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Sailing the stormy seas: Energy hedge funds strategy innovation, and market uncertainties[☆]

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ABSTRACT

This paper examines the relationship between idiosyncratic volatility of energy hedge funds and a range of uncertainty measures relevant to the global energy markets. Using GARCH-family models, we find a consistent negative relationship between idiosyncratic volatility and economic, climate, and energy market uncertainties. This evidence points to specialist hedge funds developing innovative hedging capabilities during energy markets transformation toward the net zero and idiosyncratic volatility associated with it, with commodity strategies demonstrating a stronger effect. Our analysis reveals non-linear interactions: increased climate policy uncertainty during high economic policy uncertainty periods is associated with larger decreases in idiosyncratic volatility. Additionally, simultaneous success of bond and commodity trend-following strategies corresponds with substantial reductions in idiosyncratic volatility, suggesting synergistic risk-management benefits.

1. Introduction

The onset of the Global Financial Crisis (GFC) has ushered in a new era in the nexus between financial markets intermediation, energy markets (Chong and Miffre, 2010; Urom et al., 2021) and the strategic decision-making environment of specialist hedge funds (Noori and Hitaj, 2023). These changes have altered correlations between energy prices, financial markets and influenced systemic risk dynamics in energy markets (Urom et al., 2021). Financialization-related transformation of the energy markets took place along the revolutionary changes in energy production and delivery systems (Kilian, 2016). Per growing literature on the subject of energy markets transformations, summarized in the Literature Review section below, these and other economic and financial markets changes are influencing the context within which energy-specialized investment funds operate (Christoffersen et al., 2019; Foglia et al., 2023; Cheikh and Zaied, 2023 & Cheikh and Zaied, 2024). The transformation of the investment markets involving energy-related assets, therefore, is inextricably linked to the structural or systemic changes taking place in financial markets, energy production sector, and energy demand and suppy systems, all shaped by geoeconomic, geopolitical and environmental shocks and uncertainties.

In light of these developments, our study provides novel insights that contribute significantly to the understanding of energy hedge fund dynamics and financial innovation in energy markets. We find a consistent negative relationship between the idiosyncratic volatility of energy hedge funds returns and various uncertainty measures, including Economic Policy Uncertainty (EPU), Climate Policy Uncertainty (CPU), and Energy Uncertainty Index (EUI). This relationship persists across different volatility modeling techniques (GARCH, TGARCH, and EGARCH), suggesting that energy hedge funds may effectively provide a hedge against multiple types of systemic uncertainties.

Our analysis also finds an important role of trend-following strategies in risk management for equity markets-focused energy hedge funds for both bond (BD) and commodity (COM) trend-following strategies which show significant negative relationships with idiosyncratic volatility. Energy hedge funds may use these strategies to diversify their

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otherwise equity-focused portfolios, thereby reducing overall idiosyncratic risk. Additionally, successful implementation of trend-following strategies might coincide with periods of lower market volatility, indirectly leading to reduced idiosyncratic risk. These strategies may serve as effective hedging tools, allowing funds to mitigate specific risks associated with the energy sector, including dynamically evolving geopolitical and environmental uncertainties. Furthermore, we show that the success of trend-following strategies might reflect periods of greater market efficiency, which correspond to lower idiosyncratic volatility.

Next we consider the non-linear impacts of uncertainities. We find that during periods of elevated economic policy uncertainty, increases in climate policy uncertainty are associated with a larger decrease in the idiosyncratic volatility of hedge funds. These findings are important, considering the fact that climate uncertainty is strongly linked to economic uncertainty, and that despite this, no studies to-date considered the impact of the twin uncertainties interactions on hedge funds or energy sector-focused investment funds returns volatilities. Additionally, we observe that the effectiveness of trend-following strategies as risk management tools may be reduced during periods of higher inflation or positive economic sentiment. Our analysis shows a consistent negative relationship between the Consumer Price Index (CPI) and idiosyncratic volatility. This inverse relationship suggests that positive economic sentiment, as reflected by rising consumer prices, is associated with reduced fund-specific risk. These findings are unique to our study and are novel to the literature on hedge funds in general, and energy markets intermediation in particular.

Overall our findings suggest the adaptive capabilities of energy hedge funds in navigating complex uncertainty environments, covering economic, climate and energy sector uncertainties. These are entirely novel results for the literature on hedge funds returns and energy sector investment funds. Furthermore we show the importance of considering both linear and non-linear relationships when analyzing the risk profiles and performance of energy hedge funds. These interactions allow us to capture the reality of economic, climate and energy systems interdependencies that are common to the broader finance analysis, but are new to the literature on hedge funds and energy sector-specialized investment funds.

The theoretical underpinnings of this study are rooted in the seminal work of Fung & Hsieh (2001 and 2011), who show the distinctive risk-return profiles of hedge funds through their dynamic trading strategies, and Christoffersen et al. (2019), who provide an analysis of factor structures in commodities futures volatility. Our study extends the understanding of hedge fund volatility by focusing on energy-specific hedge funds within the context of multiple uncertainty measures. Unlike Fung and Hsieh, who primarily focus on systematic risk factors and their impact on hedge funds at a general level, our study analyzes the idiosyncratic volatility to understand how it interacts with economic, climate, and energy markets uncertainties for energy-focused hedge funds. Additionally, while Christoffersen et al. (2019) employed a static factor analysis approach, our study uses rolling correlation analysis as a dynamic method to examine the evolving relationships between uncertainty indices and energy hedge fund voltilities over time. This method allows for the capture of intertemporal variations in correlations that static methods overlook. We are therefore able to show how energy hedge funds dynamically react to shifts in various uncertainity measures, and how interactions between a range of uncertainty environments shape these reactions.

Our work is also related to, motivated by and builds on the current state of play in several strands of financial literature. Notably, Noori and Hitaj (2023) study of hedge funds indices spillover effects into other financial markets. Their findings, reviewed in Section 2 below, prompt us to look at the idiosyncratic volatility in the energy sector-focused hedge funds. In addition to the current interest in hedge funds' volatility dynamics, our study looks at the dynamic aspects of the energy hedge funds' strategies. Chong and Miffre (2010) and Singleton (2013) are two influential studies that informed our interest in the trend-following and risk management strategies of hedge funds. At the same time, more current literature on ESG and clean energy role in the financial markets contributed to our interest in more targeted approach to risk management strategies in energy hedge funds sector. The key studies informing our work in this context are Kuang (2021), Geng et al. (2021), Elie et al. (2019), Song et al. (2019) and others, as reviewed in Section 2 below.

In summary, we contribute to the literature on energy hedge funds and innovations in their risk management strategies by examining the dynamic relationship between idiosyncratic volatility and varioussystemic uncertainty measures. Our analysis extends previous work on hedge fund performance in energy markets, addressing the limited research on fund behavior in relation to specific energy sector risks. By focusing on economic, climate, and energy uncertainties, we provide new evidence into how these specialized funds navigate the complex and evolving energy landscape. Our examination of trend-following strategies and their effectiveness under different economic conditions provides a better understanding of risk management practices by a large cross-section of energy hedge funds. Our additional focus on interactions between different types of uncertainties as they impact hedge funds volatility dynamics reflects the complex and dynamic nature of climate change, economic shocks and energy markets developments not covered in the prior literature on hedge funds returns. By analyzing energy hedge fund behavior in response to multiple market uncertainties, we contribute to the understanding of risk management in energy finance during a period of significant innovation.

The remainder of the this paper is organized as follows: in Section 2, we describe the data, their sources and our empirical methods, Section 3 presents the results and Section 4 concludes.

2. Literature review

2.1. Changing environment for energy hedge funds

A key post-Global Financial Crisis (GFC) development is the growth of energy sector-specialized hedge funds (HFJ, 2018), reflecting the increasing financialization of commodities (Singleton, 2013; Büyükşahin and Robe, 2014).

This shift toward energy-focused hedge funds has occurred alongside significant changes in the broader financial landscape. Hedge funds have increasingly adopted alternative data sources and analytical techniques to gain an edge in energy markets (Ke et al., 2020), potentially leading to increased market efficiency but also heightened volatility (Hasbrouck and Saar, 2013). The post-GFC era has also seen a surge in energy derivatives trading, particularly in crude oil futures and options (Bessembinder et al., 2016).

The fast-paced financialization of commodity markets has increased correlation between energy prices and broader financial assets, with institutional trading in commodity futures potentially generating spillover effects between equity and commodity markets, thereby increasing systemic risk (Basak and Pavlova, 2016; Urom et al., 2021). Additionally, post-GFC regulatory changes, such as the Dodd-Frank Act, have altered hedge fund risk-taking behavior, impacting market liquidity and driving innovations in price discovery in energy markets (Agarwal et al., 2017).

These financial developments have coincided with shifts in the global energy production landscape, including the U.S. shale oil revolution, the rise of the natural gas as a 'transition fuel', growing emphasis on renewable energy, followed by the more formal adoption of net zero paths to curbing global energy-related emissions. Kilian (2016) argues that these structural changes have fundamentally altered energy price formation dynamics, creating both challenges and opportunities for specialized hedge funds.

Thus, the growth of energy-focused hedge funds has occurred within a context of multidimensional change in both energy production sector and financial markets for energy. Firstly, the energy landscape is being disrupted by alternative energy sources, retirement of traditional plants, and at first declining, and since the start of the 2020s renewed interest in nuclear power, reflected in changing investor exposures to energy subsectors (Sadamori, 2020; Kuang, 2021; Wealer et al., 2021). Secondly, rising environmental concerns are influencing investments and operations in the traditional energy sector (Kuang, 2021; Dutta et al., 2020). Thirdly, the sector has experienced significant geopolitical shocks, including supply and demand disruptions in the Middle East and Eastern Europe, and sanctions on major economies. These shocks have both direct and indirect impacts on energy-specialized investment funds, as highlighted by Christoffersen et al. (2019), on energy commodities (Foglia et al., 2023), and on global transition to clean energy (Cheikh and Zaied, 2023 & Cheikh and Zaied, 2024).

2.2. Hedge funds strategies and the changing nature of energy markets

Recently, Noori and Hitaj (2023) studied the dynamics of four major hedge fund industry indices in relation to equity markets, commodity markets, currencies, and debt markets using (ADCC) GJR-GARCH model over the period of April 2003 to May 2021. The authors break down the performance, riskiness, investing style, volatility, dynamic correlations, and shock transmissions of each hedge fund strategy, while also considering the impact of commodity futures on funds' return. The key finding of importance to our study is that since the peak of GFC in 2009, there are strong and pervasive shock spillovers from hedge fund industry to other financial markets, and especially to commodities futures, so that an increase in the futures basis of commodities drives up hedge funds' performance. While Noori and Hitaj (2023) found strong shock spillovers from the hedge fund industry to other financial markets, their research does not consider longer term structural shocks to the commodities and other financial markets. Our research addresses this gap by examining the idiosyncratic volatility of energy hedge funds in relation to economic, climate, and energy uncertainties.

Singleton (2013) analyzed the impact of investor fund flows and financial market environment on oil futures highlighting the role of speculative activity on oil prices drift away from fundamentals-derived valuations, leading to price booms and busts. Singleton (2013) focuses on the role of the imperfect information about real economic activity (supply and demand), and speculative activity in oil markets. The study found that the main impacts on futures prices arose from intermediate-term growth rates of index positions, managed-money spread positions and hedge funds' trading in spread positions in futures. This indirectly supports our interest in hedge funds' propensity to engage in trend following and the dynamics of energy markets pricing.

Meanwhile, Chong and Miffre (2010) relate energy commodities markets dynamics to the changes in investment funds' strategies between the tactical and the strategic asset allocation strategies pre-GFC and during the crisis. The study indicated that following the onset of the GFC, institutional investors re-allocations to commodity markets were consistent with taking strategic approach to the asset class, while prior to 2008, investors' positioning in the commodities markets was reflective of tactical allocations. Our study extends the work of Chong and Miffre (2010) by examining the behavior of energy hedge funds in the post-GFC era, with a specific focus on their risk management strategies.

Kuang (2021) presents robust evidence that clean energy assets are creating new opportunities for institutional investors. The study focuses on clean energy equities, showing that these tend to outperform dirty energy stocks. As covered in the study, the shift in popularity of cleaner energy technologies among the investors is captured not only in the aggregate investment flows to the clean tech, but also by financial properties of the energy markets. This conjecture is supported by other studies. Specifically, Geng et al. (2021) argue that while shocks in oil prices and clean energy stocks co-move, oil returns predominantly act as a net information receivers of shocks originating in the clean energy subsector. This opens strong risk hedging opportunities for investors allocating into clean energy vis-à-vis energy price shocks. Similarly, Elie et al. (2019) and Song et al. (2019) suggest that crude oil prices act at best as only weak risk-diversifiers for clean energy prices, once again indicating weak and incomplete markets connectedness between fossil fuels and clean energy. Broadly, the same findings were reported by Saeed et al. (2020).

