Sustainable Assets in a Political Landscape: Analyzing COVOL During Key Political Elections

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Abstract

This dissertation examines the impact of major political events on the volatility of high Environmental, Social, and Governance (HESG) and low Environmental, Social, and Governance (LESG) assets, using common volatility (COVOL) as a risk measure. Through an event study approach, the analysis identifies short-term volatility spikes following elections and referendums, showing that LESG assets exhibit sharper but short-lived reactions, while HESG assets experience more sustained but moderate shifts.

The findings emphasize that shorter event windows (e.g., three days post-event) better capture immediate market reactions, whereas longer windows may obscure short-term fluctuations. Graphical analysis of COVOL confirms volatility peaks directly after political events, underlining the importance of precise event window selection.

These results contribute to research on political risk and sustainable finance, offering insights for investors and policymakers in managing ESG-related risks. Future research should explore global markets, sector-specific patterns, and alternative risk models to improve understanding of ESG-related volatility dynamics.

Keywords: ESG assets, volatility shocks, political uncertainty, COVOL, elections, regulatory risk.

Título: Ativos Sustentáveis em um Cenário Político: Análise do COVOL Durante Eleições Políticas Chave

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Resumo

Esta dissertação analisa o impacto de eventos políticos na volatilidade de ativos com alto (HESG) e baixo (LESG) desempenho em critérios Ambientais, Sociais e de Governança, utilizando a volatilidade comum (COVOL) como medida de risco. Por meio de um estudo de eventos, a análise identifica picos de volatilidade de curto prazo após eleições e referendos, indicando que ativos LESG têm reações acentuadas e passageiras, enquanto HESG mostram flutuações mais moderadas e sustentadas.

Os resultados mostram que janelas mais curtas (por exemplo, três dias) capturam melhor reações imediatas do mercado, enquanto janelas mais longas suavizam flutuações de curto prazo. A análise gráfica do COVOL confirma picos após eventos políticos, reforçando a importância da escolha da janela.

As conclusões oferecem insights a investidores e formuladores de políticas sobre a gestão de riscos ESG. Pesquisas futuras podem explorar mercados globais, efeitos setoriais e modelos alternativos para aprimorar a avaliação da volatilidade ESG.

Palavras-chave: Ativos ESG, choques de volatilidade, incerteza política, COVOL, eleições, risco regulatório.

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1. Introduction

Environmental, Social, and Governance (ESG) investments are becoming an integral part of financial markets, as sustainability concerns and regulatory frameworks increasingly influence investment decisions. The transition towards a low-carbon economy and the rise of responsible investing have led to growing interest in ESG assets (Foley et al., 2024). However, the extent to which ESG assets differ from traditional investments in terms of risk and volatility remains a crucial question. Andersson and Mårtensson (2019) argue that prioritizing ESG factors over financial performance may compromise portfolio efficiency. On the other hand, Clarvis et al. (2015) highlight the resilience and long-term benefits of sustainable investments. Understanding the volatility dynamics of high-ESG (HESG) and low-ESG (LESG) assets is therefore essential for investors seeking to balance financial returns with sustainability objectives.

Political risk is a key driver of market uncertainty, influencing investment strategies, regulatory developments, and corporate decision-making (Quaye et al., 2016). Elections, referendums, and major policy shifts have historically triggered market volatility, as investors adjust expectations based on political outcomes. While financial markets have been extensively studied in the context of political uncertainty, little research has examined whether high-ESG assets respond differently to political events compared to their low-ESG counterparts. Given the increasing role of government policies in shaping sustainability initiatives, it is important to assess whether high-ESG investments offer greater stability during politically uncertain periods or whether they are equally exposed to volatility shocks.

This thesis investigates the impact of major political events on the volatility of high-ESG and low-ESG assets using common volatility (COVOL) as a risk measure. Through an event study approach, it analyzes the extent to which elections and referendums generate volatility spikes across asset classes. The study specifically examines whether high-ESG investments provide greater resilience to political risk or whether they exhibit similar or higher volatility dynamics as traditional assets. To capture these effects, various event windows are employed, ranging from broad 10-day pre- and post-event windows to narrower windows that focus only on the days immediately surrounding the event. Additionally, graphical analysis of COVOL is used to visually assess volatility responses to political events such as the US Election 2016 and the Brexit Referendum 2016.

The results of this study reveal important insights into the behavior of high-ESG and low-ESG assets under political uncertainty. The findings suggest that shorter event windows more effectively isolate immediate market reactions, whereas longer event windows may hide short-term volatility spikes. Furthermore, while high-ESG assets tend to show more sustained periods of volatility, low-ESG assets often display sharper but shorter volatility fluctuations. These differences indicate that investor sentiment, regulatory exposure, and policy expectations shape the volatility patterns of high-ESG and low-ESG assets differently.

Beyond its empirical contributions, this research holds practical implications for investors, policymakers, and financial market participants. Investors incorporating ESG factors into their portfolios must consider how political events influence volatility dynamics, while policymakers should recognize that inconsistent regulatory signals may contribute to market uncertainty.

The structure of this dissertation is as follows: Chapter 2 provides a literature review on political risk, ESG scoring, and financial market volatility. Chapter 3 outlines the methodological framework, explaining the use of COVOL. Chapter 4 presents the empirical findings and the event study approach including statistical and graphical analyses of HESG and LESG asset volatility. Chapter 5 discusses the study’s limitations. Chapter 6 discusses possible future research venues, and the implications for financial markets. Finally, Chapter 7 concludes the dissertation by summarizing key insights and their broader significance in the field of sustainable finance and political risk analysis.

By analyzing how political events impact the volatility of high-ESG and low-ESG assets, this study contributes to the growing literature on sustainable finance and political risk assessment. Understanding these dynamics is crucial for investors navigating an increasingly complex financial landscape shaped by both political and environmental considerations.

2. Literature Review

The literature review provides a comprehensive overview of key concepts and research areas relevant to this thesis. It explores geopolitical risk, ESG scoring, and global common volatility (COVOL), as well as their intersection in the context of major political events and their impact on financial markets. Moreover, it highlights important findings from previous studies and establishes the basis for the research question of this thesis. Ultimately, it lays the groundwork for the methodology used to examine the impact of geopolitical events on the COVOL of sustainable and traditional assets.

2.1. Geopolitical Risk and Political Elections

Geopolitical risk can impact a wide range of areas and affect our world in a very significant way. Bohl et al. (2017) define geopolitical risk as the potential for a worldwide disruption of political-economic trends conducive to human well-being. Additionally, Nomikou (2024) describes geopolitical risk as arising from interactions between governments and countries, including trade relationships, security partnerships, supply chains, climate initiatives, and territorial disputes.

The rising importance of geopolitical risk and the need for its quantification have attracted increasing attention from both practitioners and academics. In this context, numerous researchers are now developing their own indicators to measure geopolitical risk (Engle et. al, 2023). The geopolitical risk measures are mainly divided into text-based and empirical measures.

One example for a text-based measure is the "Global economic policy uncertainty index" (GPU). It was developed by Davis (2016) and represents a GDP-weighted average of national EPU indices from 16 countries, which together account for two-thirds of global output. Each national EPU index is based on the relative frequency of domestic newspaper articles containing a specific set of terms related to the economy, uncertainty, and policy matters.

Another example for a text-based measure is the World Uncertainty Index (WUI) developed by Ahir et. al (2022). It is calculated on a quarterly basis for an unbalanced panel of 143 countries, starting from 1952. It measures the frequency of the term "uncertainty" in the quarterly country reports by the Economist Intelligence Unit. Globally, the index exhibits significant spikes during major events such as the Gulf War, the Euro debt crisis, the Brexit referendum, and the COVID-19 pandemic.

Engle and Campos-Martins (2023) introduced COVOL, a numerical (empirical) measure of global financial risk which is derived from a multivariate generalized volatility model. COVOL has demonstrated greater efficiency in explaining ACWI volatility compared to text-based geopolitical indices. These models not only provide faster detection of changes, making them more effective for preparing for global shocks, but they are also easier to replicate and implement due to their numerical nature.

Additionally, Karagozoglu, Wang, and Zhou (2022) conducted a comparison of 11 indicators and found that empirical measures are more effective in quickly capturing changes in geopolitical risk, outperforming text-based measures.

Political events, especially elections, can undoubtedly be subsumed under the definition of geopolitical risk, as they determine how governments will shape their relationships with other governments and countries. These events often have a substantial impact, as they can reshape geopolitical relationships, influence economic strategies, disrupt global supply chains, affect human well-being, and ultimately alter the business environment for companies. Furthermore, political elections and their outcomes often extend beyond national borders. As a result, financial markets, which are particularly sensitive to uncertainty, tend to react strongly to such elections and their results. Bialkowsky et al. (2016) found that during the week surrounding a key election, return variance can easily double. This is confirmed by Khalid and Rajauru (2010), who found that both domestic and international elections have a significant impact on the domestic economy and financial markets, leading to substantial changes in market volatility.

To a large extent, the uncertainty arising from unknown election results reflects policy uncertainty, which places risks on companies that might be affected by adverse policy changes. Pasquerillo (2014) describes this policy uncertainty as the uncertainty associated with government policies (macroeconomic, monetary, and fiscal policies) and the effects they have on economic development and financial markets. Political uncertainty encompasses both the uncertainty of election results and the uncertainty regarding the policies that evolve from the election outcome. Extensive research has already been conducted on the topic of political elections, including elections in European, African, and Asian states, as well as EU elections. However, the vast majority of research has focused on US presidential elections. Existing literature generally finds that political uncertainty significantly affects both return levels and, as previously described, the risk levels of financial assets (Pantzallis et al., 2000).

