HOW DO SIGNIFICANT CLIMATE EVENTS AND MEDIA COVERAGE INFLUECE THE RETURNS AND VOLATILITY OF COMMODITIES

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Dissertation written under the supervision of professor Susana Campos Martins

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Abstract

I propose a different approach to measure all commodities behaviour when affected by global effects of climate change. The study is divided in two different approaches to analyse that. In the first one, we started by calculate the global common volatility of all commodities. And then, a text-based proxies of climate change news is project onto climate-related shocks. Finally, the commodities volatility shocks are projected on the variation of that climate index. In the second approach, the commodities common returns (obtained through a principal component analysis (PCA)) are projected on the variation of that climate index. I show that for commodities in general, rising concerns regarding climate change are not making commodities prices move at a global scale, controlling for shocks to the agriculture, oil, gold and silver prices, the US stock market and commodities markets. However, we see that specific groups of commodities are more affected than others. The group most impacted is the energy commodities. Therefore, the direction and intensity of influence vary depending on the commodity and the time span that we are analysing. Data from the period following the Paris Agreement indicate that climate-related news now exerts a different influence on commodities, making the climate index a significant factor in global commodity volatility for all commodities. Lastly, the findings show that climate news is starting to affect the commodities market, most notably after important climate meetings.

Title: How do significant climate events and media coverage influence the returns and volatility of commodities

Author: Tomás Fernandes

Keywords: Commodities, climate change, global volatility, climate-related news, Paris Agreement

Sumário

Decidi propor uma abordagem diferente para medir o comportamento de todas as *commodities* quando afetadas pelos efeitos das alterações climáticas. O estudo encontra-se dividido em duas partes distintas. Primeiramente, começamos por calcular a volatilidade comum global de todas as *commodities*. Posteriormente, são utilizados indicadores baseados em texto de notícias sobre alterações climáticas para a projetar em choques relacionados com o clima. Por último, os choques de volatilidade das *commodities* são projetados na variação desse índice climático. Na segunda abordagem, os retornos comuns das *commodities* (obtidos através de uma análise de componentes principais (ACP)) são projetados na variação desse índice climático. Demonstrou-se que, em geral, as crescentes preocupações com as alterações climáticas não estão a fazer com que os preços das *commodities* se alterem, controlando-se os choques nos preços da agricultura, do petróleo, do ouro e da prata, do mercado de ações dos EUA e do mercado de *commodities*. No entanto, verificamos que determinados grupos de *commodities* são mais afetados do que outros. O grupo mais afetado é o das *commodities* de energia. Assim, a direção e a intensidade da influência variam conforme a *commodity* e o período que estamos a analisar. Datas posteriores ao Acordo de Paris mostram que as notícias relacionadas com o clima exercem agora uma influência diferente sobre as *commodities*, tornando o índice climático um fator significativo na volatilidade global das *commodities*. Por último, as conclusões mostram que as notícias sobre o clima começam a afetar o mercado das *commodities*, sobretudo após importantes reuniões sobre o clima.

Título: Como é que os eventos climáticos significativos e a cobertura mediática influenciam os retornos e a volatilidade das *commodities*

Autor: Tomás Fernandes

Palavras-chave: *Commodities*, alterações climáticas, volatilidade global, notícias relacionadas com o clima, Acordo de Paris

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1. Introduction

Climate change is not a recent topic; it began gaining attention in the 1970s when researchers started examining the effects of human activities on the planet's climate system. Over the past two decades, the topic has gained significant momentum, with considerable progress documented by organizations such as the World Meteorological Organization. Landmark events, such as the Kyoto Protocol in 1997 and the recent COP meetings in Dubai, underline the urgency of addressing climate change. This global focus highlights the substantial impacts that climate events and associated policies have on businesses, economies, and financial markets. For instance, companies whose operations are very sensitive to extremes of rainfall suffer higher capital costs and often a drop in market value, as excessive rainfall can damage their infrastructure, while a severe lack of rain can drastically reduce demand and lead to underutilization of assets (Rao, Sandeep, et al. (2022)).

Commodities, as primary or raw products, are essential components of financial markets. They serve as valuable tools for portfolio diversification, as their prices tend to move inversely to stocks, making them particularly attractive during periods of market volatility. However, commodities are not immune to the effects of climate change. Evidence shows that extreme climate events, such as rising temperatures and persistent water stress, profoundly disrupt agricultural commodity markets by reducing yields, increasing price volatility, and reshaping global trade patterns. Negative climatic anomalies, like droughts and heatwaves, have particularly strong economic repercussions, driving significant price increases and exacerbating food insecurity, especially in vulnerable regions (Chatzopoulos, Thomas, et al., 2020). In the case of energy commodities, growing concerns about the energy transition have caused fluctuations in oil and gas prices, reflecting global market uncertainty (Campos-Martins, Susana, and David F. Hendry (2024)). Additionally, studies on metalic commodities show that gold price volatility is negatively correlated with physical climate risks (Zhu, Jiaji, et al. (2023)). These findings demonstrate the vulnerability of commodities to climate-related news and underline the need for further investigation.

While there is research exploring the relationship between climate risks and commodities, most studies have been focused on a single type of commodity. This thesis seeks to address this gap by examining whether co-movements of different types of commodities prices respond and how they are influenced at the same time by climate risks and identifying the most influential factors for each category. By analyzing commodities both collectively and individually, the study aims to determine if aggregated analysis masks significant climate-related effects compared to separate analyses.

Moreover, this thesis aims to address gaps in the existing literature by introducing a climate-related information index, such as the media climate change concerns (MCCC) index, which measures the media coverage related to climate concerns, as applied by Campos-Martins, Susana, and David F. Hendry. (2024). To explore with two distinct analyses, how the synchronized volatility and the common returns of different types of commodities are affected by climate news. Specifically, it examines whether climate media sentiment generates distinct patterns in commodity price behavior and how these influences vary among different commodity classes. The analysis also considers the interaction of climate media sentiment with U.S. macroeconomic variables, financial instruments, and sector-specific indices. Additionally, events such as the Paris Agreement are evaluated to understand market reactions to decisions made during major climate meetings.

To sum up this study contributes to a deeper understanding of how climate events shape financial markets. By integrating climate media sentiment, global market indicators, and commodity-specific factors, it offers insights for investors seeking to anticipate volatility spikes and refine risk management strategies. From an academic perspective, the study enriches the climate-finance literature by incorporating a text-based climate index into the analysis of multiple commodity types.

The structure of this thesis is as follows: Section 2 presents the relevant literature review, Section 3 describes the data and variables, Section 4 outlines the methodology, Section 5 presents the results, and Section 6 the limitations and Section 7 concludes with key findings, implications, and suggestions for future research.

2. Literature Review

With the increasing importance of climate change in the global markets, it has become crucial in the last few years to understand how it affects the financial markets and economic stability. Recent studies focused on the impacts of climate change showed that climate events have become very important to economic and financial performance. For example, Burke, Marshall, et al. (2015) found that economic productivity peaks at an annual temperature of 13°C and declines significantly at higher temperatures. Furthermore, they projected that global income is expected to decrease by 23% relative to a no-climate-change scenario. Similarly, Colacito, Riccardo, et al (2018) revealed that rising summer temperatures significantly reduce economic productivity in high-temperature regions, noting that the southern U.S. is particularly sensitive, with substantial output declines linked to rising heat. Moreover, the creation and inclusion, in more recent studies, of climate news indexes (like the media climate change concerns index (MCCC)) offers a new perspective on how climate change affects the financial markets - a factor that is becoming increasingly relevant in market studies (Ardia, David, et al.(2022)).

Furthermore, understanding the effect of external shocks, from climate events to macroeconomic fluctuations, on commodities prices is crucial for investors, policy makers and researchers. Kilian, Lutz (2009) highlights the importance of analyzing how external events affect the market, whether they are geopolitical or climate, because both can impact the volatility of energy commodities. This is crucial because he concluded that the recent surge in oil prices was primarily driven by global demand shocks, which helps explain why this shock did not lead to a major recession in the United States. Teltock, Paul C. (2007) shows that high media pessimism leads to price movements (downward price pressure followed by reversion to fundamentals), while extreme sentiment drives higher trading volume. These findings align with noise trader theories and challenge the idea of media as a proxy for fundamental asset values or market volatility. This idea demonstrates that to make results more robust, it is crucial to incorporate climate news indexes for a better understanding of the commodities' behavior in response to climate events.

Nowadays, there are some gaps in literature related to the simultaneous impact of climate events and media coverage on a wide set of commodities. The studies that have already been conducted focus more on specific types of commodities, like energy commodities (Kilian, Lutz (2009)), agricultural commodities (Makkonen, Adam, et al. (2021)) or precious metal commodities (Zhu, Jiaji, et al. (2023)). This creates an opportunity to conduct a deeper study to different types of commodities, and understand the interactions between them, rather than focusing on only one type of commodity. The aim of the study is to use the MCCC Index together with different types of commodities to address that gap and capture the market reaction to climate events across various types of commodities, following the same methodology of Campos-Martins, Susana, and David F. Hendry. (2024), focused on the Oil and Gas industry only.

2.1. Importance of Commodities in the Global Economy and Impact of External Shocks

Agriculture, energy and metal commodities are very important to the global economy, performing a crucial role in it. This becomes even more important and interesting to study, when these commodities are subject to external shocks, like extreme climate events. One example is Kilian, Lutz (2009), who showed that energy prices are significantly influenced by supply shocks in the oil market, with their impacts often amplified by external factors such as climate events and geopolitical tensions. These amplifiers exacerbate the volatility of oil prices, further complicating their effects on macroeconomic stability. This is particularly significant for economies dependent on energy resources. The relationship between energy commodities and climate events has been, however underexplored in literature. Early studies, such as Bessembinder, Hendrik (1992), highlighted that hedging pressure is a key determinant of risk premiums in futures markets and that risk premiums are influenced by market-specific conditions beyond systematic risk. This underscores the importance of including additional economic control variables to capture these effects on predictive models.

2.2. Climate Events and Commodity Volatility

Concerning volatility, recent studies have explored the relationship between climate events and the commodities market. Hong, Harrison, et al. (2019) demonstrated that persistent trends in climate events, such as droughts, disrupt markets by impacting production, supply, and profitability, leading to predictable movements in stock returns. It further highlights that markets underreact to these risks, resulting in inefficiencies in pricing long-term climate impacts. In addition, Makkonen, Adam, et al. (2021) showed that temperature anomalies significantly impact agricultural commodity futures returns, with asymmetric effects: negative in bearish markets for corn, soybeans, and wheat and positive in bullish markets for the same commodities. Macroeconomic variables like the S&P 500 and USD exchange rate also showed asymmetric influences, limiting commodities' hedging benefits during downturns. Uncertainty measures, such as VIX and Economic Policy Uncertainty (EPU), shaped returns, reflecting heightened risk aversion and flight-to-safety behavior. Additionally, climate risk and market uncertainty were shown to interact, amplifying volatility in extreme conditions. These findings highlight the critical role of climate and economic factors in shaping commodity market dynamics and investment strategies. Kilian, Lutz (2009) also discussed how climate events in oil production regions could provoke abrupt increases in the volatility of oil and gas prices. Similarly, metal commodities are also affected by extreme climate events, particularly gold, which has been frequently studied due to its important role as a store of value and a hedge against macroeconomic risks. Zhu, Jiaji, et al. (2023) analyzed the impact of climate risks, particularly El Niño, on gold price volatility using the Southern Oscillation Index (SOI). They found a negative correlation between gold price volatility and physical climate risks, with the seasonal component of SOI showing strong predictive power. The study highlights how El Niño influences gold markets indirectly through its effects on agriculture, commodity prices, and inflation. Moreover, Tang, Yusui, and Juandan Zhong. (2023) analyzed the behavior of gold futures volatility in response to extreme risk in the commodities markets. To conduct their study, they developed an autoregressive (AR) model as a tail risk indicator constructed from the commodity price index. Their findings demonstrate that tail risk indicators significantly improve predictions of gold futures volatility, particularly during periods of extreme market stress. This highlights the crucial role of modeling extreme risks in financial markets and underscores gold's unique position as a safe-haven asset. The study further emphasizes that the predictive power of tail risk is most pronounced during high-volatility periods, reinforcing the importance of tail risk indicators for managing risks and understanding gold's dynamics within the broader commodity market.

