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Policy Uncertainty and the Volatility of the S&P 500: Before and After the Launch of the S&P 500 ESG

Manel Mahjoubi[1] & Jamel Eddine Henchiri[1]

[1] UR.RED, Higher Institute of Management, University of Gabes, Tunisia

Correspondence: Manel Mahjoubi, UR.RED, Higher Institute of Management, University of Gabes, Tunisia. E-mail: mnlmahjoubi@yahoo.com

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Abstract

This paper examines the asymmetric effect of economic policy uncertainty, geopolitical risk, and climate policy uncertainty on the volatility of the S&P 500 stock index, before and after the launch of the S&P 500 ESG Index, by using a Non-linear Autoregressive Distributed Lag (NARDL) model, for the period January 2010 to august 2022.We provide evidence on the asymmetric impact of climate policy uncertainty on the volatility of the S&P 500 both in the short-run and in the long-run, and this asymmetry is more frequent after the launch of the S&P 500 ESG Index. Moreover, in the long-run, a decrease in the economic policy uncertainty after the launch of the S&P 500 ESG has greater effect on volatility of the S&P 500, than the short-run. We also find that positive and negative shocks to geopolitical risk before and after the launch of the S&P500 ESG index do not affect the volatility of the S&P 500 stock market index in the short -run and long.

Keywords: Volatility, economic policy uncertainty, geopolitical risk, climate policy uncertainty, S&P 500, S&P 500 ESG Index

1. Introduction

Market efficiency is one of the important concepts that have been extensively researched in neoclassical finance. The Efficient Market Hypothesis (EMH) is based on the original contributions of Bachelier (1900), Cowles (1933), Kendall and Hill (1953), Samuelson (1965) and Fama (1965). These authors argued that in an informationally efficient market, price changes cannot be predicted if security prices reflect all investor expectations and all available market information. Specifically, Fama (1970) defined the information efficiency of a market such that stock or security prices always fully reflect all available market information. According to this hypothesis, there is a correlation between stock or security prices and information, because stock or security prices are always formed according to new information announced.

Efficiency and volatility are inseparable, since efficiency is a function of market returns, while volatility is a function of the variation of those returns. Financial market returns and its volatility are among the most important indicators for practitioners, Therefore, determining factors that drives financial market returns and volatility is of paramount importance, as it helps them in capital budgeting and portfolio management decisions, asset pricing, security valuation, monetary policy formulation, and risk management, as they directly reflect the financial health and prospects of firms (Engle & Ng, 1993).

Predicting the volatility in financial markets has been the topic of academic and practical research in the past decade. Moreover, for academics, financial market movements based on predictors challenge the idea of market efficiency, and in turn, assists in building realistic asset pricing models (Rapach & Zhou, 2013). Today, several factors have been found that have a reflection on the volatility of the stock market. Hence, determining factors that drives financial market returns and volatility is of paramount importance to both practitioners and academics in finance. One of the most important factors that have been studied recently, we find economic policy uncertainty (EPU), geopolitical risk (GPR) and climate policy uncertainty (CPU). Furthermore, political, social, economic and climate regulations are used to detect recent events or predict the dynamic developments. Dynamism at times turns into uncertainty, which can cause shocks in the stock market. Policy changes are inevitable and can occur unexpectedly. Uncertainty leads to a variety of adjustments in individual and organizational decisions.

After the global financial crisis of 2007-2008, governments intensified their interventions in financial markets to ensure economic stability, due to the complexity and long-term nature of policymaking. Since this crisis, the influence of economic policy uncertainty (EPU) on stock market volatility has been studied (Nakai et al., 2016; Yuan et al., 2022b).

Much attention has been devoted to understanding the vital role of economic policy uncertainty in driving economic activities. The relationship between EPU and the stock market was first investigated by Bansal and Yaron (2004), who found that economic uncertainty broadens asset market volatility. Subsequently, Baker et al., 2016 developed a new economic policy uncertainty index (EPU) based on a quantitative study of economic and policy press coverage. The EPU indicator is getting more attention from scholars, who are investigating links between this indicator and the volatility and returns of the stock market (or other markets). Furthermore, strand of evidence demonstrated a favorable effect between EPU and volatility of stock market (Liu & Zhang, 2015; Arouri et al., 2016; Fang et al., 2017; Ma et al., 2018; Li et al., 2019; Oliyide et al., 2021; Chang, 2022; Lv et al., 2023;Yang et al., 2023).

In fact, there are other factors that do not seem to be closely related to the stock market that can affect stock market fluctuations, especially since the world is experiencing a lot of uncertainty and instability due to the proliferation of events and issues. For many years, the world has not known such instability: conflicts in the Middle East, the Arab revolution, the Sino-American trade war, the covid-19, Russia-Ukraine war, the actions of terrorist groups... Indeed, geopolitical events are widely reported by the press and can influence the risk premium demanded by investors. For this reason, the geopolitical risk (GPR) plays an important role in determining the volatility of the stock market (Li et al., 2023; Zhang et al., 2023; Khan et al., 2023….), and when the government announces many policy changes and leaves a lot of uncertainty, it leads to volatilities and correlations among stocks (Pastor & Veronesi, 2012).