He et al. (2009) researched the impact of political uncertainty from US presidential elections on stock markets and found that ongoing uncertainty over the elections is strongly reflected, both positively and negatively, in the behavior of stock prices. Using polling data from US presidential elections between 1964 and 2000, Li and Born (2006) demonstrated that stock prices tend to rise ahead of elections when the outcome is highly uncertain. Conversely, Goodell and Bodey (2012) observed that reduced uncertainty surrounding US presidential elections leads to a decline in stock prices. Goodell and Vahamaa (2013) researched how political uncertainty and election processes influence implied stock market volatility during US presidential elections. Their findings show a positive relationship between implied volatility and the probability of the eventual winner. Ultimately, Bouoiyour and Selmi (2017) concluded that financial markets generally react to new information regarding political events that could significantly impact a country's macroeconomic, fiscal, or monetary policies. They emphasize that investors closely monitor these events and adjust their expectations based on the outcomes.

2.2. Sustainable and Traditional Assets

For risk-averse investors, it is especially important to understand where the volatility around elections comes from and to find ways to minimize portfolio risk exposure. Questions arise about how this might be possible. A potential starting point would be to determine which assets are more robust during election periods, such as sustainable versus traditional assets.

Environmental, Social, and Governance (ESG) factors, and sustainability in general, are nowadays central cornerstones in shaping modern economic and business practices. Sustainability drives companies to adopt more responsible strategies that not only generate more profits but also protect the environment and promote social well-being and peace. This increasing focus on ESG reflects the growing demand for long-term solutions to global challenges, both in society and in the economy.

GSIA (2020) stated that over the last decade there has been a significant increase in ESG and sustainability-related investments. According to ESG News (2024), sustainable funds reached a record high of $3.5 trillion in assets under management (AUM) in 2024. Furthermore, ESG investments are promoted in many different areas, and it has become clear that sustainability is at the core of many institutions. Many different regulatory approaches to promote sustainable investments have emerged in recent years. Most importantly, the EU's agenda for sustainable finance, with its goal to include and foster transparency on companies' environmental impact, and to reorient capital flows toward a more sustainable economy, is key (European Commission, 2020).

The question arises whether ESG scores reliably signal the true sustainability of a company. Rajesh (2019) observed the sustainability performance of 39 Indian firms listed in the Thomson

Reuters ESG scores and consistently rated for their Environmental, Social, and Governance performance over five years, from 2014 to 2018. He concluded that the ESG scores were very reliable tools for investors to assess sustainability performance. Furthermore, Rajesh (2020) concluded that, according to the latest literature on sustainability performance, ESG scores appear to be a strong indicator of a company's sustainability performance.

Ngo (2020) states that investors with sustainability preferences build their ESG-related portfolios based on ESG scores by including companies with the best ESG ratings. Investors not interested in sustainability include any stocks in their portfolio, regardless of their ESG score (Hvidkjaer, 2017). Furthermore, they can also include so-called sin stocks, which were researched and defined by Hong and Kacperczyk (2009) as stocks in the tobacco, alcohol, and gambling industries.

Additionally, it is in investors' interest to understand how sustainable assets perform in comparison to traditional assets regarding their financial characteristics. Albuquerque et al. (2020) stated that during the 2020 pandemic, money flows into ESG investments soared to new heights and found that companies with high-ESG scores earned relatively higher stock returns and showed lower levels of unpredictability. Riedl (2017) found that sustainable investments provide advantages in terms of higher returns and lower levels of volatility, especially during turbulent periods. Broadstock et al. (2021) additionally stated that companies engaged in environmentally responsible initiatives tend to have higher transparency regarding their sustainability, as such environmentally conscious firms are less vulnerable to systemic threats. In another study, Aslan et al. (2021) used data from 902 publicly listed firms in the US from 2002 to 2017 to research whether companies with high-ESG scores have higher or lower default probabilities. They found that the probability of corporate credit default was significantly lower for firms with high ESG performance.

A study by Rehman et al. (2024) however analyzed the relative performance of sustainable indices (ESG) compared to conventional benchmarks using daily stock price data from global, regional, and country-specific ESG indices of the Dow Jones Sustainability Index (DJSI) and MSCI families for the period from October 1, 2010, to March 1, 2021. They found that, in terms of risk and return characteristics and other modern portfolio metrics, there was only mixed evidence, with some ESG indices slightly outperforming traditional benchmarks and others staying around parity. They state that a more sophisticated regulatory framework should be established in order to create appreciable outperformance of sustainable investments.

Burger et al. (2022) examined the impact of relatively better ESG performance of companies on their implied and historical share volatility. Their regressions clearly showed that better ESG performance, as measured by the company's ESG score, has a risk-reducing effect in the form of lower stock volatility.

2.3. Hypothesis development

After reviewing the previous literature on geopolitical risk and the role of political elections, it became clear that financial markets are heavily dependent on and react strongly to such events. These events can lead to significantly higher returns for some companies and significantly lower returns for others. It also became evident that volatility increases substantially around these elections, which has a major influence on investors' decision-making. A large portion of this volatility stems from the fact that elections, and the resulting new governments or committees, often introduce new policies. This creates uncertainties for companies regarding how they can cope with policy changes and the potential shifts in macroeconomic, monetary, and fiscal environments. Additionally, it was noted that elections in one country can impact companies in other countries and are therefore considered geopolitical events.

Furthermore, the importance of ESG considerations in today's market was emphasized. ESG scores are a useful tool for screening sustainable companies and are widely used by investors. It became clear that investing in companies with high-ESG scores offers numerous advantages in terms of both returns and risk considerations. The aspect of ESG however has received little attention from researchers focusing on political events in connection with financial markets.

As a result, current literature is yet to explore how risk considerations, as measured by COVOL, vary during geopolitical events when comparing HESG and LESG assets. Therefore, I investigate the following question: Do companies with higher ESG scores have lower COVOL during key political events?

3. Methodology and Data

This section gives a detailed explanation of how COVOL is measured for the HESG and LESG groups, what data is used and how the subsequent event studies are used to investigate the research question.

3.1. Methodology

3.1.1. Volatility modelling with GARCH

In the first step, a mean model is developed by selecting factors that can best explain the log-returns (r_{it}) of the HESG and LESG groups assets. Unlike the approach of Engle and Campos-Martins (2023), who use the ACWI as the primary factor, I have considered that this analysis focuses exclusively on US assets and have adjusted the factor selection accordingly by using the S&P500, 3FF, Momentum and the Cross-Sectional-Mean. Furthermore I need to add the AR(1) factor $\left(r_{i,(t-1)}\right)$ into the mean model. I did an AR(1) test for all assets and apply this AR(1) factor to all assets for which an AR(1) test has shown significant autocorrelation effects. The inclusion of the AR(1) effect is determined by D_i, which is a binary variable that equals 1 if the time series of asset i shows significant first-order autocorrelation and otherwise, it takes the value of 0. The $u_{i,t}$ in the end of the equation shows the residuals from the established factor model.

$$r_{it} = c_i + D_i \delta_i r_{i,(t-1)} + \beta_{1i} 3FF_t + \beta_{2i} Mom_t + \beta_{2i} CSM_t \, u_{i,t} \,, \quad |\delta_i| < 1 \; for \; i = 1, \dots, N$$

As the time series shows heteroscedasticity it means that the residuals from the factor model are uncorrelated but not independent. The reason is that they are related through the second moments. As a result, $u_{i,t}$ is modeled using the first order generalized autoregressive conditional heteroscedasticity (GARCH) framework, as introduced by Engle and Bollerslev (1986). To estimate the volatility of the time series I use a GARCH 1,1) as the results of Miah and Rahman (2016) as well as other literature show that the GARCH(1,1) model is superior to other GARCH(p,q) models for capturing volatility in daily stock returns.

In the GARCH (1,1) the residual $u_{i,t}$ is represented as a multiplicative decomposition by

$u_{i,t} = h_{i,t}e_{i,t}$, where $h_{i,t}$ is the conditional variance and $e_{i,t}$ is a standard normal random variable. The conditional variance is modeled as

$$h_{i,t} = \omega_i + \alpha_{i,1}u_{i,t-1}^2 + \beta_{i,1}h_{i,t-1}$$

indicating that the current variance depends on both the squared residuals from the previous period and the past variance. To ensure stationarity in the model I follow the constraint:

$$\omega_i , \alpha_{i,1}, \beta_{i,1} \geq 0, \alpha_{i,1} + \beta_{i,1} < 1 \, for \; i = 1, \ldots, N.$$

3.1.2. Measuring COVOL (Common Volatility)

After estimating the volatility model for each time series of both, the HESG and LESG group, the residuals are standardized to eliminate covariances, resulting in $e_{i,t}$, which now solely have idiosyncratic returns. These standardized residuals are uncorrelated as any systematic effects have been addressed by the factor model. Assuming that the factor model is correctly specified and captures the cross-sectional dependencies, the contemporaneous correlations among the standardized residuals approach zero. Consequently, the variance-covariance matrixes $\sum_t$ become an identity matrix of order N (I_N), indicating that each residual time series has a unit variance and that no linear dependencies remain across the series.

The key result of the model shows that, although the standardized residuals are orthogonal, this does not guarantee that they are fully independent. Specifically, the absolute or squared values of these residuals can still have positive cross-sectional correlation (Engle & Campos-Martins, 2023). From the standardized residuals, volatility shocks for ESG markets are derived as:

$$\emptyset_{i,t}^{\sigma} = e_{i,t}^2 - 1 = \frac{u_{i,t}^2 - h_{i,t}}{h_{i,t}} - 1$$

where $e_{i,t}$ are the standardized residuals, $u_{i,t}$ represents the original residuals from the factor model, and $h_{i,t}$ is the conditional variance derived from the volatility model. This equation measures deviations in realized volatility from the expected variance, normalized by the conditional variance.

