Climate policy uncertainty and commodity futures market nexus: evidence from energy and metals markets

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Abstract

In this study, we investigate the influence of climate policy uncertainty (CPU) on energy (crude oil, heating oil and gas) and metal (gold, silver, copper and platinum) commodity futures markets, using data from 2000 to 2020. we employ a quantile regression approach, which allows for a more complete analysis of various conditions in the commodity markets (i.e. bearish, normal, and bullish markets). Our results reveals that the impact of CPU shocks on commodity futures are market condition specific. CPU exerts significantly negative effect on all commodities, except natural gas, under low quantiles. Under the normal market, the impact of CPU on energy returns varies across commodities and is only significant for heating oil and platinum. When the market is bullish, the impact of CPU on commodity returns is heterogeneous and insignificant. Natural gas is discovered to be a good hedge tool for climate policy risk. Drawing on commodity futures pricing theories, we also examine the mediating effect of inventory and hedging pressure between the relationship of CPU and commodity price. We find some evidence of inventory as the channel through which CPU affects commodity returns for copper. These findings can be meaningful to policymakers and investors.

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Keywords: Commodity futures; Climate Policy Uncertainty; Energy; Metals; Quantile Regression; Channel Analysis

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1 Introduction

Commodity market stability is a critical determinant for economic development and growth (Kang and Kwon (2020); Ge and Tang (2020)). Given its strategic role as both an investment asset and for food security, commodity markets are largely influenced by and often reflect the macroeconomic conditions as they serve as diversifies and safe-haven instruments (Gong and Xu (2022)). Over the past decades, financialization of commodities has led to a proliferation in the number of studies investigating interconnectedness, and cross-sectoral co-movement in commodity market with other economic variables. It is clear in the literature that commodity assets are more integrated and could act as either transmitters or receivers of shocks from the economy (Prokopczuk et al. (2021), Diebold et al. (2017)). Taking the on-going Russia-Ukraine war for example, it is obvious to see the impact on commodity prices which is reflective of the broader global macroeconomic sentiments and conditions (i.e., supply chain disruptions, effect of trade sanctions, geopolitical divide, and tensions, etc.). Thus, understanding the determinants of commodity futures fluctuations is critical for timely macro-prudential policy planning and to attenuate the possibility of market systemic risk. Indeed, commodity prices respond heterogeneously to different economic cycles depending on the macroeconomic fundamentals including, governments or producer supply policies, aggregate demand shocks, global uncertainties as well as investor sentiments (Cabrera and Schulz (2016); Gong and Lin (2021); Kang et al. (2017b)). Globally, sluggish growth recovery, skyrocketing inflation and food prices, ongoing Russia-Ukraine conflicts (with its concomitant impact on commodity and energy prices) and the existential threat of climate change constitute major challenges for all economies. These challenges continue to create enormous uncertainties, volatilities and ambiguities among market participants. As noted by Su et al. (2019), an unanticipated uncertainty often creates market disruptions and induces governments to make abrupt adjustments in their policies with deeper implications on volatility and investor sentiments. Indeed, recent studies has shown that textual-based measures of uncertainties including geopolitical risk and economic policy uncertainty can influence asset prices and commodity prices is no exception (see, Demirer et al. (2018); Alqahtani and Klein (2021),Bouri et al. (2022)). While commodity futures is regarded as common investment vehicle for portfolio risk diversification from hedging/speculation perspective, commodity prices are also strongly influenced by economic, financial, geopolitical events and abrupt policy changes (see Kang et al. (2017b)). Therefore, in this paper, we seek to examine how climate policy uncertainties affect commodities markets and in particular, we aim to shed light on the dynamic linkage between climate policy uncertainty and commodity futures prices under various market conditions.

Climate policy uncertainty broadly relates to the uncertainty regarding climate risks, emissions, global warming/climate change, regulations related to decarbonization, renewable energy economy, etc, which are likely to cause major policy changes to government's commitments, and actions towards transition to low-carbon economy. Climate policy uncertainty focuses on issues regarding carbon risk as well as how to reduce carbon emissions. Given that conventional energy-related commodities and industrial manufacturing process are carbon intensive, it is critical to ascertain the pricing implication of climate policy uncertainties/carbon risk on commodities market. Indeed, most commodities are either direct or indirect inputs (raw materials) in the final production process and thus are influenced by global market demand and supply factors. In addition, majority of commodity contracts are traded in the futures market, which means that climate risk or uncertainties relating to supply and demand could impact commodity futures. For example, the "phasing-out and phasing-down" policy conundrum over fossil fuels/energies (UNF (a), UNF (b), p. 4; Saha and Carter (2022)) presents both a demand and supply side pressure from climate policy uncertainty on the commodity markets. On the demand side for instance, increase climate policy uncertainty by governments to curtail consumption of some commodities (e.g., crude energy or dairy products) could cause commodity producers to reduce their inventories level by increasing current supply to both futures and the spot markets. This excess supply can lead to decline in commodity prices. In addition, according to so-called Working Curve theory, lower inventories level could increase the convenience yields which then increases future stockout or commodity scarcity (Routledge et al. (2000); Carter and Giha (2007); Alquist et al. (2014)). On the supply side, climate policy uncertainties (and climate physical risks) could lead to disruption in the production or extraction process of commodities thereby prompting precautionary hoarding of inventories by producers against any future disruptions in production. For example, Muñoz (2021) note a greater sensitivity in carbon-intensive fossil fuels and metals commodities following the announcement of the US withdrawal from the Paris Agreement and Trump's loosened environmental regulations. The interruptions could reduce supply in the physical market causing an increase in the spot prices of commodities while decreasing risk premiums in the futures markets. As precautionary inventories or stock hoarding increases, convenience yield will also be reduced.

In the literature, the focus has been on economic policy uncertainty (EPU) with several studies investigating its linkage with commodity markets (Wang et al. (2015); Reboredo and Wen (2015); Yin and Han (2014); Shahzad et al. (2017); Handley and Limão (2017); Huang et al. (2021a); Lyu et al. (2021); Naeem et al. (2021); Bahloul et al. (2018); Fang et al. (2018); Zhu et al. (2020); Yang and Hamori (2021); Mokni et al. (2020); Ren et al. (2022)). The consensus from the majority of these studies is that EPU has substantial and heterogeneous effect on commodities returns depending on the market conditions. On the contrary, some studies also reveal that no co-movement and Granger causality exist between commodity prices and policy uncertainty (see Reboredo and Uddin (2016)). However, our paper diverges from the extant literature by focusing on climate policy uncertainty and its interaction with the commodities futures market. To the best of our knowledge, there is little evidence in the literature regarding how climate policy uncertainties affect commodities market apart from Nam (2021) and Makkonen et al. (2021) which investigate extreme weather and commodities nexus. For example, Nam (2021) noted that climate uncertainty (proxied by El Nino weather shocks) induces a negative supply shock which can generate inflationary pressure on commodities prices (in particular agricultural, energy and non-energy commodities).

