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Weathering the Markets: Exploring the Empirical Relationship between Climate Change Concerns and Commodity Futures Contracts

by

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1 Introduction

Climate change poses tangible risks to both the environment and the global economy as a whole. With increased awareness of the physical effects of climate change, governments worldwide have established objectives to reduce their carbon footprints. This transition towards carbon neutrality introduces multiple channels through which climate change can interact with financial markets. In addition to more frequent and variable adverse weather events that have the ability to impair productive physical assets, producers and investors must also monitor the added layers of climate-mitigating policies.

These uncertainties related to climate change pose both physical and transitory risks to commodity producers worldwide. Variability in extreme temperatures, water availability, and fertilization can have both positive and negative effects on crop yields, posing physical risks that translate into supply-side uncertainties for agricultural commodities (Antón et al., 2013; Lewis and Witham, 2012). More strict climate policies aimed at reducing emissions can increase the costs of extracting fossil fuels or outright limit extraction and oil exploration, which can create uncertainty in oil and gas supplies (Diaz-Rainey et al., 2021). Furthermore, the emergence of biofuels as a relatively cleaner source of energy has increased the connectedness between energy and cereal commodity markets as they are derived from grains such as corn and soybeans (Mensi et al., 2014).

Commodity producers should pay close attention to climate-mitigating policies as they can shift investments towards carbon-reducing activities by placing a price on carbon that monetarily rewards producers for reducing their emissions and increases emissions-related costs for those that do not. As a result, there is an urgent need to develop and implement new technologies that can effectively reduce carbon emissions in production, storage, and transportation (Martinez-Diaz and Keenan, 2020). Another element that is often overlooked as part of transitory climate change risk is the aspect of social inclusion, as the increasing awareness of climate change can update both investor and consumer preferences in the short run (Bolton and Kacperczyk, 2023).

The growing movement in achieving net-zero goals has led researchers to investigate the links between climate change and financial assets. Numerous studies have shown that climate uncertainty has a significant impact on equities, bonds, and real assets, either through cash flow channels or discount rate channels in the long run (Giglio et al., 2021a).

However, due to the limited availability of data on climate change, it has been challenging to study its potential interactions with financial markets at the daily or even monthly level. To overcome this obstacle, scholars have made use of alternative data by creating text-based proxies that capture both the physical and transitory risks of climate change, as highlighted in works of Engle et al. (2020), Batten et al. (2016), Gavriilidis (2021), and Faccini et al. (2023). Particularly, Ardia et al. (2023) developed both aggregate and thematic media-based climate change concern indices at the daily level constructed from a large corpus of news articles. The thematic indices aim to capture different aspects of unexpected physical and transition climate change concerns, whereas the aggregate index is a global measure of climate change concerns. The study found that on days when there were unexpected increases in climate change concerns, equities of lower-emitting firms outperformed those with higher carbon emissions. On the other hand, commodities are tangible goods that are consumed and are therefore susceptible to scarcity along with the forces of supply and demand. They do not constitute claims on equity, debt, or physical properties, and it is their inventories that are significantly vulnerable to the impact of both physical and transitory climate change risk. With the rise of globalization and increasing inflows of speculative capital into commodity futures markets (Basak and Pavlova, 2016; Cheng and Xiong, 2014), the growing uncertainties associated with combatting climate change have been responsible for major price fluctuations in agricultural and energy commodities (Mensi et al., 2014). Furthermore, commodities prices can respond differently to uncertainty due to different degrees of speculation, government policies, and dependence on weather conditions (Joëts et al., 2017)

To this end, we use the aggregate and thematic proxies of climate change concerns developed by Ardia et al. (2023) to empirically analyze the potential linear and non-linear relationships between physical and transitory climate change concerns and the futures contracts returns of various grains (corn, soybeans, wheat, and oats), softs (cotton, cocoa, and coffee), and energy (crude oil, natural gas, and ethanol) commodities. To achieve this, we regress the commodity futures returns on the climate change concern indices of Ardia et al. (2023) contemporaneously and at a lag of one day using the multivariate regression model and the quantile regression framework of Koenker and Bassett (1978). The advantage of using the quantile regression framework is that it allows us to study the non-linear relationships between unexpected climate change concerns and the extremes of the return distributions of the commodity contracts. In order to ensure the robustness of our results, we carefully select potential alternative drivers of commodities futures markets as contemporaneous control variables in our analysis.

The analysis is conducted using daily returns of the first, second, and third nearby contracts of the selected commodities between January 2010 to June 2018. A motivating reason behind using media-based proxies of climate change at the daily level is that market participants rely on the media as a link between them and the current state of the world (Nimark and Pitschner, 2019). The media can capture the general public's current sentiment related to climate change and also influence it as an agenda-setting channel (Ardia et al., 2023). Additionally, climate change is transient in nature, and a daily frequency is preferred to ensure the timeliness of potential market speculation to spikes in physical or transitory climate change concerns (Ardia et al., 2023).

Our results indicate a statistically significant and positive linear relationship between the transitory climate change concern proxies and the nearby futures contracts of crude oil at a lag of one day. This is in line with the findings of Zhou et al. (2023), who report that periods of high climate policy uncertainty, as measured by the text-based index of Gavriilidis (2021), lead to high crude oil prices on average. In addition, the quantile regression results reveal statistically significant asymmetries between climate change concerns and agricultural commodity contract returns that would have otherwise been missed by the multivariate regression model. We also find that the coefficient estimates of the climate change concern factors are opposite in signs when the return distributions of the nearby contracts of select grains and softs commodities are conditioned on their upper and lower quantile levels. This result indicates that unexpected increases in climate change concerns can be associated with extremely positive and negative price movements in agricultural commodity markets at the daily level. This finding can further support the polarizing ways that climate change can affect agricultural commodities (Lewis and Witham, 2012; Antón et al., 2013), as we show that periods of high unexpected physical and transitory climate change concerns are non-linearly related to crop yields.

2 Literature Review

2.1 Overview

Climate change on aggregate already impacts or is anticipated to impact various real parts of the economy, including infrastructure, agriculture, and real estate (Antón et al., 2013), and the nature of climate change itself poses a complex risk for the global financial system as a whole.

We conduct a literature review that disentangles the relevant sources of climate change risks and what their implications might be for asset pricing. More specific to commodities, we review classical theories on the fundamental drivers of commodity futures markets. We also examine the scope of literature surrounding the actual financialization of commodities markets, their connectedness, and the potential channels through which they can be affected by climate change. Lastly, we examine how climate risks have been proxied to circumvent limited data availability.

2.2 Sources of Climate Change Risks and Their Interactions with Financial Markets

As commonly examined in relevant literature on climate change risks, we categorize the sources of uncertainty linked to climate change as physical risk and transition risk.

Physical climate risk encompasses the risks of the direct impairment of productive assets. Examples would include weather-related events such as extreme temperatures affecting cropland output or rising sea levels increasing the threat of damaging firms' coastal production facilities (Giglio et al., 2021a). Painter (2020) finds that there is a risk premium associated with municipal bonds belonging to coastal communities exposed to the risk of rising sea levels. An analysis by Giglio et al. (2021b) infers long-run discount rates when evaluating real estate investments exposed to the adverse effects of climate change. The magnitude of which countries or regions are exposed to climate disasters may shape investors' beliefs about the cost of material damages due to climate change. Transition risk results from the effects of climate mitigation activities and the overall process of decarbonization. These risks emerge from new regulations or government policy, technological innovation, and social or market sentiment (Ardia et al., 2023).

The Paris Agreement poses a global transitional risk as it is a legally binding international treaty on combatting climate change that was adopted by 196 parties at the UN Climate Change Conference in December 2015 (UNFCCC, 2015). Its underlying goal is to limit the rate of global average temperature increases to 1.5°C, which is the pre-industrial level. More countries are establishing carbon neutrality targets and intend to meet these targets by passing legislation, which can have material implications for the financial system and the economy. Countries aiming to transition towards carbon neutrality might impose domestic climate policies, such as the introduction of a carbon tax, which can impact companies' operations and disrupt their cash flows. The monetary incentive to reduce emissions can lead to fossil-fuel-dependent assets suffering from write-downs or devaluations prematurely (Atanasova and Schwartz, 2019). Technological change is an important facet of transitory risk. New technologies are needed to advance net-zero commitments for energy production, distribution, storage, and utilization (Martinez-Diaz and Keenan, 2020). Companies with incentives to shift to carbon neutrality may find themselves having to take a closer look at their factors of production as they adapt to greener alternatives. Bolton and Kacperczyk (2023) examine the technological change in energy production and stipulate that firms located in countries with a diversified energy mix will be more exposed to uncertainty behind unexpectedly high costs of green energy production, which would translate to a larger carbon premium. Moreover, they find that firms located in countries whose energy production mix contains a larger fraction of renewable energy have lower carbon premia. The authors find that there is strong evidence suggesting that a country's energy production mix is a predictor of how investors price short-term changes in emissions and that the direction of the results is consistent with the claim that uncertainty about technological change increases transition risk. The increased awareness and sentiment of climate change can likely shift consumer and investor behavior. Bolton and Kacperczyk (2023) find that social factors do not appear to matter for investors' perception of carbon risk in the long run, but they do in the short run and that social inclusion in climate mitigation plays a transitory role in pricing carbon risk. The authors also find that investors have significantly updated their beliefs about the long-term transitory risk following the Paris Agreement in 2015. Furthermore, investors view the extent to which tightening climate policy may be costly to firms as permanent effects (Bolton and Kacperczyk, 2023). Institutional investors are already screening investments for direct carbon emissions (Bolton and Kacperczyk, 2021).

Krueger et al. (2019) explore investor approaches to managing climate risk through a survey of active investment managers and report that market participants, on aggregate, believe that climate risks have significant implications for portfolio allocation. A growing number of institutional investors are adopting environmental, social, and corporate governance (ESG) sustainability frameworks in their investment processes, which can include an exclusionary screening of high-polluting firms (Krueger et al., 2019). Larry Fink of Blackrock writes that climate-integrated portfolios lead to higher risk-adjusted returns and that there will be a significant reallocation of capital as a response to climate change (Fink, 2020).

A large amount of literature is being dedicated to how climate risk is priced in various financial assets, many of which focus on equities and equity valuation. Pastor et al. (2020) motivate the existence of a carbon premium when finding that equities of "green" firms outperform "brown" firms where climate change concerns increase unexpectedly. Kapfhammer et al. (2020) report that when climate risk is high, commodity currencies tend to depreciate and that unexpected increases in climate change transition risk can cause lower equity valuations on aggregate. Bolton and Kacperczyk (2023) quantitatively estimate that firms associated with higher emissions are valued at a discount and track this effect partly to the exclusionary screening of institutional investors who limit carbon risk in their portfolios. Engle et al. (2020) report that firms with higher E-scores are less exposed to climate policy uncertainty and exhibit higher returns during periods of negative news on the future path of climate change. Ilhan et al. (2023) find that there is a greater cost of downside risk protection in equity options markets for carbon-intensive firms when attention towards climate change is high.

2.3 Fundamentals of Commodities Futures Markets: Inventory Risk and Hedging Pressure

To grasp the potential channels through which climate risk can interact with commodity markets, we identify the fundamentals underlying the dynamics of commodity futures markets. Commodity futures are not claims on future cash flows or debt but rather physical goods with inherent scarcity.

One distinct feature of commodity markets is that they are uniquely subject to inventory risk. Participants in commodities futures markets include speculators who enter the market to seek a profit and commodity producers who enter the market to hedge their costs related to inventory.