This indicates that shocks to volatilities within HESG and LESG datasets may have distinct patterns of correlation. As I am working with two different datasets, on the one hand the HESG group and on the other hand for the LESG group, two separate latent factors are introduced: $f^{\sigma}_{HESG,t}$ for the HESG dataset and $f^{\sigma}_{LESG,t}$ for the LESG dataset. These factors capture the shared volatility dynamics within their respective groups.
For each group, the parameter s_i is interpreted as a factor loading or fixed effect, representing how strongly a specific company is influenced by its group-specific variance factor. The following conditions hold separately for HESG and LESG datasets:

$$E_{t-1}\left(f^{\sigma}_{HESG,t}\right) = 1,\ \ E_{t-1}\left(f^{\sigma}_{HESG,t} - 1)^2\right) = v_t{}^{HESG},\quad v_t{}^{HESG} > 0,\quad 0 \leq s_i{}^{HESG} \leq 1,$$

and

$$E_{t-1}\left(f^{\sigma}_{LESG,t}\right) = 1,\ \ E_{t-1}\left(f^{\sigma}_{LESG,t} - 1)^2\right) = v_t{}^{LESG},\quad v_t{}^{LESG} > 0,\quad 0 \leq s_i{}^{LESG} \leq 1,$$

for $t = 1, \dots, T$ and $i = 1, \dots, N$ in each group. This approach allows for a direct comparison of the volatility dynamics and shock responses between companies with high and low ESG scores.

For the HESG and LESG groups, the global volatility factors ($f^{\sigma}_{HESG,t}$ and $f^{\sigma}_{LESG,t}$) are modeled as positive scalar random variables with an expected value of one. The standardized residuals ($e_{i,t}$) are generated as:

$$e_{i,t} \ = \ \sqrt{g\left(s_i, f^{\sigma}{}_{group,t}\right)} \in_{i,t}, \qquad \in_{i,t} \ \sim N(0,1)$$

where $g\left(s_i, f^{\sigma}_{group,t}\right) = \ s_i\left(f^{\sigma}_{group,t} - 1\right) + 1$ and s_i represents the factor loading, indicating the extent to which a company's volatility depends on its group-specific global factor. This setup ensures $E\left(e^2_{i,t}\right) = 1$ for all observations, maintaining statistical consistency. By applying this framework to both groups, it becomes possible to compare their respective volatility dynamics and responses to shared shocks.

The assumption that the variances of the group-specific factors $f^{\sigma}_{HESG,t}$ and $f^{\sigma}_{LESG,t}$ are strictly positive shows that the squared residuals e^2 in each group have positive correlation over time. This shows that volatility shocks are persistent. Furthermore, the variance-covariance matrices

of the squared residuals ($\sum_{e^2}^{HESG}$ and $\sum_{e^2}^{LESG}$) are not diagonal due to cross-sectional dependence, which means that volatility shocks in one company can be correlated with volatility shocks in others within the same group.
The model analyzes the off-diagonal elements of these variance-covariance matrices for HESG and LESG datasets separately.
Here, a significant positive correlation between squared residuals in the HESG or LESG datasets show the presence of common volatility shocks that are specific to each group. By analyzing these off-diagonal elements, this framework enables to identify and compare shared volatility shocks which affect companies with high and low ESG scores, respectively.

To show the significance of shared volatility shocks within the HESG and LESG datasets, the test statistic proposed by Engle and Campos-Martins (2023) is used. It analyzes whether squared residuals show significant cross-sectional correlations, which would indicate the presence of common shocks. The statistic is defined as:

$$\varepsilon_{e^2} \frac{\sqrt{\frac{NT}{\frac{N-1}{2}}} \sum_{i>j}^{N} \sum_{t=1}^{T} \left(e_{i,t}^2 - 1\right)\left(e_{j,t}^2 - 1\right)}{\sum_{i=1}^{N} \sum_{t=1}^{T} \left(e_{i,t}^2 - 1\right)^2}$$

Under the null hypothesis of no common volatility, ε_{e^2} follows a standard normal distribution. Significant positive values of the statistic show evidence of shared volatility shocks, meaning that the squared residuals within HESG or LESG datasets are positively correlated.

This methodology refines the factor model iteratively to identify common volatility shocks separately for the HESG and LESG datasets. The log-likelihood function is established under the assumption of normality, treating $f_{HESG,t}^{\sigma}$ and $f_{LESG,t}^{\sigma}$ as if they were observed. It is defined as:

$$L\left(s, f_{group,t}^{\sigma}; e\right) = -\frac{1}{2} \sum_{i=1,t=1}^{n,T} \left\{ \log g\left(s_i, f_{group,t}^{\sigma}\right) + \frac{e_{it}^2}{g\left(s_i, f_{group,t}^{\sigma}\right)} \right\}$$

where $group \in \{HESG, LESG\}$. Parameters are estimated iteratively until the log-likelihood is maximised, enabling a comparison of shared volatility shocks between the two groups.

The model estimates two sets of unknowns: the latent volatility factor ($f^{\sigma}_{group,t}$) and the factor loadings (s_i) which are multiplicatively linked. To address this dependency, a maximum likelihood estimation is used, where each set of parameters is iteratively updated while holding the other set of parameters constant. This process continues until the estimates converge.

The iterative procedure alternates between cross-sectional and time-series regressions to estimate the factor loadings (s_i) and the latent volatility factors ($f^{\sigma}_{group,t}$) for HESG and LESG datasets. The cross-sectional relationship is modeled as:

$$e_{i,t} = \epsilon_{i,t}\sqrt{\hat{s}_i(f^{\sigma}_{group,t} - 1) + 1}, \qquad for\ t = 1, \dots, T,$$

and the corresponding time-series representation is:

$$e_{i,t} = \epsilon_{i,t}\sqrt{s_i(\hat{f}^{\sigma}_{group,t} - 1) + 1}, \qquad for\ t = 1, \dots, N,$$

The estimation process follows these steps:

1. **Initial cross-sectional estimates:** The starting values for (s_i) are obtained using the principal components of the squared standardized residuals, providing a basis for estimating ($f^{\sigma}_{group,t}$) over time.
2. **Time-series adjustment:** With the newly estimated ($f^{\sigma}_{group,t}$) values, the factor loadings (s_i) are refined for all companies in the dataset.
3. **Iterative refinement:** These steps are repeated until the parameter estimates stabilize, ensuring that the log-likelihood function is maximized.

This iterative approach captures the heteroskedasticity present in both the cross-sectional and time-series dimensions, providing a robust framework for modeling shared volatility patterns in HESG and LESG datasets.

The geovol R package developed by Campos-Martins (2021) is used to perform ESG cross-sectional correlation tests and estimate the ESG common volatility factor.

3.2. Data

To answer the research question, I examine financial data from the S&P 500 constituents as of December 2022. I select 2022 as the base year for my research, as it is the first year where ESG data is available for all S&P 500 constituents. In the first step, I retrieve the yearly ESG scores data for the years 2012 to 2022 from LSEG (formerly Refinitiv Eikon) for all S&P500 constituents in December 2022.

According to LSEG (2025), the ESG scores are designed to transparently and objectively measure a company's relative ESG performance, commitment, and effectiveness across ten main themes, based on publicly available and auditable data. LSEG's ESG scores are categorized into quartiles based on their numerical range, reflecting a company's relative ESG performance and transparency in reporting material ESG data. Companies scoring between 0 and 25 fall into the first quartile, indicating poor ESG performance and low transparency. Scores between 25 and 50 represent the second quartile, characterized by satisfactory performance and moderate transparency. The third quartile, with scores from 50 to 75, indicates good performance and above-average transparency, while the fourth quartile (75 to 100) reflects excellent performance and high transparency. As these are relative comparisons also oil companies such as Chevron Corp. are included in the HESG group.

In the next step, I calculate the average ESG scores of each company over these 10 years. I then sorted the companies from low to high average ESG scores to differentiate between LESG companies (low average ESG scores) and HESG companies (high average ESG scores). For my analysis, I selected the top 10% and bottom 10% of companies based on their ESG scores. This approach was chosen to focus on the most clearly defined groups, those with the highest and lowest ESG performance, allowing for a more distinct comparison in the context of my study.

The 10% best companies in terms of ESG scores form the HESG group, while the 10% worst companies form the LESG group, resulting in 50 companies per group, which accounts for 50 equities in each group. A full list of these companies and their respective ESG scores used in this study can be found in Appendix 1.

In the final step, I use price data for the companies in both the HESG and LESG groups over 10 years, from January 1, 2013, to December 30, 2022, for a total of 2609 time observations.

The timeframe used covers many different major political elections, such as the U.S. Presidential Election in 2016, the Brexit Referendum 2016, the U.S. Presidential Election 2020, several German Federal Elections as well as European Parliament Elections. Therefore, the timeframe is considered well suited to answer the research question, as it covers major political events with potentially global implications, including effects on markets in other countries such as the United States.

