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Research article

Geopolitical crises and ESG market dynamics: The role of commodity prices, gold, and investor sentiment

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Abstract: Geopolitical events, such as the 2023 Israeli-Palestinian war, pose risks to sustainable finance by amplifying volatility in ESG stock indices, yet their interplay with investor sentiment and commodity prices remains underexplored. In this study, we analyzed how these factors shape ESG market dynamics across the United States, United Kingdom, France, Italy, and Canada. We applied GARCH models to volatility, alongside Probit and Logit regressions, using daily data from 2022–2024. Investor sentiment was derived via Natural Language Processing (NLP) for Twitter data, processed with Python and Hugging Face models; commodity prices included oil, natural gas, and gold. Our results revealed that the war significantly heightened ESG index volatility, with stronger effects in Europe than North America. Oil price shocks positively correlated with volatility, while investor sentiment showed limited influence before and after the event. These findings underscored ESG indices' vulnerability to geopolitical and commodity risks, informing risk management in sustainable portfolios.

Keywords: ESG indices; geopolitical risk; GARCH models; investor sentiment; sustainable finance; Natural Language Processing

JEL Codes: G15, G17, G11, F51, Q56

1. Introduction

Financial markets are increasingly shaped by geopolitical crises, global environmental challenges, and evolving societal expectations. These factors contribute to significant volatility in stock indices.

In this landscape, Environmental, Social, and Governance (ESG) indices have emerged as key instruments to assess market resilience and sustainability-oriented investment behaviors (Flourous et al., 2022; D'Ecclesia et al., 2024; Ahad et al., 2024; Alnafrah, 2024). In this study, we investigated how green finance, investor sentiment, and geopolitical disruptions interact to influence ESG markets, focusing on the Israeli-Palestinian war that began on October 7^{th}, 2023.

Green finance, anchored in sustainability and responsible corporate governance, is a strategic response to ecological and social risks. Its theoretical foundations lie in stakeholder theory (Freeman, 1984), behavioral finance (Shiller, 2000; Kahneman and Tversky, 1979), and the theory of ecological transition, which emphasises aligning economic systems with environmental objectives (World Commission on Environment and Development, 1987; Carney, 2015).

Green finance promotes sustainable development by integrating ESG factors into financial decisions. The concept originated with the Brundtland Report, 1987, and gained momentum in the early 1990s through initiatives by the World Bank and the European Investment Bank, leading to the first green bonds in 2007.

Carney (2015) highlighted climate related systemic risks, while Hawken (1993) argued for regenerative economics; businesses actively contributing to environmental sustainability. These perspectives have shaped ESG indices and investment strategies. By integrating non-financial risks, ESG investments are theorised to enhance market stability and reduce exposure to energy and climate shocks (D'Ecclesia et al., 2024; Ozkan et al., 2024).

Investor sentiment, shaped by digital and social media, has become increasingly relevant for explaining market behavior. Real-time opinions on platforms such as Twitter can influence investment decisions and price dynamics (Zeitun et al., 2022; Nyakurukwa and Seetharam, 2023).

Moreover, geopolitical crises are known to amplify a range of behavioral biases (see Section 2.1).

Despite growing interest in ESG finance, significant gaps remain. A key unresolved question is how geopolitical shocks collectively influence ESG index volatility and performance. These indices are not immune to such events. Impacts can arise through increased uncertainty and macroeconomic risks (Flourous et al., 2022), sectoral reallocation (Ozkan et al., 2024; D'Ecclesia et al., 2024), commodity price fluctuations (Mignon and Saadaoui, 2024; Ahad et al., 2024), policy sensitivity (Kovacs et al., 2024), investor sentiment (Oubani, 2024; Katsampoxakis et al., 2024), and long term ESG adoption (Alnafrah, 2024).

We have several objectives. We analyze the effect of geopolitical shocks during the Israeli Palestinian war on ESG index volatility (Alnafrah, 2024). We also assess how commodity prices (WTI oil, natural gas, gold) influence ESG market fluctuations across countries (Martins, 2024; Cui and Maghyereh, 2024). Furthermore, we evaluate the role of social media-based investor sentiment in explaining these variations (Boungou and Yatié, 2022; Qing et al., 2022; Renault, 2019; López Cabarcos et al., 2019).

We compare ESG index behavior across five national contexts, the United States, United Kingdom, France, Italy, and Canada, to identify structural patterns. Finally, we propose a robust econometric framework combining GARCH-X, Probit, and Logit models to capture the dynamic interplay between volatility, sentiment, and macro financial factors (López Cabarcos et al., 2019; Schaeffer et al., 2012; Neifar, 2020; Neifar et al., 2022).

However, most researchers examine ESG volatility through a single lens, commodity price transmission, investor sentiment, or geopolitical risk, without integrating all three mechanisms into a unified framework. Furthermore, the role of social media sentiments during the acute phase of the Israel-Hamas war remains unexplored.

We fill these gaps by simultaneously analysing commodity price transmission, Twitter based investor sentiments, and country specific volatilities within a unified GARCH-X framework across five ESG markets before and after the outbreak of the war.

This research offers a novel interdisciplinary contribution by integrating financial econometrics with behavioral finance and natural language processing. Using Python and Hugging Face NLP tools, investor sentiment is extracted from Twitter and linked to ESG market dynamics, particularly around a high-impact geopolitical event (Neifar et al., 2022; Zeitun et al., 2022).

By combining big data analytics and volatility modeling, this study advances our understanding of the factors driving ESG performance during periods of geopolitical uncertainty, contributing to academic literature and investment practice.

2. Literature review and hypothesis setting

2.1. Investor sentiment and market behavior

Measuring investor sentiment remains a methodological challenge. Traditional approaches rely on indirect proxies such as the Baker and Wurgler (2006) sentiment index, survey data, or attention-based measures derived from search engine queries (e.g., Google Trends, Wikipedia usage).

Studies by Moat et al. (2013) and Audrino et al. (2019) showed that these attention indicators improve volatility forecasts because they capture shifts in investor focus and information demand.

With the rise of social media, direct textual analysis has become prominent. Early lexicon-based methods assigned predefined polarity scores to words, but they often fail to capture contextual nuances, irony, or domain specific meanings.

To overcome this, researchers have adopted machine learning (ML) and, more recently, deep learning techniques. Ranco et al. (2015) and Renault (2019) compared ML classifiers and concluded that model performance is highly sensitive to preprocessing choices, training data quality, and domain adaptation of sentiment dictionaries.

A major advancement came with transformer-based models such as BERT. Nguyen et al. (2020) developed BERTweet, which was pre-trained on a large corpus of English tweets and substantially improves classification accuracy for short, informal texts.

Domain-specific variants like FinBERT further adapt the model to financial language. Paes Herrera et al. (2022) applied deep learning to renewable energy stock forecasting using Twitter sentiments, while Bapat et al. (2022) examined market reactions to ESG disclosures through sentiment analysis.

Comparative evaluations by Renault (2019) and Zvonarev and Bilyi (2019) consistently revealed that deep learning approaches outperform classical ML when combined with robust preprocessing pipelines.

The empirical literature converges on the view that investor sentiment is related to asset prices and volatility, but the magnitude, direction, and persistence of effects vary across markets, time periods, and asset classes.

For example, Audrino et al. (2019) showed that sentiment and attention indicators improve volatility forecasts, especially in high attention periods. Zeitun et al. (2022) identified Granger causal effects from Twitter sentiments to US sectoral returns, with differences in sensitivity across sectors.

Piñeiro Chousa et al. (2018) reported that social network sentiments can act as a transmission channel between equity and commodity markets.

In the ESG context, López Cabarcos et al. (2019) found that sentiments extracted from social networks influence the volatility of the S&P 500 Environmental & Socially Responsible Index, suggesting that sustainable assets are not insulated from investor mood swings. This is corroborated by Bapat et al. (2022), who showed that market reactions to ESG disclosures are mediated by sentiment dynamics.

The sentiment-market link becomes more pronounced during crises or geopolitical instability. Qing et al. (2022) found that the synergy between stock prices and investor sentiment strengthens under high uncertainty.

This is especially true during geopolitical crises, which amplify emotional and behavioral biases: fear and euphoria (Kahneman and Tversky, 1979; Shiller, 2000), herding (Bikhchandani et al., 1992; Chang et al., 2000; Bogdan et al., 2022), loss aversion (Kahneman and Tversky, 1979; Hersh and Meir, 1985; Benartzi and Thaler, 1995), media and social network effects (Tetlock, 2007; Garcia, 2013; Luo et al., 2013; Wang et al., 2020), ambiguity (Camerer and Weber, 1992; Epstein and Schneider, 2008; Bossaerts et al., 2010), FOMO (Shiller, 2000; Hirshleifer, 2001; Altundal et al., 2024), and emotional contagion (Lynch, 2000; Bollen et al., 2011).

Jena Ranjan and Majhi (2022) showed that Twitter sentiments during the COVID-19 pandemic were a critical determinant of stock market movements. Boungou and Yatié (2022) highlighted how geopolitical shocks, such as the Russia-Ukraine conflict, amplify sentiment driven volatility.

These findings directly motivate analysing sentiment effects before and after acute events like the Israel-Hamas conflict, using models that capture volatility clustering and regime shifts.

Despite these advances, several challenges persist. First, noise and representativeness are major concerns: Twitter users do not mirror the broader investor population, and sentiment signals may be dominated by non-financial chatter. Renault (2019) and Zvonarev and Bilyi (2019) stressed the importance of filtering tweets for relevance and weighting sentiment scores appropriately.

Second, preprocessing sensitivity, i.e., negation handling, tokenisation, and labelling accuracy, significantly affects sentiment estimates (Paes Herrera et al., 2022; Xiang et al., 2022), making cross-study comparisons difficult without standardisation.

Third, causality remains elusive; while many researchers find contemporaneous relationships, causal inference requires event study designs, lag structures, or instrumental variables. Zeitun et al. (2022) and wavelet/TVP VAR approaches offer promising strategies.

Fourth, heterogeneity across assets, sectors, and time horizons calls for models that enable time variation and structural breaks; hence, the adoption of GARCH-X specifications, time varying parameter VARs, and wavelet coherence methods.

Taken together, the literature supports integrating social media sentiments into volatility modeling for ESG indices. Twitter provides high frequency, real time mood measures, and advanced NLP models like BERTweet or FinBERT enhance classification accuracy. However, the limitations, noise, representativeness, preprocessing sensitivity, and causal ambiguity, demand robust methodological designs.

We address these issues by focusing on a clearly defined event window around the Israel-Hamas war, using a GARCH-X framework with sentiment as an exogenous regressor, employing advanced NLP tools, and comparing pre and post event dynamics. Thus, we hypothesise:

- *H1: Investor sentiments, as extracted from social media, have a significant impact on ESG index volatility.*

2.2. Impact of geopolitical conflicts on financial markets

Geopolitical conflicts are well-recognised sources of financial instability, manifesting in heightened uncertainty, increased volatility, and abrupt capital flows, as investors reallocate portfolios and seek safe havens.

