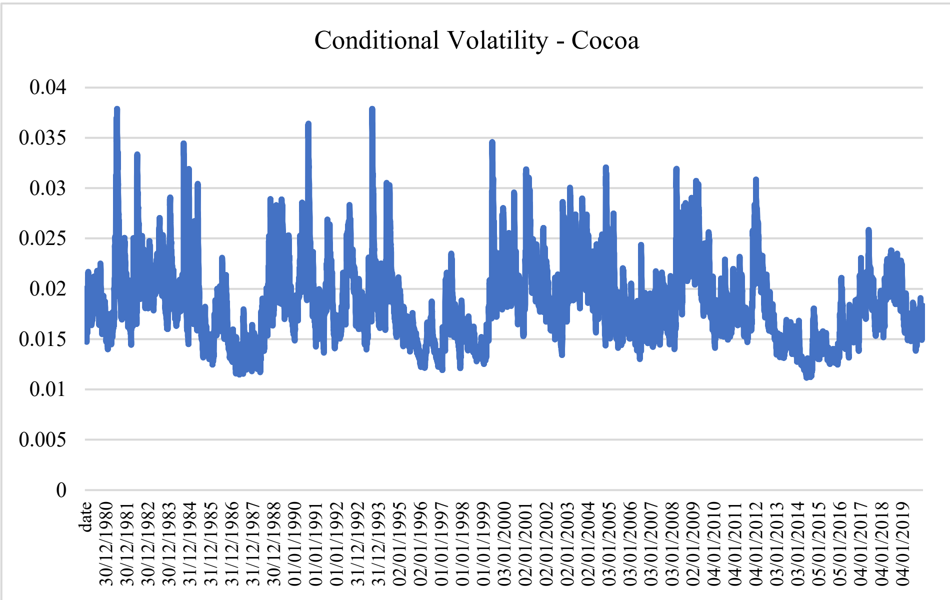
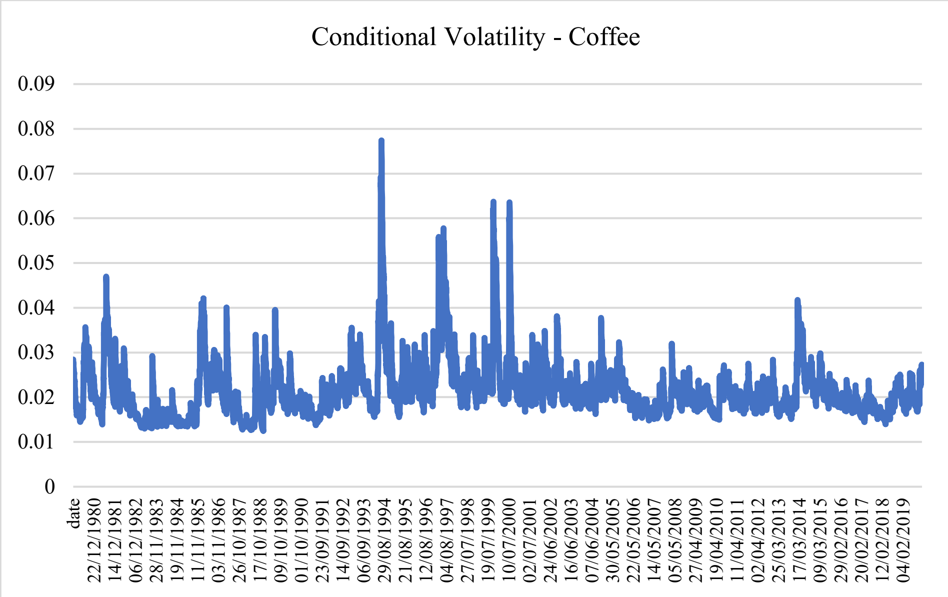
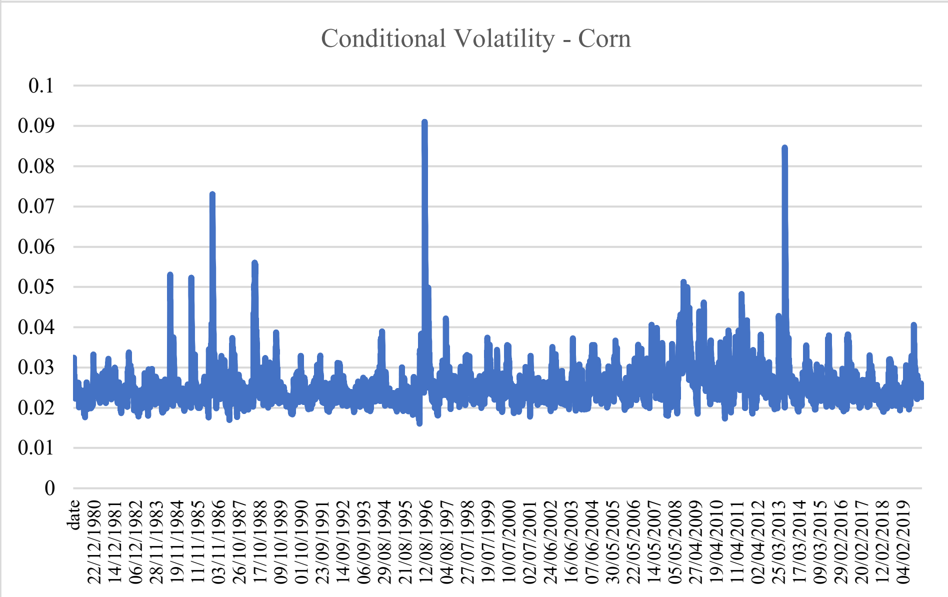
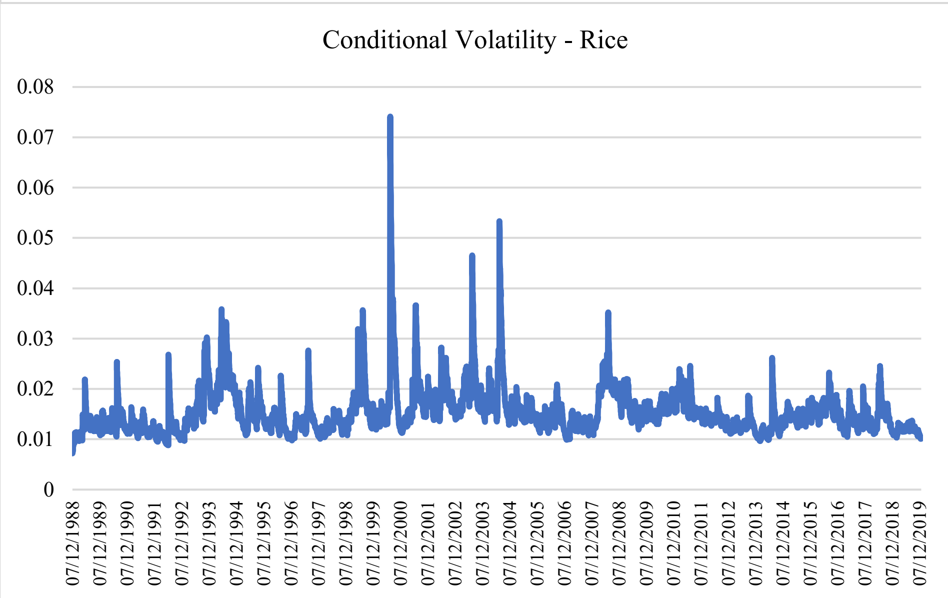


