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Research article

From brown to green: how renewable deployment and geopolitical risk shape the pathway to a sustainable energy market transition

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ABSTRACT

The deployment of renewable energy has expanded rapidly to meet the growing demand for a sustainable green economy. However, existing literature has largely overlooked its impact on stock market performance, particularly energy stocks. This paper offers new insight into how renewable energy deployment and geopolitical risk together influence the transition from brown to green energy markets. It is the first to examine the dynamic relationship between renewable energy deployment and energy stock performance, distinguishing between traditional (brown) and renewable (green) energy stocks, while also assessing how geopolitical risk shapes this evolving relationship. Using the dynamic autoregressive distributed lag simulations, our results show heterogeneous reactions of brown and energy stocks to renewable energy deployment. Specifically, (i) renewable energy deployment has no significant effect on brown energy stocks but has a positive and significant impact on green energy stocks, which reflects the ongoing shift towards a cleaner energy economy, and (ii) geopolitical risk plays a critical moderating role, as heightened geopolitical tensions may slow the green energy transition by affecting investor behaviour. These findings underscore the importance of incorporating geopolitical risks into energy market analysis. Such risks can create market inefficiencies and misalignments with sustainability-driven fundamentals, potentially affecting the performance of energy-related assets.

1. Introduction

In the recent decade, renewable energy deployment has grown rapidly to meet the growing clean energy demand and reduce carbon emissions for sustainable development. The International Energy agency (IEA, 2024) indicated investment in clean energy has accelerated since 2020, with spending on renewable power, grids, and storage now exceeding total investment in oil, gas, and coal. In 2015, investment in clean power was about twice as much as that in unabated fossil fuel power. By 2024, this gap is expected to grow significantly, with clean power investment reaching ten times that of fossil fuel power.

In tandem with the swift expansion in the renewable industry, the EIA Renewables Report (2020) noted that renewable energy companies' stocks outperformed most major stock markets indices and the overall energy sector.

There has been an increasing interest among scholars in understanding the dynamics of the renewable energy industry. Literature has stressed the global environmental, economic, and social benefits of renewable energy deployment and clean energy transition (see, for example, Armeanu et al., 2021; Doytch and Narayan, 2021; Q. Wang et al., 2022; Y. Wang et al., 2022; Yang et al., 2024; García-Riazuelo, 2025; Virah-Sawmy et al., 2025). Surprisingly, the literature disregarded investigating the linkage between renewable energy deployment changes and the energy stocks performance that have been noted in the EIA reports. Identifying this linkage is useful for investors and portfolio managers for their risk management strategies and hedging plans.

Intuitively, investors' expectations on the energy market are greatly influenced by the clean energy transition trend and the continuous reduction of reliance on traditional energy sources. This transition may prompt investors to adjust their portfolio allocations, either favouring or reducing exposure to stocks of companies involved in these changes, ultimately influencing the performance of energy stocks (Chang et al., 2020). Hence, a comprehensive empirical investigation is imperative to understand energy stocks' reaction to the changes in renewable energy deployment.

Energy stocks can generally be divided into two main categories: green and brown stocks. Green stocks represent companies that focus on

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eco-friendly energy sources, including wind, solar, geothermal, and wave power. In comparison, brown stocks are the stocks of companies that invest in energy sources that include fossil fuels. Henriques and Sadorsky (2008) claimed that these two stock types have different features. Green stocks have similar technical features to high-tech industries stocks, and their investment risk is higher than the brown stocks. Many studies agreed that green stock is commonly used to reduce the risk associated with brown energy, and the price performance of green stock has a significant impact on the effectiveness of hedging strategies (Karkowska and Urjasz, 2024).

The importance of this discussion arises at a time when stock market performance has been witnessed more volatile during the past few years due to several events like the COVID-19 pandemic and the escalating geopolitical risk brought by the conflict between Russia and Ukraine and the US-China trade war. Geopolitical risk has emerged as a global concern and is widely recognized as a major threat with significant spillover effects on stock markets (Dogan et al., 2021; Shen et al., 2021; Coldara and Iacoviello, 2022; Saâdaoui et al., 2022; Wang et al., 2024; Yilmazkuday, H., 2024). It plays a vital role in shaping the volatility patterns of clean energy assets (Dutta and Dutta, 2022) which may hinder the global efforts of coping with environmental challenges and delay the clean energy transition.

While we understand how geopolitical risk directly affects stock prices and economic activities, our focus is on how it influences the relationship between renewable energy deployment and energy stocks. Understanding this interaction is crucial for investors and market participants in managing risks and making informed decisions.

As far as we know, no empirical study has yet explored this question. Thus, through examining the effects of renewable energy deployment on brown and green energy stocks independently, our study adds to the body of previous literature. We also examine the direct impact of geopolitical risk on energy stock performance, as well as its indirect role by moderating the relationship between renewable energy deployment and stock performance. This provides deeper insight into the complex transition from brown to green energy in the move towards a more sustainable energy market. It is worth noting that this study takes a global approach and is not limited to any single country. A global perspective is relevant for this study because geopolitical risks, energy transitions, and financial markets are increasingly interconnected across borders. Events such as the Russia–Ukraine war, the COVID-19 pandemic, and global trade tensions do not affect only one country; they influence energy supply chains, investment flows, and stock market reactions worldwide.

We hypothesize that the expansion of renewable energy deployment will increase green stocks' returns with two rationales. First, an increase in renewable energy deployment is often associated with increased spending on capital equipment and R&D by firms. Such an increase in R&D helps firms to reduce their costs, which prompts further production to utilize economics of scale.[1] This is reflected in the firm's profitability and higher expected cash flow. In response, the investors will react positively to the green energy firms' profitability. Second, the expansion of renewables production will attract more institutional investors who invest in long-term renewables assets (Barber and Odean, 2008). Such investors are key market participants who help to increase firm performance and create liquidity in the stock markets (Vo, 2016).

On the other hand, renewable energy deployment may have a negative linkage with brown stocks. This is due to the link between renewable energy consumption and the transition to clean energy (Diezmartínez, 2021). Research suggests that renewable energy could account for 94% of the required reductions in emissions by 2050 (Hassan et al., 2024). As a result, an increase in the clean energy transition may drive a substitution effect, shifting reliance from fossil fuel-based energy to renewables, which could impact the profitability and performance of brown energy companies.

Furthermore, we hypothesize that other factors, particularly geopolitical risks, play a significant role in shaping the relationship between renewable energy deployment and energy stock performance. While renewable energy deployment is expected to enhance energy market performance, this trajectory can be disrupted by geopolitical shocks. Such shocks act as an external force that alters investor expectations, increases financing costs, and heightens policy and regulatory uncertainty which can pose real challenges to energy markets (Su et al., 2025).

Events such as the Russia–Ukraine war, the Israel–Palestine conflict, and the U.S.–China trade tensions (including the Trump-era) have caused major disruptions to global energy markets (Qin and Zhang, 2024; Alessandri and Gazzani, 2025; Liu et al., 2025). These events have affected energy supply chains, triggered volatility in fossil fuel prices, and influenced government policies related to energy security and green investment (Lee et al., 2024; Su et al., 2025). During such periods of heightened uncertainty, hedging behaviour and investor expectations shift, often leading to short-term market reactions that may not align with long-term energy transition goals (Bloom, 2014). Even well-informed institutional investors adjust their outlooks and investment strategies in response to these geopolitical developments (Zuckerman, 2009). As a result, the pathway from brown to green becomes more uneven, as these risk factors affect how markets respond to renewable energy deployment.

By framing geopolitical risk as a destabilising mechanism that interacts with both structural energy transformation and financial market dynamics, our study provides a more comprehensive and policy-relevant perspective on why the pathway from brown to green is nonlinear and sensitive to external shocks. This framing underscores the importance of studying renewable energy deployment and geopolitical risk jointly to capture the real-world complexity of the energy transition.

Owing to the above discussion, this study makes three key contributions to the body of literature. First, it is the first to examine and compare the impact of renewable energy deployment on disaggregated energy stocks, specifically brown and green stocks. Second, no study has assessed how geopolitical risk moderates the relationship between the deployment of renewable energy and these energy stocks. Previous studies like Mei et al. (2020), Caldara and Iacoviello (2022), Chen et al. (2024) Wang et al. (2024) and many others mainly focused on the direct impact of geopolitical risk on carbon emissions, financial markets, energy transition or aggregate economic indicators. No studies have been conducted at the sectoral stock level, especially on energy type stocks.

Finally, the present paper utilizes the Dynamic Autoregressive Distributed Lag (DARDL) approach. This approach dynamically simulates the traditional ARDL method by using stochastic simulation techniques. Using this approach, spurious fluctuations in the dependent variable generated by a regressor can be estimated, visualized, and predicted while holding all other variables in the equation constant (Jordan and Philips, 2018). Additionally, for robustness purposes, we use the Kernel-based Regularized Least Squares (KRLS) machine learning technique. This method enables us to determine whether the impact of renewable energy deployment on energy stocks varies across data points and helps to determine the marginal effects of covariates (Hailemariam and Ivanovski, 2021).