The theory of normal backwardation (Keynes, 1930; Hicks, 1939) is an early study that explains the relationship between spot prices and futures prices of commodities. It suggests that commodity futures markets are used as a mechanism for transferring risk, where long investors earn a risk premium for bearing the future spot risk that commodity producers want to hedge. The theory of normal backwardation argues that commodity producers are naturally net short hedgers as they are more prone to insure their spot price risk. The net hedging pressure hypothesis (Cootner, 1960, 1967) is a generalization of the theory of normal backwardation and argues that futures prices depend on the net position of hedgers and speculators. The argument of Cootner (1960, 1967) is again primarily centered on the risk-sharing mechanism of commodity futures markets but also links hedging positions to inventory and storage costs. The direct cost of storage includes marginal costs of warehouse space, interest rate changes, and insurance against physical damage, while the implied indirect cost is either the threat or benefit it poses to the inventory holder. The net hedging pressure hypothesis (Cootner, 1960, 1967) poses that holding inventory exposes the commodity producer to price risk as well as variable storage costs; a risk-averse commodity producer is willing to pay a premium in the form of insurance to share this risk. Under the assumption that commodity producers are risk-averse, they thus enter the futures market to offset the implied risk of holding inventory, and speculators enter the futures market to seek a profit to bear that risk. When the hedging positions of commodity producers are net short, futures prices are set at a discount to expected spot prices at maturity. When hedgers are net long, futures prices are set at a premium to expected future spot prices at maturity. These market conditions are referred to as backwardation and contango, respectively. In either market condition, the futures risk premium is the compensation paid by hedgers to speculators for subsuming the net demand of hedging spot price risk (Cootner, 1960, 1967).

The theory of storage of Kaldor (1939), Working (1949), and Brennan (1958) assumes that holders of commodity inventories receive a convenience yield that declines as inventory increases and that futures prices are set through the cost of carry arbitrage. It is worth noting that expressing the basis to be the difference between nearby and distant contracts as a percentage of the nearby is synonymous with the concept of carry. In order to induce storage, futures prices and expected spot prices have to rise sufficiently over time to compensate inventory holders for the storage costs. The cost of carry arbitrage argument is the link between the futures curve and the inventory levels of commodities. The backwardation and contango cycle is an intrinsic concept of the theory of storage, which stipulates that scarce levels of inventory are linked to a "backwardated" futures curve while abundant levels of inventory are linked to a "contangoed" futures curve.

An entire topic in the commodity futures literature has emerged from the theory of storage and the Keynesian net hedging pressure hypothesis. There has been much debate about whether the fundamental cause of futures risk premium is dependent on the net hedging positions of the commodity producers or whether it is dependent on the inventory levels of the commodity itself. Using data provided by CTFC (Commodity Futures Trading Commission), Gorton et al. (2013) provide evidence that the net positions of hedgers are contemporaneously correlated with the price level of the futures curve but that there is no evidence that these positions are correlated with ex-ante risk premiums of the commodity futures. Gorton et al. (2013) conclude that hedgers simply adjust their positions according to future prices and that future prices are set based on inventory levels. In addition, the author also shows that commodity inventories are reflected in the shape of their respective futures curves and that the futures' basis, prior futures returns, and prior spot returns are price-based measures of inventory risk.

In short, the shape of the futures curve contains priced-based measures of inventory risk as well as general sentiment surrounding the uncertainties related to commodity inventories. In recent studies, authors have attempted to exploit the information contained in the term structure of the futures curves. Karstanje et al. (2015) make use of the information contained in the full futures curve by using Principal Component Analysis on the term structure of the commodity futures. The authors motivate the use of incorporating more distant contracts since they have become more traded and liquid over time. In addition, Schwartz and Smith (2000) pose that long-term contracts provide information about the equilibrium level while the shape of the term structure can provide insights into short-term movements. Boons and Prado (2018) construct the basis-momentum in light of the fact that prior returns and the basis are price-based measures of inventory risk (Gorton et al., 2013).

2.4 Financialization of Commodities

Commodity futures markets have evolved since they were first introduced for producers and manufacturers to share spot-price risk as they have become popular assets to institutional investors and commodity index traders (Goldstein and Yang, 2015). Basak and Pavlova (2016), as well as Cheng and Xiong (2014), reference the increasing number of institutional investors entering commodity futures markets as the financialization of commodities. Basak and Pavlova (2016) find that futures prices of different commodities have been displaying increasing correlations as these markets become more and more "financialized". They also find that the correlations between equities and commodities have increased as well, which can motivate connectedness between these two distinct markets. Cheng and Xiong (2014) argue that this financialization has affected the underlying mechanisms of commodity futures markets, which are information discovery and risk-sharing, but note that it has not affected storage. The authors argue that the inflow of institutional investors and increasing globalization have caused informational frictions in the futures prices of many key agricultural and energy commodities and that speculators' heterogeneous expectations can lead to price drifts in these markets. Cheng and Xiong (2014) also suggest that the inflow of investors helps risk-sharing by mitigating the hedging pressure of producers (Keynes, 1930; Hicks, 1939), but also recognize that this might also transmit exogenous shocks from other markets into commodity markets, which might imply spillover effects. Goldstein and Yang (2015) agree with the notion that financialization helps with the risk-sharing mechanism but suggest that financial institutions bring more new information to the futures market, which can improve the information-sharing mechanism and reduce the overall risk faced by all market participants.

The effects of increasing globalization have been related to a rising dependence structure between equity and commodity markets. Mensi et al. (2013) deployed a VAR-GARCH and reported that past shocks of the S&P 500 have significantly influenced commodity markets, more specifically for gold and oil. Using a copula-based approach, Mensi et al. (2017a) further report that there is mean dependence between oil and equity markets in the short run and a tail dependence in the long run.

2.5 Connectedness of Commodity Markets

The financialization of commodities suggests that individual commodity markets have been becoming increasingly correlated, but their connectedness goes slightly further. Energy and agricultural commodities have been subject to large price fluctuations in recent years, some of which occur at the same time (Mensi et al., 2017b; Cheng and Xiong, 2014). Mensi et al. (2014) attribute the likely drivers of these fluctuations to macroeconomic uncertainties, economic and financial crises, and climate change. The authors examine the dynamic spillovers between energy and cereal commodities through VAR-BEKK-GARCH and VAR-DCC-GARCH models and find significant links between these markets. They argue that these markets interreact through cost-push effects, the parallel growth of world population with increased economic activity of select countries, and, notably, climate change uncertainty. They also argue that energy and cereal commodity markets have been becoming intertwined because of the emergence of biofuels and how they can be derived from agricultural commodities (Mensi et al., 2014). In addition, higher energy prices can increase the costs of cultivation, fertilizer, and transportation of both inputs and outputs (Ji et al., 2018). Kapfhammer et al. (2020) find that there are substitute effects within different fossil fuel products in countries where the commodity basket contains a large share of gas exports and associate climate risk with these effects. Chen et al. (2010) investigate the relationships between the prices of crude oil and corn, soybeans, and wheat. They empirically show that the price of grains is significantly influenced by an increase in crude oil prices and the prices of other grains. They also note that climate change is a common factor that has caused commodity price fluctuations. In recent years, there has been an emergence of literature supporting the connectedness of energy and agricultural commodity markets through time-varying vector auto-regression models and causality-in-quantile approaches (Balcılar et al., 2016; Balcilar et al., 2021).

2.6 Climate Risk and Energy Commodities

The global energy industry has been paying attention to the carbon contents of fossil fuel energies, especially with rising concerns about reducing carbon emissions. As the Organization of Petroleum Exporting Countries (OPEC) is dependent on crude oil, they perceive the pricing of crude oil under new climate regimes as an economic threat (Dike, 2014). Dike (2014) examines the theoretical grounds for studying the impact of climate mitigation activities on crude oil prices. Under the assumption that crude oil markets are competitive, the author finds that climate mitigation activities affect crude oil prices in the long run and writes that demand shocks driven by energy efficiency, substitution effects driven by renewable energy, and the distortion of supply and demand equilibrium driven by the introduction of carbon taxes are potential reasons for the theoretical effect on fossil fuel markets (Dike, 2014). Atanasova and Schwartz (2019) find that the growth of oil companies' fossil fuel reserves has a negative effect on their firm value and associates the cause to be linked to undeveloped reserves becoming "stranded assets". Furthermore, they document that this effect is stronger in countries where climate policy is tighter, which holds the implication that markets can penalize future investments in undeveloped reserves due to climate policy risk. Diaz-Rainey et al. (2021) highlight that it seems as though investors are currently pricing climate policies. In addition, the authors find that climate policies affected the oil industry through either increased costs or limitations of exploration, drilling, and production. Zhou et al. (2023) reports that periods of high climate policy uncertainty result in higher crude oil prices for most of the periods between 2005 and 2021 through a time-varying vector autoregression model.

2.7 Climate Risk and Agricultural Commodities

Liang et al. (2017) show that temperature and precipitation account for approximately 70% of the variations in the total factor productivity growth of the U.S. agricultural economy and that the projected climate changes could cause productivity to drop by an average of 2.84% to 4.34% per year under above average emissions scenarios. The authors also implicitly highlight an important example of how physical climate risks can interact with transition risks by showing that the aggregate effects of regional climate trends on the total factor productivity have been outweighed by improvements in technology between the years 1981 to 2010. Chatzopoulos et al. (2020) find that physical climate extremes on a regional level can have significant impacts on agriculture markets on both domestic and international levels. They report that crop prices generally react asymmetrically to extreme climate shocks with stronger responses to negative anomalies. Gupta and Pierdzioch (2022) find that integrating climate risks in HAR-RV models improves the prediction of agricultural commodity price volatility. Physical climate change risks have been linked to impacting agricultural commodity prices, such as droughts, flash floods, and degradation of soil and water supply. Batten et al. (2016) writes that climate change is most likely to have the greatest effect on agricultural commodities. Antón et al. (2013) note that climate change affects the variability of weather conditions and the frequency of abnormal weather events, which greatly contributes to the variability of crop yields. Lewis and Witham (2012) find that climate change has both positive and negative impacts on wheat and barley yields. The authors identify these impacts to include temperature changes, water availability, fertilization, and higher latitude geographic regions.

2.8 Climate Uncertainty Proxies

Since data for proxying climate change uncertainty is limited, the recent academic focus has shed light on NLP (natural language processing) methods to develop text-based indices constructed from large corpora of newspaper articles to capture physical and transitory risks and assess asset pricing implications associated with climate change. Investors rely on the media as a link between them and the current state of the world (Nimark and Pitschner, 2019). Though the media can capture the general public's current sentiment related to climate change, it can also influence it as an agenda-setting channel (Ardia et al., 2023).

Engle et al. (2020) extract innovations from a monthly climate news series that are constructed through textual analysis of Wall Street Journal newspaper articles and construct a climate hedging portfolio based on these innovations. The authors acknowledge that they do not attempt to distinguish between different types of climate risk. Batten et al. (2016) constructed a text-based index to capture regulatory climate risk and found a positive relationship between the price of renewable energy firms and transition risk. Gavriilidis (2021) constructs a textual-based climate policy uncertainty index constructed from major U.S. newspapers following the methodology of Baker et al. (2016). The author's findings suggest that climate policy uncertainty has a strong and negative effect on carbon emissions. Kapfhammer et al. (2020) constructed climate risk indices from word embeddings of news articles published by Dow Jones News Services to explore how climate change uncertainty affects the currencies of major commodity exporters and find that the currencies depreciate when transition risk as measured by the news media-based proxy of transition risk is high. Bua et al. (2022) developed text-based indicators to proxy physical and transition climate-related risks and provide evidence supporting a risk premium in European equity markets for both types of risks. Faccini et al. (2023) use textual and narrative analysis of Reuters climate-change-related news to construct four different risk measures of climate uncertainty that are natural disasters, global warming, international summits, and U.S. climate policy. The climate risk factors constructed by Faccini et al. (2023) are another text-based measure that is related to natural disasters, global warming, international summits, and U.S. climate policy. The authors find that only the climate policy is priced in U.S. equities and that investors are hedging imminent transition risks from government intervention rather than the actual physical risks of climate change. Ardia et al. (2023) constructed the daily Media Climate Change Concern Index (MCCC Index) using news published about climate change topics. The authors then obtain a proxy for unexpected climate change concerns, which they refer to as the unexpected media climate change concerns (UMC), using the prediction error of an autoregressive time series regression model calibrated on the MCCC index. Notably, the authors provide evidence suggesting that on days when there is an increase in unexpected climate change concern as measured by the UMC index, the price of green firms tends to increase while the price of brown firms tends to decrease. In our paper, we consider the climate risk proxies developed by Ardia et al. (2023).