Indeed, climate change risk are often decomposed into two main components: 1) Physical risks (risks arising from climate and weather-related events, for example, droughts, floods, heat waves etc.), and 2) Climate transition risks (resulting from the process of adjustment towards a lower-carbon economy). Our study focuses on the later which is transitional risk using the newly constructed climate policy uncertainty (CPU) index by Gavriilidis (2021). Analogues to Engle et al.

(2020), climate risks can significantly impact firm's investment decision and the CPU index presents an additional tool for capturing climate-related policy uncertainty at the macroeconomic level (Gavriilidis (2021)). As recently observed by Erten and Ocampo (2021), one of the three main factors that could potentially affect global commodity prices is the major changes that are required to occur in the global energy economy to mitigate climate change which involves decarbonization of production processes and additional demand for metals and cleaner energy materials (copper, cobalt, nickel, etc) associated with growing renewable energy production. Thus, in this paper we extend the literature by investigating the importance of CPU in the pricing mechanisms of commodity futures which fills the literature gap on the macroeconomic channels of climate policy uncertainties impact. To achieve our research aim, we address the following research questions: 1. Do CPU shocks influence commodity futures returns? 2. Does the impact differ across market conditions and by commodities sectors/classifications? 3. What are the channels by which CPU influence different commodity classes?

1.1 Theoretical linkage between CPU and commodities futures

Hypothetically, we conjecture the following mechanisms by which CPU can influence commodity futures markets. First is the direct/indirect impact via fundamental demand and supply channels: For example, when a major economy (US as case in point) pull out of a binding climate policy, it may send a mixed signal to the global market that climate friendly or clean energy products are not a priority and thus business can "continue as usual". This could lead to a potential increase in the demand for more [conventional] carbon-intensive products as a precautionary measure against future interruptions from policy change. As precautionary demand increases (decreases) due to climate policy uncertainty signal, prices of commodities will be pulled-along thereby distorting futures contracts (see Ren et al. (2019)). If the uncertainty decreases (increase) the supply from the producer-side may increase (decrease). For example, Kang et al. (2017a) observed that government's supply policies often affected energy and agriculture commodities as they constitute strategic materials in most economies.

In addition, climate policy uncertainty can induce shocks to macroeconomic fundamentals and hence the business cycle-including investment, and production activity which can spillover to commodities market. Following from the same argument by Bloom (2009), macroeconomic uncertainty shocks are anticipated to have a swift drop-bounce-overshoot trajectory on output, employment and productivity as firms defer their short-term investment and hiring decisions. Thus, uncertainty shocks (including CPU) could pose similar impact on commodity futures market as they can largely be seen as aggregate demand shocks (Cabrera and Schulz (2016); Leduc and Liu (2016); Nam (2021)).

Second relates to the flight to (from) safety mechanism: Climate policy uncertainty can also distort market dynamics in terms of investment into cleaner technologies and divestment from fossil fuels. Investors (speculators) expect a guaranteed streams of cashflows or ROI on their investments in renewable or sustainable climate products. However, when policies around climate change initiatives are uncertain, investors adopt the "let's wait and see attitude" and instead may divert their investable funds which can push up prices of other commodities due to the mechanism of "flight to (from) safety" or safe haven mentality (see, Arouri et al. (2016) and Liu and Zhang (2015)). For example, Nerger et al. (2021) documents the energy industry (in particular coal) benefited when Trump loosened environmental regulations and climate policies to strengthen the US economy. Moreover, Nam (2021) also demonstrates that, in order to hedge against climate uncertainty investors may reallocate their commodity portfolio via buying more gold in times of climate uncertainty as gold is often regarded a safe-haven asset, and thereby pushing up gold (precious metal) prices in the market.

Third, the financialization of commodity markets means that there is a strong linkage between commodities, in particular gold and crude oil (which are often used as diversifiers) with the global financial/equity markets. Thus, policy uncertainties can potentially affect global capital flow and credit expansion which can depress investment appetite as well as the stock markets. This can spillover to the commodities due to the interconnectedness of strategic commodities in particular gold/precious metals and crude oil to the global financial market. (Tang and Xiong (2012); Huang et al. (2021b); Tang et al. (2021)).

Theoretically, our paper fits into the two main pillars of commodity futures pricing literature which are the theory of storage (ToS) and the hedging pressure hypothesis (HPH). According to ToS, inventory levels or slope of the futures curve are the main drivers or determinants of commodity futures prices. However, one needs to ascertain the factors responsible for the inventory levels. While some of these factors may be obvious (such as the conventional supply-side or demand-side determinants), others may be less direct. For example, when climate related transitional policies become uncertain, it creates "precautionary fear" or panic among market participants (as explained in our first mechanism). In response to these fears, market participants may decide to increase or decrease their storage of the commodities that are likely to be affected by the policy uncertainty. As a result, inventory levels or slope of the futures curve will change and thereby reflect in the commodity futures prices. The second pillar, which focuses on hedging pressure, argues hedgers' net position as the principal determinant of commodity futures prices. Nevertheless, the net position of a hedger is predominantly determined by both market and economic conditions (apart from the hedgers' own risk preferences) among other factors. Climate policy uncertainty constitute part of both market (in situation where the policy is commodity specific - for example, uncertainty about 'phasing out' and 'phasing down' crude oil production or cutting down on diary product consumption) and economic conditions which can impact on the hedging dynamics of market participants. In particular, with climate-sensitive commodities class (such as energy, precious metals) it is plausible that climate policy uncertainties would put pressure on investment activities and thereby affect the hedging decisions of market participants. For example, in the presence of climate policy uncertainty regarding potential ban on crude oil fracking (in the US) or ban on certain agricultural commodities, producers may increase their short hedges and consumers decrease their long hedges compared to the hedging strategy that they could adopt if otherwise. Empirically, our paper conducted channel analysis on both hedging pressure and inventory level to ascertain the pricing mechanism of climate policy uncertainty on commodity futures market.

This paper makes a significant contribution to literature in four ways. To begin with and to the best of our knowledge, this paper is the first to shed light on the linkage between commodity futures market and CPU index. With the ever-increasing polarization and geo-politicking of climate policy issues, it is critical to understand how ambiguous or opaque climate actions (which create these uncertainties) could impact the broader economic fundamentals such as commodity prices. Secondly, a unique feature in our paper is that we account for heterogeneities in commodity market conditions on the premise that bullish market conditions may cause commodity futures to respond differently to CPU shocks compared to bearish markets for example. Thus, by employing quantile regression techniques we are able to specifically ascertain whether commodity futures reaction to CPU shocks are heterogeneous depending on market conditions-bearish, normal and bullish. In addition, by utilizing the QR approach we analyze the nonlinear impact of CPU on commodity futures under different market regimes with consistent and robust estimates (accounting for any heteroskedasticity and skewness in our dependent variables). Thirdly, according to Gospodinov and Jamali (2018) and Zhu et al. (2020), commodity sectors are composed of highly dissimilar asset classes and thus, the determinants of price fluctuations may be heterogeneous across different sector categories. Thus, we contribute to the literature by shedding empirical insights on the response of both individual and sector-level commodities to CPU shocks. Fourthly, this study also contributes to the literature by providing a channel analysis which sheds new and novel insights on the pricing mechanism of climate policy uncertainty into commodity futures market. The channels of CPU transmission analysis are imperative for investment decisions and for portfolio investors' trading strategies. To the best of our knowledge, our study is the first to offer empirical evidence on the transmission channels of CPU into commodity markets.