While I develop ESG scores from LSEG to classify companies into high (HESG) and low (LESG) ESG performance groups, it is important to identify certain limitations. The availability of ESG data is restricted to what is published during the study, and discrepancies in reporting standards across companies and industries may affect score comparability. Additionally, the methodology used in this thesis, focusing on the top and bottom 10% of ESG scores, is one of many possible approaches for distinguishing between high and low ESG groups. Other methods, such as selecting the top and bottom 20% or splitting the dataset based on the median ESG score, could add more perspectives and potentially bring different results. However, the 10% threshold was chosen to ensure clear differentiation and focus on the most extreme cases, which is in line with the objectives of this thesis.

4. Results

4.1. Summary Statistics

In the following section, I will present the summary statistics of my analysis. I consider two datasets: one for HESG assets and one for LESG assets. The summary statistics are displayed in Table 5 and 6 in the Appendix. These tables provide an overview of the key characteristics of both datasets, allowing for a direct comparison between the asset groups. The initial analysis allows us to compare the key metrics and identify fundamental differences between the LESG and HESG asset groups.
Both datasets have the same number of observations with 2517 datapoints each. The high-ESG (HESG) assets, representing sustainable investments, show a lower average return of 2.85% compared to 5.23% for the low-ESG (LESG) assets. Sustainable assets however also show lower volatility, with a standard deviation of 1.81 versus 2.31 for traditional assets, indicating more stable price movements.

Regarding the skewness, both asset groups tend to have slightly negative skewness, meaning large negative returns are more common sometimes. However, traditional (LESG) assets show more evident left-skewness, particularly Global Payment Technologies, which has the most skewed return distribution with -3.62. This indicates a higher likelihood of extreme downward movements. In comparison, the most negatively skewed sustainable asset, PG&E, has a skewness of -3.04.

Kurtosis, which measures tail risk, is higher for traditional assets, suggesting a more leptokurtic distribution, meaning extreme price movements occur more often. The highest kurtosis value is observed for Global Payment Technologies (LESG) at 117.79, while PG&E (HESG) also has an unusually high kurtosis of 101.10 among sustainable assets.

Furthermore, all time-series show significant ARCH effects, indicating time-varying volatility across both asset groups. Additionally, 11 HESG assets and 12 LESG assets also display significant autocorrelation effects, as supported by ARCH and AR statistical test results.

These results suggest that while (LESG) assets offer higher average returns, they also come with greater volatility and tail risk, whereas sustainable (HESG) assets are relatively more stable but seem to offer lower expected returns.

4.2. GARCH Volatility Estimation

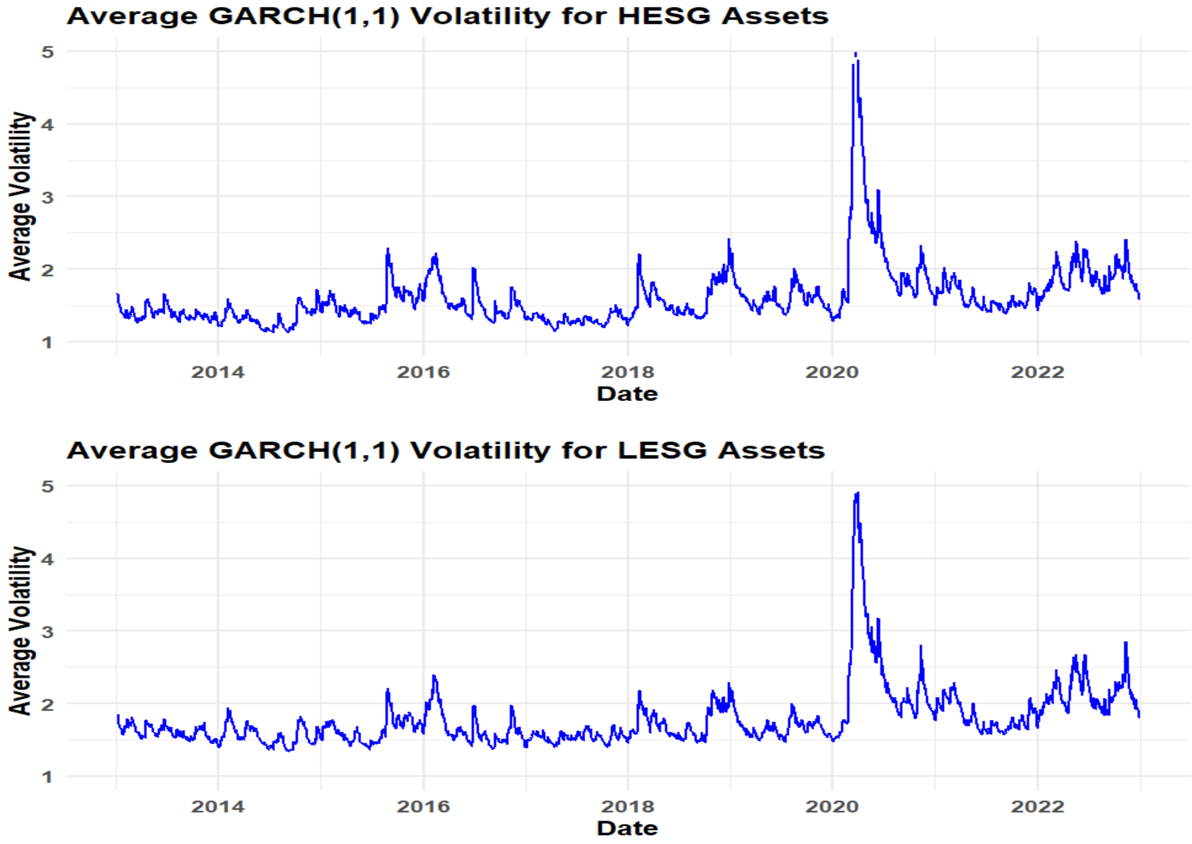

Figure 1: Evolution of GARCH(1,1) Volatilities for HESG and LESG Assets (2013–2022).

Figure 1 presents the evolution of GARCH(1,1) estimated volatilities for HESG and LESG asset groups over the period 2013–2022. Both volatility series show similar trends, indicating a high degree of correlation between HESG and LESG assets.

The strongest volatility peak is observed in 2020, showing with the outbreak of the COVID-19 pandemic, which triggered significant market uncertainty and turbulence across almost all asset classes. Another period of high volatility is seen in 2015–2016, likely reflecting a combination of global economic disruptions, including China's stock market crash, the oil price collapse, and heightened uncertainty surrounding the Brexit referendum. Additionally, the US presidential election in November 2016 introduced further volatility, as markets reacted to the uncertainty about Donald Trump's economic policies, initially leading to strong market reactions before the markets recovered and entered a post-election rally. Post-COVID, a structural shift appears in both series, where volatility remains at a higher level compared to pre-pandemic levels. This long-lasting increase suggests that the pandemic had a lasting effect on financial markets. However, a closer comparison suggests that HESG assets tend to exhibit

slightly lower volatility on average, which may indicate a relatively more stable risk profile compared to LESG assets. This could be attributed to investor preferences for sustainable assets in times of crisis or differences in sectoral exposure between the two groups.
The results here provide empirical insights into the risk dynamics of HESG versus LESG assets, particularly in response to major financial shocks.

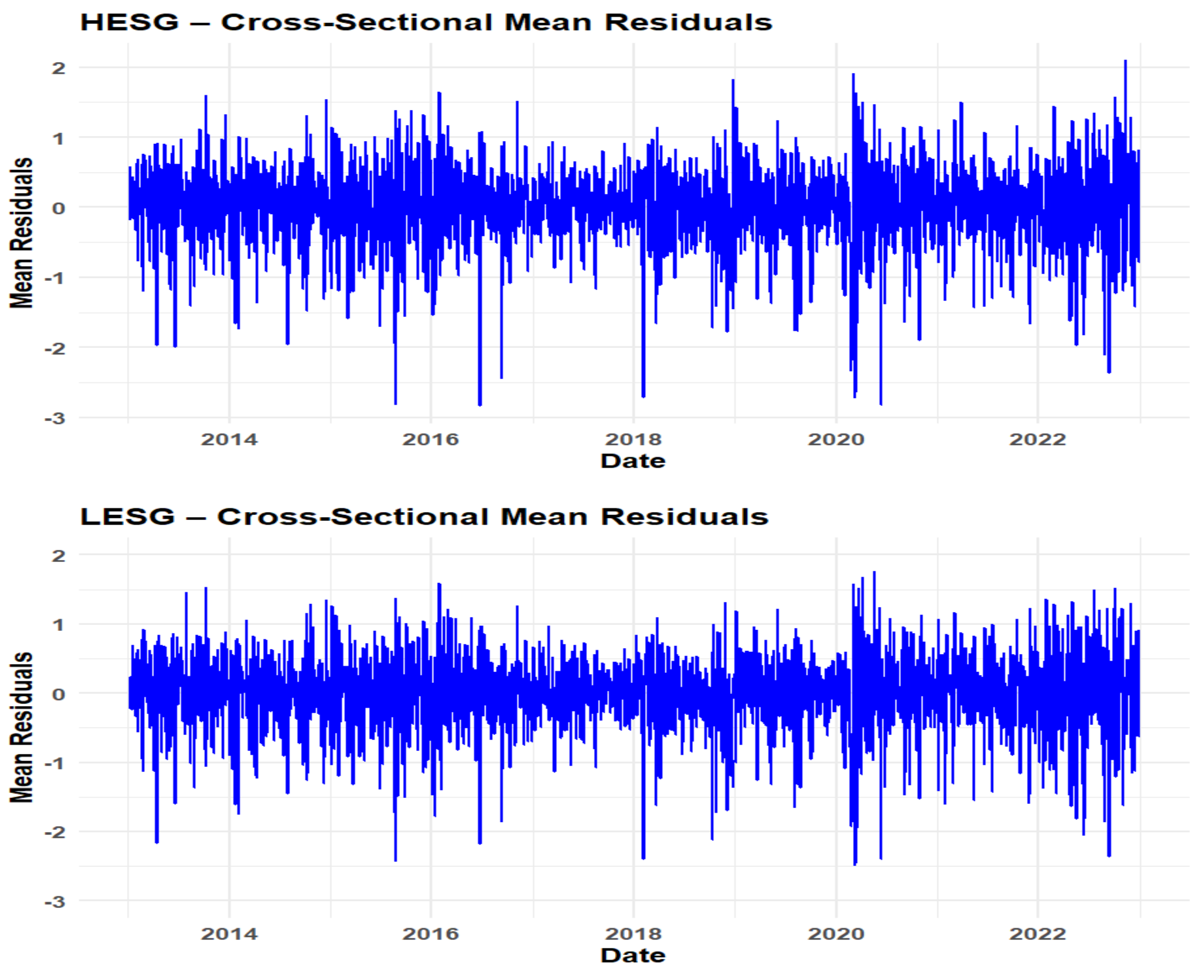

Figure 2: Cross-Sectional Mean Residuals of HESG and LESG assets between 2013-2022