3 Methodology

3.1 Overview

To empirically examine the relationship between daily commodity futures returns and unexpected increases in climate change concerns, we use multivariate and quantile regression frameworks. We first construct the first, second, and third nearby futures contracts for various grains, softs, and energy commodities and take their log-returns as the dependent variables in our analysis. The rationale behind including more distant contracts is that they have been becoming increasingly more liquid from speculators in commodity markets (Boons and Prado, 2018).

We motivate the use of many types of commodities by noting that commodity markets have been becoming more connected since their financialization (Basak and Pavlova, 2016; Cheng and Xiong, 2014; Goldstein and Yang, 2015). The adverse effects of climate change and the inflow of speculators into commodity markets have been responsible for extreme price movements (Mensi et al., 2014). In addition, it has been documented that increases in fossil fuel prices often lead to increases in agricultural commodities prices by rising costs of cultivation and transportation (Ji et al., 2018). Furthermore, the emergence of biofuels has presented another link between fossil fuel and agricultural commodity markets since grains are used as an input in biofuel production Mensi et al. (2014). If biofuels are seen as a substitute for fossil fuels, then a rise in fossil fuel prices can lead to an increase in demand for agricultural commodities. A larger sample of commodities would allow us to investigate whether climate change uncertainty is prevalent across these potential links.

To ensure the robustness of our results, we carefully select control variables to include in the regression models.

3.2 UMC: Climate Change Factors

As the focal point in our analysis, we measure climate change concerns at the daily level using the global UMC factor developed by Ardia et al. (2023) along with its four underlying thematic indices. The UMC indices aim to capture unexpected climate change concerns as expressed through the media. Ardia et al. (2023) constructed the UMC index from climate change-related news published by the New York Times, the Washington Post, the Los Angeles Times, the Wall Street Journal, the Houston Chronicle, the Chicago Tribune, the Arizona Republic, the USA Today, the New York Daily News, and the New York Post newspapers. In addition, they consider articles published by the Associated Press Newswires and Reuters News. The authors filter out news articles that are not tagged as "climate change". With this corpus of articles, the authors apply NLP techniques to infer latent correlated topics among the collection of texts. The authors then manually label the topics by looking at the top ten most probable words for each inferred topic. The authors group the individual topics into manually labeled themes using clustering and network analysis, which gives the thematic UMC indices. Table 1 reports the underlying themes and topics of the UMC index (Ardia et al., 2023).

Themes/Topics	Top ten keywords in terms of probability	Risk
Theme 1: Business Impact		Transition
Climate summits	agreement, country, climate change, nation, world, talk, deal, meeting, develop, country, summit	Transition
Agreements/actions	percent, emission, level, target, greenhouse gas emission, goal, country, government, greenhouse gas, year	Transition
Climate legislation/regulations	bill, state, cap, legislation, vote, lawmaker, measure, program, global warming, year	Transition
Legal actions	state, administration, rule, regulation, agency, plan, court, decision, law, case	
Renewable energy	oil, energy, natural gas, gas, pipeline, fossil fuel, renewable energy, wind, nuclear power, world	Transition
Carbon reduction technologies	coal, plant, power plant, electricity, carbon dioxide, technology, power, utility, gas, year	Transition
Carbon credits market	market, price, scheme, government, credit, euro, tonne, carbon, year, permit	Transition
Carbon tax	cost, tax, carbon, energy, price, policy, fuel, carbon tax, biofuel, economy	Transition
Government programs	project, money, fund, program, year, development, government, budget, funding, plan	Transition
Corporations/investments	company, business, climate change, investor, group, investment, firm, industry, risk, chief executive	Transition
Car industry	car, vehicle, standard, methane, gas, year, fuel, industry, automaker, carbon dioxide	Transition
Airline industry	airline, flight, ship, emission, aviation, plane, air, pollution, shipping, aircraft	Transition
Theme 2: Environmental Impact		Physical
Extreme temperatures	year, record, weather, temperature, winter, day, summer, climate change, heat, global warming	Physical
Food shortage/poverty	climate change, people, crop, country, farmer, world, food, woman, agriculture, foundation	Physical
Hurricanes/floods	flood, storm, hurricane, climate change, sea level, island, disaster, damage, flooding, risk	Physical
Glaciers/ice sheets	ice, glacier, year, scientist, foot, ice sheet, mile, melting, sea ice, satellite	Physical
Ecosystems	species, animal, plant, bird, disease, climate change, population, year, habitat, extinction	Physical
Forests	tree, forests, forest, fire, land, deforestation, carbon, acre, area, soil	Physical
Water/drought	water, state, region, river, rivers, drink, year, lake, area, dam	Physical
Tourism	site, town, day, mountain, year, snow, mile, park, foot, people	Physical
Arctic wildlife	polar bear, sea ice, bear, seal, ice, habitat, species, wildlife, year, population	Physical
Marine wildlife	fish, water, sea, oceans, ocean, scientist, coral, alga, year, reef	Physical
Agriculture shifts	food, farm, year, wine, plant, meat, production, farmer, coffee, cow	Physical
Theme 3: Societal Debate		Transition
Political campaign	climate change, issue, leader, president, campaign, election, party, country, speech, policy	Transition
Social events	people, world, time, life, climate change, child, year, student, book, global warming	Transition
Controversies	climate change, science, global warming, scientist, climate, issue, question, evidence, research, document	Transition
Cities	city, people, building, home, energy, light, resident, community, mayor, group	Transition
Theme 4: Research		Physical/Transition
Global warming	degree, global warming, warming, world, scientist, year, carbon dioxide, atmosphere, greenhouse gas, century	Physical/Transition
UN/IPCC Reports	report, climate change, risk, impact, global warming, panel, effect, government, world, study	Physical/Transition
Scientific Studies	study, research, scientist, researcher, data, atmosphere, researchers, climate, effect, model	Physical/Transition

Table 1: UMC Themes and Topics

This table outlines the 30 topics identified by Ardia et al. (2023) together with the ten keywords with the highest probability for each topic. The topics are regrouped into four themes.

In our analysis, we examine different facets of climate risk as proxied by the aggregate UMC index, along with its thematic indices: 'Theme 1: Business Impact' ("BI"), 'Theme 2: Environmental Impact' ("EI"), 'Theme 3: Societal Debate' ("SD"), 'Theme 4:

Research' ("R").

An advantage of using the aggregate UMC index along with its thematic indices is that it allows us to investigate the multiple channels in which climate change risk can interact with commodity markets. The topics of the BI index capture transition risks that are often linked to climate policy uncertainty, such as the carbon credits market, the carbon tax, renewable energy, carbon reduction technologies, climate regulations, agreements/actions, government programs, investments, and the transportation industry. Climate policies can lead to increasing costs of extraction of crude oil or limiting the extraction of crude oil altogether (Diaz-Rainey et al., 2021), as well as placing a price on carbon.

The EI thematic factor covers concerns surrounding the physical impacts that climate change has on the environment. This includes news on natural disasters, alarming weather changes, animal wildlife, ecosystems, deforestation, and agriculture shifts. Given the wide range of topics that the EI factor captures, it is important to note that the events or concerns covered by the topics may not materialize at the same time. It is, therefore, a measure of physical climate change concerns on the global environment.

The SD theme represents a transition risk that includes public discourse on climate change as well as political campaigns. The topic of political campaigns likely captures policymakers' speeches and discussions on climate mitigation activities. As noted by Bolton and Kacperczyk (2023), societal factors appear to matter for investors' perception of carbon risk in the short run, and social inclusion plays a transitory role in carbon risk.

The R thematic index captures both physical and transition risk in topics that include global warming, reports from the United Nations ("UN") and the Intergovernmental Panel on Climate Change ("IPCC"), and general scientific studies of the physical impact of climate change. This likely contains concerns for more urgent emphasis on climate mitigation activities based on reports about the current climate environment. Furthermore, the UN/IPCC reports are comprehensive assessments of the rate of global temperature increases, as well as options for reducing this rate. It also produces 'Special Reports' on topics agreed to by its member governments (IPCC, 2023).

Given the transient nature of climate change (Ardia et al., 2023), we analyze the unexpected increases in climate change concerns using daily observations to ensure the timeliness of the potential market reactions.

3.3 Controlling for Potential Alternative Drivers of Commodity Markets

Several control variables are introduced to enhance the validity of the potential interactions between climate change concerns and commodity futures' returns and ensure that our results are more robust from netting the effects of potential confounders. To control for extraneous variables, we consider controls for both commodity-specific effects as well as exogenous sources of risk.

3.3.1 Commodity-Specific Controls: Basis-Momentum

We construct the basis-momentum factor for each individual commodity (Boons and Prado, 2018). The motivation behind using the basis-momentum factors stems from the amount of fundamental commodity-specific information embedded in them. We abstain from using the spot price of commodities in computing the basis-momentum factor due to their illiquidity and sometimes irregular behavior. Boons and Prado (2018) construct the basis-momentum factor as follows.

First, the authors define the daily returns of the n-th nearby commodity futures contract at day t.

$$R_{t+1}^{T_n} = \frac{F_{t+1}^{T_n}}{F_t^{T_n}} - 1\,,$$

where $F_t^{T_n}$ is the closing price on day t of the n-th nearby commodity futures contract with maturity T_n. The basis returns B_t and momentum factor M_t can be written as:

$$B_t = \frac{F_t^{T_{n+1}}}{F_t^{T_n}} - 1 \text{ and } M_t = \prod_{s=t-a}^{t} \left(1 + R_s^{T_n}\right) - 1\,,$$

for a given aggregation window, a. The basis-momentum factor BM_t^n for an individual commodity is:

$$BM_t^n = \prod_{s=t-a}^{t} \left(1 + R_s^{T_n}\right) - \prod_{s=t-a}^{t} \left(1 + R_s^{T_{n+1}}\right),$$

Since we are using log-returns, the analogous formulation of the basis-momentum factor is written as:

$$bm_t^n = \sum_{s=t-a}^{t} r_s^{T_n} - \sum_{s=t-a}^{t} r_s^{T_{n+1}},$$

where the aggregation window, a, is chosen to be one month or 20 trading days. In our analysis, we consider $n = 1$; that is, we use the basis-momentum with respect to the first and second nearby futures contracts of each commodity.

Similar to bond markets, the common primary risk drivers across commodity futures markets are their levels, slopes, and curvatures of their respective term structures due to the information that they convey (Karstanje et al., 2015; Gorton et al., 2013). A feature of the basis-momentum factor that we wish to exploit is that it contains information about the slope and curvature of the futures curve, which is determined by the decisions of investors, hedgers, speculators, and intermediaries (Boons and Prado, 2018). Under the framework of the theory of storage of Kaldor (1939), Working (1949), and Brennan (1958), the basis provides insight into the net storage costs of the commodity and the marginal risk premium for holding the commodity. Furthermore, following the logic of Gorton et al. (2013), the basis and prior returns are price-based measures of commodity inventory risk and volatility risk.