Previewing our results, we find that in general, the impact of CPU shocks on commodity futures are sector and market condition specific. In particular, CPU has significantly negative effects on all commodities, except natural gas, under low quantiles. Whereas in the normal market, the impact of CPU on energy returns vary across commodities and is only significant for heating oil and platinum. However, under the bullish market, the impact of CPU on commodity returns is heterogeneous and insignificant with natural gas identified as a good hedging instrument for climate policy risk. In addition, our channel analysis which draws on futures pricing theories, reveals some evidence of inventory as the channel through which CPU affects commodity returns. This finding has significant implication for regulators, asset managers and market participants with regards to commodity pricing strategies under climate risks as we transition to a low-carbon economy. The remainder of the paper is structured as follows. Section 2 provides the data and empirical method whereas Section 3 presents the results and discussions. Summary and conclusion are covered in Section 4.

2 Data and empirical method

2.1 Data and sample

Our investigation is conducted with respect to seven commodity futures contracts from January 2000 to February 2020. The interval was chosen because the CPU index developed by Gavriilidis (2021) are available from January 2020 and COVID-19 broke out in early 2020. Using the scaled frequency of articles in eight major U.S. newspapers, CPU index measures the uncertainty related to climate policy at monthly frequency.[1] To match the data of CPU index (totalling 241 observations), all other variables are collected and/or constructed at the end of each month. The difference of CPU index is used in this study to measure the CPU index shocks.

The contracts included in this study include three energy commodities (crude oil, heating oil and natural gas) and four metals (copper, platinum, gold and silver) that are heavily traded on the New York Mercantile Exchange (NYMEX). Data on commodity futures contracts, including prices, are obtained from the Commodity Research Bureau (CRB) dataset. For each commodity, we obtain several futures contracts with different time-to-maturities. We construct continuous time series, similar to the practice of Fernandez-Perez et al. (2018), by rolling from the closest-to-maturity contract to the second-nearest contract when the front-end contract is less than one month before maturity.

The first channel variable in our study is inventory. For all three energy commodities, the weekly (Friday) inventory data can directly be downloaded from the Energy Information Administration (EIA) web page. Four metals (copper, platinum, gold and silver) traded on Comex and NYMEX have records of warehouse

[1] CPU index can be found from the website: https://www.policyuncertainty.com/climate_uncertainty.html. This index is related to the climate change news index constructed by Engle et al. (2020), which applies textual analysis on articles from the Wall Street Journal. All news related to climate change (e.g. natural disasters) in one newspaper are included in their index construction.

stock data at daily basis and we obtain the data from Bloomberg. The detailed proxies for each commodity inventory levels are listed in the Panel A of Table 1 together with other commodity basic information, including CRB tickers and exchanges.

Positions data in the Commitment of Trader (COT) report are by the *Commodity Futures Trading Commission* (CFTC) every Tuesday and are released to the public the following Friday. The COT reports detail the aggregate long and short positions of various types of participants in commodity futures markets, including commercials and, noncommercials, and nonreportables.[2]

We also use aggregate controls to account for sources of risk premium that is not related to CPU. The control variables included in this study are change in short-term Treasury-bill yields (3 Month Treasury-bill yields), change in default premium (Baa - Aaa rated corporate bond yields), S&P 500 Index, the implied volatility of the S&P 500 index (VIX index), change in the term spread (the spread between the US 10 year Treasury-bond yield and the U.S. 2 year Treasury-note yield), change in Baltic dry index, and change in the US News based Economic policy uncertainty index (EPU)[3] (following earlier literature for example, Acharya et al. (2013), Bakshi et al. (2010), Bosch and Smimou (2022) and Bessembinder (1992)). Control variables are also obtained from Bloomberg. Data sources of these variables can be found in the Panel B of Table 1.

2.2 Variables and summary statistics

We compute the excess return for commodity i in month t using the front month continuous price time series,[4]

$$R_{i,t} = \frac{F_i(t,T) - F_i(t-1,T)}{F_i(t-1,T)}, \tag{1}$$

[2]All of a trader's reported futures positions in a commodity are classified as commercial if the trader uses futures contracts in that particular commodity for hedging as defined in CFTC Regulation 1.3(z).

[3]These data are available at http://www.policyuncertainty.com

[4]Its rolling method is stated in Subsection 2.1 to ensure our contract selection strategy generally takes the most liquid portion of the futures curve.

Table 1: Data sources

This tables includes the basic data information of the commodity futures contracts and macroeconomic variables used in this study over the sample period between January 2000 and February 2020. Each of the data series studied are at monthly frequency, yielding 241 observations. Panel A lists the details of the three energy and four metal commodity futures, showing the exchange in which they are traded, the CRB ticker and their inventory sources. EIA refers to the U.S. Energy Information Agency. Panel B reports the sources of CPU and macroeconomic control variables.

Panel A: Commodity futures contracts

Commodity name	**CRB ticker**	**Inventory source and proxies**	
Crude oil, WTI	CL	EIA	U.S. ending stocks excluding Strategic Petroleum Reserve
Heating oil, ULSD NY Harbor	HO	EIA	U.S. ending stocks of distillate fuel oil
Natural gas, Henry Hub	NG	EIA	U.S. Working natural gas total estimated Storage
Copper, High Grade/Scrap No. 2 Wire	HG	Bloomberg	LME warehouse stocks (LSCA Index)
Gold	GC	Bloomberg	COMEX warehouse stocks (COMXGOLD Index)
Silver 5,000 Troy Oz.	SI	Bloomberg	COMEX warehouse stocks (COMXSILV Index)
Platinum	PL	Bloomberg	NYMEX warehouse stocks (NYMXPLAT Index)

Panel B: Macroeconomic Variables

Variables	**Abbr.**	**Data sources**
Climate policy uncertainty index	CPU	Economic policy uncertainty webpage
Baltic dry index	BDY	Bloomberg (BDIY Index)
3 Month Treasury Bill yield	TB	Bloomberg (GB3 Govt)
Default spread	DFS	Bloomberg (MOODCBAA - MOODCAAA)
VIX index	VIX	Bloomberg (VIX Index)
S&P 500 index	SP	Bloomberg (SPX Index)
Term spread	TS	Bloomberg (USYC2Y10 Index)
Economic policy uncertainty index	EPU	Economic policy uncertainty webpage

where $F_i(t, T)$ is the futures price at the end of month t for a futures contract maturing on date T.

Regarding the inventory data, we follow Gorton et al. (2013) and Acharya et al. (2013), and remove the deterministic trend by taking the ratio of the log observed inventory level to the Hodrick-Prescott filtered level with the recommended smoothing parameter of $1600 * (12/4)^4$ for the monthly data as recommended by Ravn and Uhlig (2002). To control for seasonality in inventories, we regress the de-trended inventory against monthly dummy variables and employ the residuals of this regression if the F-test is significant at the 1% level. The p-values and these F-statistics are reported in Table 1. Energy commodities potentially have strong seasonality in the inventory series which can be explained by demand cycles.