The reminder of this paper is organized as follows A review of the relevant literature is provided in Section 2, and the study's data and methodology are described in Section 3. The empirical results and discussion are presented in Section 4. Finally, the conclusion is presented in Section 5.

2. Literature review

This paper is based on the efficient market hypothesis (EMH) and

[1] The International Renewable Energy Agency (IRENA, 2020) reported that from 2010 to 2018, the global average cost of solar energy dropped significantly, reaching a level comparable to the cost of electricity generation from fossil fuels, particularly oil.

investment under uncertainty theories. Together, these theories provide a framework for understanding how renewable energy deployment and geopolitical risk interacts with different energy sectors and shapes investor behavior.

According to efficient market theory, stock prices reflect all available information. So, if investors believe that renewable energy will grow due to government policies or technological progress, energy stock prices will react in response to that expectation. In other words, energy markets are fully efficient and respond rationally to new information regarding renewable energy expansion or geopolitical risk events (Courtault et al., 2002).

The theory of investment under uncertainty also helps to explain how geopolitical risks can shape investor preferences between green and brown stocks. The pioneering studies by Brennan and Schwartz (1985) and McDonald and Siegel (1986), introduced a framework to understand investment decisions in uncertain conditions. In such uncertain settings investors may choose to delay or avoid irreversible investments, particularly in industries seen as more exposed to risk or dependent on policy changes. In our case, green investments, often reliant on long-term regulatory support, may be seen as more vulnerable under such conditions. Conversely, brown assets, linked to more established industries, might be perceived as safer in the short term. As a result, geopolitical uncertainty can make both investors and managers more cautious, reducing their appetite for risk and altering their investment decisions and market behaviour (Zuckerman, 2009; Song et al., 2019; Dutta and Dutta, 2022).

To better understand how these dynamics are reflected in the recent literature, we review the key studies, structured into three sub-sections. First, we discuss the concept of renewable energy deployment and its linkage with economic activities. Second, we delve into the related recent discussions on brown and green energy stocks. Finally, we review the relationship between geopolitical risk and stock returns.

2.1. Renewable energy deployment and economic activities

Examining the effects of renewable energy deployment on economic activities is an emerging research area. Most discussions in this field have centered on identifying the factors influencing renewable energy deployment and its impact on economic activities. Bourcet(2020) provided comprehensive literature on the determinants of renewable energy deployment including economic, environmental, energy, demographic, regulatory, and institutional factors. Based on Bourcet's discussion, Sweidan (2021a,b) introduced two studies to identify the impact of geopolitical risk as one of the institutional quality factors in the US and 10 oil-importing countries. Similarly, Belaïd et al. (2021) investigated the factors that influence the rise of renewable energy, highlighting the importance of financial development and political stability. Along the same vein, Dogan et al. (2023) analyzed the impact of energy and environmental taxes on renewable energy deployment in EU from 1995 to 2019. The authors found that environmental taxes and energy taxes have a negative impact on renewable energy deployment.[2]

Conversely, numerous researchers have explored the benefits of renewable energy deployment for economic activities. Several socio-economic and environmental benefits are generated from renewable energy deployment. For instance, the deployment of renewable energy can contribute to lowering CO2 emissions, increasing international trade, and boosting globalization and per capita spending (Paramati et al., 2017; Dong et al., 2020; Ben Jebli and Ben Youssef, 2015; Sun et al., 2022).

We notice a remarkable gap in the literature regarding the impact of renewable energy deployment on stock markets, particularly the performance of energy stocks. Existing research suggests that the renewable energy sector is closely linked to the energy stock market, as it serves as a key source of financing (Ji and Zhang, 2019; Song et al., 2019). However, the two components of the energy stocks markets (i.e. brown and green stocks) have different features. So, there is a need to explore how the impact of renewable energy development varies between these two energy stocks (Henriques and Sadorsky, 2008). This is an important gap that this study aims to bridge.

2.2. Brown and green energy stocks

The deteriorating climate conditions and environmental concerns have accelerated the shift from brown energy to green energy. Such a movement has attracted great interest and debate in the academic circles, financial institutions, and investors which stimulate the emergence of the green energy market as a new asset class to substitute for the brown energy market (Rizvi et al., 2022).

Two main streams are identified in the energy stocks literature. Ferrer et al. (2018), Maghyereh et al. (2019), Bondia et al. (2016), and Ahmad (2017), have all examined the connection between oil prices and the performance of green energy stocks. Most of these studies concluded that there was a positive correlation between oil prices and the markets for renewable energy. For example, Kumar et al. (2012) contended that the primary factors driving the rise in green energy investment are the volatility and uncertainty of the oil price. Reboredo (2015), Bondia et al. (2016), Dutta (2017), Ahmad et al. (2018), and Kocaarslan and Soytas (2019) all supported this claim.

Another stream has focused on how different uncertainties affect renewable energy stocks. Dutta (2017) investigated how the volatility of green energy stocks was affected by oil price uncertainty. The author found that renewable energy stocks were significantly impacted by oil price uncertainties. In a similar vein, Ahmad et al. (2018) showed that the price of clean energy stocks correlates negatively with the volatility of the stock and oil markets. According to Yang et al. (2021), the downside risks of green energy companies are very sensitive to changes in the stock and oil markets. Climate policy uncertainty's impact on the brown and green stocks market has also been studied by Bouri et al. (2022), who found that climate uncertainty significantly influences how well green energy stocks perform in comparison to brown energy stocks. Alharbey and Salha (2024) also found that climate policy uncertainty affects returns of renewable energy stocks, depending on the type of renewable sector and overall market conditions.

In conclusion, the majority of earlier studies reported that green energy stocks are highly sensitive to uncertainties in major financial and commodity markets. However, they have not accounted for recent developments in the renewable energy sector, which could influence the performance of both green and brown energy stocks, particularly under heightened geopolitical risk.

2.3. Geopolitical risk and stock markets

Geopolitical risk has attracted wide attention among scholars during the last two decades due to its effects on financial markets and business cycle (Balcilar et al., 2018). Caldara and Iacoviello (2022) defined geopolitical risk as "*the risk associated with wars, terrorist acts, and tensions between states that affect the normal course of domestic politics and international relations*."

Geopolitical risks may influence investors' perceptions of market conditions and impact their investment decisions (Apergis et al., 2018; Bouri et al., 2022; Dogan et al., 2021; Caldara and Iacoviello, 2022; Yilmazkuday, 2024). Bloom (2009) argued that the uncertainty associated with geopolitical risk encourages consumers and investors to defer their consumption and investment decisions. This could result in a decline in stock returns.

Empirical research on the relationship between geopolitical risk and green stocks is, nevertheless, lacking. Three important studies were introduced by Yang et al. (2021), Sohag et al. (2022) and Helmi et al.

[2] Read Virah-Sawmy and Strumberg et al. (2025) for comprehensive review on socio economic and environmental impact of renewable energy deployment.

(2024). While Sohag et al. (2022) assessed how green securities react to several geopolitical risk measures and found that different measures of geopolitical risk cause positive shocks to green investments. Yang et al. (2021) evaluated the reaction of five renewable energy stocks to geopolitical risk. Significant risk spillovers from geopolitical risk to renewable energy stock markets were found by their research. Helmi et al. (2024) studied how geopolitical risk (GPR) affects green, clean, and socially responsible markets. They found that GPR has a negative effect on all these markets. However, during times of increased geopolitical tension, clean energy stands out as a promising option, especially because traditional energy sources such as crude oil face certain limitations. None of these studies, however, examined the broader indirect effects of geopolitical risk on energy stocks.

The main message that can be drawn from the literature is that the expansion of the renewable energy industry not only promotes sustainability and environmental protection but also has a significant impact on economic activity and stock markets. Nevertheless, there is an important gap that requires to be bridged which is the impact of renewable deployment on the performance of brown and green stocks and how geopolitical risk can moderate this impact. Our study aims to address this gap based on the graphical framework in Fig. 1. First, we study the direct impact of renewable deployment on brown and green stocks respectively. Second, we investigate how geopolitical risk moderates the linkage between renewable energy deployment and the respective brown and green stocks.

3. Data, models specification and methodology

3.1. Data

This study utilizes monthly data from July 2007 to January 2025. The green stocks index's availability determines the start date, while the end date is based on the most recent data available on renewable energy deployment. This time frame is particularly important as it captures several major geopolitical and economic shocks that have influenced global markets, including the 2008 financial crisis, the U.S.-China trade tensions and Trump-era, the COVID-19 pandemic, the Russia–Ukraine war, and the Gaza–Israel conflict. These events contribute to significant geopolitical risk, making the selected period highly relevant for studying the relationship between renewable energy deployment, energy stocks, and geopolitical risk.