Figure 2 shows the cross-sectional mean residuals of the HESG and LESG asset groups. These residuals represent the deviations between the actual and modeled conditional volatility, providing insights into how well the GARCH(1,1) model captures market fluctuations for each group.
Significant spikes occur during periods of high market uncertainty, such as 2015–2016 and the COVID-19 crisis in 2020, suggesting that extreme events lead to fluctuations that the model may not completely reflect.

A closer comparison between the two groups shows that HESG assets show more pronounced extreme residual spikes than LESG assets. This suggests that sustainable assets, while potentially less volatile on average, may experience stronger deviations from expected volatility during certain periods, possibly due to specific shocks affecting ESG-related sectors.

4.3. Common volatility shocks to HESG and LESG assets

4.3.1. Testing for COVOL

In the following steps I test for the presence of cross-sectional correlation between standardized residuals as well as for the cross-sectional correlation between the shocks to volatility. I do both for, on the one hand, the LESG asset group and on the other hand for the HESG asset group. The first null hypothesis to test is:

H0: The mean of the correlation values of the residuals is equal to 0

For the HESG asset group the mean correlation of the standardized residuals is 0.316 with a p-value of < 2.2e-16 signaling a significant correlation. For the LESG asset group the mean correlation of the standardized residuals is 0.303 with a p-value of < 2.2e-16 also signaling a significant correlation. This shows that the model does not fully account for dependencies in the data. Ideally, if the factors sufficiently explain the first moment, the average of the off-diagonal elements in the variance-covariance matrix should be close to zero. The factors used in the model were the 3FF, the Momentum factor and the cross-sectional mean which minimized the correlation for the two datasets. However, this does not imply that the residuals are independent, as shocks to the HESG and LESG asset groups may still be correlated. For this reason, it is necessary to test the same hypothesis for the shocks to the time series.

The following null hypothesis to test is:

H0: The mean correlation of Squared residuals is equal to 0

For the HESG asset group the mean correlation of volatility shocks is 0.1008, with a t-statistic of 155.445 and a p-value of 0, signaling a significant correlation and a clear rejection of the null hypothesis. For the LESG asset group the mean correlation of volatility shocks is 0.0923, with a t-statistic of 138.647 and a p-value of 0, signaling a significant correlation and a clear rejection of the null hypothesis for this group as well. The test results show the clear existence of co-movements in the HESG assets group and in the LESG asset group.

4.3.2. Estimating COVOL for HESG and LESG asset groups

In the following section I calculated the daily COVOL for the HESG and for the LESG group to compare their behavior and to observe spikes in the two time-series triggered by global events.

Table 1: Highest Absolute Values of COVOL for HESG and LESG Assets with Corresponding Events

Date	f^{σ}_{HESG}	r_{CSM}	Event
24.06.2016	5.83	-3,83	Day after the Brexit Referendum
24.08.2015	5.16	-4,39	"Black Monday": China slowdown fears
11.06.2020	5.11	-6,76	Fear of second COVID-19 wave
09.03.2020	4.91	-9,41	COVID-19 fears & oil price war
05.02.2018	4.88	-4,08	Inflation fears & Fed rate hike concerns

Date	f^{σ}_{LESG}	r_{CSM}	Event
12.03.2020	4,66	-8,49	"Black Thursday": COVID-19 panic & U.S. travel ban
09.03.2020	4,63	-7,14	COVID-19 fears & oil price war
24.08.2015	4,61	-4,39	"Black Monday": China slowdown fears
24.06.2016	4,42	-3,22	Day after the Brexit Referendum
05.02.2018	4,36	-3,47	Inflation fears & Fed rate hike concerns

Note: The upper section presents the highest COVOL values for HESG assets, while the lower section presents the corresponding values for LESG assets.

The estimation of COVOL for HESG and LESG asset groups show strong spikes during major international events, highlighting the sensitivity of both groups to systemic shocks. The highest observed levels of COVOL for HESG assets occurred as a response to important global events, including the Brexit Referendum on June 24, 2016, the sharp market downturn on August 24, 2015, known as "Black Monday," fears of a second COVID-19 wave on June 11, 2020, and the impact of both COVID-19 fears and the oil price war on March 9, 2020. Additionally, inflation concerns and expectations of Federal Reserve rate increases on February 5, 2018, also contributed to higher volatility in HESG assets.

Similarly, LESG assets showed peak COVOL levels during almost the same events. The highest COVOL value occurred on March 12, 2020, during "Black Thursday," when fears surrounding the COVID-19 pandemic intensified following the U.S. government's announcement of a

European travel ban. Other COVOL spikes were observed on March 9, 2020, during the initial COVID-19 market crash, on August 24, 2015, amid concerns over China's economic slowdown, and on June 24, 2016, following the Brexit referendum. The market turbulence on February 5, 2018, driven by inflation expectations and monetary policy uncertainty, also led to a sharp rise in COVOL for LESG assets.

The findings suggest that both HESG and LESG asset groups show high COVOL on major macroeconomic and geopolitical events. While both groups were impacted by systemic crises such as COVID-19 and Brexit, the magnitude of COVOL spikes appears to be more pronounced for HESG assets.

A key factor contributing to the higher COVOL levels in HESG assets during these events is the unexpectedness of these events. Unlike elections, where companies, especially those with high-ESG governance and policy strength, can anticipate potential outcomes and adapt their strategies accordingly, sudden crises such as the COVID-19 pandemic, or financial crashes give only little time to the companies to adapt.

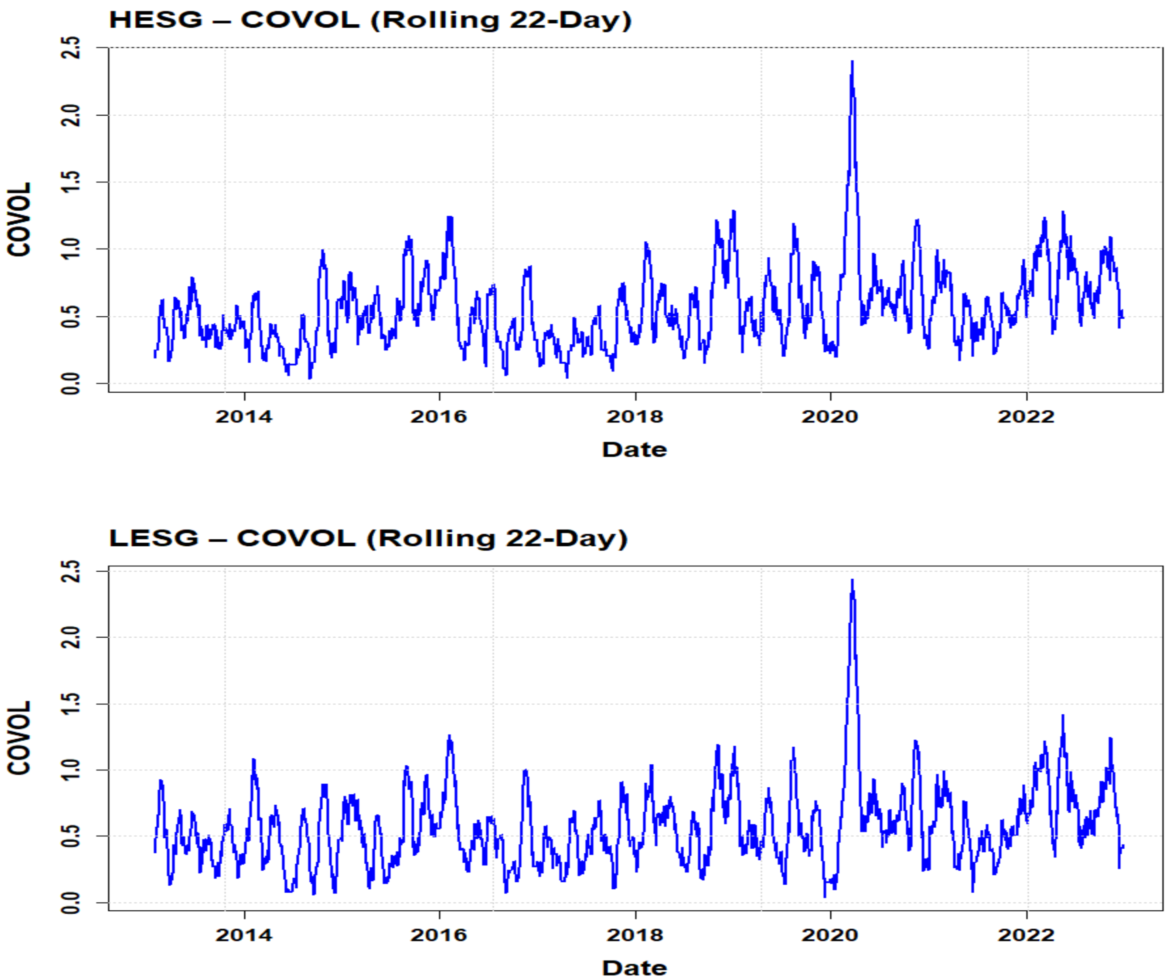

Figure 3: Evolution of monthly ESG COVOL factor for HESG and LESG assets between 2012 and 2022