2.3. Common Volatility (COVOL) as a Measure for Synchronized Volatility in Commodities, Media Coverage and the Role of MCCC in Climate Concern

To study and model the common volatility between all commodities and the different types of commodities, we follow Engle, Robert F., and Susana Campos-Martins (2023) who introduced COVOL, a statistical measure of the simultaneous volatility between different classes of assets. They demonstrated that negative climate news amplifies market uncertainty, increasing global common volatility. Their findings also highlighted the importance of synchronized market behavior, introducing the concept of COVOL as a valuable tool for analyzing climate-related shocks. This measure of common volatility, when combined with climate news, enables capturing the impact of extreme climate events on commodities volatility in a synchronized way. Unlike other studies we will differentiate by using COVOL applied to agricultural, energy, and metal commodities, allowing for a broader volatility analysis under driver changing conditions.

News from around the world has an impact on the economy, especially on the commodities market, which makes the role of media coverage in this market an important factor to study. As mentioned in the introduction Teltock, Paul C. (2007) showed that high media pessimism leads to price movements, while extreme sentiment drives higher trading volume. The media climate change concerns (MCCC) index, by Ardia, David, et al. (2022), to measure media attention to climate issues and public perception of climate risks. Given the importance of climate coverage and MCCC, we study the co-movement of agricultural, energy, and metal commodities in order to understand how media coverage amplifies price and volatility fluctuations in response to climate events.

2.4. Economic and Financial Control Variables for Modeling the Common Volatility Regression and the Common Returns Regression

2.4.1. Common Volatility Regression

The MCCC index is applied as a text-based measure of media climate change concerns to reflect and understand the impact of significant climate events on financial markets (see Campos-Martins, Susana, and David F. Hendry, 2024). Additionally, to MCCC other variables should be used as controls, such as SPDR S&P 500 (SPY), which captures stock market volatility in the US, as they may also drive common volatility in commodities, compounding our results on the impact of climate news.

In addition to these, we will use the S&P GSCI Commodity Total Return Index, because this index represents the behavior of all commodities in the market, unlike XLE, which focuses on the energy industry only. This approach will allow the model to capture general shocks in commodities markets, acting as an essential control variable to evaluate the impact of climate events on common volatility.

Campos-Martins, Susana, and David F. Hendry (2024) found that the O&G sector's (Oil and Gas sector) volatility is positively correlated with volatility shocks in SPY, which shows that this sector is affected by economic instability. Volatility shocks in all country world index (ACWI) are also positively correlated, indicating that global economic instability events impact volatility in the O&G sector, even if these shocks are related to other topics besides oil and gas.

Campos-Martins, Susana, and David F. Hendry (2024) also showed that news about climate events and the energy transition affect volatility in the O&G sector. It was also demonstrated that negative news about the climate increases global volatility in the O&G sector, and price shocks in oil amplify these climate effects. Conversely, global stock market shocks (ACWI) and shocks to the US market (SPY) dampen the influence of climate news.

2.4.2. Common Returns Regression

Laubsch, Joshua, et al. (2024) explored economic uncertainty's impact on commodity returns and highlighted that the Economic Policy Uncertainty (EPU) index is negatively correlated with commodity returns, reflecting reduced demand during high uncertainty. They further observed that macroeconomic factors such as credit spreads and interest rates shape commodity market behavior. These findings suggest the need to include variables like the 3-month T-Bill yield and the Baa-Aaa credit spread to account for credit conditions and interest rate structures. In their study, the following variables were used: the economic policy uncertainty index (EPU), the 3-month T-Bill yield, the Baa-Aaa credit spread, the 2y10y term structure, the S&P500 index dividend yield, and the CBOE volatility index (VIX). These variables provided insights into credit conditions, interest rate structures, and implied volatility. They showed that EPU is negatively correlated with commodities returns, which is explained by the fact that as economic policy uncertainty increases, consumption and investment in the economy decrease, leading to a reduction in demand for commodities. Regarding the remaining control variables, the 3-month T-Bill yield has a similar relationship with returns as EPU, likely because a rise in short-term interest rates puts pressure on commodities returns, prompting investors to seek safer investments. The Baa-Aaa credit spread has a positive relationship, indicating that economic growth is associated with increased commodity returns. The S&P500 index dividend yield is negatively correlated, demonstrating that an increase in stock dividend yields makes investors less attracted to commodities. Finally, the VIX is negatively correlated. VIX, like EPU, is a measure of economic uncertainty. In times of economic uncertainty, there is less demand for commodities. The authors note that the response of traders' returns and positions varies with the context, with the influence of the geopolitical risk (GPR) being more relevant in periods of high uncertainty, while EPU has a greater impact in periods of recession. In other words, the authors concluded that uncertainty has a significant impact on commodities markets, affecting returns and trader behavior differently depending on the source of uncertainty: geopolitical (GPR) or political (EPU).

Is because of the above evidence that, as referred in the introduction, in this study we seek to measure how important climate events and media attention affect commodity returns and volatility. By leveraging the media climate change concerns index (MCCC) as a proxy for climate sentiment, we explore how climate-related shocks affect commodities both as a collective group and within individual categories, namely, agricultural, energy, and metal commodities. The study employs different and separate approaches: first, by analyzing global common volatility (COVOL) to capture synchronized volatility shocks across all commodities; and second, by examining commodity common returns (obtained through a PCA). This dual approach allows us to assess whether climate-driven media sentiment impacts market behavior at a systemic level or in commodity-specific ways. Interaction terms between MCCC and key macroeconomic variables, are included to capture potential amplifying or mitigating effects.

3. Data

The data covers the period between 1st January 2009 and 31st December 2023. This data encompasses agricultural, metal, and energy commodities prices, index data (media climate change concerns index (MCCC), economic policy uncertainty index (EPU), S&P GSCI commodity total return index (GSCI), SPDR S&P 500 ETF (SPY), energy select sector SPDR fund (XLE), invesco DB agriculture fund (DBA), SPDR gold shares (GLD), iShares silver trust(SLV)), and macroeconomic control variables (3-month T-Bill yield (TBILL), Baa-Aaa credit spread (CRDSPRD), 2y10y term structure (TERM), CBOE volatility index (VIX)). The reason why only data from the past 14 years is included is because climate change concerns have become more important to the financial markets in recent years. This is reflected in some recent studies (Ahmed, Rizwan, et al. (2024); Allahdadi, Mohammad R., et al. (2024)), which show that discussions about this topic have increased in the last two decades.

Table 1

Dataset of commodities for building dependent variables in the study.

Type	Variable Name	Desc.[1]	Type	Frequency	Currency	From
Agriculture Commodities	**Corn**	Corn No.2 Yellow U$/Bushel	Price	Daily	USD	LSEG Workspace
	Soyabeans	Soybeans No.1 Yellow $/Bushel	Price	Daily	USD	LSEG Workspace
	Wheat	Wheat No.2 Soft Red U$/Bu	Price	Daily	USD	LSEG Workspace
	Cocoa	Cocoa-ICCO Daily Price US$/MT	Price	Daily	USD	LSEG Workspace
	Oats	Oats Mpls Term U$/BSH	Price	Daily	USD	LSEG Workspace
	Palm Oil	Palm Oil Crude MAL CIF Rdam US$/MT	Price	Daily	USD	LSEG Workspace
Metal Commodities	**Gold**	Gold Bullion LBM $/t oz DELAY	Price	Daily	USD	LSEG Workspace
	Silver	LBMA Silver Price USD/t oz DELAY	Price	Daily	USD	LSEG Workspace
Energy Commodities	**Crude Oil WTI**	Crude Oil-WTI Spot Cushing U$/BBL	Price	Daily	USD	LSEG Workspace
	Brent Oil	Crude Oil BFO M1 Europe FOB $/BBL	Price	Daily	USD	LSEG Workspace
	Natural Gas	EIA NAT GS NYMEX HH Spot PRC DLY PRD	Price	Daily	USD	LSEG Workspace
	Coal	Coal ICE API2 CIF ARA Nr Mth $/MT	Price	Daily	USD	LSEG Workspace
	Conventional Gasoline in NY	NY Conv GLN REG Spot Price FOB U$/GAL	Price	Daily	USD	LSEG Workspace
	Heating Oil	NY No. 2 HO Spot Price FOB U$/GAL	Price	Daily	USD	LSEG Workspace

[1] Description

These prices are daily, which will allow for an almost real-time analysis of volatility and returns in response to climate events. These prices are converted into commodities returns and excess returns. To deal with outliers that could potentially create problems in the estimation of volatilities, extreme returns are truncated at -10% and +10%. This truncation helps reduce the influence of extreme observations while preserving the integrity of the results.

To conduct this study, it was necessary to include other control variables to account for external factors that could also influence commodities returns and volatility during that period. We also include four more control variables related with each type of commodity.

As Laubsch, Joshua, et al. (2024), to control for commodities returns, it is necessary to include other control variables, different from the ones used in the common volatility equation.

Table 2

Dataset of explanatory variables used for constructing the common volatility and common returns regressions.

Variable Name	Desc.	Def. [2]	Form. [3]	Exp. [4]	Reg.[5]
S&P GCSI	S&P GSCI Commodity Total Return - RETURN IND. (OFCL)	Reflects the aggregate performance of commodities, and it is used as a broad measure of market shocks	-	Positive with commodity growth; negative during declines	Vol.[6]
SPDR S&P500	SPDR S&P 500 ETF TRUST (SPY)	Proxy to capture the risk perception and the economic conditions of the country	-	Positive in growth; negative in risk aversion	Vol.
DBA	DB Agriculture Fund	Control for specific shock in the agriculture sector	-	Positive with demand; negative with agriculture oversupply	Vol.
XLE	Energy Select Sector SPDR Fund	Control for energetic shocks	-	Positive with energy growth; negative during downturns	Vol.
GLD	SPDR Gold Shares	Control for Gold Shocks	-	Positive during uncertainty; negative with economic confidence	Vol.
SLV	iShares Silver Trust	Control for Silver Shocks	-	Positive industrial demand; negative with reduced risk appetite	Vol.
TBILL	3-month T-Bill Yield	Indicator of investor preference for low-risk assets during periods of heightened	-	Positive with confidence; negative during economic uncertainty	Ret.[7]

[2] Definition
[3] Formula
[4] Expectation
[5] Regression
[6] Volatility
[7] Returns

		economic uncertainty.			
TERM	Term Structure	Difference between 10-year yields and 2-year yields (in %). Good indicator of economic growth expectations.	$TERM_t = yield_{10y} - yield_{2y}$	Positive growth expectations; negative during economic stress.	Ret.
CRDSPRD	Baa-Aaa Credit Spread	Difference between the yield of Baa corporate bonds and the yield of Aaa corporate bonds (in %). Reflects the perceived riskiness of corporate debt and broader economic stability.	$CRDSPRD_t = yield_{Baa} - yield_{Aaa}$	Positive with risk; negative with economic stability.	Ret.
CBOE VIX	CBOE Volatility Index: VIX, Index, Daily, Not Seasonally Adjusted	Implicit volatility measure in the US stock market. Capture the risk aversion of investors during periods of economic uncertainty	-	Positive with volatility; negative during market stability.	Ret.
MCCC	Media Climate Change Concerns Index	Text-based index calculated by counting the number of expressions related to climate concerns	$\mathrm{MCCC}_t = h(1/S \sum_{s=1}^{S} \mathrm{concern}_{t,s}^{norm})$ $concern_{n,t,s} = 100 \frac{\omega_{n,t,s}^{risk}}{N_{n,t,s}} \left\{\left(\frac{\omega_{n,t,s}^{-} - \omega_{n,t,s}^{+}}{\omega_{n,t,s}^{-} + \omega_{n,t,s}^{+}} + 1\right)/2\right\}$ *Normalized by $\sigma_s \rightarrow concern_{t,s}^{norm} = concern_{t,s}^{norm}/\sigma_s$.	Positive with climate focus; negative with reduced coverage.	Vol. and ret.
EPU	Economic Policy Uncertainty Index	Index of uncertainty constructed using newspaper articles referring to economic and	-	Positive with uncertainty; negative during economic stability.	Ret.

		political uncertainties			

All the variables are in US dolars, variables S&P GCSI, SPDR S&P500, DBA, XLE, GLD, SLV were retrieved form LSEG workspace the remaining from FRED (Federal Reserve Economic Data), except MCCC, that was extracted from the Sentometrics Research website, all on a daily basis.