Dutta et al. (2020); Liu and Hamori (2021) find that informational connectedness and shocks transmission is weaker for returns than for volatility of returns for energy stocks, suggesting that any hedging strategy can be more effective when allowing for volatility exposures, such as, via trend following strategies. The former study shows that oil prices have a positive, but statistically insignificant impact on environmental investments. At the same time, as the authors put it, environmental assets tend to be more vulnerable to oil market volatility rather than to oil price changes. The logic of using clean energy assets as a risk management tool for fossil fuels-intensive asset holdings is also explored in Saeed et al. (2020), as well as in Miralles-Quirós and Miralles-Quirós (2019) for energy sector ETFs, and Henriques and Sadorsky (2018) for equities. Liu et al. (2021) study shocks transmission across a range of financial assets and markets, showing that energy sector funds (ETFs) are distinct from oil price index in volatility connectedness. However, both energy sector funds and crude oil prices act as net transmitters during periods of elevated energy prices and net receivers of volatility during negative shocks to energy prices. Liu et al. (2021) also show that financial sector in general acts as a net shocks transmitter and this role of the financial sector peaks in periods of financial markets turmoil.

The literature on hedge funds performance and energy markets focuses on macroeconomic drivers and factors underlying the investment markets environment (e.g. Bali et al., 2014; Agarwal et al., 2017; Racicot and Théoret, 2019 for macro shocks transmission). Fewer studies, as noted in Noori and Hitaj (2023) consider properties of hedge funds returns in the context of other assets classes, beyond equities. Only a small sub-strand of this literature relates investment funds (including hedge funds) performance to energy prices, predominantly proxied by oil prices. For example, Junttila et al. (2018) use daily data from 1989 to 2016 study risk hedging properties between oil market futures and equity returns in the aggregate US market, and in the energy sector stocks.

More fundamentally, some literature is starting to question the extent to which the financial services sector, including institutional investors, have cut their links to dirty energy. Ruzzenenti et al. (2023) shows that as the society is paring back its exposure to oil industry, despite the promise to divest or reduce investments, financial sector continues to retain strong connections with the dirty energy sector. Specifically, the study indicates that investment funds that are commonly marketed as 'climate-themed' continue to retain shares in major polluters, including oil majors. This phenomenon became even more pronounced during the current bout of energy prices volatility triggered by the war in the Ukraine.

Nikkinen and Rothovius (2019) argue that energy stocks face two types of uncertainty: crude oil uncertainty and stock market uncertainty, with the former dominating in importance, especially in more recent years. Subsequently, the authors argue that hedging properties of the energy stocks are distinct to other sectors and can be actively targeted by institutional investors. This is the closest that we come in the literature to an analysis of the risk management and returns properties of the institutional investors in the energy sector in the presence of general market and energy price uncertainty. Dutta et al. (2020) relies on the above thinking and develops analysis of uncertainty impact on clean energy ETFs. The authors use energy sector implied volatility index (VXXLE) to model energy sector volatility and apply it to clean energy ETFs across low and high volatility regimes. While overall energy price volatility has negative impact on clean energy sector firms, this effect is stronger during the periods of high volatility regimes. Interestingly, the results of the study remain robust when controlling for oil prices, oil volatility and other shocks. Again, these findings suggest that passive longer-term trend following strategies involved in investing in clean energy sector are likely to benefit investors in periods of relative geopolitical and geoeconomic stability associated with lower structural volatility in the energy prices. More active risk management strategies, in contrast, can be more productive in periods of high energy price distress. Notably, Dutta et al. (2020) are also qualitatively mirrored in Fahmy (2022).

2.3. Key research questions and hypotheses

In line with observed high volatility of the energy markets and the complex strategies used generally by investment funds in response to such volatility (Nikkinen and Rothovius, 2019; Dutta et al., 2020; Noori and Hitaj, 2023) we examine the impact of the uncertainty environments (reflected in the Economic Policy Uncertainty (EPU) index, the Climate Policy Uncertainty (CPU) index, and the Energy Uncertainty Index (EUI)) on specialized hedge funds voltililties. Our key hypotheses here are that hedge funds focused on energy sector should exhibit similar risk management properties to those of energy commodities, notably:

Hypothesis 1. Hedge funds specializing in energy sector investments should exhibit risk-hedging properties with respect to CPU, EPU and EIU-modeled general uncertainty environments.

When it comes to trend-following strategies, we expect that energy hedge funds should exhibit similar dynamics to the more general findings of Fung & Hsieh (2001 and 2011), Singleton (2013), Agarwal et al. (2017):

Hypothesis 2. Hedge funds specializing in energy sector exhibit voltilities consistent with a part of their strategies associated with trend following in equities, debt and commodities markets.

Inflationary impacts on energy markets dynamics can be expected to feed through to energy sector hedge funds via several channels established in the literature. On the one hand, energy commodities are known to be a hedge against inflation. In addition, periods of high inflation are commonly coincident with periods of higher economic growth and greater demand for energy resources. Lastly, trend following and other strategic responses to uncertainty can lead the funds to be more responsive to inflationary and other markets pressures. We add complexity to this analysis by controlling the relationship between inflation dynamics and energy sector hedge funds returns for general economic policy, climate policy and energy markets uncertainty.

Hypothesis 3. Hedge funds specializing in energy sector exhibit volatilities consistent with the hedging properties of energy assets in relation to inflationary pressures.

Hypothesis 3.1. The inflation hedging property of energy sector hedge funds is influenced by the funds' responses to general sources of economic, climate and energy uncertainty.

Lastly, reflective of the aforementioned arguments concerning the complexity of the energy sector and specialist hedge funds strategic responses to different forms of uncertainty, we hypothesize that:

Hypothesis 4. Energy sector hedge funds volatilities will exhibit complex and dynamic interactions with different types of uncertainty, conditioned by macroeconomic environment and trading opportunities (trend following strategies).

Hypothesis 4.1. The second dimension of complexity analysis indicates that sources of uncertainty shocks (EPU, CPU and EUI) will exhibit non-linear, interactive effects on hedge funds' voltilities.

Overall, hypotheses H.1, H.3, H.3.1, and H.4.1 are novel contributions to the literature on energy markets dynamics in response to climate, economic and energy uncertainties, as well as to the literature on specialist hedge funds.

3. Data and methodology

3.1. Data

Our sample comprises monthly data on U.S. energy-related hedge funds from January 2008 to May 2024, obtained from Datastream. We include the S&P500 Energy Select Sector Index and the Global Price of Energy Index from Datastream and FRED, respectively. To assess the impact of policy uncertainties, we incorporate the Economic Policy Uncertainty (EPU), Energy Uncertainty Index (EUI) and Climate Policy Uncertainty (CPU) indices from Baker et al. (2016), Dang et al. (2023), and Gavriilidis (2021). Following Fung and Hsieh (2001) and Fama and French (2015), we include additional risk factors. We also include the Consumer Price Index (CPI) to proxy for economic sentiment. We identify energy-focused funds using 13F filings and publicly available investment data, resulting in a final sample of 47 funds out of 376 initially considered. To mitigate the impact of outliers, we winsorize all variables at the 1st and 99th percentiles. This comprehensive dataset allows us to examine the long-term relationship between hedge fund idiosyncratic volatility and various energy market uncertainties, spanning multiple energy crises and significant market events.

Fig. 1 plots the historical trends in energy prices from January 2008 to May 2024, depicting the S&P500 Energy Select Sector Index and the Global Price of Energy Index. One can observe significant volatility in energy markets over the sample period, with both indices exhibiting large fluctuations.

Key events are also evident in the price movements. The 2008 GFC is reflected in a sharp decline at the beginning of the sample period. The subsequent years show the impact of the U.S. shale oil boom, followed by the 2014–2016 oil price crash. The graph also captures the unprecedented price collapse during the COVID-19 pandemic in 2020 and the subsequent rapid recovery. The latter part of the sample period displays the energy price surge associated with the Russia-Ukraine conflict. Throughout these events, the Global Price of Energy Index exhibits less volatility compared to the S&P500 Energy Index, potentially reflecting the broader, more diversified nature of the global energy market.

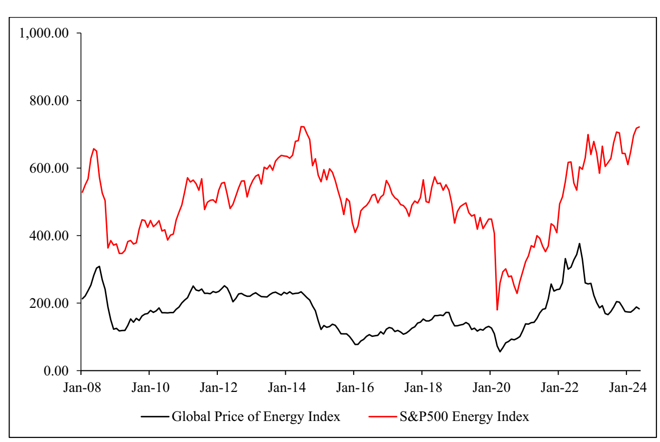

Fig. 1. History of energy price movements.

3.2. Methodology

To estimate the idiosyncratic volatility, we first employ Fama and French (2015) five-factor model (FF5) as follows:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{i,t} - R_{f,t}) + s_i SMB + h_i HML + r_i RMW + c_i CMA + \varepsilon_{i,t} \tag{1}$$

FF5 is an extension of the capital asset pricing model (CAPM) developed by Sharpe (1964) and Fama and French (1993) three-factor model, providing more comprehensive estimates and better explanatory power compared to other two models. From the five-factor model, we collect each residual, $\varepsilon_{i,t}$, and then estimate the conditional idiosyncratic volatility by utilizing time-varying measurements.

We use three GARCH-family models in our analysis to address the need to model the time-varying volatility characteristic of energy hedge fund flow data. GARCH (1,1), introduced by Bollerslev (1986), is utilized for its efficacy in modeling general volatility clustering. This standard model provides properties for time aggregation and stationarity but does not capture the leverage effect. To address the potential asymmetry and leverage effects, which are particularly pertinent in energy markets where negative shocks might have different impacts compared to positive ones, we employ TGARCH (1,1). Based on the study of Zakoian (1994), TGARCH (1,1) model is crucial for understanding how energy hedge funds react differently to market ups and downs, reflecting the reality of investors' risk-averse behavior and allows us to capture the asymmetric impact of good and bad news. Furthermore, to handle heteroskedasticity and potential non-linear effects without the constraints of non-negative coefficients required in standard GARCH and TGARCH models, EGARCH (1,1) is included. This model variation provides a more flexible response to the size and sign of shocks. EGARCH is particularly relevant for our study as it shows how volatility responses to shocks in uncertainty indices are not merely proportional but also depend on the direction and magnitude of the changes.

We based our general models on those of Zakoian (1994), TGARCH (1,1) model, described as follows:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \lambda_1 d_{t-1} \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{2}$$

where d_{t-1} is a dummy variable that is equal to one if $\varepsilon_{i,t} < 0$ (bad news) otherwise 0 ($\varepsilon_{i,t} \geq 0$), which indicate good news. From the outcomes of TGARCH (1,1), we collect residuals as the conditional idiosyncratic volatility. We do the same process employing EGARCH (1,1) model developed by Nelson (1991) and GARCH (1,1) as well.

