Crude Climate Economics: Oil Shocks, Climate Risk Exposure, and the Responsive Behaviour of Stock Markets

Abstract

This study investigates the interplay between oil price fluctuations, corporate climate risk exposure, and stock market reactions. Employing a novel classification system, it segregates firms into 'brown' (high emissions) and 'green' (low emissions), exploring the intensified market response to oil price changes given climate risks. 'Brown firms' show varying impacts. The study further examines the influence of geopolitical tensions and extreme weather events revealing a noticeable but limited effect on the market. However, climate risk consistently amplifies market volatility, influencing investor strategies to protect against such volatility. This research contributes to understanding the complex connections between environmental issues, energy economics, and financial markets, emphasizing the systemic nature of climate risk in market stability. Our findings highlight the importance of integrating environmental factors into financial analysis and decision-making, providing empirical evidence of the financial implications of climate risks. Our results remain consistent following numerous robustness tests.

Keywords: firm-level climate risk exposures; oil price changes; stock markets.

1. Introduction

Bridging a crucial gap in financial and accounting research, this paper links the burgeoning green assets market and sustainable investment practices with oil price shocks and geopolitical events. While the greenium debate persists in literature (Baker et al., 2022; Zerbib, 2019; Larcker & Watts, 2020), the focus shifts to how geopolitical upheavals, like the 2022 Russia-Ukraine conflict, disrupt global energy markets and financial stability (Jones & Kaul, 1996; Sadorsky, 1999; Kilian & Park, 2009; Ghittie et al. 2023, Tian et al., 2023). This study empirically investigates the influence of firm-specific climate risks on market responses to oil price fluctuations amidst such geopolitical disruptions, thereby expanding the discourse on environmental risks (Brooks, & Schopohl, 2021), energy economics, and financial market dynamics. Our study ventures into uncharted territory by empirically investigating the degree to which firm-specific climate risks may amplify stock market responses to oil price fluctuations. We further broaden the analysis in light of significant geopolitical disruptions such as the Russia-Ukraine conflict (RUC). Our research serves as a bridge, connecting the dots between ESG research, oil price shocks, geopolitical and extreme weather events, and sentiment, thereby filling a crucial gap in the existing literature.

Adopting the methodologies proposed by Choi et al. (2020), we categorize firms into 'brown firms' or 'green firms' contingent on their carbon emissions. The first methodology identifies a firm as a 'brown firm' if it operates within industries traditionally associated with high carbon emissions (full sample). The second methodology employs MSCI ESG carbon emission scores (carbon sample) to classify firms. In the full sample spanning from January 1990 to December 2022, firms entrenched in traditionally high-carbon-emission industries are labelled as 'brown firms.' On the other hand, the carbon sample, which covers the period from January 2007 to December 2022, concentrates on firms that record carbon emission scores below the threshold of 3, categorizing them as 'brown firms.' Consequently, we hypothesize that the stock returns of firms with elevated carbon emissions would exhibit a higher sensitivity to oil price fluctuations (Bolton & Kacperczyk, 2021; Pástor, Stambaugh, & Taylor, 2022).

Our research aims to answer the following questions: How significantly does exposure to climate risk alter the stock market's reaction to shifts in oil prices? How do these reactions differ during times of geopolitical unrest and under extreme temperature conditions (a surrogate for severe climate events)? Therefore, we are primarily examining the three-way interaction between oil price instability, company-specific climate risk, and stock market performance. We also delve deeper into how geopolitical occurrences and severe weather events influence this dynamic.

To empirically validate these research inquiries, we employ a range of regression models. We also execute a series of robustness tests, such as propensity score matching, alternative regression configurations, subsample analyses, and instrumental variable techniques, to safeguard our results against potential endogeneity and omitted variable biases. Furthermore, we devise a war sentiment index that encapsulates investor sentiments during the Russia-Ukraine conflict (RUC), serving as a gauge for geopolitical risk. We investigate the implications of our classifications on investment strategies by performing a portfolio analysis of our green versus brown stocks.

Our research offers an all-encompassing viewpoint, suggesting that exposure to climate risk could intensify the impact of oil price fluctuations on stock returns. For instance, we observe that alterations in oil prices are significantly correlated with a 1.5% increase in stock returns for brown firms in the full sample and a 3.5% rise for the carbon sample compared to green firms. This effect remains statistically significant even amidst geopolitical tensions.

This investigation enhances previous literature by amalgamating oil price dynamics, market responses, and climate risks into a unified analysis at the firm level, diverging from the traditional focus on industry or macro-level impacts. Firstly, it adds to the vast literature on the market for green assets and their premiums (Baker et al., 2022; Bhutta et al., 2022; Dorfleitner et al., 2022; Flammer, 2021; Karpf & Mandel, 2017; Sangiorgi & Schopohl, 2022; Tang & Zhang, 2020; Zerbib, 2019). Secondly, to the best of our knowledge, our paper is the first to present evidence on the interaction between ESG research and its linkage to oil price shocks, geopolitical events, extreme weather conditions, and sentiment. Our study effectively bridges this crucial gap.

This study is organised as follows: Section 2 presents a comprehensive literature review. In Section 3, we develop our hypotheses. Section 4 presents our data and empirical methodology. This is followed by Section 5, where we detail our empirical results and robustness tests. Finally, Section 6 concludes our study.

2. Literature Review

2.1 Oil Price Changes and Stock Returns

This study delves into the intricate relationship between the global oil market and stock markets, an area of interest since the last century. It introduces additional layers, examining how climate and geopolitical risks, along with investor sentiment, interplay with and influence this longstanding dynamic. Jones and Kaul (1996) performed an analysis of quarterly data from 1947 to 1991, revealing substantial negative effects of oil price shocks on stock prices in four key economies, reinforcing market rationality. Sadorsky (1999), using a Vector Autoregression (VAR) model on data from the same era, underscored the dominant role of oil prices over interest rates on stock returns, underlining the pivotal role of oil shocks. Conversely, Huang et al. (1996) found no significant impact of oil prices on U.S. stock markets during the 1980s, offering a contrasting perspective to earlier results. As we transitioned into the new millennium, research emphasis moved beyond mere oil-stock correlations. Kilian (2009) and Kilian and Park (2009) employed structural Vector Autoregressive (SVAR) models for a more in-depth analysis. They spotlighted the demand-side effect of oil price shocks on stock prices. Kang et al. (2015) presented a time-varying SVAR model, demonstrating the evolution of oil price effects on stock markets over time. Despite these advancements, Ready (2018) highlighted the limitations of the SVAR model, suggesting an innovative approach. He recommended using the VIX index and oil producer stock returns for a more precise analysis. This technique has since gained traction in recent studies on oil price fluctuations.

In conclusion, a multitude of studies have explored the varied reactions to oil price shocks across different countries and sectors. Park and Ratti (2008) concentrated on the U.S. and thirteen European countries, identifying distinct responses between oil-exporting and importing nations. Driesprong et al. (2008) scrutinized 48 countries, revealing that oil prices could forecast negative future stock returns. Mohanty et al. (2011) examined the Gulf Cooperation Council (GCC) countries, accentuating the diverse effects of oil price shocks. These studies highlight the necessity for a sophisticated comprehension of the oil-stock relationship, considering the intricacy and diversity of market responses.

2.2 Climate Risk and Stock Returns

The escalating intensity of environmental issues has ignited an increase in research on the correlation between climate risk and stock markets. Three primary economic theories discuss this relationship. It is increasingly evident that shifts in investment preferences towards sustainable (green) assets and away from fossil fuels (brown) have been driven by elements such as international climate conferences and agreements (GSIA 2018; Halcoussis and Lowenberg 2019). Research in this domain, including models by Pástor et al. (2021) and reviews like Giglio et al. (2021), thoroughly investigates the connection between climate change impacts and stock returns. Studies such as those by Hong et al. (2019), Choi et al. (2020), and Bertolotti et al. (2019) illustrate how climate-related factors influence stock prices across various sectors. Ramelli et al. (2021) scrutinize the market reaction to political events associated with climate change. Concurrently, Görgen et al. (2020) and Engle et al. (2020) probe into carbon risk factors and climate change risk proxies.

Bolton and Kacperczyk (2021) discussed the first theory, asset pricing risk premium, suggesting that investors demanded higher returns for stocks with higher carbon emission risks. Analysing U.S. data from 2005 to 2017, they categorized carbon emissions into direct emissions by firms, indirect emissions owned by firms, and indirect emissions not owned by firms. Their findings indicated a positive correlation between stock returns and carbon emission levels, supporting the idea of a carbon risk premium. This concept has roots in Matsumura et al.'s (2014) work on firm valuation and carbon emissions. More recently, Hsu et al. (2023) found a pollution premium tied to environmental policy volatility, not explained by traditional asset pricing factors. Their results highlight that high-emission firms face a steeper profitability drop when regulations tighten.

Bolton and Kacperczyk (2021) proposed an alternative theory where certain investors might overlook carbon risks, potentially resulting in the under-valuation of stocks linked with such risks. This theory is empirically backed by the work of Choi et al. (2020), who employed google search volume as a measure to assess investor consciousness of global warming issues. Through the analysis of temperature data from 1973 to 2017, they developed a portfolio strategy that was bullish on emission-intensive stocks and bearish on clean stocks. Their research showed that even in areas with unusually high temperatures—where investors were more aware of climate issues—stocks of emission-heavy companies continued to be under-valued. This pattern of under-valuation persisted despite an increasing public interest in environmental issues in more recent years.

The third theory relates to the classification of environmentally detrimental stocks as "brown" or "sin" stocks, as elaborated by Bolton and Kacperczyk (2021), and is consistent with the divestment hypothesis. Investors who are environmentally conscious may shun these stocks, perceiving them as socially irresponsible. Pástor et al. (2021, 2022) added to this discourse. In 2021, they employed an equilibrium model demonstrating investors' inclination towards greener assets, perceived as safer and a buffer against climate shock. They discovered that green firms surpass brown ones during positive environmental shocks. In their extended model in 2022, they confirmed the existence of a "greenium," indicating a market trend favouring environmentally responsible investments. While green stocks tend to excel, brown stocks forecast higher anticipated returns, consistent with the risk premium theory. Ardia et al. (2022) presented a climate change concern index, corroborating the superior performance of green stocks during times of escalated climate concern.

2.3 Oil price, Clean Energy and Stock Returns

As climate-related concerns escalate and investors explore alternatives to hedge against uncertainties in conventional energy, the correlation between oil markets and green stock prices has become a focal point. The anticipation is that a rise in conventional energy prices or carbon emission expenses may stimulate interest in alternative energy stocks. The first facet of this relationship is based on the theory that escalating energy costs would compel firms to consider alternative, non-fossil fuel energy sources. Consequently, there could be a positive correlation between increasing oil prices and alternative energy stock valuations.