A key transmission channel is the fluctuation of major commodity prices, oil, natural gas, and gold, which are vital economic inputs and widely traded financial assets sensitive to supply, demand, and sentiment shocks.

Studies on the Russia-Ukraine and Israel-Hamas wars illustrate these dynamics. Boungou and Yatié (2022) found that the Russia-Ukraine conflict significantly depressed global stock returns with regional variations. Wu et al. (2023) documented substantial volatility increases in global equity markets during that conflict.

In the Middle East, Necati et al. (2024) found that the October 7th, 2023 Hamas-Israel conflict generated significant abnormal returns, mostly negative, in regional markets.

Using an event study methodology, Martins (2024) reported that the negative impact on global equity markets was concentrated in the Middle East, while commodity and bond markets recorded positive abnormal returns during the escalation, highlighting their hedging role.

Pandey (2024) adds a behavioral dimension: Stock markets in "happier" countries exhibited greater resilience, suggesting that cultural and institutional factors matter. Goyal and Soni (2024) found heterogeneous spillovers globally, with emerging markets more sensitive.

Commodities serve dual roles: As transmission channels and potential safe havens. Oil and gas are highly responsive to geopolitical risk due to their strategic importance and concentrated production in sensitive regions. Mignon and Saadaoui (2024) showed that heightened risk events lead to significant oil price adjustments, with magnitude varying by conflict type and market conditions.

Cui and Maghyereh (2024) examined higher order moment risk spillovers across oil, gas, gold, and equity markets in Israel and Palestine. They found that the outbreak of the war sharply intensified total volatility spillovers and higher moment risks, with magnitudes exceeding prior periods, which is evidence of structural change in commodity-equity interdependence.

Gold consistently acts as a stabiliser. In ESG contexts, GARCH-based models show gold's dampening effect during conflicts, reinforcing its role as a portfolio diversifier and hedge.

Martins (2024) and Lin et al. (2024) further documented positive abnormal returns for precious metals and energy products during geopolitical tensions, as investors rebalance toward hard assets. Using time-frequency and network analysis, Lin et al. (2024) showed that the Israel-Hamas war intensified global risk spillovers, with short term effects dominating and altering market community structures.

The impact is not uniform. Ozkan et al. (2024) analyzed dynamic volatility connectedness between fossil energy, clean energy, and major assets during the Russia-Ukraine war and COVID

19 pandemic. Fossil fuel ETFs often benefit from supply disruptions, while clean energy ETFs and ESG indices may underperform due to reliance on stable supply chains and critical materials (e.g., lithium and cobalt).

D'Ecclesia et al. (2024) similarly reported that fossil fuel focused ETFs outperform during energy crises, whereas renewable energy focused indices face temporary setbacks.

Geopolitical disruptions also increase volatility in renewable energy sectors due to dependency on imported raw materials and global manufacturing chains, meaning price shocks in oil, gas, or rare metals ripple into ESG and green energy indices.

Risk spillover models such as DCC GARCH and TVP VAR are widely used to map shock propagation. Lin et al. (2024) showed that during the Israel-Hamas war, net risk transmission between commodities and equities shifted dramatically, altering short and long term hedging relationships.

Cui and Maghyereh (2024) found that higher-order moment spillovers, i.e., capturing skewness and kurtosis effects, are especially pronounced in crisis periods, suggesting that extreme event risks become more interlinked.

These patterns are consistent with evidence from the Russia-Ukraine war (Boungou and Yatié, 2022) and multi conflict studies (Martins, 2024), underscoring the interconnected nature of modern financial and commodity markets.

The ESG focused literature adds another layer. Ahad et al. (2024) investigated safe haven dynamics between European ESG and energy assets during the Russia-Ukraine war, showing that sustainable investments offer diversification benefits, though their safe haven properties are context dependent.

Alnafrah (2024) found that ESG firms exhibit greater resilience to geopolitical risks than non-ESG firms, suggesting that integrating ESG criteria may provide partial insulation. However, the exclusion of fossil fuel companies from many ESG indices can reduce defensive capacity during energy price surges when oil and gas outperform due to supply shocks.

Despite extensive research, gaps remain. Most researchers focus on aggregate market indices rather than ESG-specific indices, which may respond differently to commodity shocks. Gold's safe haven role is well established, but the conditions under which ESG assets can serve as safe havens, especially during commodity price surges, are underexplored.

Higher order risk spillovers in ESG contexts are only beginning to be analyzed. We address these gaps by combining event study and GARCH-X modeling to assess the impact of oil, gas, and gold price fluctuations on ESG index volatility before and after the Israel-Hamas war.

By focusing on multiple developed economies, we contribute to understanding how commodity–equity linkages evolve under geopolitical stress. Thus, we hypothesise:

- *H2: The geopolitical conflict in Gaza has increased the volatility of ESG indices, altering their risk-return dynamics.*
- *H3: Commodity prices, particularly oil, gas, and gold, mediate the relationship between geopolitical events and ESG index movements.*

3. Research methodology

We employ a dual methodological framework to examine the effects of geopolitical shocks, particularly the Ukrainian and Israeli-Palestinian conflicts, on the volatility and dynamics of ESG stock indices across G7 countries.

3.1. GARCH-X volatility modeling

To assess the time-varying nature of volatility in ESG indices, we utilize the Generalized Autoregressive Conditional Heteroskedasticity with the exogenous variables (GARCH-X) model. This approach captures the conditional volatility patterns in financial time series, enabling the inclusion of external factors such as:

- Investor sentiment extracted from social media (SENT; the construction of SENT is detailed in Section 4.2).
- Global commodity prices, including WTI crude oil, natural gas (NG), and gold (GOLD).
- Domestic market volatility indices (e.g., VOL and its country-specific equivalents).

3.2. Probit and Logit models for binary event analysis

Probit and Logit models are regression-based tools commonly used to estimate the probability of an event occurring based on a set of explanatory variables. In the context of this study, these models are applied to analyze the probability of ESG index variations in response to factors such as commodity price changes, market volatility, and investor sentiment.

These models belong to the binary regression family, designed to estimate the likelihood of a dichotomous outcome (e.g., increase or decrease in ESG index values). The distinction between the two lies in the distribution function used:

- The Probit model relies on the standard normal cumulative distribution function (CDF) and assumes that errors follow a normal distribution. It is particularly suitable when the response variable is influenced by continuous predictors.
- The Logit model is based on the logistic CDF and is appropriate when the errors follow a logistic distribution. It is often favoured for its robustness in estimating probabilities.

In this study, the Probit and Logit specifications are employed as complementary approaches to the GARCH-X framework rather than as sequential extensions of the volatility model. While the GARCH-X specification is designed to capture the conditional volatility dynamics of ESG returns under geopolitical stress, the Probit and Logit models estimate the probability of observing post-war market conditions as a function of commodity prices, investor sentiment, and market-related indicators. Therefore, the binary models do not directly use the conditional variance generated by the GARCH process as the dependent variable, but instead focus on identifying regime-switching characteristics associated with geopolitical events.

Given the extreme volatility generated by the Israel-Hamas conflict, the sample is divided into pre-war and post-war sub-periods to account for potential structural breaks and regime changes in ESG market dynamics. This decomposition reduces estimation bias associated with abrupt geopolitical shocks and enables the GARCH-X framework to capture time-varying volatility patterns under different market conditions.

4. Data collection

4.1. Data

We employ daily closing prices of ESG stock indices from five major G7 countries (USA, Canada, United Kingdom, France and Italy) to analyze market dynamics in response to geopolitical tensions. The indices used include: the S&P 500 ESG for the United States, the S&P/TSX 60 ESG for Canada, the FTSE4GOOD US 100 for the United Kingdom, the CAC 40 ESG for France, and the MIB ESG for Italy. In addition to these indices, country-specific volatility measures are included, such as the CBOE Volatility Index (VIX) for the U.S. market, the S&P/TSX Composite Volatility Index for Canada, and the volatility of the iShares MSCI EFA ETF (EFA ETF VOL) as a proxy for UK, French, and Italian market volatilities.

To account for global macroeconomic risk factors, the dataset also integrates daily prices of key commodities: crude oil (West Texas Intermediate - WTI), natural gas (LNG), and gold. All data are retrieved from Bloomberg Terminal and Investing.com. In Appendix 2, we summarize the collected variables and their sources.

To avoid spurious correlations, all non-stationary variables are transformed into logarithmic returns or first differences after unit root testing.

The use of differenced variables (ΔLWTI, ΔLNG, ΔLGOLD, ΔLVIX) ensures stationarity and improves the reliability of volatility estimations.

In the variable names, the prefix 'L' denotes the natural logarithm (e.g., LWTI = log of WTI oil price).

The volatility of the iShares MSCI EAFE ETF is denoted as LEFAETFVOL.

4.2. Sentiment index determination

Investor sentiment is measured using Natural Language Processing (NLP) techniques applied to Twitter data. The methodology follows a four-step process: Data Extraction: Tweets are collected using the Playwright tool in Python, enabling asynchronous scraping and structured retrieval. For the search, we focus on keywords such as "S&P500 ESG", "Green Finance", and "Sustainability" (Table 1), following the method outlined by Kevin et al. (2021) and implemented using open-source automation libraries. To reduce noise and irrelevant content commonly associated with Twitter data, tweets are filtered using ESG- and finance-related keywords and cleaned through preprocessing procedures, including token normalization, duplicate removal, and irrelevant-content filtering. Daily sentiment scores are then aggregated to construct a standardized sentiment index. Preprocessing: To ensure the semantic clarity of the data, tweets undergo preprocessing operations, including the removal of URLs, punctuation, special characters, and duplicate entries. Tokenization and stop-word removal are performed using standard Python NLP libraries, which is consistent with the sentiment processing approaches detailed in Neifar (2020). Sentiment Analysis: To address cross-cultural and cross-linguistic comparability of sentiment analysis across the five countries (US, UK, France, Italy, Canada), we employ the Hugging Face "cardiffnlp/twitter-xlm-roberta-base-sentiment model". This is a multilingual transformer-based classifier pre-trained on approximately 198 million tweets in multiple languages, including English, French, and Italian. Unlike monolingual models (e.g., BERTweet for English only), this model has been shown to achieve consistent sentiment classification performance across languages, reducing language-induced bias (Nguyen et al., 2020). Nevertheless, we acknowledge that cultural differences in sentiment expression (e.g., intensity, sarcasm, and emoticon usage) may affect cross-country comparability. To mitigate this, we apply the same preprocessing pipeline (URL removal, tokenization, stop-word filtering) to all tweets regardless of language, and we do not translate tweets, thereby preserving original linguistic nuances. Furthermore, our sentiment index is aggregated daily and used as a relative measure (changes over time) rather than an absolute cross-country benchmark. This approach, which is common in the literature (López-Cabarcos et al., 2019), focuses on the temporal dynamics of sentiment within each country rather than direct level comparisons across countries. As a brief validation of the sentiment measure, we verify that the constructed SENT index is stationary (unit root tests, Appendices 3–7), exhibits plausible behavioral shifts (e.g., mean sentiment shifts from slightly negative pre-war to positive post-war in most countries, as shown in Table 4), and is not spuriously correlated with commodity prices (Appendix 8). These properties support its use in time-series volatility modelling. Regarding the comparability of financial indices across economies, we recognize that ESG index compositions differ by country (e.g., S&P 500 ESG vs. CAC 40 ESG vs. MIB ESG). However, all indices share the common characteristic of being ESG-filtered versions of their respective national benchmarks, and each is calculated by reputable providers (S&P, FTSE Russell, Euronext, Borsa Italiana). For our analysis, we focus on each country's ESG return dynamics separately, and we do not directly compare coefficient magnitudes across countries without contextual qualification. Aggregation: A daily sentiment index is calculated by averaging the sentiment scores for all tweets per day. The aggregation follows the sentiment index methodology proposed by López-Cabarcos et al. (2019), which is adapted for time-series financial analysis. This process results in a dynamic variable, "SENT", capturing investor mood across ESG-related topics in real time.