Next, we provide three different versions of our analysis – restricted, extended, and full – to investigate the relationship between idiosyncratic volatility and uncertainty measures, as well as between the idiosyncratic volatility and other variables to see the comprehensive views of these relationships. Note that we control time and firm-level factors for all three versions. First, the restricted version is described as follows:

$$\psi_{i,t} = \gamma_0 + \gamma_1 \mathit{Uceratinty}_{i,t-1} + \mathit{Time\ Dummy} + \mathit{Firm\ Fixed\ Effects} + e_{i,t} \tag{3}$$

where $\psi_{i,t}$ indicates the idiosyncratic volatility of each firm taking log of the conditional variance based on three time-varying measurements for FF5 model. We employ three uncertainty measures – EPU, CPU, or EUI – as our uncertainty proxy. In the extended version, we add additional variables, and the model is described as follows:

$$\begin{aligned}\Psi_{i,t} = \gamma_0 + \gamma_1 \mathrm{Uceratinty}_{i,t-1} + \gamma_2 \mathrm{HF}_{i,t-1} + \gamma_3 \mathrm{BD}_{i,t-1} + \gamma_4 \mathrm{COM}_{i,t-1} \\ + \gamma_5 \mathrm{Sentiment}_{i,t-1} + \mathrm{Time\ Dummy} + \mathit{Firm\ Fixed\ Effects} + e_{i,t}\end{aligned} \tag{4}$$

Beyond the first extended version, we add three different types of returns and sentiment variables for further analysis. The full relationship tested is described as follows:

$$\begin{aligned}\Psi_{i,t} = \gamma_0 + \gamma_1 \mathrm{Uceratinty}_{i,t-1} + \gamma_2 \mathrm{Interaction}_{1\,i,t-1} + \gamma_3 \mathrm{HF}_{i,t-1} + \gamma_4 \mathrm{BD}_{i,t-1} \\ + \gamma_5 \mathrm{COM}_{i,t-1} + \gamma_6 \mathit{Sentiment}_{i,t-1} + \gamma_7 \mathit{Interaction}_{2\,i,t-1} \\ + \mathit{Time\ Dummy} + \mathit{Firm\ Fixed\ Effects} + e_{i,t}\end{aligned} \tag{5}$$

Along with other variables, we provide two interaction terms – *interaction*$_1$ (EPU * CPU, CPU * EUI, and EUI * EPU) and *interaction*$_2$ (BD * COM). Lastly, we also provide another versions of the models as follows:

$$\begin{aligned}\Psi_{i,t} = \gamma_0 + \gamma_1 \mathrm{Uceratinty}_{i,t-1} + \gamma_2 \mathrm{Interaction}_{1\,i,t-1} + \gamma_3 \mathrm{HF}_{i,t-1} + \gamma_4 \mathrm{BD}_{i,t-1} \\ + \gamma_5 \mathrm{COM}_{i,t-1} + \gamma_6 \mathit{Sentiment}_{i,t-1} + \gamma_7 \mathit{Interaction}_{2\,i,t-1} \\ + \mathit{Time\ Dummy} + \mathit{Firm\ Fixed\ Effects} + e_{i,t}\end{aligned} \tag{6}$$

$$\begin{aligned}\Psi_{i,t} = \gamma_0 + \gamma_1 \mathrm{Uceratinty}_{i,t-1} + \gamma_2 \mathrm{Interaction}_{1\,i,t-1} + \gamma_3 \mathrm{HF}_{i,t-1} + \gamma_4 \mathrm{BD}_{i,t-1} \\ + \gamma_5 \mathrm{COM}_{i,t-1} + \gamma_6 \mathit{Sentiment}_{i,t-1} + \mathit{Time\ Dummy} \\ + \mathit{Firm\ Fixed\ Effects} + e_{i,t}\end{aligned} \tag{7}$$

The difference between full versions is different combinations of interaction term in each models (5), (6), and (7).

4. Empirical findings

4.1. Preliminary analysis

Table 1 reports the summary statistics for our sample data, consisting of energy-related hedge funds over the period from January 2008 to May 2024.[1] These funds exhibit substantial volatility, with an average monthly return of 0.60 % and a standard deviation of 5.25 %. The maximum monthly return observed is 38.31 %, while the minimum is −38.87 %, indicating significant potential for both gains and losses. This high volatility is consistent with the nature of energy markets and the complex strategies used by hedge funds in this sector (Noori and Hitaj, 2023).

Among the uncertainty indices examined, the CPU index shows the largest fluctuations, with an average monthly change of 6.96 %. This is substantially higher than the EUI, which exhibits an average monthly change of 2.49 %, and the EPU index, which shows an average monthly change of 4.13 %. We also note that all three uncertainty indices scaled in the same manner.

Turning to the trend-following strategy returns, we observe a disparity between bond and commodity trend-following strategies. The BD yields a positive mean monthly return of 2.58 %, while the COM produces a near-zero mean monthly return of −0.21 %. Both strategies, however, are characterized by high volatility, with standard deviations of 23.01 % and 14.58 % for BD and COM, respectively. This is consistent with the findings of Fung & Hsieh (2001 and 2011) on the uniqueness of risk-return profiles of hedge funds returns.

The broader energy market indices show positive but volatile returns over the sample period. The S&P500 Energy Index and Global Price of Energy Index exhibit mean monthly returns of 0.65 % and 0.44 % respectively, with standard deviations of 8.64 % and 8.48 %. Regarding the FF5 factors, the MktRF shows a mean monthly return of 0.92 % with a standard deviation of 4.77 %. The SMB and HML factors show slight negative mean returns of −0.04 % and − 0.09 % respectively, while the RMW and CMA factors show positive mean returns of 0.41 % and 0.05 % respectively. Lastly, the risk-free rate (RF) has a mean of 0.10 % per month with a standard deviation of 0.14 %, reflecting the low-interest rate environment that prevailed for much of the sample period. This low-interest rate environment has implications for hedge fund strategies and performance (Agarwal et al., 2017).

Table 2 presents the correlation analysis for our sample data, reveals = ing several interesting relationships in our data. Hedge fund returns

[1] Appendix A provides variable descriptions.

Table 1
Summary statistics.

Variables	Mean	Std Dev	Max	Median	Min	Skewness	Kurtosis
Return	0.0060	0.0525	0.3831	0.0050	−0.3887	0.2545	11.3021
IVOL_Garch	0.0458	0.0257	0.2063	0.0382	0.0172	2.1179	8.3789
IVOL_Tgarch	0.0457	0.0255	0.1971	0.0381	0.0172	2.0939	8.1910
IVOL_Egarch	0.0450	0.0210	0.1699	0.0402	0.0114	1.7460	7.0687
EPU	0.0413	0.3187	1.9345	−0.0020	−0.6010	1.6534	9.0560
CPU	0.0696	0.4124	2.4304	−0.0085	−0.6109	1.8769	10.1099
EUI	0.0249	0.3015	1.3753	−0.0115	−1.0000	1.1111	7.1207
S&P500 Energy	0.0065	0.0864	0.4459	0.0077	−0.5573	−0.9090	16.0930
Global Energy	0.0044	0.0848	0.2759	0.0085	−0.3321	−0.3531	4.9718
BD	0.0258	0.2301	1.2577	−0.0280	−0.2663	2.1291	9.5925
COM	−0.0021	0.1458	0.7542	−0.0294	−0.2465	1.3950	6.7822
CPI	0.0022	0.0031	0.0125	0.0023	−0.0177	−0.7702	9.7088
MktRF	0.0092	0.0477	0.1365	0.0140	−0.1723	−0.4809	3.7397
SMB	−0.0004	0.0277	0.0733	−0.0006	−0.0828	0.1892	3.3396
HML	−0.0009	0.0357	0.1275	−0.0037	−0.1387	0.1005	5.0557
RMW	0.0041	0.0207	0.0720	0.0044	−0.0475	0.4512	3.7092
CMA	0.0005	0.0221	0.0773	−0.0009	−0.0722	0.2761	4.6120
RF	0.0010	0.0014	0.0047	0.0001	0.0000	1.4869	4.0525

Table 1 reports the summary statistics for this study, including energy and energy-related hedge funds in the United States. Also, it includes uncertainty, additional returns, sentiment and risk factors. The sample data is based on monthly frequency and spans from January 2008 to May 2024.

exhibit a weak negative correlation with both EPU and CPU, with correlation coefficients of −0.0715 and − 0.0536 respectively, both statistically significant at the 5 % level. This suggests that increases in policy uncertainties are associated with slightly lower hedge fund returns. Interestingly, hedge fund returns show a positive and significant correlation with both the S&P500 Energy Index (0.0750) and the Global Price of Energy Index (0.1602). This indicates that energy hedge funds tend to perform better when global energy prices are rising, consistent with the observations of Singleton (2013) regarding the impact of investor fund flows on oil prices.

The CPI shows a positive and significant correlation with hedge fund returns (0.1593), suggesting that these funds may offer some inflation protection or that hedge funds perform better when sentiment is positive as proxied by CPI. However, CPI is negatively correlated with both EPU (−0.0985) and CPU (−0.0804), implying that periods of higher policy uncertainty are associated with lower inflation rates or lower sentiment.

Among the uncertainty measures, EPU and CPU show a moderate positive correlation (0.2715), indicating some alignment between economic and climate policy uncertainties. However, the EUI shows only weak positive correlations with EPU (0.0736) and CPU (0.1030), which imply that energy-specific uncertainties may be driven by factors distinct from other policy uncertainties.

The trend-following strategies, BD and COM, show positive correlations with EPU (0.2227 and 0.2770 respectively) and weaker positive correlations with CPU (0.1010 and 0.0467 respectively). This suggests that these strategies may perform better during periods of higher policy uncertainty, consistent with the findings of Fung and Hsieh (2001) regarding the unique risk-return profiles of hedge funds. However, both strategies are negatively correlated with the S&P500 Energy Index and Global Price of Energy Index, indicating they may serve as potential hedges against energy price movements.

Lastly, it's worth noting that while the correlations between hedge fund returns and the uncertainty indices are relatively weak, they are statistically significant, suggesting a weak persistent relationship between policy uncertainties and energy hedge fund performance. It is also worth nothing that none of the correlations are significantly high to warrant too much concern over mulicollinearity in our regressions models to be presented later in this paper.

4.2. Rolling correlation analysis

Figs. 2, 3, and 4 display the 12- and 24-month rolling correlations between our three main uncertainty indices: EPU, CPU, and EUI. Rolling correlation analysis is useful in this setting due to its ability to reveal changing patterns in data relationships over time, which helps to understand the behavior of energy hedge fund flows under different market conditions. This approach is consistent with the dynamic nature of hedge fund strategies in response to fluctuations uncertainity and traces back to earlier literature on hedges and safe havens properties (Ciner et al., 2013) while remaining current as a preliminary research tool today (Anas et al., 2025). Given that hedge fund managers adjust their strategies based on market conditions further argues for an analysis of the dynamic correlation stuctures. This dynamic adjustment is similar to our analytical approach, which captures changes in correlations that could signal shifts in risk or opportunities for hedging.

Fig. 2 shows the relationship between EPU and CPU. The correlation between these two indices fluctuates over time, suggesting that while economic and climate policy uncertainties are related, they are driven by distinct factors. Periods of high correlations may indicate times when climate policy is a significant factor influencing economic policy uncertainty. For instance, we observe stronger correlations during major climate policy events such as the Paris Agreement negotiations. On the other hand, periods of low or negative correlation might occur when economic policy uncertainty is driven by factors unrelated to climate, such as trade disputes or monetary policy changes. This dynamic relationship aligns with the findings of Nikkinen and Rothovius (2019), who argue that energy stocks face multiple types of uncertainties.

Fig. 3 illustrates the correlation between CPU and EUI. This relationship provides insights into how climate policy uncertainty relates to broader energy market uncertainty. Periods of strong positive correlation might suggest that climate policies are significantly influencing energy market dynamics. For example, announcements of stricter emissions regulations or incentives for renewable energy. Fig. 4 presents the correlation between EUI and EPU. This relationship helps us understand how energy-specific uncertainties correspond with broader economic policy uncertainties. Periods of strong positive correlation might occur during times of economic crisis or major policy shifts that significantly impact the energy sector. For instance, the correlation might strengthen during discussions about energy subsidies, trade policies affecting energy commodities, or major changes in environmental regulations. These observations are consistent with the work of Nikkinen and Rothovius (2019) as noted earlier, and Dutta et al. (2020), who examined the impact of uncertainties on clean energy ETFs.

Figs. 5, 6, and 7 show the correlations between CPI and the three return measures (HF, BD, and COM). These relationships show how inflation (or sentiment) relate to different investment strategies. Fig. 5 displays the correlation between CPI and hedge fund returns (HF). The relationship tends to be positive, consistent with the 0.1593 correlation

Table 2
Correlation analysis (January 2008–May 2024).