As for the second channel variable hedging pressure, we follow the convention in the literature, and consider commercial traders as hedgers and non-commercial traders as speculators. We compute the hedging pressure (HP) as follows:

$$HP_{i,t} = \frac{\text{Commercial Total Short}_{i,t} - \text{Commercial Total Long}_{i,t}}{\text{Open Interest}_{i,t}} \tag{2}$$

Thus a positive (negative) value means an overall short (long) position of hedgers. The occurrence of net short positions over the sample period (number of net short position divided by the total number of observations) is reported in Table 1 column 'HP +%'. We can observe some heterogeneity of net commercial trader positions across commodities. Gold (34.3%) is the only commodity where net long positions occur most of the time. All other markets exhibit net short positions more often than net long positions, where platinum, silver and heating oil have net short commercial positions most of the time (98.9%, 95.9% and 94.2%).

Table 2 reports the descriptive statistics of commodity excess returns and macroeconomic variables. From Panel A, we can observe that the average monthly excess returns are positive for all commodities. The return of gold has the lowest dispersion while natural gas shows the highest standard deviation. All the return series are asymmetric and fat tailed as indicated by the skewness and kurtosis values. The Jarque-Bera normality test also indicates that the excess returns series are not normally distributed. Also, the unit root (the augmented Dickey and Fuller (1979)) test suggests that all the excess return series are stationary at the

Table 2: Descriptive statistics of futures contracts, inventory, hedging position and macroeconomic data

*This table provides descriptive information of the futures contracts, inventory level and hedging positions of each commodity considered as well as macroeconomic data. The sample period is January 2000 to February 2020. In panel A, descriptions of commodity specific data is shown, which include commodities of crude oil (CL), heating oil (HO), natural gas (NG), copper (HG), gold (GC), silver(SI) and platinum (PL). The columns headed Excess Return list the arithmetic mean (mean), standard deviation (S.D.), skewness (Skew), kurtosis (Kurt), augmented Dickey-Fuller (ADF) test and Jarque-Bera (J-B) tests statistics. The columns headed Invt. presents the F-statistics of the regression of monthly de-trended inventory level against seasonal monthly dummies. The column headed HP +% shows the occurrence of net short positions taken by commercial traders during the sample period. Panel B shows the arithmetic mean (mean), standard deviation (S.D.), skewness (Skew), kurtosis (Kurt), augmented Dickey-Fuller (ADF) test and Jarque-Bera (J-B) normality tests statistics of the growth rates of CPU index, Baltic dry index (BDY), 3 Month Treasury-bill yield (TB), Default spread (DFS), VIX, S&P 500 index (SP), term spread (TS) and Economic policy uncertainty (EPU) index. The asterisks ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.*

Panel A Commodity Specific								
	Excess Return						**Invt.**	**HP**
	Mean	S.D.	Skew	Kurt	ADF	J-B	F stats.	+\%
CL	0.073	1.056	-0.287	3.486	-13.47***	5.32**	4.44***	84.7%
HO	0.077	1.009	-0.003	3.847	-13.85***	6.62***	4.74***	94.2%
NG	0.092	1.661	0.646	5.188	-15.20***	62.26***	74.48***	51.7%
HG	0.089	0.900	-0.056	6.475	-13.91***	116.69***	0.20	80.2%
GC	0.099	0.575	-0.089	3.721	-17.00***	5.06**	0.04	34.3%
SI	0.100	1.026	0.085	3.780	-16.34***	5.87**	0.15	95.9%
PL	0.058	0.773	-0.645	5.722	-14.10***	87.58***	0.51	98.8%
Panel B Macroeconomic								
	Mean	S.D.	Skew	Kurt	ADF	J-B		
CPU	0.407	1.969	8.504	99.188	-16.14***	93413.41***		
BDY	0.023	0.227	0.448	5.220	-13.70***	55.09***		
TB	-0.008	1.577	-5.742	89.841	-14.66***	75115.65***		
DFS	0.006	0.105	1.523	10.222	-13.15***	598.58***		
VIX	0.026	0.239	1.588	7.490	-17.03***	294.49***		
SP	0.004	0.043	-0.548	4.595	-14.72***	35.96***		
TS	0.345	4.844	12.598	172.115	-15.90***	286270.52***		
EPU	0.047	0.335	2.164	11.300	-18.40***	854.92***		

conventional levels. Panel B of Table 2 reports the sample statistics for the growth rates of CPU and macroeconomic control variables. The growth rate of CPU index shows positive mean and high dispersion. The results also indicate no unit root and reject the normality test with positive skewness and kurtosis.

2.3 Empirical model

2.3.1 Quantile regression

Our primary motivation is to study the responses of the commodity futures prices to CPU shocks under different circumstances. Thus, the quantile regression proposed by Koenker and Bassett Jr (1978) is applied to demonstrate the conditional distribution of commodity futures returns (y_t). $Q_{y_t}(\tau|X_t)$ represents the τ^{th} conditional quantile of the dependent variable, which is influenced by CPU and other control variables as in Equation (3):

$$Q_{y_t}(\tau|X_t) = i(\tau) + \gamma(\tau)X_t, \tag{3}$$

where X_t are the $(k * 1)$ dimensional vector of explanatory variables at time t and the parameters $i(\tau)$ and $\gamma(\tau)$ account for the unconditional quantile and the changes in the independent variables on the return quantile, respectively. The parameter values in the parameter vector $\gamma(\tau)$ capture the structure of the dynamics between the dependent and independent variables across τ, where $\tau \in [0, 1]$. In any particular τ, if $\gamma(\tau)$ is statistically different from zero it indicates significant impact from the explanatory variable to the dependent variable. If $\gamma(\tau)$ values are similar (different) between low and high quantiles, the dependence structure is symmetric (asymmetric) (see Baur (2013)).

In this study, we choose seven quantiles $(0.05, 0.1, 0.25, 0.5, 0.75, 0.9, 0.95)$. Previous literature (e.g.Naifar (2016)) has indicated lower quantiles $(0.05, 0.1, 0.25)$ as bearish, the medium quantile (0.5) as normal, and upper quantiles $(0.75, 0.9, 0.95)$ as bullish markets, respectively.

For a given τ, the estimated coefficients in Equation (3) were obtained by solving

$$\arg\min \sum_{t=1}^{T} \rho_\tau(y_t - i(\tau) - \gamma(\tau)X_t), \tag{4}$$

where $\rho_\tau(v) = v[\tau - I(v < 0)]$ is quantile loss function. $I(\bullet)$ is an indicator function of the residual vector. The minimization problem in Equation (4) can be formulated as linear programming problems.[5] Standard errors for the parameters are estimated using the design matrix bootstrapping procedure.

