Climate change and fossil fuel prices: A GARCH-MIDAS analysis

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Abstract

In this study, we investigate the connection between climate change and the volatility of fossil fuel prices using the GARCH-MIDAS framework which accommodates mixed data frequencies and by extension circumvents information loss due to splicing or aggregation of one variable for the other. We conduct a battery of robustness tests that allow for nominal and real prices of fossil fuels as well as global financial crises (GFC). We show a strong connection between climate change and the volatility of fossil fuel prices albeit with stronger evidence in the post-GFC period. The outcome is positive in the recent period and therefore climate change seems to have heightened the volatility in the fossil fuel market. Even when the real prices are considered, results remain consistent, indicating that inflationary pressures do not diminish the effect of climate change on fossil fuel price volatility. We also show that own market risk positively impacts the volatility of fossil fuel prices and the volatility tends to persist when there is a shock to the fossil fuel market. More conscious efforts are needed to effectively discourage increased investments in environmentally-degrading assets.

Keywords: Fossil fuel prices, Climate change, Predictability, Global financial crisis, GARCH-MIDAS, Volatility
JEL Codes: P28, Q02, Q32, Q54

1. Introduction

Fossil fuel constitutes a huge energy source, accounting for about 88% of the commercial energy sources used (Judkins, 1993). Given the economic significance of non-renewable fossil fuel products and the inherent volatility of their prices, achieving accurate prediction of fossil fuel prices has become the focus of researchers, investors, and policymakers in recent years (see for example, Anand, 2016; Chen et al., 2022; Dash and Dash, 2022; Day and Day, 2017; Wang and Su, 2021; Zhang, 2022). As noted by Day and Day (2017), fossil fuel prices increased significantly between 2000 and 2008, slumped during the global financial crisis, but increased again between 2009 and 2011, and remained steady until 2014. Shafiee and Topal (2010) added that the natural gas and coal prices had the highest volatility in the historical trend of fossil fuel prices in 2008, and the incidence of the global financial crisis was worsened by oil price fluctuations and weaknesses in other fossil fuel prices. Similarly, the ongoing Russian – Ukraine war has further impacted this volatility given various sanctions that have been meted out against Russia, a major supplier of the product. Despite the rising advocate for shifting energy use to renewable energy products, fossil fuel products remained in high consumption, and the volatility of their prices affects economic planning at individual, national, and global levels (Qian et al. 2022).[3] This justifies the need to examine the predictability of fossil fuel price volatility in this study.

Meanwhile, the extant studies have investigated the predictability of fossil fuel prices, albeit with a special focus on the predictability of crude oil prices in tranquil period (see for recent studies, Chatziantoniou et al., 2021; Chen et al., 2022; Degiannakis and Filis, 2022; Guo et al. 2022; Qian et al. 2022; Ren et al., 2022a; Zhang, 2022) and turbulent period including COVID period and the Russia-Ukraine war (see for recent examples, Appiah-Otoo, 2022; Devpura and Narayan, 2020; Iyke, 2020; Narayan,2020; Qin et al., 2020). Specifically, Chen et al. (2022) evaluate the information content of stock markets in forecasting both oil prices and oil price volatility. The result shows strong threshold effects of stock volatility for oil volatility forecasting. Examining the forecasting ability of global economic activity for WTI crude oil price volatility by Guo et al. (2022), they find that model incorporating the global economic conditions has a strong predictive power in predicting oil price volatility. Similarly, Qian et al. (2022) investigate the geopolitical risk (GPR) predictability of oil price volatility and find that high GPR leads to high fluctuations in the oil market in-sample, and GPR is a good predictor of oil market volatility out-of-sample. More so, Chatziantoniou et al. (2021) investigate global determinants of oil price volatility and find that oil supply, oil demand, oil inventory, financial market uncertainty, and financial interbank stress can cause higher oil price volatility. Shafiee and Topal (2010) consider the predictability of not only crude oil but of also coal and natural gas with a novel method.

Apparently, despite the rising problem of global warming and the need for switching energy sources to renewable ones (Judkins et al., 1993), and increasing advocacy for responsible and green investment in and divestment from fossil fuel firms (Al Ayoubi and Enjolras, 2022), very limited attention has been paid to the potential effect of climate change on fossil fuel price volatility. Recent evidence also suggests the need to observe climate change in asset pricing (see for example, Akpa et al., 2022; Faccini et al., 2021; Lasisi et al., 2022; Oloko et al., 2022; Zhang et al., 2019). We, therefore, advance this literature to examine how such investment decisions of pricing climate risk in asset pricing may have influenced the pricing and volatility of fossil fuels

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[3] We refer our readers to review various policy actions undertaken by government and policy-makers during these periods (see for example, various WB and IMF's working papers such as Krichene (2006) via https://www.imf.org/en/Publications/WP/Issues/2016/12/31/Recent-Dynamics-of-Crude-Oil-Prices-20195; Nagle and Tema (2022) via https://blogs.worldbank.org/opendata/oil-prices-remain-volatile-amid-demand-pessimism-and-constrained-supply).

which are often described as the largest emitters of environmental pollution. In the last century, the global average temperature has increased by approximately one degree Celsius, and at an accelerating rate, while fossil fuel price volatility has been unstable over the period (Xie et al., 2022). Given that the global increase in the discovery and use of alternative energy due to unfavourable trends in climate change may stimulate a gradual reduction in demand for fossil fuel products and the crash in their prices (see also, Wuebbles and Jain, 2001; Xie et al., 2022), climate change's predictability of fossil fuel prices volatility is a possibility. Earlier studies on this subject include Nick and Thoenes (2014), Saeed and Tularam (2017), Shafiee and Topal (2010), and Xie et al. (2022).

There are three channels through which climate change can influence carbon price or fossil fuel price fluctuations (Xie et al., 2022). The first channel is through changes in fossil energy consumption. Climatic variation can change fossil energy consumption, thereby influencing the fluctuation of carbon prices. Specifically, extreme high and low temperatures lead to more energy consumption and carbon dioxide emissions, for instance, by increasing the usage of air conditioning or heating. The second channel is through changes in the energy structure. Extreme climate and natural disasters expose new energy companies to substantial physical risks, causing changes in the energy structure and eventually, carbon prices. For instance, drought leads to a reduction in water storage which hinders hydroelectric power generation. Thus, the consumption of fossil fuels would need to increase to ensure a regular supply of electricity. This change in energy structure will affect carbon price fluctuations. The third channel is through government activities. For example, increasing government intervention in carbon dioxide emissions would stimulate changes in the supply of carbon emissions rights, thereby influencing carbon prices.