We use the basis-momentum factor to control for endogenous inventory risks inherent to commodity futures markets (Boons and Prado, 2018).

3.3.2 Market and Currency Factors

Other than commodity-specific, price-based measures of inventory risk as measured by the basis-momentum factor, we consider controlling for the broad movements in commodity markets through the S&P GSCI index returns, which serve as a benchmark measure for commodity performance. The index is composed of 24 commodities from energy, agricultural, metal, and livestock sectors, with the commodities being weighted based on each of their average quantity of production globally.

Exchange rates influence commodity prices and play a role in the way commodity markets are linked (Harri et al., 2009). The value of currencies has a significant impact on imported and exported goods in global trade, as many commodities are denominated in the U.S. dollar. Logically, since most commodities are denominated in the U.S. dollar, a strengthening dollar can negatively influence commodity demand as it increases the cost for foreign buyers Conversely, a weakening dollar can increase demand for commodities denominated in foreign currencies. Exchange rates also show a strong link with the business cycle and general macroeconomic conditions (Colacito et al., 2020). To control for the currency impact on commodities, we use the U.S. dollar index. The index is geometrically averaged across 6 component currencies, which include the Euro, Japanese Yen, British Pound, Canadian Dollar, Swedish Krona, and Swiss Franc.

We also consider controlling for potential spillover effects from the equities using the Fama-French excess market return factor. We acknowledge that commodity markets are distinct from equity markets, however, the use of an equity-based market factor can be justified by noting that commodities have been increasing in correlation and connectedness with equity markets since their financialization (Basak and Pavlova, 2016; Cheng and Xiong, 2014; Goldstein and Yang, 2015).

3.3.3 Economic and Geopolitical Uncertainty

Aggregate supply and demand shocks drive commodity prices, and in times of a likely economic disruption looming, the price elasticity of commodity supply and demand increases (Bakas and Triantafyllou, 2020). Higher macroeconomic uncertainty can influence the decision-making process of economic agents, which can increase the price sensitivity of shocks (Yin, 2015; Bloom et al., 2007; Bloom, 2009). Wang et al. (2015) provide evidence of a link between economic policy uncertainty and commodity returns.

To control for the induced volatility that arises from times of economic and political uncertainty on a daily level, we introduce the Economic Policy Uncertainty Index ("EPU"). The EPU constructed by Baker et al. (2016) is a daily media-based index reflecting the frequency of coverage from ten major newspapers. The EPU index has been popular in recent works in measuring the price impact that economic and financial uncertainty has on several asset classes.

Furthermore, geopolitical risks have been among the driving factors of commodity price development (Hudecová and Rajčániová, 2023) and of recent interest in literature considering the ongoing Russia-Ukraine war. Wars and increased geopolitical tensions pose a shock and a supply-side disruption to commodity markets, as seen by the impact the Russia-Ukraine war had on global agriculture prices. Gong and Xu (2022) find that geopolitical risk significantly impacts the overall connectedness of commodity markets and how volatility is transmitted from one commodity market to another. We control for geopolitical risk as a potential extraneous variable in our analysis by introducing the Geopolitical Risk Index ("GPR") of Caldara and Iacoviello (2022). It is a news-based measure of adverse geopolitical events and associated risks.

The reason for introducing the EPU and GPR indices is that they are specific to global commodity markets. Each index captures the possible impact of global supply chain shocks and the uncertainty of future supply shocks on the price. Furthermore, following our logic for using text-based measures to proxy for climate change concern, investors rely on news as a means of informing investment decisions and reacting to unexpected shocks efficiently in markets (Nimark and Pitschner, 2019).

With our control variables thoroughly defined, we next describe our regression frameworks.

3.4 Multivariate Regression

We examine the linear relationships between commodity contract returns and the aggregate UMC and thematic indices by means of a multivariate linear regression framework to control for the other potential drivers of the commodity futures returns. We regress the log-returns of the commodity futures contracts,

$$r_s^{T_n} = \log\left(F_s^{T_n}\right) - \log\left(F_{s-1}^{T_n}\right),$$

on the UMC (and thematic UMC) under the following framework:

$$r_t^n = cst + \beta\, UMC_t + \gamma'\, CTRL_t + \varepsilon_t\,,$$

where r_t^n is the n-th nearby daily return for a given commodity contract at day t, UMC_t is the examined climate change concern factor at time t, and $CTRL_t$ is a vector containing the controls at time t. The estimates for β and γ are obtained by Ordinary-Least Squares (OLS).

The control set we use for analysis includes general commodity market conditions control with the S&P GSCI Index ("SPGSCI"), exchange rate effects with the U.S Dollar Index ("DXY"), the commodity-specific basis-momentum factors bm_t^n, potential exogenous impacts from economic and geopolitical uncertainty using the Economic Policy Uncertainty Index ("EPU") and the Geopolitical Risk Index ("GPR"), and the potential spillovers from equity markets using the Fama-French excess market return factor ("Mkt-Rf").

In addition, we consider one day-lagged values of the climate change factors:

$$r_t^n = cst + \beta\, UMC_{t-1} + \gamma' CTRL_t + \varepsilon_t \,.$$

We note that we estimate the coefficients β for each climate change factor separately to provide insight into the potential ways that climate risks are related to commodities. The coefficients are estimated with heteroskedasticity and autocorrelation consistent estimators of the variance-covariance matrix (Newey and West, 1987) to alleviate potential serially correlated error terms ε_t.

3.5 Quantile Regression

Expanding on the multivariate regression analysis, we consider a quantile regression framework that enables us to study the relationship between commodity futures returns and climate change factors along the entire conditional distribution of the returns. In quantile regression, the quantiles of a dependent variable are assumed to be linearly associated with a set of conditioning variables, which generally translates into a nonlinear relationship between the dependent and the independent variables considering the whole distribution (Koenker and Bassett, 1978). Quantile regression provides a way to find any potential influences of the magnitude of the response of climate change factors in the tails of the return distribution, which are not necessarily symmetric around the mean. By their construction, quantile regression frameworks are known to be robust to outliers (Uribe and Guillén, 2020), which is of relevance when studying commodity futures returns or any financial time series. In addition, quantile regression models require minimal assumptions on the distribution of the underlying data-generating process. We turn to quantile regression as it allows for more flexibility than linear regression frameworks to model different market or economic scenarios and is more convenient when the error structure is heterogeneous and not well described by a standard Gaussian distribution.

The quantile regression model is written as:

$$Q_{r_t^n|UMC}(\tau) = \beta_{(\tau)}\, UMC_t + \gamma'_{(\tau)} CTRL_t + \varepsilon_t \,.$$

The quantile coefficients $\beta_{(\tau)}, \gamma_{(\tau)}$ for quantile level τ are found by optimizing:

$$(\beta_{(\tau)}, \gamma_{(\tau)}) = \text{argmin}_{\beta,\gamma}\, E\left[\rho_\tau\left(r_t^n - \left(\beta_{(\tau)}\, UMC_t + \gamma'_{(\tau)}\, CTRL_t\right)\right)\right] \ ,$$

where $\rho_\tau(u) = (1-\tau)I_{(u<0)}|u| + \tau I_{(u>0)}|u|$ is the loss function. The quantile is defined as the minimized loss. For each commodity contract, we estimate the coefficients of the climate change factors at the quantile levels $\tau = \{0.10, 0.15, \ldots, 0.85, 0.90\}$.

Likewise, we also estimate the conditional quantile coefficients of the climate change factors at a lag of one day.

We then perform the Wald test on the coefficients at each quantile to give us a preliminary idea as to whether there is a nonlinear relationship between climate uncertainty and commodity contract returns. The Wald test hypotheses are formulated as:

$$H_0 : \begin{bmatrix} \beta_{(\tau=0.1)} \\ \vdots \\ \beta_{(\tau=0.9)} \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix} ,$$

$$H_1 : \begin{bmatrix} \beta_{(\tau=0.1)} \\ \vdots \\ \beta_{(\tau=0.9)} \end{bmatrix} \neq \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}$$

To further examine the potential asymmetric relationship between the climate change factors and the commodity returns, we investigate the sequence of quantile regression summaries and isolate the coefficients of the climate change proxies at the individual quantile levels.

4 Data

In this section, we outline the data collection and pre-processing methods and describe the variables used throughout the multivariate and quantile regression analyses. Figure 1 illustrates the prices of the first, second, and third nearby futures contracts for each commodity throughout the sample period. To provide additional insight into the movements in the term structure of the commodities, we illustrate the differences between the first and second nearby contracts, as well as the difference between the second and third nearby contracts in Figure 2. Table 3 presents the descriptive statistics of the dependent variables in our analysis.

4.1 Data Collection and Pre-Processing

Commodity Nearby Futures Contracts We first retrieve the raw daily closing prices of expired futures contracts for various grains, softs, and energy commodities with a sample period beginning in January 2010 and ending in June 2018. The daily data is sourced from https://www.barchart.com/ and is padded for holidays. The exchanges that the chosen commodities trade on are the Chicago Board of Trade (CBOT), New York Mercantile Exchange (NYMEX), and Intercontinental Exchange (ICE). Table 1 presents the commodities that we examine in our analysis, their assigned abbreviations, their contract symbols, and the market exchanges that they trade on. The abbreviations shown in Table 2 will hereby be used to denote their respective commodities when reporting our results.

	Commodity	Abbreviation	Symbol	Maturity Code	Exchange
Grains	Corn	COR	ZC	HKNUZ	CBOT
	Soybeans	SOY	ZS	FHKNQUX	CBOT
	Wheat	WHT	ZW	HKNUZ	CBOT
	Oats	OAT	ZO	HKNUZ	CBOT
Softs	Cotton	COT	CT	HKNVZ	CBOT
	Coffee	COF	KC	HKNUZ	ICE
	Cocoa	CCO	CC	HKNUZ	ICE
Energy	Crude Oil	WTI	CL	FGHJKMNQUVXZ	NYMEX
	Natural Gas	NG	NG	FGHJKMNQUVXZ	NYMEX
	Ethanol	ETH	ZK	FGHJKMNQUVXZ	CBOT

Table 2: Commodity Information

This table presents the commodities under study, the abbreviation they are referred to as throughout the analysis, their respective contract symbol, the maturity codes corresponding to their expiry months, and the exchanges they trade on.

Then, we process the expired futures contracts into continuous time series of first, second, and third nearby contracts by rolling the contracts over on the last day of the month prior to the delivery month of each commodity. We use this precautionary treatment to avoid irregularities in price movements that can occur as futures contracts approach maturity, namely stale pricing (Szymanowska et al., 2014).

We take the log-returns of the constructed first, second, and third nearby futures contracts as the first set of dependent variables in our multivariate regression and quantile regression models. That is, the daily return for the n-th nearby commodity futures contract is:

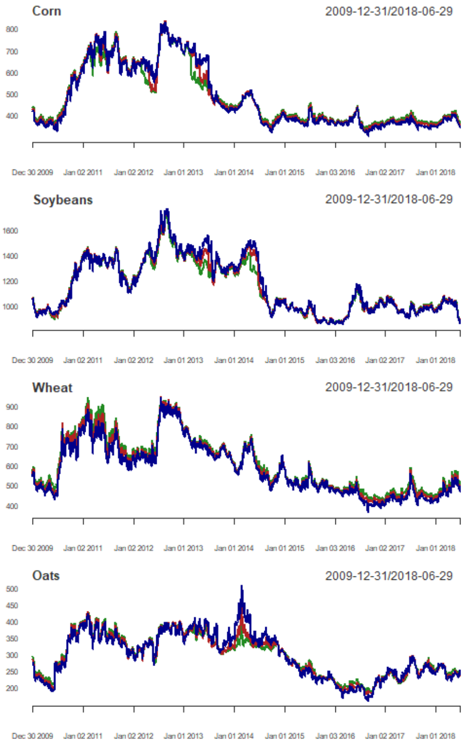
$$r_s^n = \log\left(F_s^{T_n}\right) - \log\left(F_{s-1}^{T_n}\right) \ ,$$

where $F_t^{T_n}$ is the daily closing price of the n-th nearby futures contract for a given commodity.