Understanding the impact of geopolitical events on volatility is important, given the important role in investment decisions and policy making, allows us to assess the systemic nature of geopolitical risk. The authors consider that geopolitical risk arises from all kinds of political uncertainties and that the increase in geopolitical risk causes economic shocks, negative investor sentiment, and delays in decision-making processes due to the negative impact on supply and demand channels and increased business costs (Burch et al., 2016; Gupta et al., 2021; Segnon et al., 2023). For exemple, Brogaard et al. (2020) find that as uncertainty increases, global stock market returns decline, in the U.S federal election.

Moreover, the GPR is now higher than ever, because of the Russian-Ukrainian war. Zhang et al. (2022) examine the co-movements between the daily geopolitical risk index (GPR) and the daily returns and volatility of 36 global defense and aerospace firms spanning ten countries and three continents during the war in Ukraine. They found that the GPR index influences the returns and volatility of several U.S. and European firms in the medium and long term throughout this war, and that its impact is mostly positive. In this sense, Zhou and Lu (2023) find that investors' attention to the Russia-Ukraine conflict affects the volatility of the Chinese stock market.

The theoretical link between stock market volatility and GRP can be traced back to Sharpe (1964); Eugene and French (1992) and Frey and Kucher (2001) based on the idea that asset prices reflect historical events (Segnon et al., 2023). For example, two hours after the London bombings in July 2005, the FTSE 100 index fell 200 points. On the other hand, during the September 11,2001, attacks, Wall Street's losses were staggering. The Dow Jones lost 14.26% of its value, while the S&P 500 and the NASDAQ were down 11.6% and 16.1%. Similarly, the Tokyo Stock Exchange index, the NIKKEI, plunged nearly 7% on September 12.

We found Several studies examining the predictive power of geopolitical tensions and terrorist attacks on international stock market indices (Chen & Siems, 2004; Abadie & Gardeazabal, 2008; Aslam & Kang, 2015; Balcilar et al., 2018; Apergis et al., 2018). At all events, much of the relevant literature also demonstrates the impact of GPR on financial markets (Bouras et al., 2019; Smales, 2021; Ndako et al., 2021; Li et al., 2022; Ma et al., 2022; Salisu et al., 2022; Zhang et al., 2023; Zhang et al., 2023; Lee, 2023). One of the key findings of these studies is that GAR often negatively impact stock market returns, which then impacts the decision-making processes of domestic and international investors. As a result, investors experience panic selling and attempt to reshuffle their portfolios by considering less risky investments, which leads to large price fluctuations and increased volatility in financial markets.

The dangers threatening the world and humanity today are not limited to wars, terrorism, and the political and security instability of countries. The problem today is greater than that because environmental disasters and climate change have become a threat to humanity. It will have an impact on the economy and stock market volatility. As climate change is becoming increasingly severe, the issue of climate finance becomes even more important and it has been the most important issue in the current climate change negotiations (Michael Bourdeau-Brien & Kryzanowski, 2017; Giglio et al., 2021; Stroebel & Wurgler, 2021). It is worth mentioning that climate finance is not only an economic cost, but also an investment in natural capital, from the perspective of synergies. Therefore, climate change has a significant economic effect on capital and the whole economy including the stock market (Hong et al., 2019; Lee et al., 2022; Zhao et al., 2022). In addition, it is important to consider different stock sectors (Baumöhl & Lyócsa, 2017; Lu et al., 2022).

Climate change impacts have induced numerous natural disasters, such as rising sea levels and more frequent floods and droughts, posing significant challenges to financial stability and societies (Carney, 2015; Dafermos et al., 2018). Climate change has recently been recognized as a potential systemic risk factor, and its shocks to the financial system are expected to materialize in the near future (Bolton et al., 2021; Wu & Wan, 2023; Mao et al., 2023). In addition, it is important to consider different stock market sectors (Baumöhl & Lyócsa, 2017; Lu et al., 2022; Flori et al., 2021). Therefore, regulators are increasingly worried about the extent to which stock markets efficiently price climate change risks (Hong et al., 2019).

Although climate policy uncertainty is an important driver of stock market volatility because there is no precise measure of climate policy uncertainty, it is difficult to effectively capture its impact, including its nonlinear and lagged effects, on stock market volatility. However, climate policy uncertainty has received little attention in empirical studies due to its difficulty in measurement prior to the CPU index developed by Gavriilidis (2021). Gavriilidis (2021) introduces a new measure of climate policy uncertainty based on newspaper coverage. Therefore, the existing literature has focused on the relationship between climate change and stock market volatility (Lasisi et al., 2022; Liang et al., 2022;Ye, 2022; Bonato et al., 2023, Lv & Li, 2023; Sakariyahu et al., 2023).