Empirically, Nick and Thoenes (2014), Saeed and Tularam (2017), and Xie et al. (2022) are the studies that have examined the relationship between climate change and fossil fuel prices. Specifically, Nick and Thoenes (2014) examine the drivers of natural gas prices using a structural VAR approach. They predicted that fluctuations in the global climate would affect fossil fuel prices only in the short term. Saeed and Tularam (2017) investigate the relationship between fossil fuel returns and climate change variables using canonical correlation analysis and find that the climate change variables contribute lesser to the relationship. More so, Xie et al. (2022) evaluate carbon price prediction by climate change using a text-based framework.[4] They find that climate change exerts an impact on carbon price fluctuations and that the proposed climate-related textual variable reflects relevant aspects of climate change.

The current study is similar to Xie et al. (2022) in that it examines the effect of climate change on fossil fuel price volatility. It however makes some unique contributions to the literature which distinguish it from the earlier studies. First, it measures climate change with temperature anomalies and considers six classes of oil (crude oil, gasoline, heating oil, diesel fuel, jet fuel, and propane). Temperature anomalies measure the deviation of the global temperature from expected. A positive/negative value implies a higher/lower temperature than expected. Temperature anomalies have been found to reflect the trend in global climate change (see Oloko, et al. 2022) and other measures such as level of temperature and temperature growth, among others. In addition, the consideration of six classes of fossil fuels provides wider coverage than other related studies whose analyses are limited to crude oil. Analyzing the variants of fossil fuels enables us to establish whether the response of these variants to climate change is heterogeneous and make useful generalizations about the connection between the two variables. Second, it employs the GARCH-MIDAS[5] modeling framework in analyzing the relationship. The stylized facts for high-frequency data such as fossil fuel prices suggest they exhibit volatility clustering (see Salisu and Oloko, 2015) which suggests the appropriateness of GARCH model variants. Different methods have been used in the literature including the threshold autoregressive regression (TAR) model (Chen et al., 2022), Markov-switching model (Qian et al., 2022), and time-varying parameter vector autoregressive (TVP-VAR) model (Chatziantoniou et al., 2021). However, we favour the GARCH-MIDAS framework for two reasons. One is its ability to deal with the inherent conditional heteroscedasticity effect like other variants of the GARCH model. This effect is typical of high-frequency series like the frequency for the fossil fuels used in this study and there is evidence in the literature suggesting improved forecast performance for predictive models that account for this effect, among other salient features of time series (see Westerlund and Narayan, 2012, 2015). The second reason involves the need to accommodate the variables of interest at their natural frequencies rather than splicing or aggregating one variable for the other as done in the

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[4] Ren et al. (2022b) also suggest using a high-dimensional model to forecast carbon prices although the role of climate change is not explicitly captured in the study.

[5] GARCH-MIDAS is technically defined as the Generalized Autoregressive Conditional Heteroscedasticity-Mixed Data Sample.

previous literature involving TAR, TV-PVAR, or the Markov-switching model. That is, while fossil fuel prices are expressed in daily frequency, climate change indicator is expressed in monthly frequency. Therefore, the use of the GARCH-MIDAS framework accommodates both the conditional heteroscedasticity effect and the mixed frequencies for fossil fuels and climate change.

Our third contribution relates to determining the role of the global financial crisis (GFC) in the climate change-fossil fuels nexus. The trends in fossil fuel prices reveal that fossil fuel prices increased consistently before GFC and have been inconsistent after the GFC, while climate change increased over the two periods. This suggests that the predictability of climate change for fossil fuel prices may be different in the two eras. We also expressed fossil fuel prices in nominal and real terms for the robustness and sensitivity of our result to U.S. inflation. Theoretically, Post global financial, concern was more about economic recovery than climate change. Thus, increased economic activity that utilizes oil more as input would raise emission levels, and by extension, climate-induced risk. Given this risk, it is predictable that the global energy sector would switch from fossil-based systems of energy production and consumption to renewable sources to meet the requirement for net zero emissions, with the ensuing effects being felt on global economic activity. The preceding follows the popular EKC theory that hypothesizes a U-shaped nexus between real economic activity and environmental degradation/climate risk. Thus, commodity (including oil) prices are expected to respond to these variations, as they constitute a distortion to the existing equilibrium, since it is believed that shock to the business cycle tends to impact real commodity prices (see Kilian and Zhou, 2018), and by extension, their volatility. There are indications that oil price is always out of equilibrium.[6]

Foreshadowing our findings, our results show that fossil fuel price volatility responds differently to climate change; while it increases the volatility of some fossil fuel prices, it appears to reduce it for others. The results are consistent for real and nominal prices, suggesting that they are robust and not sensitive to changes in U.S. inflation.

This study has five sections. Following this introduction section, section 2 deals with data issues and preliminary analysis. Section 3 discusses the GARCH-MIDAS framework. Section 4 deals with the presentation and discussion of results. Section 5 concludes the study.

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[6] https://www.imf.org/en/Publications/WP/Issues/2016/12/31/Recent-Dynamics-of-Crude-Oil-Prices-20195

2. Data Issues and Preliminary Analysis

The main objective of this study is to examine the effect of fossil fuel prices on climate change. To pursue this objective, we utilize data for prices of six different fossil fuels (crude oil, gasoline, heating oil, diesel fuel, jet fuel, and propane) and data for global temperature anomalies[7] (as a proxy for climate change). The data for fossil fuels prices are obtained from the United States Energy Information Administration (EIA) (see https://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm), while the data for climate change data published by National the Aeronautics and Space Administration (NASA) Goddard Institute for Space Studies (GISS) was also utilized (see https://data.giss.nasa.gov/gistemp/). The fossil fuels prices are expressed in US dollars per gallon except for crude oil whose prices are expressed in US$ per barrel (where a barrel is 31.5 US gallons). On the other hand, climate change is measured in degrees grade. The data for fossil fuel prices are available in daily frequency, while the data for climate change is available in monthly frequency. This inconsistency in the data frequency justifies the consideration of the MIDAS-type methodology in this study. To maintain uniform data frequency for all the fossil fuel prices, the scope of this study is from June 1996 to May 2022.