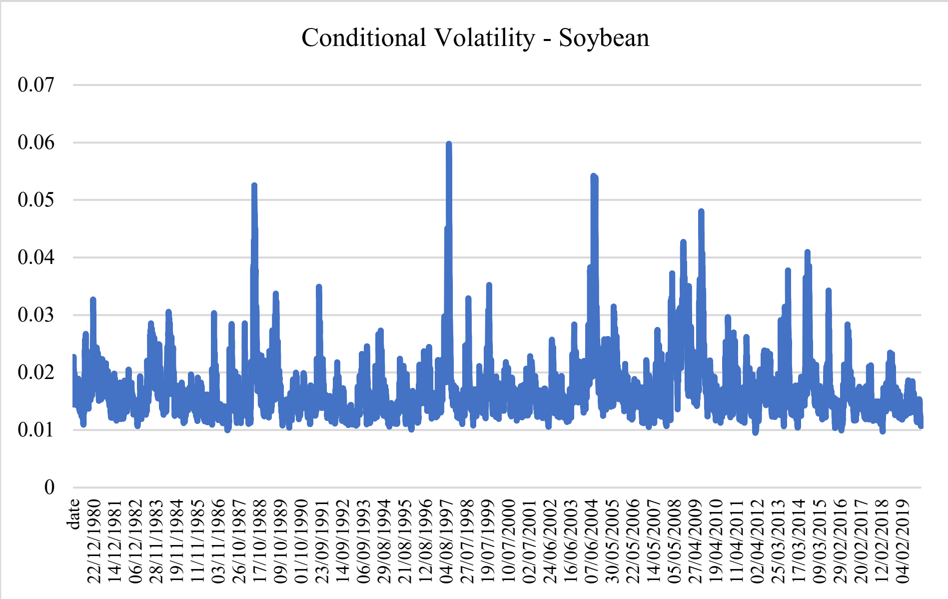
Figure 2: Daily Conditional Volatility - Agricultural Commodities