The data contains several dates where the value is recorded as #N/A. These dates have been removed. Since the data for commodities originated from a different source, the datasets were merged such that there are no missing values only included dates, i.e., ensure all variables have the same number of observations.

4. Methodology

As referred before, the aim of this study is to understand the influence of significant climate events and media coverage on common volatility of commodities (using COVOL) (Point 4.1.) and on common returns of commodities (Point 4.2.). The commodity-based COVOL captures the extent of synchronized volatility shocks across multiple commodities. It measures the magnitude of global risks that simultaneously affect our set of commodities, which can lead to increased uncertainty and higher potential losses for traders in commodity markets.

Understanding the impact of climate events on commodities is very complex due to the variability in climate conditions, the economy, and media coverage of climate-related news. These factors can vary significantly depending on the country and the type of commodity being analyzed. To address these challenges, the volatility regression includes the MCCC index, the GSCI index and the SPDR S&P500 index.

4.1. Projecting commodities common variance on the variance shocks to the media climate change concerns index

To reach the first final OLS equation we are going to follow four steps: initially, we will model the excess returns of each commodity using a factor model combined with a GARCH(1,1) approach to account for conditional heteroskedasticity. Next, we will extract the standardized residuals from these models and conduct tests to identify the presence of common volatility shocks across the commodities. Subsequently, we will estimate the common volatility factor through a multiplicative volatility decomposition method, ensuring that the factor captures the systemic volatility inherent in the market. Once the common volatility factor is obtained and centralized, we will regress it against the climate-related variance shocks, specifically the MCCC index, along with other relevant control variables.

This regression will allow us to quantify the impact of climate concerns on market volatility. Finally, the results from these regressions will be integrated into the final OLS equation, providing a comprehensive understanding of how climate-related news influences the volatility of commodities.

The four steps described above are going to be explained in detail below:

4.1.1. Modeling Excess Returns with Factor Models and GARCH(1,1)

In the first step, we used the prices of commodities to calculate the returns of each commodity in each day ($\tilde{r}_{i,t}$).

$$\tilde{r}_{i,t} = \log\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{1}$$

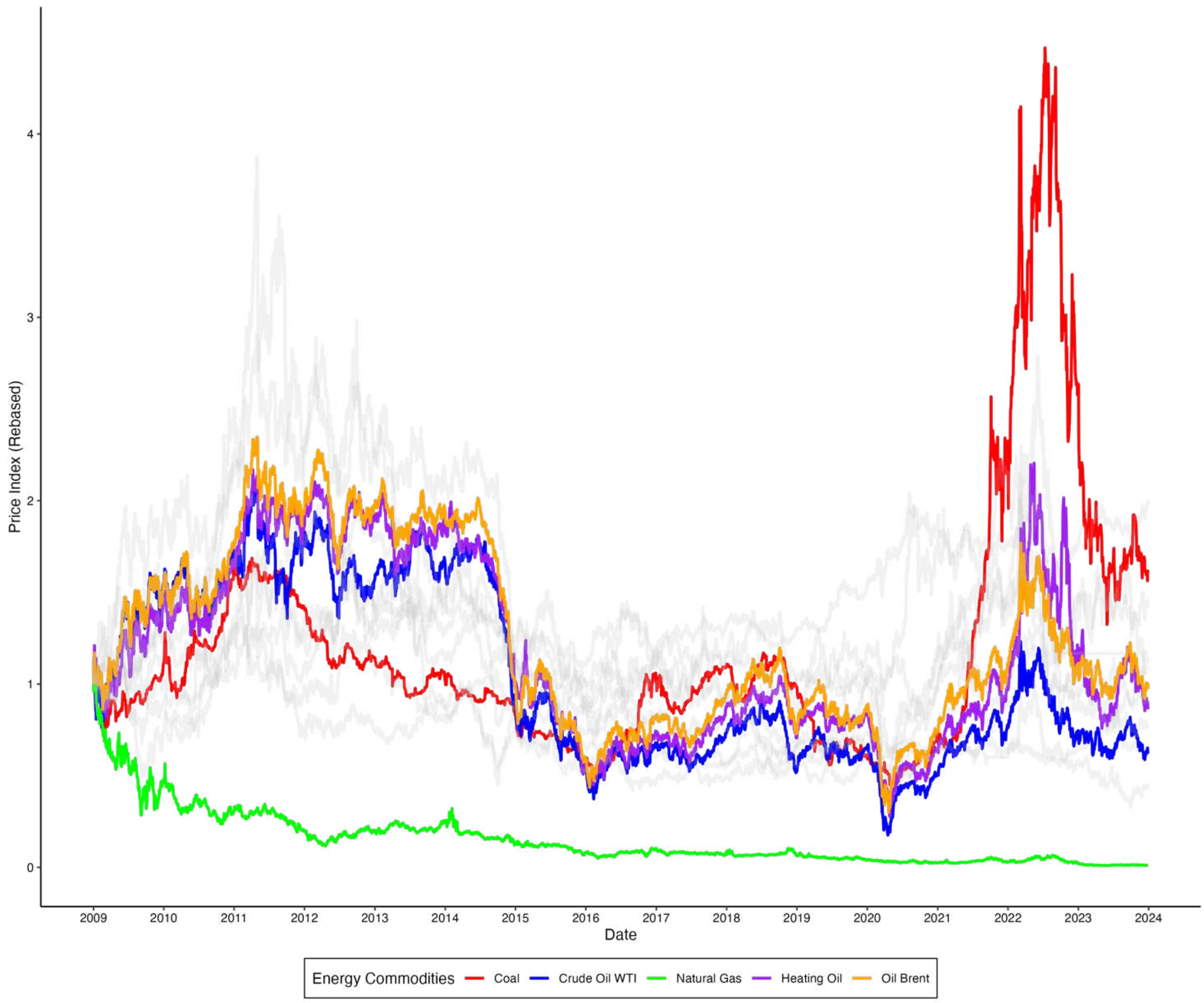

Fig.1. Commodity returns (Rebased to 100).

Since we want to model the excess returns of each commodity using a factor model combined with a GARCH(1,1) model, we need to calculate from the returns, the excess returns for each commodity in each day ($r_{i,t}$):

$$r_{i,t} = \tilde{r}_{i,t} - r_{f,t} \quad (2)$$

Where $r_{f,t}$ is the risk-free at time t (we use the 3-month T-Bill yield).

After that we reach our final factor model for excess returns, represented by the following (mean) equation:

$$r_{i,t} = c_i + \delta_i r_{i,t-1} + \beta_i{}' f_t + u_{i,t} \quad (3)$$

In this equation, c_i is the constant term for commodity δ_i is the AR (1) coefficient for commodity i, $\beta_i{}'$ the $p \times 1$ of factor loading of commodity i, and f_t the $p \times 1$ vector of risk factors at time t. The number of risk factors used in this regression are 4 (p = 4), the 3 factors from fama and French (Size (SMB), Book-to-Market value (HML) and the Market Excess Returns), lastly was included the excess returns of the S&P GSCI index.

We assume GARCH (1,1) errors, such that:

$$u_{i,t} = h_{i,t}^{1/2} e_{i,t} \tag{4}$$

$$h_{i,t} = \omega_i + \alpha_{i,t} u_{i,t-1}^2 + \beta_{i,,1} h_{i,t-1} \tag{5}$$

Where $h_{i,t}$ is the conditional variance of $u_{i,t}$ and ω_i, $\alpha_{i,t}$ and $\beta_{i,1}$ are the GARCH parameters for commodity i, with ω_i, $\alpha_{i,t} > 0$, $\beta_{i,1} \geq 0$ and $\alpha_{i,t} + \beta_{i,1} < 1$ and $e_{i,t}$ are the standardized residuals, with zero mean and unit variance. Where $e_{i,t}$ are the standardized residuals with zero mean and unit variance.

4.1.2. Extraction and Testing of Standardized Residuals

After estimating the factor model with the GARCH for each series of commodities excess returns, we get the standardized residuals $\hat{e}_{i,t}$. This residual will be used to identify possible co-movements through the analyses of the common volatility factor (COVOL).

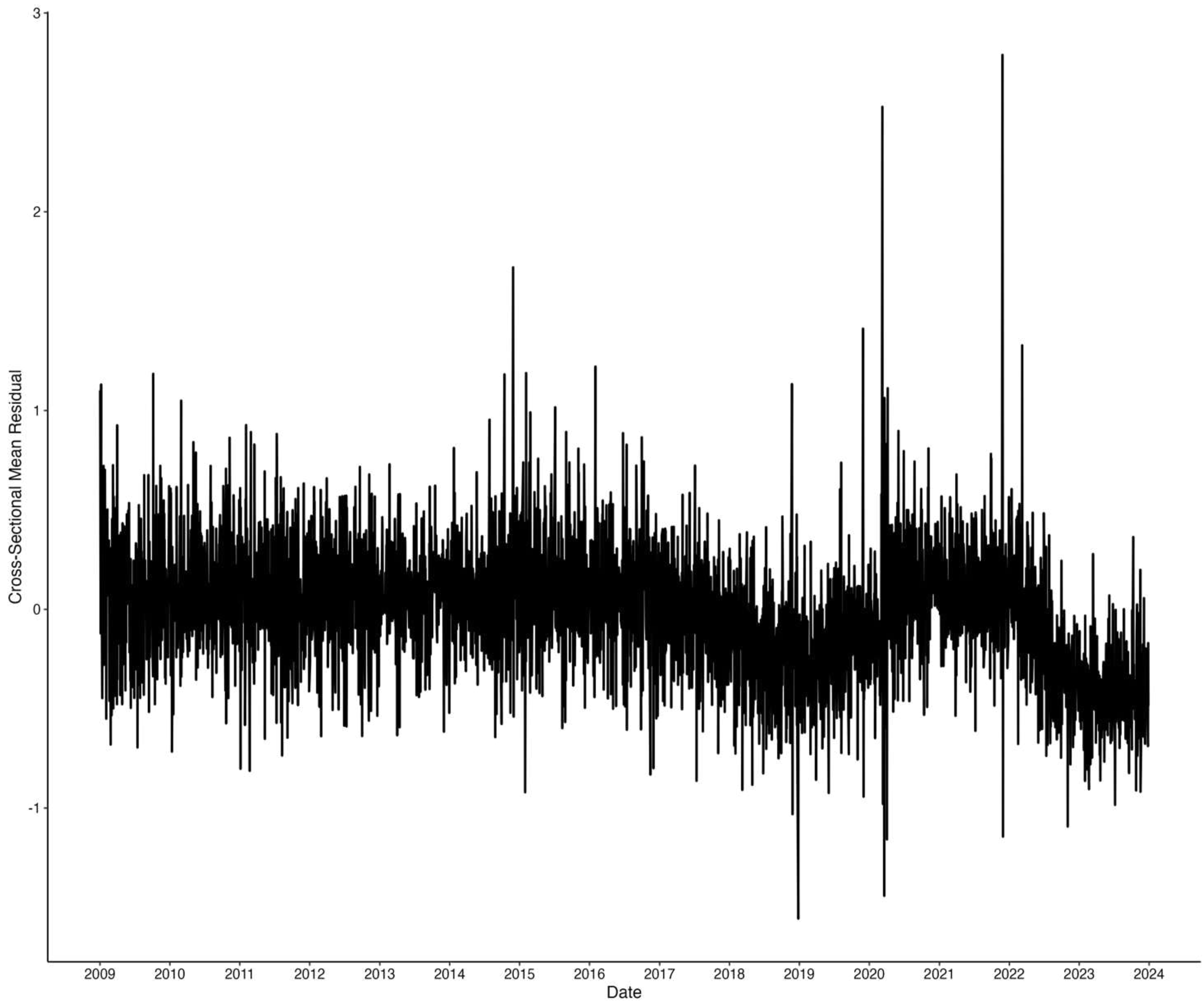

Fig.2. Cross-sectional mean of commodities residuals from the mean regressions.