In line with Bouri et al. (2022), the Energy Select Sector SPDR Fund is used to assess the price performance of brown stocks, whereas the Invesco Global Clean Energy ETF represents the performance of green energy firms. The Energy Sector SPDR Fund tracks the energy sector of the S&P 500 Index, covering companies engaged in oil, gas, consumable fuels, energy equipment, and related services. The WilderHill New Energy Global Innovation Index serves as the foundation for the Invesco Global Clean Energy ETF, which allocates at least 90 % of its total assets to index stocks. These securities stand for companies that are committed to conservation and the development of greener energy solutions.

For renewable energy deployment, many definitions were introduced by Bourcet (2020). We mainly follow Sweidan (2021a,b) by measuring renewable energy deployment as the percentage of renewable energy consumption to the total primary energy consumption. We also use total renewable energy production as another proxy for robustness purposes (Belaïd et al., 2021).

We utilize the Caldara and Iacoviello (2022) index, which is a popular tool in literature as a proxy for geopolitical risk. This index is divided into two components: current event risks and emerging risks linked to the escalation of ongoing events. It is constructed by analyzing archives from major English-language newspapers, such as The Financial Times and The Daily Telegraph. Six-word categories—two linked to actions (terrorist and war) and four linked to threats (war, nuclear, geopolitical, and terrorist)—are used in the search process to find relevant geopolitical risk indicators. Finally, we control other variables which have been widely considered as determinants of stock market performance like oil price, interest rate (Henriques and Sadorsky, 2008;

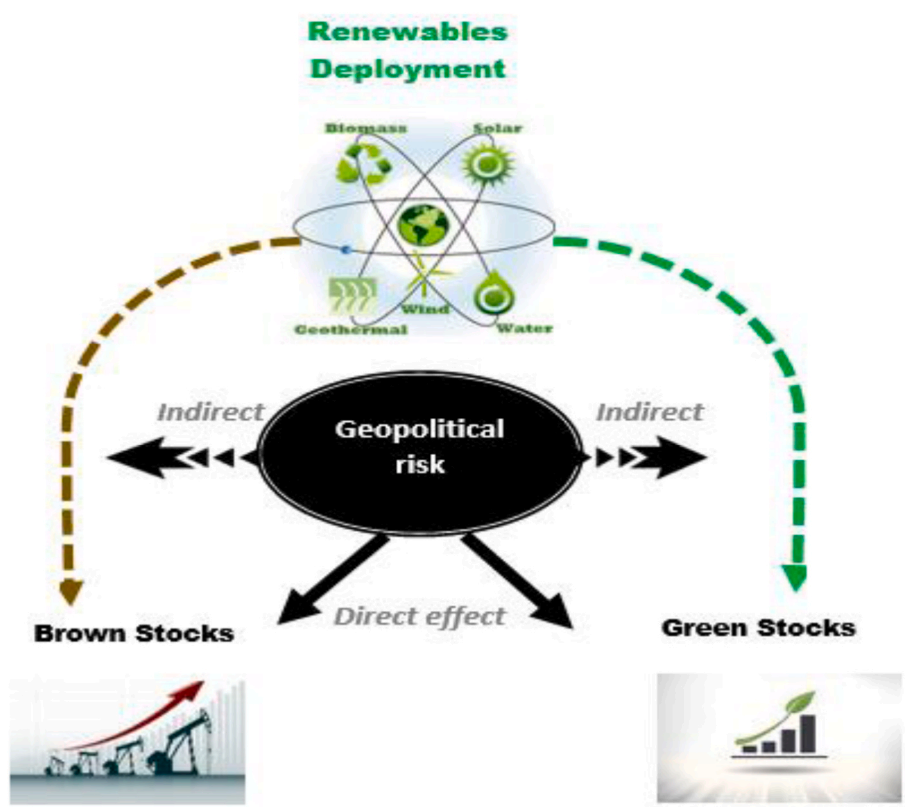


Fig. 1. Graphical representation of theoretical framework.

Badeeb and Lean, 2018), as well as a dummy variable of the covid-19 pandemic. Table 1 provides a full data description and sources.

3.2. Model specification

This study aims to investigate the impact of renewable deployment on brown and green energy stocks respectively and assess the role of geopolitical risk in moderating these relationships. We first estimate the following baseline model (Model 1):

$$ESI_t = \beta_0 + \beta_1 END_t + \beta_2 WTI_t + \beta_3 INT_t + \beta_4 DUM_t + \varepsilon_t \tag{1}$$

Where ESI represents energy stocks, END denotes renewable energy deployment, INT refers to the interest rate, and WTI stands for the West Texas Intermediate oil price. For ESI, we proxy with the brown energy stocks (BRN) and green energy stocks (GRN) and Green-to-Brown Ratio (GBR) respectively. The reason for including GBR is to evaluate the impact of renewable energy deployment on the relative performance of green energy versus brown energy stocks (Bouri et al., 2022). This ratio can be used to assess whether investors shift funds from brown energy to green energy stocks. Finally, ε is the error term.

Next, we examine the direct and indirect impact of geopolitical risk by incorporating the geopolitical risk index into Equation (1), along with an interaction term between geopolitical risk and renewable energy deployment. This argument seeks to assess if the geopolitical risk has an indirect weakening effect on the renewable energy deployment and energy stock performance relationship. Any negative (positive) effect of the interaction term would weaken (strengthen) this relationship. This will indicate that any improvement in renewable energy deployment is not necessarily reflected in energy stock performance when the geopolitical risk index is high. Accordingly, Eq. (2) (Model 2) can be specified as follows:

Table 1
Variables and data sources.

Variable	Symbol	Description	Source
Brown stocks	BRN	The natural logarithm of Energy Select Sector SPDR fund (XLE)	Refinitiv Eikon
Green stocks	GRN	The natural logarithm of the Invesco Global Clean Energy ETF (PBD)	Refinitiv Eikon
Geopolitical Risk	RSK	The index is constructed by searching in the archives of major English-language newspapers including The Daily Telegraph and The Financial Times. Six-word categories are used during the search process: four are threats (war, nuclear, geopolitical, and terrorist), and two are acts (terrorist and war).	The Caldara and Lacoviello (2022) www.policyuncertainty.com
Renewable energy Deployment	END	The proportion of renewable energy consumption relative to total primary energy consumption.	www.eia.gov
Interest Rate	INT	US 3-month T-bill rate	Refinitiv Eikon
Oil Price	WTI	The natural logarithm of West Texas Intermediate price	Refinitiv Eikon
COVID 19	$DUM_{covid19}$	Dummy variable to reflect the period after COVID-19. It will take 1 if the observation between February 2020 and May 2022 and 0 otherwise (see Bouri and Demir, 2025)	

$$ESI_t = \delta_0 + \delta_1 END_t + \delta_2 WTI_t + \delta_3 INT_t + \delta_4 RSK_t + \delta_5 (END^*RSK)_t + \delta_6 DUM_t + \varepsilon_t \tag{2}$$

where RSK is the geopolitical risk index. (END*RSK) is the interaction term between renewable energy deployment and geopolitical risk. When δ_1 is positive and the interaction term's coefficient (δ_5) is negative, it means that a slight increase in the risk index would subsequently weaken the relationship between energy stocks and the deployment of renewable energy. While the stronger linkage between energy stocks and renewable energy deployment is established in the case of both δ_1 and δ_5 being positive.

3.3. Methodology

3.3.1. Dynamic ARDL approach

This study adopts the dynamic ARDL approach introduced by Jordan and Philips (2018). This approach is proposed to eliminate the shortcomings of ARDL techniques by Pesaran et al. (2001). For example, the first differences, multiple lags, and lagged first differences are examples of complex dynamic specifications that may be present in traditional ARDL models in their error-correction version. This makes it more challenging to interpret the impacts of changes or shocks in the independent variable, particularly in the short- and long-term (Jordan and Philips, 2018). To address this issue, the innovative dynamic approach can estimate, simulate, and visualize counterfactual changes in the dependent variable driven by a regressor at a specific point in time. This method utilizes up to 5000 vector simulations of standard multivariate distributed parameters. Additionally, graphical representations are employed to validate the exact variation in the regressor and its corresponding impact on the response variable.

3.3.2. Kernel-based regularized least square (KRLS)

The KRLS algorithm is a machine learning technique that utilizes pointwise derivatives to examine the causal relationship between variables. This method allows for the assessment of whether the specific predictor's effect on energy stocks fluctuates across different data points. Additionally, a closed-form estimation of pointwise marginal derivatives is produced, which makes it possible to determine the covariates' marginal effects (Hailemariam and Ivanovski, 2021). When these marginal effects display variability, the insights provided by KRLS can be particularly valuable (Choi and Lee, 2020).