Discuss with the growing global awareness of environmental protection, international stock markets for environmental, social and governance (ESG) values are developing rapidly, in parallel with the increasing linkages between risks in global markets.

ESG criteria have become a benchmark for responsible investment in recent years. They are true indicators of a company’s contribution to society and sustainable development. Find out everything you need to know about ESG criteria. The financial community used this acronym to designate the Environmental, Social and Governance (ESG) criteria that generally constitute the three pillars of extra-financial analysis. They are considered in socially responsible management. Thanks to ESG criteria, it is possible to assess the responsibility of companies towards the environment and their stakeholders (employees, partners, subcontractors, and customers). The environmental criterions considered are: waste management, reduction of greenhouse gas emissions and prevention of environmental risks.

The growing role of ESG investments has given rise to a new literature that analyzes whether ESG indices outperform conventional indices (Pérez-Gladish et al., 2013; Durán-Santomil et al., 2019). ESG indices underperform in normal times, while in turbulent times, such as the 2007 global financial crisis, they outperform conventional indices because they play an “insurance role” (Nofsinger & Varma, 2014; Becchetti et al., 2015; Leite & Cortez, 2015). Dios-Alija et al. (2021) analyzed monthly and weekly sustainable and conventional indexes of the Dow Jones, Eurostoxx, and Hang Seng; high levels of persistence were observed in all cases, and no differences were detected between markets.

By the way, the S&P 500 ESG Index was launched on January 28, 2019. The S&P 500 ESG Index is an index offering broad exposure, weighted by market capitalization, and designed to measure the performance of securities of companies meeting sustainability criteria, while maintaining sector diversification close to that of the S&P 500 Index. Therefore, the Benchmark Index has been designed to provide a risk and return profile comparable to that of the S&P 500 Index, while improving ESG characteristics.

The launch of this index marked an evolution in sustainable investing. The S&P 500 ESG Index provides investors with an additional benchmark or tool to assess the performance of the US large-cap equity market, qualified based on minimum ESG scores and company exclusions.

Compared to previous studies, the main innovation in this article is to study the impact of climate policy uncertainty, geopolitical risk, and economic policy uncertainty on the volatility of the S&P 500 index, using the launch of the S&P 500 index as a benchmark. Also, Previous literature provides mixed results on the relationship between of climate policy uncertainty, geopolitical risk, and economic policy uncertainty on the volatility of the S&P 500 stock index. This paper examines the asymmetric effects of these different variables, by using the Nonlinear Autoregressive Distributed Lag (NARDL) approach. Furthermore, the study is significant because there are a variety of factors that can have an impact on stock market.

One of the most important results that we discovered in this study is the positive and negative climate policy uncertainty shocks after the launch of the S&P500 ESG index positively affects the volatility of the S&P 500 stock index in the short-run and long-run. However, positive, and negative shocks to geopolitical risk before and after the launch of the S&P500 ESG index do not affect the volatility of the S&P 500 stock market index in the short -run and long -run.Also,we found that the negative shock on economic policy uncertainty after the launch of the S&P500 ESG index has a positive impact on the volatility of the S&P 500 stock market index in the short-run and in the long -run.

For this reason and based on these results we are recommending that investors in the stock market should consider Better at the physical risks associated with climate change, take the necessary precautions and finding solutions to reduce these risks to businesses.

The rest of the paper is structured as follows. Section 2 presents the data and methodology. Findings are given in Section 3 and last section concludes the paper.

2. Method

In this paper, we investigate the impact of economic policy uncertainty (EPU), geopolitical risk (GPR) and climate policy uncertainty (CPU) on the volatility of S&P 500 index before and after the launch of the S&P 500 ESG index (January 28, 2019), for the period January 2010 to August 2020, by NARDL model.

The Non-Linear Autoregressive distributed lag (NARDL) model is an asymmetric extension of the linear autoregressive distributed lag model (ARDL) proposed by Pesaran et al. (2001). The NARDL model can not only detect the hidden cointegrating relationship between the variables, but also analyze the different impacts of positive and negative changes in the explanatory variables on the explained variables by decomposing the partial sums of the explanatory variables. This model is considered one of the latest models that captures the non-linear relationship between variables and pointing out the influences of positive and negative shocks on the dependent variable in a single-equation structure.