Henriques and Sadorsky (2008) explore the significance of renewable energy, employing a four-variable VAR model on weekly data from 2001 to 2007. They deduced that while oil prices influence alternative energy stocks, shocks in technology prices have a more profound impact. Sadorsky (2012) expanded this analysis to 2011, utilizing multivariable GARCH models. He identified volatility spillover effects, with clean firm stock prices correlating more with technology stocks than oil. Kumar et al. (2012) applied a five-variable lag-augmented VAR model on weekly data from 2005 to 2008, affirming that oil and technology prices independently affect clean energy stocks. However, they were unable to identify a significant connection between carbon markets and firm stock prices.

Inchauspe et al. (2015) utilized a state-space multi-factor asset pricing model with time-varying coefficients, using monthly data from 2001 to 2014. They identified an increase in oil's influence post-2007 and a post-crisis decline in clean energy performance. More recent literature has explored time-frequency relationships and extreme conditions. Ferrer et al. (2018) examined daily data from 2003 to 2017, concluding that oil prices do not primarily drive short- or long-term returns. Uddin et al. (2019) and Saeed et al. (2021) identified a positive correlation between oil prices and clean energy stock returns in specific quantiles, highlighting the need for prudence in extreme market conditions.

On the other hand, an opposing hypothesis proposes that renewable energy companies, due to their immature technology and the associated elevated development costs, might be exposed to increased risk. Such companies could potentially encounter difficulties or even halt operations if traditional energy prices drop. Ferrer et al. (2018) findings mentioned earlier suggest that investors may take into account the cost competition of renewable energy and with escalating climate change awareness, their investment decisions may not be primarily influenced by the changes in oil prices. Fahmy's study (2022) further validated this viewpoint. He investigated the post-Paris Agreement era from 2009 to 2019, observing a weakened connection between oil and clean energy, implying a shift in investor behaviour towards green energy, irrespective of oil price surges.

However, it is crucial to note that previous research has predominantly concentrated on clean energy companies or indexes, neglecting other environmentally friendly companies not directly linked to alternative energy. Our study brings a fresh viewpoint to the table, dual classifying firms as green or brown based on industry perception and the MSCI Carbon Emission score. This approach is significant as it broadens the scope of analysis beyond clean energy firms, providing a more comprehensive understanding of the environmental impact across various industries. It also allows for a more nuanced understanding of the relationship between environmental performance and financial performance, which is not fully captured by focusing solely on clean energy firms or indexes.

3. Hypothesis Development

This research delves into the interplay between oil price fluctuations and stock returns, particularly emphasizing firms classified according to their susceptibility to climate risks. Drawing on Fama's (1970) efficient market hypothesis, which suggests that markets swiftly adapt to fresh information, we investigate the influence of oil price alterations on stock returns with the added dimension of climate risk. Jones and Kaul's (1996) prior research have already tackled the market's reaction to oil price shocks. Consistent with the carbon risk premium narrative, current literature links "brown stocks" with a carbon risk premium, portraying them as riskier investments relative to "green stocks" (Bolton & Kacperczyk, 2021; Pástor et al., 2022). However, stock performance can undergo substantial volatility due to external shocks, with brown stocks generally exhibiting more noticeable fluctuations (Hsu et al., 2023).

Given the prevailing environmental concerns, discerning investors should consider the complex interplay between climate risks and oil price shifts. The substantial role of oil in carbon emissions necessitates this as a crucial factor for portfolio risk management (Henriques & Sadorsky, 2008; Sadorsky, 2012; Kumar et al., 2012). With these considerations in mind, we propose the following hypotheses:

H1a: In reaction to oil price volatility, companies with higher climate risk (brown firms) are predicted to demonstrate a more marked carbon premium effect in their stock returns.

H1b: Green stocks are expected to exhibit increased resilience to oil price shocks, especially in situations of escalated climate risk.

Moreover, oil price swings can have a significant impact on financial markets, particularly during periods of crisis (Tsai, 2015). Post the 2008 financial crisis, Tsai (2015) identified a positive association between the S&P 500 stock index and oil prices. In a similar vein, Xie et al. (2021) pointed out that external events influencing oil prices could put pressure on the Chinese stock market. Considering the earlier discussed theories, it is crucial to consider the potential influence of oil price changes on the stock performance of both brown and green firms. This understanding can provide valuable insights for investors and policy makers in managing climate risks and shaping sustainable investment strategies.

Our research seeks to unravel the interplay between oil price variations, shaped by climate risk, and stock returns in the context of the Russia-Ukraine Conflict (RUC). Given Russia's crucial position as a leading oil exporter, this geopolitical event's significance is underscored, raising queries about how such global occurrences might reshape investment patterns. Recent patterns suggest a movement towards sustainable investments (Uddin et al., 2019; Fahmy, 2022; Umar et al., 2022), with the RUC potentially heightening market instability and catalyzing a shift from fossil fuels to green energy (Karkowska & Urjasz, 2023; Umar et al., 2022). In light of these observations, we put forth the following hypotheses:

H2a: The Risk-Adjusted Carbon Premium (RUC) might amplify the effect of oil price alterations on the returns of brown stocks, as investors may demand higher compensation for the escalated perceived risk.

H2b: The RUC is anticipated to stimulate a turn towards green-energy investments, which could serve as a safeguard for brown stock returns against the unpredictability of oil prices.

Finally, the study scrutinizes investor responses to concerns about global warming within the framework of oil price shifts and stock returns. The significant contribution of oil to greenhouse gas emissions suggests that stocks with lower climate risk might outperform those with higher risk, especially if investors prioritize climate risk (Bolton and Kacperczyk, 2021;

Pástor et al., 2021; Ardia et al., 2022). Choi et al. (2020) discovered a correlation between extreme temperature anomalies in cities and lower stock returns for carbon-intensive firms, indicating an investor preference for environmentally friendly alternatives in areas with significant temperature variations. However, some might contend that firms with higher risk could yield superior returns, in line with the carbon risk premium theory (Matsumura et al., 2014; Bolton and Kacperczyk, 2021). To this end, we introduce the third set of hypotheses:

H3a: In regions with significant temperature extremes, the returns of brown stocks might be more profoundly affected by fluctuations in oil prices.

H3b: In areas experiencing notable temperature anomalies, green firms, which generally have lower climate risks, are expected to surpass brown firms in terms of stock performance.

4. Data

4.1 Data Sources and Sample Classification

Our study employs a broad spectrum of data sources to investigate the influence of oil price fluctuations on stock returns, considering varying degrees of climate risk exposures. We primarily rely on two datasets, as classified by Choi et al. (2020): the Carbon Sample and the Full Sample. The Carbon Sample concentrates on MSCI's carbon emission scores, spanning from January 2007 to December 2022, its range constrained by the availability of Compustat data. On the other hand, the Full Sample extends from January 1990 to December 2022, encapsulating significant oil price incidents such as the Gulf War.

Table 1: Data Sources

Data	Source
West Texas Intermediate Crude Oil Prices	DataStream database
Stock Returns	CRSP database
MSCI ESG Ratings	MSCI database
Fama and French Five Factors	Kenneth French data library
Economic Indicators (CPI, GDP, 10-Year Bond Factor)	FRED database
State-Level Temperature Data	cli-MATE database within MRCC
Investor Sentiment on the Russia-Ukraine Conflict	Google Search Volume Index
Firm Fundamentals	Compustat

4.2 Data Cleaning

The dataset in this study is standardized by managing missing values and mitigating outliers through a process known as winsorization at the 1% and 99% percentiles. Firms in the financial and insurance sectors, identified by SIC codes 6000-6999, are excluded from the study. The extensive Full Sample encompasses 3,044 firms, yielding 467,356 observations, while the more specialized Carbon Sample is composed of 2,650 firms, amounting to 175,741 observations. All independent variables are lagged by one period.

4.3. Summary Statistics

Table 2 provides a comparative overview of essential variables within the two samples. These variables encompass firm stock returns (both raw and size-adjusted), fluctuations in oil prices, and a collection of control variables such as return on equity (ROE), Leverage, Cash, Tobin's Q, Size, and Book to Market (BTM) ratio. The table further integrates influences from the systematic market (S&P 500) and adjustments based on macroeconomic factors (CPI and GDP).

Table 3 presents a matrix of pairwise correlation coefficients for fundamental variables, indicating a positive correlation between shifts in oil prices and stock returns. Panel B of Table 3, while largely maintaining consistency with the relationships in Panel A, exhibits a significant deviation in the relationship of the Brown Dummy variable to stock returns. This deviation shows a reverse pattern in the carbon sample compared to the full sample. This discrepancy likely arises from the differing classification criteria for "brown" and "green" firms across samples, as illustrated by Choi et al. (2020). For example, a firm deemed as "brown" in the full sample due to its industry classification might be considered "green" in the carbon sample owing to its high carbon score. This instance emphasizes how varying classification standards can affect research results, particularly in interpreting the impact of the Brown Dummy variable on stock returns between samples.