4.3.3. Factor Loadings

The estimated factor loadings show how strong individual companies contribute to the common volatility factor (COVOL) within the HESG and LESG groups. Table 2 presents the top-ranking firms in each category, sorted by their respective factor loadings in descending order. Among HESG companies, 3M exhibits the highest factor loading S = 2.002 followed by Cisco Systems, State Street, and Accenture.
The highest factor loading is observed in Global Payment Technologies S = 0.2058, with Equifax, Expedia Group, and Booking Holdings also contributing significantly to COVOL

Table 2: Factor Loadings of HESG and LESG Assets

HESG	
Compay	S
3M	0.2002
CISCO SYSTEMS	0.1883
STATE STREET	0.1812
ACCENTURE CLASS A	0.1791
INTL.FLAVORS & FRAG.	0.1767
AIR PRDS.& CHEMS.	0.1725
MICROSOFT	0.1714
LEIDOS HOLDINGS	0.1712
JP MORGAN CHASE & CO.	0.1691
MOTOROLA SOLUTIONS	0.1632

Compay	S
GLOBAL PAYMENT TECHS.	0.2058
EQUIFAX	0.1820
EXPEDIA GROUP	0.1745
BOOKING HOLDINGS	0.1729
JACK HENRY AND ASSOCIATES	0.1726
ROLLINS	0.1714
O REILLY AUTOMOTIVE	0.1697
LIVE NATION ENTM.	0.1692
CORPAY	0.1691
BERKSHIRE HATHAWAY 'B'	0.1651

4.4. Event study approach

To analyze the impact of major political events on COVOL, I designed an event study approach, focusing on the COVOL dynamics of HESG and LESG asset groups. The event study follows a two-step process, consisting of an estimation window and an event window, to isolate abnormal volatility changes around the event date.
The estimation window spans 500 trading days before the event and is a baseline to find the usual level of COVOL without major political events. This period helps to identify normal market developments, which are then compared to the event period. The event window covers the days around the event and captures the market reaction concerning the event. This window includes days before and after the event, to account for both, broad anticipatory market movements and delayed effects.

The key number calculated from this analysis is the Cumulative Abnormal COVOL (CAC), which measures the total excess COVOL observed during the event window compared to the average estimation window COVOL. CAC is calculated as the sum of daily abnormal COVOL during the event window:

$$CAC = \sum_{t=-10}^{+10} (COVOL_t - COVOL_{estimation})$$

Where $COVOL_t$ represents the daily COVOL during the event window, and $COVOL_{estimation}$ denotes the average COVOL level from the estimation period.

To assess the impact of political events on market volatility, we examine whether COVOL increases during the event window compared to the estimation window for both HESG and LESG assets. Additionally, we analyze whether the magnitude of this increase differs between the two groups, highlighting potential differences in how HESG and LESG assets react to major political events.

Table 3: COVOL Analysis for Major Political Events (10+/10- Event Window)

Election Event	Group	Mean Estimation COVOL	Mean Event COVOL	CAC	HESG vs. LESG
US Election 2016	HESG	0,5532	0,8776	0,3244	
	LESG	0,5249	1,0011	*0,4762	0,1518
Brexit 2016	HESG	0,5448	0,7388	**0,1940	0,0534
	LESG	0,5364	0,677	*0,1406	
US Election 2020	HESG	0,7123	1,2147	**0,5024	
	LESG	0,6796	1,2224	*0,5428	0,0404
EU Elections 2019	HESG	0,5373	0,6674	0,1301	0,2219
	LESG	0,5663	0,4745	- 0,0918	
Paris 2016	HESG	0,546	0,8488	0,3028	
	LESG	0,5207	1,001	*0,4803	0,1775

Note: Table 3 presents the results of the event study analyzing the impact of major political events on the cumulative abnormal COVOL (CAC) of HESG and LESG assets. The CAC column measures the excess volatility during the event window compared to the estimation window. In the last column ("HESG vs. LESG"), the value represents the absolute difference between the CAC values of HESG and LESG. A number is shown only for the group with the higher CAC, indicating the extent to which one group exhibited stronger volatility compared to the other. Statistical significance levels are indicated by asterisks: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3 presents the results of the event study analyzing the impact of five major political events on the COVOL of HESG and LESG asset groups with an event window of 10 days before and 10 days after the event. A key observation is that COVOL almost consistently increases during the event window compared to the estimation window, indicating that political events trigger heightened market volatility. However, the extent of this increase and whether HESG or LESG assets show a stronger reaction varies across the events. The only exception to this is the European Parliament elections, where no real difference was observed. This can be attributed to the fact that the outcome had no direct economic consequences for the US companies, reducing their sensitivity to the event. The US Election 2020 shows the highest overall CAC values (0.5024 for HESG and 0.5428 for LESG), where LESG assets show a slightly stronger volatility response. This suggests that lower-ESG-scoring assets might have been more sensitive to the election's outcome, possibly due to expectations regarding deregulation or policy shifts favoring traditional industries.

Conversely, in the Brexit Referendum 2016, HESG assets experienced a more pronounced volatility surge (CAC = 0.1940) compared to LESG assets (CAC = 0.1406). This could indicate that high-ESG-scoring stocks were more exposed to concerns over international trade and regulatory uncertainty following Brexit. Other events, such as the EU Parliament Elections and the Paris Climate Agreement 2016, exhibit less pronounced volatility shifts. While COVOL still increases during these events, the differences between HESG and LESG assets are smaller, with neither group showing a consistently stronger reaction. The Paris Agreement, an ESG-specific policy event, resulted in a stronger volatility response for LESG assets (CAC = 0.4803) compared to HESG assets (CAC = 0.3028), possibly reflecting market expectations around sustainability commitments.

To further analyze the volatility effects of political events, two more event windows were applied: a 3-day window before and after the event and a 3-day window after the event only. The results of these alternative event windows are reported in Appendix Table 7 and 8. Comparing the results across these event windows reveals that the observed volatility effects are significantly influenced by the length of the event window. Shorter event windows provide a sharper picture of immediate market reactions, while longer event windows include periods of stabilization that dilute the effects.

In the US Election 2016, CAC for HESG assets increases from 0.3244 in the long event window (10 days) to 1.1966 when focusing only on the three days post-event, while LESG assets rise from 0.4762 to 0.8903 under the same adjustment. The Brexit referendum shows an even sharper increase, with CAC values more than doubling for both asset groups when shifting to a shorter event window. This suggests that the market's response to the referendum was concentrated immediately after the vote, rather than being spread across a broader timeframe. Similarly, the Paris Agreement 2016, which initially showed moderate volatility shifts (CAC of 0.3028 for HESG and 0.4803 for LESG in the longer window), shows a far greater reaction when shortening the event window to three post-event days. CAC values reach 1.4315 for HESG and 1.0076 for LESG, suggesting that initial market reactions were stronger than previously captured. However, as more days were included in the analysis, the volatility effect appeared smaller due to stabilization afterwards.

The US Election 2020 deviates from the general pattern, as HESG CAC decreases when the event window is shortened, while LESG CAC increases. The long-window CAC values (0.5024 for HESG and 0.5428 for LESG) drop to 0.3446 for HESG but rise to 0.6216 for LESG in the medium-window analysis. When focusing only on the three days after the event, HESG CAC remains lower at 0.4080, whereas LESG CAC further increases to 0.7665, indicating a stronger and longer volatility response among LESG assets. While the absolute increase is less strong than in Brexit or the Paris Agreement, it strengthens that political events drive short-term volatility spikes, which are best captured using a short, focused event window. An exception to this is the EU Elections 2019, where CAC values remain relatively low across all event windows and even turn negative in some cases. This suggests that the market reaction to these elections was limited, and adjusting the event window does not significantly alter this finding. The lack of a strong response suggests that institutional elections, which do not directly change national economic policies, tend to have a weaker impact on volatility compared to major national elections or referendums. This effect may be further strengthened by the fact that the analysis focuses on US-based assets, for which European institutional elections may hold less economic relevance, leading to a smaller market reaction.

A further key finding is the difference in volatility responses between HESG and LESG assets, which becomes more pronounced when using shorter event windows. Contrary to the assumption that LESG assets are always more volatile, HESG assets show higher CAC values in several cases, particularly when the event is associated with regulatory uncertainty or international trade implications. The relative magnitude of these differences varies across events and depends on the length of the event window.

For example, in the US Election 2016, HESG assets show higher CAC values than LESG assets in both the 3+3-day and 3-day post-election event windows. In the 10-day event window, LESG assets have a slightly higher CAC than HESG assets (0.4762 vs. 0.3244), indicating that low-ESG firms reacted more strongly in the broader event period. However, when shortening the window to -3+3 days, HESG CAC increases to 1.1637, while LESG CAC remains lower at 0.7962. This trend continues in the 3-day post-election window, where HESG CAC rises further to 1.1966, while LESG CAC remains at 0.8903.