	Return	IVOL_Garch	IVOL_Tgarch	IVOL_Egarch	EPU	CPU	EUI	S&P500 Energy	Global Energy	BD	COM	CPI
Return	1.0000											
IVOL_Garch	0.0971*	1.0000										
IVOL_Tgarch	0.0952*	0.9988*	1.0000									
IVOL_Egarch	0.0924*	0.9846*	0.9859*	1.0000								
EPU	−0.0715*	−0.0163	−0.0167	−0.0134	1.0000							
CPU	−0.0536*	−0.0093	−0.0112	−0.0157	0.2715*	1.0000						
EUI	−0.0195	−0.0254*	−0.0261*	−0.0284*	0.0736*	0.1030*	1.0000					
S&P500 Energy	0.0750*	0.0176	0.0177	0.0151	−0.2995*	−0.0787*	−0.1081*	1.0000				
Global Energy	0.1602*	0.0553*	0.0525*	0.0462*	−0.1773*	−0.0202	−0.0626*	0.4227*	1.0000			
BD	−0.0209	0.0047	0.0016	−0.0029	0.2227*	0.1010*	0.0587*	−0.2587*	−0.1464*	1.0000		
COM	−0.0043	−0.0113	−0.0111	−0.0104	0.2770*	0.0467*	0.1893*	−0.3232*	−0.1738*	0.2416*	1.0000	
CPI	0.1593*	0.0343*	0.0272*	0.0175	−0.0985*	−0.0804*	−0.0415*	0.1593*	0.5382*	0.0205	−0.1350*	1.0000
	MktRF	SMB	HML	RMW	CMA	RF						
MktRF	1.0000											
SMB	0.3598*	1.0000										
HML	0.1183*	0.3141*	1.0000									
RMW	−0.1218*	−0.3918*	0.0442*	1.0000								
CMA	−0.1619*	0.0374*	0.6309*	0.1297*	1.0000							
RF	−0.0351*	−0.1356*	−0.0722*	0.0380*	−0.1490*	1.0000						

Note: * indicates a significant at the 95 % level.
In Table 2, we provide the correlation analysis for variables, separately in Panels A and B. In Panel A, we provide returns, uncertainties, and sentiment information; we report risk factors in Panel B. The sample spans from January 2008 to May 2024.

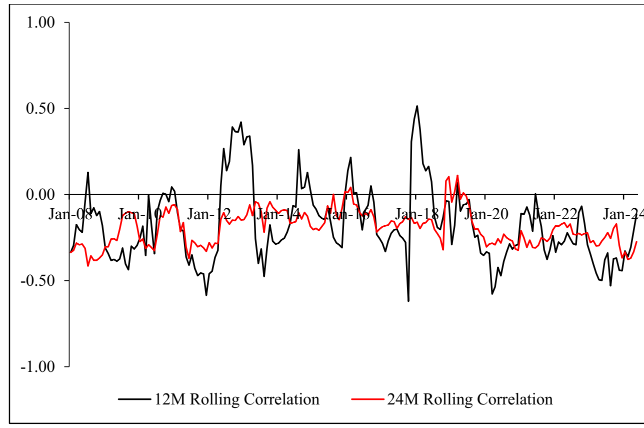

Fig. 2. EPU and CPU.

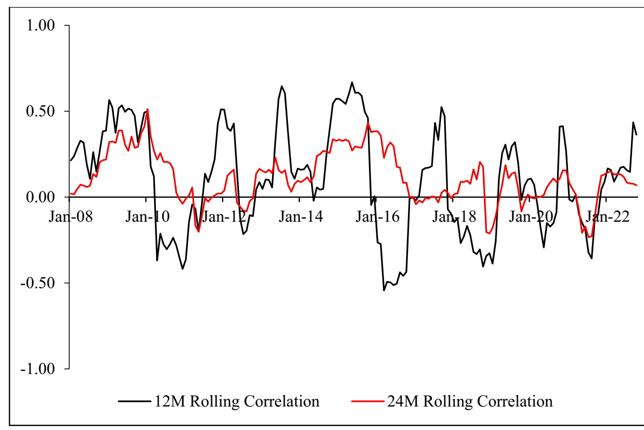

Fig. 3. CPU and EUI.

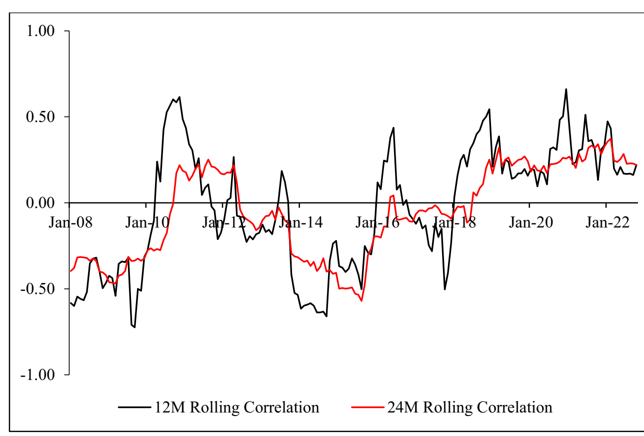

Fig. 4. EUI and EPU.

coefficient in Table 2. This suggests that hedge funds may offer some inflation protection or perform better when economic sentiment is positive. Some potential explanation for this include: 1) Energy assets often being considered a hedge against inflation, benefiting energy-focused hedge funds during inflationary periods; 2) Higher inflation often coinciding with periods of economic growth, which can benefit energy demand and, consequently, energy hedge fund performance; and 3) The ability of hedge funds to adjust their strategies in response to inflationary pressures, potentially capitalizing on price trends in energy commodities.

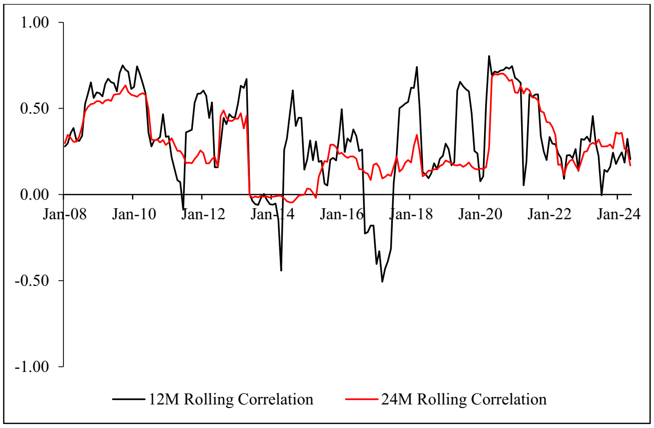

Fig. 5. CPI and HF.

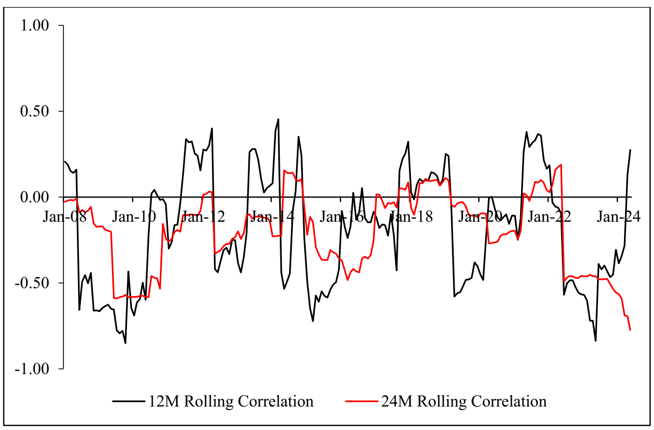

Fig. 6. CPI and BD.

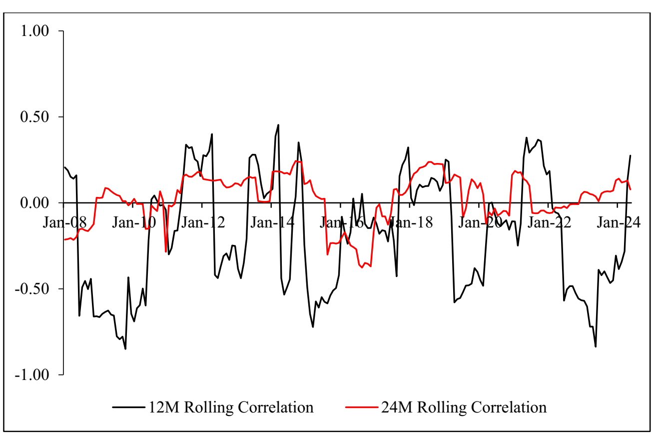

Fig. 7. CPI and COM.

Figs. 6 and 7 show the correlations between CPI and the trend-following strategies (BD and COM). These relationships appear to be weaker and more variable compared to hedge fund returns. This is consistent with the lower correlation coefficients reported in Table 2 (0.0205 for BD and − 0.1350 for COM). The negative correlation between CPI and COM (commodity trend-following) is particularly interesting, as it suggests that this strategy might struggle during inflationary periods.

Figs. 8, 11, and 14 show the correlations between hedge fund returns (HF) and the three uncertainty indices (EPU, CPU, and EUI,

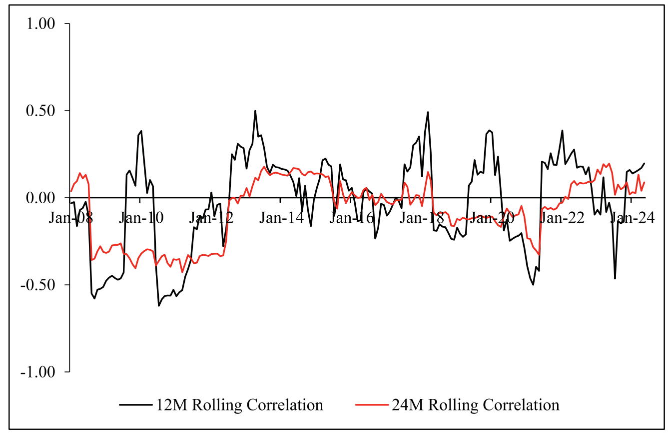

Fig. 8. EPU and HF.

respectively). These relationships are important for understanding how different types of uncertainties impact the performance of energy hedge funds and motivates variables in our regression models in the next section. Fig. 8 displays the rolling correlation between EPU and hedge fund returns. The relationship appears to be largely negative, consistent with the correlation coefficient of −0.0715 reported in Table 2. This suggests that increases in economic policy uncertainty are generally associated with lower hedge fund returns, though the relationship is not strong. Reasons for this consistent negative relationship could be due to delays or cancellations of energy projects due to unclear economic policies, affecting the performance of companies in the energy hedge funds' portfolios or higher volatility in energy commodity prices during uncertain economic times, making it more challenging for hedge funds to generate consistent returns. However, the weakness of this correlation suggests that energy hedge funds may have some ability to mitigate the negative impacts of economic policy uncertainty.

Fig. 11 illustrates the correlation between CPU and hedge fund returns. Similar to EPU, this relationship tends to be negative, consistent with the −0.0536-correlation coefficient in Table 2. This indicates that higher climate policy uncertainty is also associated with slightly lower hedge fund returns. Fig. 14 shows the correlation between EUI and hedge fund returns. The relationship appears more variable compared to EPU and CPU, which is consistent with the weaker and statistically insignificant correlation of −0.0195 reported in Table 2. This suggests that energy-specific uncertainties may have a less consistent impact on hedge fund returns compared to broader policy uncertainties.

The weaker correlation with EUI compared to EPU and CPU might indicate that energy hedge funds are better equipped to navigate energy-specific uncertainties than broader policy uncertainties. This is due to

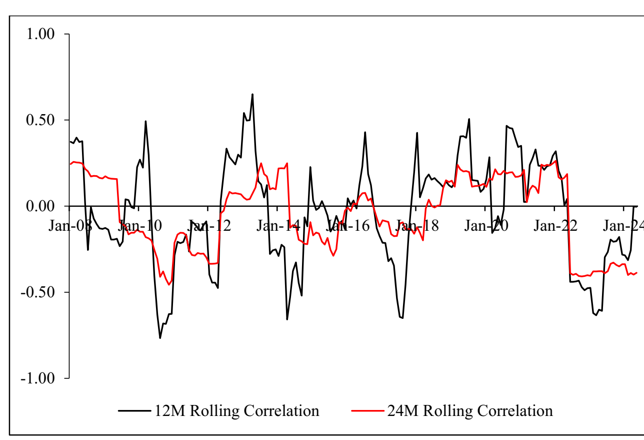

Fig. 9. EPU and BD.

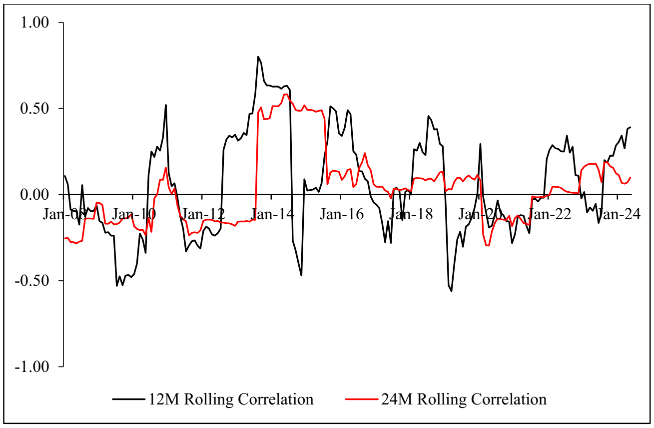

Fig. 10. EPU and COM.