Table 2 Summary Statistic

Panel A: Full Sample (1990.01 – 2022.12)

Variables	**Min**	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max**	**S.D.**
Dependent variables							
Return(Raw)	-34.347	-5.791	0.924	1.237	7.513	46.226	12.951
Return (Size adjusted)	-35.421	-7.123	-0.624	-0.185	5.983	44.783	12.901
Key independent variable							
Oil	-26.842	-6.045	1.413	0.699	8.069	24.650	10.160
Brown Dummy	0.000	0.000	0.000	0.210	0.000	1.000	0.407
Firm-level control variables							
ROE	-1.865	-0.003	0.094	0.027	0.174	0.968	0.366
Leverage	0.000	0.066	0.432	0.862	0.984	10.668	1.512
Cash	0.000	0.029	0.098	0.196	0.277	0.941	0.232
TobinQ	0.711	1.238	1.677	2.266	2.601	10.436	1.694
Size	1.220	2.492	3.021	3.051	3.590	4.985	0.799
BTM	0.029	0.239	0.421	0.534	0.697	2.911	0.443
Macro-economic control variables							
S&P500 Index	-11.001	-1.782	1.153	0.686	3.417	10.755	4.293
CPI	-0.643	0.068	0.211	0.215	0.348	0.952	0.266
GDP	-8.828	0.781	1.217	1.134	1.602	8.788	1.510

Panel B: Carbon Sample (2007.01 – 2022.12)							
Dependent variables							
Return(Raw)	-34.347	-5.068	0.885	0.898	6.506	46.226	11.421
Return (Size adjusted)	-31.741	-6.008	-0.212	-0.115	5.452	36.276	11.020
Key independent variable							
Oil	-26.842	-7.826	1.830	0.564	8.457	24.650	10.557
Brown Dummy	0.000	0.000	0.000	0.101	0.000	1.000	0.301
Firm-level control variables							
ROE	-1.865	0.014	0.094	0.060	0.186	0.968	0.339
Leverage	0.000	0.274	0.712	1.218	1.354	10.668	1.772
Cash	0.001	0.026	0.081	0.167	0.213	0.941	0.212
TobinQ	0.711	1.261	1.685	2.278	2.594	10.436	1.694
Size	1.220	3.063	3.597	3.626	4.186	4.985	0.751
BTM	0.029	0.210	0.386	0.488	0.658	2.911	0.405
Macro-economic control variables							
S&P500 Index	-11.001	-1.551	1.718	0.813	3.577	10.755	4.464
CPI	-0.643	0.078	0.226	0.243	0.404	0.952	0.289
GDP	-8.828	0.811	1.234	1.220	1.610	8.788	2.237

Table 3 Correlation Matrix

Panel A: Full sample (1990.01 – 2022.12)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	*Return (Raw)*	1							
(2)	*Return (Size adjusted)*	0.996***	1						
(3)	*Oil*	0.050***	0.045***	1					
(4)	*Brown Dummy*	0.004**	0.004**	0.000	1				
(5)	*ROE*	-0.001	-0.009***	-0.006***	0.056***	1			
(6)	*Leverage*	-0.004*	-0.006***	-0.004**	-0.060***	-0.025***	1		
(7)	*Cash*	0.002	0.007***	0.001	-0.073***	-0.374***	-0.207***	1	
(8)	*TobinQ*	0.052***	0.048***	0.016***	-0.106***	-0.083***	-0.117***	0.443***	1
(9)	*Size*	-0.017***	-0.038***	-0.000	0.023***	0.287***	0.244***	-0.414***	-0.208***
(10)	*BTM*	0.034***	0.043***	0.009**	0.077***	-0.053***	-0.027***	-0.247***	-0.509***
(11)	*S&P500 Index*	0.017***	0.009***	0.115***	0.002	-0.006***	-0.002	0.004**	0.031***
(12)	*CPI*	-0.041***	-0.038***	-0.521***	-0.012***	-0.007***	0.013***	0.016***	0.034***
(13)	*GDP*	-0.016***	-0.013***	-0.069***	-0.007***	-0.008***	-0.001	0.014***	0.048***

Panel A (continued)

		(9)	(10)	(11)	(12)	(13)
(9)	*Size*	1				
(10)	*BTM*	0.033***	1			
(11)	*S&P500 Index*	-0.001	0.013***	1		
(12)	*CPI*	0.016***	-0.025***	-0.011***	1	
(13)	*GDP*	0.001	-0.052***	0.047***	0.327***	1

Table 3 Correlation Matrix (continued)

Panel B: Carbon Sample (2007.01 – 2022.12)

		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
(1)	*Return (Raw)*	1							
(2)	*Return (Size adjusted)*	0.988***	1						
(3)	*Oil*	0.044***	0.026***	1					
(4)	*Brown Dummy*	-0.008***	-0.007**	-0.010***	1				
(5)	*ROE*	0.008***	-0.003	-0.014***	-0.011***	1			
(6)	*Leverage*	0.000	-0.004	-0.003	-0.033***	0.014***	1		
(7)	*Cash*	-0.008***	0.002	0.015***	-0.129***	-0.378***	-0.183***	1	
(8)	*TobinQ*	0.052***	0.043***	0.036***	-0.141***	-0.048***	-0.100***	0.485***	1
(9)	*Size*	0.010***	-0.026***	-0.007**	-0.012***	0.297***	0.188***	-0.476***	-0.292***
(10)	*BTM*	0.021***	0.031***	0.002	0.211***	-0.088***	-0.084***	-0.292***	-0.528***
(11)	*S&P500 Index*	-0.024***	-0.027***	0.205***	-0.005*	-0.013***	-0.003	0.005*	0.029***
(12)	*CPI*	-0.072***	-0.076***	0.547***	-0.062***	-0.043***	0.015***	0.073***	0.072***
(13)	*GDP*	-0.038***	-0.029***	0.053***	-0.035***	-0.032***	-0.006*	0.042***	0.050***

Panel B (continued)

		(9)	**(10)**	**(11)**	**(12)**	**(13)**
(9)	*Size*	1				
(10)	*BTM*	0.159***	1			
(11)	*S&P500 Index*	-0.008***	0.021***	1		
(12)	*CPI*	-0.027***	-0.055***	0.010***	1	
(13)	*GDP*	-0.022***	-0.048***	-0.019***	0.407***	1

Table 3 presents the Pearson correlation results for both the full sample and the carbon sample. *, **, *** Indicate the figure statistical significance at 10 %, 5 %, and 1 %, respectively.

4.3 Key Variables

4.3.1 Oil Price Changes

This study adopts Tsai (2015)'s definition of oil prices, which utilizes the logarithmic percentage change in West Texas Intermediate (WTI) oil prices to signify oil fluctuations, formulated as:

$$\Delta Oil\_Price_t = [\log(WTI_t) - \log(WTI_{t-1})] * 100\% \qquad (1)$$

Where WTI_t and WTI_{t-1} represent the crude oil price in month t, and month t-1, respectively.

4.3.2 Brown Dummy

This research investigates the connection between fluctuations in oil prices and stock market returns, with a particular emphasis on the impact of firms' susceptibility to climate-related risks on this correlation. Drawing from the approach employed by Choi et al. (2020), we classify firms into "brown" and "non-brown" categories within an extensive dataset spanning from January 1990 to December 2022. This classification is based on Carbon Emission scores derived from MSCI ESG ratings, from January 2007 to December 2022. We further refine our categorization by categorizing firms into "brown", "natural", and "green" groups based on their emission scores.

Firms with a greater exposure to climate risk, referred to as "brown" firms, are categorized using a two-pronged approach that adheres to the framework established by Choi et al. (2020). Within our full sample, firms operating in high-emission sectors such as Coal, Construction, Construction Materials, Electronic Equipment, Machinery, Petroleum and Natural Gas, Automobiles and Trucks, and Aircraft are designated as "brown". In the carbon sample focusing on carbon emissions (from January 2007 to December 2022), a firm's categorization hinges on its MSCI ESG carbon emission score, which varies from 0 to 10. Scores under 3 classify a firm as "brown", while those exceeding 7 are considered "green". In the full sample a Brown Dummy value of 1 is assigned to firms from identified brown industries, and 0 to all others. Similarly, within the carbon-specific sample, firms with emission scores below 3 are given a Brown Dummy value of 1, with all other firms receiving a 0. This methodology provides a clear, consistent framework for classifying firms across both our samples.

4.3.3. War Sentiment

This study proposes an additional hypothesis that delves into the intricate impacts of oil price volatility during times of substantial geopolitical turbulence, particularly in areas crucial to oil production. It specifically scrutinizes potential shifts in investor behavior in response to the conflict between Russia and Ukraine. To measure investor sentiment associated with Russia-Ukraine conflict (RUC), we employ the Google Search Volume Index (SVI) as a proxy, in line with previous research (Choi et al., 2020; Khalfaoui et al., 2023).

Thus, the creation of the War sentiment index begins by the meticulous selection of search terms that are intimately connected with the RUC. A specific subset of these terms, which have a direct correlation with the conflict as depicted in media reports, is subsequently chosen for in-depth analysis. A detailed list of these terms can be found in the Appendix. Following this, the War Sentiment Index (WSI) is computed as the mean of the pertinent SVI indices, offering a quantifiable gauge of investor sentiment towards the conflict. This strategy enables us to gauge how geopolitical strains might shape investment strategies, especially in relation to oil market dynamics.

$$War\ Sentiment\ Index = \frac{1}{n}\sum_{i=1}^{n} SVI_i \quad (2)$$

The above equation (2) ensures a robust and representative measurement of investor sentiment regarding the conflict. Moreover, recognizing the historical backdrop of the conflict between Russia and Ukraine, which has been ongoing since 2014 prior to open warfare (Khalfaoui et al., 2023), is essential for our analysis. Consequently, we integrate monthly Google Search Volume Indices from January 2014 to December 2022, with a specific focus on data originating from the United States. The chosen time frame and geographic concentration are instrumental in tracing the progression of investor sentiment over the span of the entire RUC. Such a detailed examination is vital for discerning the influence of the Russia-Ukraine tensions on investment strategies, particularly in the volatile context of oil price movements.

4.3.4. Temperature Dummy

To examine the third hypothesis, we utilize a technique influenced by Choi et al. (2020), which involves categorizing abnormal temperature data into quantiles. A "Temperature Dummy" variable is incorporated, assigned a value of 1 for temperatures in the top two quantiles, signifying extreme heat, and 0 in all other instances. This method provides a systematic way to investigate the effects of atypical temperature variations on the variables being studied.

5. Empirical Results

The fundamental analysis of this study assesses how a corporation's susceptibility to climate-related risks affects the impact of oil price fluctuations in terms of its stock performance. To aid this investigation, we integrate a 'Brown Dummy' variable into our regression analysis, acting as a marker of a company's exposure to climate risk. This variable is an essential instrument in differentiating firms based on their carbon footprint, allowing a detailed evaluation of how oil price instability affects firms variably depending on their levels of climate risk.

$$R_{i,t} = \beta_0 + \beta_1 Brown\ Dummy_{t-1} + \beta_2 Oil_{t-1} + \beta_3 Brown\ Dummy_{t-1} x\ Oil_{t-1} + \beta_n FirmControls_{i,t-1} + \beta_m MacroControls_{t-1} + \varepsilon_{i,t} \quad (3)$$

Where the $R_{i,t}$ represents the stock return of each firm *i* at month *t*. The brown dummy variable indicates a firm’s industry-based climate risk in the full sample or its carbon emission score in the carbon sample at month *t-1*. The interaction term, Brown $Dummy_{t-1}$ x Oil_{t-1} is crucial as it determines whether firms with higher climate risks exhibit increased reactions to oil price changes in terms of their stock returns.

Our preliminary hypothesis suggests that a firm's climate risk exposure has a significant bearing on its stock return in relation to oil price shifts, implying that the coefficient β_3 should not be zero. The findings outlined in Table 4 validate this hypothesis, indicating that climate risk indeed has a significant impact on the association between oil prices and stock returns. Panel A of Table 4 displays the results of a comparative analysis between raw and size-adjusted returns. This is done to pinpoint any discrepancies that might occur due to the firm's size, following Choi et al. (2020). It's crucial to note that industry-fixed effects are intentionally excluded from the full sample analysis. This choice is made to avoid multicollinearity problems, especially since the 'Brown Dummy' variable in this sample is defined based on industry categorizations.