Table 1 presents the descriptive statistics for climate change and fossil fuel price returns. It shows that WTI has the highest price return of US$0.0003/gallon of the fossil fuels considered. This is followed by Brent, gasoline, heat oil, and jet fuel with price returns of (US$0.0002/gallon) each. Propane and diesel are the least expensive of the fuels with price returns of US$0.0001/gallon each. The average climate change (temperature anomalies or deviation from normal) is positive 0.68ºC, indicating that the global temperature increased, on average, over the study period. The minimum and maximum values of climate change and fossil fuel prices are widely separated, suggesting high variability. Except for diesel with a standard deviation of 0.02, all fossil fuels have standard deviation values of 0.03. Using the skewness and kurtosis statistics, Jarque Bera's statistics reveal that climate change is normally distributed, but fossil fuel prices are not normally distributed.

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[7] According to NASA, temperature anomalies indicate how much warmer or colder it is than normal for a particular place and time. For the GISS analysis, normal always means the average over the 30 years 1951-1980 for that place and time of year.

Table 1: Descriptive Statistics

Variables	Mean	Max.	Min.	S. Dev.	Skew.	Kurt.	J.-Bera	Prob.	Corr.	Obs.
Climate change	0.68	1.37	0.19	0.21	0.27	3.06	4.00	0.14	1.00	314
Brent Crude Oil Price	0.0002	0.41	-0.64	0.03	-1.77	74.41	1400000	0.00	-0.06	6691
Conv. Gasoline Price	0.0002	0.24	-0.30	0.03	-0.41	13.49	30000	0.00	0.03	6568
Heating Oil Price	0.0002	0.23	-0.47	0.03	-1.24	32.79	420000	0.00	0.01	6568
Diesel Fuel Price	0.0001	0.27	-0.23	0.02	-0.16	13.51	30000	0.00	-0.00	6564
Jet Fuel Price	0.0002	0.33	-0.28	0.03	-0.33	15.66	44000	0.00	-0.01	6565
Propane	0.0001	0.20	-0.51	0.03	-1.58	34.94	280000	0.00	-0.06	6559
WTI Crude Oil Price	0.0003	0.43	-0.28	0.03	0.56	28.10	180000	0.00	-0.06	6689

Note: The descriptive statistics cover the period from May 1996 to June 2022. Climate change indicator (temperature anomalies) is in monthly frequency, while fossil fuels price returns are in daily frequency. The fossil fuel price returns are expressed in US dollars per gallon except for crude oil whose price returns are expressed in US$ per barrel. On the other hand, climate change is measured in degrees centigrade.

Figure 1 shows that graphical representation of the trends in climate change and fossil fuel prices. As evident from the figure, the dynamics of fossil fuel prices appear similar, particularly before the Global Financial Crisis (GFC). This suggests that the effect of a shock to one fossil fuel market spills to other fossil fuel markets. Fossil fuel prices also follow a similar trend after the GFC except for Propane, which appears to trend differently between 2010 and 2014. On average, climate change followed an upward trend during the period under consideration, but the trend in fossil fuel prices is inconsistent (it increased and decreased at different times). Meanwhile, the correlation coefficients (see Table 1) reveal that fossil fuel prices are positively correlated with climate change indicators. This suggests that higher fossil fuel prices (which indicates higher demand for fossil fuels in this study) could potentially lead to higher climate change. The objective of this study is to validate or refute this hypothesis.