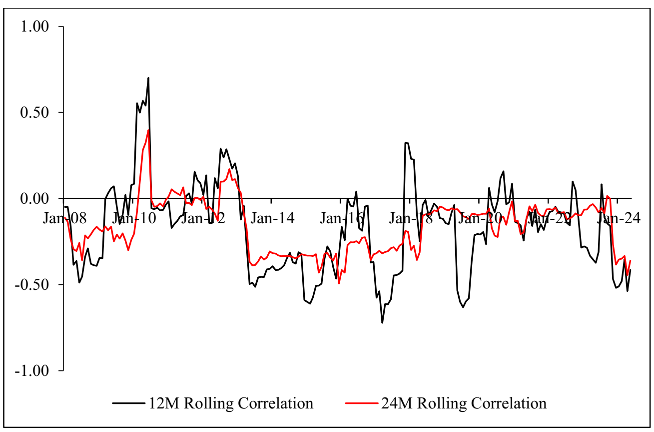

Fig. 11. CPU and HF.

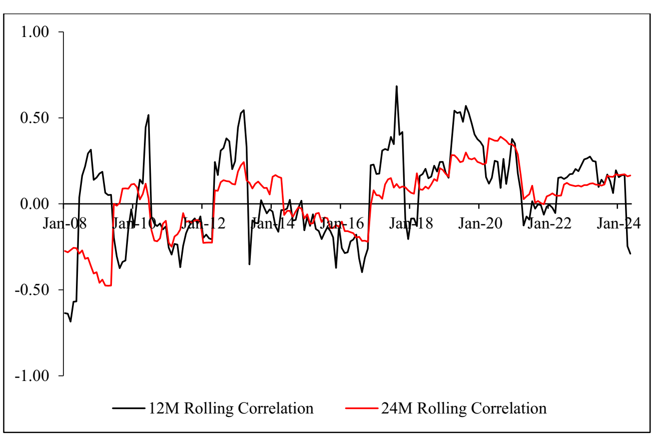

Fig. 12. CPU and BD.

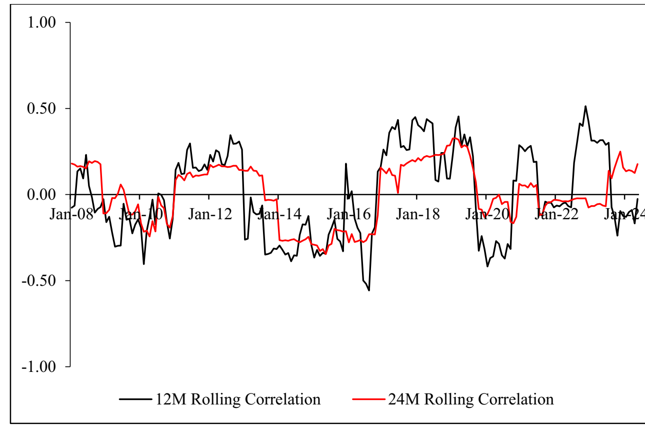

Fig. 13. CPU and COM.

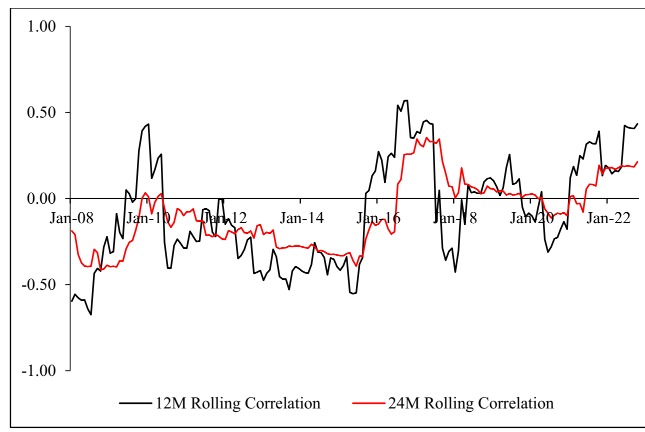

Fig. 14. EUI and HF.

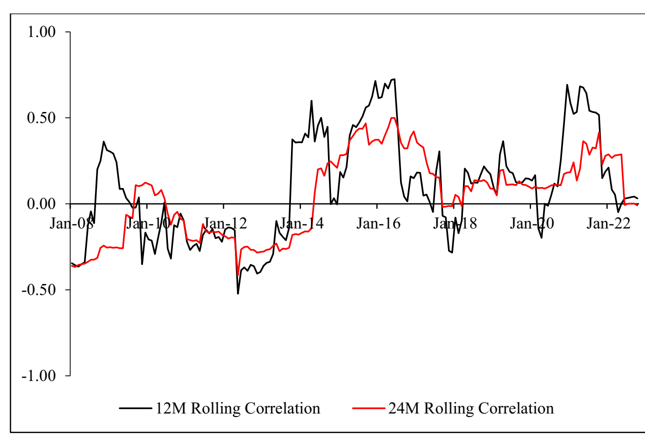

Fig. 15. EUI and BD.

their specialized focus and expertise in the energy sector. Figs. 9, 10, 12, 13, 15, and 16 display the correlations between the trend-following strategies (BD for bonds and COM for commodities) and the uncertainty indices.

Figs. 9 and 10 show the correlations of EPU with BD and COM, respectively. These relationships tend to be positive, consistent with the correlation coefficients of 0.2227 and 0.2770 reported in Table 2. This suggests that trend-following strategies, particularly in commodities, tend to perform better during periods of higher economic policy uncertainty. The stronger positive correlation for commodities (COM) compared to bonds (BD) suggests that commodity trend-following strategies may be particularly effective during periods of high economic policy uncertainty.

Figs. 12 and 13 illustrate the correlations of CPU with BD and COM. These relationships are generally weaker compared to EPU, consistent with the lower correlation coefficients of 0.1010 and 0.0467 in Table 2. This indicates that CPU has a less pronounced impact on trend-following strategies compared to general EPU.

Figs. 15 and 16 present the correlations of EUI with BD and COM. These relationships appear to be the weakest among the uncertainty

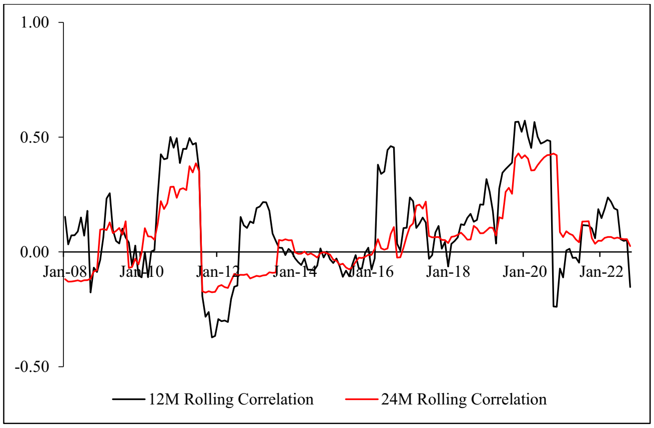

Fig. 16. EUI and COM.

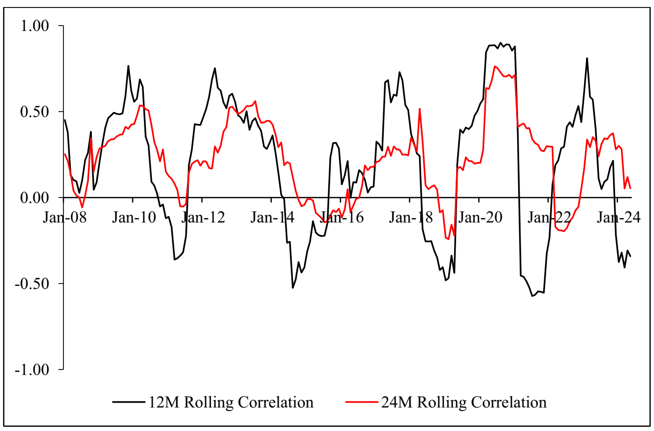

Fig. 17. BD and COM.

indices, which is consistent with the relatively low correlation coefficients reported in Table 2 (0.0587 for BD and 0.1893 for COM). The weak correlations suggest that energy-specific uncertainties may not consistently drive trends in bond or commodity markets.

Finally, Fig. 17 shows the correlation between the two trend-following strategies, BD dand COM. This relationship is generally positive but variable, aligning with the 0.2416 correlation coefficient reported in Table 2. The varying strength of this correlation over time suggests that while these strategies often move in the same direction, there are periods when they diverge, potentially offering diversification benefits. The positive correlation might be due to: 1) Both strategies benefiting from clear market trends, regardless of the underlying asset class; and 2) Macroeconomic factors simultaneously affecting both bond and commodity markets, leading to similar trend opportunities. However, the variability in the rolling correlations highlights that these strategies can also provide diversification benefits, especially during periods when the correlation weakens or turns negative.

4.3. Panel regression analysis

Table 3 presents the results of our restricted panel analysis, examining the relationship between idiosyncratic volatility and various uncertainty measures. We employ three distinct volatility estimation techniques: Models 1–3 utilize GARCH (1,1), Models 4–6 implement TGARCH (1,1), and Models 7–9 apply EGARCH (1,1). This approach allows us to capture potential asymmetric effects and leverage in volatility, as suggested by Bollerslev (1986), Zakoian (1994), and Nelson (1991). We also believe this provides a more robust assessment of volatility dynamics in this specific sector, which goes beyond the single-model approach often used in hedge fund studies (e.g., Noori and Hitaj, 2023).

Across all models, we observe a consistently negative relationship between idiosyncratic volatility and our three uncertainty measures: Economic Policy Uncertainty (EPU), Climate Policy Uncertainty (CPU), and Energy Uncertainty Index (EUI).[2] The coefficients for EPU range from −0.0019 to −0.0023, for CPU from −0.0011 to −0.0012, and for EUI from −0.0008 to −0.0010, all statistically significant at the 1 % level. These findings indicate that the idiosyncratic volatility of energy hedge funds' returns is inversely related to economic and climate policy uncertainties, as well as uncertainty surrounding future energy prices which expands on previous work that typically focuses on single uncertainty measure (e.g., Nikkinen and Rothovius, 2019).[3]

The magnitude of the coefficients suggests that EPU has the strongest impact on idiosyncratic volatility, followed by CPU and then EUI. The consistency of these negative relationships across different volatility modeling techniques (GARCH, TGARCH, and EGARCH) strengthens the robustness of our findings. The R-squared values, ranging from 0.1655 to 0.1808, indicate that while these uncertainty measures explain a significant portion of the variation in idiosyncratic volatility, other factors not included in this restricted model also play a role.

Our initial findings suggest that energy hedge funds may be effectively providing a hedge against these types of uncertainties, extending Fung & Hsieh (2001 and 2011) theoretical framework to the context of energy hedge funds, and demonstrating their potential hedging capabilities against multiple types of uncertainties. Such a hedging effect may indicate that energy hedge funds offer unique risk-return profiles that differ from traditional asset classes.

Table 4 extends our analysis from Table 3 by incorporating additional variables to capture a broader range of market dynamics and investor sentiment building on the work of Bali et al. (2014) and Agarwal et al. (2017) on macro shocks transmission in hedge funds. Specifically, we include hedge fund returns, as well as the BD (i.e. Primitive Trend Following Strategy for Bonds) and COM (i.e. Primitive Trend Following Strategy for Commodities) factors from Fung and Hsieh (2001) to account for trend-following strategies in bond and commodity markets. Additionally, we introduce the Consumer Price Index (CPI) as a proxy for overall economic sentiment. Results presented in Table 4 show a persistent negative relationship between various measures of idiosyncratic volatility (IV) and both EPU and CPU, with coefficients ranging from −0.0010 to −0.0014 for EPU and − 0.0010 to −0.0011 for CPU, all statistically significant at the 1 % level. These findings support our hypothesis that policy uncertainties impact the risk profiles of energy hedge funds, and are consistent with the findings of Noori and Hitaj (2023) regarding the impact of policy uncertainties on hedge fund dynamics.

Interestingly, while the EUI maintains a negative relationship with IV (coefficients ranging from −0.0005 to −0.0006), its statistical significance diminishes in this extended model, with *p*-values now at the 10 % level or insignificant. This result suggests that the inclusion of additional market factors may partially explain the relationship between energy price uncertainty and fund-specific risk. We find a consistent positive relationship between hedge fund returns and their idiosyncratic volatility across all models, with coefficients ranging from 0.0201 to 0.0351, significant at the 1 % level, consistent with the risk-return tradeoff principle in finance. In general, energy hedge funds with higher idiosyncratic risk tend to generate higher returns.