4. Empirical results and discussion

4.1. Preliminary tests

Some monthly and quarterly macroeconomic data suffer from seasonal unit root problems, which may provide biased results (Wooldridge, 2013; Sweidan, 2021a). Thus, we begin with the seasonal unit root tests of Canova and Hansen (1995) (CH) and Hylleberg et al.

Table 2
Seasonal unit root test.

Variable	Traditional HEGY (All Frequencies)	Canova-Hansen (Joint LM Statistic)
BRN	145.32***	0.289
GRN	26.15***	0.738
GBR	19.26***	0.525
RSK	59.30***	0.478
END	8.88	3.80***
INT	26.83***	0.469
WTI	261.10**	0.736

Notes The HEGY test's null hypothesis suggests the presence of a unit root at a given frequency, whereas the CH test's null hypothesis assumes no unit root at the specified frequencies. ***P < 0.01.

(1990) (HEGY). Table 2 presents the findings of the seasonal unit root test. The tests confirm the absence of a seasonal unit root in all variables except renewable energy deployment (END). To tackle this problem, seasonal differences to eliminate non-stationarity in END[3] is used.

We also use two slandered unit root tests; Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests along with Clemente et al. (1998) structural break unit root. We report the results in Table 3. The key conclusion from the tests is that all variables are either I(0) or I(1) which validates the use of DARDL.

After examining the time series characteristics of all variables, the presence of a potential long-term equilibrium relationship is analyzed using the ARDL approach. The optimal lag selection for each variable is determined based on the Akaike Information Criterion (AIC). Table 4 displays the ARDL cointegration test results.

The computed F-statistic displayed in Table 4 is greater than the upper bound critical value at the 5 % significance level in Models (3–6), indicating the existence of a cointegration relationship. These results offer compelling evidence that the variables in these models have a long-term relationship. However, in the first and second models, F-statistic failed to prove the existence of a cointegration relationship among the variables in the first and second models resulting in inconclusive results. Therefore, we can establish cointegration using an alternative approach by looking at the significant coefficient of the lagged error correction term (ECM) (Kremer, 1992; Badeeb et al., 2016). The coefficient of the lagged ECM is significant and negative in all models which confirms that all models have a long-run relationship.

Additionally, Table 4 demonstrates that the models pass all diagnostic evaluations for serial correlation, autoregressive conditional heteroskedasticity, and model specification. We also checked for the possibility of endogeneity using Durbin-Wu-Hausman test. Rejecting the null hypothesis implies that endogeneity exists in the model. The results from the Durbin-Wu–Hausman test show that the null hypothesis is not rejected, indicating that endogeneity is not a concern in our models.

Fig. 2 demonstrates that the CUSUM of recursive residuals test remains within the critical boundaries at the 5 % significance level, confirming the stability of the short-run and long-run coefficients in the error correction model.

4.2. Dynamic ARDL estimations

This paper applies DARDL simulation to investigate the reaction of brown and energy stocks to the deployment of renewable energy and to assess the impact of geopolitical risk on this reaction. Table 5 presents the findings from the DARDL model, offering several valuable insights. The following discussion highlights the key results for both categories of energy stocks, as well as the Green to Brown ratio.

4.2.1. Brown energy stocks

In the case of brown energy stocks, Model 1 and 2 reveal that renewable energy deployment does not have a significant impact on brown energy stocks. This could be due to the ongoing strong demand for fossil fuels, especially in sectors where renewables are not yet a full substitute. It also may reflect the slow pace of energy transition (World Economic Forum, 2024) and the ability of fossil fuel firms to maintain profitability despite clean energy deployment.

Geopolitical risk shows a direct, positive, and significant effect in both Models in line with Su et al. (2025). However, we did not find any evidence of an indirect effect. Geopolitical risk is well documented in the literature as a factor that alters investors' expectations and affects the incentives to invest (Apergis et al., 2018; Salisu et al., 2022; Liu et al., 2024) which ultimately has an impact on how underlying financial assets will perform. Su et al. (2025) suggest that geopolitical risk has a strong positive effect on brown energy stocks because of the vital role energy plays in the economy. They explain that such risks often disturb global energy supply chains, which raises demand and draws more investment into brown energy assets.

In the short run, our findings mirror the long-run effect of renewable deployment. However, geopolitical risk has a positive and significant direct impact on brown-energy stock prices, while the negative interaction term shows a significant indirect effect. This suggests that as renewable capacity grows it cuts the normal short-term lift in brown energy stocks caused by geopolitical tensions, since investors turn to green investments as a fast hedge against supply shocks.

To examine how rising marginal returns from renewable energy deployment influence brown stocks, we utilize DARDL simulations to analyze counterfactual shocks. The plot in Fig. 3 reveals that a +10 % shock in predicted renewables deployment may negatively affect brown stock performance during the next two years. In Fig. 4, we plot the counterfactual shocks of geopolitical risk and the interaction term. It reveals that a +10 % shock in predicted geopolitical risk and interaction term positively affects brown energy stocks.

4.2.2. Green energy stocks

Next, we discuss the reactions of green energy stocks. Despite the insignificant impact in Model 1, the results indicate that in both the long and short run more energy deployment is associated with a significant increase in the performance of green stocks in Model 2. This is not surprising and comes in line with our hypothesis that the increase in deployment is often associated with increased spending on capital equipment and R&D by firms. This action prompts further production to utilize economics of scale, which in turn is reflected in the firm's profitability and higher expected cash flow. In response, investors react positively to green energy stocks.

The role of geopolitical risk appears also clearly in Model 2. We found that there are two different effects, positive direct effect, and negative indirect effects. The positive direct effect aligns with the findings of Sohag et al. (2022), who observed that geopolitical risk generates positive shocks for green investments. This finding is further supported by Liu et al. (2024). With regards to the indirect negative geopolitical risk impact, we found that the interaction term inters the model negatively and significant which infers that the benefits of increasing deployment of green stocks can be absorbed by increasing geopolitical trends. This may explain the findings reported by Helmi et al. (2024) who claim that geopolitical tensions represent a "*dual-edged phenomenon, an opportunity and a challenge*".

To explain the economic mechanism behind this moderating effect, we draw on investment under uncertainty theories. Green energy investments are typically high-risk and capital-intensive (Xu and Gallagher, 2017). Geopolitical risk further amplifies these risks across multiple dimensions, making such investments even less attractive. It increases the cost of capital for green projects by creating uncertainty around policy support and technology adoption. Geopolitical risk also heightens concerns about technological obsolescence and supply chain disruptions (Qin et al., 2023), especially for long-term, capital-intensive projects. In response, investors often take a "wait and see" approach, shifting capital toward more liquid and established brown assets that seem safer in uncertain times.

So, during the high geopolitical risk trend, companies and investors adopt a "wait and see" strategy and prefer holding liquid assets to mitigate the risk of potential insolvency.

The effect of increasing marginal returns of renewables deployment on green stocks is plotted in Fig. 5. In Model 1, we notice that a +10 % shock in predicted renewables deployment may negatively affect green stocks but the result is insignificant. In Model 2, a +10 % shock in predicted renewables deployment positively affects green stocks in the next two years. Fig. 6 also plots the counterfactual shock of geopolitical risk and interaction term in Model 2. A +10 % shock in predicted geopolitical risk positively affects green energy stocks while +10 % in predicted interaction term reduces green energy stocks.

[3] We use $END\_SA = \Delta END = END_t - END_{t12}$ in our monthly data.

Table 3
Standard unit root test.

Panel A: Unit root test without Structural Break				
Variable	ADF		PP	
	Level	1st Difference	Level	1st Difference
BRN	−2.178	−10.206 ***	−2.265	−15.286***
GRN	−2.436	−9.697 ***	−2.253	−12.984***
GBR	−2.104	−6.120***	−1.773	−10.442***
RSK	−5.807 ***	–	−6.942***	–
END_SA	−2.148	−12.479***	−2.181	−22.528***
INT	−3.765 **	–	−3.453**	–
WTI	−3.437**	–	−2.845	−10.664***

Panel B: Unit root test with structural break						
	Level			1st Difference		
	t-stats	TB1	TB2	t-stats	TB1	TB2
BRN	−4.728	11:2019	9:2020	−5.182 **	12:2008	1:2020
GRN	−3.222	1:2020	11:2022	−11.442**	8:2008	9:2020
GBR	−2.489	4:2020	2:2022	−7.259**	6:2020	11:2020
RSK	−7.854 **	12:2013	1:2022	–	–	–
END_SA	−1.382	5:2010	11:2015	−5.853**	2:2019	11:2023
INT	−5.527**	6:2017	12:2022	–	–	–
WTI	−5.824**	2:2015	7:2021	–	–	–

*** and ** denote significance at 1 % and 5 % respectively.

Table 4
Result from ARDL cointegration test.