In contrast, the US Election 2020 presents a different pattern. Under the 10-day event window, LESG assets show a slightly higher CAC than HESG assets (0.5428 vs. 0.5024). When the event window is shortened to 3+3 days, LESG still maintains a higher CAC (0.6216 vs. 0.3446 for HESG). However, in the 3-day post-election window, LESG CAC continues to increase (0.7665), while HESG CAC remains at 0.4080. This suggests that LESG assets had a more prolonged volatility reaction to the US Election 2020, while HESG volatility was more short-lived.

For the Brexit referendum, CAC values for HESG and LESG assets are relatively close in the 10-day and 3+3-day windows, with no strong dominance of one group. In the 10-day event window, HESG and LESG show similar CAC values (0.1940 vs. 0.1406, respectively), indicating that Brexit uncertainty impacted both asset groups in a comparable way. However, in the 3+3-day window, CAC values rise more significantly, with HESG at 0.9650 and LESG at 0.8404, suggesting a slightly stronger reaction among HESG assets. When reducing the window to only the 3 days after the referendum, CAC values increase sharply for both groups (2.0939 for HESG vs. 2.3885 for LESG), showing that Brexit triggered an extreme short-term volatility event affecting both asset groups almost equally.

The comparison across event windows confirms that shorter windows highlight more distinct volatility patterns. The assumption that LESG assets are systematically more volatile is not supported by the data, as HESG assets sometimes exhibit higher CAC values, particularly in cases like US Election 2016. However, in events like US Election 2020, LESG assets show a more sustained volatility response.

Ultimately, the findings suggest that political events do not induce a uniform volatility response across ESG asset groups. Instead, the nature of the political event, whether it is trade-related (Brexit), regulatory (Paris Agreement), or policy-driven (US Elections), plays a key role in shaping market reactions.

4.5. Graphical Analysis

To further explore the volatility patterns surrounding major political events, I conducted a graphical analysis, focusing on two events: the US Election 2016 and the Brexit Referendum 2016. These two events were chosen because they exhibited significant volatility shifts in the previous CAC analysis. Additionally, an aggregated analysis across multiple elections provides a broader perspective on common volatility trends around political events.

The figure 4 illustrates COVOL development around the US Election 2016, highlighting how HESG and LESG assets reacted three days before and three days after the election. Prior to the event, volatility increased for both asset groups, reflecting rising market uncertainty. However, on election day itself (November 8), LESG volatility dropped sharply, whereas HESG volatility remained relatively stable. This pattern suggests that investors in lower-ESG assets might have momentarily reassessed their risk exposure, leading to a temporary dip in volatility. Alternatively, this effect could also reflect the fact that the election outcome was announced after market hours, shifting the volatility reaction to the following trading day.

Immediately after the election, both HESG and LESG assets experienced a strong volatility spike, with LESG briefly peaking at a higher level than HESG on one of the post-election days. This suggests that at its most extreme point, LESG assets showed a sharper short-term reaction. However, when looking at the cumulative abnormal COVOL (CAC) over the 3+3-day and 3-day post-election windows, HESG exhibits a higher overall volatility response, indicating that its elevated volatility was more sustained across multiple days rather than concentrated in a single peak. This highlights that while LESG may have reacted more sharply right after the election, HESG assets remained volatile for a longer period. By November 10, volatility for both asset groups declined, suggesting that markets quickly adjusted to the election outcome, further reinforcing the idea that political events primarily induce short-term volatility shocks that weaken within a few days.

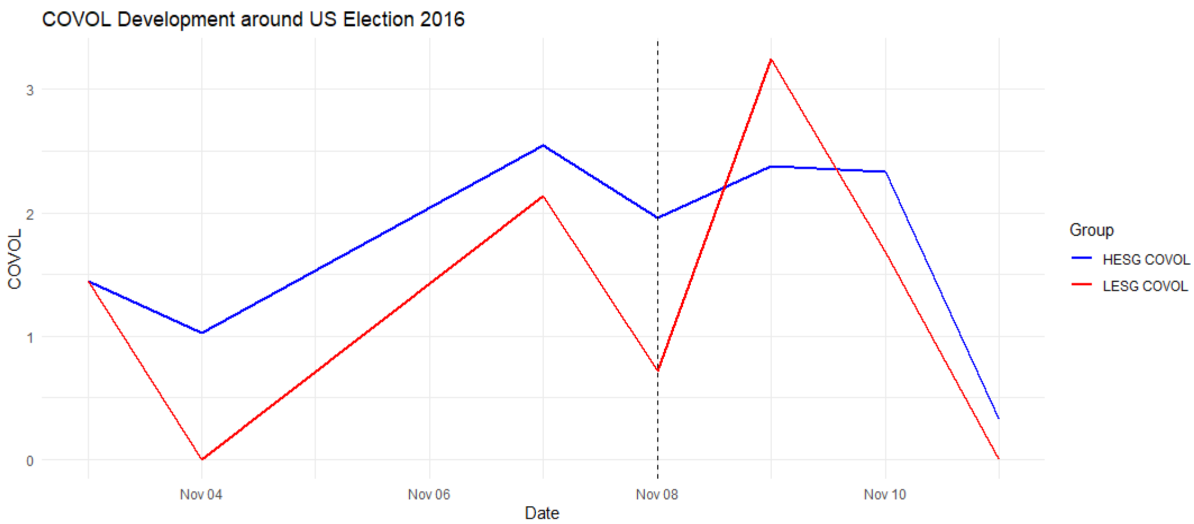

Figure 4: COVOL Development Around the US Election 2016

Figure 5 represents COVOL development around the Brexit Referendum on June 23, 2016, capturing how market volatility evolved for HESG and LESG assets in the immediate days before and after the event. Unlike the US Election 2016, where HESG and LESG displayed some divergence in their post-election behavior, the Brexit referendum resulted in a highly synchronized volatility response for both asset groups. Both HESG and LESG volatility spiked sharply right after the referendum, reaching their highest levels within a day of the vote.

A key observation is that while both groups followed a nearly identical pattern, HESG volatility peaked at a higher level than LESG, suggesting that high-ESG firms experienced a slightly stronger volatility shock in the immediate aftermath of Brexit.

Additionally, the timing of the peak is particularly insightful. The highest volatility is observed immediately after the referendum, reinforcing the idea that political shocks lead to an almost instantaneous market reaction. This aligns with the previous CAC analysis, where shorter event windows captured the strongest volatility effects, confirming that Brexit was perceived as an immediate and systemic market risk. After the initial shock, volatility declined gradually for both asset groups, converging to pre-event levels within a few days.

Comparing the two events, a key difference emerges: while the US Election 2016 caused a sharper reaction in LESG assets, Brexit had a more significant impact on HESG assets. This contrast highlights that different types of political events produce varying volatility responses depending on the expected economic and regulatory consequences for different asset classes.

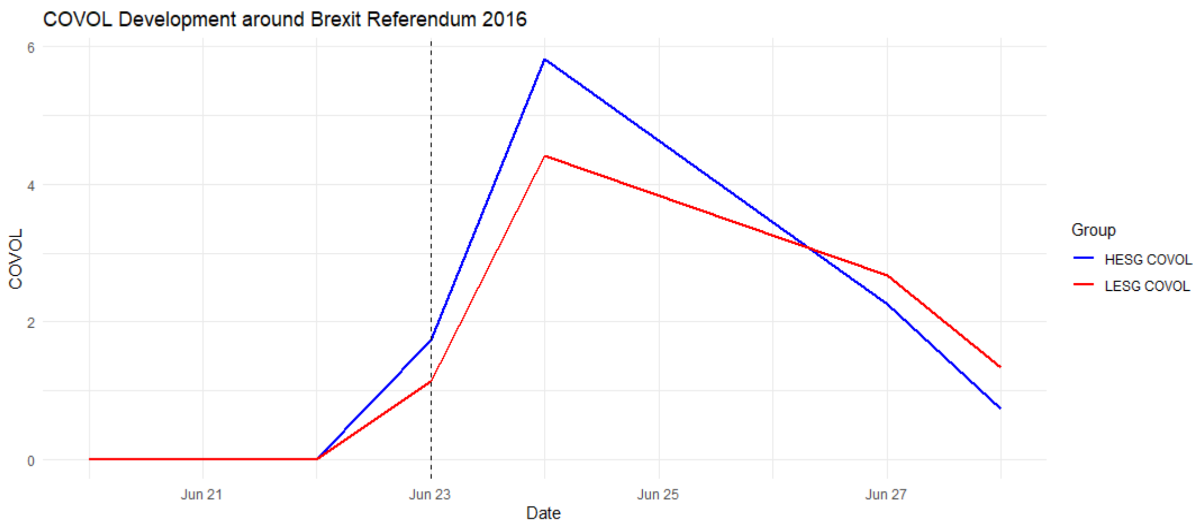

Figure 5: COVOL Development Around the Brexit Referendum 2016.

To provide a broader perspective on election-related volatility, Figure 6 presents the average COVOL response across 11 major political events, including the U.S. Presidential Elections (2016, 2020), the Brexit Referendum (2016), the EU Parliament Election (2019), the Paris Agreement Enforcement (2016), the German Federal Election (2021), the French Presidential Election (2022), the UK General Election (2019), and the Brazilian Presidential Elections (2014, 2022). First, volatility starts increasing in the days leading up to a political event, reflecting market uncertainty and investor speculation. As seen in the US Election and Brexit graphs, the peak in COVOL occurs immediately after the event (Day 0 to Day +1), confirming that political events induce sharp but short-lived volatility spikes. Additionally, HESG and

LESG assets follow a similar development overall, but LESG assets tend to experience a sharper post-event volatility drop, whereas HESG assets decline more slowly. This suggests that while both asset groups react strongly to elections, LESG assets might adjust more quickly after initial speculation subsides, while HESG assets remain volatile for a longer period.