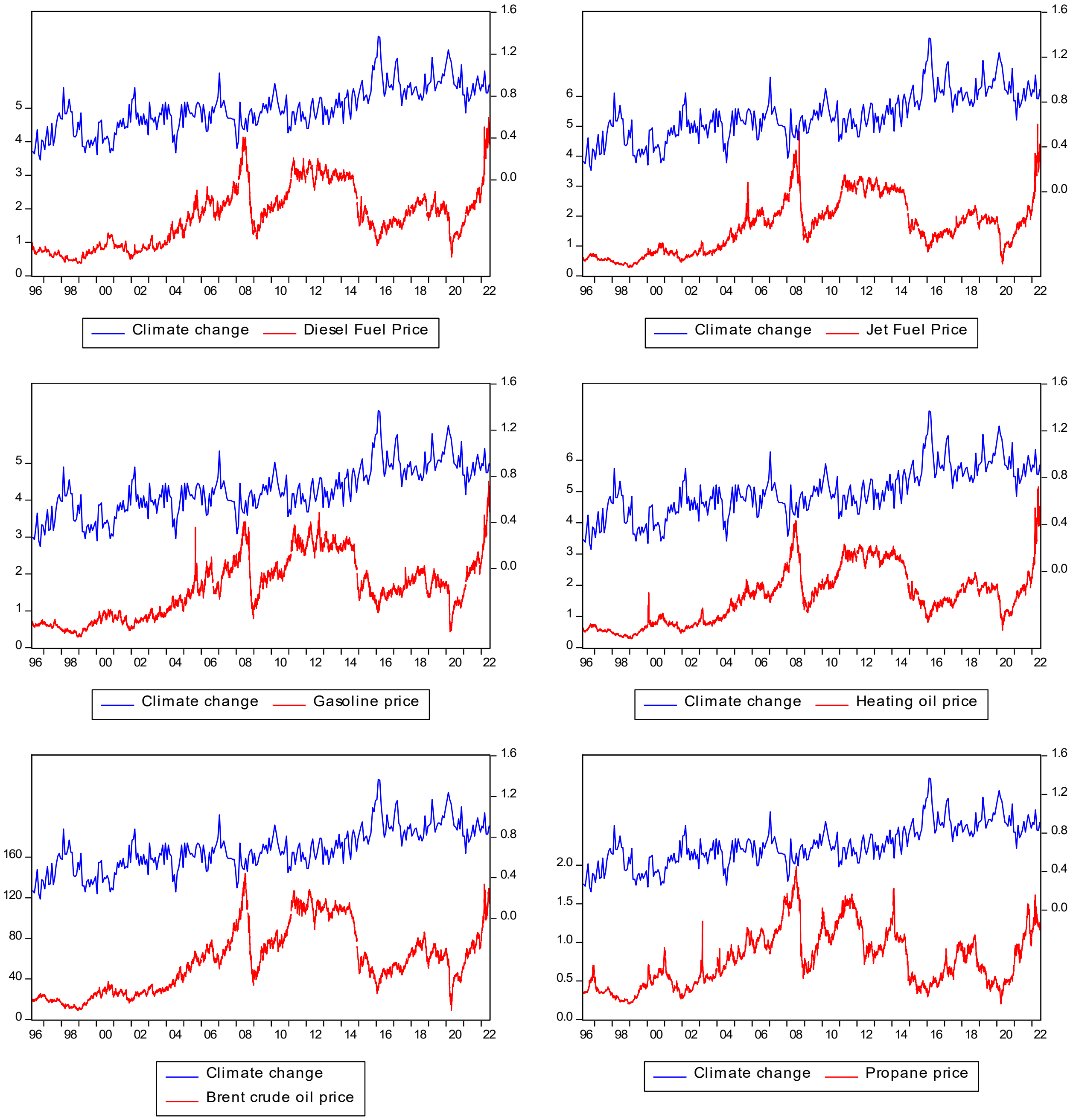

Figure 1: Climate Change and Fossil Fuel Price

3. Methodology

In this study, we employ the Generalized Autoregressive Conditional Heteroskedasticity variant of the Mixed Data Sampling (GARCH-MIDAS) model by Engle et al. (2013). This is necessary to deal with variations in the frequencies of our dependent (fossil fuel price returns) and independent variables (climate change). The daily fossil fuel return series is computed as -

$r_{i,t} = ln\left(P_{i,t}\right) - ln\left(P_{i-1,t}\right)$, where $P_{i,t}$ represents the price index for the day *i* in month *t* with $t = 1,...,T$ and $i = 1,...,N_t$ denoting the monthly and daily frequencies, respectively. In other words, N_t is the number of days in a given month *t*. We construct a GARCH-MIDAS-X model where our exogenous variable (X), is climate change. Like the conventional GARCH models, the GARCH-MIDAS model has mean and conditional variance equations. The conditional variance equation is further divided into short and long-run components to accommodate the predictor series.

$$r_{i,t} = \mu + \sqrt{\tau_t \times h_{i,t}} \times \varepsilon_{i,t}, \quad \varepsilon_{i,t} \left| \Phi_{i-1,t} \sim N\left(0,1\right), \quad \forall \;\; i = 1,...,N_t \right. \tag{1}$$

$$h_{i,t} = \left(1-\alpha-\beta\right) + \alpha \frac{\left(r_{i-1,t} - \mu\right)^2}{\tau_t} + \beta h_{i-1,t} \tag{2}$$

$$\log(\tau_t) = m + \theta \sum_{k=1}^{K} \phi_k \left(w_1, w_2\right) X_{t-k} \tag{3}$$

Equation (1) is the mean equation while equations (2) and (3) are the conditional variance components for short and long-run components, respectively. In terms of the definition of parameters, μ is the unconditional mean of the return series; $h_{i,t}$ is the short-run conditional volatility of the high frequency (fossil fuels) variable. This is specified following $\text{GARCH}\left(1,1\right)$ process, where α and β are the ARCH and GARCH terms, respectively, conditioned to be positive and/or at least zero (α>0 and $\beta \geq 0$) and sum up to less than unity$\left(\alpha + \beta < 1\right)$. The term τ_t captures the long-run component of conditional volatility, and this incorporates the role of climate change (denoted by X), and it involves repeating the monthly value throughout the days in that month. Also, $\log(\tau_t)$ is considered rather than τ_t, to ensure the positivity of the long-term volatility, and $\phi_k\left(w_1, w_2\right)$ is the Beta weighting scheme:

$$\phi_k\left(w_1, w_2\right) = \frac{(k/(K+1))^{w_1-1} \cdot (1-k/(K+1))^{w_2-1}}{\sum_{l=1}^{K} (l/(K+1))^{w_1-1} \cdot (1-l/(K+1))^{w_2-1}}, \tag{4}$$

The weights, ϕ_k, are completely determined by two parameters w_1 and w_2. It is easy to discover that $\phi_k \geq 0$ for $k = 1,...,K$, and $\sum_k^K \phi_k = 1$. Accordingly, a positive (negative) coefficient of X,

(θ), will imply that climate change increases (reduces) long-term fossil fuel price returns volatility.

4. Results and Discussion

4.1 Main Findings

The nexus between climate change and the variants of fossil fuel (crude oil, diesel, jet fuel, heat oil, gasoline, and propane) price volatilities is estimated using the GARCH MIDAS approach. As previously noted, this subject is important owing to the current global campaign for climate sustainability and therefore research is continuously unfolding to offer some technical inputs into the decision-making process by relevant economic agents toward mitigating the consequences of climate change. The results are presented in three dimensions: first, the predictability of fossil fuels relative to their market risks as well as climate change are analyzed; second, the effects of systemic and climate risks on the real values in addition to nominal values of various fossil fuels are also analyzed since climate change impacts on nominal prices of fossil fuels through its effects on output; lastly, the analysis is conducted over the full sample period covering May 1996 to June 2022 and the post-GFC period, from January 2010 to June 2022 to examine the effects of GFC on the price volatility of fossil fuels. The estimated parameters include the unconditional mean for fossil fuel returns (μ); ARCH coefficient (α); GARCH coefficient (β); the slope coefficient (ϴ) that indicates the impact of the predictor; adjusted beta polynomial weight (w) and the long run constant term (m).