Our results[1] reveal a consistent trend across both sample types and return measures. A significant observation in the Oil x Brown Dummy interaction term, as depicted in Panel A of Table 4, is the positive association between oil price shifts and stock returns for firms with higher climate risks. These firms exhibit enhanced performance - 1.4% more in the full sample (Column 1) and 3.6% more in the carbon sample (Column 3) compared to average returns. This substantial disparity, detailed in both the full sample (1.24%) and the carbon sample (0.90%), highlights the economic significance of climate risk on returns.

However, the divergent outcomes for the brown dummy variable between the full and carbon samples, as shown in Table 3, could be attributed to different sample classifications, variable definitions, or climate risk evaluation methods[2]. The impact of control variables on stock returns is clear, with firm-level factors such as leverage and Tobin's Q positively affecting

[1]We include clustered error tests at both firm and year levels, addressing heteroscedasticity and autocorrelation issues.

[2]Firstly, the different criteria employed to designate the 'brown' category in this study could explain the different results. In the full sample, a firm might be labelled as 'brown' based on industry categorization, while in the carbon sample, the classification might depend on carbon emission scores. Secondly, the carbon sample might provide a more direct and detailed evaluation of a firm's climate risk through carbon emission scores, compared to the full sample's more general, industry-based classification.

returns, while a higher cash holding ratio is associated with decreased returns. Macroeconomic indicators also play a role, with GDP demonstrating a positive correlation and the S&P 500 index and CPI showing a negative relationship with stock returns. While some findings from Panel A lose their significance following the robustness check, the interaction terms within the carbon sample maintain their statistical significance, though at a diminished confidence level. This outcome is consistent with the carbon risk premium theory, implying that investors perceive fluctuations in oil prices as an elevated risk. Thus, demanding higher returns from firms with increased exposure to climate risk.

Table 4 Baseline Analysis

Panel A:	**Dependent Variable: Return**			
	Full Sample (1990.01 – 2022.12)		**Carbon Sample (2007.01 – 2022.12)**	
	Raw	**Size_Adjusted**	**Raw**	**Size_Adjusted**
Oil	0.109***	0.096***	0.144***	0.110***
	(0.002)	(0.002)	(0.004)	(0.003)
Brown Dummy	0.197***	0.182***	-0.340***	-0.408***
	(0.046)	(0.046)	(0.104)	(0.101)
Brown Dummy x Oil	0.014***	0.015***	0.036***	0.034***
	(0.005)	(0.005)	(0.009)	(0.008)
ROE	0.215***	0.143**	-0.064	-0.027
	(0.058)	(0.057)	(0.092)	(0.089)
Leverage	0.082***	0.104***	0.055***	0.067***
	(0.013)	(0.013)	(0.016)	(0.016)
Cash	-1.236***	-1.221***	-1.589***	-1.536***
	(0.106)	(0.105)	(0.181)	(0.175)
TobinQ	0.767***	0.730***	0.724***	0.595***
	(0.014)	(0.014)	(0.021)	(0.020)
Size	-0.112***	-0.456***	0.298***	-0.344***
	(0.028)	(0.028)	(0.046)	(0.045)
BTM	1.968***	2.183***	1.704***	1.916***
	(0.051)	(0.051)	(0.086)	(0.083)
S&P500 Index	-0.080***	-0.104***	-0.191***	-0.186***
	(0.005)	(0.005)	(0.006)	(0.006)
CPI	-4.442***	-3.939***	-6.830***	-6.215***
	(0.099)	(0.098)	(0.157)	(0.152)
GDP	0.013	0.040***	0.073***	0.107***
	(0.014)	(0.014)	(0.014)	(0.013)
Industry FE	No	No	YES	YES
Year FE	YES	YES	YES	YES
Obs.	467,356	467,356	175,741	175,741
Adj. R^2	0.030	0.030	0.036	0.034

Table 4 (Continued)

Panel B: Cluster Error	**Dependent Variable: Return**			
	Full sample (1990.01 – 2022.12)		**Carbon Sample (2007.01 – 2022.12)**	
	Raw	**Size_Adjusted**	**Raw**	**Size_Adjusted**
Oil	0.109***	0.096**	0.144***	0.114**
	(0.040)	(0.038)	(0.053)	(0.048)
Brown Dummy	0.197	0.182	-0.340**	-0.408***
	(0.157)	(0.155)	(0.157)	(0.148)
Brown Dummy x Oil	0.014	0.015	0.036*	0.034
	(0.022)	(0.022)	(0.020)	(0.021)
ROE	0.215	0.143	-0.064	-0.027
	(0.213)	(0.211)	(0.310)	(0.278)
Leverage	0.082**	0.104***	0.055	0.067*
	(0.032)	(0.033)	(0.035)	(0.034)
Cash	-1.236***	-1.221***	-1.589***	-1.536***
	(0.396)	(0.405)	(0.737)	(0.714)
TobinQ	0.767***	0.730***	0.724***	0.595***
	(0.064)	(0.064)	(0.115)	(0.101)
Size	-0.112	-0.456***	0.298**	-0.344***
	(0.083)	(0.092)	(0.118)	(0.123)
BTM	1.968***	2.183***	1.704***	1.916***
	(0.296)	(0.303)	(0.455)	(0.427)
S&P500 Index	-0.080	-0.104	-0.191	-0.186
	(0.078)	(0.080)	(0.117)	(0.139)
CPI	-4.442**	-3.939**	-6.830**	-6.215**
	(1.743)	(1.743)	(2.860)	(2.664)
GDP	0.013	0.040	0.073	0.107
	(0.071)	(0.065)	(0.092)	(0.085)
Industry FE	NO	NO	YES	YES
Year FE	YES	YES	YES	YES
Obs.	467,356	467,356	175,741	175,741
Firm Clustered	YES	YES	YES	YES
Year Clustered	YES	YES	YES	YES
Adj. R^2	0.030	0.030	0.036	0.034

Table 4 displays the baseline results from equation (3). Panel A shows results without considering clustered errors, while Panel B includes errors clustered at the firm and year levels. Both panels cover the full sample and the carbon sample. The dependent variables are the raw stock return (*RAW*) and the size-adjusted return (*Size_Adjusted*). The full sample is categorized based on industry; to prevent multicollinearity, industry fixed effects are not included in the full sample regression. T-statistics are shown in parentheses, with *, **, and *** denoting statistical significance at 10%, 5%, and 1% levels, respectively.

5.1 Robustness Tests

5.1.1 Propensity Score Matching

To mitigate potential biases in characterizing the 'brown' category, this study employs the Propensity Score Matching (PSM) method[3], in line with Rosenbaum & Rubin (1983) and Shipman, Swanquist & Whited (2017). We execute the Propensity Score Matching (PSM) using the nearest neighbor technique, pairing each unit in the treatment group with the most comparable unit in the control group based on their attributes. This matching process led to the exclusion of a substantial number of observations from both the full sample (271,034 observations) and the carbon sample (140,403 observations) due to mismatched firm characteristics. Post matching, the full sample was downsized to 98,161 observations and the carbon sample to 17,669 observations for each respective group.

Table 5 in the study displays the results of the Propensity Score Matching analysis. Panel A reviews the covariates for both full and carbon samples, essential for confirming the efficacy of the PSM process. Although some p-values in the matched sample are significant, likely due to large sample sizes, the Standardized Mean Differences (SMD) offer a less size-sensitive assessment[4]. Panel B of Table 5 in the study presents the baseline regression model applied to a matched dataset, where a positive correlation between oil price changes and stock returns is observed, significant at 10% level for the carbon sample. The Brown Dummy x Oil interaction term shows statistical significance, particularly in the carbon sample, at 0.049. This indicates that firms with higher environmental risk (brown firms) experience a 4.9% greater increase in stock returns compared to greener firms when oil prices rise. This effect surpasses typical returns in the carbon sector, emphasizing the significant influence of a company's climate risk

[3]This approach ensures an equitable representation between the treatment and control groups, minimizing reliance on specific variable relationships. In our research, the 'Brown Dummy' is determined using industry classification in the full sample and based on MSCI carbon emission scores in the carbon sample. Firms are then categorized into treatment or control groups depending on their 'Brown Dummy' status, with high-emission industries or those with lower carbon scores constituting the treatment group.

[4]Generally, an SMD below 0.1 indicates minimal mean differences between treated and control groups, suggesting effective matching. The results show a notable consistency in means post-matching, with most SMDs below 0.1, thus affirming the balanced nature of the matched samples and validating the PSM process.

profile on its stock performance amid oil price fluctuations. The findings align with patterns observed in Table 4, reinforcing the robustness of the results despite minor variations in statistical significance.

5.1.2. Robustness tests for PSM Matched Samples

To validate the Propensity Score Matching (PSM) methodology used in this study, we incorporate an interaction term with firm size and conduct separate analyses for instances of positive and negative oil price changes. This approach is aimed at determining if the relationship between oil price, stock returns, and climate risk varies under different market conditions. As detailed in Table 6, while some specifications result in insignificant coefficients, the direction of the Brown Dummy x Oil interaction term remains consistently positive, reinforcing our primary findings.

Furthermore, to ensure the robustness of our PSM results, we employ an alternative matching method, radius matching. The findings from this method, detailed in the Appendix, further confirm our earlier PSM strategy-based results, confirming the consistency and reliability of our matching strategy.