In this paper, we employ the nonlinear autoregressive distributed lag model (NARDL) proposed by Shin et al. (2014) to study the impact of economic policy uncertainty(EPU), geopolitical risks (GPR) and climate policy uncertainty (CPU) on stock realized volatility (RV) of the S&P 500 index, before and after the launch of the S&P 500 ESG Index. The general relationship between all variables is presented by the following linear regression model:

$$RV_t = \beta_0 + \theta_0 RV_{t-1} + \theta_1^+ ESG * EPU_{t-1}^+ + \theta_1^- ESG * EPU_{t-1}^- + \theta_2^+ NESG * EPU_{t-1}^+ + \theta_2^- NESG * EPU_{t-1}^- + \theta_3^+ ESG * GPR_{t-1}^+ + \theta_3^- ESG * GPR_{t-1}^- + \theta_4^+ NESG * GPR_{t-1}^+ + \theta_4^- NESG * GPR_{t-1}^- + \theta_5^+ ESG * CPU_{t-1}^+ + \theta_5^- ESG * CPU_{t-1}^- + \theta_6^+ NESG * CPU_{t-1}^+ + \theta_6^- NESG * CPU_{t-1}^- + \sum_{j=1}^{q_0} \beta_{0,i}\, \Delta RV_{t-\mathrm{j}} + \sum_{j=1}^{q_1^+} \beta_{1,j}^+\, \Delta(ESG * EPU)_{t-j} + \sum_{j=1}^{q_1^-} \beta_{1,j}^-\, \Delta(ESG * EPU)_{t-j} + \sum_{j=1}^{q_2^+} \beta_{2,j}^+\, \Delta(NESG * EPU)_{t-j} + \sum_{j=1}^{q_2^-} (\beta_{2,j}^-\, \Delta(NESG * EPU)_{t-j} + \sum_{j=1}^{q_3^+} \beta_{3,j}^+\, \Delta(ESG * GPR)_{t-j} + \sum_{j=1}^{q_3^-} \beta_{3,j}^-\, \Delta(ESG * GPR)_{t-j} + \sum_{j=1}^{q_4^+} \beta_{4,j}^+\, \Delta(NESG * GPR)_{t-j} + \sum_{j=1}^{q_4^-} \beta_{4,j}^-\, \Delta(ESG * GPR)_{t-j} + \sum_{j=1}^{q_5^+} \beta_{5,j}^+\, \Delta(ESG * CPU)_{t-j} + \sum_{j=1}^{q_5^-} \beta_{5,j}^-\, \Delta(ESG * CPU)_{t-j} + \sum_{j=1}^{q_6^+} \beta_{6,j}^+\, \Delta(NESG * CPU)_{t-j} + \sum_{j=1}^{q_6^-} (\beta_{6,j}^-\, \Delta(NESG * CPU)_{t-j} + \varepsilon_t \tag{1}$$

Where variables RV,ESG*EPU, NESG*EPU, ESG*GPR, NESG*GPR, ESG*CPU and NESG*CPU represent the realized volatility, economic policy uncertainty after the launch of S&P500 ESG, economic policy uncertainty before the launch of S&P500 ESG, geopolitical risks after the launch of S&P500 ESG, geopolitical risks before the launch of S&P500 ESG, geopolitical risks, climate policy uncertainty before the launch the launch of S&P500 ESG, geopolitical risks after the launch of S&P500 ESG ,climate policy uncertainty before the launch of S&P500 ESG, respectively. Furthermore, The S&P 500 ESG Index was launched on January 28, 2019.

Partial sums of the positive and negative changes of the variables can be represented by positive and negative signs, respectively.

To obtain the stock market volatility variable for the S&P 500 index we sum the square of the daily returns to measure the monthly realized volatility (RV) of the S&P 500 index (Zhang et al., 2022). Specifically, the RV can be calculated as follows:

$$RV_t = \sum_{j=1}^{M_{i,t}} r_{t,j}^2 \tag{2}$$

Where $M_{i,t}$ represents the number of trading day in the t-th month r. (t,j)is the j-th daily return.

For the U.S.EPU, we downloaded it from the Economic Policy Uncertainty Index website. It was created by

Baker et al. (2016) drawing on collections of daily and weekly newspapers for Washington, D.C., and every state in the United States, excluding national newspapers published in a particular state such as the NY Times or Wall Street Journal.

Moreover, Caldara and Iacoviello (2022) develop the Geopolitical Risk Index (GPR). They construct a new measure of adverse geopolitical events based on a count of newspaper articles covering geopolitical tensions and examine its evolution and economic effects since 1900.

Gavrilidis (2021) developed an index of US climate policy uncertainty (CPU) by searching for major US newspaper articles containing terms related to the environment and climate {carbon dioxide, emissions or global warming, climate change, green energy, or renewable energy...) from January 2000 to March 2021. For each newspaper, it measures the number of relevant articles per month against the total number of articles in the same month. These series are then normalized to a unit standard deviation, and the newspapers are averaged for each month.

To construct the EPU, CPU and GPR series, before the launch of the S&P 500 ESG index, we multiplied these different variables by a dummy variable (ESG) which equals 0 before the launch of the S&P 500 ESG index and 1 after the launch of this index.

Similarly, to construct the EPU, CPU and GPR series after the launch of the S&P 500 ESG index, we multiplied these different variables by a dummy variable (NESG) which equals 1 before the launch of the S&P 500 ESG index and 0 after the launch of this index.