Results for the effects of climate change on the nominal and real fossil fuel price volatilities using the full sample are presented in Table 2. The results show that all the variants of fossil fuels both in nominal (panel A) and real (Panel B) values can be predicted by climate change since the slope coefficients (ϴ) are statistically significant for all the estimates and the results are consistent in both panels. However, in terms of the direction of the relationship, the outcome is mixed. While it is positive for Brent, Heating oil, and Propane, it is negative for other fossil fuels. What does this outcome imply? It suggests that while climate change has increased trading in the first category of fossil fuels (i.e., those with a positive sign) and by extension their volatility[8], it may have reduced the trading for the second category with a negative sign. In other words, the selected fossil fuels respond differently to climate change. There are two implications of these findings. First, the

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[8] It is hypothesized here that higher (lower) trading would lead to higher (lower) price volatility.

increased trading of Brent crude oil, heating oil, and propane, notwithstanding the campaign against alternative sources of energy is an indication that more work still needs to be done toward encouraging wider adoption of alternative energy sources that are environmentally (eco-) friendly. Second, the fact that all the fossil fuels do not share the same sign with consistent evidence between nominal and real values signals some successes in the climate change campaign against the increased use of energy sources that are not eco-friendly. Given the preceding results and justifications, similar studies such as Wuebbles and Jain (2001) submit that fossil fuel use contributes immensely to climate risk, thus, policies relating to climate change issues will always influence oil trading, and by extension, oil price movements (see Nick and Thoenes, 2014). In the same vein, studies have documented the positive volatility impact of other sources of uncertainties such as geopolitical risk (Qian et al., 2022) and health risk (Wang and Su, 2021), among others, on the oil market. Lasisi et al. (2022) present similar results relating climate change to stock market volatility. In stemming the tide, Lazarus and van Asselt (2018) suggest a renewed effort that focuses more on the supply side than the demand side. Importantly, they contend that actions taken against fossil fuels and their suppliers can exert additional pressure on the climate change mitigation efforts required for international climate action. Finally, the results also indicate high volatility persistence, as the sum of the ARCH and GARCH coefficients is close to unity implying that any shock to the fossil fuel market tends to persist over a long period. This result supports the findings by Isah et al. (2023) who equally identify a high degree of volatility in the oil market owing to climate-induced risk factors.

We examine the role of GFC in the nexus by performing distinct analyses for the post-GFC period and the results obtained are presented in Table 3 Panels A and B are for the nominal and real values for the fossil fuels. The slope coefficients (Ө) are statistically significant for virtually all the proxies for fossil fuels validating the significant role of climate change in the predictability of volatility of fossil fuel prices. This outcome further validates the evidence previously reported in the full sample case in terms of the statistical significance of the predictability coefficient. However, a look at the direction of the relationship appears to depart from that of the full sample. We find that after the global financial crisis, the volatility of fossil fuels responds positively to climate change even for Brent, Propane, and Heating oil. In essence, the need for faster recovery from the dampening effects of the GFC on the global economy may have necessitated the increased demand for these sources of energy. Like the full sample case, the sum of ARCH and GARCH coefficients is also close to unity implying the presence of volatility persistence for a unit shock to the fossil fuel market. Corroborating this finding, Zhang and Zhang (2015) contend that the price of Brent rose sharply, following GFC.

Table 2: Using a full sample with climate change as the predictor

Panel A: Nominal fossil fuels						
Fossil fuel	μ	α	β	Ɵ	w	m
WTI	0.0007***	0.0929***	0.8892***	-0.0003*	2.9271	0.0009***
	[0.0002]	[0.0039]	[0.0049]	[0.0002]	[5.8469]	[0.0002]
Brent	0.0007***	0.0898***	0.9028***	0.0007**	12.865	0.0004**
	[0.0002]	[0.0039]	[0.0044]	[0.0003]	[12.272]	[0.0002]
Diesel	0.0005**	0.0840***	0.9008***	-0.0004*	2.4407	0.0010***
	[0.0002]	[0.0035]	[0.0042]	[0.0002]	[2.7340]	[0.0001]
Jet fuel	0.0007***	0.1008***	0.8915***	-0.0005*	5.1632	0.0015***
	[0.0002]	[0.0052]	[0.0059]	[0.0003]	[13.2950]	[0.0003]
Heat oil	-0.0055***	0.0503***	0.9001***	0.0116***	5.0000***	-0.0038***
	[0.0007]	[0.0025]	[0.0058]	[0.0001]	[0.0046]	[0.0000]
Gasoline	0.0006**	0.0503***	0.9005***	-0.0004***	5.0002	0.0009***
	[0.0003]	[0.0022]	[0.0059]	[0.0001]	[4.0860]	[0.0000]
Propane	0.0008***	0.1397***	0.8336***	0.0004***	1.1552	0.0006***
	[0.0003]	[0.0052]	[0.0050]	[0.00008]	[1.6062]	[0.0001]
Panel B: Real fossil fuels						
Fossil fuel	μ	α	β	Ɵ	w	m
WTI	0.0007***	0.0932***	0.8888***	-0.0004*	2.8129*	0.0010***
	[0.0003]	[0.0040]	[0.0050]	[0.0002]	[5.6573]	[0.0002]
Brent	0.0006***	0.0899***	0.9032***	0.0008**	14.6310**	0.0004**
	[0.0003]	[0.0040]	[0.0045]	[0.0004]	[12.7160]	[0.0002]
Diesel	0.0005*	0.0851***	0.8998***	-0.0004**	2.4469	0.0010***
	[0.0003]	[0.0036]	[0.0043]	[0.0002]	[2.7606]	[0.0002]
Jet fuel	0.0007***	0.1003***	0.8921***	-0.0006*	5.0654	0.0015
	[0.0003]	[0.0052]	[0.0060]	[0.0003]	[13.2020]	[0.0004]
Heat oil	0.0005*	0.0561***	0.9038***	-0.0002**	4.9627	0.0006***
	[0.0003]	[0.0023]	[0.0044]	[0.0001]	[8.1585]	[0.0001]
Gasoline	0.0005	0.1096***	0.8642***	-0.0005**	1.1002	0.0012***
	[0.0003]	[0.0052]	[0.0071]	[0.0003]	[1.5160]	[0.0002]
Propane	0.0007***	0.1407***	0.8324***	0.0004***	2.3660	0.0007***
	[0.0003]	[0.0053]	[0.0051]	[0.0002]	[3.5467]	[0.0002]

Note: The results are the estimated parameters of a monthly (N = 22) rolling window GARCH–MIDAS regression using climate change indicator, and temperature anomalies, as the predictor. The parameters: μ is the unconditional mean for stock return; α and β are the ARCH and GARCH terms, respectively, in the short-term component, with the latter indicating the degree of persistence; θ is the sum of weighted rolling window realized volatilities, indicating the predictability of the monthly oil shocks for the daily stock returns; w is adjusted beta polynomial weight; and m is the long-run constant term. The "*", "**", and "***" are 10%, 5%, and 1% significance levels; while the values in brackets are the standard errors.