Table 5 Propensity Score Matching

Panel A: Covariate Balance Sheets (Full Sample: 1990.01 – 2022.12)

Variable	Treated Mean	Control Mean	Std. Mean Dif	T-stat	P-value
Oil	0.707	0.767	-0.006	1.314	0.189
ROE	0.067	0.065	0.007	-1.502	0.133
Leverage	0.687	0.710	-0.019	4.534	0.000
Cash	0.163	0.158	0.027	-5.637	0.000
TobinQ	1.917	1.906	0.009	-2.013	0.044
Size	3.087	3.087	0.001	-0.168	0.867
BTM	0.600	0.611	-0.024	5.331	0.000
S&P500	0.699	0.702	-0.001	0.144	0.885
CPI	0.209	0.210	-0.002	0.335	0.528
GDP	1.115	1.119	-0.003	0.631	0.737

Panel B: Covariate Balance Sheets (Carbon Sample: 2007.01 – 2022.12)					
Oil	0.233	0.275	-0.004	0.372	0.710
ROE	0.048	0.053	-0.015	1.528	0.127
Leverage	1.041	1.000	0.030	-2.949	0.003
Cash	0.086	0.092	-0.061	5.526	0.000
TobinQ	1.563	1.592	-0.037	3.490	0.000
Size	3.600	3.516	0.147	-12.818	0.000
BTM	0.744	0.718	0.045	-4.294	0.000
S&P500	0.740	0.708	0.008	-0.696	0.487
CPI	0.189	0.191	-0.007	0.673	0.501
GDP	0.990	0.979	0.006	-0.436	0.662

Panel C: Regression Results with PSM

	Dependent Variable: Return	
Variable	**Full Sample (1990.01 – 2022.12)**	**Carbon Sample (2007.01 – 2022.12)**
Oil	0.103***	0.126*
	(0.040)	(0.065)
Brown Dummy	0.322*	-0.122
	(0.168)	(0.245)
Brown Dummy x Oil	0.014	0.049***
	(0.019)	(0.019)
ROE	0.279	0.016
	(0.285)	(0.604)
Leverage	0.129***	0.091
	(0.048)	(0.065)
Cash	-1.470***	-1.881**
	(0.401)	(0.951)
TobinQ	0.917***	1.381***
	(0.094)	(0.198)
Size	-0.130	0.339**
	(0.080)	(0.134)
BTM	1.992***	1.662***
	(0.342)	(0.569)
S&P500 Index	-0.077	-0.264**
	(0.082)	(0.114)
CPI	-4.425**	-6.805**
	(1.781)	(3.488)
GDP	-0.015	0.102
	(0.085)	(0.125)
Industry FE	NO	YES
Year FE	YES	YES
Obs.	196,322	35,338
Firm Clustered	YES	YES
Year Clustered	YES	YES
Adj. R^2	0.031	0.039

Table 5 presents the results from the propensity score matching for the baseline model. Panel A and Panel B display the covariate balance tests for the matched data in the full sample and carbon sample, respectively. The t-value and p-value columns in these panels highlight the differences between the matched treated and control groups. Panel C provides the results from re-evaluating the baseline model (equation (3)) using the matched data for both the full and carbon samples. All results consider errors clustered at both the firm and year levels.The full sample is categorized based on industry; to prevent multicollinearity, industry fixed effects are not included in the full sample regression. In Panel C, t-statistics are shown in parentheses, with *, **, and *** denoting statistical significance at 10%, 5%, and 1% levels, respectively.

Table 6 Robustness Check for PSM Matched Samples

	Dependent Variable: Return					
Variable	**Size Effect**		**Positive Oil Changes**		**Negative Oil Changes**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Oil	0.067	0.030	0.067	-0.016	0.049	-0.188
	(0.068)	(0.117)	(0.089)	(0.133)	(0.106)	(0.173)
Brown Dummy	0.323*	-0.122	-0.133	-0.634	0.488	1.022
	(0.168)	(0.229)	(0.380)	(0.533)	(0.312)	(0.623)
Brown Dummy x Oil	0.014	0.047***	0.062	0.069	0.026	0.132**
	(0.019)	(0.018)	(0.039)	(0.067)	(0.030)	(0.065)
Size	-0.138*	0.342**				
	(0.081)	(0.138)				
Size x Oil	0.012	0.027				
	(0.014)	(0.021)				
Firm-level controls	YES	YES	YES	YES	YES	YES
Macroeconomic controls	YES	YES	YES	YES	YES	YES
Industry FE	NO	YES	NO	YES	NO	YES
Year FE	YES	YES	YES	YES	YES	YES
Firm Clustered	YES	YES	YES	YES	YES	YES
Year Clustered	YES	YES	YES	YES	YES	YES
Obs.	196,322	35,338	108,072	19,365	88,250	15,973
Adj. R^2	0.031	0.040	0.051	0.066	0.065	0.064

Table 6 presents the robustness checks for the PSM analysis, it only uses the after matched dataset. The first two columns evaluate the additional size effects; columns (3) and (4) examine the effects of positive oil changes; while columns (5) and (6) focus on the effects of negative oil changes. Column (1), (3) and (5) represent the portfolio based on full sample from 1990 – 2022. Column (2), (4) and (6) represent the portfolio based on the MSCI ESG time series extended carbon emission score from 2007 to 2022. The full sample is categorized based on industry; to prevent multicollinearity, industry fixed effects are not included in the full sample regression. T-statistics are shown in parentheses, with *, **, and *** denoting statistical significance at 10%, 5%, and 1% levels, respectively.

5.1.2 Portfolio Strategies

In addressing the issue of market-wide effects of uniform oil price changes, known as "clustering," this study adopts a portfolio approach, as suggested by Schwert (1981). This involves creating a Green Minus Brown (GMB) portfolio, where long positions are taken in 'green' stocks (environmentally friendly) and short positions in 'brown' stocks (high carbon emissions). This strategy, is applied to both the full (comprehensive) and carbon samples, allowing us to analyze investment strategy implications of the differential impacts of oil price changes based on environmental classifications.

$$GMB_t = \beta_0 + \beta_1 Oil_{t-1} + \beta_2 S\&P500\ Index_{t-1} + \beta_3 SMB_{t-1} + \beta_4 HML_{t-1} + \beta_5 RMW_{t-1} + \beta_6 CMA_{t-1} + \beta_7 MOM_{t-1} + \beta_8 TERM_{t-1} + \beta_9 GDP_{t-1} + \beta_{10} CPI_{t-1} \quad (4)$$

In the portfolio analysis of this study, GMB_t represents the value-weighted stock returns for green minus brown firms at month t, while Oil_{t-1} signifies the oil price changes in the preceding month. This approach integrates additional controls like the S&P500 Index, Fama-French 5 factors (SMB, HML, RMW, CMA, MOM), and TERM for bond factors, along with macro-economic variables such as CPI and GDP. As depicted in Table 7 for both the full and carbon samples, the results suggest a negative correlation between the Oil variable and the GMB portfolio, implying that brown firms' stock returns typically surpass green firms when oil prices vary. However, these coefficients across both samples lack statistical significance.

The examination of stock returns for green and brown stocks, as elaborated in Columns (3) to (6) of Table 5, further validates the positive association between oil prices and stock returns, especially for brown firms, echoing the patterns observed in our baseline analysis.

Table 7 Portfolio Test

Variable	Dependent Variable: Value Weighted Return					
	GMB		Green		Brown	
	(1)	(2)	(3)	(4)	(5)	(6)
Oil	-0.008	-0.016	0.096***	0.111***	0.104**	0.127**
	(0.026)	(0.044)	(0.029)	(0.026)	(0.044)	(0.061)
S&P500 Index	0.039	0.241**	-0.086	0.077	-0.125	-0.164
	(0.050)	(0.110)	(0.073)	(0.085)	(0.101)	(0.166)
SMB	0.050	-0.344	0.008	0.165	-0.043	0.509**
	(0.059)	(0.226)	(0.077)	(0.132)	(0.112)	(0.251)
HML	-0.124*	-0.288*	-0.152*	-0.147**	-0.028	0.141
	(0.070)	(0.157)	(0.087)	(0.073)	(0.123)	(0.183)
RMW	0.180***	-0.060	-0.070	0.303**	-0.249*	0.363*
	(0.063)	(0.135)	(0.090)	(0.140)	(0.140)	(0.212)
CMA	0.064	-0.157	0.087	0.144	0.024	0.301
	(0.093)	(0.270)	(0.179)	(0.220)	(0.221)	(0.339)
MOM	-0.039	-0.039	-0.063*	-0.035	-0.024	0.003
	(0.050)	(0.108)	(0.033)	(0.049)	(0.063)	(0.078)
TERM	0.023	1.112***	-0.040	-0.638***	-0.064	-1.749***
	(0.117)	(0.427)	(0.128)	(0.130)	(0.175)	(0.473)
CPI	1.363	1.106	-2.568***	-2.894***	-3.931***	-4.000*
	(1.079)	(1.658)	(0.805)	(0.963)	(1.336)	(2.394)
GDP	-0.225**	-0.086	0.030	0.004	0.255	0.090
	(0.097)	(0.088)	(0.133)	(0.037)	(0.208)	(0.085)
Firm Clustered	YES	YES	YES	YES	YES	YES
Year Clustered	YES	YES	YES	YES	YES	YES
Obs.	467,356	175,741	467,356	175,741	467,356	175,741
Adj. R^2	0.026	0.136	0.060	0.202	0.041	0.141

Table 7 presents the portfolio test results derived from the baseline analysis. GMB represents the value-weighted stock returns from portfolios that are long on green stocks and short on brown stocks. “"Green”" refers to stock returns exclusively for firms classified as “"green”" based on the two sample definitions, while “"Brown”" refers to the opposite. Column (1), (3) and (5) represent the portfolio based on full sample from 1990 – 2022. Column (2), (4) and (6) represent the portfolio based on the MSCI ESG time series extended carbon emission score from 2007 to 2022. T-statistics for the coefficient estimates are reported in parentheses; *, **, *** Indicate the figure statistical significance at 10 %, 5 %, and 1 %, respectively.

5.1.3 Oil Price Changes Effects in Different Time Periods

This segment of the study explores the impact of oil price variations on stock returns over diverse time frames, with an emphasis on the implications of climate risks. Building on the perspectives of Tsai (2015), we focus on two critical events: the emergence of the 2007 global financial crisis and the approval of the Paris Agreement. The analysis of the financial crisis period is restricted to the full sample, as the carbon sample begins in 2007, devoid of pre-crisis data. However, both the periods before and after the Paris Agreement are analyzed using both the full and carbon samples, providing a comprehensive view of the varying impacts of these significant events on stock returns in relation to climate risks.

Table 8's partitioned analysis uncovers divergent stock return patterns in response to oil price alterations during the financial crisis and post-Paris Agreement eras. Columns (1) and (2) illustrate a negative pre-crisis and a positive post-crisis correlation between stock returns and oil prices. Specifically, the post-crisis period in column (2) exhibits a significant Brown Dummy x Oil interaction at the 10% level. This suggests that in the post-crisis era, brown firms experience a 0.047-unit increase in returns for each increase in oil price. In columns (3) to (6), oil prices maintain a steady positive association with stock returns around the Paris Agreement. However, the Oil x Brown Dummy interaction loses its significance, implying a diminished influence of climate risks on stock assessments during oil price fluctuations in this period.

These findings provide a deeper understanding of the dynamic relationship between oil price fluctuations, climate risks, and stock returns, reinforcing the financial theory that market conditions and external factors can significantly influence investment outcomes. These results support Pastor et al (2022) who find that although green stocks have shown strong historical performance, this may not necessarily predict future trends, especially considering the negative equity greenium. Even with the above mixed results, the strong performance in column (2) allows for some degree of confidence in the baseline finding'' robustness.