Table 1. Variable description and source of data

Variable	symbol	calculated	Data source
Dependent variable			
Realisedvolatility	RV	$RV_t = \sum_{j=1}^{M_{i,t}} r_{t,j}^2$	www.investing.com (Daily return of S&P500)
Independent variable			
Economicpolicyuncertainty	EPU	Natural logarithmic change rate in the economic policy uncertainty of U.S.A ($\Delta\ln(EPU)_t$)	www.policyuncertainty.com
Geopoliticalrisk	GPR	Natural logarithmic change rate in the the geopolitical risk of U.S.A ($\Delta\ln(GPR)_t$)	www.policyuncertainty.com
Climatepolicyuncertainty	CPU	Natural logarithmic change rate in the climate policy uncertainty of U.S.A ($\Delta\ln(CPU)_t$)	www.policyuncertainty.com

In equation (2), the short-run asymmetric effects for positive changes of economic policy uncertainty, geopolitical risks and climate policy uncertainty, e respectively given by $\beta_{1,j}^+, \beta_{2,j}^+, \beta_{3,j}^+, \beta_{4,j}^+, \beta_{5,j}^+$ and $\beta_{6,j}^+$ while the parameters for negative changes $\beta_{1,j}^-, \beta_{2,j}^-, \beta_{3,j}^-, \beta_{4,j}^-, \beta_{5,j}^-$ and $\beta_{6,j}^-$. Whereas, long-run asymmetric effects are respectively given by $\theta_{1,j}^+, \beta_{2,j}^+, \theta_{3,j}^+, \theta_{4,j}^+, \theta_{5,j}^+$ and $\theta_{6,j}^+$ for positive changes and by $\theta_{1,j}^-, \beta_{2,j}^-$, $\theta_{3,j}^-, \theta_{4,j}^-, \theta_{5,j}^-$ and $\theta_{6,j}^-$ for negative changes, normalized on θ_0.

Moreover, as represented by equations (3) and (4) defined below; the explanatory variables of the model are decomposed into positive and negative evolutions following partial sum processes:

$$X_t^+ = \sum_{j=1}^{t} \Delta X_j^+ = \max\left(\Delta X_j, 0\right) \quad (3)$$

$$X_t^- = \sum_{j=1}^{t} \Delta X_j^- = \min\left(\Delta X_j, 0\right) \quad (4)$$

Where X is a vector of the independent and control variables of the model: ESG_EPU, ESG_GPR, ESG_CPU, NESG_EPU, NESG_GPR and NESG_CPU. In fact, the increase in X represents the largest change in X or 0, while the decrease is equal to the smallest change in X or 0.

The error correction form of the NARDL model, Equation (2), can be introduced as follows:

$$RV_t = \beta_0 + \theta_0 EST_{t-1} + \sum_{j=1}^{q_0} \beta_{0,i}\, \Delta RV_{t-\mathrm{j}} + \sum_{j=1}^{q_1^+} \beta_{1,j}^+\, \Delta(ESG * EPU)_{t-j} + \sum_{j=1}^{q_1^-} \beta_{1,j}^-\, \Delta(ESG * EPU)_{t-j} + \sum_{j=1}^{q_2^+} \beta_{2,j}^+\, \Delta(NESG * EPU)_{t-j} + \sum_{j=1}^{q_2^-} (\beta_{2,j}^-\, \Delta(NESG * EPU)_{t-j} + \sum_{j=1}^{q_3^+} \beta_{3,j}^+\, \Delta(ESG * GPR)_{t-j} + \sum_{j=1}^{q_3^-} \beta_{3,j}^-\, \Delta(ESG * GPR)_{t-j} + \sum_{j=1}^{q_4^+} \beta_{4,j}^+\, \Delta(NESG * GPR)_{t-j} + \sum_{j=1}^{q_4^-} \beta_{4,j}^-\, \Delta(ESG * GPR)_{t-j} + \sum_{j=1}^{q_5^+} \beta_{5,j}^+\, \Delta(ESG * CPU)_{t-j} + \sum_{j=1}^{q_5^-} \beta_{5,j}^-\, \Delta(ESG * CPU)_{t-j} + \sum_{j=1}^{q_6^+} \beta_{6,j}^+\, \Delta(NESG * CPU)_{t-j} + \sum_{j=1}^{q_6^-} (\beta_{6,j}^-\, \Delta(NESG * CPU)_{t-j} + \varepsilon_t \quad (1)$$

Where

$$EST_{t-1} = RV_{t-1} + \sigma_1^+ ESG * EPU_{t-1}^+ + \sigma_1^- ESG * EPU_{t-1}^- + \sigma_2^+ NESG * EPU_{t-1}^+ + \sigma_2^- NESG * EPU_{t-1}^- + \sigma_3^+ ESG * GPR_{t-1}^+ + \sigma_3^- ESG * GPR_{t-1}^- + \sigma_4^+ NESG * GPR_{t-1}^+ + \sigma_4^- NESG * GPR_{t-1}^- + \sigma_5^+ ESG * CPU_{t-1}^+ + \sigma_5^- ESG * CPU_{t-1}^- + \sigma_6^+ NESG * CPU_{t-1}^+ + \theta_6^- NESG * CPU_{t-1}^- \quad (2)$$

Where ε_t is the error term. It is independently and identically distributed with zero mean and constant variance. q represents the lag order.