Table 1. Keywords used to search for tweets related to country ESG indices.

Index	Keywords	Country	Number of tweets found
S&P500 ESG	US green finance, US sustainability, S&P500 ESG, S&P 500 ESG, SP500 ESG , S&P ESG, S&P500ESG	USA	6244
S&P/TSX 60 ESG	Canada ESG, La finance verte Canada, CSR Canada, Green finance Canada, Canadian sustainability, S&P/TSX 60 ESG, S&P TSX 60 ESG, TSX60 ESG, TSX 60 ESG , S&P TSX ESG	Canada	7662
FTSE4GOOD 100	UK ESG, UK sustainability	UK	2029
CAC40 ESG	Finance verte, RSE France, CAC ESG, Durabilité France, CAC40 ESG	France	5725
MIB ESG	ambiente sociale governance, Sustainability Italia, Sostenibilità, MIB ASG, MIB ESG	Italy	29648

This sentiment index serves as a key explanatory variable in the econometric modeling of ESG index volatility during geopolitical crises such as the Israeli-Palestinian conflict.

To investigate the impact of investor sentiment and other explanatory variables on the volatility of ESG indices during geopolitical crises, we employ the GARCH model to capture conditional volatility dynamics with the following details:

Each country's ESG index return R_{it} is modelled using two equations (Table 5):

- A conditional mean equation:

$$R_{it} = c + \beta\, \Delta LVOL_{it} + u_t \tag{1}$$

- A conditional variance equation:

$$\sigma^2{}_{it} = \alpha_0 + \sum_{i=1}^{p} \alpha_i u^2{}_{t-i} + \sum_{i=1}^{q} \beta_i \sigma^2{}_{t-i} + \gamma_1\, X_t \tag{2}$$

where X_{it} includes the exogenous variables SENT, ΔWTI, ΔNG, and ΔGOLD. This framework enables a comparison of volatility persistence and sensitivity before and after the geopolitical events.

The adequacy of each model is tested using Ljung-Box tests (LB) on residuals and squared residuals (Figure 1). The significance of the exogenous regressors in the variance equation is assessed via Wald tests.

Below are country-specific versions of the GARCH-X model equations used in our research. Each set includes:

- The mean equation for the ESG index returns.
- The variance equation incorporating exogenous variables (commodity price changes and sentiment).
- Each adapted for a G7 country (see appendix 1).

Let us denote:

- R_{it} = ESG index return of country *i* at time *t*.
- $\sigma {i_t}^2$ = conditional variance of returns.
- $SENT_t$= investor sentiment at time *t*.
- $\Delta WTI_t, \Delta NG_t, \Delta GOLD_t$ = daily returns of oil, gas, and gold, respectively.
- VOL_i = domestic volatility index for country *i*.

We also employ Probit and Logit models (Table 6) to analyze the likelihood of market events with the following details:

We consider a binary outcome variable Y_t, which takes the value 1 for observations in the post-war period (after October 7, 2023) and 0 otherwise:

Y_t=1 in the post-war period (the war began on October 7th, 2023), and Y_t=0 otherwise

Next, a parametric nonlinear Probit or Logit regression is estimated, assuming the probability of the binary outcome Y_t is related to a set of potential predictors Z_t:

$P_t = P(Y_t = 1\, / Z)$

Where Z_t is one of the following combinations of explanatory variables:

$Z_t = (R, \Delta LVIX, SENT, \Delta LWTI, \Delta LGN, \Delta LGOLD)$,

Or

$Z_t = (R, \Delta LSPTSXVIX, SENT, \Delta LWTI, \Delta LGN, \Delta LGOLD)$,
Or
$Z_t = (R, \Delta EFAETFVOL, SENT, \Delta LWTI, \Delta LGN, \Delta LGOLD)$,
Depending on the country under analysis.
The general form of the model is:

$$P_i = \begin{cases} \phi(\beta_0 + \sum \beta_k Z_{kt}) \\ \Lambda(\beta_0 + \sum \beta_k Z_{kt}) \end{cases}, \quad (3) \text{ and } (4)$$

where

- Φ is the standard normal cumulative distribution function (CDF) for the Probit model.
- $\Lambda(\mathrm{w}) = \frac{\exp(w)}{1+\exp(w)}$ is the logistic cumulative distribution function (CDF) for the Logit model.
- β_k for k ∈ (1, . . ., K) represents the coefficient associated with the corresponding explanatory

variable Z_{kt} of Z_t as previously defined.

This model specification has been applied in financial studies (e.g., López-Cabarcos et al., 2019; Neifar et al., 2022). The global significance of the model is evaluated using LR (Likelihood Ratio), LM (Lagrange Multiplier), or F-tests.

5. Descriptive analysis

Table 2 summarizes the results of the PP test for variables related to the international environment (crude oil price, natural gas price, and gold price). According to Table 2, only the LNG series in the pre-war period is stationary at a level in the regression with the constant. The other series (LWTI and LGOLD) are non-stationary at a level for the pre-war and post-war periods but become stationary at first difference (I1).

The stationarity tests (unit root tests) for the variables corresponding to each country in the study, namely the United States, Canada, the United Kingdom, France, and Italy, are reported in Appendices 3, 4, 5, 6, and 7, respectively.

Figure 2 illustrates the evolution of the series: crude oil price (WTI), natural gas price (NG), and gold price (GOLD) in a logarithm scale.

1. Pre-war

2. Post war

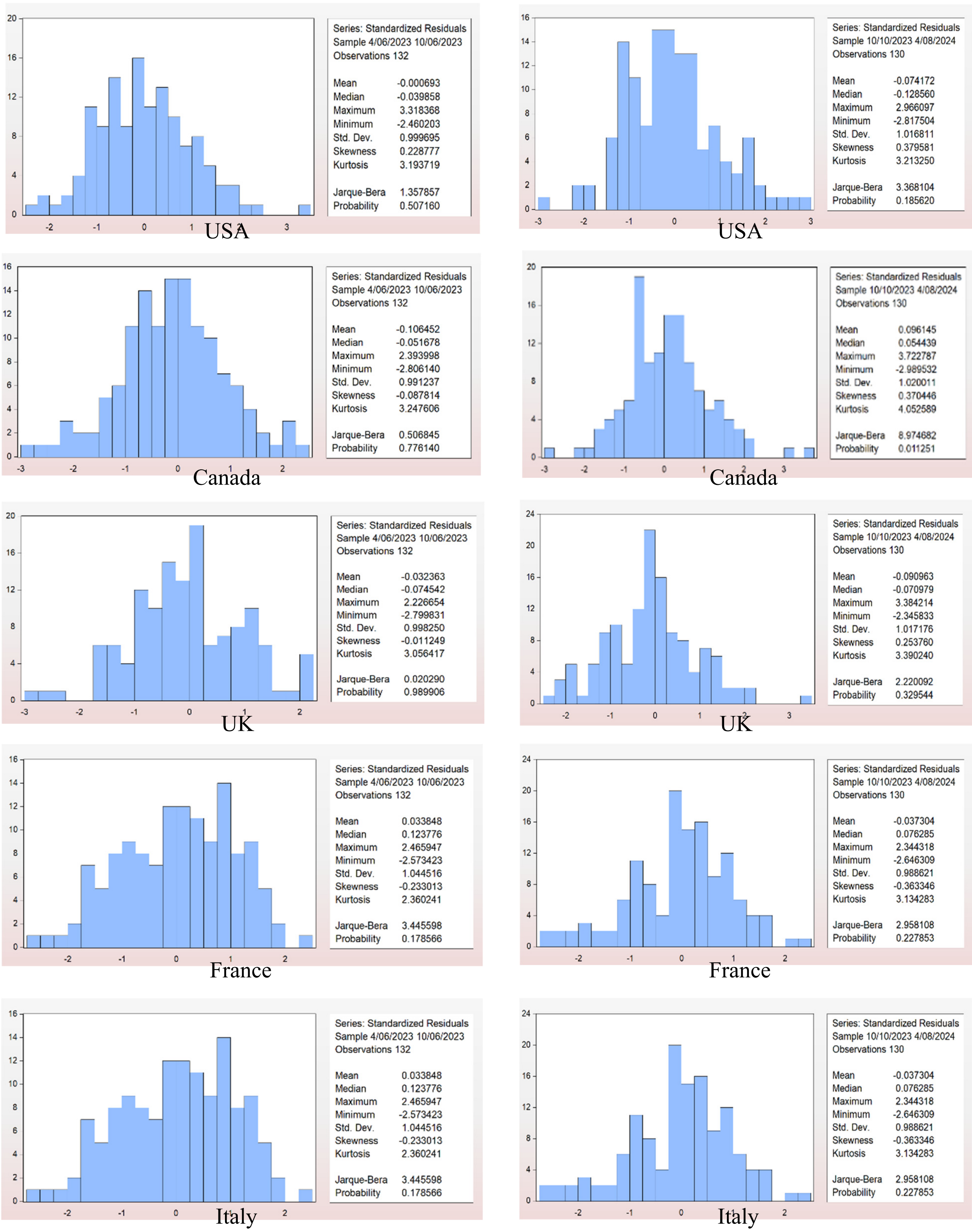
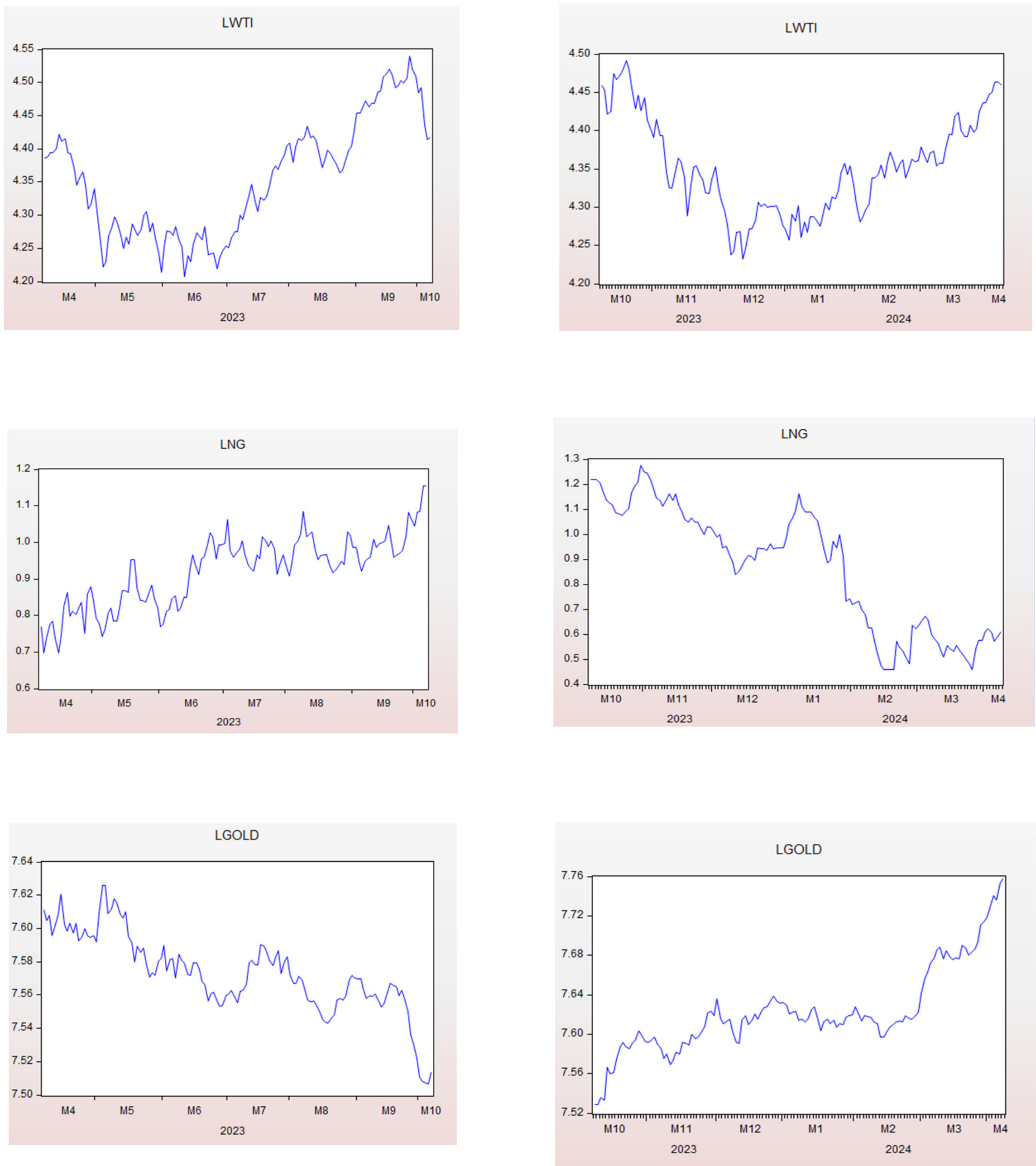