Table 8 Sub-Period Robustness Test

Variable	Dependent Variable: Return					
	Full Sample				Carbon Sample	
	Global Financial Crisis		Paris Agreement		Paris Agreement	
	Pre-crisis	***Post-crisis***	***Pre-signed***	***Post-signed***	***Pre-signed***	***Post-signed***
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Oil	-0.022	0.196***	0.090*	0.188**	0.122*	0.159**
	(0.045)	(0.050)	(0.047)	(0.084)	(0.071)	(0.073)
Brown Dummy	0.212	0.179	0.111	0.427	-0.232	-0.529*
	(0.243)	(0.184)	(0.158)	(0.338)	(0.194)	(0.309)
Brown Dummy x Oil	-0.021	0.047*	0.025	-0.022	0.034	0.006
	(0.020)	(0.028)	(0.024)	(0.026)	(0.027)	(0.022)
ROE	0.301	0.123	0.278	-0.033	-0.060	-0.096
	(0.444)	(0.243)	(0.266)	(0.325)	(0.426)	(0.353)
Leverage	0.074**	0.075*	0.100**	0.045	0.063	0.042
	(0.032)	(0.043)	(0.041)	(0.042)	(0.096)	(0.039)
Cash	-0.947*	-1.305**	-0.829***	-1.817**	-1.023***	-1.625***
	(0.536)	(0.511)	(0.300)	(0.889)	(0.393)	(0.546)
TobinQ	0.673***	0.806***	0.732***	0.820***	0.579***	0.752***
	(0.118)	(0.071)	(0.078)	(0.116)	(0.124)	(0.149)
Size	-0.391***	0.081	-0.202**	0.163	0.104	0.360**
	(0.129)	(0.080)	(0.095)	(0.138)	(0.250)	(0.175)
BTM	1.913***	1.932***	1.993***	1.862***	1.232	1.848***
	(0.221)	(0.428)	(0.355)	(0.414)	(0.908)	(0.513)
S&P500 Index	0.067	-0.200**	0.075	-0.359**	-0.120	-0.206
	(0.066)	(0.094)	(0.060)	(0.166)	(0.094)	(0.154)
CPI	-2.779***	-6.336**	-2.616	-10.132**	-3.164	-8.635**
	(0.895)	(2.671)	(1.672)	(4.671)	(3.107)	(4.149)
GDP	-0.226	0.068	-0.407	0.182	-0.426	0.132
	(0.725)	(0.094)	(0.456)	(0.141)	(0.334)	(0.126)

Industry FE	No	No	No	No	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Firm Clustered	YES	YES	YES	YES	YES	YES
Year Clustered	YES	YES	YES	YES	YES	YES
Obs.	166,124	301,232	331,633	135,723	50,233	125,508
Adj. R^2	0.020	0.045	0.031	0.047	0.045	0.037

Table 8 presents the robustness test results for the baseline analysis. Columns (1) and (2) display the outcomes for sub-periods before and after the global financial crisis for the full sample. Columns (3) to (6) showcase the results for sub-periods before and after the signing of the Paris agreement: columns (3) and (4) pertain to the full sample, while columns (5) and (6) are specific to the carbon sample. The full sample is categorized based on industry; to prevent multicollinearity, industry fixed effects are not included in the full sample regression. T-statistics are shown in parentheses, with *, **, and *** denoting statistical significance at 10%, 5%, and 1% levels, respectively.

5.1.4 Endogeneity Concerns

To mitigate potential biases arising from omitted variables and endogeneity between stock returns and oil price alterations, we employ instrumental variables (IV) as specified in equations (5) and (6). This strategy is paramount to guarantee the robustness of our findings, given the potential simultaneous impact of stock returns and oil prices on each other (simultaneity) or the effect of unobserved factors (omitted variables). Building on Brückner et al. (2012), we initially consider the lagged oil price changes (Oilt-2) as an instrumental variable (IV) to alleviate simultaneous correlation with stock returns. An additional IV, Oilt-2 x Brown Dummy, was utilized for the interaction term. Results in Table 9 indicated that while this IV resulted in the key variable (Oil) insignificant in the full sample, it was itself insignificant in the first stage of the two-stage least squares (2SLS) method in the carbon sample. However, the IV for the interaction term was statistically significant in both samples. The high F-statistics in the first stage permitted the rejection of the hypothesis of weak instrumental variables. Importantly, the interaction with the IV in the second stage for the carbon sample bolstered our earlier baseline results.

$$Oil_{t-1}^{*} = \alpha + \alpha_1 Brown\ Dummy_{t-1} + \alpha_2 Oil_{t-2} + \alpha_3 Brown\ Dummy_{t-1} x\ Oil_{t-2} + \alpha_n FirmControls_{i,t-1} + \alpha_m MacroControls_{\,t-1} + \mu_{i,t} \quad (5)$$

Where Oil_{t-2} represents the instrumental variable, and the Brown $Dummy_{t-1}$ x Oil_{t-2} represents the instrumental variable[5] for the interaction term. Other variables remain the same as in equation (3). For the second stage, the equation is:

$$R_{i,t} = \beta_0 + \beta_1 Brown\ Dummy_{t-1} + \beta_2 Oil_{t-1}^{*} + \beta_3 Brown\ Dummy_{t-1} x\ Oil_{t-1}^{*} + \beta_n FirmControls_{i,t-1} + \beta_m MacroControls_{\,t-1} + \varepsilon_{i,t} \quad (6)$$

[5]Considering the constraints of using lagged oil price changes as an instrumental variable (IV), this study also considers alternative IVs. One such possibility is the frequency of terrorist attacks related to oil shocks. These events could impact oil prices without directly influencing stock returns. However, the emergence of multicollinearity during analysis necessitates caution. Ensuring the IV is not excessively correlated with other model variables is key. Future research might refine this approach, perhaps by focusing on specific types of attacks or geographic areas, to find a more suitable IV.

Where Oil^{*}_{t-1}represent the oil price changes that were regressed by its IV in the first stage. Other variables remain the same as in equation (3).

Table 9 Instrument Variable Estimation

Panel A: Full Sample (1990.01 – 2022.12)			
Independent Variable:	$\boldsymbol{Oil_{t-1}}$	$\boldsymbol{Oil_{t-2}}$	$\boldsymbol{Oil_{t-1}}$
	(1)	**(2)**	**(3)**
	OLS	2SLS	
		First-Stage	Second-Stage
Oil_{t-1}	0.109***		0.043
	(0.040)		(0.129)
Oil_{t-2}		-0.183***	
		(0.001)	
Brown Dummy	0.197	0.051*	0.191
	(0.154)	(0.029)	(0.152)
Oil_{t-1} x Brown Dummy	0.014		0.025
	(0.022)		(0.029)
Oil_{t-2} x Brown Dummy		-0.020***	
		(0.003)	
ROE	0.215	-0.116***	0.207
	(0.213)	(0.036)	(0.215)
Leverage	0.082***	0.0005	0.082**
	(0.032)	(0.008)	(0.032)
Cash	-1.236***	-0.238***	-1.249***
	(0.394)	(0.066)	(0.407)
TobinQ	0.767***	0.079***	0.772***
	(0.061)	(0.009)	(0.063)
Size	-0.112	0.029*	-0.110
	(0.082)	(0.017)	(0.083)
BTM	1.968***	0.285***	1.983***
	(0.291)	(0.032)	(0.314)
S&P500 Index	-0.080	0.300***	-0.065
	(0.078)	(0.003)	(0.091)
CPI	-4.442**	25.990***	-2.936
	(1.742)	(0.053)	(3.782)
GDP	0.013	-0.546***	-0.035
	(0.071)	(0.009)	(0.132)
First-Stage F-statistics		993.519***	
Industry FE	NO	NO	NO
Year FE	YES	YES	YES
Firm Clustered	YES	YES	YES
Year Clustered	YES	YES	YES
Adj. R^2	0.030	0.393	0.025

Table 9 (Continued)

Panel B: Carbon Sample (2007.01 – 2022.12)

	(1)	(2)	(3)
	OLS	2SLS	
		First-Stage	Second-Stage
Oil_{t-1}	0.144***		0.164
	(0.053)		(0.590)
Oil_{t-2}		-0.012	
		(0.081)	
Brown Dummy	-0.340**	0.027	-0.344**
	(0.157)	(0.094)	(0.171)
Oil_{t-1} x Brown Dummy	0.036*		0.050*
	(0.020)		(0.030)
Oil_{t-2} x Brown Dummy		-0.075***	
		(0.023)	
ROE	-0.064	-0.324	-0.056
	(0.310)	(0.208)	(0.330)
Leverage	0.055	0.021	0.054
	(0.035)	(0.022)	(0.043)
Cash	-1.589***	-0.289**	-1.583*
	(0.737)	(0.123)	(0.834)
TobinQ	0.724***	0.172**	0.720***
	(0.115)	(0.076)	(0.085)
Size	0.298**	0.038	0.297**
	(0.118)	(0.076)	(0.133)
BTM	1.704***	0.662	1.686***
	(0.455)	(0.483)	(0.626)
S&P500 Index	-0.191	0.382***	-0.199
	(0.117)	(0.123)	(0.207)
CPI	-6.830**	29.321***	-7.482
	(2.860)	(5.616)	(17.470)
GDP	0.073	-0.879***	0.094
	(0.092)	(0.162)	(0.544)
First-Stage F-statistics		312.572***	
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Firm Clustered	YES	YES	YES
Year Clustered	YES	YES	YES
Adj. R^2	0.036	0.449	0.026

Table 9 shows results using an instrumental variable to address the endogeneity concerns in the baseline analysis. Panel A is for the full sample and Panel B is for the carbon sample. *2SLS* columns show separate stages of the IV procedures. The full sample is categorized based on industry; to prevent multicollinearity, industry fixed effects are not included in the full sample regression. T-statistics are shown in parentheses, with *, **, and *** denoting statistical significance at 10%, 5%, and 1% levels, respectively.