[2] We note that all three uncertainty measures are based on the same scale.

[3] As a robustness check, we employ the variance inflation factor (VIF) to ensure that there are no multicollinarity concerns. Since the panel data included both time-invariant variables and time-varying variables, it will not well-suited for VIF tests. Therefore, we run pooled ols regression and then calculate the VIFs. We find that the resulting VIF is 1.08, which is consistent with no multicollinearity issues.

Table 3
Panel regression analysis – restricted model.

Restricted Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
EPU	−0.0023***			−0.0022***			−0.0019***		
	(−5.46)			(−5.12)			(−5.00)		
CPU		−0.0012***			−0.0011***			−0.0011***	
		(−5.19)			(−5.12)			(−5.18)	
EUI			−0.0010***			−0.0009**			−0.0008***
			(−2.87)			(−2.51)			(−2.66)
Constant	0.0593***	0.0590***	0.0594***	0.0591***	0.0588***	0.0592***	0.0572***	0.0570***	0.0573***
	(31.17)	(30.85)	(30.22)	(32.33)	(32.06)	(31.34)	(35.42)	(35.19)	(35.58)
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of Observations	6792	6792	5946	6792	6792	5946	6792	6792	5946
R2	0.1680	0.1670	0.1734	0.1665	0.1655	0.1723	0.1743	0.1735	0.1808

Note: *, **, and *** indicate a significant at the 90 %, 95 %, and 99 % levels, respectively.
Table 3 provide the results of estimating the fixed effects panel regression models for energy and energy-related hedge funds. The dependent variable is the firm's conditional idiosyncratic volatility measured using GARCH (1,1) [Models (1)–(3)], TGARCH (1, 1) [Models (4)–(6)], and EGARCH (1, 1) [Models (7)–(9)] from estimating the FF5 model. In Table 3, we provide the restricted version as flows:

$$\psi_{i,t} = \gamma_0 + \gamma_1 \text{Induceratinty}_{i,t-1} + \text{Time Dummy} + \text{Firm Fixed Effects} + e_{i,t}$$

Without other variables or additional control variables, the main independent variables EPU, CPU and EUI, respectively. Following the notion of Rogers (1994), we collect t-statistics. The sample period spans from January 2008 to May 2024.

Table 4
Panel regression analysis – extended model.

Extended Version	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
EPU	−0.0013***			−0.0014***			−0.0012***		
	(−3.19)			(−3.30)			(−3.19)		
CPU		−0.0010***			−0.0010***			−0.0010***	
		(−3.94)			(−4.21)			(−4.49)	
EUI			−0.0006*			−0.0006			−0.0005*
			(−1.72)			(−1.60)			(−1.84)
HF	0.0315***	0.0315***	0.0351***	0.0203***	0.0204***	0.0236***	0.0201***	0.0201***	0.0228***
	(4.10)	(4.13)	(4.39)	(2.73)	(2.76)	(3.04)	(3.13)	(3.15)	(3.39)
BD	−0.0033***	−0.0035***	−0.0046***	−0.0034***	−0.0036***	−0.0047***	−0.0029***	−0.0031***	−0.0040***
	(−5.16)	(−5.16)	(−5.79)	(−5.24)	(−5.23)	(−5.81)	(−5.25)	(−5.24)	(−5.72)
COM	−0.0035***	−0.0042***	−0.0038***	−0.0034***	−0.0041***	−0.0037***	−0.0027***	−0.0033***	−0.0030***
	(−6.26)	(−6.55)	(−6.27)	(−6.05)	(−6.21)	(−6.08)	(−6.16)	(−6.30)	(−6.39)
CPI	−0.4358***	−0.4440***	−0.4764***	−0.4649***	−0.4739***	−0.5037***	−0.4226***	−0.4313***	−0.4551***
	(−4.28)	(−4.32)	(−4.45)	(−4.38)	(−4.42)	(−4.53)	(−5.11)	(−5.16)	(−5.22)
Constant	0.0598***	0.0597***	0.0601***	0.0597***	0.0596***	0.0600***	0.0577***	0.0576***	0.0580***
	(31.89)	(31.82)	(31.37)	(32.53)	(32.49)	(31.96)	(35.45)	(35.44)	(35.93)
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of Observations	6792	6792	5946	6792	6792	5946	6792	6792	5946
R2	0.1819	0.1819	0.1916	0.1763	0.1763	0.1857	0.1868	0.1870	0.1973

Note: *, **, and *** indicate a significant at the 90 %, 95 %, and 99 % levels, respectively.
Table 4 provide the results of estimating the fixed effects panel regression models for energy and energy-related hedge funds. The dependent variable is the firm's conditional idiosyncratic volatility measured using GARCH (1, 1) [Models (1)–(3)], TGARCH (1, 1) [Models (4)–(6)], and EGARCH (1, 1) [Models (7)–(9)] from estimating the FF5 model. In Table 4, we provide the restricted version as flows:

$$\psi_{i,t} = \gamma_0 + \gamma_1 \text{Uncertainty}_{i,t-1} + \gamma_2 \text{HF}_{i,t-1} + \gamma_3 \text{BD}_{i,t-1} + \gamma_4 \text{COM}_{i,t-1} + \gamma_5 \text{Sentiment}_{i,t-1} + \text{Time Dummy} + \text{Firm Fixed Effects} + e_{i,t}$$

Along with other variables, the main independent variables are EPU, CPU and EUI, respectively. Following the notion of Rogers (1994), we collect t-statistics. The sample period spans from January 2008 to May 2024.

Both BD and COM factors exhibit significant negative relationships with the IV of hedge funds, with coefficients ranging from −0.0029 to −0.0047 for BD and − 0.0027 to −0.0042 for COM, all significant at the 1 % level. This negative relationship implies that as the performance of trend-following strategies in bonds and commodities improves, the fund-specific risk of energy hedge funds tends to decrease. This finding suggests that energy hedge funds may be employing these trend-following strategies as a means of risk management, effectively reducing their exposure to idiosyncratic risk during periods when these strategies are profitable (Fung and Hsieh, 2001). Our analysis also shows a consistent negative relationship between the CPI and IV, with coefficients ranging from −0.4226 to −0.5037, significant at the 1 % level. This inverse relationship suggests that positive economic sentiment, as reflected by rising consumer prices, is associated with reduced fund-specific risk.

Given the observed non-linearities in the correlations among various explanatory variables, we re-estimated our models to include several interaction terms. Table 5 presents these results. Furthermore, we

Table 5
Panel regression analysis – full model.

Full Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
EPU	−0.0011***		−0.0006*	−0.0011***		−0.0014***	−0.0009**		−0.0012***
	(−2.73)		(−1.76)	(−2.81)		(−2.92)	(−2.56)		(−2.90)
CPU	−0.0010***	−0.0011***		−0.0010***	−0.0012***		−0.0010***	−0.0012***	
	(−4.27)	(−4.06)		(−4.57)	(−4.32)		(−4.85)	(−4.58)	
EUI		−0.0004	−0.0013***		−0.0003	−0.0006		−0.0003	−0.0006**
		(−1.07)	(−2.82)		(−0.91)	(−1.62)		(−1.16)	(−2.11)
EPU * CPU	−0.0011***			−0.0012***			−0.0015***		
	(−2.68)			(−2.78)			(−4.01)		
CPU * EUI		−0.0025**			−0.0025**			−0.0030***	
		(−2.42)			(−2.48)			(−3.40)	
EUI * EPU			−0.0041***			−0.0040***			−0.0045***
			(−4.19)			(−4.02)			(−5.88)
HF	0.0307***	0.0339***	0.0340***	0.0196***	0.0223***	0.0224***	0.0194***	0.0216***	0.0218***
	(3.99)	(4.18)	(4.19)	(2.62)	(2.84)	(2.85)	(3.01)	(3.18)	(3.19)
BD	−0.0028***	−0.0038***	−0.0038***	−0.0028***	−0.0039***	−0.0038***	−0.0025***	−0.0033***	−0.0033***
	(−4.89)	(−5.63)	(−5.69)	(−4.99)	(−5.63)	(−5.70)	(−5.08)	(−5.53)	(−5.65)
COM	−0.0031***	−0.0035***	−0.0024***	−0.0030***	−0.0034***	−0.0023***	−0.0025***	−0.0028***	−0.0017***
	(−5.82)	(−5.94)	(−4.22)	(−5.63)	(−5.77)	(−4.16)	(−5.90)	(−6.27)	(−4.09)
CPI	−0.4234***	−0.4582***	−0.4585***	−0.4528***	−0.4859***	−0.4856***	−0.4121***	−0.4386***	−0.4409***
	(−4.20)	(−4.40)	(−4.36)	(−4.31)	(−4.47)	(−4.43)	(−5.03)	(−5.17)	(−5.14)
BD * COM	−0.0153***	−0.0158***	−0.0151***	−0.0155***	−0.0161***	−0.0154***	−0.0121***	−0.0128***	−0.0121***
	(−5.25)	(−5.31)	(−5.22)	(−5.17)	(−5.25)	(−5.15)	(−4.59)	(−4.74)	(−4.58)
Constant	0.0599***	0.0603***	0.0604***	0.0598***	0.0601***	0.0602***	0.0578***	0.0582***	0.0582***
	(31.87)	(31.05)	(31.40)	(32.51)	(32.07)	(31.95)	(35.44)	(36.01)	(35.90)
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of Observations	6792	5946	5946	6792	5946	5946	6792	5946	5946
R2	0.1838	0.1961	0.1962	0.1805	0.1905	0.1906	0.1913	0.2025	0.2025

Note: *, **, and *** indicate a significant at the 90 %, 95 %, and 99 % levels, respectively.
Table 5 provide the results of estimating the fixed effects panel regression models for energy and energy-related hedge funds. The dependent variable is the firm's conditional idiosyncratic volatility measured using GARCH (1, 1) [Models (1)–(3)], TGARCH (1, 1) [Models (4)–(6)], and EGARCH (1, 1) [Models (7)–(9)] from estimating the FF5 model. In Table 5, we provide the full version as flows:

$$\psi_{i,t} = \gamma_0 + \gamma_1 \text{Uncerainty}_{i,t-1} + \gamma_2 \text{Interaction}_{1\,i,t-1} + \gamma_3 \text{HF}_{i,t-1} + \gamma_4 \text{BD}_{i,t-1} + \gamma_5 \text{COM}_{i,t-1} + \gamma_6 \text{Sentiment}_{i,t-1} + \gamma_7 \text{Interaction}_{2\,i,t-1} + \text{Time Dummy} + \text{Firm Fixed Effects} + e_{i,t}$$

Along with other variables, we provide two interaction terms – Interaction_1 (EPU * CPU, CPU * EUI, and EUI * EPU) and Interaction_2 (BD * COM). Following the notion of Rogers (1994), we collect t-statistics. The sample period spans from January 2008 to May 2024.

present the rolling correlations alongside the results presented in Table 5.

The interaction between EPU and CPU shows a statistically significant negative coefficient, ranging from −0.0011 to −0.0015 across different volatility models. This finding indicates that during periods of elevated economic policy uncertainty, increases in climate policy uncertainty are associated with a more pronounced decrease in the idiosyncratic volatility of hedge funds. This relationship may indicate enhanced risk management practices or more conservative investment strategies employed by fund managers in response to compounded policy uncertainties. Consistent with the rolling correlation analysis (Fig. 2) which showed varying degrees of correlation between EPU and CPU over time, suggesting that their combined effect on hedge fund risk is not simply additive.

Similarly, the interaction between CPU and the EUI is negative and significant, with coefficients ranging from −0.0025 to −0.0030. This shows that higher levels of climate policy uncertainty intensify the negative impact of energy market uncertainty on idiosyncratic volatility of energy hedge funds. Such a relationship could be interpreted as evidence of energy hedge funds' increased capability to navigate complex risk environments, potentially through more sophisticated hedging strategies or diversification techniques. This finding is particularly interesting in light of the weak correlation between CPU and EUI observed in the rolling correlation analysis (Fig. 3), and suggests that their interaction has a more substantial impact on hedge fund risk than their individual effects.

The interaction between EPU and EUI is similar to the effect observed with EPU and CPU, with coefficients ranging from −0.0040 to −0.0045, providing additional evidence for the notion that compound uncertainties in the policy and energy markets prompt energy hedge funds to adopt more robust risk management approaches, resulting in lower idiosyncratic volatility. These findings are generally consistent with Christoffersen et al. (2019) with respect to different market factors in shaping hedge fund risk profiles.