	Brown energy stocks		Green energy stocks		Green-to-Brown ratio	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
F-statistic	1.8351	2.8197	6.3169**	5.1651**	5.2382**	4.3511**
ECM_{t-1}	−0.1238***	−0.1310***	−0.1023***	−0.1159***	−0.1018***	−0.1056***
Critical Values (5 %)						
Lower pound	2.790	2.27	2.790	2.390	2.790	2.390
Upper pound	3.670	3.28	3.670	3.380	3.670	3.380
Diagnostics						
ARCH	0.3994	0.9038	2.3159	1.7530	0.0309	0.1705o
	[0.8089]	[0.4631]	[0.1296]	[0.187]	[0.8604]	[0.6801]
LM	0.1608	0.1753	0.3387	0.5811	2.1376	1.3272
	[0.8516]	[0.8393]	[0.7131]	[0.5603]	[0.1207]	[0.2677]
Ramsey	0.1104	0.3441	0.3033	0.2527	1.2270	0.71128
	[0.9122]	[0.7312]	[0.7620]	[0.8007]	[0.2213]	[0.4778]
Durbin-Wu-Hausman Endogeneity test [P-value]						
	0.2310	0.1562	0.1949	0.0969	0.0179	0.0028
	[0.6314]	[0.6932]	[0.6594]	[0.7559]	[0.8936]	[0.9576]

Note: P-values in brackets. *** and ** denote significance at 1 % and 5 % respectively. Durbin-Wu-Hausman Endogeneity test: H0: Variables are exogenous.

4.2.3. *Green-to-Brown ratio*

The findings in Table 5 indicate that as renewable energy deployment grows, the green to brown ratio increases. This aligns with market dynamics where increased investment in renewable energy encourages investors to reallocate capital from brown to green energy stocks, leading to the outperformance of green stocks over brown stocks. This result provides empirical evidence to the EIA Renewables Report (2020) that indicated the outperforming pattern of renewable energy companies' stocks compared with other major energy stocks.

The negative sign of the interaction term between geopolitical risk and the deployment of renewable energy indicates that higher geopolitical risk is linked to a weaker relationship between the deployment of energy and the green-to-brown ratio. This outcome can be explained by the oil price, which is the channel that governs the connection between geopolitical risk and the green market (Sohag et al., 2022). Geopolitical risk leads to an increase in oil price, which in turn has an inverse effect on green market investment (Dutta and Dutta, 2022; Lee et al., 2021; Yang et al., 2021). In response to the rise in geopolitical risk, investors have reduced their investments in risky assets such as green stocks in favor of more stable brown stocks. Brown energy companies have a long development history and well-established technologies, so their performance is driven by profitability (Christophers, 2021). In comparison, green companies are emerging companies that require significant technological innovations to drive their performance (Al Mamun et al., 2018). As innovation is a high-risk and long process, it involves uncertainty and low return on investment (Hsu et al., 2014). This may lead the investors to prefer the more profitable brown stocks during high geopolitical risk times.

It is not surprising that we see no significant short-run effect. Moving from brown energy stocks to green takes time. Investors must shift their money, and green projects need planning and construction before they start working. Markets only react once the new capacity is up and running and the supporting rules are in place, which usually happens over the long term.

The effect of increasing marginal returns of renewables deployment on the green-to-brown ratio stocks is plotted in Fig. 7. We notice that a +10 % shock in predicted renewables deployment may positively affect the green-to-brown ratio. Finally, plots in Fig. 8 reveal the positive and negative impact of shocks in the predicted geopolitical risk and interaction term on Green-to-Brown ratio respectively. A +10 % shock in the

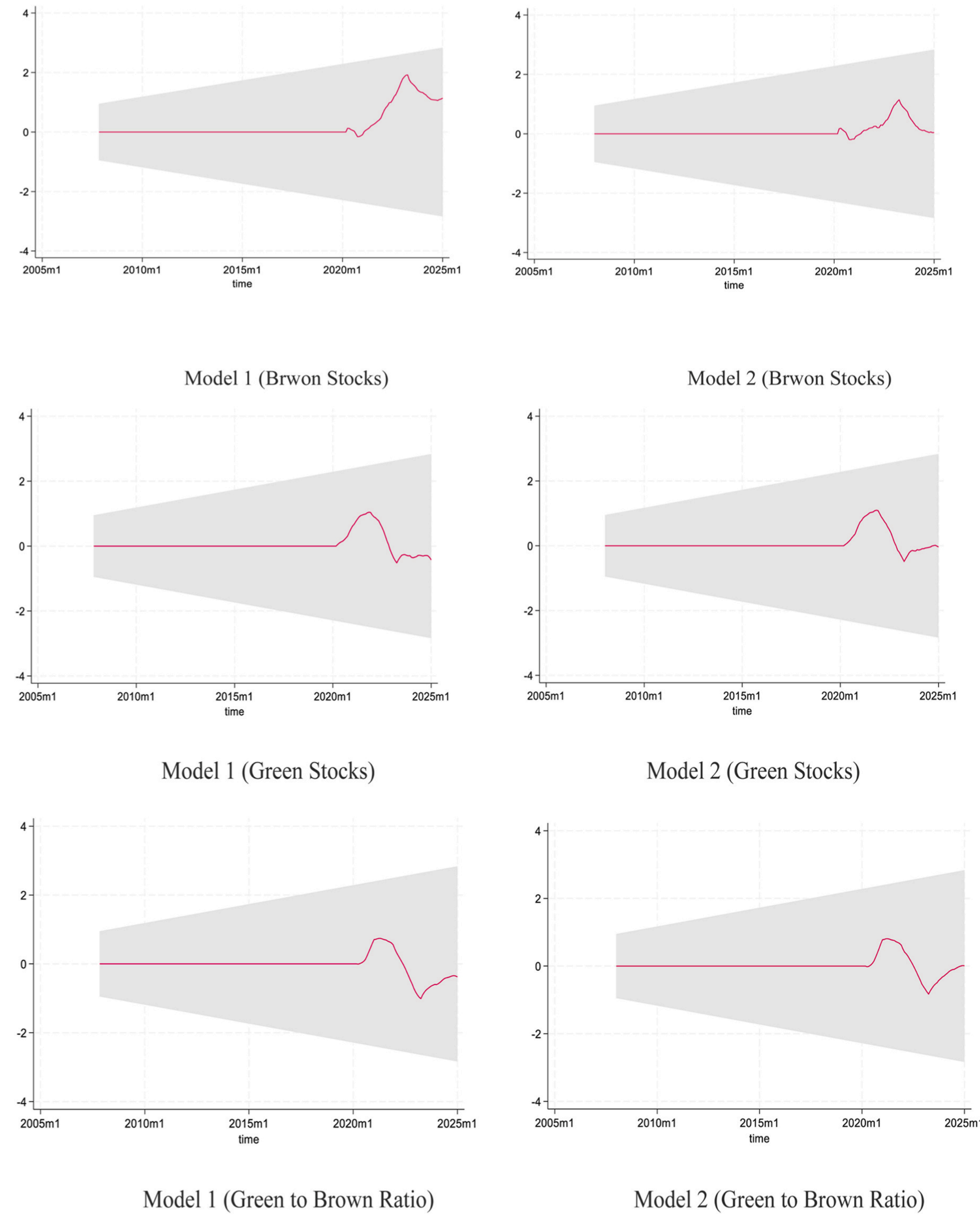


Fig. 2. Plots of the recursive CUSUM

predicted geopolitical risk positively affects green to brown ratio while a +10 % shock in the predicted interaction term reduces the ratio.

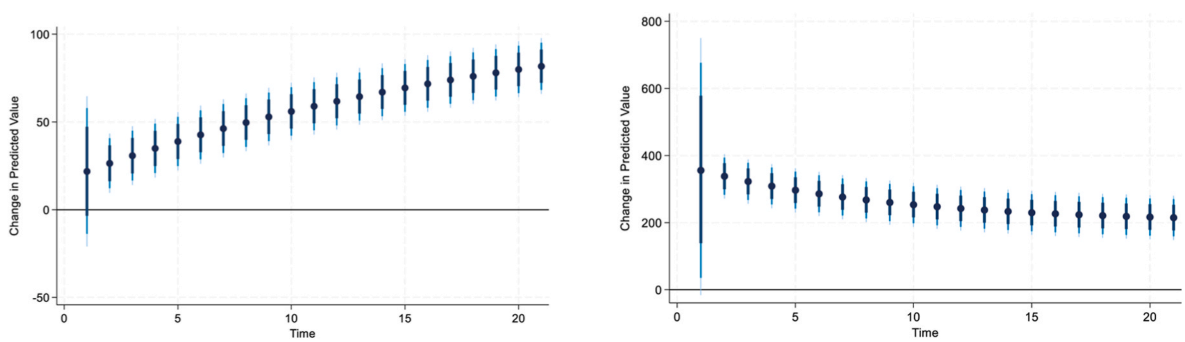
A quick glance at Table 5's other explanatory variables reveal that, unsurprisingly, oil price enters the brown stocks model positively and highly significant. This is due to increase profit margins for fossil fuel firms, leading to stronger performance in brown energy stocks. It confirms that these stocks are still heavily influenced by commodity price movements. In contrary, oil price has an adverse effect on green stocks and green to brown ratio which comes in line with Zhao et al. (2024).