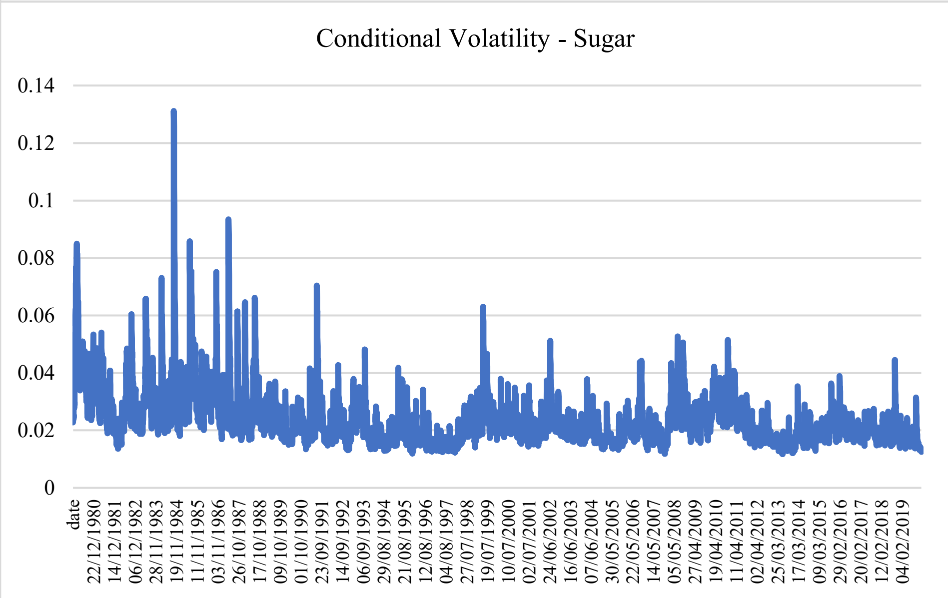


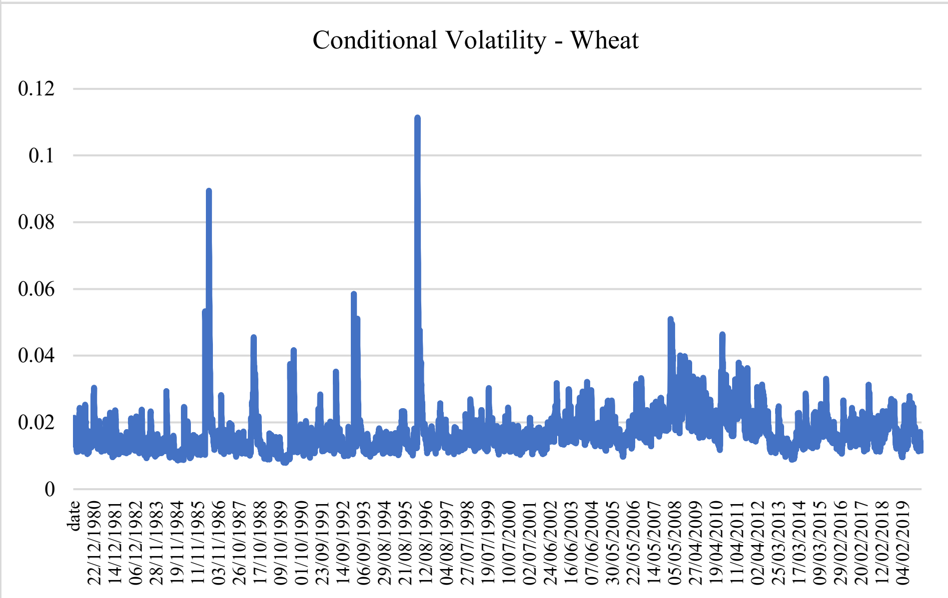

Conditional Volatility - Coffee
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
date
22/12/1980
14/12/1981
06/12/1982
28/11/1983
19/11/1984
11/11/1985
03/11/1986
26/10/1987
17/10/1988
09/10/1989
01/10/1990
23/09/1991
14/09/1992
06/09/1993
29/08/1994
21/08/1995
12/08/1996
04/08/1997
27/07/1998
19/07/1999
10/07/2000
02/07/2001
24/06/2002
16/06/2003
07/06/2004
30/05/2005
22/05/2006
14/05/2007
05/05/2008
27/04/2009
19/04/2010
11/04/2011
02/04/2012
25/03/2013
17/03/2014
09/03/2015
29/02/2016
20/02/2017
12/02/2018
04/02/2019


Conditional Volatility - Corn
0.1
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
date
22/12/1980
14/12/1981
06/12/1982
28/11/1983
19/11/1984
11/11/1985
03/11/1986
26/10/1987
17/10/1988
09/10/1989
01/10/1990
23/09/1991
14/09/1992
06/09/1993
29/08/1994
21/08/1995
12/08/1996
04/08/1997
27/07/1998
19/07/1999
10/07/2000
02/07/2001
24/06/2002
16/06/2003
07/06/2004
30/05/2005
22/05/2006
14/05/2007
05/05/2008
27/04/2009
19/04/2010
11/04/2011
02/04/2012
25/03/2013
17/03/2014
09/03/2015
29/02/2016
20/02/2017
12/02/2018
04/02/2019


Conditional Volatility - Rice
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
07/12/1988
07/12/1989
07/12/1990
07/12/1991
07/12/1992
07/12/1993
07/12/1994
07/12/1995
07/12/1996
07/12/1997
07/12/1998
07/12/1999
07/12/2000
07/12/2001
07/12/2002
07/12/2003
07/12/2004
07/12/2005
07/12/2006
07/12/2007
07/12/2008
07/12/2009
07/12/2010
07/12/2011
07/12/2012
07/12/2013
07/12/2014
07/12/2015
07/12/2016
07/12/2017
07/12/2018