5.2 Geopolitical Uncertainties & War Sentiment

To further investigate Hypothesis 2, this research employs the Google Trend index to construct an investor war sentiment index, with a specific emphasis on the Russia-Ukraine Conflict (RUC). Considering Russia's position as a major oil exporter, the RUC could significantly influence oil supply mechanisms and subsequently, crude oil prices. The primary aim is to comprehend how geopolitical incidents such as the RUC shape investor inclinations towards climate risk-associated stocks amidst oil price instability. The regression model used is designed to illuminate these intricate dynamics:

$$R_{i,t} = \beta_0 + \beta_1 Brown\ Dummy_{t-1} + \beta_2 Oil_{t-1} + \beta_3 Brown\ Dummy_{t-1} x\ Oil_{t-1} + \beta_4 WSI_{t-1} + \beta_5 WSI_{t-1} x\ Oil_{t-1} + \beta_6 Brown\ Dummy_{t-1} x\ WSI_{t-1} + \beta_7 Brown\ Dummy_{t-1} x\ WSI_{t-1} x Oil_{t-1} + \beta_n FirmControls_{i,t-1} + \beta_m MacroControls_{\,t-1} + \varepsilon_{i,t} \quad (7)$$

In the above refined version of equation (6), the focus is on the raw stock returns of a firm in each month. The model incorporates the previous month's War Sentiment Index (WSI), along with its interaction with prior oil price changes and the Brown Dummy variable. The WSI, an average of various indices as detailed in Section 4.4.3, is a key measure for assessing investor sentiments regarding war. A significant β_7 coefficient would suggest that oil price fluctuations are influenced by war-induced investor sentiments, especially when comparing brown and green stocks.

Table 10 displays the results of incorporating War Sentiment Index (WSI) into the regression analysis, focusing on phrases linked to the Russia-Ukraine Conflict (RUC). Both general RUC-related terms (WSI) and more specific conflict-related terms (High Related WSI) were carefully selected, with details provided in the Appendix. These findings show that the Brown Dummy x Oil variable in the carbon sample is significant with a coefficient of -0.046 at the 5% level, suggesting a negative relationship. However, this significance is not observed when employing the High Related WSI, indicating that while war sentiment may interact with brown firms, oil prices, and stock returns, it does not have a profound impact.

Our analysis reveals a significant negative correlation between both WSI and High-Related WSI with stock returns, suggesting that geopolitical events shape investor sentiments towards market uncertainties. Which in turn can adversely affect stock performance, aligning with findings from Da et al. (2014). These results imply that while war sentiment interacts with stock returns in the context of oil price changes and climate risk, its overall impact is not strong enough to significantly alter investor behavior. Delving deeper into the triple interaction term, we discover an increased impact of war sentiment on the reaction of brown firms' stock returns to oil price changes.

Specifically, in the carbon sample, the Brown Dummy x High Related WSI x Oil term has a 0.005 percentage point coefficient at the 5% significance level. This suggests that during periods of geopolitical tension, brown firms experience a marginally greater positive response in their stock returns due to oil price shifts, by an additional 0.005 units compared to non-brown firms. Economically, this translates to a modest 0.5% increase for climate risk-exposed companies when oil prices fluctuate, influenced by Russia-Ukraine war sentiments. However, the effect of these war sentiments on the intertwined relationship of climate risk exposure, oil price changes, and stock returns appears to be limited, and it doesn't carry the same significance for the full sample.

In Panel B of Table 10, the quadratic regression analysis focuses on the war sentiment from the RUC. MSCI carbon emission score is used instead of the brown dummy variable. The 'Carbon Score x Oil' interaction term shows a negative correlation with stock returns, with a coefficient of -0.024 in column (2). This implies that with each unit rise in oil prices, the positive impact of the carbon score on stock returns increases by 0.024 units. The quadratic term 'Carbon Score^2 x Oil' has a coefficient of 0.002, indicating a more subtle diminishing influence of the carbon score as oil prices escalate. The war sentiment, denoted by the WSI coefficient, adversely affects stock returns, but this effect lessens as its intensity increases (WSI^2 coefficient). The interaction terms 'WSI x Oil' and 'High Related WSI x Oil' with a 0.04 coefficient at the 1% level show that the negative correlation weakens with rising oil prices. The diminishing effect becomes even weaker, as indicated by 'WSI^2 x Oil'.

Table 10 Results Related to the War Sentiment of Russia-Ukraine Conflict

Panel A: War Sentiment & High Related War Sentiment

	Dependent Variable: Stock Return			
	Full Sample 1990.01 – 2022.12		**Carbon Sample 2007.01 – 2022.12**	
Variable	**(1)**	**(2)**	**(3)**	**(4)**
Brown Dummy	-0.573	-0.236	-1.074	-0.899*
	(0.409)	(0.370)	(0.658)	(0.497)
Oil	0.127	0.159**	0.106	0.125*
	(0.078)	(0.074)	(0.070)	(0.064)
WSI	-0.167***		-0.126***	
	(0.039)		(0.038)	
High Related WSI		-0.191***		-0.152***
		(0.036)		(0.040)
Brown Dummy x Oil	0.016	0.004	-0.046**	-0.007
	(0.036)	(0.030)	(0.019)	(0.020)
WSI x Oil	0.008***		0.006**	
	(0.003)		(0.002)	
High Related WSI x Oil		0.009***		0.007***
		(0.003)		(0.003)
Brown Dummy x WSI	0.079***		0.048	
	(0.026)		(0.044)	
Brown Dummy x High Related WSI		0.089***		0.060
		(0.033)		(0.054)
Brown Dummy x WSI x Oil	-0.003		0.006***	
	(0.002)		(0.002)	
Brown Dummy x High Related WSI x Oil		-0.004		0.005**
		(0.002)		(0.003)
Firm-level controls	YES	YES	YES	YES
Macroeconomic controls	YES	YES	YES	YES
Industry FE	NO	NO	YES	YES
Year FE	YES	YES	YES	YES
Firm Clustered	YES	YES	YES	YES
Year Clustered	YES	YES	YES	YES
Obs.	180,992	180,992	148,125	148,125
Adj. R^2	0.048	0.048	0.040	0.040

Table 10 (Continued)

Panel B: Non-linear effect

Variable	**Return (Carbon Sample)** (1)	(2)
Oil	-0.134***	0.070
	(0.018)	(0.065)
Carbon Score	0.282***	0.289*
	(0.056)	(0.165)
Carbon Score^2	-0.021***	-0.021*
	(0.004)	(0.012)
WSI	-0.601***	
	(0.022)	
WSI^2	0.013***	
	(0.001)	
High Related WSI		-0.536***
		(0.201)
High Related WSI^2		0.015***
		(0.004)
Carbon Score x Oil	-0.019***	-0.024**
	(0.004)	(0.011)
Carbon Score^2 *x Oil*	0.002***	0.002**
	(0.000)	(0.001)
WSI x Oil	0.047***	
	(0.002)	
WSI^2 *x Oil*	-0.001***	
	(0.000)	
High Related WSI x Oil		0.041***
		(0.009)
High Related WSI^2 *x Oil*		-0.001***
		(0.000)
Firm-level controls	YES	YES
Macroeconomic controls	YES	YES
Industry FE	YES	YES
Year FE	YES	YES
Obs.	148,125	148,125
Adj. R^2	0.044	0.045

Table 10 presents the impact of War sentiment on our baseline analysis. Panel A differentiates the War sentiment index into WSI (columns 1 and 3) and High-related WSI (columns 2 and 4) for both samples. Columns (1) and (2) belong to the full sample, while columns (3) and (4) are for the carbon sample. Panel B illustrates the non-linear effects by introducing a quadratic term. This panel is exclusive to the carbon sample and employs the Carbon Score to highlight the non-linear impact. The full sample is categorized based on industry; to prevent multicollinearity, industry fixed effects are not included in the full sample regression. T-statistics for the coefficient estimates are reported in parentheses; *, **, *** Indicate the figure statistical significance at 10 %, 5 %, and 1 %, respectively.

5.3 Extreme Temperature Effects

Building upon Choi et al. (2020), our third hypothesis investigates the influence of abnormal temperature fluctuations on investment strategies. Utilizing a 'Temperature Dummy' for the top quintile of abnormal temperatures, we explore the potential heightened impact on stock returns in regions experiencing extreme weather. This could be due to increased policy focus or changing investor attitudes towards climate risks.

We hypothesize that in such areas, oil price increases may not significantly affect the stock returns of firms with high climate risk exposure, reflecting the specific environmental and economic dynamics of these regions. Table 11 demonstrates the effects of abnormal temperatures on stock returns. Consistent with earlier findings, the 'Oil' variable positively correlates with stock returns. The 'Brown Dummy x Oil' interaction term remains significant for the carbon sample, with a coefficient of 0.064 at a 5% significance level.

This significance persists even after factoring in the abnormal temperature variable, reinforcing our original conclusions about the relationship between oil prices, climate risk, and stock returns. In our analysis, the interaction terms 'Oil x Temperature Dummy' and 'Oil x Brown Dummy x Temperature Dummy' did not produce significant results in either sample. This suggests that in areas with extreme temperature anomalies, oil price fluctuations don't significantly affect stock returns of brown firms. Possible reasons might include existing regulatory measures on such firms or investor tendencies to overlook brown firm stocks in these scenarios. Therefore, investors may not significantly adjust their strategies in response to oil price changes in these contexts.

Table 11 Extreme Temperature, Oil Price Changes and Climate Risk

Variable	Dependent Variable: Stock Return Full Sample (1990.01-2022.12)	Carbon Sample (2007.01-2022.12)
Oil	0.112***	0.148***
	(0.042)	(0.050)
Temperature Dummy	-0.128	-0.631**
	(0.256)	(0.315)
Brown Dummy	0.096	-0.667***
	(0.118)	(0.256)
Oil x Temperature Dummy	-0.005	-0.011
	(0.028)	(0.024)
Temperature Dummy x Brown Dummy	0.245	0.872
	(0.269)	(0.630)
Brown Dummy x Oil	0.033	0.064**
	(0.028)	(0.027)
Oil x Brown Dummy x Temperature Dummy	-0.052	-0.086
	(0.037)	(0.068)
Firm-level controls	YES	YES
Macroeconomic controls	YES	YES
Industry FE	NO	YES
Year FE	YES	YES
Firm Clustered	YES	YES
Year Clustered	YES	YES
Obs.	458,629	173,145
Adj. R^2	0.030	0.037

Table 11 shows the impact of extreme weather on our baseline analysis. Column (1) pertains to the full sample, while column (2) is for the carbon sample. The Temperature Dummy denotes firms located in states that experienced temperatures in the top two quintiles of abnormal readings. The full sample is categorized based on industry; to prevent multicollinearity, industry fixed effects are not included in the full sample regression. T-statistics for the coefficient estimates are reported in parentheses; *, **, *** Indicate the figure statistical significance at 10 %, 5 %, and 1 %, respectively.

6. Conclusion

This research probes into the extent to which a firm's climate risk exposure could intensify the correlation between oil price alterations and stock returns. The principal findings of this study are in accordance with the carbon risk premium theory, proposing that elevated climate risk exposure would magnify the effect of oil price alterations on stock returns. Our preliminary analysis revealed a significant surge in stock returns for corporations with high climate risk exposure when oil prices fluctuate. Essentially, a 1% change in oil prices results in approximately 1.5% and 3.5% higher returns for these firms in the full and carbon samples, respectively, with a 1% significance. Moreover, the interaction term in the carbon sample, which still exhibited significance but at a much lower following extensive robustness test.