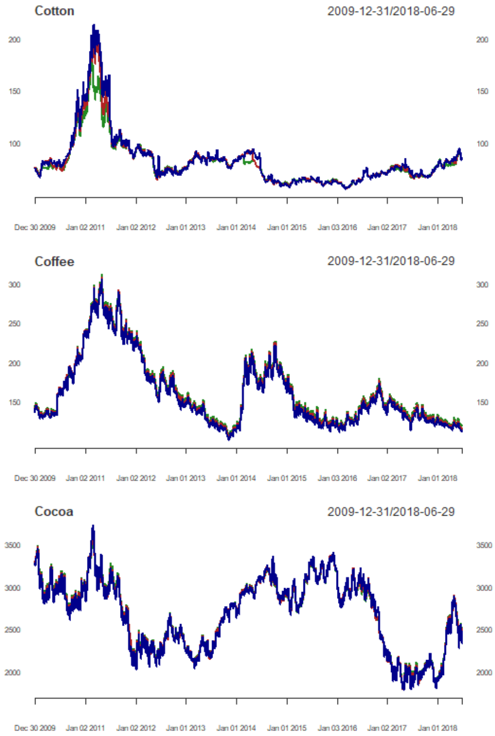
Climate Factors: The climate change concern factors of Ardia et al. (2023) were directly provided by the authors. Table 6 in the appendix reports the descriptive statistics for the global UMC index along with its underlying thematic indices.

Control Variables: We retrieve daily levels of the U.S Dollar Index and S&P GSCI Index from https://www.barchart.com/. We use their log-returns in our control set. In addition, we retrieve the EPU Index (Baker et al., 2016) and GPR Index (Caldara and Iacoviello, 2022) from https://www.policyuncertainty.com/. We use the constructed basis-momentum factors for each commodity as the commodity-specific controls. The excess market return factor is obtained by Kenneth R. French Data Library (French, 2023). The descriptive statistics of the control variables are reported in Table 6 of the appendix.

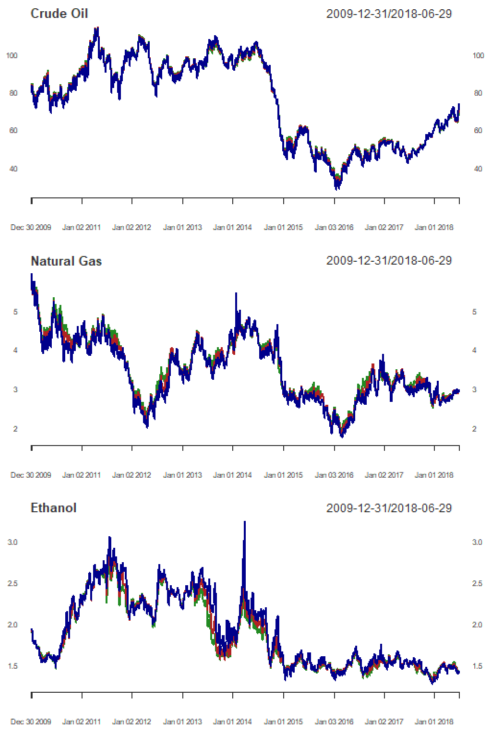
4.2 Data Description



(a) Grains



(b) Softs

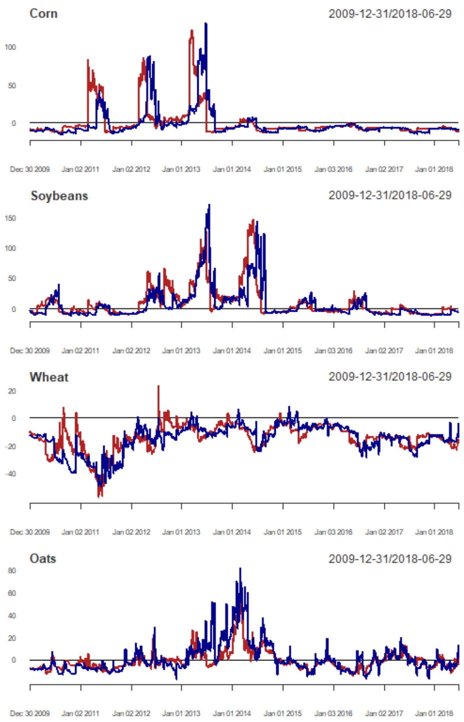


(c) Energy

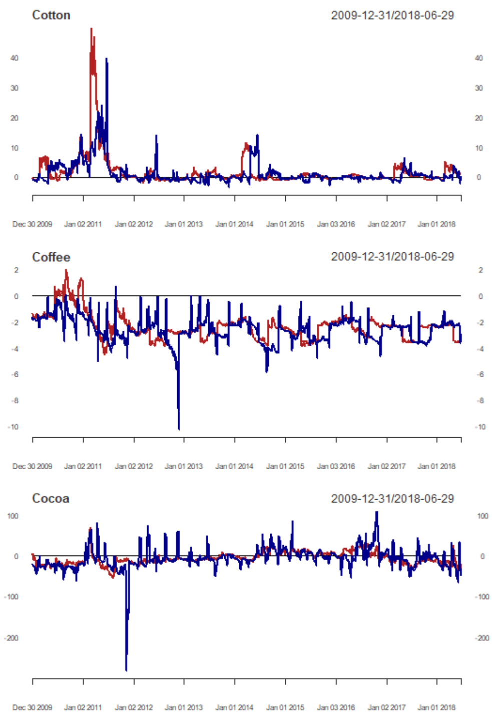
Figure 1: Nearby Contract Prices

This figure plots the constructed first (Blue), second (Red), and third (Green) nearby futures contracts of grains, softs, and energy over the sample period of January 2010 - June 2018.

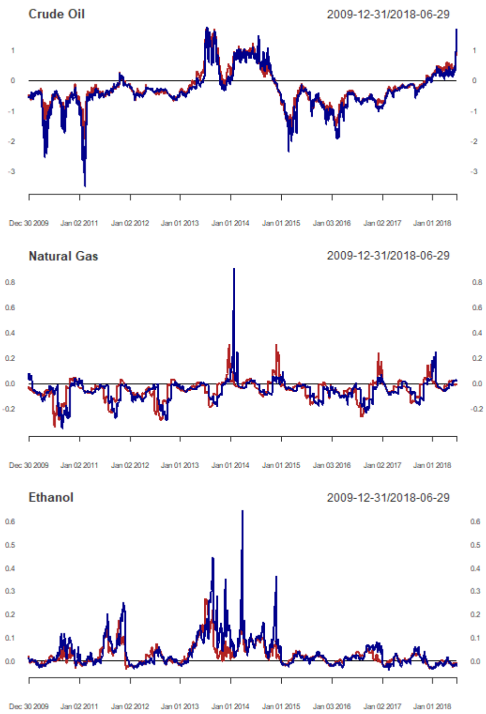
In Figure 1, we see that the prices of agricultural commodities display co-movement during distinct periods. In 2010, droughts in Russia caused a rapid spike in the price of wheat. Corn, soybeans, and oats experienced a price rally at a lag partly due to increased demand following the Global Financial Crisis, along with growing concerns that dry conditions would materialize in other grain-exporting countries. Softs also show similar behaviors. In 2012, historic droughts in the United States particularly affected corn producers. With decreased corn yields, demand for wheat increased as a substitute for feeder grains. In 2014, oats particularly suffered from supply chain issues in Canada, one of the world's largest oats exporters. Canada's accelerating oil exports at the time posed logistic issues that reduced its grain exports. Crude oil and ethanol experienced a steady upward trend due to increased energy demand following the rebound from the 2008 Global Financial Crisis. In 2014, increasing shale oil production in the United States drove crude oil prices down. Ethanol experienced a sharp increase in demand following the passage of the Renewable Fuel Standard.



(a) Grains



(b) Softs



(c) Energy

Figure 2: Nearby Contract Prices

This figure plots the difference between first and second nearby contracts (Blue) and the difference between second and third nearby contracts (Red) of grains, softs, and energy over the sample period of January 2010 - June 2018. Values above zero indicate backwardated markets, while values below zero indicate contangoed markets.

The basis expressed as the difference in nearby and farther contract prices provides insight into the general conditions of the respective commodity markets.

In Figure 2, we observe that wheat, coffee, natural gas, and crude oil appear to be more contangoed throughout the sample period relative to corn, soybeans, cotton, and ethanol, which seem to be more backwardated. Cocoa and oats exhibit fluctuations between backwardated and contangoed markets.

In Table 3, we report descriptive statistics for the first three nearby contract returns of each commodity.

Commodity		Mean	Std	Skew	Kurt	Max	Q(90)	Q(75)	Q(50)	Q(25)	Q(10)	Min	N	ADF
Panel A: First Nearby														
Grains	COR	-0.01	1.75	-1.10	20.12	10.99	1.82	0.90	0.00	-0.94	-1.87	-24.53	2139	-13.11***
	SOY	-0.00	1.36	-0.64	4.40	6.37	1.54	0.77	0.02	-0.74	-1.55	-10.42	2139	-12.88***
	WHT	-0.01	1.93	0.33	1.95	9.10	2.23	1.11	-0.06	-1.14	-2.19	-7.94	2139	-13.71***
	OAT	0.00	2.07	-0.22	3.72	10.37	2.38	1.17	0.00	-1.16	-2.35	-15.75	2139	-13.97***
Softs	COT	0.01	1.80	-1.96	26.22	5.85	2.07	0.89	0.00	-0.84	-1.88	-27.07	2139	-12.82***
	COF	-0.01	1.96	0.23	1.84	11.79	2.38	1.07	0.00	-1.17	-2.31	-8.42	2139	-13.16***
	CCO	-0.01	1.67	-0.06	1.41	7.24	1.98	0.95	0.00	-0.94	-2.04	-8.14	2139	-14.1***
Energy	WTI	-0.00	2.00	0.07	2.87	10.70	2.20	1.06	0.05	-1.08	-2.32	-10.79	2139	-12.86***
	NG	-0.03	2.49	0.08	1.73	12.79	2.91	1.47	-0.05	-1.54	-3.03	-11.78	2139	-14.09***
	ETH	-0.00	1.89	-2.01	17.78	9.40	1.93	0.98	0.08	-0.85	-1.80	-19.04	2139	-13.31***
Panel B: Second Nearby														
Grains	COR	-0.01	1.68	-0.14	5.91	11.40	1.80	0.86	0.00	-0.90	-1.82	-12.84	2139	-12.49***
	SOY	-0.01	1.33	-0.92	9.19	6.31	1.51	0.74	0.00	-0.71	-1.49	-14.35	2139	-12.55***
	WHT	-0.01	1.82	0.40	2.31	10.28	2.11	1.03	-0.08	-1.11	-2.05	-7.64	2139	-13.49***
	OAT	-0.01	1.80	-0.18	3.10	8.34	2.06	1.02	0.00	-1.04	-2.07	-14.03	2139	-14.31***
Softs	COT	0.01	1.56	-0.48	3.47	5.54	1.75	0.81	0.03	-0.76	-1.74	-11.51	2139	-11.39***
	COF	-0.01	1.92	0.21	1.68	10.85	2.36	1.02	0.00	-1.13	-2.26	-8.42	2139	-13.21***
	CCO	-0.01	1.57	-0.04	1.23	7.14	1.83	0.92	0.03	-0.89	-1.96	-6.20	2139	-13.53***
Energy	WTI	-0.00	1.94	0.03	2.95	10.45	2.13	1.01	0.05	-1.06	-2.28	-10.72	2139	-12.93***
	NG	-0.03	2.25	0.13	1.25	12.28	2.67	1.36	-0.03	-1.45	-2.79	-8.76	2139	-13.57***
	ETH	-0.01	1.55	-0.61	4.40	8.87	1.72	0.88	0.06	-0.82	-1.69	-10.73	2139	-13.08***
Panel C: Third Nearby														
Grains	COR	-0.01	1.62	-0.32	8.32	11.65	1.69	0.82	0.00	-0.86	-1.73	-15.25	2139	-12.37***
	SOY	-0.01	1.28	-0.50	4.49	6.26	1.44	0.71	0.02	-0.69	-1.44	-9.65	2139	-12.6***
	WHT	-0.01	1.71	0.40	2.43	9.48	2.03	0.97	-0.08	-1.03	-1.91	-7.62	2139	-13.28***
	OAT	-0.01	1.66	-0.10	3.66	8.41	1.88	0.93	0.00	-0.91	-1.95	-13.05	2139	-14.03***
Softs	COT	0.00	1.52	-1.00	7.88	5.58	1.59	0.74	0.05	-0.66	-1.55	-13.76	2139	-12.15***
	COF	-0.01	1.87	0.22	1.74	10.79	2.29	1.01	0.00	-1.12	-2.19	-8.16	2139	-13.17***
	CCO	-0.01	1.51	-0.03	1.24	7.08	1.77	0.87	0.03	-0.89	-1.91	-5.88	2139	-13.41***
Energy	WTI	-0.01	1.89	-0.01	3.01	9.90	2.06	0.97	0.06	-1.02	-2.21	-10.58	2139	-13.00***
	NG	-0.03	2.09	0.04	1.17	11.30	2.48	1.28	-0.04	-1.36	-2.59	-9.91	2139	-13.36***
	ETH	-0.01	1.45	-0.71	6.36	8.90	1.62	0.80	0.05	-0.77	-1.61	-12.49	2139	-13.09***