Accounting for both CPU and macroeconomic factors, the empirical model investigates the effect of CPU shocks on each individual commodity returns in a quantile regression framework with other control variables as follows:

$$\begin{aligned} Q_{y_t}(\tau|X_t) =& i_\tau + \gamma_1(\tau)CPU_t + \gamma_2(\tau)BDY_t + \gamma_3(\tau)TB_t + \gamma_4(\tau)DFS_t \\ &+ \gamma_5(\tau)VIX_t + \gamma_6(\tau)SP_t + \gamma_7(\tau)TS_t + \gamma_8(\tau)EPU_t, \end{aligned} \tag{5}$$

2.3.2 Quantile mediation model

To further investigate the pathways through which the commodity futures prices respond to climate policy uncertainty, we use the mediation models. The conventional mediation model specifies the variable of interest Y (e.g., commodity prices), treatment or exposure X (e.g., CPU), and M as the mediator of interest (e.g., inventory level and hedging pressure) and characterises the pathway analysis using Equations (6) and (7). The parameters α, β and $\gamma^{'}$ refer to the associations between the pairs (X, M), (M, Y) and (X, Y) respectively; γ normally refers to the association between X and Y without considering M. The common approach to estimating mediation decomposes the total effect (γ) of treatment or exposure as the sum of indirect ($\alpha\beta$) and direct effects ($\gamma^{'}$) following the seminal paper of Baron and Kenny (1986).[6]

$$OutcomeModel : Y = i_1 + \beta M + \gamma^{'} X + u \tag{6}$$

$$MediatorModel : M = i_2 + \alpha X + v \tag{7}$$

[5]For the quantile regression parameters estimation, we use interior point algorithm, proposed by Koenker and Park (1996), in Matlab.

[6]A detailed review of statistical mediation analysis is beyond the focus of this paper and interested readers can refer to MacKinnon (2012).

Such conventional mediation techniques do not accommodate a potential mediating effect between the outcome and exposure for other parts of the outcome distribution beyond the mean. They assume that the mediational relationship is the same for the mean outcome variable as it is for outcome extreme values. Shen et al. (2014) combine the traditional mean-based mediation models with conditional quantile analysis and demonstrate different mediating effects across the outcome distribution using the Healthy Places data. In their study, different estimation and inference methods are compared and recommendations are given. We follow their suggestions of estimation method and inferences for our quantile mediation analysis.

Equations (8) and (9) specify the conditional quantile analog of the mediation model from Equations (6) and (7) where X, M, Y and parameters are defined as above:

$$\begin{aligned} QuantileOutcomeModel : Q_{y_t}(\tau|M_t, Y_t, Z_t) =& i_1(\tau) + \beta(\tau)M_t + \\ & \gamma^{'}(\tau)X_t + \psi(\tau)Z_t \end{aligned} \tag{8}$$

$$MediatorModel : E(M_t|X_t, Z_t) = i_2 + \alpha X_t + \phi Z_t \tag{9}$$

The estimation strategy can directly build on the regression based approach of Causal Steps method (Baron and Kenny (1986)), which separately estimates regressions of mediator and outcome models in Equations (6) and (7). We apply the same principle to quantiles of outcome distribution. Specifically, the quantile-analog of the Causal Steps method estimates the parameters of Equation (8) using linear regression and conducts quantile regression to estimate the parameters in Equation (9).[7] We adopt the simplest inference approach as in early literature on mediation - Joint Significance Test - suggested by MacKinnon (2012), which does not entail assumption on probability distribution of the product.

[7]Shen et al. (2014) compares different approaches for estimating (and making inferences about) such quantile mediation model and find that the regression-based approach embedded in the Causal Steps method produce almost the same estimate of indirect effect as the one from the Quantile Causal Mediation Effect approach of Imai et al. (2010).

3 Results and discussions

This section summarizes the dynamic relationship between commodity futures returns and CPU index as well as macroeconomic fundamentals. We will present the ordinary least squares (OLS) regression as the baseline results in subsection 3.1, quantile regression results in subsection 3.2 and channel analysis discussion in 3.3.

3.1 OLS regression results

As the baseline, OLS regressions are estimated for each commodity against the CPU index and macroeconomic factors and the results are reported in Table 3.[8] We observe that CPU index shows a negative effect on the current returns of all metal commodities and a positive relationship with energy commodities. The relationship is only significant for silver at 5% significance level. A one unit change in CPU produces a silver price return of -6.6% over 1-month as compared to its mean monthly return of 10%. The estimated coefficients indicate that higher uncertainty in respect to climate policy or climate risk may discourage metal consumption, which has high greenhouse gas emissions (GHG) footprint in the mining process[9]. This potential mechanism is supported by the findings from Gavriilidis (2021) about the strong negative relationship between CPU index and CO_2 emissions.

Regarding the control variables, the intertemporal substitution of marginal rate of commodity investors - the stock market (proxied by S&P 500) exert significant positive impact on the commodity markets, except for gold, similar to the findings reported in Silvennoinen and Thorp (2013). These results are in line with the findings of increased co-movement of commodities with other asset classes during the decade after 2004, see *e.g.* Bhardwaj et al. (2015). Most commodity prices are observed to move in the opposite direction to the short-term (expect natural gas)

[8]We also included monthly dummy variables in all the OLS analysis and the results are similar with the ones reported without seasonality dummies. The results using seasonality dummies are not reported but are available from the contact author upon request.

[9]McKinsey reported that the mining sector is responsible for 4 to 7 percent of greenhouse gas (GHG) emissions globally. The report can be found from the web page https://www.mckinsey.com/business-functions/sustainability/our-insights/sustainability-blog/here-is-how-the-mining-industry-can-respond-to-climate-change.

Table 3: Commodity futures returns, CPU index and macroeconomic fundamentals: OLS regression results

This table displays the results of simple regressions of individual commodity futures returns against the CPU index and macroeconomic factors. The monthly data between January 2000 and February 2020, total of 241 observations, for each commodity analysis. Adj R^2 denotes the adjusted R^2. Estimated coefficients and their t-statistics after adjusting with Newey and West (1987) and 12 lags in parenthesis below are presented. BDY, TB, DFS, SP, TS and EPU denote Baltic dry index, 3 Month Treasury bill yield, Default spread, S&P 500 index, term spread and Economic policy uncertainty index, respectively. Intercepts are included in each regression estimation but their results are not displayed due to space constraint. Note: $***$, $**$, $*$ respectively indicate statistical significance at the 1%, 5% and 10% levels.