In the short term, both brown and green stocks benefit from the price of oil. Henriques and Sadorsky (2008), Reboredo (2015), Bondia et al. (2016), Dutta (2017), Ahmad et al. (2018), Jie et al. (2018), and Kocaarslan and Soytas (2019) all support this finding. It is documented in the literature that rising oil prices increase green investments through the substitution effect (Song et al., 2019). The rise in oil prices stimulates investors and consumers to switch to affordable alternative energy sources, which boosts the use of green energies. As a result, the substitution effect significantly boosts the earnings of renewable energy companies and enhances the performance of green energy equities (Umar et al., 2022). But at the same time, the results show that the oil

Table 5
Dynamic ARDL estimations.

	Brown energy stocks		Green Energy Stocks		Green-to-Brown ratio	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
Long Run						
END_SA_{t-1}	0.2658	1.0777	0.6218	5.5738***	0.3563**	2.8994***
	(0.4324)	(1.6277)	(0.4409)	(1.8741)	(0.1598)	(0.7114)
WTI_{t-1}	0.0431**	0.0385**	−0.0037	−0.0480***	−0.0049*	−0.0180***
	(0.0196)	(0.0195)	(0.0106)	(0.0177)	(0.0027)	(0.0065)
INT_{t-1}	0.0002	0.0027	−0.0039	0.0026	−0.0011	0.0016
	(0.0031)	(0.0036)	(0.0036)	(0.0040)	(0.0013)	(0.0015)
RSK_{t-1}	–	0.0759***	–	0.0657***	–	0.0152*
		(0.0247)		(0.0221)		(0.0078)
$(END\_SA*RSK)_{t-1}$	–	−0.3447	–	−1.2940***	–	−0.5930***
		(0.3577)		(0.4124)		(0.1550)
Short Run						
$\Delta\ END\_SA_{t-1}$	1.0094	16.6870	0.4930	29.6601***	−0.2971	0.9028
	(1.0461)	(1.2264)	(1.2166)	(10.5713)	(0.4435)	(3.9133)
ΔWTI	0.2254***	0.2243***	0.1791***	0.1602***	−0.0047	−0.0159
	(0.0464)	(0.0462)	(0.0549)	(0.0534)	(0.0199)	(0.0197)
ΔINT	0.0852***	0.0878***	0.0652**	0.0828***	−0.0083	0.0037
	(0.0252)	(0.0266)	(0.0296)	(0.0305)	(0.0108)	(0.0113)
ΔRSK	–	0.2685*	–	0.4576**	–	0.0093
		(0.1540)		(0.1760)		(0.0652)
Δ(END_SA*RSK)	–	−3.5132*	–	−6.3699***	–	−0.2505
		(1.9828)		(2.2713)		(0.8408)
$DUM_{covid19}$	−0.0593	−0.0760	−0.0179	−0.0291	0.0235	0.0255
	(0.0548)	(0.0541)	(0.0642)	(0.0620)	(0.0234)	(0.0229)
ECM_{t-1}	−0.0480**	−0.1129***	−0.0113	−0.0291*	−0.0228*	−0.0397***
	(0.0229)	(0.0305)	(0.0155)	(0.0158)	(0.0153)	(0.0146)

Note: SE in parentheses. ***, **, * denote significance at 1 %, 5 % and 10 % respectively.



Model 1 **Model 2**

Fig. 3. Counterfactual shock in predicted brown stocks and renewables deployment using dynamic ARDL simulations. Notes: The black dot represents the projected brown stock values following a 10 % shock in renewable energy deployment.

price has a long-run detrimental impact on the green-to-brown ratio, suggesting that the high price of oil hinders the shift to green stocks in the long run. High oil prices increase inflation, which may lead central banks to increase interest rates and result in an increase in the cost of capital for renewable energy companies.

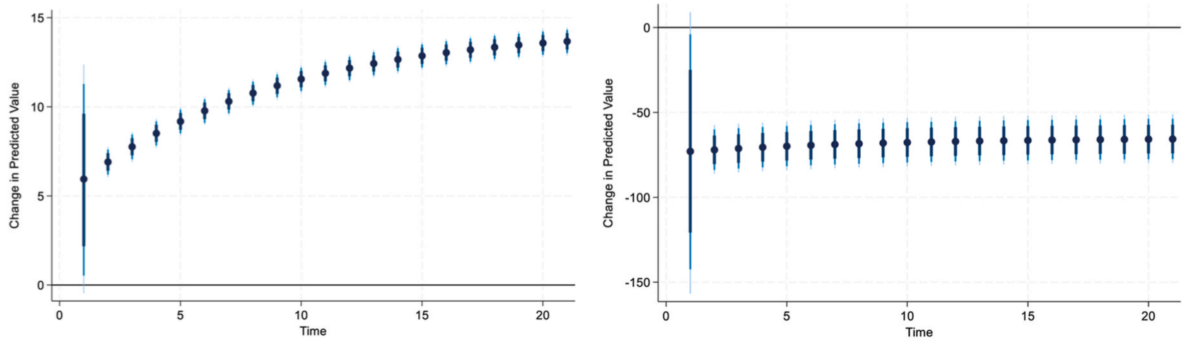
For the interest rate, we find that interest rates have a significant positive effect on both brown and green energy stocks, but only in the short run. This is probably because higher interest rates usually come with rising inflation, which can drive up energy prices and boost profits for energy companies. However, this effect doesn't last. Over time, the economy adjusts, inflation settles down, and energy stock performance becomes more influenced by key factors like oil prices.

Finally, the COVID-19 dummy variable is found to be insignificant across all models. This may be because COVID-19 only caused a temporary drop in energy demand, particularly during lockdowns, but the markets recovered quickly (Sahraei and Ziaei, 2024). The impact was sudden but short-lived and did not alter the long-term fundamentals of either brown or renewable green energy companies.[4]

4.3. Kernel-based regularized least square (KRLS)

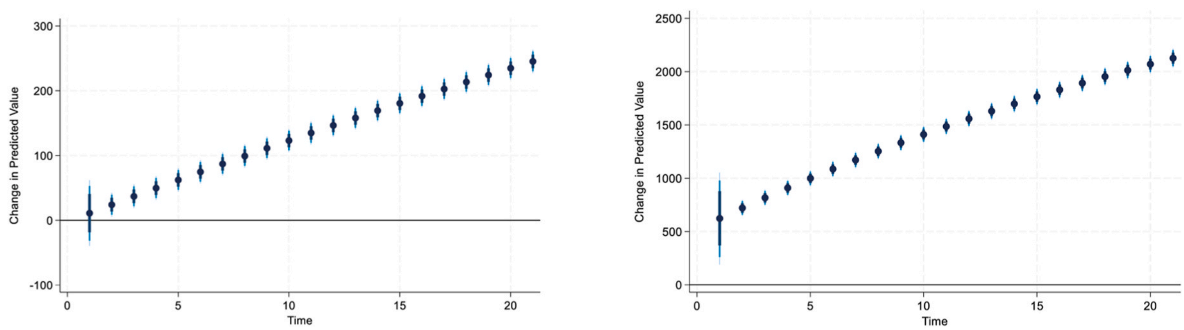
Table 6 presents the pointwise derivatives of the estimated KRLS model. All models have a predictive power of over 0.90 as shown by R^2, making them statistically significant at the 10 % level. Meaning that the regressors explain over 90 % variation in brown and green stocks. Table 6 presents the 25th, 50th, and 75th percentiles of the

[4] It is worth noting that this result contradicts previous studies that found a strong impact of COVID-19 on the energy market (e.g., Guo et al., 2024). This difference may be because those studies covered a shorter period after 2018, during which the COVID-19 years represented a significant share of the data. In contrast, our study covers a longer period from 2007 using monthly data, which makes the COVID-19 period relatively short and less influential.