Table 3: Summary Statistics - Nearby Contracts

This table reports the descriptive statistics of the log-returns of the first, second, and third nearby futures contracts for each commodity. ‘Q(θ)’ denotes the θ-th quantile of the nearby futures contract log-returns. ‘N’ denotes the total number of observations (days). ‘ADF’ denotes the Augmented Dickey-Fuller test statistic. ‘***’ denotes statistical significance at the 1% level, indicating that the null hypothesis of non-stationarity is rejected in favor of the alternative hypothesis of stationarity.

We confirm the stationarity of each of the variables used in the analysis at the 1% level, as shown by Augmented Dickey-Fueller test statistics, avoiding the possibility of spurious regression.

5 Empirical Results

5.1 Investigating the Linear Relationship Between Climate Change Concerns and Commodity Futures

We outline the results from regressing the nearby contract returns on the individual climate change factors after contemporaneously netting the effects of the control variables. We report the estimated coefficients of the climate change factors in Table 4 for both the contemporaneous and lagged regression.

		Grains				Softs			Energy		
Panel A: First Nearby		COR	SOY	WHT	OAT	COT	COF	CCO	WTI	NG	ETH
Lag 0	UMC	-0.04	0.01	-0.18	-0.16	0.04	-0.23	-0.02	-0.02	-0.25	0.00
	BI	-0.06	0.00	-0.23	-0.22	0.02	-0.22	-0.09	-0.07	-0.22	-0.04
	EI	-0.12	-0.12	-0.13	0.03	0.10	-0.18	0.05	0.05	-0.21	-0.01
	SD	-0.06	0.05	-0.16	-0.23	0.00	-0.15	0.03	0.02	-0.19	0.01
	R	0.15	0.05	-0.04	0.02	-0.02	-0.21	0.05	-0.06	-0.25	0.13
Lag 1	UMC	0.12	0.07	0.06	0.17	-0.08	-0.06	-0.01	0.13**	-0.26	-0.07
	BI	0.08	0.08	0.17	0.18	-0.11	-0.01	-0.04	0.15**	-0.22	-0.08
	EI	0.13	0.05	-0.05	0.06	-0.03	-0.12	0.02	0.05	-0.21	-0.03
	SD	0.20**	0.09	0.14	0.24**	0.01	-0.02	-0.01	0.08	-0.20	0.06
	R	0.00	0.02	-0.13	0.02	-0.08	-0.19	0.06	0.17***	-0.14	-0.18
Panel B: Second Nearby		COR	SOY	WHT	OAT	COT	COF	CCO	WTI	NG	ETH
Lag 0	UMC	-0.01	0.01	-0.15	-0.09	0.07	-0.24	0.00	-0.01	-0.17	-0.06
	BI	-0.05	-0.02	-0.19	-0.14	0.06	-0.21	-0.09	-0.06	-0.16	-0.13
	EI	-0.06	-0.13	-0.12	0.05	0.12	-0.18	0.08	0.06	-0.13	-0.01
	SD	-0.04	0.05	-0.15	-0.16	0.05	-0.16	0.02	0.02	-0.13	-0.06
	R	0.18	0.09	-0.03	0.04	0.03	-0.22	0.07	-0.05	-0.17	0.11
Lag 1	UMC	0.10	0.09	0.01	0.11	-0.02	-0.10	-0.05	0.11	-0.26	-0.08
	BI	0.05	0.10	0.12	0.13	-0.08	-0.04	-0.03	0.12**	-0.26	-0.09
	EI	0.12	0.05	-0.07	0.02	0.01	-0.15	-0.02	0.04	-0.16	-0.03
	SD	0.17	0.14	0.10	0.21	0.03	-0.05	-0.06	0.07	-0.20	0.04
	R	-0.01	0.01	-0.15	-0.02	-0.02	-0.22	0.00	0.14***	-0.14	-0.18
Panel C: Third Nearby		COR	SOY	WHT	OAT	COT	COF	CCO	WTI	NG	ETH
Lag 0	UMC	0.00	0.00	-0.17	0.02	0.09	-0.24	0.01	-0.01	-0.09	-0.10
	BI	-0.04	-0.03	-0.19	-0.07	0.05	-0.21	-0.07	-0.06	-0.09	-0.16
	EI	-0.03	-0.13	-0.15	0.12	0.13	-0.18	0.08	0.06	-0.06	-0.06
	SD	-0.03	0.05	-0.15	-0.07	0.07	-0.17	0.03	0.02	-0.07	-0.09
	R	0.17	0.08	-0.06	0.10	0.04	-0.22	0.08	-0.04	-0.11	0.08
Lag 1	UMC	0.12	0.13	-0.04	0.09	-0.01	-0.12	-0.05	0.09	-0.25	-0.05
	BI	0.10	0.12	0.07	0.16	-0.05	-0.05	-0.04	0.11	-0.28**	-0.09
	EI	0.10	0.09	-0.11	-0.03	0.03	-0.17	-0.02	0.02	-0.15	0.02
	SD	0.12	0.15**	0.07	0.18	-0.01	-0.06	-0.06	0.06	-0.19	0.06
	R	-0.01	0.04	-0.19**	-0.01	0.02	-0.23	0.00	0.13**	-0.13	-0.13

Table 4: Multivariate Regression Results

This table reports the estimated multivariate regression coefficients of the aggregate UMC and thematic indices. '***' and '**' denotes statistical significance at the 1% and 5% level, respectively.

Grains: The estimated coefficients for the SD factor are significantly positive at the 5% level when analyzing the returns of the first nearby futures contract for corn and oats, as well as the third nearby contract returns for soybeans. Furthermore, the estimate for the R factor is strongly negative at the 5% level for the third nearby contract of wheat.

Softs: Our analysis indicates that there is no linear relationship between any of the UMC indices and the mean level of the softs nearby contract return distributions. Nonetheless, we conduct further investigation to determine if the UMC indices have any nullifying effects on the return distributions of the softs contract returns when conditioned on their upper and lower quantile levels.

Energy: When analyzing the returns of crude oil futures contracts, we find that the estimated coefficients for the aggregate UMC factor are positive at the 5% level for the first and second nearby contracts, each with a lag of one day. Similarly, the BI thematic factor shows a positive relationship at the 5% significance level for the first and second nearby contracts of crude oil. Additionally, we observe positive coefficients for the R factor at the 1% significance level for the first and second nearby contracts and at the 5% level for the third nearby contract. Furthermore, at a lag of one day, we estimate a negative coefficient at the 5% level for the BI factor when examining the third nearby contract of natural gas.

5.2 Investigating the Asymmetric Relationship Between Climate Change Concerns and Commodity Futures

We now expand the analysis to investigate the relationship between climate change risk and the entire conditional distribution of commodity returns through the quantile regression framework. We estimate the coefficients at each quantile level for each of the commodity contract returns. In Table 5, we report the results upon applying the Wald tests on the quantile coefficients $\beta_{(\tau)}$, which can provide insight into potential non-linearities along the distribution of commodity futures contract returns when regressed on the individual climate factors.

		Grains				Softs			Energy		
Panel A: First Nearby											
		COR	SOY	WHT	OAT	COT	COF	CCO	WTI	NG	ETH
Lag 0	UMC	-	-	-	-	-	-	-	-	-	-
	BI	-	-	**	-	-	-	-	-	-	-
	EI	***	-	-	-	-	-	-	-	-	-
	SD	**	-	**	-	-	-	-	-	***	-
	R	-	**	**	-	-	-	-	-	-	-
Lag 1	UMC	-	-	-	-	-	**	-	-	-	-
	BI	-	-	-	-	-	-	-	-	-	-
	EI	-	-	-	-	-	***	-	-	-	-
	SD	-	-	-	-	-	**	-	-	-	-
	R	-	-	-	-	-	-	-	-	-	-
Panel B: Second Nearby											
		COR	SOY	WHT	OAT	COT	COF	CCO	WTI	NG	ETH
Lag 0	UMC	**	-	-	-	-	-	-	-	-	-
	BI	-	-	***	-	-	-	-	-	-	-
	EI	-	**	-	-	-	-	-	-	-	-
	SD	***	-	**	-	-	-	-	-	-	-
	R	**	**	***	-	-	-	-	-	-	-
Lag 1	UMC	-	-	-	-	-	**	-	-	-	-
	BI	-	-	-	-	-	-	***	-	-	-
	EI	-	-	-	-	-	-	-	-	-	-
	SD	-	-	-	-	-	-	**	-	-	-
	R	-	-	-	-	***	**	***	-	-	-
Panel C: Third Nearby											
		COR	SOY	WHT	OAT	COT	COF	CCO	WTI	NG	ETH
Lag 0	UMC	-	-	-	-	-	-	-	-	-	-
	BI	-	-	-	-	-	-	-	-	-	-
	EI	-	-	-	-	***	-	-	-	-	-
	SD	***	-	-	-	-	-	-	-	-	-
	R	-	-	***	-	-	-	-	-	-	-
Lag 1	UMC	-	-	-	-	***	**	-	-	-	-
	BI	-	-	-	-	-	-	***	-	-	-
	EI	-	-	-	-	***	-	-	-	-	-
	SD	-	-	-	-	-	**	-	-	-	-
	R	-	-	-	-	***	**	***	-	-	-

Table 5: Wald Test - Commodity Contract Returns

This table reports the statistical significance of the Wald test statistics indicating non-equal coefficients across the conditional quantile distributions of the commodity contract returns. '***' and '**' denotes statistical significance at the 1% and 5% level, respectively.