	CPU	**BDY**	**TB**	**DFS**	**VIX**	**SP**	**TS**	**EPU**	**Adj R^2**
CL	0.021	0.706*	-0.05	-1.829***	-0.162	5.083	-0.003	-0.157	14.08%
	(0.664)	(1.892)	(-1.092)	(-2.892)	(-0.299)	(1.49)	(-0.273)	(-0.895)	
HO	0.035	0.596**	-0.026	-1.753***	0.002	5.696*	-0.034***	-0.104	15.27%
	(0.994)	(1.978)	(-1.079)	(-2.786)	(0.004)	(1.907)	(-16.704)	(-0.639)	
NG	0.059	0.617	0.005	-0.906	-0.55	0.016	-0.09***	0.276	6.05%
	(1.585)	(1.452)	(0.075)	(-1.274)	(-0.915)	(0.005)	(-13.547)	(1.057)	
HG	-0.014	0.371	-0.037*	-2.087***	0.055	7.819***	-0.007**	0.234	23.64%
	(-0.443)	(1.619)	(-1.853)	(-3.966)	(0.194)	(4.097)	(-2.502)	(1.193)	
GC	-0.009	0.128	-0.053***	-0.789	0.081	-0.001	-0.006***	0.226**	2.27%
	(-0.376)	(0.556)	(-3.656)	(-1.487)	(0.409)	(-0.001)	(-2.714)	(2.224)	
SI	-0.066*	0.443	-0.074**	-0.946	-0.199	2.635	0.005	0.36**	4.45%
	(-1.841)	(1.13)	(-2.255)	(-1.302)	(-0.633)	(1.131)	(1.242)	(2.187)	
PL	-0.02	0.301	-0.062**	-1.349**	-0.093	2.756	-0.008***	-0.224	11.08%
	(-0.704)	(1.013)	(-2.591)	(-2.292)	(-0.242)	(1.141)	(-3.23)	(-1.107)	

and long-term (except silver) interest rates. When interest rate is higher, Frankel (2006) attributes the lower commodity prices to the lower demand for inventory caused by higher storage cost and higher supply from incentive of higher returns of proceeds of commodity sold by producers. Similar to findings of Bessembinder and Chan (1992), all commodities exhibit negative relationship with default spread and the results are significant for crude oil, heating oil, copper and platinum at conventional levels. Gold and silver act as safe heaven (with significant positive responses) to higher economic policy uncertainty. In contrast, the option volatility index VIX, commonly used in the literature to explain financial market uncertainty, appear to play a slightly less important role in determining returns. No commodity shows significant negative responses to VIX positive shocks. The regression coefficients of BDY index have the predicted sign: as the higher BDY - a leading indicator of economic activity, thus reflecting demand for raw materials. All the commodity returns have positive signs but only crude oil and heating oil are statistically significant at 10% and 5%, respectively. Overall, the OLS regression explains the copper the most (adjusted R^2 being 23.65%) and gold the least (adjusted R^2 being 2.27%).

3.2 Quantile regression results

To explore the heterogeneity of the effect of CPU on commodity futures prices, in this subsection we discuss the quantile regression results for commodity futures returns and CPU index. The quantile model estimation results are displayed in Table 4. Concerning the energy commodities, the CPU index negatively affects futures returns in lower quantiles for crude oil and heating oil. The estimated coefficients are significant at 10% for crude oil only at 5th percentile and at 5% level for heating oil at 10th and 25th percentiles, despite the fact that the OLS coefficient estimates are positive yet insignificant at conventional levels. These results indicate that in times of bearish markets, the increasing climate policy uncertainty is accompanied with a decrease in futures returns for crude oil and heating oil. This may be related to the market demand supply conditions. When commodity futures returns are lower, the lower demand for the commodity can be further impeded with concerns about climate policy instability. The production of commodity is relatively inelastic (Kogan et al. (2009)). When facing high climate policy uncertainty and commodity demand uncertainty, commodity producers may change their inventory holding strategies to store more to prepare for future potential stock-outs. Both crude oil and heating oil respond positively, yet insignificant, to the CPU shocks at the median and high quantiles, except crude oil at 95th quantile. On the other hand, natural gas shows significant positive responses to the CPU shocks from the bad ($\tau = 0.05$) condition, despite that the OLS estimation result is of low magnitude and insignificant. Under the bearish market condition, the estimated coefficient is at high economic value and significant at 10%, which suggests that natural gas can potentially be a good hedge tool against heightened climate policy risk. Overall, the varying responses across quantiles for all three energy commodities imply that CPU shocks exert asymmetric impact on energy futures, depending on the state of the market.

Regarding the metals futures, the impacts of CPU shocks on commodity returns are significantly negative in the lower quantiles for four of them, similar to the

Table 4: Estimation for the Commodity futures returns, CPU index and macroeconomic fundamentals: Quantile regression results

This table displays the quantile regression results of commodity futures returns against the CPU index and macroeconomic factors. The monthly data between January 2000 and February 2020 for each commodity analysis. OLS regression results are also included in the table under the 'OLS ' for reference. The control macroeconomic variables of BDY, TB, DFS, SP, VIX, TS and EPU are also included in the quantile regressions but left out of the table for brevity. Standard errors are estimated using the design matrix bootstrapping procedures. The t-statistics are presented in parenthesis below the coefficients. Note: $***$, $**$, $*$ respectively indicate statistical significance at the 1%, 5% and 10% levels.

	Q(0.05)	**Q(0.10)**	**Q(0.25)**	**Q(0.50)**	**Q(0.75)**	**Q(0.90)**	**Q(0.95)**	**OLS**
CL	-0.095*	-0.031	-0.009	0.046	0.021	0.011	-0.004	0.021
	(-1.829)	(-0.71)	(-0.479)	(1.379)	(0.707)	(0.546)	(-0.666)	(0.664)
HO	-0.048	-0.101**	-0.074**	0.057*	0.041	0.022	0.014	0.035
	(-1.225)	(-2.088)	(-2.016)	(1.728)	(1.277)	(0.666)	(0.401)	(0.994)
NG	0.007	0.124*	0.081	0.047	0.028	-0.028	-0.091	0.059
	(0.505)	(1.798)	(1.563)	(0.879)	(0.74)	(-0.664)	(-0.883)	(1.585)
HG	-0.16***	-0.183***	-0.058*	-0.042	0.01	-0.003	-0.021	-0.014
	(-5.003)	(-6.427)	(-1.961)	(-1.513)	(0.703)	(-0.49)	(-0.755)	(-0.443)
GC	-0.094***	-0.094***	-0.035	0.019	0.005	-0.01	-0.026	-0.009
	(-3.029)	(-3.225)	(-1.523)	(0.979)	(0.446)	(-0.565)	(-0.979)	(-0.376)
SI	-0.268***	-0.072	-0.01	-0.029	-0.053	-0.074	-0.078	-0.066*
	(-4.726)	(-1.451)	(-0.431)	(-0.94)	(-1.227)	(-1.339)	(-1.207)	(-1.841)
PL	-0.051	-0.107***	-0.09***	-0.045*	-0.004	0.02	-0.022	-0.02
	(-1.451)	(-2.635)	(-3.126)	(-1.913)	(-0.488)	(0.858)	(-0.701)	(-0.704)

results of crude oil and heating oil. These results may be due to the reason that during bad market conditions, an increase in CPU shocks are considered as an increased risk and thus impeding further the demand for metals. The climate policy uncertainty potentially drives up the hedging pressures from producers. Under such circumstances, the hedging pressure premium increases and futures prices decrease. Different from energy futures, under normal market conditions ($\tau = 0.5$) futures returns of copper, silver and platinum also respond negatively to the CPU shocks, with platinum significant at 10% level; and under extremely good market conditions ($\tau = 0.95$), CPU shows negative effects for all four commodity prices, albeit insignificant at conventional levels.