07/12/2019


Conditional Volatility - Soybean
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
date
22/12/1980
14/12/1981
06/12/1982
28/11/1983
19/11/1984
11/11/1985
03/11/1986
26/10/1987
17/10/1988
09/10/1989
01/10/1990
23/09/1991
14/09/1992
06/09/1993
29/08/1994
21/08/1995
12/08/1996
04/08/1997
27/07/1998
19/07/1999
10/07/2000
02/07/2001
24/06/2002
16/06/2003
07/06/2004
30/05/2005
22/05/2006
14/05/2007
05/05/2008
27/04/2009
19/04/2010
11/04/2011
02/04/2012
25/03/2013
17/03/2014
09/03/2015
29/02/2016
20/02/2017
12/02/2018
04/02/2019


Conditional Volatility - Sugar
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
date
22/12/1980
14/12/1981
06/12/1982
28/11/1983
19/11/1984
11/11/1985
03/11/1986
26/10/1987
17/10/1988
09/10/1989
01/10/1990
23/09/1991
14/09/1992
06/09/1993
29/08/1994
21/08/1995
12/08/1996
04/08/1997
27/07/1998
19/07/1999
10/07/2000
02/07/2001
24/06/2002
16/06/2003
07/06/2004
30/05/2005
22/05/2006
14/05/2007
05/05/2008
27/04/2009
19/04/2010
11/04/2011
02/04/2012
25/03/2013
17/03/2014
09/03/2015
29/02/2016
20/02/2017
12/02/2018
04/02/2019


Conditional Volatility - Wheat
0.12
0.1
0.08
0.06
0.04
0.02
0
date
22/12/1980
14/12/1981
06/12/1982
28/11/1983
19/11/1984
11/11/1985
03/11/1986
26/10/1987
17/10/1988
09/10/1989
01/10/1990
23/09/1991
14/09/1992
06/09/1993
29/08/1994
21/08/1995
12/08/1996
04/08/1997
27/07/1998
19/07/1999
10/07/2000
02/07/2001
24/06/2002
16/06/2003
07/06/2004
30/05/2005
22/05/2006
14/05/2007
05/05/2008
27/04/2009
19/04/2010
11/04/2011
02/04/2012
25/03/2013
17/03/2014
09/03/2015
29/02/2016
20/02/2017
12/02/2018
04/02/2019