Table 3: Using Post-GFC sample with climate change as the predictor

Panel A: Nominal fossil fuels						
Fossil fuel	μ	α	β	Ɵ	_w_	_m_
WTI	0.0005	0.1123***	0.8662***	0.0019***	_6.9027*_	_-0.0009***_
	[0.0004]	[0.0066]	[0.0068]	[0.0004]	_[3.6854]_	_[0.0003]_
Brent	0.0004	0.1082***	0.8755***	0.0018	3.6495***	-0.0008***
	[0.0004]	[0.0069]	[0.0077]	[0.0004]	[1.3542]	[0.0003]
Diesel	-0.0002	0.0504***	0.9006***	0.0147***	4.9999***	-0.0086***
	[0.0005]	[0.0064]	[0.0110]	[0.0023]	[0.0545]	[0.0014]
Jet fuel	0.0001	0.0503***	0.9006***	0.0110***	5.0000***	-0.0063***
	[0.0004]	[0.0061]	[0.0174]	[0.0015]	[0.0402]	[0.0009]
Heat oil	0.0004	0.0504***	0.9007***	0.0008***	4.9999***	-0.0003***
	[0.0004]	[0.0035]	[0.0069]	[0.0001]	[1.4087]	[0.0001]
Gasoline	0.0003	0.1643***	0.7812***	0.0013***	40.6470	-0.0005***
	[0.0004]	[0.0119]	[0.0161]	[0.0003]	[28.7940]	[0.0002]
Propane	0.0003	0.0556***	0.9016***	0.0018***	4.9983***	-0.0009***
	[0.0005]	[0.0035]	[0.0065]	[0.0002]	[1.3756]	[0.0001]
Panel B: Real fossil fuels						
Fossil fuel	μ	α	β	Ɵ	_w_	_m_
WTI	-0.0001	0.0533***	0.9003***	0.0533***	4.9978***	-0.0308***
	[0.0004]	[0.0159]	0.0246	[0.0147]	[0.0841]	0.0084586
Brent	0.0003	0.1087***	0.8747***	0.0018***	3.1109***	-0.0008***
	[0.0003]	[0.0069]	[0.0078]	[0.0004]	[1.1854]	[0.0002]
Diesel	0.0006	0.0502***	0.9004***	0.0468***	5.0000***	-0.0270***
	[0.0004]	[0.0178]	[0.0435]	[0.0052]	[0.0697]	[0.0030]
Jet fuel	0.0000	0.1091***	0.8887***	0.0119	3.1943**	-0.0067003
	[0.0003]	[0.0075]	[0.0078]	[0.0084]	[1.3684]	[0.0049]
Heat oil	0.0002	0.1071***	0.8737***	0.0013***	1.9784*	-0.0005***
	[0.0003]	[0.0073]	[0.0080]	[0.0003]	[1.0565]	[0.0002]
Gasoline	0.0001	0.1655***	0.7787***	0.0012***	40.1320	-0.0004***
	[0.0004]	[0.0119]	[0.0162]	[0.0002]	[28.8230]	[0.0002]
Propane	0.0003	0.1361***	0.8304***	0.0034***	1.7484***	-0.0018***
	[0.0004]	[0.0092]	[0.0087]	[0.0005]	[0.5108]	[0.0003]

Note: The results are the estimated parameters of a monthly (N = 22) rolling window GARCH–MIDAS regression using the climate change indicator such as temperature anomalies, as the predictor. The parameters: μ is the unconditional mean for stock return; α and β are the ARCH and GARCH terms, respectively, in the short-term component, with the latter indicating the degree of persistence; θ is the sum of weighted rolling window realized volatilities, indicating the predictability of the monthly oil shocks for the daily stock returns; w is adjusted beta polynomial weight; and m is the long-run constant term. The "*", "**", and "***" are 10%, 5%, and 1% significance levels; while the values in brackets are the standard errors.

Overall, the statistical significance of climate change indicates that achieving climate protection objectives would significantly impact fossil fuel profits and render a significant fraction of oil reserves and resources unburnable. Climate protection and broader environmental concerns might lead to the premature retirement of fossil fuel reserves and supply infrastructures and thus result in "stranded assets" and associated financial losses for investors and governments (Lazarus and van Asselt, 2018).

4.2 Some additional analyses

We further extend our analyses to include the response of the volatility of fossil fuels to another factor captured as market risk. This approach is inherently accommodated in the GARCH-MIDAS framework where there is no explicit exogenous factor to be used in the estimation process. The results for the full sample are presented in Table 4 while those of the post-GFC period are presented in Table 5. The parameters of interest are not different from those of climate change in Tables 2 and 3 where the focus is on how fossil fuels respond to climate change. In this section, however, we examine the connection of fossil fuels with their own market risk. The idea is to see whether these energy sources respond differently to their own risk relative to climate change. Recall that for the full sample, the behavior of the fossil fuels to climate change is found to be heterogeneous while in recent times (post-GFC period), the response appears to be homogenous. As shown by the predictability coefficient (ϴ) in Panel A of Table 4, all the variants of fossil fuels are significant, and positively correlated with market risk. In other words, rising market risk may fuel higher volatility in fossil fuel prices. The significant estimates obtained appear to validate the argument that climate-induced market uncertainties can influence fossil fuel production and consumption and by extension the associated prices. When the real fossil fuel prices are considered (see Panel B of Table 4), results confirm that all the variants of fossil fuels are significant, and positively correlated with market risk, except Brent crude which is negatively correlated. An increase in the market risk for Brent oil implies a marginal reduction in its price volatility. This could be explained by the possibility that increasing economic activities favour the use of other variants of crude oil (e.g. WTI), forcing Brent producers to reduce the price to attract demand. Results appear to be consistent irrespective of whether the nominal or real prices of fossil fuels are used. In both scenarios, α and β are statistically significant for all the fossil fuels and their sum is close to one implying the presence of high volatility persistence in the fossil fuel market.