4.1.3. Estimation of the Common Volatility Factor (COVOL)

Firstly, we need to define for all the variables, the variance shocks. Variance shocks are computed as the proportional difference between the squared idiosyncrasy and its expected value.

$$\phi_{i,t}^{\sigma} \equiv \frac{u_{i,t}^2 - h_{it}}{h_{it}} = e_{i,t}^2 - 1 \quad (6)$$

To capture the common volatility between different commodities the following multiplicative model was adopted:

The residual $e_{i,t}$ are assumed to have the following data generating process:

$$e_{i,t} = \sqrt{g(s_i, f_{comm,t}^{\sigma})} \times \epsilon_{it} \quad (7)$$

where

$$g\left(s_i, f^{\sigma}_{comm,t}\right) = s_i\left(f^{\sigma}_{comm,t} - 1\right) + 1 \tag{8}$$

Ensuring positivity for all t and $E\left[g\left(s_i, f^{\sigma}_{comm,t}\right)\right] = 1$,

where s_i is the factor loading for commodity i, the factor loading (s_i) are normalized, such that $\sum_{i=1}^{N} s_i^2 = 1$ to ensure identification, with $0 \leq s_i \leq 1$. $f^{\sigma}_{comm,t}$ is the global common volatility factor at time t, with $E\left[f^{\sigma}_{comm,t}\right] = 1$ and $f^{\sigma}_{comm,t} > 0$, and ϵ_{it} is an independent and identically distributed standard normal variable. Under these assumptions $E\left[e^2_{i,t}\right] = 1$ for every i, and $e^2_{i,t}$ presents positive correlation due to the cross-sectional dependence in $e_{i,t}$

Table 3
Estimated commodities common variance factor loadings.

Commodity	$\hat{s}_i$
Coal	0.4348
Corn	0.3410
Soyabeans	0.3356
Wheat	0.3229
Crude Oil WTI	0.3137
Conventional Gasoline in NY	0.2926
Oil Brent	0.2886
Heating Oil	0.2625
Silver	0.2431
Palm Oil	0.1678
Gold	0.1653
Oats	0.1254
Cocoa	0.0849
Natural Gas	0.0631

To validate the presence of common volatility shocks across commodities, we apply the GeoVol Test. This test examines equicorrelation among the squared standardized residuals ($e^2_{i,t}$, derived from the previous step).

After this the correlation ρ_{e^2} tests on the residuals are performed to confirm if there are correlation between $e_{i,t}$ and $e_{j,t}$. If we reject that $\rho_{e^2} = 0$ (Null Hypothesis) (no equicorrelation among squared standardized residuals), there is evidence that there is common volatility, which leads to the estimation of the global common volatility factor using multiplicative volatility composition method. The GeoVol Test (ξ_{e^2}) assesses whether there is significant cross-sectional dependence in the squared residuals, which would indicate the existence of common volatility shocks. It is based on the covariance matrix of squared standardized residuals to formally test for the presence of common volatility shocks.

To test for the presence of common variance shocks, we use the covariance matrix of squared residuals, $\sum_{e^2}$. The off-diagonal elements of this matrix represent the covariances between the squared residuals of different commodities. Since there are N commodities, the total number of unique pairwise covariances is $\frac{N(N-1)}{2}$. This comes from the fact that a symmetric $N \times N$ matrix has $N(N-1)$ off-diagonal elements, and we count each pair only once.

The test statistic (ξ_{e^2}) leverages these $\frac{N(N-1)}{2}$ pairwise covariances to evaluate whether the residuals exhibit significant cross-sectional dependence, as follows:

$$\xi_{e^2} = \frac{\sqrt{\frac{NT}{(N-1)/2}} \sum_{i>j,j=1}^{N} \sum_{t=1}^{T} (e_{it}^2 - 1)(e_{jt}^2 - 1)}{\sum_{i=1}^{N} \sum_{t=1}^{T} (e_{it}^2 - 1)^2} \tag{9}$$

The likelihood function is defined as:

$$L(s_i, f_{comm}^{\sigma}; e) = -\frac{1}{2} \sum_{i=1}^{N} \sum_{t=1}^{T} \{\log g(s_i, f_{comm,t}^{\sigma}) + g(s_i, f_{comm,t}^{\sigma})\} \tag{10}$$

We estimate s_i and $f_{comm,t}^{\sigma}$ alternately using maximum likelihood. Cross-sectional regression estimates $f_{comm,t}^{\sigma}$ based on the factor loadings, and time-series regression estimates s_i using the latent volatility factor.

Give two heteroscedasticity relationships:

$$\text{Cross-Section: } e_{i,t} = \epsilon_{i,t} \sqrt{\hat{s}_i \left(f_{comm,t}^{\sigma} - 1\right) + 1} \text{ for } t = 1, \ldots, T \tag{11}$$

$$\text{Time-Series: } e_{i,t} = \epsilon_{i,t} \sqrt{s_i \left(\hat{f}_{comm,t}^{\sigma} - 1\right) + 1} \text{ for } i = 1, \ldots, N \tag{12}$$

The cross-sectional regression facilitates the estimation of the latent factor $f_{comm,t}^{\sigma}$, for $t = 1, \ldots, T$, often beginning with the loadings on the first principal component of the squared standardized residuals as initial estimates. It's worth noting that the choice of these initial values does not seem to significantly affect the robustness of the estimation process. Subsequently, the time-series regression generates estimates for s_i, where $i = 1, \ldots, N$, conditioned on the estimated latent factor. This iterative procedure alternates between estimating s_i based on the current values of $\hat{f}^{\sigma}_{comm,t}$ and refining $\hat{f}^{\sigma}_{comm,t}$ using the updated $\hat{s}_i$ values. By repeating this process until convergence, both estimations satisfy their respective first-order conditions, leading to a joint maximization of the likelihood function.

By maximum likelihood, alternating the "cross-sectional" and "time-series" estimates until they converge, ensuring both first-order conditions are satisfied, and a joint maximum is achieved.

For the sample in study, for all commodities, the equicorrelation is estimated as $\rho_{e^2} = 0.0522$, with a test statistic of $\xi_{e^2} = 29.19$ and a p-value of 0. Specifically, for metals, the estimated equicorrelation is $\rho_{e^2} = 0.3214$, with a test statistic of $\xi_{e^2} = 19.25$ and a p-value of 0. For energy, the estimated equicorrelation is $\rho_{e^2} = 0.0767$, with a test statistic of $\xi_{e^2} = 17.19$ and a p-value of 0. For agriculture, the estimated equicorrelation is $\rho_{e^2} = 0.0699$, with a test statistic of $\xi_{e^2} = 17.53$ and a p-value of 0. Based on those results, we conclude that for all commodities and for the individual regressions of metals, energy, and agriculture, the results confirm the presence of common covolatility shocks. That is, the null hypothesis of the absence of common covolatility shocks is strongly rejected. This justifies the estimation of the global common variance for the commodities analyzed. The estimation was carried out using the geovol package in the R.

Finally, we obtain $\hat{f}^{\sigma}_{comm,t}$, where $\hat{f}^{\sigma}_{comm,t}$ is the estimated global common volatility factor, which represents the estimated global common volatility factor for the commodities at time t. And we will perform a centralization to interpret them as deviations from the mean:

$$\tilde{f}^{\sigma}_{comm,t} = \hat{f}^{\sigma}_{comm,t} - 1 \quad (13)$$

$\tilde{f}^{\sigma}_{comm,t}$ will be our dependent variable in the volatility regression. It represents centered global common volatility factor. By subtracting 1, $\tilde{f}^{\sigma}_{comm,t}$ has mean zero. This allows us to interpret the factor as deviations from the average global common volatility, making it easier to assess the influence of explanatory variables like climate change news.

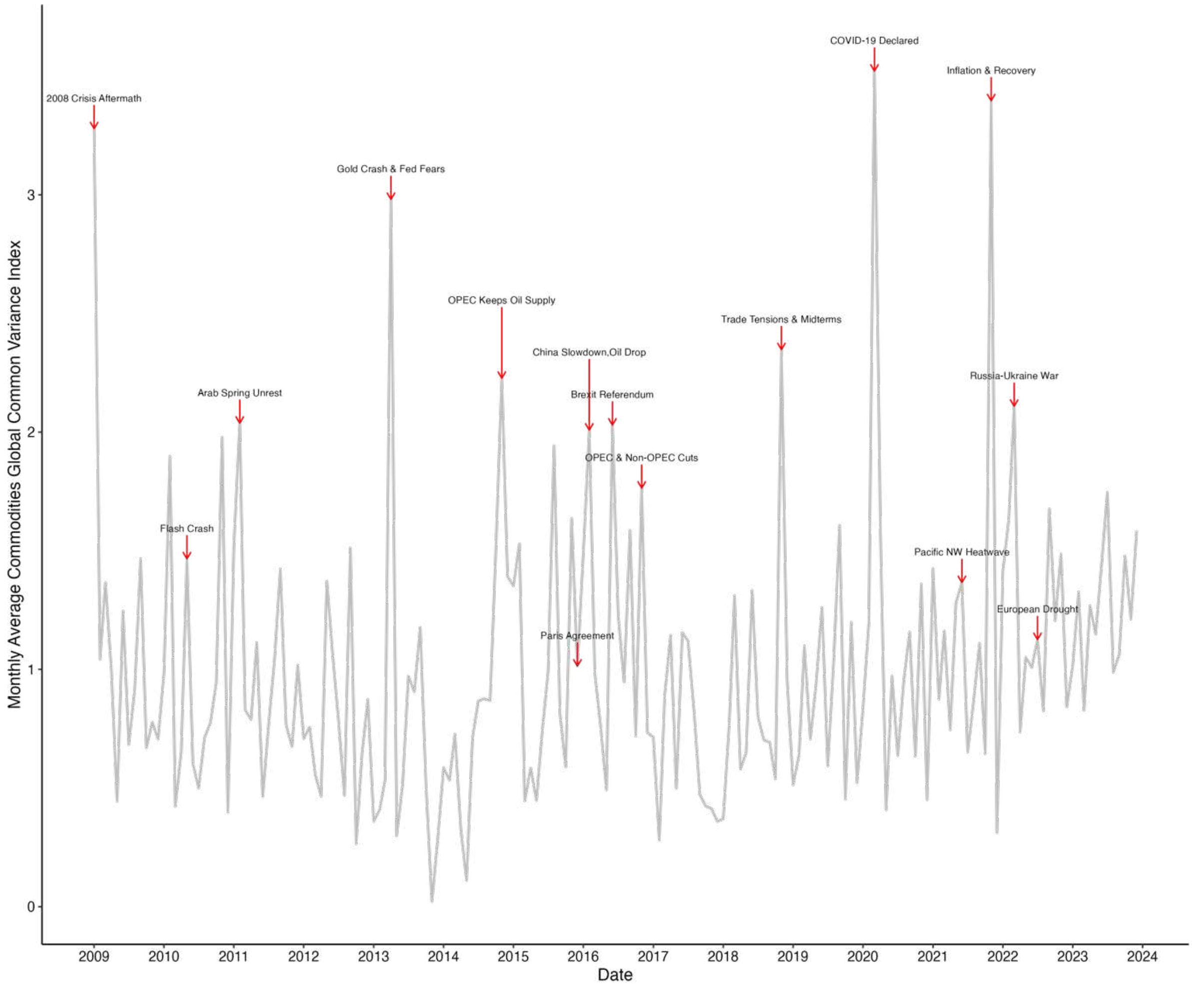

Fig. 3. The monthly average commodities global common variance index.

4.1.4. Volatility Regression (COVOL) as a Function of Climate and Financial Shocks

In the final step for this point of the methodology, we will analyze how the variance shocks of certain independent variables affect the common volatility of different types of commodities (first analyzing common volatility shocks across all commodities, and then within individual types of commodities).

$$\tilde{f}^{\sigma}_{comm,t} = \alpha\phi^{\sigma}_{MCCC,t} + \beta_1{}'x^{\sigma}_t + \beta_2{}'\{x^{\sigma}_t \times \phi^{\sigma}_{MCCC,t}\} + \delta i\tilde{f}^{\sigma}_{comm,t-1} + \upsilon_t \quad (14)$$

υ_t is the error of the equation and it is distributed with zero mean and constant variance, x^{σ}_t is the set of control variables (SPDR S&P 500, S&P GSCI Index, XLE, DBA, GLD and SLV) and $x^{\sigma}_t \times \phi^{\sigma}_{MCCC,t}$ represents the interaction terms between the control variables and the climate variable. The interaction terms allow to capture potential amplifying or mitigating effects. The independent variables to be used are the MCCC, the SPDR S&P 500 exchange-traded fund

(SPY), and the GSCI Index, as well as specific control variables to account for shocks occurring in the different types of commodities, namely XLE, DBA, GLD, and SLV. Given that MCCC, by default, is not a stationary variable, we computed its first-difference as the difference between MCCC today and MCCC yesterday.