Interestingly, the environmental policy, specifically the Paris Agreement, seems to have an insignificant influence on brown firms. However, the global financial crisis appears to amplify investor consideration of the higher risk associated with these firms. The interaction term (Brown Dummy x Oil) displayed an even larger economic significance, with a 3% greater effect than the baseline result in the full sample. Moreover, sentiments surrounding the Russia-Ukraine conflict displayed minor effects (with a mere 0.005 coefficient at the 5% significance level) on the interplay between climate risk, oil prices, and stock returns. This suggests that when investors devise hedging strategies against oil price fluctuations, geopolitical events may not be their primary consideration.

However, our study has limitations, which could be addressed by future research. First, the study utilises a single market climate risk criteria database (MSCI). Future studies may compare our results across different ESG data providers. Second, the study is limited to the U.S. Considering petroleum's global reach, it is essential to account for the impact and stock market behaviours of other nations, as there could be potential spill-over effects.

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Appendix A. Words List of War Sentiment

Key Words Searched for the War Sentiment Index (WSI)		
	WSI	**High related WSI**
Wordlists	air defense	Russia Fires
	military threat	Russian airstrikes
	invasion	Russian defense ministry
	Russia	Russian forces
	Russia Fires	Russian missile
	Russian airstrikes	Russo-Ukrainian War
	Russian defense ministry	Russia troop
	Russian forces	Ukraine troop
	Russian missile	Ukraine navy
	Russo-Ukrainian War	Ukrainian President
	Russia troop	Vladimir Putin
	Ukraine troop	Volodymyr Zelenskyy
	Ukraine Defense Ministry	
	Ukraine navy	
	Ukraine	
	Ukrainian President	
	Vladimir Putin	
	Volodymyr Zelenskyy	

Appendix A reports the wordlists from Google's search index used to obtain war sentiment for this study. The keywords, derived from frequent terms used in various media reports about the Russia-Ukraine conflict, were manually collected. To better capture heightened sentiment, we additionally filtered for terms that are closely related to the Russia-Ukraine conflict.

Appendix B. Robustness Test of PSM Analysis

Propensity Score Matching with Radius Matching Method					
Panel A: Covariate Balance Sheets (Full Sample: 1990.01 – 2022.12)					
Variable	**Treated Mean**	**Control Mean**	**Std. Mean Dif**	**T-stat**	**P-value**
Oil	0.707	0.767	-0.006	1.314	0.189
ROE	0.067	0.065	0.007	-1.502	0.133
Leverage	0.687	0.710	-0.019	4.534	0.000
Cash	0.163	0.158	0.027	-5.637	0.000
TobinQ	1.917	1.906	0.009	-2.013	0.044
Size	3.087	3.087	0.001	-0.168	0.867
BTM	0.600	0.611	-0.024	5.331	0.000
S&P500	0.699	0.702	-0.001	0.144	0.885
CPI	0.209	0.210	-0.002	0.335	0.737
GDP	1.115	1.119	-0.003	0.631	0.528

Panel B: Covariate Balance Sheets (Carbon sample: 2007.01 – 2022.12)					
Oil	0.229	0.261	-0.003	0.277	0.782
ROE	0.050	0.055	-0.017	1.726	0.084
Leverage	1.043	0.999	0.032	-3.123	0.002
Cash	0.086	0.093	-0.059	5.301	0.000
TobinQ	1.571	1.600	-0.036	3.392	0.000
Size	3.603	3.519	0.146	-12.608	0.000
BTM	0.734	0.705	0.032	-3.181	0.000
S&P500	0.730	0.699	0.007	-0.663	0.507
CPI	0.190	0.192	-0.008	0.743	0.792
GDP	0.999	0.993	0.003	-0.263	0.457

Panel C: Regression Results with PSM

	Dependent Variable: Return	
Variable	**Full Sample (1990.01 – 2022.12)**	**Carbon Sample (2007.01 – 2022.12)**
Oil	0.103***	0.124*
	(0.040)	(0.065)
Brown Dummy	0.323*	-0.090
	(0.168)	(0.236)
Brown Dummy x Oil	0.014	0.051***
	(0.019)	(0.019)
ROE	0.280	0.137
	(0.284)	(0.701)
Leverage	0.129***	0.099
	(0.048)	(0.065)
Cash	-1.471***	-1.835*
	(0.401)	(0.959)
TobinQ	0.917***	1.399***
	(0.094)	(0.176)
Size	-0.130	0.317**
	(0.080)	(0.128)
BTM	1.993***	1.760***
	(0.347)	(0.502)
S&P500 Index	-0.077	-0.259**
	(0.082)	(0.115)
CPI	-4.425**	-6.593*
	(1.782)	(3.466)
GDP	-0.014	0.099
	(0.085)	(0.124)
Industry FE	NO	YES
Year FE	YES	YES
Obs.	196,320	34,974
Firm Clustered	YES	YES
Year Clustered	YES	YES
Adj. R^2	0.031	0.039

Appendix B presents an alternative method for the PSM analysis for Table 5, which is applying the radius (or caliper) matching approach. This method ensures that matches for treated units fall within a predefined range of the propensity score. In this analysis, a caliper value of 0.05 is used. If a match isn't found within this range for a treated unit, that unit is omitted. After matched, there remain 98,160 observations for each group in the full sample, and 17,487 observations for each group in the carbon sample. The outcomes in this table align with those in Table 6 and are consistent with the baseline analysis.

Appendix C. Alternative IV Estimation: Frequency of Oil-Related Terrorist Attacks

Alternative Instrument Variable Estimation

Panel A: Full Sample (1990.01 – 2020.12) **Independent Variable:**	$\boldsymbol{Oil_{t-1}}$	$\boldsymbol{Terror_{t-1}}$	$\boldsymbol{Oil_{t-1}}$
	(1)	**(2)**	**(3)**
	OLS	2SLS	
		First-Stage	Second-Stage
Oil_{t-1}	0.098**		0.069
	(0.040)		(0.527)
$Terror_{t-1}$		1.328	
		(0.971)	
Brown Dummy	0.088	0.061	0.092
	(0.138)	(0.052)	(0.139)
Oil_{t-1} *x Brown Dummy*	0.022		0.015
	(0.022)		(0.027)
$Terror_{t-1}$ *x Brown Dummy*		-0.014	
		(0.020)	
ROE	0.071	-0.086	0.068
	(0.225)	(0.087)	(0.215)
Leverage	0.092***	-0.007	0.092**
	(0.035)	(0.008)	(0.037)
Cash	-0.627***	-0.156	-0.632**
	(0.240)	(0.101)	(0.258)
TobinQ	0.794***	0.052	0.796***
	(0.068)	(0.046)	(0.066)
Size	-0.134*	0.017	-0.134*
	(0.081)	(0.031)	(0.081)
BTM	1.893***	0.173	1.900***
	(0.333)	(0.210)	(0.330)
S&P500 Index	-0.015	0.277*	-0.007
	(0.065)	(0.145)	(0.144)
CPI	-4.243**	23.760***	-3.527
	(1.953)	(2.969)	(12.633)
GDP	-0.009	-0.704***	-0.030
	(0.089)	(0.161)	(0.373)
Industry FE	NO	NO	NO
Year FE	YES	YES	YES
Firm Clustered	YES	YES	YES
Year Clustered	YES	YES	YES
Adj. R^2	0.029	0.377	0.025

Panel B: Carbon Sample (2007.01 – 2020.12)			
Independent Variable:	Oil_{t-1}	$Terror_{t-1}$	Oil_{t-1}
	(1)	**(2)**	**(3)**
	OLS	2SLS	
		First-Stage	Second-Stage
Oil_{t-1}	0.104		0.485
	(0.071)		(0.917)
$Terror_{t-1}$		3.065	
		(2.378)	
Brown Dummy	-0.368**	0.734	-0.373**
	(0.174)	(1.182)	(0.185)
Oil_{t-1} *x Brown Dummy*	0.040*		0.035
	(0.023)		(0.030)
$Terror_{t-1}$*x Brown Dummy*		-0.204	
		(0.345)	
ROE	-0.468	-0.127	-0.422
	(0.318)	(0.104)	(0.263)
Leverage	0.065*	0.0004	0.065
	(0.039)	(0.009)	(0.039)
Cash	-0.813**	-0.204*	-0.724
	(0.400)	(0.117)	(0.478)
TobinQ	0.843***	0.098	0.799***
	(0.107)	(0.078)	(0.059)
Size	0.216	-0.048	0.229*
	(0.140)	(0.099)	(0.134)
BTM	1.744***	0.425	1.552***
	(0.563)	(0.302)	(0.311)
S&P500 Index	-0.089	0.504***	-0.290
	(0.140)	(0.120)	(0.387)
CPI	-6.781	31.078***	-18.702
	(4.464)	(5.237)	(29.907)
GDP	0.070	-0.932***	0.411
	(0.139)	(0.215)	(0.864)
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Firm Clustered	YES	YES	YES
Year Clustered	YES	YES	YES
Adj. R^2	0.033	0.494	0.029

This table shows results using an alternative instrumental variable to address the endogeneity concerns in the baseline analysis. Panel A is for the full sample and Panel B is for the carbon sample. *2SLS* columns show separate stages of the IV procedures. The full sample is categorized based on industry; to prevent multicollinearity, industry fixed effects are not included in the full sample regression. T-statistics are shown in parentheses, with *, **, and *** denoting statistical significance at 10%, 5%, and 1% levels, respectively.

In Appendix C, we employ the frequency of oil-related terrorist attacks as an instrumental variable for our baseline model. Following the methodology of Chen et al. (2021), we obtained data on terrorist attacks from the Global Terrorism Database (GTD). We used the monthly frequency of attacks targeting oil-related infrastructure—specifically, those categorized as targeting "Oil," "Gas/Oil/Electric," "Oil Tanker," and "Police Patrol (including vehicles and convoys)"—as the instrumental variable. This database's information extends only until December 2020; thus, our full and carbon sample timelines are consistent with this cutoff.

However, when we tested for multicollinearity using the Variance Inflation Factor (VIF) for both the first-stage models, we encountered issues with the instrumental variable, the brown dummy, and the interaction term. This indicated that the chosen instrumental variable may not be suitable for our study. Despite this, we have documented the entire process. Columns (2) and (3) of our report demonstrate that the instrumental variable is not significantly related to the variable of our primary interest. This lack of a significant relationship further suggests that this IV may not be appropriate for our study.