Related evidence from other studies also conforms to the fact that oil price volatility is usually connected to oil-related events, and by extension, risks associated with these events. These events in turn exacerbate a rapid increase in the volatility of crude oil prices by tinkering with the equilibrium in the supply of and demand for crude oil (Bouoiyour et al., 2019; Demirer et al., 2010; Ji and Guo, 2015; Robe and Wallen, 2016; Sharif et al., 2020). In addition, others have contended that the stability in the crude oil market is dependent on the activities of the major world producers of the product(s), particularly the decision of the major cartel (OPEC) to raise or cut production (Al-Fattah, 2020; Liu et al., 2019; Schmidbauer and Rösch, 2012). Examples abound that rise in crude oil prices between the years 2006 and 2007 was due to aggregate demand shocks orchestrated by growth in China and other emerging economies (Kilian and Murphy, 2014). By the same token, oil prices have been highly volatile since 2014, owing to an excess supply of energy products and a drop in global demand for the products (Baumeister and Kilian, 2015). On the hand, speculations and financialization in the crude oil market have also prompted oil price volatilities (Jarrett et al., 2019). For instance, the all-time increase in crude oil prices in 2008 was attributed to the precautionary demand shock caused by excess liquidity in the financial market following the subprime mortgage crisis (Juvenal and Petrella, 2015). Thus, in consonance with our results, oil as an asset and its associated risk play an important role in influencing the volatility of crude oil prices (see Razek and Michieka, 2019).

The results obtained in the post-GFC era are similar to those obtained from the full sample, except for WTI and gasoline as confirmed by the slope parameter (ϴ). As indicated in Table 5 (Panel A), while the nominal prices of other variants of fossil fuels significantly and positively adjust to market uncertainties, the effect of those uncertainties appear to be neutral on the prices of WTI and gasoline. The significant results are consistent with the argument that GFC-induced market uncertainties significantly affect fossil fuel price volatilities. Again, α and β are statistically significant for all fossil fuel returns, and their summation being close to one indicates that the effect of market risk on fossil fuel returns may take a longer time to fizzle out. The GFC does not appear to cause significant changes in the reaction of fossil fuel price returns to market risk. The responses of real prices of fossil fuels to market uncertainties are depicted in Table 5 (Panel B).

The results mirror that of nominal prices, except for the price of gasoline which now significantly reacts to market uncertainties.

Table 4: Using a full sample with market risk as the predictor

Panel A: Nominal fossil fuels						
Fossil fuel	μ	α	β	Ө	w	m
WTI	0.0005**	0.1270***	0.6712***	0.0362***	24.0670***	0.0002***
	[0.0002]	[0.0070]	[0.0250]	[0.0019]	[3.7695]	[0.0000]
Brent	0.0006***	0.0785***	0.9132***	0.0047***	49.557	0.0007***
	[0.0002]	[0.0040)	[0.0048)	[0.0022]	[38.173]	[0.0001]
Diesel	0.0004*	0.1067***	0.8589***	0.0255***	1.1140***	0.0003***
	[0.0002]	[0.0052]	[0.0075]	[0.0031]	[0.2125]	[0.0000]
Jet fuel	0.0006**	0.1396***	0.6947***	0.0433***	16.6160***	0.0001***
	[0.0002]	[0.0085]	[0.0274]	[0.0019]	[2.9983]	[0.0000]
Heat oil	0.0005*	0.1317***	0.7133***	0.0395***	13.3890***	0.0001***
	[0.0002]	[0.0078]	[0.0200]	[0.0023]	[1.9318]	[0.0000]
Gasoline	0.0005*	0.1267***	0.7929***	0.0303***	2.7105	0.0003***
	[0.0003]	[0.0068]	[0.0155]	[0.0034]	[0.6487]	[0.0000]
Propane	0.0007***	0.1742***	0.6387***	0.0324***	49.1370***	0.0003***
	[0.0003]	[0.0085]	[0.0170]	[0.0013]	[6.3365]	[0.0000]
Panel B: Real fossil fuels						
Fossil fuel	μ	α	β	Ө	w	m
WTI	0.0005*	0.1269***	0.6719***	0.0361***	24.3260***	0.0002***
	[0.0003]	[0.0072]	[0.0251]	[0.0019]	[3.8291]	[0.0001]
Brent	0.0006**	0.0782***	0.9168***	-0.0063***	1.1694***	0.0010***
	[0.0003]	[0.0033]	[0.0038]	[0.0018]	[0.1342]	[0.0003]
Diesel	0.0004	0.1074***	0.8586***	0.0256***	1.1082***	0.0004***
	[0.0003]	[0.0052]	[0.0075]	[0.0032]	[0.2130]	[0.0001]
Jet fuel	0.0005**	0.1413***	0.6776***	0.0438***	18.6480***	0.0002***
	[0.0003]	[0.0088]	[0.0291]	[0.0020]	[3.3254]	[0.0001]
Heat oil	0.0004	0.1317***	0.7142***	0.0395***	13.5290***	0.0002***
	[0.0003]	[0.0079]	[0.0200]	[0.0022]	[1.9566]	[0.0001]
Gasoline	0.0005**	0.1271***	0.7927***	0.0302***	2.6650***	0.0003***
	[0.0003]	[0.0068]	[0.0154]	[0.0034]	[0.6429]	[0.0001]
Propane	0.0007***	0.1740***	0.6404***	0.0323***	49.8240***	0.0003***
	[0.0003]	[0.0086]	[0.0170]	[0.0014]	[6.5699]	[0.0001]

Note: The results are the estimated parameters of a monthly (N = 22) rolling window GARCH–MIDAS regression using realized volatility as the predictor. The parameters: μ is the unconditional mean for stock return; α and β are the ARCH and GARCH terms, respectively, in the short-term component, with the latter indicating the degree of persistence; θ is the sum of weighted rolling window realized volatilities, indicating the predictability of the monthly oil shocks for the daily stock returns; w is adjusted beta polynomial weight; and m is the long-run constant term. The "*", "**", and "***" are 10%, 5%, and 1% significance levels, while the values in brackets are the standard errors.