Figure 1. Behavior of the Residuals from the GARCH-X1 Model (Pre-War) and GARCH-X2 Model (Post-War).

Table 2. PP test results.

		All			Pre			Post		
In level		**LWTI**	**LNG**	**LGOLD**	**LWTI**	**LNG**	**LGOLD**	**LWTI**	**LNG**	**LGOLD**
With C	t-Statistic	−1.7877	−1.3443	0.7385	−1.1966	−1.2978	−0.9053	−1.6434	−1.1958	0.0905
	Prob.	0.3862	0.6092	0.9928	0.6748	0.6294	0.7840	0.4576	0.6751	0.9639
		n0	n0	n0	n0	n0	n0	n0	n0	n0
With C & T	t-Statistic	−1.9088	−1.7483	−0.7139	−2.1967	−3.8945	−2.7564	−1.3819	−1.8405	−1.1344
	Prob.	0.6471	0.7268	0.9704	0.4871	0.0149	0.2162	0.8619	0.6793	0.9184
		n0	n0	n0	n0	**	n0	n0	n0	n0
Without C & T	t-Statistic	0.2179	−0.5286	1.0612	0.1146	1.8520	−1.3409	−0.0146	−1.5499	2.3560
	Prob.	0.7488	0.4861	0.9246	0.7172	0.9845	0.1661	0.6761	0.1135	0.9956
		n0	n0	n0	n0	n0	n0	n0	n0	n0
In first difference	**ΔLWTI**	**ΔLNG**	**ΔLGOLD**	**ΔLWTI**	**ΔLNG**	**ΔLGOLD**	**ΔLWTI**	**ΔLWTI**	**ΔLNG**	**ΔLGOLD**
With C	t-Statistic	−15.672	−15.195	−15.7752	−10.6866	−14.8437	−11.6385	−11.3583	−9.86797	−11.1207
	Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		***	***	***	***	***	***	***	***	***
With C & T	t-Statistic	−15.6964	−15.3034	−15.988	−10.6858	−14.7201	−11.6327	−12.3315	−9.8385	−11.0946
	Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		***	***	***	***	***	***	***	***	***
Without C & T	t-Statistic	−15.6994	−15.2255	−15.7390	−10.7266	−13.1729	−11.5590	−11.4071	−9.8061	−10.7377
	Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		***	***	***	***	***	***	***	***	***
Conclusion		I(1)	I(1)	I(1)	I(1)	In level	I(1)	I(1)	I(1)	I(1)

Notes: (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1%; and (no) Not Significant. *MacKinnon (1996) one-sided p-values.



(a) Pre war (b) post war

Figure 2. Evolution of the series: oil price (WTI), natural gas price (NG), gold price (GOLD) in log scale.

Table 3 indicates that the correlation between gas and oil prices is significant only in the pre-war period, while the correlation between gas and gold prices is significant only in the post-war period. Similarly, the correlation between oil and gold prices is significant before the war but not after. This suggests that regressions for both periods can include all three variables: oil, gas, and gold prices. Therefore, a single regression model including these three commodity prices can be applied separately for the pre-war and post-war periods.

Table 3. Correlation matrices (for the study period, pre-war, and post-war).

All				Pre				Post			
	ΔLWTI	ΔLNG	ΔLGOLD		ΔLWTI	LNG	ΔLGOLD		ΔLWTI	ΔLNG	ΔLGOLD
ΔLWTI	1.0000			ΔLWTI	1.0000			ΔLWTI	1.0000		
	-----				-----				-----		
ΔLNG	0.1325	1.0000		LNG	0.07450	1.0000		ΔLNG	0.0433	1.0000	
	(0.0317)	-----			(0.3928)	-----			(0.6248)	-----	
ΔLGOLD	0.0897	0.0072	1.0000	ΔLGOLD	−0.0215	−0.0073	1.0000	ΔLGOLD	0.1630	0.0073	1.0000
	(0.1468)	(0.9078)	-----		(0.8065)	(0.9334)	-----		**(0.0639)**	(0.9346)	-----

Table 4 presents descriptive statistics that highlight key differences in ESG market behavior across the US, Canada, UK, France, and Italy during the study period. The UK's FTSE4GOOD index has the highest average ESG levels, while the US S&P 500 ESG shows the lowest, reflecting structural market differences. Investor sentiments from Twitter are generally positive, except for a slightly negative average in the US before the Israeli-Palestinian war on October 7th, 2023. Volatility indices decline across all countries post-war, indicating that markets absorb initial geopolitical uncertainty, while sentiment increases, suggesting a more stable investor outlook. Distributional tests reveal persistent non-normality and asymmetry, especially in sentiment and volatility, with ARCH-LM tests (Autoregressive Conditional Heteroskedasticity Lagrange Multiplier) confirming heteroskedasticity, notably in the US and Italy, justifying the use of GARCH-X models. Overall, ESG markets show resilience to geopolitical shocks, with post-war increases in ESG index levels, reduced volatility, and improved sentiment, except in Italy where conditional volatility persists. These findings suggest strategic capital shifts toward safer or more responsible assets during geopolitical crises.

The following variable symbols are used in Table 4 and subsequent analyzes: LSPESG (log of S&P 500 ESG index), LVIX (log of VIX), SENT (investor sentiment index), R (daily return of the ESG index), LSPTSXESG (log of S&P/TSX 60 ESG), LSPTSXVIX (log of S&P/TSX Composite Volatility Index), LFTSE4GOOD (log of FTSE4GOOD 100), LEFAETFVOL (log of EFA ETF volatility), LCACESG (log of CAC 40 ESG), and LMIBESG (log of MIB ESG).

Figure 3 shows that the levels of ESG index variables for the US (LSPESG), Canada (LSPTSXESG), UK (LFTSE4GOOD), France (LCACESG), and Italy (LMIBESG) markets are non-stationary (Figure 3a). However, their first differences, ΔLSPESG, ΔLSPTSXESG, ΔLFTSE4GOOD, ΔLCACESG, and ΔLMIBESG, exhibit stable means and variances, indicating possible stationarity (I(1)). This is confirmed through unit root tests (ADF and PP) detailed in Appendices 3 to 7. Additionally, the variables LVIX, SENT, and LEFAETFVOL are stationary with stable mean and variance across all markets, as shown in Figure 3b.

Table 4. Descriptive statistics of ESG indices, volatility measures, sentiment, and returns before and after the Israeli-Palestinian conflict.