The Wald test results in Table 5 indicate non-linearities between the first, second, and third nearby grains contracts and the UMC indices contemporaneously, more specifically for corn and wheat. On the other hand, the results indicate asymmetries in the relationship between climate change concerns and softs at a lag of one day. We recall that the Wald tests report the significance of non-equal coefficients when regressing the conditional quantile commodity contract returns on the climate concern proxies and, therefore, only provide a preliminary indication of an asymmetric relationship between the dependent and independent variables. To further investigate the potential non-linearities between unexpected climate change concerns and commodity futures, we examine the estimated coefficients $\beta_{(\tau)}$ at each of the quantile levels.

Without loss in generality, we illustrate the sequences of the quantile regression summaries for grains second nearby contracts at lag 0, softs third nearby contracts at lag one day, and energy first nearby contracts at a lag of one day. Figures 3, 4, and 5 plot the sequences of summary results.

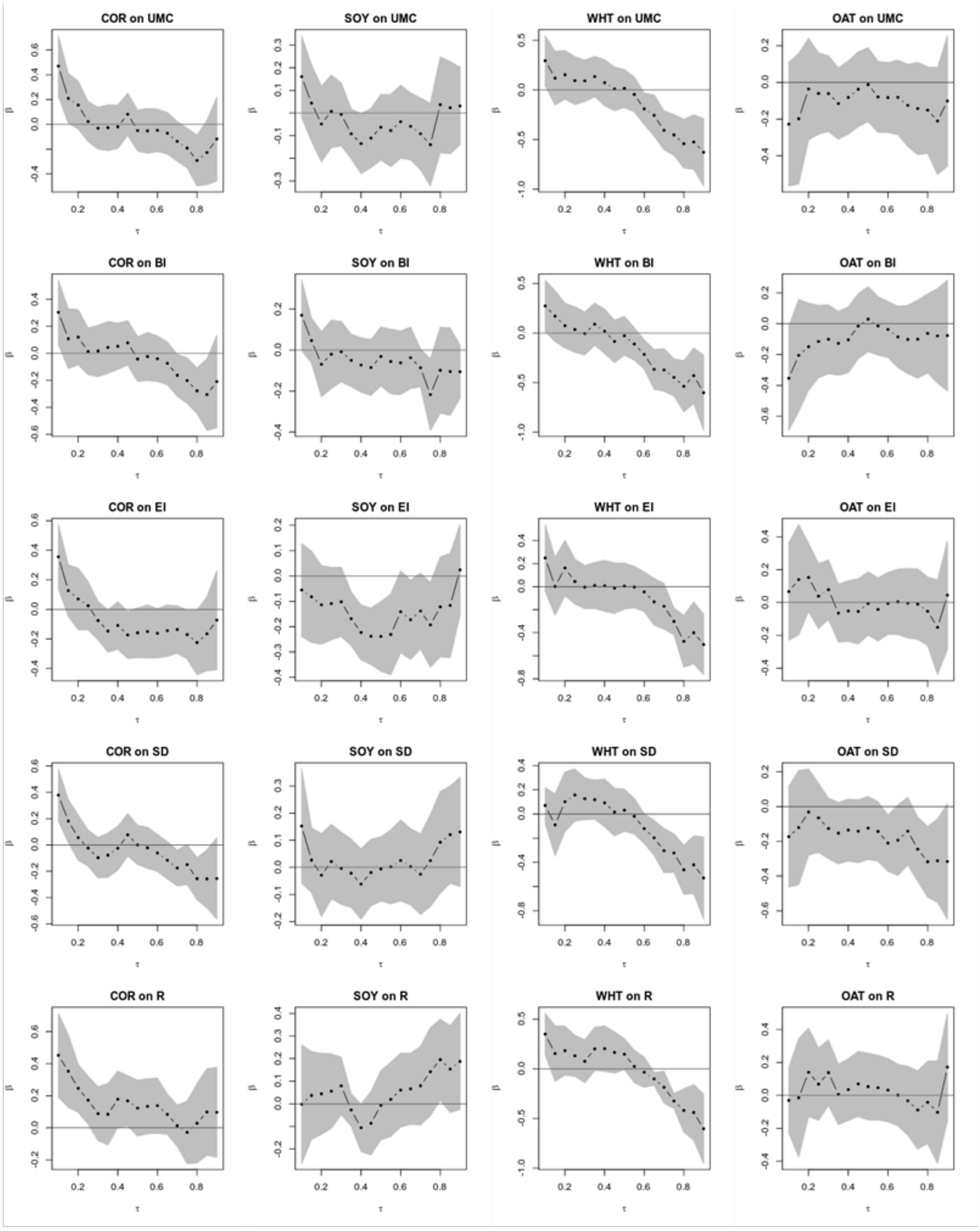


Figure 3: Contemporaneous Quantile Regression Summary - Grains Second Nearby Contracts

This figure plots the coefficients of the UMC aggregate and thematic indices by quantile in the models of second nearby grains returns at a lag of 0. The quantiles of the dependent variable are on the horizontal axes, and the coefficients are on the vertical axes. The choked black lines represent the quantile regression coefficient estimates, and the gray shaded boundaries represent the 90% confidence interval of the quantile coefficient estimates.

In Figure 3, we observe that the contemporaneous coefficient estimates of the UMC and thematic indices are decreasing as the quantile levels of the conditioned returns of corn and wheat increase.

When examining corn, we notice that the coefficient estimates of the UMC, EI, and SD factors are significantly positive when the returns are conditioned on lower quantiles. We also notice that the BI and SD factors show significance in the upper quantiles of the conditional distributions of corn nearby contracts. In addition, the SD factor is significantly negative when examining the distribution of oats conditioned on the upper quantiles.

We observe a similar pattern in wheat for the coefficients of each of the UMC indices. Lower quantile levels are generally associated with positive coefficients of the climate change factor, while we observe statistically significant negative coefficients at the upper quantile ranges.

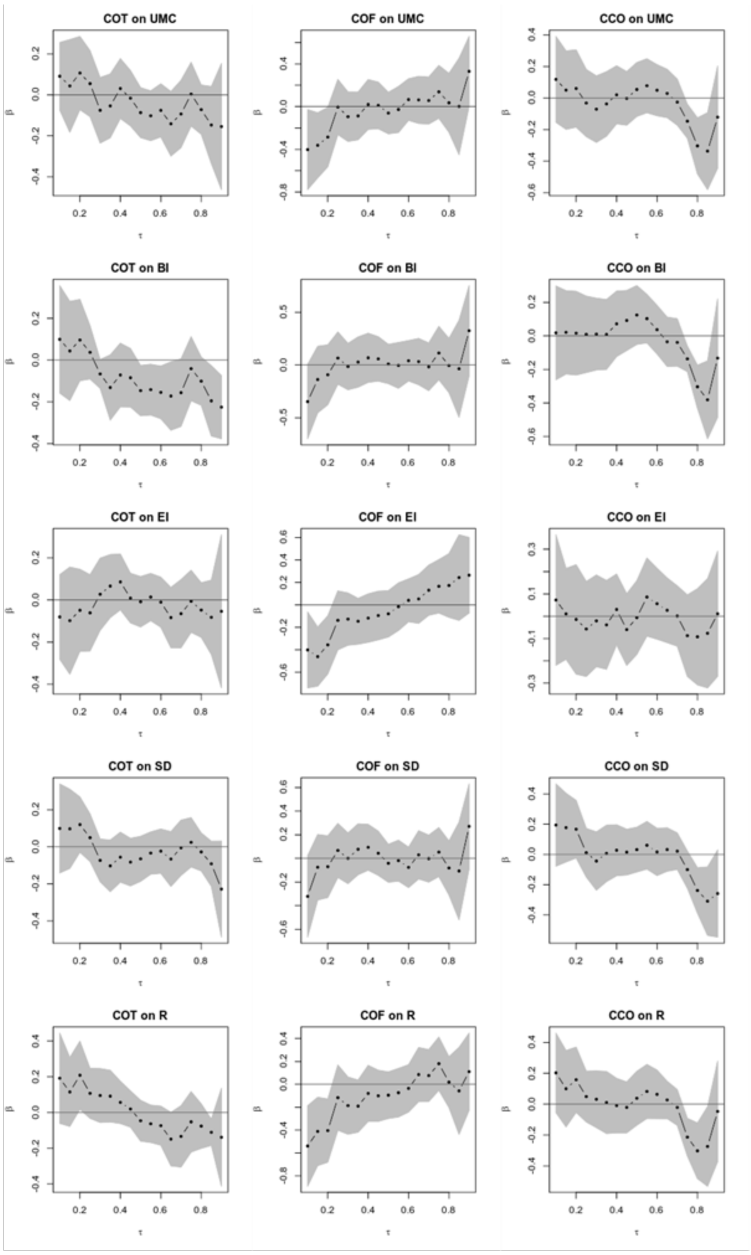


Figure 4: Lagged Quantile Regression Summary - Softs Third Nearby Contracts

This figure plots the coefficients of the UMC aggregate and thematic indices by quantile in the models of third nearby softs returns at a lag of 1. The quantiles of the dependent variable are on the horizontal axes, and the coefficients are on the vertical axes. The choked black lines represent the quantile regression coefficient estimates, and the gray shaded boundaries represent the 90% confidence interval of the quantile coefficient estimates.

For the third nearby contract of cotton and cocoa, we notice that the coefficients displayed in Figure 4 for the UMC, BI, SD, and R factors are decreasing at upper quantile levels. For coffee, however, we see the opposite pattern. The estimated coefficients of the climate change proxies are negative at the lower conditional quantiles of coffee and increase in the quantile level.

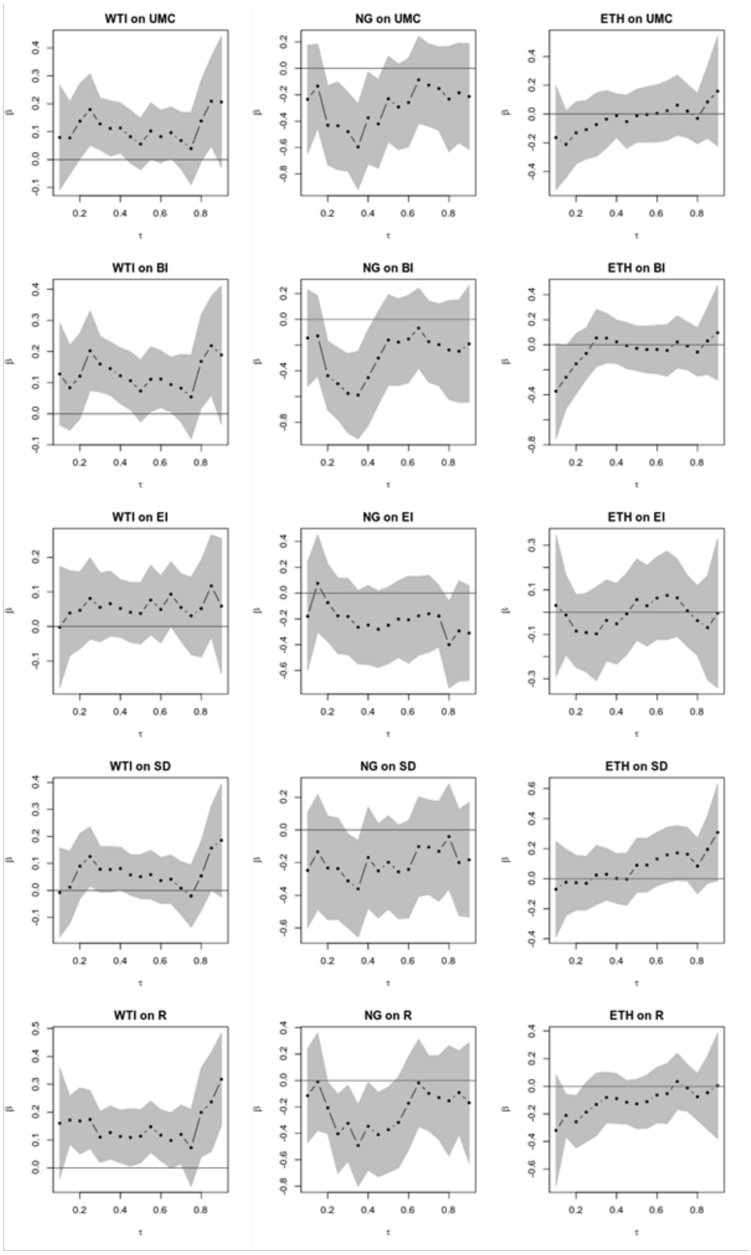


Figure 5: Lagged Quantile Regression Summary - Energy Third Nearby Contracts

This figure plots the coefficients of the UMC aggregate and thematic indices by quantile in the models of the first nearby energy returns models at a lag of 0. The quantiles of the dependent variable are on the horizontal axes, and the coefficients are on the vertical axes. The choked black lines represent the quantile regression coefficient estimates, and the gray shaded boundaries represent the 90% confidence interval of the quantile coefficient estimates.