The long run asymmetric effects of the explanatory variables on the dependent variable are estimated by: $\sigma_1^+ = -\frac{\theta_1^+}{\theta}$, $\sigma_1^- = -\frac{\theta_1^-}{\theta}$, $\sigma_2^+ = -\frac{\theta_2^+}{\theta}$, $\sigma_2^- = -\frac{\theta_2^-}{\theta}$, $\sigma_3^+ = -\frac{\theta_3^+}{\theta}$, $\sigma_3^- = -\frac{\theta_3^-}{\theta}$, $\sigma_4^+ = -\frac{\theta_4^+}{\theta}$, $\sigma_4^- = -\frac{\theta_4^-}{\theta}$, $\sigma_5^+ = -\frac{\theta_5^+}{\theta}$, $\sigma_5^- = -\frac{\theta_5^-}{\theta}$, $\sigma_6^+ = -\frac{\theta_6^+}{\theta}$ and $\sigma_6^- = -\frac{\theta_6^-}{\theta}$. The Short run asymmetric effects are estimated $\sum_{j=1}^{q^+} \beta_j^+$ and $\sum_{j=1}^{q^-} \beta_j^-$

The error correction term, as presented in equation (6), captures the speed of adjustment to long-run equilibrium. In other words, the associated coefficient explains how long it takes to reach long-run equilibrium under the explanatory variable shocks.

The empirical study of this paper is conducted in the following four steps. The first step in estimating the NARDL model involves performing the unit root test, which checks to certify that no variable is I(2). The augmented Dickey-Fuller (ADF) and Phillips Perron (PP) unit root tests are used to ascertain the stationary nature of all variables at the start of the survey.

Second, the linked test for cointegration provides two asymptotic critical values me (0) and me (1). If the value of the F-statistic is greater than the upper critical bound, I(1), then the variables are cointegrated and there is a long-term relationship between them. We use equation (2) to test the null hypothesis of non-cointegration ($\theta_0 = \theta_1 = \theta_2 = \theta_3 = \theta_4 = \theta_5 = \theta_6 = 0$), which means that there is no long-term effect between the variables in the model. While the alternative hypothesis ($\theta_0 \neq \theta_1 \neq \theta_3 \neq \theta_4 \neq \theta_5 \neq \theta_6 \neq 0$), means the existence of a long-run effect between the variables in the model. Third, once the cointegration between the variables is validated, the estimation of the short-run and long-run coefficients can be implemented. Finally, in addition, we also use the CUSUM and CUSUM-SQ tests to check the stability of the model.

3. Results

Table 2**.** Descriptive statistics

	RV	ESG*CPU	NESG*CPU	ESG*EPU	NESG*EPU	ESG*GPR	NESG*GPR
Mean	0.002613	2.64E-06	-0.092150	-0.07190	-0.119018	0.013158	-0.005658
Median	0.001258	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Maximum	0.074739	0.069809	0.017749	245.3583	67.00769	1.940000	1.090000
Minimum	0.000150	-0.06075	-7.003961	-160.182	-98.72581	-1.50000	-1.230000
Std. Dev.	0.006403	0.007645	0.800705	31.71821	21.77974	0.359369	0.410055
Skewness	9.67124	1.70732	-8.544682	2.81698	-0.222884	0.93409	-0.022790
Kurtosis	107.772	72.9419	74.01218	32.3966	6.915209	14.8978	3.826952
Jarque-Bera	71892.44	31055.74	33786.92	5674.066	98.34130	918.6352	4.344206
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.113938
Sum	0.397201	0.000401	-14.00683	-10.9293	-18.09073	2.00000	-0.860000
Sum Sq. Dev.	0.006190	0.008826	96.81030	151912.8	71627.92	19.50108	25.38993
Observations	152	152	152	152	152	152	152

Table 2 presents the descriptive statistics of the variables in this study. Note that the political uncertainty index after the period of the creation of the S&P500 ESG index reaches a high value (245.3583) with a standard deviation of 31.71821. We can explain this by the uncertainty during this period (April 2019 until August 2022) due to the persistent economic panic of the COVID-19 pandemic and the War between Ukraine and Russia.

The correlation coefficient matrices of the variables are calculated and presented in Table 3. The results indicate that there is no obvious correlation between all the variables, and the highest correlation exists between the volatility of the index S&P 500(RV) and the climate policy uncertainty after the launch of the S&P500 ESG index (ESG* CPU) and this correlation is equal to 0.597074.