Table 5: Using Post-GFC sample with market risk as the predictor

Panel A: Nominal fossil fuels						
Fossil fuel	μ	α	β	Θ	*w*	*m*
WTI	0.0006	0.1062***	0.8751***	0.0054	18.388	0.0006***
	[0.0004]	[0.0061]	[0.0092]	[0.0034]	[13.3580]	[0.0002]
Brent	0.0003	0.1084***	0.7049***	0.0477***	46.3390	0.0001***
	[0.0004]	[0.0088]	[0.0451]	[0.0025]	[11.7690]	[0.0001]
Diesel	0.0005	0.1242***	0.8067***	0.0295***	2.1351***	0.0002***
	[0.0004]	[0.0102]	[0.0204]	[0.0044]	[0.7070]	[0.0001]
Jet fuel	0.0003	0.1711***	0.7253***	0.0354***	13.817***	0.0002***
	[0.0003]	[0.0125]	[0.0280]	[0.0043]	[4.6115]	[0.0001]
Heat oil	0.0003	0.1896***	0.5333***	0.0409***	22.8100***	0.0002***
	[0.0003]	[0.0166]	[0.0422]	[0.0027]	[4.4444]	[0.0001]
Gasoline	0.0005	0.1787***	0.7385***	0.0200	3.2792***	0.0004***
	[0.0004]	[0.0120]	[0.0195]	[0.0043]	[1.1667]	[0.0001]
Propane	0.0004	0.1425***	0.8288***	0.0485***	1.0010***	0.0003***
	[0.0004]	[0.0087]	[0.0077]	[0.0091]	[0.1023]	[0.0001]
Panel B: Real fossil fuels						
Fossil fuel	μ	α	β	Θ	*w*	*m*
WTI	0.0004	0.1065***	0.8740***	0.0055	18.086	0.0006***
	[0.0003]	[0.0061]	[0.0094]	[0.0035]	[12.882]	[0.0001]
Brent	0.0001	0.1065***	0.7162***	0.0474***	46.84***	0.0001***
	[0.0003]	[0.0087]	[0.0446]	[0.0025]	[12.6410]	[0.0000]
Diesel	0.0004	0.1256***	0.8061***	0.0291***	2.1279***	0.0002***
	[0.0003]	[0.0102]	[0.0202]	[0.0043]	[0.7210]	[0.0000]
Jet fuel	0.0002	0.17483***	0.7020***	0.0371***	17.1270***	0.0002***
	[0.0003]	[0.0131]	[0.0317]	[0.0038]	[5.3332]	[0.0000]
Heat oil	0.0002	0.1887***	0.5454***	0.0405***	21.8400***	0.0001***
	[0.0003]	[0.0166]	[0.0418]	[0.0026]	[4.2227]	[0.0000]
Gasoline	0.0003	0.1798***	0.73666***	0.0198***	3.3461***	0.0004***
	[0.0004]	[0.0121]	[0.0196]	[0.0043]	[1.1983]	[0.0000]
Propane	0.0003	0.1421***	0.8292***	0.0483***	1.0010***	0.0003***
	[0.0004]	[0.0087]	[0.0077]	[0.0091]	[0.1056]	[0.0001]

Note: The results are the estimated parameters of a monthly (N = 22) rolling window GARCH–MIDAS regression using realized volatility as the predictor. The parameters: μ is the unconditional mean for stock return; α and β are the ARCH and GARCH terms, respectively, in the short-term component, with the latter indicating the degree of persistence; θ is the sum of weighted rolling window realized volatilities, indicating the predictability of the monthly oil shocks for the daily stock returns; w is adjusted beta polynomial weight; and m is the long-run constant term. The "*", "**", and "***" are 10%, 5%, and 1% significance levels; while the values in brackets are the standard errors.

5. Conclusion

The ongoing concern by environmentalists on the need for net-zero central banking can largely be justified considering that climate changes affect the prices of biofuels. Our evidence suggests that the response of fossil fuels to climate change is positive in recent times (post-GFC period) which may suggest that the efforts towards tackling climate have not yielded the desired results. This is justified on the ground that improved trading usually fuels higher price volatility and by extension, climate change has not noticeably discouraged investments in fossil fuels. Overall, a lot still needs to be done from the policy perspective involving both monetary and fiscal authorities to discourage increased investments in environmentally-degrading assets. This goes to say that to control environmental footprints, biodiversity loss, and climate change, central banks have roles to play, hence the strong need to align both monetary policy and macro-prudential regulation to the realization of net-zero central banking. Thus, central banks are encouraged to conduct monetary and prudential policies in a way that reduces the financing of activities that negatively impact the climate. Other depository corporations as well as other financial corporations are profit-oriented in nature and can therefore be unwilling to take cognizance of creating assets in sectors or industries that are environmentally friendly. Thus, the critical role of central banks as regulators is to take proactive policy measures to direct and redirect the financing activities of financial institutions within their regulatory purview to those industries that are willing to use environmentally friendly technologies for production activities. Some preliminary results in the study of Zhang et al. (2022) offer strong support for the role of monetary policy in encouraging investment in clean energy.

The results also bring to the fore the need for fiscal policies that discourage the continuous production of goods and services through technologies that are already identified to be hazardous to the environment, as well as incentivize the use of emerging technologies that do not negatively impact the environment. In other words, efforts of the fiscal authorities should be directed towards investments that promote environmental sustainability. The collective efforts of monetary and fiscal authorities can refocus investment toward eco-friendly economic activities. This will not only moderate the volatility of fossil fuel prices but also curb ecological degradation and biodiversity loss. For specific monetary, prudential, and fiscal policy prescriptions, there is a need for a study that will focus on proactive macroeconomic policy options to address lending to eco-friendly industries, while discouraging investment into industries that use environmentally unfriendly technologies.

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