In Figure 5, we notice that the coefficient estimates when opining on crude oil are consistent across the entirety of its conditional quantile distribution for the UMC, BI, and EI factors. We also point out that the coefficient estimates for the SD and R thematic indices increase for distribution conditioned on the 80th percentile level and above.

In addition, we observe the estimates to increase in conditional quantile levels in a similar fashion when examining the nearby contract returns for ethanol at the one-day lag as well. The coefficient estimates for the SD factor are statistically significant and positive for extreme upper quantiles

5.3 Discussion

In this section, we elaborate on the empirical results of each of the commodity groups. We note that we abstain from making causal inferences throughout our discussion.

Grains: We observe that the societal debate thematic index displays a positive relationship with the first nearby contracts of corn and oats, as well as the third nearby contract of soybeans, each being at a lag of one day. We expand on this by revealing that unexpected increases in climate change concerns are non-linearly related to commodity contracts through the quantile regression results. Though the OLS estimates did not provide significance for the grains' second nearby contracts contemporaneously, we identify a statistically significant relationship between the climate change concern proxies at the tails of the return distribution of corn and wheat. This highlights the advantage of using the quantile regression framework, as the relationships at the extremes of the return distributions would have otherwise been missed by the OLS method.

In Figure 3, we see that an increase in climate change concerns has a positive relationship with bearish corn markets. This is shown by the climate change proxies at the lower quantiles. This result is intuitive by noting that bearish corn markets are most likely directly related to abundant supplies and increased crop yields. Therefore, an unexpected increase in climate change concerns can ignite speculation on the supply and increase prices.

We also find that there is a negative relationship between climate change concerns and bullish wheat markets. This means that an unexpected increase in climate change concerns can lead to speculation on increased crop yields due to more favorable weather conditions and, consequently, lower returns. Although this result appears to contradict that of corn, the interactions between climate change and agriculture are quite complex. Climate change affects the variability of weather conditions, and its impact on crops is highly dependent on their respective geography Antón et al. (2013). The difference in the way climate change concerns affect corn and wheat illustrates the potential positive and negative effects that climate change can have on crop yields, which is consistent with the findings of Lewis and Witham (2012). Our results are consistent with the general finding of Chatzopoulos et al. (2020), which is that climate change is asymmetrically associated with agricultural commodities.

Softs: Climate change concerns also exhibit a relationship in the extremes of cotton, cocoa, and coffee return distributions. According to the results of the quantile regression analysis, bullish cotton and cocoa markets have a negative relationship with the aggregate UMC index at a lag of one day. Furthermore, in bearish coffee markets, the potential influence of climate change concerns is negative, while it is positive during bullish markets. Similar to the results obtained when examining grain commodities, it appears that climate change concerns can have both a positive and negative impact on crop yields for agricultural commodities (Lewis and Witham, 2012). This highlights the heterogeneity across agricultural commodity markets, which is likely due to their dependence on their respective geographies. Unlike grain commodities, however, non-linearities between climate change concerns and softs appear to occur in more distant contracts.

Energy: For energy, we remarkably observe that, at a lag of one day, the unexpected increases in climate change concerns result in upward pressure on the term structure of the crude oil futures. When isolating for the potential asymmetries of the first nearby contracts of the energy commodities with unexpected climate change factors at a lag of one day, we find that increases in climate change concerns are positively associated with oil up-markets. More specifically, the societal debate and research thematic indices positively relate to crude oil in the extreme right tail of its return distribution. A logical reason for this can likely be attributed to the public rhetoric in political campaigns and agenda-setting research associated with climate change and how social inclusion can play a role in transitory role in climate risk in the short term, as stipulated by Bolton and Kacperczyk (2023). The business impact thematic index is also positively related to the first and second crude oil nearby contracts. As previously discussed, the business impact index captures business-related concerns on climate mitigation efforts. As examined by Diaz-Rainey et al. (2021), investors seem to price climate policies affecting the oil industry through either increased costs or limitations in exploration, drilling, and production, which pose a supply-side risk to the crude oil market.

In addition, we reveal the societal debate thematic index to be positively related to ethanol's first nearby contracts at a lag of one day when conditioned on its upper quantile. We find a significant negative relationship for natural gas when looking at the lagged coefficient of the business impact thematic index for its second nearby contract. A potential reason for this might be due to investments in natural gas extraction as it is a substitute for relatively cleaner energy than oil and coal and thus increases speculation on an increased supply.

6 Conclusion

With the acceleration of climate mitigating activities and growing awareness of the physical impacts of variable weather events, rising climate change concerns are shown to have a significant relationship with global commodity markets at the daily level. This paper uses a multivariate regression framework to empirically analyze the unconditional relationship between the commodity futures contracts and the climate change concern proxies of Ardia et al. (2023). Additionally, we examine potential non-linearities between commodity futures markets and climate change by use of the quantile regression framework of Koenker and Bassett (1978).

Our results reveal that climate change concerns are associated with commodity contract returns conditioned on their upper and lower quantile levels. We emphasize the robustness of our results as several key commodity-specific and global drivers of commodity markets are contemporaneously controlled for in the regression frameworks. Our findings uncover that there is a positive link between transition climate risk and crude oil futures contract returns at a lag of one day over the full sample period. Furthermore, we shed light on the possibility that the potential relationship between climate change and agricultural commodities is non-linear.

We acknowledge the limitations of our analysis by noting that a more precise study of the physical effects of climate change concerns on agricultural commodities would most likely require geographic climate change concern proxies. Even though increased globalization and the inflow of speculative capital into commodities futures markets can bring rise to their respective connectedness, extreme price movements related to increased climate change concerns may not be uniform across different markets, making it difficult to pinpoint any causal relationship. Additionally, although studying unexpected increases in climate change concerns at the daily level is preferred for the sake of timeliness, analyzing daily commodities futures contract returns foregoes the opportunity of using critical information, such as the net positions of hedgers and speculators provided by the CFTC at a weekly basis. Further research could focus on the relationship between climate change concerns and products such as commodity-linked notes or commodity options, as we can suspect them to be more susceptible to financial speculation.

7 Appendix

In this appendix, we provide additional information on the data for the climate change concern factors and control variables. In Tables 6 and 7, respectively.

Control Variable	mean	sd	skew	kurt	max	Q(90)	Q(75)	Q(50)	Q(25)	Q(10)	min	N	ADF
DXY	0.01	0.47	-0.04	1.36	1.87	0.58	0.27	0.01	-0.27	-0.55	-2.29	2139	-12.54 ***
SPGSCI	-0.03	1.21	-0.23	1.77	4.78	1.38	0.65	0.00	-0.71	-1.47	-7.33	2139	-12.63 ***
EPU	1.05	0.62	1.54	3.45	4.91	1.87	1.34	0.90	0.61	0.43	0.03	2139	-6.12 ***
GPRD	103.04	38.23	1.27	2.92	354.05	151.33	121.93	95.59	76.8	61.57	25.32	2139	-9.25 ***
Mkt-Rf	0.05	0.96	-0.44	4.44	4.97	1.11	0.53	0.07	-0.36	-1.05	-6.97	2139	-13.41 ***
bm - COR	0.01	2.30	1.20	16.78	13.87	1.01	0.42	0.06	-0.36	-1.30	-18.30	2139	-8.14 ***
bm - SOY	0.00	1.52	-1.89	14.66	6.87	1.14	0.38	0.01	-0.23	-0.92	-12.10	2139	-9.40 ***
bm - WHT	0.00	0.96	0.10	1.28	4.07	1.18	0.48	-0.02	-0.51	-1.16	-3.62	2139	-10.44 ***
bm - OAT	0.04	3.19	-0.34	2.56	10.85	3.79	1.49	-0.03	-1.34	-3.35	-15.39	2139	-11.19 ***
bm - COT	0.02	3.28	-0.87	14.11	19.98	3.00	1.07	-0.12	-1.11	-2.48	-26.78	2139	-10.41 ***
bm - COF	-0.01	0.70	0.54	7.04	5.04	0.78	0.26	-0.04	-0.29	-0.75	-3.82	2139	-10.94 ***
bm - CCO	0.00	1.19	0.25	11.75	11.12	1.17	0.49	-0.01	-0.49	-1.23	-10.37	2139	-13.24 ***
bm - WTI	0.02	0.68	0.4	5.61	4.17	0.64	0.25	0.02	-0.21	-0.70	-3.38	2139	-8.84 ***
bm - NG	0.00	2.21	-0.08	4.96	15.96	2.69	1.02	0.01	-1.15	-2.35	-16.37	2139	-8.62 ***
bm - ETH	-0.01	2.68	0.05	7.41	19.33	2.40	1.06	0.06	-0.98	-2.70	-18.82	2139	-10.83 ***

Table 6: Summary Statistics - Control Variables

This table reports the descriptive statistics of the control variables used throughout the analysis. 'Q(θ)' denotes the θ-th quantile of the control variable. 'N' denotes the total number of observations (days). 'ADF' denotes the Augmented Dickey-Fuller test statistic. '***' denotes statistical significance at the 1% level, indicating that the null hypothesis of non-stationarity is rejected in favor of the alternative hypothesis of stationarity.

Climate Factor	mean	sd	skew	kurt	max	Q(90)	Q(75)	Q(50)	Q(25)	Q(10)	min	N	ADF
UMC	0.04	0.31	0.81	1.74	1.66	0.42	0.21	0.00	-0.16	-0.31	-0.88	2139	-10.49 ***
BI	0.03	0.31	1.12	3.59	2.05	0.40	0.19	0.00	-0.16	-0.31	-0.75	2139	-10.09 ***
EI	0.04	0.33	1.15	2.34	2.03	0.47	0.21	-0.00	-0.20	-0.32	-0.75	2139	-11.67 ***
SD	0.04	0.34	1.10	2.92	2.13	0.45	0.22	-0.02	-0.19	-0.33	-0.89	2139	-9.78 ***
R	0.04	0.32	1.42	4.69	2.33	0.43	0.20	-0.01	-0.18	-0.29	-1.03	2139	-11.24 ***

Table 7: Summary Statistics - Climate Factors

This table reports the descriptive statistics of the daily UMC climate change concern factors of Ardia et al. (2023). 'Q(θ)' denotes the θ-th quantile of the UMC climate change concern factors. 'N' denotes the total number of observations (days). 'ADF' denotes the Augmented Dickey-Fuller test statistic. '***' denotes statistical significance at the 1% level, indicating that the null hypothesis of non-stationarity is rejected in favor of the alternative hypothesis of stationarity.

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