Overall, we observe that under bad market conditions most commodities show significant negative relationships with CPU shocks, except natural gas. And their responses (except silver) to CPU index vary, even with alternating signs, across quantiles. Silver shows persistent negative relationship with CPU at all market conditions investigated and is the only commodity with a significant result in the OLS estimation. On the contrary, natural gas, as a cleaner energy, demonstrates positive responses to high CPU at bearish market conditions and can be considered as hedging tool of climate policy risk.

3.3 Channel analysis results

Given the heterogeneous effects under different market conditions for energy and metals, in this subsection we continue exploring plausible mechanisms behind the significant impacts of CPU. Relying on the two commodity pricing theories, we focus on inventory level and hedging pressure as the potential mediators. We employ a two-step procedure described in Subsection (2.3.2) and present estimation results in Table (5), where the inventory and hedging pressure as the intermediary variable are displayed separately in panel A and panel B. Since the quantile regression results show significant relationships for commodities at low and median quantiles only, our mediation quantiles analysis will also discuss the results under bearish and normal market conditions.

First, we assume that increased CPU can affect the commodity inventory holding strategy, therefore influencing the commodity futures prices. As a first step, we explore whether our potential channel variable inventory level is correlated with CPU shocks. In panel A of Table (5), the column headed with α (following Equation (9)) shows a negative influence of CPU on inventory level for most commodities, except crude oil and gold. The estimated coefficient is statistically significant for copper at 5%, which indicates that CPU hinders inventory holding. After establishing the association between our potential channel variable and CPU shocks, in the second step of channel analysis, we include the channel variable as additional covariates as in the quantile outcome equation (Equation (8)). The results show that CPU and inventory (captured by $\gamma\prime$ and β in respectively) both have significant negative effects on commodity futures returns across the quantiles from Q(0.05) to Q(0.25). These findings indicate that the mediating effect of inventory level on commodity futures return is significant. A possible explanation is that an increase in climate policy risk poses increased uncertainty about the future demand of commodities, given potential future high carbon emission standards. Such concerns will demotivate producers to stock up the commodity and thus make them reduce inventory holding and sell more commodities in spot and/or futures markets, which causes commodities prices to decline. Although the mediating effect of inventory level is not significant for other commodities studied, we still observe negative relationship between inventory levels and commodities futures returns.

Second, we also assume that CPU influences the commodity futures prices through risk premiums provided by hedgers to speculators. During times of high CPU, demand uncertainty of consuming high carbon footprint commodities is high. Thus, commodity producers want to sell more commodity futures contract to hedge. Under such circumstances of high uncertainty, the hedging pressure from trader positions to sell commodity futures is higher. To entail more speculators to buy futures, hedgers need to offer to sell the commodity at a lower price. In panel B of Table (5), the hedging pressures of crude oil, heating oil and gold are negatively related to CPU, where the coefficient is significant at 10% for crude oil. Against our expectation, these findings suggest that hedgers of these commodity markets take fewer short positions when facing high CPU. On the contrary, CPU has a positive influence on hedging pressure of natural gas, copper, silver and platinum and the estimated coefficient is significant at 5% for natural gas, which indicates overall more short positions are taken by hedgers, consistent with hedging pressure assumption. Although the link between CPU and hedging pressure is established for crude oil and natural gas, in the second step the association between hedging pressure and commodity futures returns (measured by β) are only significant for crude oil at Q(0.10) and Q(0.25) and for natural gas at Q(0.05) and Q(0.50), which suggests significant indirect effect ($\alpha\beta$) of hedging pressure for the impact of CPU on commodity futures prices. However, under these market conditions, the quantile analysis does not show significant relationship between CPU and commodity returns without considering intermediate variable, captured by columns of γ. Thus, there is no evidence supporting the mediating effects of hedging pressure on the impact of CPU on commodity futures prices.

In sum, our mediation quantile analysis shows some evidence of mediating effect of inventory level, but not of hedging pressure. Specifically, CPU reduces commodity futures returns for copper through reducing the inventory holding at low quantiles, which affects the supply dynamics given the rigidity of commodity production.

4 Summary and Conclusion

This paper examines the effect of climate policy uncertainty shock on individual commodity futures returns. This study is meaningful for investors, commodity producers and policy makers, given the increasing climate risk and government policies tasked to mitigate the same climate risk. Our findings could help inform policymakers how their decisions might impact the commodity markets under various market conditions. Commodities have been receiving increasing attention during the recent decades under the financialization. Investors shall be alert to the climate policy uncertainty in terms of portfolio composition and risk management. This study contributes to the literature on nexus of climate related risk and commodity, which is an under-studied strand. In this study, we collect the historical monthly dataset covering the period between January 2000 and February 2020 for energy and metal commodities. To gain a more detailed understanding of the impact from CPU, we also consider two potential channels - inventory level and hedging pressure.

Table 5: Channel analysis through inventory and hedging pressure: Quantile mediation model

This table reports the mediator effects of inventory and hedging pressure on the climate policy uncertainty's impact on the commodity futures returns at quatiles of 0.05, 0.1, 0.25 and 0.5. The Panel A reports the results with inventory as the mediating variable and Panel B shows results with hedging pressure as the mediator. Columns headed with α, β, $\gamma\prime$ are defined as in Equations:$MediatorModel : E(M_t|X_t, Z_t) = i_2 + \alpha X_t + \phi Z_t$ and $QuantileOutcomeModel : Q_{y_t}(\tau|M_t, Y_t, Z_t) = i_1(\tau) + \beta(\tau)M_t + \gamma^{'}(\tau)X_t + \psi(\tau)Z_t$. The control macroeconomic variables Z_t consist of BDY, TB, DFS, SP, VIX, TS and EPU but left out of the table for brevity. The t-statistics of the α estimates after adjusting with Newey and West (1987) and 12 lags in parenthesis are presented below the coefficients. Quantile outcome models are estimated using the design matrix bootstrapping procedures. The t-statistics are presented in parenthesis below the coefficients. Columns headed with γ also show the quantile regression results between CPU and commodity returns (without mediator variable) for comparison. They are estimated following the Equation $Q_{y_t}(\tau|Y_t, Z_t) = i(\tau) + +\gamma(\tau)X_t + \gamma_i(\tau)Z_t$. In panel A, the coefficient estimates of α for crude oil is multiplied by 100 to ease interpretation. Note: $***$, $**$, $*$ respectively indicate statistical significance at the 1%, 5% and 10% levels.