Table 3. Correlations coefficient matrix

	RV	ESG*CPU	NESG*CPU	ESG*EPU	NESG*EPU	ESG*GPR	NESG*GPR
RV	1	0.597074	0.007956	0.090987	0.060591	-0.283898	-0.008186
ESG*CPU	0.597074	1	4.00E-05	-0.444209	1.90EE-06	-0.316489	4. 80E-06
NESG*CPU	0.0079556	4.00E-05	1	-0.000263	0.024079	0.004242	0.095797
ESG*EPU	0.090987	-0.444209	-0.000263	1	-1.25E-05	0.142165	-3.15E-05
NESG*EPU	0.060591	1. 90E-06	0.024079	-1.25E-05	1	0.000201	-0.162911
ESG*GPR	-0.283898	-0.316489	0.004242	0.142165	0.000201	1	0.000509
NESG*GPR	-0.008186	4. 80E-06	0.095797	-3.15E-05	-0.162911	0.000509	1

Table 4. Findings of ADF and PP test for non-stationarity

Level I(0)								
Method		VR	ESG*CPU	NESG*CPU	ESG*EPU	NESG*EPU	ESG*GPR	NESG*GPR
ADF test	Constant	-9.697769***	-14.10814***	-12.12400***	-10.19698***	-9.753365***	-9.531823***	-17.61809***
	constant & trend	-9.735907***	-14.06000***	-11.84713***	-10.16424***	-9.718888***	-9.649296***	-17.55843***
PP test	Constant	-9.697769***	-115.3116***	-111.2299***	-10.90447***	-18.36755***	-24.84164	-36.70912***
	constant & trend	-9.735437***	-114.7836***	-106.6466***	-10.86147***	-19.35517***	-32.10294***	-36.61437***
First difference I(1)								
Method		VR	ESG*CPU	NESG*CPU	ESG*EPU	NESG*EPU	ESG*GPR	NESG*GPR
ADF test	Constant	-13.90328***	-9.907794***	-9.588675***	-10.16612***	-7.916194***	-8.098635***	-8.465657***
	constant & trend	-13.85538***	-9.870895***	-9.557512***	-10.12983***	-7.884021***	-8.247646***	-8.430424***
PP test	Constant	-98.89971***	-228.6554***	-12.24353***	-29.59311***	-64.43163***	-72.11416***	-172.2523***
	constant & trend	-99.36173***	-229.8839***	-12.45358***	-29.45784***	-64.14378***	-72.88071***	-194.6701***

Note. ***,**,* present significance at level 1%, 5%, and 10% respectively.

According to the augmented Dickey-Fuller and Phillips-Perron tests (table 4), we show that all the variables are stationary at level I (0), which indicates that the characteristics of all variables meet the requirements of the NARDL model for data stationarity.

Table 5. Cointegration Bounds Test

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	17.02385	10%	4.78	4.94
K	12	5%	5.73	5.77
		2.5%	6.68	6.84
		1%	7.84	5.59

Table 5 shows the results of the Bounds tests, where the F statistic is mapped to the two crucial values of the upper (I1) and lower (I0) bound. This model has an F-statistic of 17.023 and its upper bounds at the 1% and 10% significance levels are 5.59 and 4.94, respectively. The F-statistic of this model crosses the critical values of 1% and 10%, confirming the long-term asymmetric association of the variables. Therefore, the NARDL model could be used in the future.

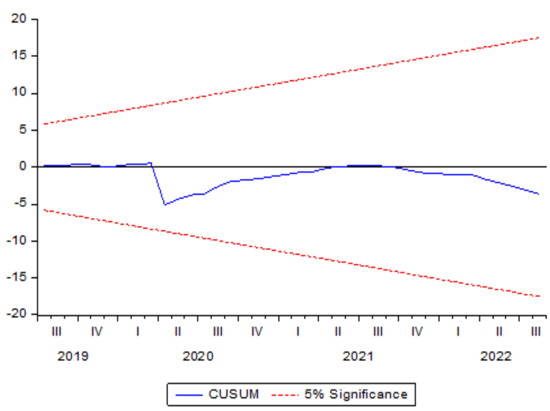

Figure 1. NARDL CUSUM tests

As shown in Figure 1, CUSUM is located within critical values, with a 5% significance, which indicates the stability and reliability of the selected model.

Finally, we apply the NARDL approach after checking the necessary conditions. The NARDL model results are exposed in Table 6.