For the variance shocks to the SPDR S&P 500 exchange traded fund (SPY) ($\phi^{\sigma}_{SPY,t}$), an increase in the value of this variable indicates an increase in systemic risk and, therefore, an increase in uncertainty. This may make investors more risk-averse and, consequently, bring greater volatility to the commodities market. On the other hand, for the variance shocks to the S&P GSCI commodity total return ($\phi^{\sigma}_{\text{GSCI},t}$), an increase in its value signifies greater stability in investors' expectations of commodity prices.

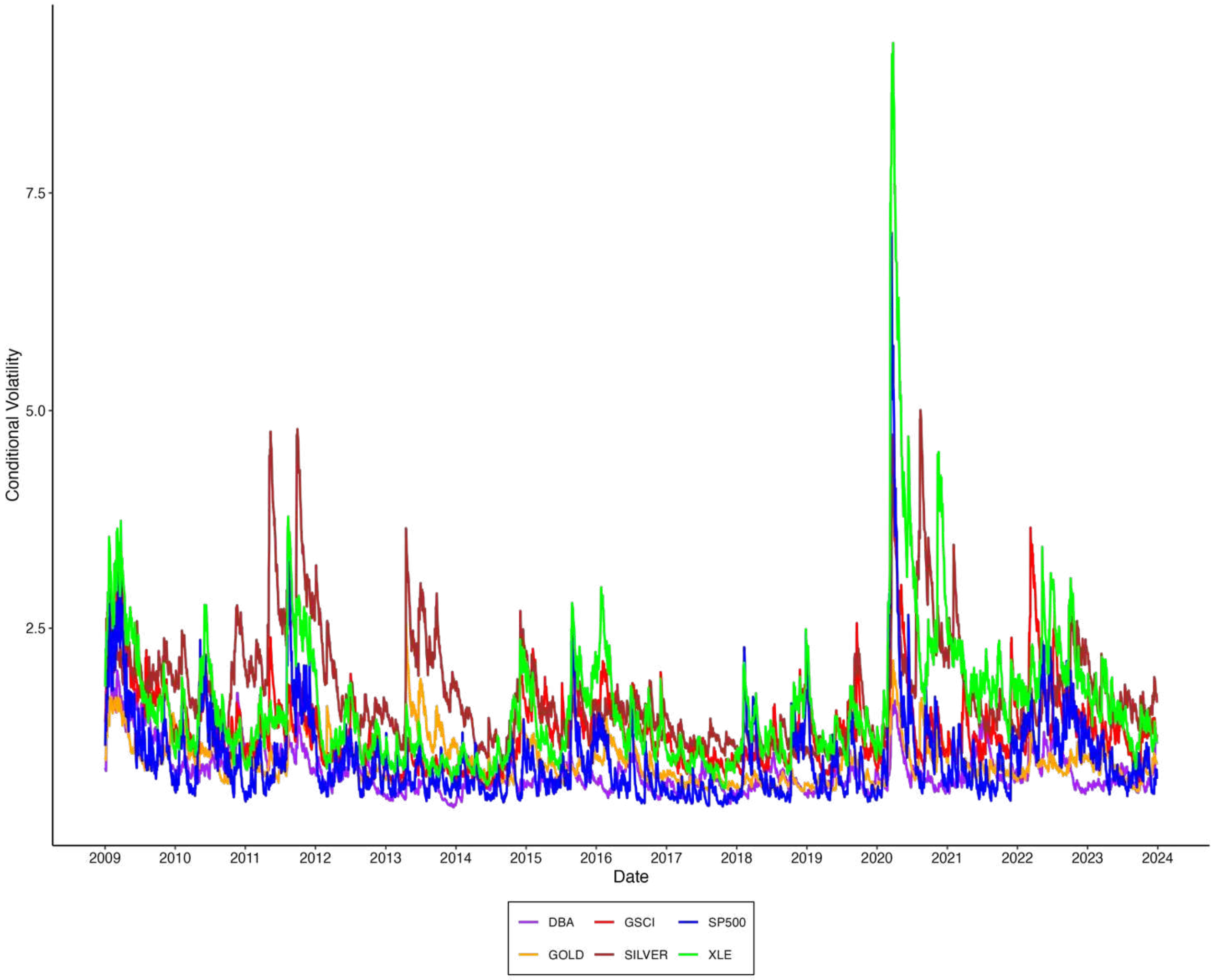

Fig. 4. Volatility of the GSCI index, of the SPDR S&P500 index, DBA, XLE, GLD and SLV.

With this model, it is possible to understand how volatility shocks to different independent variables affect commodities volatility both in general and within different groups of commodities, especially during extreme climate events. The combination of an index like MCCC, related to climate news, and other financial asset prices allows us to capture the amplifying and mitigation effects of the news.

The results obtained from this equation will provide a consistent, methodical evaluation of the global risks associated with climate change as perceived by the public, international investors, and policymakers. The constant was not included in this equation because $\tilde{f}^{\sigma}_{comm,t}$ is obtained as $\tilde{f}^{\sigma}_{comm,t} = \hat{f}^{\sigma}_{comm,t} - 1$, where $\hat{f}^{\sigma}_{comm,t}$ is the estimated global common volatility factor, which represents the estimated global common volatility factor.

This analysis further identifies notable historical events, such as the 2008 Crisis, Arab Spring, OPEC decisions, the COVID-19 pandemic, and the Russia-Ukraine war (see Fig.3.), as key drivers of spikes in the global common volatility factor (COVOL). These events underline the model's capacity to capture systemic shocks stemming from geopolitical, economic, and climate-related disruptions, offering a contextual understanding of the quantitative results.

4.2. Projecting commodities common returns on the media climate change concerns index

The returns regression will analyze the relationship between the common returns of different commodities and the independent variables, specifically the MCCC Index and the EPU. More precisely, we will examine how the common returns are influenced by the MCCC and the other control variables, such as the EPU, as well as variables more closely related to the economy, including the 3-month T-Bill yield, Baa-Aaa credit spread, 2y10y term structure, and CBOE volatility index.

Additionally, the following control variables will be included as independent variables: the 3-month T-Bill yield (TBILL), Baa-Aaa credit spread (CRDSPRD), 2y10y term structure (TERM), S&P500 index dividend yield (DIVYLD), and CBOE volatility index (VIX). These external factors, along with the MCCC, must be controlled for to reduce potential distortions in the analysis of commodities returns.

The common returns analysis is divided in 3 main steps.

4.2.1. Principal Component Analysis (PCA)

In the first step, is made a principal component analysis (PCA) which will allow to study the aggregate behavior of commodity returns through this common factor obtained in the PCA.

Principal Component Analysis (PCA) is a statistical method that reduces the dimensionality of a dataset by transforming correlated variables into a smaller set of uncorrelated variables called principal components. The first component captures the maximum variance in the data, with subsequent components capturing progressively less variance. PCA simplifies complex datasets, making them easier to analyze while retaining most of the original information. It is commonly used for summarization, pattern recognition, and noise reduction in large datasets. Liang, Chao, et al. (2020) used the PCA method in its commodities study.

This is applied to the commodity returns ($\tilde{r}_{i,t}$) dataset to extract the common return factor ($r_{comm,t}^{PCA}$). This approach reduces dimensionality and identifies the dominant factor driving the returns, which simplifies the analysis and allows us to focus on a single representative variable. This is done to assess how the MCCC explains the returns of multiple commodities simultaneously. By including all commodities in the same regression framework, this approach captures the shared influences of media climate change concerns across different markets.

4.2.2. Common Returns Factor

From the first step, we obtain $\hat{r}_{comm,t}^{PCA}$, where $\hat{r}_{comm,t}^{PCA}$ is the estimated global common returns factor, which represents the estimated global common returns factor for the commodities at time t.

Different from the common volatility regression $\hat{r}_{comm,t}^{PCA}$ does not need to be transformed, given that it already represents centered global common returns factor. That is, $\hat{r}_{comm,t}^{PCA}$ has already mean zero. This allows us to interpret the factor as deviations from the average global common returns, making it easier to assess the influence of explanatory variables like climate change news.

4.2.3. Regression Analysis

The last step, is testing the OLS regression. The OLS regression model is specified as follows:

$$r_{comm,t}^{PCA} = \gamma_1 MCCC_t + \gamma_2 \log(EPU_t) + \gamma_3 r_{comm,t-1}^{PCA} + \sum \rho_m \psi_t + \varepsilon_t \qquad (15)$$

This regression accounts for heteroskedasticity using robust standard errors, ensuring the reliability of results.

As in Laubsch, Joshua, et al. (2024), in the return's equation, the natural logarithm of the EPU Index will be used instead of the EPU Index directly. This transformation allows for better capturing non-linear effects and percentage changes in policy uncertainty. It helps not only to stabilize the variance of the data but also to improve the model's robustness in dealing with fluctuations in policy uncertainty over time.

Lagged returns $r^{PCA}_{comm,t-1}$ are introduced to account for the possibility of serial correlation. Additionally, ψ_t represents the set of control variables (TBILL, CRDSPRD, TERM, and VIX).

In sum, commodity common returns models will be analyzed while controlling for lagged common returns and the set of control variables.

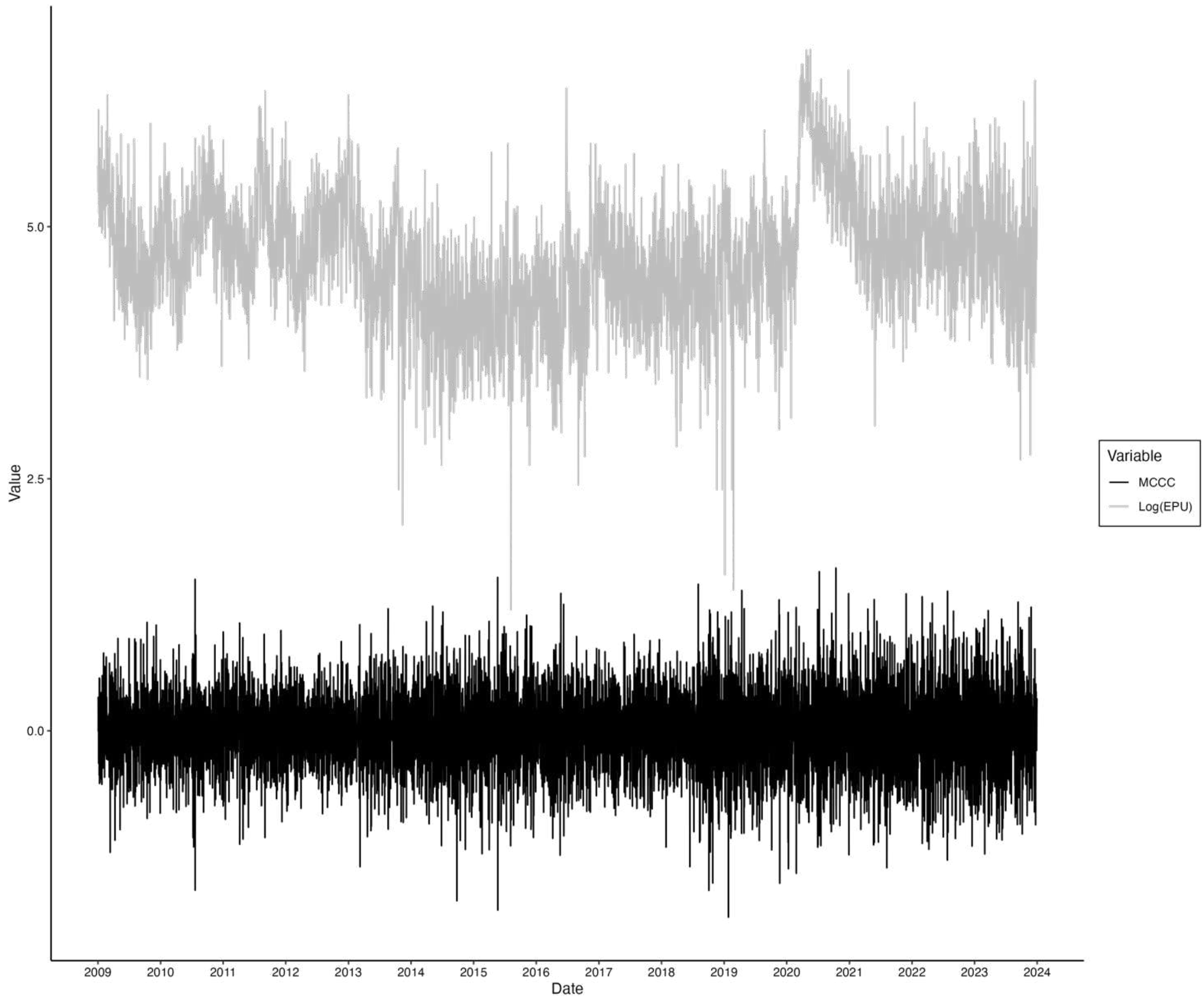

Fig. 5. Media climate change concerns index (MCCC) and logarithmic of economic policy uncertainty index (EPU).