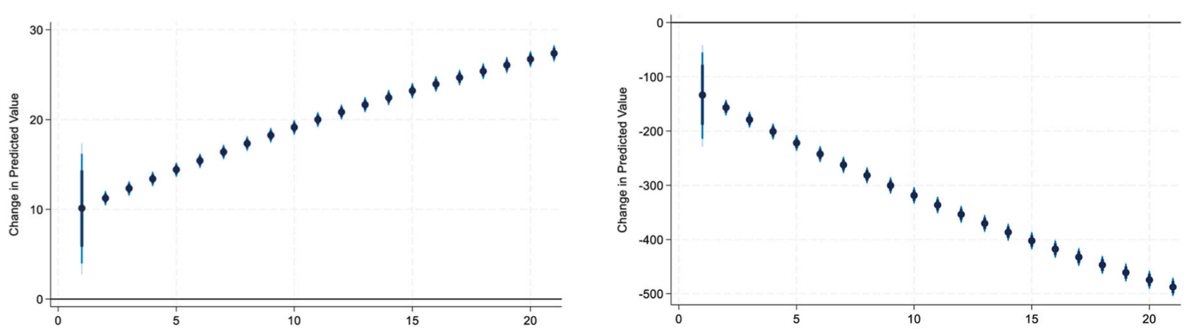
Model 2 Model 2

Fig. 4. Counterfactual shock in predicted brown stocks, geopolitical risk and interaction term using dynamic ARDL simulations. Notes: black dot is the predicted brown stocks by +10 % shock in geopolitical risk (Model 2). The left-hand graph shows how geopolitical risk affects brown stocks directly while the right-hand graph shows how geopolitical risk affects brown stocks indirectly (interaction term).



Model 1 Model 2

Fig. 5. Counterfactual shock in predicted green energy stocks and renewables deployment using dynamic ARDL simulations. Notes: black dot is the predicted brown stocks by + 10 % shock in renewables deployment.



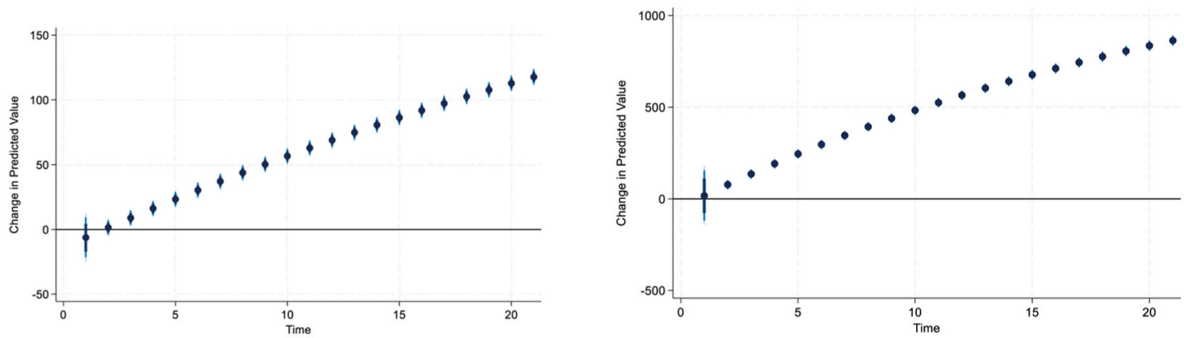
Model 2 Model 2

Fig. 6. Counterfactual shock in predicted green energy stocks, geopolitical risk and interaction term using dynamic ARDL simulations. Notes: black dot is the predicted brown stocks by + 10 % shock in geopolitical risk. The left-hand graph shows how geopolitical risk affect green stocks directly while the right-hand graph shows how geopolitical risk affect green stocks indirectly (interaction term).

heterogenous marginal effects derived from regressor derivatives. The results obtained through the KRLS approach align with those from the DARDL method, reinforcing the reliability and consistency of our findings.

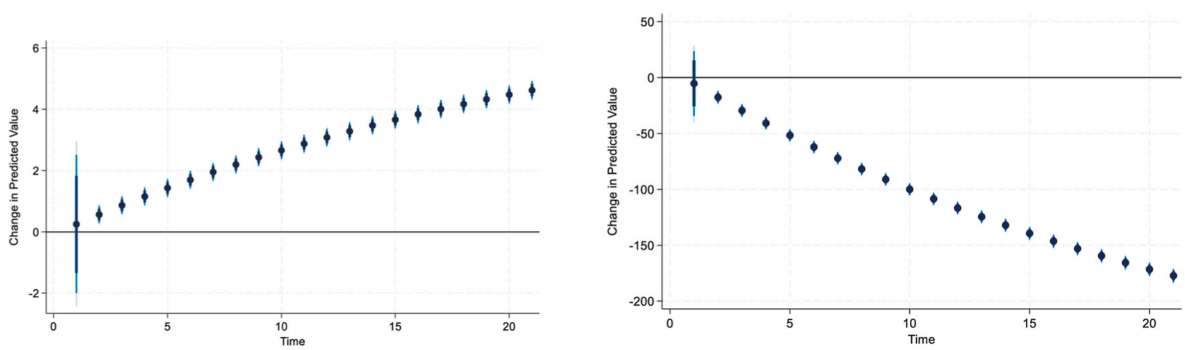
4.3.1. Another robustness check

For more robustness checks, we re-estimate all models using alternative proxies for brown and green stocks as well as a novel proxy for renewable deployment. Our alternative brown stocks proxy is iShares Global Energy ETF (IXC), which invests in a basket of the largest oil and gas producing companies in the world. The alternative proxy of green energy stock is Invesco WilderHill Clean Energy ETF (PBW). The Index is made up of the equities of American publicly traded companies that are engaged in business to increase conservation and greener



Model 1 **Model 2**

Fig. 7. Counterfactual shock in predicted green to brown ratio and renewables deployment using dynamic ARDL simulations. Notes: black dot is predicted brown stocks by +10 % shock in renewables deployment.



Model 2 **Model 2**

Fig. 8. Counterfactual shock in predicted green to brown ratio, geopolitical risk and interaction term using dynamic ARDL simulations. Notes: black dot is the predicted brown stocks by +10 % shock in geopolitical risk. The left-hand graph shows how geopolitical risk affects green to brown ratio directly while the right-hand graph shows how geopolitical risk affects green to brown ratio indirectly (interaction term).

energy. Finally, for renewable deployment alternative proxy, we follow Belaïd et al. (2021) by using total renewable energy production. The findings, which are tabulated in Appendix 1 are consistent with our key hypotheses and support our stated argument and conclusion.

5. Conclusion

In recent years, the deployment of renewable energy has grown rapidly, drawing significant attention from researchers for its impact on economic activities. However, surprisingly, scholars ignored delving into the topic from the energy stocks perspective.

This study makes a novel contribution to literature by being the first to examine how renewable energy deployment influences both brown and green energy stocks while also considering the moderating role of geopolitical risk. Our findings show that renewable energy deployment does not have a significant impact on brown energy stocks, whereas geopolitical risk has a clear, positive, and significant effect.

On the contrary, renewables deployment is linked to a significant increase in the performance of green stocks. This is not surprising as the increase in deployment is often associated with increased spending on capital equipment and R&D by firms. This prompts further production to utilize economics of scale, which in turn is reflected in firms' profitability and higher expected cash flow. In response, investors in the stock market react positively to green energy firms' profitability. We also observed a moderating effect of geopolitical risk which infers that the benefits of increasing renewable deployment on green stocks can be absorbed by increasing geopolitical trends. Green energy investment is often characterized as high risk and high capital intensity investment (Xu and Gallagher, 2017), so during the high geopolitical risk trend, companies and investors adopt cautious strategies, prioritizing liquid assets to reduce exposure to financial instability. This strategy helps mitigate the risk of insolvency.

We take our analysis further to investigate the impact on the Green-to-Brown ratio to assess if investors are transferring money from brown energy stocks to green energy stocks. We found that green energy stocks outperform brown energy stocks when there is a higher degree of renewable deployment. This performance is hindered by the high geopolitical risk that leads to an increase in the oil price which in turn has an inverse effect on green market investment. In response to the rise in geopolitical risk, investors have reduced their investments in risky assets such as green stocks in favor of more stable brown stocks. Our results are robust using different methods and different proxies.

In sum, our findings stress that more renewables deployment may result in reducing the dominance of brown energy stocks in favor of green energy stocks as they possess more sustainable features and are in line with the recent investment in low-carbon energy innovation. However, the escalating geopolitical risk and high oil prices may hinder this transition among investors, making the path to a sustainable energy market transition more challenging.

From a policy standpoint, our findings highlight a significant issue: geopolitical risk can hinder the advancement required to meet long-term climate objectives. Policy makers should take steps to make green energy investments more stable and less vulnerable to global shocks. This can be achieved by providing investors with steady support like long-

Table 6
Pointwise derivatives using Kernel-Based Regularized Least Square (KRLS).