Next, we find a significant negative interaction between the BD and the COM, with coefficients ranging from −0.0121 to −0.0161. This result suggests that the simultaneous success of trend-following strategies in both bond and commodity markets is associated with a more substantial reduction in the idiosyncratic volatility of energy hedge funds. Energy hedge funds may be effectively utilizing a combination of bond and commodity trend-following strategies to diversify their portfolios and thereby reducing overall idiosyncratic risk. This result is supported by the positive correlation observed between BD and COM in the rolling correlation analysis (Fig. 17), suggesting that their combined effect on reducing idiosyncratic volatility is greater than the sum of their individual effects.

In Table 6, we conduct further analysis of non-linear relationships between CPI and various return measures to understand their impacts on the idiosyncratic volatility (IV) and risk management effectiveness of energy hedge funds. Firstly, we observe a positive interaction between CPI and hedge fund returns, with coefficients ranging from 7.0610 to 7.3915, all significant at the 1 % level. This suggests that during periods of higher consumer prices (positive sentiment), the positive impact of hedge fund returns on idiosyncratic volatility is strenghened. This relationship may indicate that when economic sentiment is bullish, the risk-taking behavior of energy hedge funds increases. Fund managers

Table 6
Panel regression analysis – full model.

Full Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
EPU	−0.0010**		−0.0012**	−0.0011***		−0.0013***	−0.0008**		−0.0010***
	(−2.39)		(−2.50)	(−2.72)		(−2.87)	(−2.35)		(−2.63)
CPU	−0.0008***	−0.0009***		−0.0010***	−0.0011***		−0.0009***	−0.0010***	
	(−3.57)	(−3.44)		(−4.39)	(−4.20)		(−4.62)	(−4.32)	
EUI		−0.0003	−0.0006		−0.0004	−0.0007*		−0.0002	−0.0006**
		(−0.66)	(−1.38)		(−1.22)	(−1.93)		(−0.90)	(−2.01)
EPU * CPU	−0.0019***			−0.0020***			−0.0021***		
	(−3.88)			(−4.16)			(−5.08)		
CPU * EUI		−0.0028***			−0.0027***			−0.0033***	
		(−2.71)			(−2.64)			(−3.48)	
EUI * EPU			−0.0051***			−0.0051***			−0.0053***
			(−4.61)			(−4.49)			(−6.02)
HF	0.0327***	0.0361***	0.0361***	0.0200***	0.0229***	0.0229***	0.0198***	0.0221***	0.0223***
	(4.54)	(4.83)	(4.83)	(2.68)	(2.91)	(2.91)	(3.07)	(3.25)	(3.26)
BD	−0.0036***	−0.0048***	−0.0047***	−0.0032***	−0.0042***	−0.0041***	−0.0026***	−0.0033***	−0.0034***
	(−5.42)	(−5.88)	(−6.07)	(−4.99)	(−5.51)	(−5.58)	(−5.28)	(−5.64)	(−5.73)
COM	−0.0045***	−0.0050***	−0.0038***	−0.0035***	−0.0040***	−0.0027***	−0.0028***	−0.0033***	−0.0021***
	(−5.75)	(−5.78)	(−4.88)	(−6.17)	(−6.55)	(−5.11)	(−6.25)	(−6.61)	(−5.08)
CPI	−0.4682***	−0.5060***	−0.5094***	−0.4697***	−0.5098***	−0.5119***	−0.4293***	−0.4612***	−0.4642***
	(−5.22)	(−5.45)	(−5.43)	(−4.52)	(−4.70)	(−4.68)	(−5.13)	(−5.30)	(−5.29)
CPI * HF	7.0610***	7.3607***	7.3915***						
	(4.66)	(4.78)	(4.78)						
CPI * BD				0.1047	0.1423**	0.1776**			
				(1.56)	(2.18)	(2.32)			
CPI * COM							0.4745**	0.6438***	0.6110***
							(2.36)	(2.85)	(2.85)
Constant	0.0589***	0.0607***	0.0593***	0.0598***	0.0602***	0.0603***	0.0579***	0.0583***	0.0584***
	(33.12)	(32.32)	(32.43)	(32.56)	(32.31)	(32.08)	(35.36)	(36.10)	(35.94)
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of Observations	6792	5946	5946	6792	5946	5946	6792	5946	5946
R2	0.1933	0.2041	0.2046	0.1772	0.1866	0.1871	0.1884	0.1992	0.1996

Note: *, **, and *** indicate a significant at the 90 %, 95 %, and 99 % levels, respectively.
Table 6 provide the results of estimating the fixed effects panel regression models for energy and energy-related hedge funds. The dependent variable is the firm's conditional idiosyncratic volatility measured using GARCH (1, 1) [Models (1)–(3)], TGARCH (1, 1) [Models (4)–(6)], and EGARCH (1, 1) [Models (7)–(9)] from estimating the FF5 model. In Table 5, we provide the full version as flows:

$$\psi_{i,t} = \gamma_0 + \gamma_1 \text{Unceratinty}_{i,t-1} + \gamma_2 \text{Interaction}_{1\,i,t-1} + \gamma_3 \text{HF}_{i,t-1} + \gamma_4 \text{BD}_{i,t-1} + \gamma_5 \text{COM}_{i,t-1} + \gamma_6 \text{Sentiment}_{i,t-1} + \gamma_7 \text{Interaction}_{2i,t-1} + \text{Time Dummy} + \text{Firm Fixed Effects} + e_{i,t}$$

Along with other variables, we provide two interaction terms. Interaction_1 (EPU * CPU, CPU * EUI, and EUI * EPU) is same about the Table 5, but Interaction_2. Compared to Table 5, in this model, another interaction term, Interaction_2 (CPI * HF, CPI * BD, and CPI * COM), provide different information. Following the notion of Rogers (1994), we collect t-statistics. The sample period spans from January 2008 to May 2024.

may be more inclined to pursue higher-risk strategies leading to increased fund-specific risk. This finding is supported with the positive correlation between CPI and hedge fund returns observed in the rolling correlation analysis (Fig. 5), but suggests that the relationship becomes stronger during inflationary periods.

The interaction between the BD and CPI also exhibits a positive relationship, with coefficients ranging from 0.1047 to 0.1776, significant at the 5 % level in two out of three models. This implies that when consumer prices are elevated, the impact of bond trend-following strategies on idiosyncratic volatility becomes positive. We note that the coefficient on the interaction term is greater than the coefficient on BD, which makes the aggregate impact positive. This finding suggests that the effectiveness of bond trend-following as a risk management tool may be diminished in inflationary (high sentiment) environments. This result is particularly interesting when considered alongside the weak correlation between CPI and BD observed in the rolling correlation analysis (Fig. 6), indicating that their interaction has a more substantial impact on hedge fund risk than their individual effects.

Similarly, we find a positive interaction between the COM and CPI, with coefficients ranging from 0.4745 to 0.6438, significant at the 5 % or 1 % level. The positive coefficient on the interaction term is much greater than the negative coefficient on COM, making the aggregate impact positive. Showing that as consumer prices rise (or sentiment becomes bullish), the impact of commodity trend-following strategies on idiosyncratic volatility also becomes positive. This relationship could be interpreted as a reduction in the risk management efficacy of commodity trend-following during inflationary periods.

Taken together, our findings suggest that when economic sentiment is positive, as proxied by higher CPI, the effectiveness of trend-following strategies (both in bonds and commodities) as risk management techniques may be reduced. This could be due to several factors: 1) Increased market volatility: Inflationary environments may lead to more erratic price movements in both bond and commodity markets, making trends less reliable and potentially increasing rather than decreasing fund-specific risk, 2) Positive economic sentiment may encourage greater risk-taking among fund managers, potentially overriding the risk management benefits typically associated with trend-following strategies, 3) Inflationary periods may alter the correlations between different asset classes, potentially reducing the diversification benefits of combining bond and commodity trend-following strategies. Several mechanisms may contribute to this pattern. First, high inflation often leads to increased market volatility, which can disrupt the normal patterns that profitable trend-following strategies rely on. Under such conditions, the signals that these strategies typically rely on may become less reliable and make said staregies unprofitable. Additionally, inflationary periods are frequently associated with shifts in investor risk preferences and therefore behaviors. As inflation erodes real returns, investors might shift their focus from speculative, trend-based strategies to more

Table 7
Panel regression analysis – full model.

Panel A. GARCH (1, 1)	(1)	(2)	(3)	(4)	(5)	(6)
EPU	−0.0013***		−0.0014***		−0.0016***	
	(−3.10)		(−3.30)		(−3.47)	
CPU		−0.0010***		−0.0013***		−0.0008***
		(−3.93)		(−4.72)		(−3.36)
HF	0.0315***	0.0316***	0.0308***	0.0313***	0.0304***	0.0316***
	(4.04)	(4.12)	(4.01)	(4.10)	(3.92)	(4.13)
EPU * HF	0.0040					
	(0.22)					
CPU * HF		0.0056				
		(0.53)				
BD	−0.0033***	−0.0034***	−0.0028***	−0.0031***	−0.0030***	−0.0033***
	(−5.16)	(−5.13)	(−5.02)	(−5.01)	(−5.09)	(−5.10)
EPU * BD			−0.0074***			
			(−4.40)			
CPU * BD				−0.0079***		
				(−6.34)		
COM	−0.0035***	−0.0042***	−0.0032***	−0.0041***	−0.0030***	−0.0042***
	(−6.22)	(−6.55)	(−5.94)	(−6.57)	(−5.68)	(−6.63)
EPU * COM					−0.0096***	
					(−3.94)	
CPU * COM						−0.0094***
						(−3.90)
CPI	−0.4359***	−0.4448***	−0.3986***	−0.4423***	−0.4425***	−0.4488***
	(−4.27)	(−4.33)	(−4.02)	(−4.31)	(−4.32)	(−4.34)
Constant	0.0598***	0.0598***	0.0598***	0.0596***	0.0602***	0.0598***
	(31.88)	(31.73)	(31.87)	(31.74)	(32.21)	(31.98)
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
# of Observations	6792	6792	6792	6792	6792	6792
R2	0.1819	0.1820	0.1839	0.1832	0.1837	0.1826

Panel B. TGARCH (1, 1)	(1)	(2)	(3)	(4)	(5)	(6)
EPU	−0.0014***		−0.0015***		−0.0017***	
	(−3.23)		(−3.41)		(−3.59)	
CPU		−0.0010***		−0.0014***		−0.0009***
		(−4.20)		(−4.95)		(−3.64)
HF	0.0204***	0.0204***	0.0197***	0.0202***	0.0192**	0.0204***
	(2.70)	(2.75)	(2.64)	(2.72)	(2.55)	(2.76)
EPU * HF	0.0025					
	(0.14)					
CPU * HF		0.0043				
		(0.45)				
BD	−0.0034***	−0.0035***	−0.0029***	−0.0032***	−0.0030***	−0.0034***
	(−5.25)	(−5.22)	(−5.14)	(−5.09)	(−5.18)	(−5.18)
EPU * BD			−0.0076***			
			(−4.41)			
CPU * BD				−0.0081***		
				(−6.30)		
COM	−0.0034***	−0.0041***	−0.0031***	−0.0041***	−0.0029***	−0.0041***
	(−6.02)	(−6.22)	(−5.74)	(−6.23)	(−5.53)	(−6.28)
EPU * COM					−0.0101***	
					(−4.04)	
CPU * COM						−0.0093***
						(−3.82)
CPI	−0.4650***	−0.4745***	−0.4266***	−0.4722***	−0.4719***	−0.4787***
	(−4.38)	(−4.44)	(−4.13)	(−4.42)	(−4.42)	(−4.44)
Constant	0.0597***	0.0596***	0.0596***	0.0594***	0.0601***	0.0597***
	(32.52)	(32.46)	(32.51)	(32.43)	(32.83)	(32.64)
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
# of Observations	6792	6792	6792	6792	6792	6792
R2	0.1763	0.1763	0.1784	0.1776	0.1782	0.1769

Panel C. EGARCH (1, 1)	(1)	(2)	(3)	(4)	(5)	(6)
EPU	−0.0012***		−0.0012***		−0.0014***	
	(−3.11)		(−3.29)		(−3.42)	
CPU		−0.0010***		−0.0013***		−0.0009***
		(−4.48)		(−5.18)		(−4.00)
HF	0.0201***	0.0201***	0.0195***	0.0198***	0.0192***	0.0201***
	(3.09)	(3.14)	(3.03)	(3.11)	(2.95)	(3.15)

(continued on next page)

Table 7 (*continued*)