Table 6. Results of NARDL model

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
Panel A: Short run				
RV-1	0.834818	0.051156	16.31896	0.0000***
$\Delta ESG * CPU^{+}$	0.939690	0.035806	26.24386	0.0001***
$\Delta ESG * CPU^{-}$	0.932904	0.033563	27.79556	0.0001***
$\Delta NESG * CPU^{+}$	2.70E-05	0.000311	0.086910	0.9309
$\Delta NESG * CPU^{-}$	0.119706	0.030615	3.910022	0.0001***
$\Delta ESG * EPU^{+}$	5.74E-06	7.51E-06	0.763848	0.4463
$\Delta ESG * EPU^{-}$	1.53E-05	7.75E-06	1.978473	0.0499**
$\Delta NESG * EPU^{+}$	7.82E-06	8.35E-06	0.935965	0.3509
$\Delta NESG * EPU^{-}$	-1.51E-06	8.14E-06	-0.185867	0.8528
$\Delta ESG * GPR^{+}$	0.000255	0.000567	0.449434	0.6538
$\Delta ESG * GPR^{-}$	-0.000536	0.000550	-0.973540	0.3320
$\Delta NESG * GPR^{+}$	-0.000116	0.000430	-0.268462	0.7887
$\Delta NESG * GPR^{-}$	-0.000126	0.000425	-0.296888	0.7670
C	0.001203	0.002103	0.571819	0.5684
Panel B: Long run				
$ESG * CPU^{+}$	5.688802	1.883717	3.019988	0.0030***
$ESG * CPU^{-}$	5.647720	1.881995	3.000921	0.0032***
$NESG * CPU^{+}$	0.000164	0.001882	0.086924	0.9309
$NESG * CPU^{-}$	0.724691	0.322273	2.248688	0.0261**
$ESG * EPU^{+}$	0.000035	0.000044	0.785498	0.4335
$ESG * EPU^{-}$	0.000093	0.000037	2.501025	0.0136**
$NESG * EPU^{+}$	0.000047	0.000052	0.906684	0.3662
$NESG * EPU^{-}$	-0.000009	0.000050	-0.183895	0.8544
$ESG * GPR^{+}$	0.001542	0.003399	0.453714	0.6508
$ESG * GPR^{-}$	-0.003243	0.003179	-1.020110	0.3095
$NESG * GPR^{+}$	-0.000700	0.002625	-0.266497	0.7903
$NESG * GPR^{-}$	-0.000765	0.002589	-0.295384	0.7681
C	0.007280	0.012839	0.567045	0.5716

Note. ***,**,* present significance at level 1%, 5%, and 10% respectively.

The table shown that positive and negative climate policy uncertainty shocks after the launch of the S&P500 ESG index positively affects the volatility of the S&P 500 stock index in the short-run and long-run at the threshold of 1٪. We also found that negative climate risk shocks before the launch of the S&P500 ESG index has a positive effect on the volatility of the S&P 500 stock market index in the short-run and at the threshold of 1 (p-value=0.0001). However, in the long-run, this effect becomes less significant as the p-value is equal to 0.0261. In addition, we found that the negative shock on economic policy uncertainty after the launch of the S&P500 ESG index has a positive impact on the volatility of the S&P 500 stock market index in the short -run and at the 5% threshold (pb=0.0499) but in the long -run we note that this effect becomes more significant as the probability is equal to 0.0136. The result also shows that positive and negative shocks to geopolitical risk before and after the launch of the S&P500 ESG index do not affect the volatility of the S&P 500 stock market index in the short -run and long -run.

4. Discussion

This paper examines the asymmetric impact climate policy uncertainty, geopolitical risk, and economic policy uncertainty on the volatility of the S&P 500 stock index: before and after the launch of the S&P 500 ESG Index, from January 2010 to august 2022. We use a Non-linear Autoregressive Distributed Lag (NARDL) approach.

Our findings suggest that positive and negative climate policy uncertainty shocks after the launch of the S&P500 ESG index positively affects the volatility of the S&P 500 stock index in the short-run and long-run Furthermore.

We also found that negative climate risk shocks before the launch of the S&P500 ESG index has a positive effect on the volatility of the S&P 500 stock market index in the short-run and long-run. Moreover, we found that the negative shock on economic policy uncertainty after the launch of the S&P500 ESG index has a positive impact on the volatility of the S&P 500 stock market index in the short-run and in the long-run. The result also shows that positive and negative shocks to geopolitical risk before and after the launch of the S&P500 ESG index do not affect the volatility of the S&P 500 stock market index in the short-run and long-run. The result also shows that positive and negative shocks to geopolitical risk before and after the launch of the S&P500 ESG index do not affect the volatility of the S&P 500 stock market index in the short-run and long-run.

These findings lead us to conclude that information about climate risks can influence stock market index price variance in general after the creation of the S&P 500 ESG stock market index. This is due to the large number of environmental hazards and disasters that have occurred over the past decade, such as droughts, earthquakes, and floods, especially in the last decade, especially since information and communication has become omnipresent and available to everyone for free in a global world where we live.

All these environmental changes contribute to increasing the volatility of the stock market. We explain the result of the negative shock on economic policy uncertainty after the launch of the S&P500 ESG index, by the repercussions of the Covid pandemic on the performance of the stock market.

Equity market provides a good framework for analysing the consequences of the physical risks associated with climate change on financial stability thanks to its central place in the financial system. By analysing the impact of this type of risk on stock market indices in general, we are recommending that investors in the stock market should consider better at the physical risks associated with climate change, take the necessary precautions and finding solutions to reduce these risks to businesses. In this sense, future research could study other stock markets that have issued an ESG index.

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