Note: Point 1 and point 2, that is, both regressions of common volatility and common returns, will be applied to all commodities. Furthermore, the same dependent variables will be used to conduct additional regressions that will analyze each type of commodity individually. The difference will be in the explanatory variables for the control variables in the common volatility regression only, will instead of using XLE, DBA, GLD and SLV, will be used only the one's applied to the specific type of commodity (for energy, XLE; for agriculture, DBA; and for precious metals, GLD and SLV). This approach will examine how all these independent variables, particularly the MCCC, affect not only the entire set of commodities but also each commodity type individually. The goal is to determine which type of commodity is more influenced by the MCCC Index.

5. Results

5.1. Projecting commodities common variance on the variance shocks to the MCCC

Table 4

Projecting the commodities common variance ($\tilde{f}^{\sigma}_{comm,t}$) on the variance shocks to the media climate change concerns ($\phi^{\sigma}_{MCCC,t}$).

	$\tilde{f}^{\sigma}_{comm,t}$				
	(1)	(2)	(3)	(4)	(5)
$\phi^{\sigma}_{MCCC,t}$	0.023	0.022	0.028	0.022	0.030
	(0.020)	(0.018)	(0.019)	(0.018)	(0.019)
$\phi^{\sigma}_{GSCI,t}$		0.348***		0.350***	
		(0.014)		(0.014)	
$\phi^{\sigma}_{SPY,t}$		0.061***	0.030*	0.055***	0.024
		(0.016)	(0.018)	(0.016)	(0.018)
$\phi^{\sigma}_{DBA,t}$			0.163***		0.164***
			(0.018)		(0.018)
$\phi^{\sigma}_{XLE,t}$			0.168***		0.166***
			(0.018)		(0.018)
$\phi^{\sigma}_{GLD,t}$			0.069***		0.069***
			(0.019)		(0.020)

$\phi^{\sigma}_{SLV,t}$			0.074^{***}		0.069^{***}
			(0.019)		(0.019)
$\tilde{f}^{\sigma}_{comm,t-1}$	0.130^{***}	0.101^{***}	0.108^{***}	0.101^{***}	0.108^{***}
	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)
$\phi^{\sigma}_{MCCC,t} \times \phi^{\sigma}_{GSCI,t}$				-0.012	
				(0.007)	
$\phi^{\sigma}_{MCCC,t} \times \phi^{\sigma}_{SPY,t}$				-0.015	-0.031^{**}
				(0.012)	(0.014)
$\phi^{\sigma}_{MCCC,t} \times \phi^{\sigma}_{DBA,t}$					0.004
					(0.012)
$\phi^{\sigma}_{MCCC,t} \times \phi^{\sigma}_{XLE,t}$					0.037^{***}
					(0.013)
$\phi^{\sigma}_{MCCC,t} \times \phi^{\sigma}_{GLD,t}$					-0.002
					(0.017)
$\phi^{\sigma}_{MCCC,t} \times \phi^{\sigma}_{SLV,t}$					-0.025^{*}
					(0.013)
Obs.	3,584	3,584	3,584	3,584	3,584
Adj. R^2	0.017	0.181	0.120	0.181	0.123
σ^2	1.965	1.794	1.859	1.794	1.857
F Stat.	32.151^{***}	198.800^{***}	70.895^{***}	133.405^{***}	42.761^{***}
Note:					$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

In Table 4, we start analyzing the simplest regression possible in column (1), and we conclude that variance shocks to the MCCC index are not significant i.e., $\hat{\alpha} = 0.023$ (but not statistically different from zero). Despite this, we see that in column (2) all the control variables included in that regression influence commodities prices globally. The statistically significant positive coefficients $(\beta_{\phi^{\sigma}_{GSCI}}, \beta_{\phi^{\sigma}_{SPY}}) = (0.348, 0.061)$ shown in column (2) of Table 4 mean that variance shocks to commodities prices or the US global equity market are likely to affect the volatilities of commodities around the world, at the same time.

Table 4 demonstrates that the global common variance for commodities ($\tilde{f}^{\sigma}_{comm,t}$) exhibits persistent effects, as shown by the significant coefficients of its lag term ($\tilde{f}^{\sigma}_{comm,t-1}$). These patterns suggest that variance shocks tend to propagate over time, often intensifying during periods of economic uncertainty, such as recessions, when global consumption declines. Furthermore, the interaction between the media climate change concerns index (ϕ^{σ}_{MCCC}) and the SPDR S&P 500 index (ϕ^{σ}_{SPY}) is negative, but not significant in column (4), indicating that media-driven climate concerns dampen variance shocks in financial markets when broader equity market volatility rises. Conversely, in column (4) the interaction with the commodity total return index ($\phi^{\sigma}_{MCCC} \times \phi^{\sigma}_{GSCI}$) shows no significant effect, suggesting that commodity variances may respond more strongly to macroeconomic uncertainty than sector-specific volatility.

For that reason, variance shocks, such as those measured by (ϕ^{σ}_{GSCI}) (representing variance shocks to the S&P GSCI Index, a proxy for the global commodity market) and (ϕ^{σ}_{SPY}) (representing variance shocks to the S&P 500 Index, a proxy for the broader U.S. equity market), tend to drive unexpected changes in commodity prices. These shocks often stem from shifts in demand or supply conditions. Additionally, the U.S. markets significantly influence the global common variance of commodities. For instance, during periods of heightened economic uncertainty in the U.S., reflected in higher ϕ^{σ}_{SPY}, there is typically increased demand for commodities as safe-haven assets. As volatility rises and variance shocks are amplified during economic crises (when production declines), the global common variance for all commodities ($\tilde{f}^{\sigma}_{comm,t}$) tends to behave countercyclically. This phenomenon, also highlighted by Engle, Robert F., and Susana Campos-Martins. (2023), underscores the relationship between global macroeconomic conditions and commodity markets.

To control for volatility shocks coming from agriculture, energy and metal commodities in the US, the variance shocks for those three types of commodities in the GSCI fund will be denoted as $\phi^{\sigma}_{DBA,t}$, $\phi^{\sigma}_{XLE,t}$, $\phi^{\sigma}_{GLD,t}$, $\phi^{\sigma}_{SLV,t}$, respectively, substituting the $\phi^{\sigma}_{GSCI,t}$ in column (5) of Table 4, when compared to column (4). The results about climate change driving common variance in commodities remaining insignificant, controlling for shocks coming from agriculture, energy and metal commodities traded in US. This suggests that, in addition to specific factors affecting the three types of commodities, other globally relevant volatility variables play a significant role in determining the common variance for all commodities.

Interaction terms between the climate change variance shocks and each of the other two control variables are included to account for amplifying and moderating effects of climate change concerns. As we've seen the interaction terms between $\phi^{\sigma}_{MCCC,t}$ and $\phi^{\sigma}_{GSCI,t}$ and between $\phi^{\sigma}_{MCCC,t}$ and $\phi^{\sigma}_{SPY,t}$, presented in column (4), were not statistically significant. If we substitute the control variable $\phi^{\sigma}_{GSCI,t}$ by $\phi^{\sigma}_{DBA,t}$, $\phi^{\sigma}_{XLE,t}$, $\phi^{\sigma}_{GLD,t}$, $\phi^{\sigma}_{SLV,t}$ and the interaction term in column (5), then energy sector investors appear to be more concerned about climate change risk during periods of volatility in the US energy market ($\hat{\beta}_{2_{\phi^{\sigma}_{MCCC,t} \times \phi^{\sigma}_{XLE,t}}} = 0.037$). Shocks to the energy sector are amplified by concerns about climate change. Silver investors also looked concerned about climate change, but it is not so intense as in the energy sector, being $\hat{\beta}_{2_{\phi^{\sigma}_{MCCC,t} \times \phi^{\sigma}_{SLV,t}}} = -0.025$, significant at only 10% significance level. Also in column (5) of Table 4, with $\hat{\beta}_{2_{\phi^{\sigma}_{MCCC,t} \times \phi^{\sigma}_{SPY,t}}} = -\,0.031$ (significant at the 5% level), US stock market shocks (ϕ^{σ}_{SPY}) and volatility shocks to the drive price appear to be attenuated by climate concerns (as investors give more importance to these over climate change).

Table 5
Projecting the energy commodities common variance ($\tilde{f}^{\sigma}_{comm,t}$) on the variance shocks to the media climate change concerns index ($\phi^{\sigma}_{MCCC,t}$).

	$\tilde{f}^{\sigma}_{comm,t}$				
	(1)	(2)	(3)	(4)	(5)
$\phi^{\sigma}_{MCCC,t}$	0.040*	0.038*	0.043*	0.041*	0.040*
	(0.023)	(0.021)	(0.022)	(0.022)	(0.023)
$\phi^{\sigma}_{GSCI,t}$		0.347***		0.351***	
		(0.017)		(0.017)	
$\phi^{\sigma}_{SPY,t}$		0.041**	0.042**	0.033*	0.033
		(0.018)	(0.021)	(0.019)	(0.022)
$\phi^{\sigma}_{XLE,t}$			0.191***		0.192***
			(0.021)		(0.021)
$\tilde{f}^{\sigma}_{comm,t-1}$	0.093***	0.079***	0.088***	0.078***	0.088***
	(0.017)	(0.016)	(0.016)	(0.016)	(0.016)
$\phi^{\sigma}_{MCCC,t} \times \phi^{\sigma}_{GSCI,t}$				-0.031***	
				(0.009)	
$\phi^{\sigma}_{MCCC,t} \times \phi^{\sigma}_{SPY,t}$				-0.012	-0.026
				(0.014)	(0.016)
$\phi^{\sigma}_{MCCC,t} \times \phi^{\sigma}_{XLE,t}$					0.006
					(0.014)
Obs.	3,581	3,581	3,581	3,581	3,581
Adj. R^2	0.009	0.128	0.042	0.131	0.043
σ^2	2.253	2.113	2.214	2.109	2.214
F Stat.	17.193***	132.572***	40.706***	90.976***	27.573***

Note: *p<0.1; **p<0.05; ***p<0.01

Because we are considering a wide range of commodity types, the same regressions were computed for each individual type of commodities, and instead of substituting the $\phi^{\sigma}_{GSCI,t}$ by the variance shocks of $\phi^{\sigma}_{DBA,t}$, $\phi^{\sigma}_{XLE,t}$, $\phi^{\sigma}_{GOLD,t}$, $\phi^{\sigma}_{SILVER,t}$, substitutions were made as follows: for agriculture commodities only $\phi^{\sigma}_{DBA,t}$, was used, for energy commodities only $\phi^{\sigma}_{XLE,t}$, and for precious metals, both, $\phi^{\sigma}_{GOLD,t}$ and $\phi^{\sigma}_{SILVER,t}$. These substitutions were made to account for commodity specific shocks.

From these three equations, only in the energy commodities regression $\phi^{\sigma}_{MCCC,t}$ is positive and statistically significant $\hat{\alpha} = 0.040$ at the 10% significance level. This indicates that the non-significant effects of $\phi^{\sigma}_{MCCC,t}$ on agricultural and metal commodities cancel out their significance for energy commodities. This explains why, when all commodities are analyzed together, $\phi^{\sigma}_{MCCC,t}$ is not significant for the global common volatility of all commodities. This provides an important result regarding the impact of physical and transition climate risks.

Physical climate risks are likely to affect agricultural commodities. But evidence is mixed as to whether these risks are already being priced, at least at the global level. Evidence on transition risk being priced is much less controversial, where many studies show that the energy transition is already impacting financial markets globally, most notably, energy markets.