Panel A: Inventory as the mediator variable

		Q(0.05)			**Q(0.10)**			**Q(0.25)**			**Q(0.50)**		
	α	β	$\gamma\prime$	γ	β	$\gamma\prime$	γ	β	$\gamma\prime$	γ	β	$\gamma\prime$	γ
CL	0.033	0.169*	0.013	-0.095*	0.161*	-0.03	-0.031	0.024	-0.01	-0.009	-0.044	0.047	0.046
	(0.016)	(1.858)	(0.435)	(-1.829)	(1.72)	(-0.878)	(-0.71)	(0.519)	(-0.495)	(-0.479)	(-0.698)	(1.238)	(1.379)
HO	-0.013	-0.03	-0.043	-0.048	0.012	-0.1**	-0.101**	0.03	-0.059	-0.074**	0.067	0.06*	0.057*
	(-0.769)	(-0.827)	(-1.023)	(-1.225)	(0.716)	(-2.242)	(-2.088)	(0.582)	(-1.63)	(-2.016)	(1.082)	(1.704)	(1.728)
NG	-0.011	-0.095	-0.002	0.007	-0.204*	0.115*	0.124*	-0.096	0.082	0.081	0.015	0.046	0.047
	(-0.727)	(-0.707)	(-0.553)	(0.505)	(-1.871)	(1.883)	(1.798)	(-1.076)	(1.598)	(1.563)	(0.508)	(0.912)	(0.879)
HG	-0.077**	-0.081***	-0.154***	-0.16***	-0.046***	-0.142***	-0.183***	-0.086***	-0.057*	-0.058*	-0.06***	-0.034	-0.042
	(-2.574)	(-17.39)	(-4.97)	(-5.003)	(-10.806)	(-4.647)	(-6.427)	(-4.594)	(-1.941)	(-1.961)	(-4.152)	(-1.258)	(-1.513)
GC	0.033	-0.019***	-0.068**	-0.094***	0.002**	-0.094***	-0.094***	-0.029***	-0.032	-0.035	-0.048***	0.011	0.019
	(1.234)	(-8.603)	(-2.244)	(-3.029)	(2.059)	(-3.301)	(-3.225)	(-4.7)	(-1.492)	(-1.523)	(-9.411)	(0.636)	(0.979)
SI	-0.016	0.018***	-0.26***	-0.268***	0.038***	-0.085*	-0.072	-0.093***	-0.01	-0.01	-0.19***	-0.038	-0.029
	(-0.764)	(13.677)	(-4.764)	(-4.726)	(4.655)	(-1.821)	(-1.451)	(-8.175)	(-0.54)	(-0.431)	(-32.311)	(-1.104)	(-0.94)
PL	-0.049	-0.054***	-0.054	-0.051	-0.049***	-0.108***	-0.107***	-0.078***	-0.09***	-0.09***	0.009*	-0.048*	-0.045*
	(-1.633)	(-9.507)	(-1.423)	(-1.451)	(-5.405)	(-3.122)	(-2.635)	(-3.534)	(-2.767)	(-3.126)	(1.758)	(-1.749)	(-1.913)

Panel B: hedging pressure as the mediator variable

		Q(0.05)			**Q(0.10)**			**Q(0.25)**			**Q(0.50)**		
	α	β	$\gamma\prime$	γ	β	$\gamma\prime$	γ	β	$\gamma\prime$	γ	β	$\gamma\prime$	γ
CL	-0.003*	0.878	-0.105*	-0.095*	1.709*	0.03	-0.031	1.59**	-0.039	-0.009	0.824	0.047	0.046
	(-1.906)	(1.217)	(-1.949)	(-1.829)	(1.954)	(0.745)	(-0.71)	(2.481)	(-1.04)	(-0.479)	(1.174)	(1.259)	(1.379)
HO	-0.002	6.587***	-0.037	-0.048	6.008***	0.062*	-0.101**	4.994***	0.072**	-0.074**	4.455***	0.062**	0.057*
	(-0.766)	(8.461)	(-1.172)	(-1.225)	(7.391)	(1.719)	(-2.088)	(6.712)	(2.008)	(-2.016)	(7.291)	(2.111)	(1.728)
NG	0.005**	3.897***	-0.016	0.007	0.498	0.121*	0.124*	0.878	0.076	0.081	4.071***	0.022	0.047
	(2.29)	(2.645)	(-0.44)	(0.505)	(0.695)	(1.907)	(1.798)	(0.931)	(1.375)	(1.563)	(4.402)	(0.847)	(0.879)
HG	0.005	0.924***	-0.158***	-0.16***	0.942***	-0.18***	-0.183***	1.011***	-0.013	-0.058*	1.179***	-0.033	-0.042
	(1.641)	(5.007)	(-5.717)	(-5.003)	(4.313)	(-6.624)	(-6.427)	(3.894)	(-0.681)	(-1.961)	(4.529)	(-1.323)	(-1.513)
GC	-0.003	0.909***	-0.101***	-0.094***	0.277	-0.098***	-0.094***	0.777***	-0.008	-0.035	0.84***	0.01	0.019
	(-0.391)	(5.498)	(-3.586)	(-3.029)	(1.451)	(-3.267)	(-3.225)	(3.929)	(-0.52)	(-1.523)	(4.341)	(0.704)	(0.979)
SI	0.001	0.761***	-0.267***	-0.268***	1.235***	-0.193***	-0.072	1.393***	-0.017	-0.01	1.781***	-0.047	-0.029
	(0.191)	(3.212)	(-4.732)	(-4.726)	(3.179)	(-4.291)	(-1.451)	(3.325)	(-0.716)	(-0.431)	(5.612)	(-1.569)	(-0.94)
PL	0.003	1.187***	-0.08**	-0.051	1.263***	-0.083*	-0.107***	1.215***	-0.088***	-0.09***	1.117***	-0.014	-0.045*
	(0.497)	(5.296)	(-2.271)	(-1.451)	(4.236)	(-1.844)	(-2.635)	(6.508)	(-3.311)	(-3.126)	(5.696)	(-0.813)	(-1.913)

Our study employs the quantiles regression to investigate the impact of CPU on commodity futures under distinct market conditions. Our results reveal several interesting findings. Different from the OLS results that only silver futures returns show significant negative responses to uncertainty of climate policy, we find that CPU has a significant negative (positive) impact on returns of all commodities (except natural gas) in bearish market conditions (between $\tau = 0.05$ and $\tau = 0.25$). This suggests that energy and metal commodity futures factor in climate policy uncertainty, along the same direction (except natural gas). Under normal market condition ($\tau = 0.05$), energy and metals behave differently, where heating oil is the only commodity that shows a significant positive response to CPU and platinum is the only commodity moving reversely with CPU. When market conditions are bullish, we find the dependence of commodity returns on CPU is heterogeneous among energy and metal commodities and not statistically significant at conventional levels. These results indicate that when commodity prices are at low quantiles, government, investor and producers shall be cautious of the negative impact from climate policy uncertainty. On the contrary, natural gas price moves in the opposite direction to other commodities under the bearish market, which is found to respond positively to CPU and can serve the role of hedging climate policy risk.

For the purpose of channel analysis, we conduct mediation quantile model, where inventory level and hedging pressure are mediator variables. Although inventory data may suffer from measurement error, we show that the state of inventory plays a role in mediating the impact from CPU to commodity futures price for copper but not other commodities. Specifically, the mediating effect of inventory level indicates that CPU index triggers the reduction of inventory holding and increases of commodity supply in the market which affects the commodity prices under bearish market. Regarding the other channel variable - positions of futures traders, we do not find supporting evidence of the mediating effect, although net traders positions of crude oil and natural gas do significantly respond to CPU shocks.

Taken together, our study highlights the importance of understanding the impact of climate policy risk on commodity futures markets. In our efforts to build environmentally friendly societies, our results shed lights on the influences of unstable government policy on commodity relevant participants, e.g. producers' inventory holding strategies and hedging decisions.

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