	USA				Canada				UK			
Panel A: All the period	**LSPESG**	**LVIX**	**SENT**	**R**	**LSPTSXESG**	**LSPTSXVIX**	**SENT**	**R**	**LFTSE4GOOD**	**LEFAETFVOL**	**SENT**	**R**
Mean	5.996	2.704	0.183	0	7.055	2.22	0.185	0	9.865	2.704	0.192	0.000
Maximum	6.14	3.078	0.857	0.004	7.122	2.605	0.625	0.005	10.031	3.034	1	0.003
Minimum	5.88	2.491	−0.389	−0.005	6.923	1.747	−0.231	−0.004	9.73	2.436	−1	−0.009
Std. Dev.	0.07	0.137	0.134	0.001	0.044	0.135	0.14	0.001	0.082	0.136	0.359	0.001
Skewness	0.399	0.673	−0.024	−0.065	−0.881	0.349	0.17	−0.08	0.483	0.3	0.39	0.105
Kurtosis	2.198	2.433	6.413	3.777	3.162	3.622	3.283	4.931	2.278	2.426	4.609	3.254
Jarque-Bera	14.097	23.454	128.156	6.807	34.303	9.574	2.146	41.169	15.922	7.548	35.031	1.188
Probability	0.001	0	0	0.033	0	0.008	0.342	0	0	0.022	0	0.552
Observations	264	264	264	263	264	264	264	263	263	263	263	263
ARCH-LM				4.305				1.000				0.160
(p)				(0.0390)				(0.318)				(0.690)
Panel B: Before the war	**LSPESG**	**LVIX**	**SENT**	**R**	**LSPTSXESG**	**LSPTSXVIX**	**SENT**	**R**	**LFTSE4GOOD**	**LEFAETFVOL**	**SENT**	**R**
Mean	5.95	3	−0.055	0.001	7.05	2.24	0.166	0	9.806	2.754	0.187	0
Maximum	6.01	3.596	0.154	0.025	7.096	2.473	0.526	0.004	9.863	3.009	1	0.002
Minimum	5.881	2.709	−0.212	−0.03	6.95	2.021	−0.128	−0.004	9.729	2.451	−0.5	−0.002
Std. Dev.	0.037	0.203	0.054	0.001	0.031	0.105	0.122	0.001	0.04	0.11	0.319	0.001
Skewness	−0.296	0.876	0.696	−0.211	−0.992	0.412	0.072	−0.346	−0.43	−0.175	0.774	0.118
Kurtosis	1.764	2.894	5.473	3.136	3.951	2.605	2.809	3.867	1.861	2.384	3.629	2.812
Jarque-Bera	10.326	9.728	199.77	3.593	26.627	4.593	0.313	6.777	11.207	2.762	15.349	0.499
Probability	0.006	0.008	0	0.166	0	0.101	0.855	0.034	0.004	0.251	0	0.779
Observations	132	132	132	131	133	133	133	132	132	132	132	132
ARCH-LM				3.630				0.907				0.747
(p)				(0.059)				(0.342)				(0.389)

Continued on next page

Panel C: After the war	LSPESG	LVIX	SENT	R	LSPTSXESG	LSPTSXVIX	SENT	R	LFTSE4GOOD	LEFAETFVOL	SENT	R
Mean	6.045	2.652	0.19	0	7.06	2.198	0.203	0	9.924	2.651	0.198	0
Maximum	6.14	3.078	0.556	0.004	7.122	2.605	0.625	0.005	10.031	3.034	1	0.003
Minimum	5.902	2.491	−0.389	−0.003	6.923	1.747	−0.231	−0.004	9.773	2.436	−1	−0.002
Std. Dev.	0.064	0.132	0.145	0.001	0.053	0.158	0.154	0.001	0.071	0.141	0.399	0.001
Skewness	−0.354	1.589	−0.815	0.031	−0.985	0.561	0.085	0.297	−0.169	1.074	0.157	0.105
Kurtosis	2.144	5.034	5.337	3.506	2.726	3.564	3.275	6.09	1.932	3.799	4.714	3.71
Jarque-Bera	6.677	77.125	43.983	1.409	21.421	8.548	0.566	53.612	6.801	28.454	16.437	2.975
Probability	0.035	0	0	0.494	0	0.014	0.753	0	0.033	0	0	0.226
Observations	130	130	130	129	131	131	131	130	130	130	130	130
ARCH-LM				0.040				2.149				0.046
(p)				(0.843)				(0.145)				(0.828)

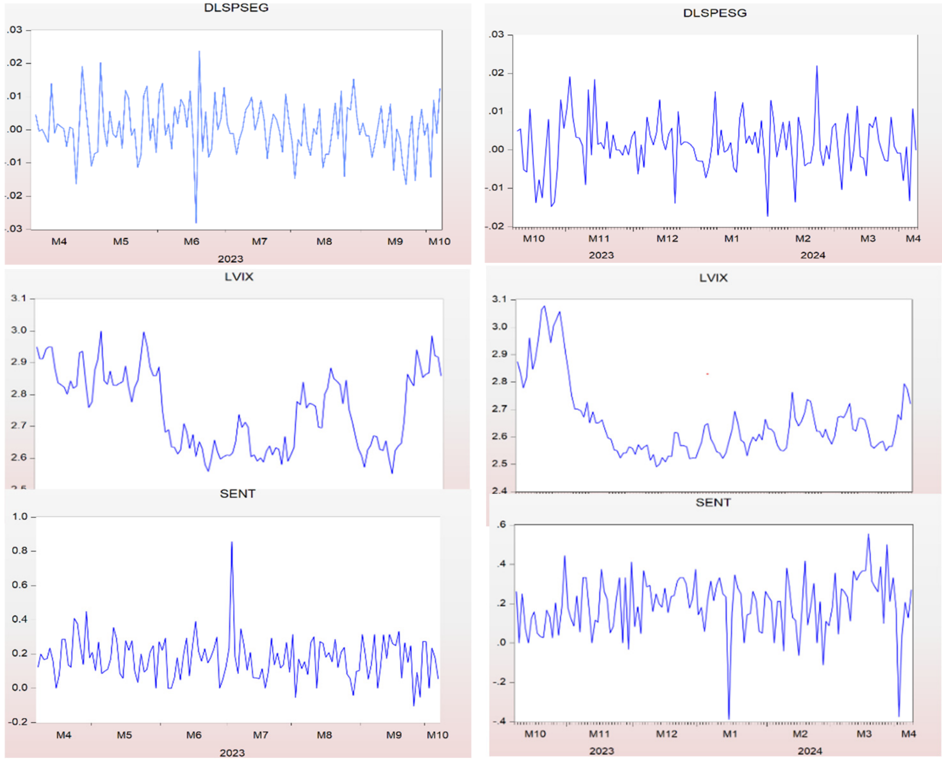
	France				Italy			
Panel A: All the period	LCACESG	LEFAETFVOL	SENT	R	LMIBESG	LEFAETFVOL	SENT	R
Mean	7.813	2.704	0	0.348	7.247	2.704	0.046	0
Maximum	7.915	3.034	0.003	1	7.409	3.034	0.643	0.004
Minimum	7.684	2.436	−0.004	−0.5	7.114	2.436	−0.561	−0.004
Std. Dev.	0.05	0.136	0.001	0.236	0.07	0.136	0.183	0.001
Skewness	−0.294	0.3	−0.229	−0.308	0.645	0.3	−0.502	−0.122
Kurtosis	3.024	2.426	3.097	4.075	2.606	2.426	4.016	3.334
Jarque-Bera	3.791	7.548	2.394	16.813	19.918	7.548	22.338	1.869
Probability	0.15	0.023	0.302	0	0	0.023	0	0.393
Observations	263	263	263	263	263	263	263	263
ARCH-LM				0.081				3.044
(p)				(0.776)				(0.082)

Continued on next page

Panel B: Before the war	LCACESG	LEFAETFVOL	SENT	R	LMIBESG	LEFAETFVOL	SENT	R
Mean	7.805	2.754	0.344	0	7.202	2.754	0.025	0
Maximum	7.857	3.009	0.875	0.003	7.274	3.009	0.643	0.004
Minimum	7.713	2.451	−0.5	−0.004	7.114	2.451	−0.561	−0.004
Std. Dev.	0.032	0.11	0.227	0.001	0.033	0.11	0.199	0.002
Skewness	−0.794	−0.175	−0.867	−0.151	−0.0167	−0.175	−0.354	−0.066
Kurtosis	3.355	2.384	5.43	2.775	2.894	2.384	3.91	2.995
Jarque-Bera	14.565	2.762	49.004	0.781	0.067	2.762	7.311	0.095
Probability	0.001	0.251	0	0.677	0.967	0.251	0.026	0.954
Observations	132	132	132	132	132	132	132	132
ARCH-LM (p)				0.110 (0.741)				1.430 (0.234)
Panel C: After the war	LCACESG	LEFAETFVOL	SENT	R	LMIBESG	LEFAETFVOL	SENT	R
Mean	7.822	2.651	0.352	0	7.294	2.651	0.066	0
Maximum	7.915	3.034	1	0.003	7.409	3.034	0.5	0.004
Minimum	7.684	2.436	−0.3	−0.003	7.152	2.436	−0.421	−0.003
Std. Dev.	0.062	0.141	0.245	0.001	0.069	0.141	0.163	0.001
Skewness	−0.507	1.074	0.142	−0.289	−0.177	1.074	−0.575	0.003
Kurtosis	2.421	3.799	2.943	3.566	2.448	3.799	3.813	3.329
Jarque-Bera	7.386	28.454	0.456	3.548	2.331	28.454	10.739	0.586
Probability	0.025	0	0.796	0.17	0.312	0	0.005	0.746
Observations	130	130	130	130	130	130	130	130
ARCH-LM (p)				0.049 (0.824)				2.544 (0.012)

1.Pre-war 2. Post war

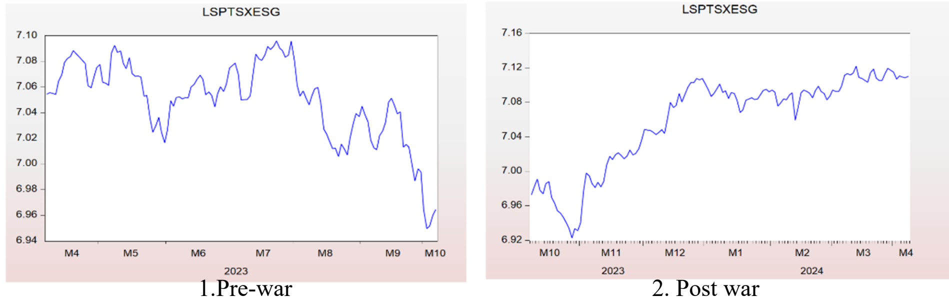
a) The series of indices in level



3.Pre-war 4. Post war

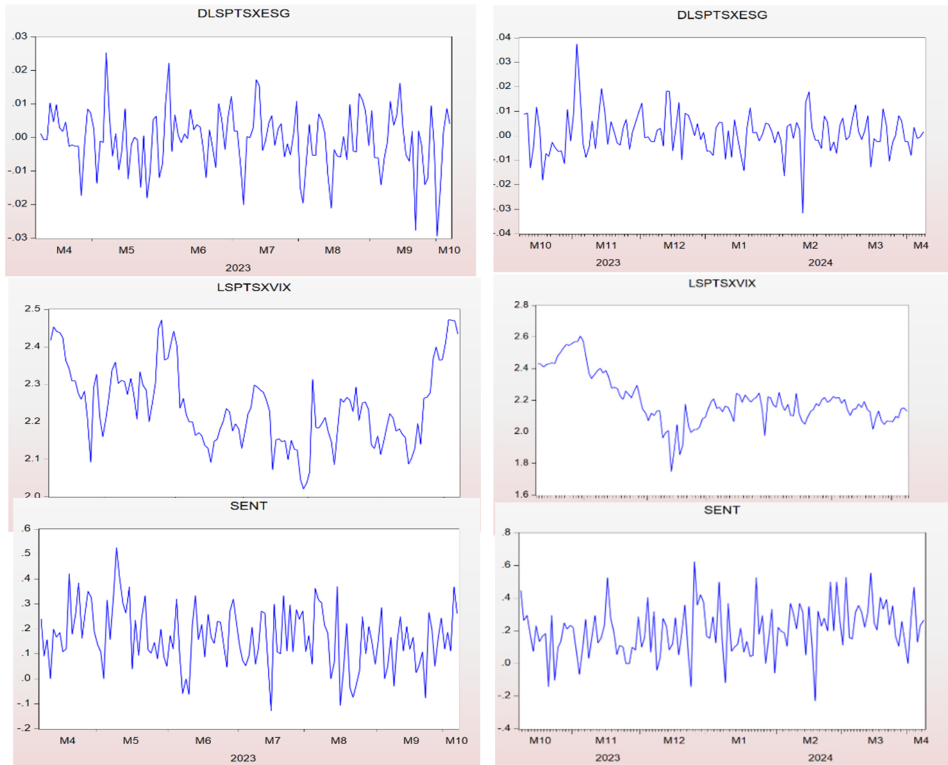
b) Stationary series (in level or in first difference)