When the interaction term $\hat{\beta}_{2,\phi^{\sigma}_{MCCC,t}\times\phi^{\sigma}_{SPY,t}} = -0.026$ is included in column (5) of Table 5, it is no longer significant (unlike in column (5) of Table 4, where it was significant at 5% significance level). The interaction term $\hat{\beta}_{2,\phi^{\sigma}_{MCCC,t}\times\phi^{\sigma}_{GSCI,t}} = -0.031$ (in column (4) of Table 4) is now significant at the 1% level (which is different from column (4) of Table 4, where it was not significant). Finally, XLE shocks are amplified by climate concerns.

Table 6
Projecting commodities common variance ($\tilde{f}^{\sigma}_{comm,t}$) on the variance shocks to the media climate change concerns index ($\phi^{\sigma}_{MCCC,t}$), before and after the Paris Agreement.

	$\tilde{f}^{\sigma}_{comm,t}$	
	Before Paris	After Paris
	(1)	(2)
$\phi^{\sigma}_{MCCC,t}$	-0.001	0.044*
	(0.030)	(0.024)
$\tilde{f}^{\sigma}_{comm,t-1}$	0.150***	0.103***
	(0.033)	(0.025)
Obs.	1,660	1,921
Adj. R^2	0.022	0.011
σ^2	1.851	2.034
F Stat.	19.583***	11.564***
Note:		*p<0.1; **p<0.05; ***p<0.01

The analysis covers the period between the beginning of 2009 and the end of 2023, which includes the Paris Agreement. It is important to understand whether MCCC becomes more significant to the global common volatility of commodities, after the agreement or if it had no notable impact.

The Paris Agreement was adopted on December 12th, 2015, as an international accord aimed at combating climate change by bringing together nearly every country to limit global warming to well below 2 degrees Celsius above pre-industrial levels, with an ambitious target of 1.5 degrees. Essentially, it fosters global cooperation by establishing legally binding commitments to reduce greenhouse gas emissions and encouraging transparency through consistent reporting.

Thus, it ensures effective global cooperation to protect the planet for present and future generations.

To analyze this, in Table 6, columns (1) and (2), we investigate the effects of $\phi^{\sigma}_{MCCC,t}$ on $\tilde{f}^{\sigma}_{comm,t}$ for all commodities, separately for the periods before and after December 12th, 2015. The model before December 12th, 2015 is called "Model Before Paris" (MBP), and the one after December 12th, 2015, is called "Model After Paris" (MAP). The results show that $\phi^{\sigma}_{MCCC,t}$ before that date is negative and not statistically significant ($\hat{\alpha}_{MBP} = -0.001$), whereas in the "Model After Paris," the variance shock of MCCC is positive and significant ($\hat{\alpha}_{MAP} = 0.044$), at the 10% level. This indicates that, in the nearly eight years following the Paris Agreement, the impact of MCCC, in all commodities, became significant and its effect changed, showing that the agreement has influenced the way climate extreme events effectively impact the global common volatility of all commodities.

Having looked at the volatility model, we now move to analyzing how common returns on commodities are affected by the MCCC index.

5.2. Projecting commodities common returns on the MCCC

Table 7
Projecting commodities common returns ($\hat{r}^{PCA}_{comm,t}$) on the first-difference of media climate change concerns index ($\Delta MCCC$).

	$\hat{r}^{PCA}_{comm,t}$			
	(1)	(2)	(3)	(4)
$\Delta MCCC$	-0.042		-0.042	-0.041
	(0.074)		(0.074)	(0.070)
$log(EPU)$		0.146^{***}	0.146^{***}	0.098^{**}
		(0.052)	(0.052)	(0.049)
$\Delta CRDSPRD$				0.431
				(1.190)
$\Delta TBILL$				2.754^{**}
				(1.186)
$\Delta TERM$				5.925^{***}
				(0.738)
ΔVIX				-0.280^{***}
				(0.016)
$\hat{r}^{PCA}_{comm,t-1}$	0.084^{***}	0.082^{***}	0.082^{***}	0.091^{***}
	(0.017)	(0.017)	(0.017)	(0.016)
Obs.	3,574	3,574	3,574	3,574
Adj. R^2	0.007	0.009	0.009	0.116
σ^2	1.847	1.845	1.845	1.742
F Stat.	12.905^{***}	16.697^{***}	11.236^{***}	68.072^{***}

Note: *p<0.1; **p<0.05; ***p<0.01

From Table 7, we conclude that the relationship between commodities returns and the MCCC index is negative but not significant ($\hat{\gamma}_1 = -0.042$), and all (but $\Delta CRDSPRD$) the control variables influence commodities common returns globally. The statistically significant coefficients ($\rho_{\Delta TBILL}, \rho_{\Delta TERM}, \rho_{\Delta VIX}$) = (2.754, 5.925, -0.280) shown in column (4) of Table 7 indicate that changes in short-term U.S. government debt yields, the term structure of interest rates, or the implied volatility of U.S. markets are likely to affect commodities returns.

Commodities returns tend to react strongly to unexpected macroeconomic shocks, Adjemian, Michael K., and Scott H. Irwin (2020) find that unexpected information in United States Department of Agriculture (USDA) crop forecasts triggers immediate and significant adjustments in agricultural futures prices, with heightened volatility observed particularly in the minutes following report releases, as market participants rapidly incorporate the new data into their trading strategies. During periods of global economic recession, commodity returns frequently become more volatile and connected. This may explain why we see $\Delta TBILL, \Delta TERM,$ ΔVIX, moving commodities returns based on demand or supply.

Higher economic uncertainty drives increased demand for commodities (especially, for gold), often due to precautionary reasons. During periods of uncertainty, investors and firms may stockpile commodities as a hedge against potential supply disruptions or future price increases, reinforcing their role as safe-haven assets. Consequently, commodity returns tend to exhibit heightened volatility and co-movement during economic downturns (as seen in Fig. 3.), as market participants adjust their portfolios to mitigate risk. This behavior reflects the dual nature of commodities as both financial and real assets, influenced by both macroeconomic conditions and precautionary motives. For instance, Bouri, Elie, et al. (2023) co-movements across commodities are shaped by crisis periods, including pandemics and geopolitical conflicts, and vary across time and frequency. Short-term correlations are weaker and volatile due to noise trading, while long-term correlations are stronger, reflecting structural integration and cyclical behaviors. These dynamics highlight the importance of analyzing time-frequency relationships to understand commodity markets during crises and guide diversification and investment strategies.

To control for changes in returns due to economic policy uncertainty events in the US, the effect of $log(EPU)$ was analyzed both independently and in combination with $\Delta MCCC$, as shown in columns (2) and (3), respectively. The results show that climate concerns do not significantly influence commodities returns, while political uncertainty affects commodities returns. This suggests that economic uncertainty plays a significant role in explaining commodities returns.

The commodities were also separated by type to study how the returns of different types of commodities perform in response to climate-related news, using $\Delta MCCC.$ However, unlike for the global common variance, no specific group of commodities was found where climate-related news is both relevant and significant in predicting commodities' performance in the market.

To investigate the impact of the Paris Agreement in the return's regression and whether MCCC becomes more significant when analyzing commodities returns, we split the sample into two subperiods: before and after the Paris Agreement.

Table 8
Projecting the commodities common returns ($\hat{r}^{PCA}_{comm,t}$) on the first-difference of media climate change concerns index ($\Delta MCCC$) for the periods before and after the Paris Agreement.

	$\hat{r}^{PCA}_{comm,t}$	
	(1)	(2)
$\Delta MCCC$	-0.146	0.023
	(0.115)	(0.098)
$\hat{r}^{PCA}_{comm,t-1}$	0.055^{**}	0.104^{***}
	(0.025)	(0.023)
Obs.	1,658	1,916
Adj. R^2	0.003	0.010
σ^2	1.743	1.932
F Stat.	3.255^{**}	10.538^{***}
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 8 is a replication of column (1) in Table 7. In Table 8, we examine the effects of climate change on commodities returns before and after 12th December 2015. The results show that, despite the effect that $\Delta MCCC$ has on commodities returns changing from negative to positive (from -0.146 to 0.023), it remains insignificant, even after 12th December 2015. This suggests that in future studies, $\Delta MCCC$ may become significant and overtime when predicting how climate extreme events affect the returns for all types of commodities.

6. Limitations

Geographic focus

While this study provides a detailed examination of how climate events and media coverage affect commodity markets, it primarily focuses on commodities traded in U.S. markets. As a result, the findings may not fully capture dynamics in other regions, where both climate exposures and regulatory frameworks can significantly differ. Extending the analysis to include data from emerging markets or regions more directly affected by extreme climate events could offer a broader perspective on how different local conditions shape commodities trading and pricing.

Reliance on text-based proxies

A second limitation arises from the reliance on text-based climate news proxies, such as the Media Climate Change Concerns (MCCC) index. Although this index provides valuable insights into how media coverage correlates with market movements, it does not necessarily capture all dimensions of climate impact. Physical indicators, such as measurable shifts in rainfall patterns, temperatures, or frequency of natural disasters, may complement or even contradict media narratives.

Limited commodity representation

Finally, the study focuses on a set of 14 commodities split into agriculture, energy, and metal categories. While this selection offers meaningful insights into core segments of the commodities market, it does not encompass the full breadth of global commodities. Including additional or more specialized commodities, like rare earth elements or niche agricultural products, could reveal different climate sensitivities and trading behaviors. Including a more diverse sample might, therefore, provide a richer understanding of climate-change-driven market dynamics.

7. Conclusions

We used daily prices of 14 different commodities from agriculture, energetic and precious metals for modelling climate driven commodities common variance and commodities common returns. To conduct this study, there were made two different and separated analysis. First, in point 4.1. of methodology we quantity the variance shocks that cause the wide range of traded commodities returns to fluctuate. Finally, in that part of the methodology, we project the commodities global common variance onto climate-related shocks, represented by a text-based news index for media climate change concern. This step helps determine whether global common movements in commodities in this context are driven by unforeseen climate-related catastrophes, or by other factors. Then in point 4.2. of methodology we regress the common returns of commodities, on a data framework, to understand how returns of all commodities, and then of specific types of commodities, are affected by climate news.

From both analyses, we conclude that, when considering all types of commodities, climate-related news does not seem to influence commodities traded in the US markets, nor does it impact commodities returns. This lack of relationship is robust controlling for shocks to the US commodities index, the US stock market, and the specific prices of each type of commodity in the market. The same is observed in the common returns equation, where climate-related news is not significant when controlling for economic policy uncertainty and other economic measures such as CRDSPRD, TBILL, TERM, and VIX.

Climate-related news can impact the prices of commodities. When analyzing them collectively, evidence is weak. However, when separated by type, we find that the volatility of climate news impacts the volatility of energy commodities. None of the type of commodities returns seems to be affected by climate news.

All types of commodities are likely exposed to climate change. In the future, climate change risks could become influential for all commodities' performance in the market. This is evident because, as we observed after the Paris Agreement, climate-related news starts giving signs of influencing the global common variance of commodities. This demonstrates the growing relevance of incorporating climate change when making investments and decisions, highlighting the importance of introducing events like the Paris Agreement when predicting commodities returns and volatilities.

Our results provide a starting point for understanding the exposure of commodities to climate transition risk on a global scale. Future investigations on this topic could be expanded to include commodities prices from other regions of the world, and account for the fact that some countries may be more exposed to climate policies imposed by more stringent governments than others. Additionally, it would help explore how certain climate events, especially physical events, may have a different impact across countries and regions.

8. References

Burke, Marshall, et al. "Global non-linear effect of temperature on economic production." *Nature*, vol. 527, no. 7577, 21 Oct. 2015, pp. 235–239, https://doi.org/10.1038/nature15725.

Colacito, Riccardo, et al. "Temperature and growth: A panel analysis of the United States." *Journal of Money, Credit and Banking*, vol. 51, no. 2–3, 3 Dec. 2018, pp. 313–368, https://doi.org/10.1111/jmcb.12574.

Teltock, Paul C. "Giving content to investor sentiment: The role of media in the stock market." *The Journal of Finance*, vol. 62, no. 3, 8 May 2007, pp. 1139–1168, https://doi.org/10.1111/j.1540-6261.2007.01232.x.

Kilian, Lutz. "Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market." *American Economic Review*, vol. 99, no. 3, 1 May 2009, pp. 1053–1069, https://doi.org/10.1257/aer.99.3.1053.