Panel C. EGARCH (1, 1)	(1)	(2)	(3)	(4)	(5)	(6)
EPU * HF	−0.0002					
	(−0.01)					
CPU * HF		0.0042				
		(0.56)				
BD	−0.0029***	−0.0030***	−0.0025***	−0.0027***	−0.0027***	−0.0029***
	(−5.27)	(−5.20)	(−5.23)	(−5.05)	(−5.27)	(−5.19)
EPU * BD			−0.0061***			
			(−3.98)			
CPU * BD				−0.0076***		
				(−6.42)		
COM	−0.0027***	−0.0033***	−0.0025***	−0.0033***	−0.0024***	−0.0033***
	(−6.14)	(−6.32)	(−6.00)	(−6.35)	(−5.88)	(−6.36)
EPU * COM					−0.0076***	
					(−3.48)	
CPU * COM						−0.0081***
						(−4.02)
CPI	−0.4226***	−0.4318***	−0.3917***	−0.4297***	−0.4279***	−0.4354***
	(−5.10)	(−5.17)	(−4.85)	(−5.15)	(−5.15)	(−5.17)
Constant	0.0597***	0.0577***	0.0577***	0.0575***	0.0580***	0.0577***
	(32.52)	(35.39)	(35.44)	(35.39)	(35.68)	(35.52)
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
# of Observations	6792	6792	6792	6792	6792	6792
R2	0.1868	0.1870	0.1889	0.1888	0.1885	0.1877

Note: *, **, and *** indicate a significant at the 90 %, 95 %, and 99 % levels, respectively.
Table 7 provide the results of estimating the fixed effects panel regression models for energy and energy-related hedge funds. The dependent variable is the firm's conditional idiosyncratic volatility measured using GARCH (1, 1) [Panel A], TGARCH (1, 1) [Panel B], and EGARCH (1, 1) [Panel C] from estimating the FF5 model. In Table 5, we provide the full version as flows:

$$\psi_{i,t} = \gamma_0 + \gamma_1 \text{Uceratinty}_{i,t-1} + \gamma_2 \text{Interaction}_{1\,i,t-1} + \gamma_3 \text{HF}_{i,t-1} + \gamma_4 \text{BD}_{i,t-1} + \gamma_5 \text{COM}_{i,t-1} + \gamma_6 \text{Sentiment}_{i,t-1} + \text{Time Dummy} + \text{Firm Fixed Effects} + e_{i,t}$$

Along with other variables, we provide one interaction terms. Interaction_1 is a variety of combination (EPU * HF, CPU * HF, EUI * HF, EPU * BD, CPU * BD, EUI * BD, EPU * COM, CPU * COM, and EUI * COM). Following the notion of Rogers (1994), we collect t-statistics. The sample period spans from January 2008 to May 2024.

conservative or value-oriented investments. This shift can alter the market dynamics, reducing the opportunities for trend-following strategies to capitalize on price movements.

In Table 7, we explore the relationships between various return measures and uncertainty indices, specifically focusing on EPU and CPU. These analyses are motivated by the non-linear relationships observed in Fig. 17 and will aid in understanding how these uncertainties interact with different investment strategies to influence the economic hedging role of energy hedge funds.

Interestingly, we find no significant impact of the interaction between EPU or CPU and hedge fund returns, with coefficients ranging from 0.0025 to 0.0056 and *p*-values well above conventional significance levels. This suggests that the relationship between fund returns and idiosyncratic volatility remains relatively stable across different levels of policy uncertainty. Such a result may indicate that energy hedge funds are adept at maintaining their risk-return profiles despite fluctuations in economic and climate policy uncertainties, possibly through adaptive investment strategies or effective hedging techniques. These findings support Noori and Hitaj (2023) who show that hedge fund strategies to policy uncertainties.

However, we observe a strong negative impact of the interaction between CPU and EPU on both the BD and the COM. For BD, the interaction coefficients range from −0.0074 to −0.0081, while for COM, they range from −0.0076 to −0.0101, all significant at the 1 % level. This finding implies that trend-following strategies more negatively impact idiosyncratic volatility when either CPU or EPU are elevated. Such a relationship could be interpreted as an enhancement of these strategies' risk management capabilities during periods of high policy uncertainty.

This result is particularly interesting when considered alongside the rolling correlation analysis. Fig. 2 showed varying degrees of correlation between EPU and CPU over time, suggesting that their combined effect on trend-following strategies is not simply additive but has a more complex. When faced with increased policy uncertainties, trend-following strategies in both bonds and commodities appear to become more effective at reducing fund-specific risk for energy hedge funds. This may be due to these strategies providing a more reliable hedge against market volatility induced by policy uncertainties, or perhaps because they capture broader market trends that become more pronounced during uncertain times. This interpretation aligns with the findings of Fung and Hsieh (2001) regarding the unique risk-return profiles offered by trend-following strategies, especially during periods of market stress. Furthermore, the differential impact of these interactions on BD and COM (with slightly larger coefficients for COM) suggests that commodity trend-following strategies may be particularly effective at mitigating risk during periods of high policy uncertainty in the energy sector.

Practically, our findings indicate that hedge funds might benefit from adapting their strategies during periods of heightened economic and policy uncertainty. Given that we show a consistent negative relationship between idiosyncratic volatility and uncertainty indices this that certain hedge fund strategies might already be mitigating risks effectively under uncertain conditions.

In response, hedge funds should consider integrating signals from uncertainty indices into their quantitative models. This would allow for dynamic adjustments to portfolio allocations based on real-time assessments of economic and climate policy landscapes. Specifically, energy hedge funds may increase their reliance on defensive strategies, such as trend-following combined with uncertainity filtering techniques, to better capture benefits during turbulent periods. In terms of developing financial instruments and risk management techniques, our research suggests the potential usefullness of derivatives that are tied to economic indicators, such as inflation or uncertainty indices, which could provide hedge funds with tailored tools to manage risks.

Furthermore, the implementation of advanced derivative strategies, such as options on inflation-linked bonds or CPI futures, could be explored to provide coverage against inflation risk, which we find to diminish the effectiveness of traditional trend-following strategies.

5. Concluding remarks

Our study of the relationships between energy hedge funds' idiosyncratic volatility, various uncertainty measures, and market factors yields important insights into the risk management practices and performance of these specialized funds, contributing to the growing body of literature on financial innovation in energy markets.

The rolling correlation analysis plots the complex and time-varying relationships between trend-following strategies and uncertainty indices. Notably, the generally positive correlations between EPU and trend-following returns suggest these strategies may be particularly effective during periods of high economic policy uncertainty. However, the weaker correlations with CPU and EUI indicate that these strategies may be less effective in managing climate and energy-specific uncertainties. These findings extend the work of Nikkinen and Rothovius (2019) and provide an understanding of how different types of uncertainties affect energy hedge fund strategies.

Our initial panel regression analysis, employing GARCH, TGARCH, and EGARCH models, consistently shows a negative relationship between idiosyncratic volatility of energy hedge funds and our three uncertainty measures. This robust finding across all model specifications and methodologies suggests that energy hedge funds may be effectively providing a hedge against these types of uncertainties, consistent with the theoretical framework proposed by Fung and Hsieh (2001). The extended model, incorporating additional market factors and sentiment indicators (CPI), reinforces the negative relationship between idiosyncratic volatility and both EPU and CPU. However, the statistical significance of EUI diminishes in this model, indicating that additional market factors may partially explain the relationship between energy price uncertainty and fund-specific risk. This result is consistent with the work of Liu et al. (2021) and shows the complex relationship between energy-specific uncertainties and broader market factors.

Our analysis of trend-following strategies (BD and COM) shows significant negative relationships with the idiosyncratic volatility of hedge funds. This implies that energy hedge funds may be employing these strategies as effective risk management tools, reducing their exposure to idiosyncratic risk during periods when these strategies are profitable. Examination of nonlinear impacts reveals that during periods of elevated economic policy uncertainty, increases in climate policy uncertainty are associated with a larger decrease in the idiosyncratic volatility of hedge funds. This indicates the importance of enhanced risk management practices when compounded policy uncertainties and elevated. Additionally, the interactions between CPI and return measures show that the effectiveness of trend-following strategies as risk management tools may be reduced during periods of higher inflation or positive economic sentiment. These results contribute to the literature by demonstrating the conditional nature of risk management strategies in energy hedge funds, an aspect not previously explored in the literature.

The negative and significant interaction between CPU and EUI reported in our study indicates that higher levels of climate policy uncertainty intensify the negative impact of energy market uncertainty on the idiosyncratic volatility of energy hedge funds. This suggests that fund managers may be particularly adept at managing risk when faced with compounded uncertainties in climate policy and energy markets. Moreover, we observe a significant negative interaction between BD and COM, implying that the simultaneous success of trend-following strategies in both bond and commodity markets is associated with a more substantial reduction in idiosyncratic volatility. These findings provide new insights into the synergistic effects of combining different strategies and managing multiple sources of uncertainty, extending the work of Christoffersen et al. (2019).

Our study establishes a novel base for the development of energy sector-focused hedge funds strategies that are designed to address complex and dynamically coupled systemic risk environments, namely economic, climate and energy sector uncertainties. Specifically, based on our results, hedge funds managers should focus on using trend following strategies with caution, properly aligning these with the uncertainty environment and market conditions that exisit. Such a tactical, as opposed to strategic, application of these strategies is a novel result to the literature. Another novel finding covers the interaction between CPU and EUI. This finding appears to support the view that energy sector hedge funds should put significant priority into controlling their holdings' exposures to climate policy risk not only to explicitly lower volatility of their returns in response to the direct climate shocks, but also to reduce their risk exposures to energy sector risks.

Overall, our findings demonstrate the complex and non-linear relationships between climate, energy and economic policy uncertainties, market factors, and the risk profiles of energy hedge funds. Results show hedge funds' ability to strategically adapt to various uncertainty environments, while also showing potential vulnerabilities during periods of positive economic sentiment. The complex interactions between various uncertainty measures suggest the need for continued innovation in financial instruments designed for the energy market. As the energy sector continues to evolve in response to technological, regulatory, and environmental changes and challenges, ongoing research in this area will be crucial for developing effective risk management practices and innovative financial instruments tailored to the unique nature of the energy market.

We belive that further research is warranted to investigate how environmental and climate pressures, influence hedge fund strategies in the energy sector, including causal relationships between hedge funds returns in these shock environments and the primitive trend following strategies in the range of various markets. An examination of how hedge funds incorporate climate policy uncertainty into their investment decisions would provide clues into adaptive strategies under varying regulatory environments. Additionally, exploring regional differences in how these strategies are deployed across markets with diverse environmental policies would improve our understanding of global hedge fund operations. Another valuable research avenue involves assessing the impact of emerging technologies like machine learning in improving the effectiveness of trend-following strategies. These technologies offer potential benifits in processing complex datasets, including predicting the impact of climate policy changes on energy markets.

CRediT authorship contribution statement

Joseph J. French: Conceptualization, Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation. **Constantin Gurdgiev:** Conceptualization, Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation. **Brian M. Lucey:** Writing – review & editing, Project administration, Conceptualization, Methodology, Validation. **Seungho Shin:** Conceptualization, Validation, Investigation, Formal analysis, Data curation, Writing – review & editing.

Appendix A. Variable descriptions

Variable	Description	Source
Return	Returns of energy and energy-related hedge funds in the United States.	Eikon Refinitiv DataStream
EPU	Economic policy uncertainty index developed by Baker et al. (2016).	Policy Uncertainty Website
CPU	Climate policy uncertainty index developed by Gavriilidis (2021).	Policy Uncertainty Website
EUI	Energy uncertainty index developed by Dang et al. (2023).	Policy Uncertainty Website
S&P500 Energy	Energy index classified as members of the GICS energy sector.	Eikon Refinitiv DataStream
Global Energy	Global price of energy index.	FRED
BD	Return or PTFS bond lookback straddle introduced by Fung & Hsieh (2001 & 2011).	Fung and Hsieh Datasets
COM	Return of PTFS commodity lookback straddle by Fung & Hsieh (2001 & 2011).	Fung and Hsieh Datasets
CPI	Consumer price index for all urban consumers: all items in US. city average	FRED
MktRF	Excess return on a market portfolio introduced by Sharpe (1964).	Fama and French Website
SMB	Size premium developed by Fama and French (1993).	Fama and French Website
HML	Value premium developed by Fama and French (1993).	Fama and French Website
RMW	Profitability premium introduced by Fama and French (2015).	Fama and French Website
CMA	Investment conservatism premium introduced by Fama and French (2015).	Fama and French Website
RF	US 1-month treasury bill rate.	Fama and French Website

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2025.108799.

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