Evolution of USA series



1.Pre-war 2. Post war

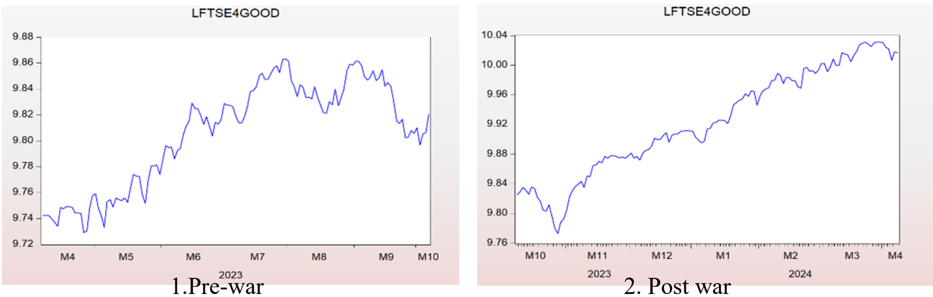
a) The series of indices in level



3.Pre-war 4. Post war

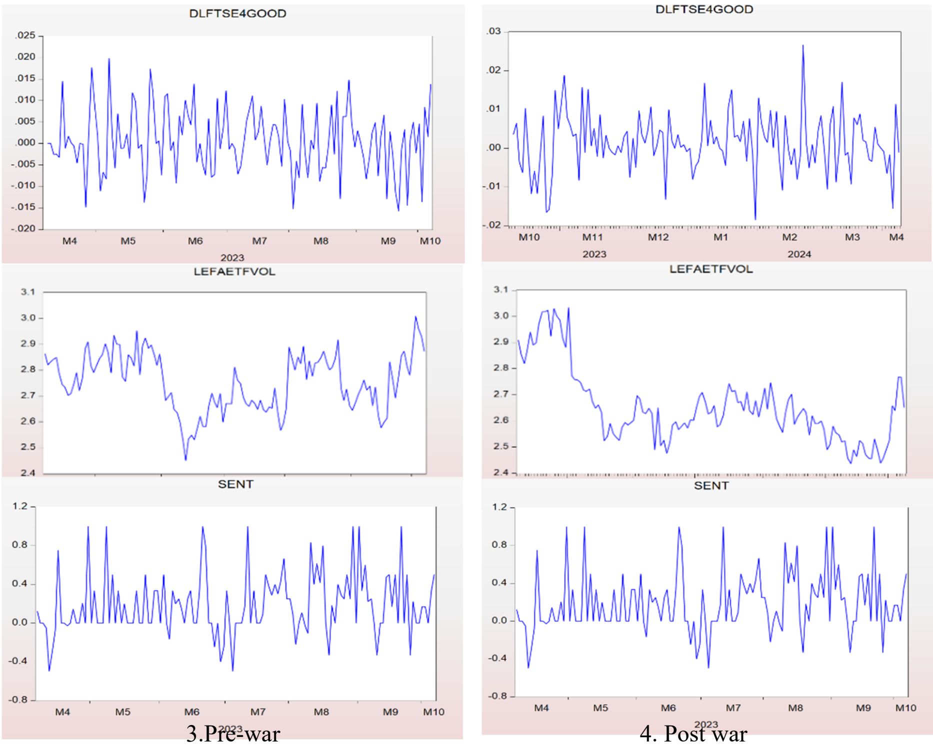
b) Stationary series (in level or in first difference)

Evolution of Canadian series



1.Pre-war 2. Post war

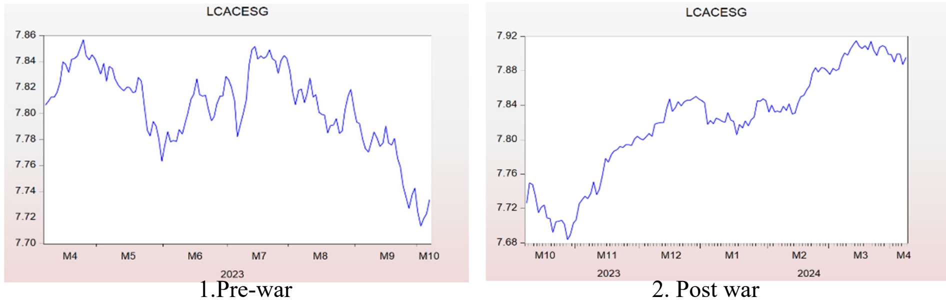
a) The series of indices in level



3.Pre-war 4. Post war

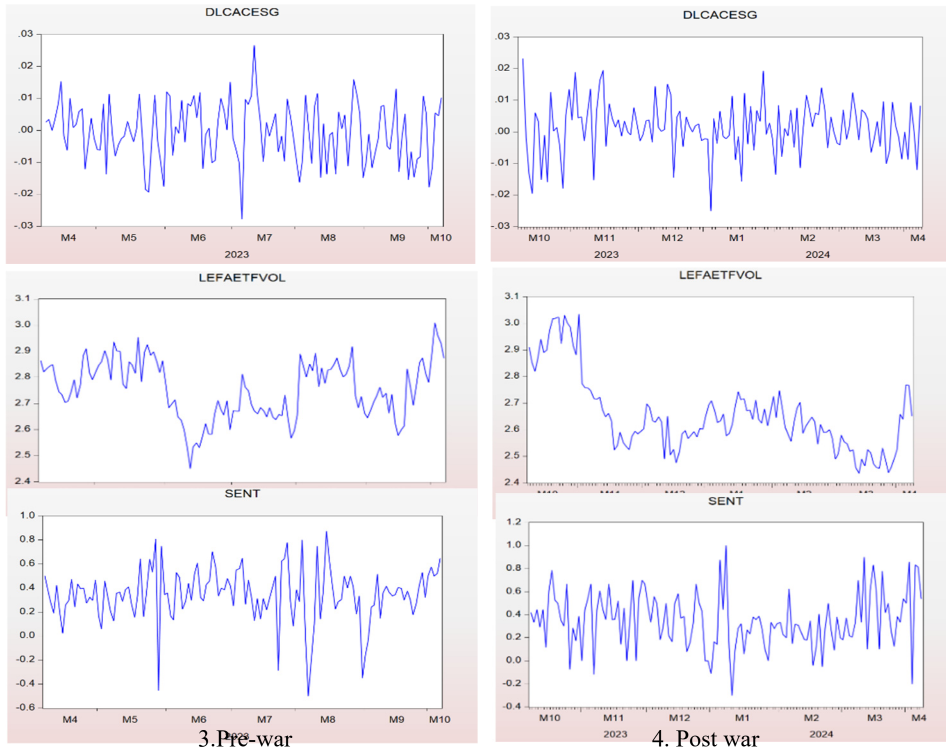
b) Stationary series (in level or in first difference)

Evolution of UK series



1.Pre-war 2. Post war

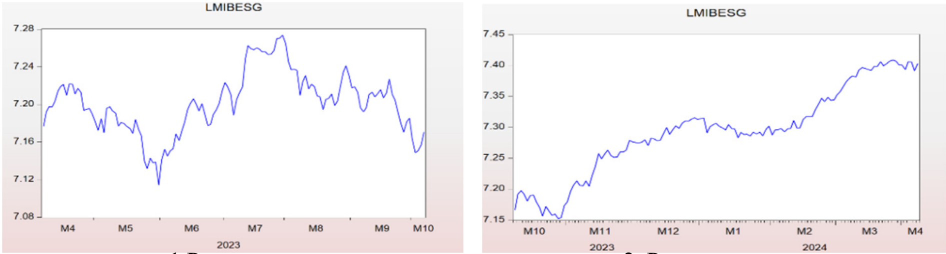
a) The series of indices in level



3.Pre-war 4. Post war

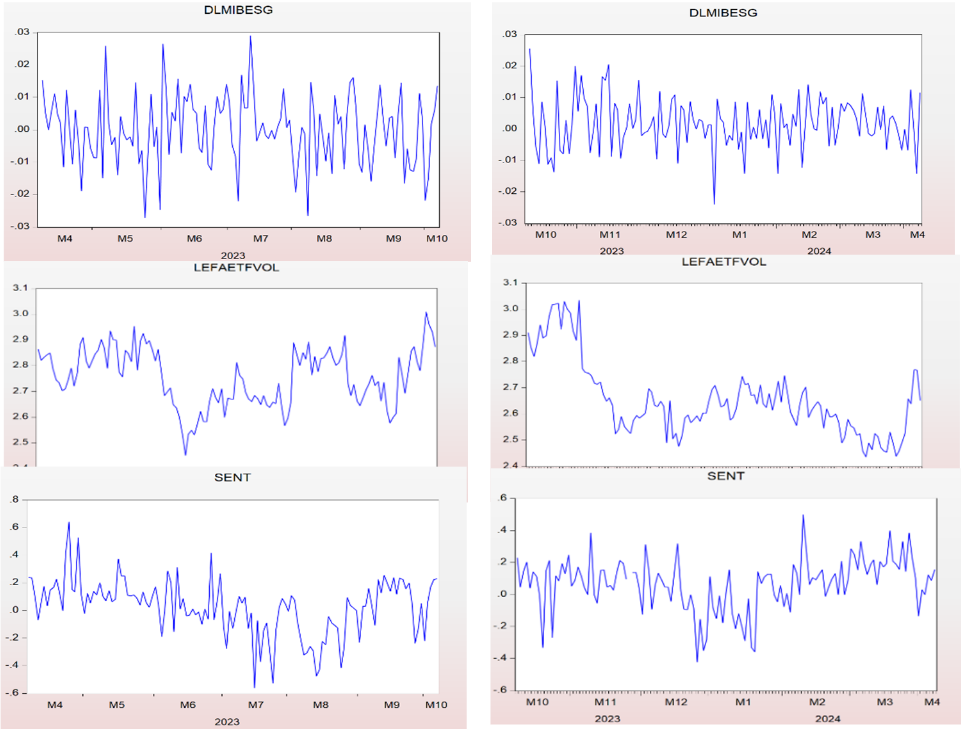
b) Stationary series (in level or in first difference)

Evolution of French series



1.Pre-war 2. Post war

a) The series of indices in level



3.Pre-war 4. Post war

b) Stationary series (in level or in first difference)

Evolution of Italian series

Figure 3. Evolution of the series relating to the markets of the G7 countries (USA, Canada, UK, France and Italy).