Guo, Xiaoxia, et al. “Contributing to sustainable smallholder agriculture through optimizing key agricultural inputs in China.” *Journal of Cleaner Production*, vol. 471, Sept. 2024, p. 143429, https://doi.org/10.1016/j.jclepro.2024.143429.

Bessembinder, Hendrik. “Systematic risk, hedging pressure, and risk premiums in futures markets.” *Review of Financial Studies*, vol. 5, no. 4, Oct. 1992, pp. 637–667, https://doi.org/10.1093/rfs/5.4.637.

Hong, Harrison, et al. “Climate risks and market efficiency.” *Journal of Econometrics*, vol. 208, no. 1, Jan. 2019, pp. 265–281, https://doi.org/10.1016/j.jeconom.2018.09.015.

Zhu, Jiaji, et al. “Does climate risk matter for gold price volatility?” *Finance Research Letters*, vol. 58, Dec. 2023, p. 104544, https://doi.org/10.1016/j.frl.2023.104544.

Tang, Yusui, and Juandan Zhong. “Predicting gold volatility: Exploring the impact of extreme risk in the International Commodity Market.” *Finance Research Letters*, vol. 58, Dec. 2023, p. 104491, https://doi.org/10.1016/j.frl.2023.104491.

Engle, Robert F., and Susana Campos-Martins. “What are the events that shake our world? measuring and hedging global COVOL.” *Journal of Financial Economics*, vol. 147, no. 1, Jan. 2023, pp. 221–242, https://doi.org/10.1016/j.jfineco.2022.09.009.

Ardia, David, et al. “Climate change concerns and the performance of Green vs. brown stocks.” *Management Science*, vol. 69, no. 12, Dec. 2023, pp. 7607–7632, https://doi.org/10.1287/mnsc.2022.4636.

Campos-Martins, Susana, and David F. Hendry. “Common volatility shocks driven by the Global Carbon Transition.” *Journal of Econometrics*, vol. 239, no. 1, Feb. 2024, p. 105472, https://doi.org/10.1016/j.jeconom.2023.05.008.

Laubsch, Joshua, et al. “The influence of uncertainty on Commodity Futures returns and trading behaviour.” *The Quarterly Review of Economics and Finance*, vol. 98, Dec. 2024, p. 101915, https://doi.org/10.1016/j.qref.2024.101915.

Ahmed, Rizwan, et al. “Climate change effects and their implications for the Financial Markets: Evidence from the United Kingdom.” *Journal of Environmental Management*, vol. 366, Aug. 2024, p. 121782, https://doi.org/10.1016/j.jenvman.2024.121782.

Rao, Sandeep, et al. "When rain matters! investments and value relevance." *Journal of Corporate Finance*, vol. 73, Apr. 2022, p. 101827, https://doi.org/10.1016/j.jcorpfin.2020.101827.

Chatzopoulos, Thomas, et al. "Climate extremes and Agricultural Commodity Markets: A global economic analysis of regionally simulated events." *Weather and Climate Extremes*, vol. 27, Mar. 2020, p. 100193, https://doi.org/10.1016/j.wace.2019.100193.

Makkonen, Adam, et al. "The effect of temperature anomaly and macroeconomic fundamentals on Agricultural Commodity Futures Returns." *Energy Economics*, vol. 100, Aug. 2021, p. 105377, https://doi.org/10.1016/j.eneco.2021.105377.

Allahdadi, Mohammad R., et al. "Value of climate change news: A textual analysis." *Global Finance Journal*, vol. 63, Dec. 2024, p. 101052, https://doi.org/10.1016/j.gfj.2024.101052.

Liang, Chao, et al. "Which Types of Commodity Price Information Are More Useful for Predicting US Stock Market Volatility?" *Economic Modelling*, vol. 93, Dec. 2020, pp. 642-650, https://doi.org/10.1016/j.econmod.2020.03.022.

Adjemian, Michael K., and Scott H. Irwin. "The market response to government crop news under different release regimes." *Journal of Commodity Markets*, vol. 19, Sept. 2020, p. 100110, https://doi.org/10.1016/j.jcomm.2019.100110.

Isengildina-Massa, Olga, et al. "The impact of situation and outlook information in corn and soybean futures markets: Evidence from WASDE reports." *Journal of Agricultural and Applied Economics*, vol. 40, no. 1, Apr. 2008, pp. 89–103, https://doi.org/10.1017/s1074070800023488.

Bouri, Elie, et al. "Dynamic co-movement in major commodity markets during crisis periods: A wavelet local multiple correlation analysis." *Finance Research Letters*, vol. 55, July 2023, p. 103996, https://doi.org/10.1016/j.frl.2023.103996.

"MCCC." *Sentometrics Research*, 14 Nov. 2020, sentometrics-research.com/download/mccc/.

"Federal Reserve Economic Data (FRED)." *Federal Reserve Bank of St. Louis*, fred.stlouisfed.org.

"Economic Policy Uncertainty Index." *Economic Policy Uncertainty,* www.policyuncertainty.com/.

"How Do Commodities Perform During Recessions?" *Thunder Said Energy*, Thunder Said Energy, thundersaidenergy.com/downloads/how-do-commodities-perform-during-recessions/.

"Evidence - NASA Science." *NASA*, science.nasa.gov/climate-change/evidence/.

"Past Conferences Overview." *United Nations Framework Convention on Climate Change (UNFCCC)*, 2021, unfccc.int/process-and-meetings/conferences/past-conferences/past-conferences-overview.

Thompson, Cedric. "Commodities Trading: An Overview." *Investopedia*, www.investopedia.com/investing/commodities-trading-overview/.

Huang, Xiaoye, and Gerold Koch. "How Could Climate Change Impact My Expected Portfolio Returns?" *Allianz Global Investors*, Allianz Global Investors, 8 Mar. 2024, www.allianzgi.com/en/insights/outlook-and-commentary/the-big-question-climate-and-returns.

Birmingham, Kyle, CFA. "Do Commodities Do Well in a Recession?" *Composer*, 22 Aug. 2024, www.composer.trade/learn/commodities-recession.

Freeman, Glenn. "Are Commodities Really a Good Recession Hedge?" *Livewire Markets*, 9 Aug. 2023, www.livewiremarkets.com/wires/are-commodities-really-a-good-recession-hedge.

9. Appendices

Table 9
Commodities descriptive statistics.

Variable	Mean	SD	Min	Max	Median	Skewness	Kurtosis
P_{Corn}	4.6934	1.5076	2.6900	8.4900	3.8850	0.6732	1.9542
$P_{Crude\ Oil\ WTI}$	71.0659	21.7863	-37.6300	123.7000	71.2900	-0.0307	2.1613
$P_{Oil\ Brent}$	77.2597	24.3790	16.5000	128.1500	75.1100	0.1163	1.9350
$P_{Natural\ Gas}$	3.4634	1.3355	1.3300	23.8600	3.1300	2.4396	20.3060
$P_{Soyabeans}$	11.5295	2.5646	7.4500	17.9000	10.6700	0.3782	1.8677
P_{Wheat}	5.8712	1.5145	2.4700	12.7900	5.6800	0.7561	3.9233
P_{Coal}	98.3005	61.3240	38.4500	439	83.2500	2.8748	11.9521
$P_{\text{Conventional Gasoline}}$	2.1467	0.6485	0.4340	4.5090	2.0650	0.1935	2.5180
P_{Gold}	1,450.6780	293.0816	810.2000	2,078.9500	1,340.9350	0.2524	1.9607
P_{Silver}	21.1074	6.3065	10.5100	48.7000	19.1100	1.1433	4.0035
P_{Cocoa}	2,667.3390	454.0116	1,817.3600	4,311.5400	2,533.7600	0.6312	3.0127
P_{Oats}	3.6250	1.1497	1.6800	8.2800	3.4550	1.7613	7.1776
$P_{Heating\ Oil}$	2.2060	0.7478	0.5620	5.1520	2.0445	0.4895	2.9664
$P_{Palm\ Oil}$	853.2303	255.1672	440	2,010	810	1.0966	4.6049
$\tilde{r}_{Corn}$	0.0041	1.8561	-21.6766	19.0843	0	-0.2338	16.2418

$\tilde{r}_{Crude\ Oil\ WTI}$	0.0306	2.7039	-28.2206	30.0229	0	0.4694	24.2019
$\tilde{r}_{Oil\ Brent}$	0.0142	2.2795	-44.1573	21.5111	0.0251	-1.7821	47.5091
$\tilde{r}_{Natural\ Gas}$	-0.0199	5.5622	-102.5103	74.5632	0	-0.4421	59.4710
$\tilde{r}_{Soyabeans}$	0.0072	1.4304	-10.9199	7.5730	0	-0.5555	8.1214
$\tilde{r}_{Wheat}$	0.0067	2.3915	-24.6683	23.9150	0	0.2368	13.6581
$\tilde{r}_{Coal}$	0.0091	2.2849	-53.6880	32.6216	0	-3.1324	118.3580
$\tilde{r}_{\text{Conventional Gasoline}}$	0.0226	2.6516	-29.9857	22.2221	0	-0.7944	21.5964
$\tilde{r}_{Gold}$	0.0223	0.9878	-10.1624	6.8653	0.0231	-0.5116	9.4067
$\tilde{r}_{Silver}$	0.0202	1.9604	-19.5856	17.3643	0	-0.5447	14.0909
$\tilde{r}_{Cocoa}$	0.0130	1.4741	-9.6950	8.8022	0	-0.0595	5.5623
$\tilde{r}_{Oats}$	0.0196	1.8375	-12.5769	17.3382	0	0.1739	8.1679
$\tilde{r}_{Heating\ Oil}$	0.0159	2.4161	-22.3144	24.6806	0	-0.2630	13.9342
$\tilde{r}_{Palm\ Oil}$	0.0148	2.1226	-12.8617	11.8290	0	0.0816	7.7683

Table 10
Descriptive statistics for returns equation variables.

Variable	Mean	SD	Min	Max	Median	Skewness	Kurtosis
$\Delta MCCC$	0.0152	0.4172	-1.7792	1.6150	0.0175	-0.0338	3.6423
$log(EPU)$	4.6348	0.5957	1.2000	6.6941	4.6231	0.0466	3.5108
$\Delta CRDSPRD$	-0.0006	0.0246	-0.3000	0.4700	0	1.2314	53.4253
$\Delta TBILL$	0.0007	0.0247	-0.2300	0.3400	0	1.2669	33.5557
$\Delta TERM$	-0.0004	0.0403	-0.2800	0.4200	0	0.3335	8.6150
ΔVIX	-0.0362	1.8585	-17.6400	24.8600	-0.1300	2.0806	31.0398

Table 11
Descriptive statistics for volatility equation variables.

Variable	Mean	SD	Min	Max	Median	Skewness	Kurtosis
$MCCC$	0.8080	0.4505	0	3.0521	0.7337	0.8692	3.8547
P_{GSCI}	3,451.0350	1,120.8960	1,260.1490	5,775.2890	3,313.8390	0.1716	1.6467
$P_{SPDR\ S\&P500}$	242.5344	110.3730	68.1100	477.7100	212.3700	0.5082	2.1047
P_{DBA}	22.4172	4.8831	13.1600	35.4400	21.3900	0.3856	2.5096
P_{XLE}	67.6526	14.5491	23.5700	101.2900	68.4800	-0.3595	2.8997
P_{GLD}	138.2219	26.4471	79.7900	193.8900	128.5000	0.2060	1.8713
P_{SLV}	20.1028	6.1548	10.4500	47.2600	18.2000	1.2798	4.3130
$\tilde{r}_{GSCI}$	-0.0072	1.4191	-12.4484	7.6166	0.0645	-0.5218	7.9540
$\tilde{r}_{SPDR\ S\&P500}$	0.0417	1.1521	-11.5887	8.6731	0.0595	-0.6154	12.9120
$\tilde{r}_{DBA}$	-0.0108	0.8969	-6.9668	3.7901	-0.0339	-0.3187	6.0367
$\tilde{r}_{XLE}$	0.0130	1.8277	-22.4910	14.8742	0.0348	-0.7544	16.4834
$\tilde{r}_{GLD}$	0.0140	1.0110	-9.1905	4.7953	0.0403	-0.4724	7.5850
$\tilde{r}_{SLV}$	0.0052	1.8495	-15.2529	8.7487	0.0461	-0.7196	9.6067