Brown energy stocks					
Model 1	Avg	SE	P-25	P-50	P-75
END_SA_{t-1}	5.6548***	0.8529	0.7328	4.6714	9.9425
WTI_{t-1}	0.5095***	0.0386	0.3096	0.5171	0.7491
INT_{t-1}	−0.0349***	0.0114	−0.0557	−0.0312	−0.0019
$DUM_{covid19}$	−0.1961***	0.0380	−0.3649	−0.1297	−0.0229
Diagnostics					
Lambda	0.1304	Sigma	4.000	R^2	0.8725
Tolerance	0.212	Eff. df	33.12	Obs	212
Model 2	**Avg**	**SE**	**P-25**	**P-50**	**P-75**
END_SA_{t-1}	3.0199***	0.4843	−0.0851	2.8214	6.1232
WTI_{t-1}	0.4635***	0.0284	0.2829	0.4558	0.6476
INT_{t-1}	−0.0203**	0.0081	−0.0327	−0.0126	0.0071
RSK_{t-1}	0.0465	0.0374	−0.1320	0.0607	0.2242
$(END\_SA*RSK)_{t-1}$	0.5012***	0.0675	0.0377	0.4156	0.9134
$DUM_{covid19}$	−0.2091***	0.0339	−0.3103	−0.1762	−0.0511
Diagnostics					
Lambda	0.1313	Sigma	6.000	R^2	0.8969
Tolerance	0.212	Eff. df	47.88	Obs	212
Green energy stocks					
Model 1	**Avg**	**SE**	**P-25**	**P-50**	**P-75**
END_SA_{t-1}	−3.5580***	1.3637	−10.9797	−2.4920	2.2778
WTI_{t-1}	0.0941	0.0627	−0.3845	0.0769	0.5077
INT_{t-1}	0.0949***	0.0187	−0.0097	0.0476	0.2045
$DUM_{covid19}$	0.5421***	0.0616	0.3876	0.6158	0.7823
Diagnostics					
Lambda	0.1188	Sigma	4.000	R^2	0.8605
Tolerance	0.212	Eff. df	33.84	Obs	212
Model 2	**Avg**	**SE**	**P-25**	**P-50**	**P-75**
END_SA_{t-1}	2.7848***	0.7916	−7.4243	1.1266	1.8890
WTI_{t-1}	0.0741	0.0473	−0.2410	0.0406	0.3545
INT_{t-1}	0.0766***	0.0136	0.0026	0.0294	0.1540
RSK_{t-1}	0.0549	0.0609	−0.2122	0.0392	0.2650
$(END\_SA*RSK)_{t-1}$	−0.4382***	0.1105	−1.0726	−0.3053	0.2280
$DUM_{covid19}$	0.5521***	0.0560	0.3940	0.6475	0.7842
Diagnostics					
Lambda	0.1193	Sigma	6.000	R^2	0.8822
Tolerance	0.212	Eff. df	49.08	Obs	212
Green-to-Brown ratio					
Model 1	**Avg**	**SE**	**P-25**	**P-50**	**P-75**
END_SA_{t-1}	−2.3280***	0.3959	−4.7583	−1.8306	0.2589
WTI_{t-1}	−0.0947***	0.0179	−0.2128	−0.1033	0.0330
INT_{t-1}	0.0231***	0.0053	−0.0054	0.0290	0.0464
$DUM_{covid19}$	0.2453***	0.0176	0.0816	0.1920	0.4229
Diagnostics					
Lambda	0.2077	Sigma	4.000	R^2	0.9273
Tolerance	0.212	Eff. df	33.12	Obs	212
Model 2	**Avg**	**SE**	**P-25**	**P-50**	**P-75**
END_SA_{t-1}	1.5717***	0.2373	−3.3130	1.1345	0.2596
WTI_{t-1}	−0.0670***	0.0125	−0.1447	−0.0677	−0.0001
INT_{t-1}	0.0140***	0.0035	−0.0001	0.0142	0.0241
RSK_{t-1}	−0.0033	0.0186	−0.0692	−0.0005	0.0558
$(END\_SA*RSK)_{t-1}$	−0.2518***	0.0328	−0.5293	−0.2048	−0.0062
$DUM_{covid19}$	0.2628***	0.0155	0.1236	0.2834	0.3781
Diagnostics					
Lambda	0.2326	Sigma	6.000	R^2	0.9284
Tolerance	0.212	Eff. df	40.91	Obs	212

Notes: Avg. refers to the average marginal effect, SE denotes the standard error, and P-25, P-50, and P-75 correspond to the 25th, 50th, and 75th percentiles, respectively. ***, **, * denote significance at 1 %, 5 % and 10 % respectively.

term incentives, stable regulations, and guaranteed pricing schemes to reduce uncertainty and keep investments flowing into renewable energy. Finally, governments should take geopolitical risks into account when creating strategies for the energy transition so that climate goals are met even in the face of global disruptions. These approaches can lessen the likelihood that short-term responses to geopolitical conflicts will undermine long-term climate initiatives.

From investors perspective our findings offer valuable insights into developing effective portfolio diversification and risk management strategies. For instanceinvestors who are having difficulty finding opportunities for diversification and hedging in the brown energy markets can take advantage of the heterogeneous reactions to the renewables deployment and geopolitical risk by investing in green energy companies that can provide hedging opportunities. Besides, investing in energy stocks involves different uncertainties such as geopolitical risk and oil prices. Our research outlines that such uncertainties may drive investors' expectations away from market fundamentals and improvement in the renewable energy industry which may alter the performance of underlying energy stocks. Thus, close watching of the different uncertainties factors is imperative for portfolio managers as their earnings expectations may be overly optimistic.

A limitation of the work is that the geographic scope is not covered. This is because the paper focuses primarily on the overall relationship between renewable energy deployment, geopolitical risk, and energy stock performance without delving into region-specific or country-level differences. Addressing geographic variations would require a more detailed and data-intensive analysis, which is beyond the scope of this study but could be explored in future research. Another limitation concerns the measurement of geopolitical risk; often based on broad indices, these measures might not accurately capture the nuances of political dynamics or investor sentiment within individual countries. For further research, it would be valuable to use more detailed or qualitative measures of geopolitical risk to improve insight into its impact.

CRediT authorship contribution statement

Ramez Abubakr Badeeb: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization, Visualization. **Hooi Hooi Lean:** Writing – review & editing, Validation, Investigation, Data curation.

Declaration of competing interest

The authors declare no conflicts of interest that could have appeared to influence the work reported in this paper.

Appendix 1

The Long run and short-run relationships of Dynamic ARDL estimations

	Brown energy stocks		Green Energy Stocks		Green-to-Brown ratio	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
Long Run						
END_SA $_{t-1}$	0.0416	0.0773	0.1816	0.2068***	0.2519*	0.2714**
	(0.0777)	(0.0272)	(0.1141)	(0.0300)	(0.1421)	(0.0362)
WTI $_{t-1}$	0.0410	0.0253	−0.0148	−0.0637**	−0.0278	−0.0527
	(0.0270)	(0.0272)	(0.0141)	(0.0321)	(0.0177)	(0.0373)
INT $_{t-1}$	0.0010	0.0074	−0.0043	−0.0031	−0.0095	−0.0086
	(0.0050)	(0.0055)	(0.0070)	(0.0071)	(0.0080)	(0.0082)
RSK $_{t-1}$	–	0.0916***	–	0.0675*		0.0381*
		(0.0340)		(0.0402)		(0.0413)
(END_SA*RSK) $_{t-1}$	–	−0.3884	–	−0.3654**		−0.2429*
		(0.3066)		(0.0440)		(0.0517)
Short Run						
Δ END_SA$_{t-1}$	−0.1299	−0.1517	0.2812	0.4080	0.41431	0.6271
	(0.2393)	(0.2670)	(0.3461)	(0.3933)	(0.4080)	(0.4645)
ΔWTI	0.2718***	0.2744***	0.2124**	0.1888*	−0.0118	−0.0092
	(0.0712)	(0.0706)	(0.0991)	(0.1003)	(0.1165)	(0.1183)
ΔINT	0.0504	0.0615	0.0776	0.1017*	−0.0701	−0.0588
	(0.0380)	(0.0380)	(0.0537)	(0.0551)	(0.0634)	(0.0652)
ΔRSK	–	−0.0066	–	−0.0371	–	0.0604
		(0.0501)		(0.0715)		(0.0845)
Δ(END_SA *RSK)	–	0.1601	–	−0.3282	–	−1.1940**
		(0.3491)		(0.5018)		(0.5923)
DUM$_{covid19}$	−0.0350	−0.0406	−0.0830	−0.0849	−0.1038	−0.1015
	(0.0812)	(0.0803)	(0.1175)	(0.1174)	(0.1382)	(0.1384)
ECM $_{t-1}$	−0.0570**	−0.1097***	−0.0149	−0.0123**	−0.0244*	−0.0219*
	(0.0262)	(0.0323)	(0.0126)	(0.0230)	(0.0138)	(0.0144)

Note: SE in parentheses. ***, **, * denote significance at 1 %, 5 % and 10 % respectively.

Data availability

Data will be made available on request.

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