In this section, we examine the correlation structure between ESG index returns, market volatility, investor sentiment and commodity prices (oil, gas, gold) across five countries (US, Canada, UK, France, Italy) before and after the Israeli-Palestinian conflict, with detailed coefficients in Appendix 8. In the US, pre-war ESG returns negatively correlate with volatility (ΔLVIX) while sentiment (SENT) shows no significant link to commodity prices; post-war, the negative correlation with volatility strengthens, and SENT becomes negatively correlated with volatility but remains uncorrelated with commodities. Canada exhibits a similar pattern. with returns negatively correlated to volatility and SENT independent of commodities and ESG performance throughout both periods. In the UK, pre-war returns negatively correlate with volatility (LEFAETFVOL) and SENT has a weak, non-significant negative relation with volatility; post-war, correlations weaken and SENT becomes uncorrelated with all variables, indicating its stability and exogeneity. France shows a negative ESG return-volatility correlation pre-war and no significant SENT correlations; post-war, the return-volatility link disappears and SENT remains uncorrelated, supporting its independent role. Italy's pre-war data reveal a negative return-volatility relationship and a notable negative SENT-natural gas price correlation, suggesting potential collinearity issues; post-war, SENT positively correlates with ESG returns but not with volatility or commodities. Overall, ESG returns and volatility maintain a consistent negative relationship across countries and periods, while SENT is generally uncorrelated with commodity prices except pre-war Italy. These findings support including SENT and commodity prices jointly in regressions analyzing ESG behavior during geopolitical shocks. The GARCH-X and Probit/Logit models described in Section 3 are now applied to quantify these relationships before and after the outbreak of the war.

6. Empirical results

The econometric framework introduced in Section 3, combining GARCH-X volatility models with exogenous variables (oil, natural gas, gold and Twitter-based investor sentiment) and binary Probit/Logit regressions, is designed to capture how the 2023 Israeli-Palestinian conflict altered ESG index dynamics across the five countries. The descriptive analysis in Section 5 has shown shifts in mean returns, volatility and sentiment after October 7th, 2023, as well as correlations that justify including all three commodity prices jointly. We now turn to the formal estimation results.

Table 5 reports the GARCH-X estimates for the pre-war and post-war periods, and Table 6 presents the Probit/Logit estimates of the probability of being in the post-war regime. Taken together, the results yield three major findings regarding ESG volatility during the geopolitical shock.

First, geopolitical shocks raise ESG volatility, but transmission channels differ by country. The US shows strong volatility persistence driven by market uncertainty (VIX). Canada and the UK are primarily affected by oil prices. Gold acts as a consistent safe haven across all markets. France exhibits the highest resilience, with ESG volatility linked to fundamentals rather than sentiment. Italy is unique: Investor sentiment gains modest importance post-conflict, alongside strong energy price effects. These cross-country differences reflect heterogeneity in energy dependence market structure and ESG maturity.

Second, contrary to behavioral finance predictions (Kahneman and Tversky, 1979; Shiller, 2000). Twitter-based investor sentiments have only limited statistical influence on ESG volatility. Where sentiment is significant (Italy pre-war Canada), the effect is weak and context-specific. This finding suggests that ESG investors are predominantly institutional and long-term oriented, relying on fundamentals (commodity prices local volatility) rather than transient social media mood. During acute geopolitical shocks, macroeconomic factors overshadow behavioral biases, which is consistent with Alnafrah (2024) and Katsampoxakis et al. (2024).

Third, geopolitical crises do not systematically destabilize ESG indices. Despite short-term volatility increases. ESG markets show resilience and recovery, supporting their role as credible components of sustainable portfolios (H2 partially supported). Gold's consistent dampening effect reinforces its value as a hedge within ESG strategies.

Table 5. GARCH model results for the pre-war and post-war periods.

USA				**Canada**				**UK**				**France**				**Italy**			
GARCH-X1 model pre war				**GARCH-X1 model pre war**				**GARCH-X1 model pre war**				**GARCH-X1 model pre war**				**GARCH-X1 model pre war**			
Mean Equation				**Mean Equation**				**Mean Equation**				**Mean Equation**				**Mean Equation**			
Variable	**Coeff**	**z-Stat**	**Prob.**	**Variable**	**Coeff**	**z-Stat**	**Prob.**	**Variable**	**Coeff**	**z-Stat**	**Prob.**	**Variable**	**Coeff**	**z-Stat**	**Prob.**	**Variable**	**Coeff**	**z-Stat**	**Prob.**
ΔLVIX	−0.122	−14.382	0.000	LSPTSXVIX	−0.018	−2.340	0.019	LEFAETFVOL	−0.012	−2.145	0.032	LEFAETFVOL	−0.020	−17.392	0.000	LEFAETFVOL	−0.023	−2.730	0.006
C	0.000	0.724	0.469	C	0.040	2.339	0.019	C	0.033	2.205	0.027	C	0.053	15.411	0.000	C	0.062	2.650	0.008
Variance Equation				**Variance Equation**				**Variance Equation**				**Variance Equation**				**Variance Equation**			
C	1.05E−05	1.411	0.158	C	6.07E−05	1.604	0.109	C	0.000	1.243	0.214	C	0.000	0.185	0.853	C	0.000	2.672	0.008
RESID(-1)^2	1.29E−01	2.115	0.034	RESID(−1)^2	−0.090	−1.774	0.076	RESID(−1)^2	−0.129	−4.141	0.000	RESID(−1)^2	−0.103	−1.353	0.176	RESID(−1)^2	0.179	1.100	0.272
GARCH(-1)	8.24E−01	9.355	0.000	GARCH(−1)	0.571	1.954	0.051	GARCH(−1)	0.896	6.33E+10	0.000	GARCH(−1)	0.318	0.917	0.359	GARCH(−1)	−0.088	−0.278	0.781
DLWTI	−3.72E−05	−0.441	0.659	DLWTI	0.000	1.433	0.152	DLWTI	−0.001	−2.659	0.008	DLWTI	0.001	2.164	0.030	DLWTI	0.000	−0.361	0.718
LNG	−6.37E−06	−0.986	0.324	LNG	0.000	−0.365	0.715	LNG	0.000	−0.374	0.709	LNG	0.000	0.565	0.572				
DLGOLD	1.88E−04	0.587	0.557	DLGOLD	−0.002	−2.507	0.012	DLGOLD	−0.001	−1.571	0.116	DLGOLD	0.002	1.798	0.072	DLGOLD	−0.002	−1.838	0.066
SENT	−1.86E−05	−1.712	0.087	SENT	0.000	−0.657	0.511	SENT	1.82E−06	0.307	0.759	SENT	0.000	1.666	0.096	SENT	0.000	3.790	0.000

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Test Ljung-Box (LB)				Test Ljung-Box (LB)				Test Ljung-Box (LB)				Test Ljung-Box (LB)				Test Ljung-Box (LB)			
LB(10)		8.571		LB(10)		10.427		LB(10)		9.833		LB(10)		13.051		LB(10)		8.201	
P-value		0.573		P-value		0.403		P-value		0.455		P-value		0.221		P-value		0.609	
$LB^2(10)$		8.589		$LB^2(10)$		4.939		$LB^2(10)$		13.189		$LB^2(10)$		14.404		$LB^2(10)$		7.948	
P-value		0.571		P-value		0.895		P-value		0.213		P-value		0.155		P-value		0.634	
DW		2.496		DW		1.484		DW		1.878		DW		1.673		DW		1.892	
ARCH		0.423	0.515	ARCH		0.441	0.508	ARCH		0.478	0.490	ARCH		0.716	0.399	ARCH		7.11E-05	0.993
GARCH-X2 model post war Mean Equation				**GARCH-X2 model post war Mean Equation**				**GARCH-X2 model post war Mean Equation**				**GARCH-X2 model post war Mean Equation**				**GARCH-X2 model post war Mean Equation**			
Variable	**Coeff**	**z-Stat**	**Prob.**	**Variable**	**Coeff**	**z-Stat**	**Prob.**	**Variable**	**Coeff**	**z-Stat**	**Prob.**	**Variable**	**Coeff**	**z-Stat**	**Prob.**	**Variable**	**Coeff**	**z-Stat**	**Prob.**
ΔLVIX	−0.116	0.010	0.000	ΔLSPTSXVIX	−0.068	−7.327	0.000	LEFAETFVOL	−0.046	−5.401	0.000	LEFAETFVOL	−0.044	−2.968	0.003	LEFAETFVOL	−0.035	−3.107	0.002
C	0.002	0.000	0.000	C	0.000	−0.219	0.826	C	0.002	3.283	0.001	C	0.001	1.848	0.065	C	0.002	3.264	0.001

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Variance Equation				**Variance Equation**				**Variance Equation**				**Variance Equation**				**Variance Equation**			
C	1.85E−05	1.24E−05	0.136	C	0.000	20.618	1.90E−94	C	1.70E−05	3.278	0.001	C	0.000	1.15E+10	0.000	C	4.21E−06	3.086	0.002
RESID(-1)^2	0.002	0.057	0.975	RESID(−1)^2	0.082	0.937	0.349	RESID(−1)^2	0.100	0.972	0.331	RESID(−1)^2	0.081	0.822	0.411	RESID(−1)^2	−0.096	−4.525	0.000
GARCH(-1)	0.584	0.283	0.039	GARCH(−1)	0.567	2.820	0.005	GARCH(−1)	0.546	1.43E+10	0.000	GARCH(−1)	0.532	3.530	0.000	GARCH(−1)	1.039	3154.451	0.000
DLWTI	−4.98E−05	0.000	0.761	DLWTI	0.001	3.143	0.002	DLWTI	−0.001	−2.002	0.045	DLWTI	0.001	1.713	0.087	DLWTI	0.000	0.219	0.826
DLNG	4.47E−05	7.24E−05	0.537	DLNG	0.000	−0.330	0.742	DLNG	0.000	−1.723	0.085	DLNG	0.000	0.610	0.542	DLNG	7.81E−05	0.779	0.436
DLGOLD	0.000	0.000	0.478	DLGOLD	0.000	0.550	0.582	DLGOLD	0.000	−1.030	0.303	DLGOLD	0.000	−0.393	0.694	DLGOLD	−0.001	−1.280	0.201
SENT	−4.18E−05	2.55E−05	0.101	SENT	0.000	−1.112	0.266	SENT	8.63E−06	0.979	0.328	SENT	0.000	−1.586	0.113	SENT	−9.45E−07	−0.109	0.913
Test Ljung-Box (LB)				**Test Ljung-Box (LB)**				**Test Ljung-Box (LB)**				**Test Ljung-Box (LB)**				**Test Ljung-Box (LB)**			
LB(10)		7.850		LB(10)		12.582		LB(10)		13.230		LB(10)		11.764		LB(10)		13.135	
P-value		0.643		P-value		0.248		P-value		0.211		P-value		0.301		P-value		0.216	
$LB^2(10)$		8.100		$LB^2(10)$		3.676		$LB^2(10)$		3.330		$LB^2(10)$		7.623		$LB^2(10)$		10.720	
P-value		0.619		P-value		0.961		P-value		0.973		P-value		0.666		P-value		0.380	
DW		2.212		DW		1.842		DW		2.246		DW		2.258		DW		2.235	
ARCH		1.422	0.235	ARCH		0.138	0.710	ARCH		0.128	0.721	ARCH		0.010	0.921	ARCH		0.0718	0.789

Table 6. Estimation Results of the Probit and Logit Models

USA							
Model (3.2.1)				**Model (3.2.2)**			
	Probit				**Logit**		
Variable	**Coeff**	**z-Stat**	**Prob.**	**Variable**	**Coeff**	**z-Stat**	**Prob.**
ΔLSPESG	14.153	0.945	0.345	ΔLSPESG	21.847	0.906	0.365
ΔLVIX	1.406	0.611	0.541	ΔLVIX	2.092	0.562	0.579
ΔLWTI	0.208	0.048	0.962	ΔLWTI	0.197	0.028	0.978
ΔLNG	−3.602	−1.703	0.089	ΔLNG	−5.787	−1.674	0.094
ΔLGOLD	31.911	2.849	0.004	ΔLGOLD	51.249	2.785	0.005
SENT	0.825	1.391	0.164	SENT	1.313	1.360	0.174
C	−0.186	−1.377	0.169	C	−0.297	−1.354	0.176
LR statistic		13.736		LR statistic		13.649	
Prob(LR statistic)		**0.033**		Prob(LR statistic)		**0.034**	
Avg. log likelihood		−0.668		Avg. log likelihood		−0.667	
Log likelihood		−175.428		Log likelihood		−175.472	
Canada							
Model (3.2.1)				**Model (3.2.2)**			
	Probit				**Logit**		
Variable	**Coeff**	**z-Stat**	**Prob.**	**Variable**	**Coeff**	**z-Stat**	**Prob.**
ΔLSPTSXESG	12.720	1.179	0.238	ΔLSPTSXESG	20.862	1.198	0.231
ΔLSPTSXVIX	0.699	0.473	0.636	ΔLSPTSXVIX	1.1623	0.488	0.626
ΔLWTI	−1.190	−0.269	0.788	ΔLWTI	−2.004	−0.280	0.780
ΔLNG	−3.527	−1.652	0.098	ΔLNG	−5.706	−1.631	0.103
ΔLGOLD	27.377	2.400	0.016	ΔLGOLD	43.850	2.360	0.018
SENT	1.245	2.178	0.029	SENT	2.005	2.145	0.032
C	−0.251	−1.918	0.055	C	−0.409	−1.903	0.057
LR statistic		16.985		LR statistic		16.947	
Prob(LR statistic)		0.009		Prob(LR statistic)		0.009	
Avg. log likelihood		−0.661		Avg. log likelihood		−0.661	
Log likelihood		−173.803		Log likelihood		−173.822	
UK							
Model (3.2.1)				**Model (3.2.2)**			
	Probit				**Logit**		
Variable	**Coeff**	**z-Stat**	**Prob.**	**Variable**	**Coeff**	**z-Stat**	**Prob.**
ΔLFTSE4GOOD	9.577	0.842	0.400	ΔLFTSE4GOOD	15.311	0.834	0.404
ΔLEFAETFVOL	0.099	0.073	0.942	ΔLEFAETFVOL	0.090	0.042	0.967
ΔLWTI	0.087	0.020	0.984	ΔLWTI	0.036	0.005	0.996
ΔLNG	−3.265	−1.558	0.119	ΔLNG	−5.262	−1.541	0.123
ΔLGOLD	31.238	2.830	0.005	ΔLGOLD	50.346	2.780	0.005
SENT	0.047	0.216	0.829	SENT	0.079	0.225	0.822
C	−0.041	−0.462	0.644	C	−0.068	−0.473	0.636
LR statistic		11.694		LR statistic		11.688	
Prob(LR statistic)		0.069		Prob(LR statistic)		0.069	
Avg. log likelihood		−0.671		Avg. log likelihood		−0.671	
Log likelihood		−176.449		Log likelihood		−176.452009	

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France							
Model (3.2.1)				**Model (3.2.2)**			
	Probit				**Logit**		
Variable	**Coeff**	**z-Stat**	**Prob.**	**Variable**	**Coeff**	**z-Stat**	**Prob.**
ΔLCACESG	14.171	1.482	0.138	ΔLCACESG	23.940	1.519	0.129
ΔLEFAETFVOL	0.374	0.279	0.780	ΔLEFAETFVOL	0.605	0.280	0.780
ΔLWTI	0.273	0.063	0.950	ΔLWTI	0.138	0.019	0.985
ΔLNG	−3.374	−1.603	0.109	ΔLNG	−5.468	-1.596	0.110
ΔLGOLD	29.902	2.718	0.007	ΔLGOLD	48.738	2.697	0.007
SENT	0.047	0.140	0.889	SENT	0.065	0.120	0.904
C	−0.045	−0.318	0.751	C	−0.067	-0.299	0.765
LR statistic		13.164		LR statistic		13.299	
Prob(LR statistic)		0.040		Prob(LR statistic)		0.039	
Avg. log likelihood		−0.668		Avg. log likelihood		−0.668	
Log likelihood		−175.714		Log likelihood		−175.646	
Italy							
Model (3.2.1)				**Model (3.2.2)**			
	Probit				**Logit**		
Variable	**Coeff**	**z-Stat**	**Prob.**	**Variable**	**Coeff**	**z-Stat**	**Prob.**
ΔLMIBESG	7.989	0.905	0.366	ΔLMIBESG	13.867	0.956	0.339
ΔLEFAETFVOL	0.170	0.130	0.896	ΔLEFAETFVOL	0.279	0.132	0.895
ΔLWTI	−0.220	−0.051	0.960	ΔLWTI	−0.628	-0.088	0.930
ΔLNG	−3.517	−1.672	0.095	ΔLNG	−5.734	-1.667	0.096
ΔLGOLD	29.923	2.698	0.007	ΔLGOLD	48.625	2.672	0.008
SENT	0.790	1.776	0.076	SENT	1.265	1.766	0.077
C	−0.067	−0.824	0.410	C	−0.107	-0.814	0.416
LR statistic		15.592		LR statistic		15.689	
Prob(LR statistic)		0.016		Prob(LR statistic)		0.016	
Avg. log likelihood		−0.663		Avg. log likelihood		−0.663	
Log likelihood		−174.500		Log likelihood		−174.451	

Note: LVIX: U.S. market volatility. LSPTSXVIX: Canadian market volatility. LEFAETFVOL: European market volatility. LWTI: crude oil price. LGOLD: gold price. LNG: natural gas price. Sent: sentiment variable. p = q = 1.

7. Conclusions

In this study, we provide an in-depth analysis of the impact of geopolitical crises, particularly the Israeli-Palestinian conflict of October 2023, on the behavior of ESG stock indices across five major economies: the United States, Canada, the United Kingdom, France and Italy. By combining GARCH-X models with Probit and Logit regressions. we capture the conditional volatility and the likelihood of structural changes in market dynamics in response to geopolitical shocks.

The empirical findings reveal that geopolitical events significantly affect ESG index volatility, with oil prices and domestic market risk (as measured by VIX-like indicators) being the most influential variables. While gold continues to play its traditional safe-haven role across all markets. natural gas prices only significantly influence volatility in countries with higher energy dependence. such as Italy.

Contrary to expectations, investor sentiment, quantified through social media analysis using NLP techniques, displays a limited and context-specific influence. Although sentiment shows weak to moderate significance in Italy and marginal relevance in Canada post-war, it does not emerge as a robust predictor of ESG market volatility across all countries. These results suggest that during periods of heightened geopolitical uncertainty, institutional and fundamental factors dominate investor behavior, overshadowing emotional or behavioral responses captured through social platforms.

The study also highlights heterogeneity across countries. The resilience of ESG indices appears stronger in markets like the United Kingdom and France, where ESG investment frameworks are more mature and less susceptible to external shocks. In contrast, Italy's market demonstrates greater sensitivity to geopolitical and behavioral variables, underlining the need for country-specific risk management strategies in ESG portfolio construction.

From a methodological standpoint, the integration of econometric volatility models and machine learning-based sentiment analysis represents a novel and interdisciplinary contribution to the literature on sustainable finance. This framework not only captures the financial implications of geopolitical events but also offers practical insights for investors and policymakers aiming to navigate ESG investments during turbulent times.

8. Implications

For investors, ESG indices offer relative stability, but country-specific risk management is essential (e.g., energy-sensitive Italy vs. more insulated France/UK). For policymakers, the limited role of social media sentiment suggests focusing on commodity market stability rather than curbing sentiment noise. For researchers, our work highlights the value of combining GARCH-X with pre/post-war analysis and the need for multilingual sentiment models in cross-country social media studies.

Author contributions

Anis Hdidar: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft, Visualization, Investigation, Project administration. The author contributed to all aspects of the research, including the design of the study, the development of the econometric models (GARCH-X, Probit, and Logit), the implementation of Natural Language Processing (NLP) techniques for sentiment analysis, data collection and processing, and the drafting of the manuscript.

Fatma Hachicha: Validation, Writing – review, editing, Supervision. The author verified the accuracy and integrity of the results, critically reviewed the manuscript for intellectual content, and provided corrections and improvements to the final version.

Anis Jarboui: Supervision, Validation, Resources, Writing – review, editing. The author provided overall research guidance, supervised the project, validated the methodological approach and findings, and contributed to the refinement of the final manuscript.

Use of AI tools declaration

The authors declare that artificial intelligence tools were used exclusively for research purposes, specifically for sentiment analysis of Twitter data. The Hugging Face transformer model "cardiffnlp/twitter-xlm-roberta-base-sentiment" was employed within a Python-based NLP pipeline to extract and classify investor sentiment across multiple languages. All econometric analyses (GARCH-X, Probit, and Logit models) were performed using standard statistical software (EViews). AI tools were not used for manuscript writing, revision, or interpretation of results. The authors assume full responsibility for the content and conclusions of this work.

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Conflict of interest

The author declares no conflict of interest.

Data Availability Statement

The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request. No proprietary or confidential data were used.

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