The broader trend observed in the aggregated data supports the previous conclusion that election-related volatility is primarily a short-term phenomenon, making shorter event windows (e.g., 3 days post-event) the most effective for capturing market reactions. The relative differences between HESG and LESG volatility suggest that policy-related uncertainty affects asset classes differently, depending on the expected regulatory and economic implications.

An important observation from figure 6 is that LESG exhibits a higher volatility peak on Day 1 following elections. This indicates that on average low-ESG assets tend to experience a more abrupt and immediate reaction to political uncertainty. However, HESG assets display more persistent volatility, as their levels remain elevated for a longer period rather than spiking sharply on a single day.

Taken together, these findings confirm that political events lead to significant but short-lived volatility spikes, with varying impacts on different asset groups depending on the event type. The US Election 2016 and Brexit Referendum illustrate how market expectations regarding policy direction, trade relations, and regulatory stability shape volatility responses, while the aggregated election data reinforce the importance of using shorter event windows to isolate the most relevant market reactions. This graphical analysis complements the previous CAC findings, providing a more dynamic view of how HESG and LESG assets respond to political uncertainty.

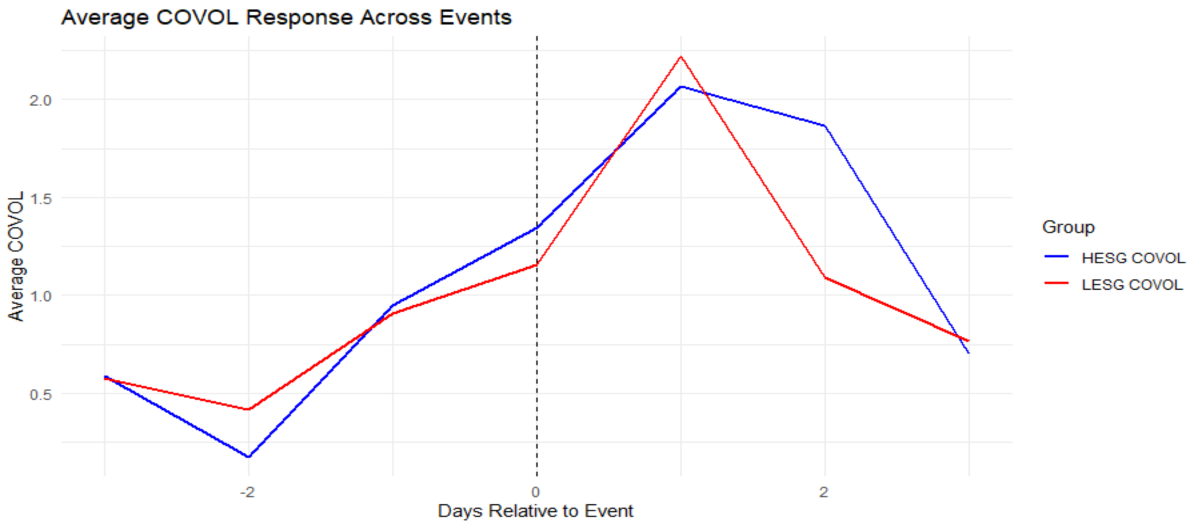

Figure 6: Average COVOL Response Across 11 Events

5. Limitations

5.1. Focus on US-based assets

This study primarily analyzes US-based assets, which might make it harder to apply these findings to other global markets. While US elections and political events have significant global spillover effects, the exclusion of assets from other regions may overlook region-specific volatility patterns. Future research could benefit from incorporating a broader asset base, including European and emerging markets, to enhance the robustness of political event studies on asset volatility.

5.2. Limited ESG classification criteria

The distinction between HESG and LESG assets in this study is based on predefined ESG scoring methodologies. However, ESG classifications can vary across data providers, and differences in sector exposure or firm characteristics could introduce bias into the results. Additionally, ESG scores are not consistently available across all years, as many ESG ratings are published with a significant time lag. For instance, data for 2023, 2024, and 2025 is largely unavailable at present. This delay limits the ability to assess the most recent market reactions with the same ESG classification criteria.

Future studies may refine ESG classifications by incorporating alternative sustainability metrics or focusing on real-time ESG indicators to improve comparability and robustness across different time periods. Expanding the dataset to include historical backfills or firm-level sustainability disclosures could also mitigate the issue of data lag.

6. Future research ideas

One possible extension of this research would be to broaden the geographical scope by incorporating HESG and LESG assets from global markets rather than focusing solely on the United States. Political events have varying impacts depending on regional regulatory environments, economic structures, and investor behavior, making it valuable to compare how different markets react to political uncertainty. A cross-country analysis could provide insights into whether the ESG volatility response differs between developed and emerging markets or across countries with varying degrees of climate and sustainability regulations.

Another important aspect for future studies would be to analyze ESG volatility responses on a sectoral level. Since political decisions often affect specific industries, such as energy, finance, or technology, differently, breaking down the analysis by industry classification could provide a clearer picture of how regulatory shifts or political uncertainty influence different sectors. This would help determine whether high-ESG industries are more resilient to certain policy risks compared to low-ESG sectors.

Finally, as ESG data availability improves, future research could work toward overcoming the limitations caused by ESG score publication lags. Since many ESG ratings are released with a one-year delay or more, current studies may not fully capture real-time shifts in ESG risk profiles. Incorporating higher-frequency sustainability indicators or alternative classification approaches could help assess whether real-time ESG assessments produce different volatility outcomes than delayed ESG scores.

Expanding on these areas could provide a deeper understanding of how political events shape ESG market dynamics and help refine the methodological approaches used to study ESG-related volatility effects.

7. Conclusion

This study examined the impact of major political events on the volatility of high-ESG (HESG) and low-ESG (LESG) assets, using an event study approach to assess short-term market reactions. By analyzing multiple event windows and comparing volatility responses across asset groups, the research provided new insights into how political uncertainty affects ESG-related investments and how market participants adjust their positions in response to elections and referendums.

A key finding is that political events consistently lead to short-term volatility spikes, confirming that markets rapidly incorporate new information. However, the magnitude and persistence of these volatility effects vary depending on the event type and the asset group analyzed. LESG assets tend to exhibit sharper but short-lived volatility peaks immediately following political events, while HESG assets often display more sustained periods of elevated volatility. This pattern suggests that investors react differently to political risk depending on ESG-related factors, possibly due to varying regulatory exposures, investor sentiment, and policy expectations. The results indicate that high-ESG portfolios may require distinct risk management approaches, as their volatility reactions differ from low-ESG assets, particularly in times of heightened political uncertainty.

The analysis also underscores the importance of event window selection in volatility studies. While longer event windows, such as ten days before and after, help identify broader trends, they may obscure short-term volatility spikes. Shorter event windows, such as 3+3 days or three days post-event, more effectively isolate immediate market reactions, reinforcing the idea that political uncertainty triggers temporary but sharp trading adjustments rather than long structural market shifts. The aggregated COVOL response analysis further confirms that volatility typically peaks immediately after political events and gradually declines, highlighting the rapid adaptation of financial markets to new political realities in line with the predictions of the Efficient Market Hypothesis.

From a methodological perspective, the findings emphasize the need for further refinement in ESG asset classification and volatility measurement. The study was constrained by the lag in ESG data publication, limiting the ability to assess real-time changes in ESG risk exposure.

Overall, these findings contribute to the growing literature on political risk and sustainable finance, providing empirical evidence that high-ESG and low-ESG assets react differently to political uncertainty. The results have implications for investors, policymakers, and portfolio managers, suggesting that high-ESG assets require tailored risk management strategies in periods of political instability. Future research could build on this study by expanding the geographical scope, incorporating sector-specific analyses, and applying alternative risk measurement techniques. Addressing these aspects could improve the understanding of how ESG markets respond to political and regulatory shifts, ultimately supporting more informed investment decision-making in times of increasing sustainability-driven financial policies.

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Appendix

Table 4: Overview of Companies and Their 10-Year Average ESG Scores

Low-ESG Companies		High-ESG Companies	
Company	**ESG Score**	**Company**	**ESG Score**
Corpay	20,23	Leidos Holdings	76,57
Netflix, Inc.	20,69	HP Inc.	76,89
Charter Communications, Inc.	21,52	Kellanova	76,96
Rollins, Inc.	22,57	Ford Motor Company	77,13
Berkshire Hathaway Inc.	22,80	Philip Morris International	77,14
LKQ Corporation	24,77	S&P Global Inc.	77,28
Global Payments Inc.	24,77	Dominion Energy, Inc.	77,54
Lennar Corporation	24,86	Air Products and Chemicals,	77,89
NVR, Inc.	25,55	Exxon Mobil Corporation	77,95
Expedia Group, Inc.	25,64	Chevron Corporation	78,08
TransDigm Group Incorporated	26,23	Humana Inc.	78,15
Monster Beverage Corporation	28,34	Best Buy Co., Inc.	78,25
Coterra Energy Inc.	28,40	Walmart Inc.	78,28
Generac Holdings Inc.	28,91	Becton, Dickinson	78,44
Monolithic Power Systems, Inc.	30,62	Linde plc (NYSE)	78,56
Genuine Parts Company	30,81	Motorola Solutions, Inc.	78,85
Fiserv, Inc.	31,11	International Flavors Inc	79,02
Extra Space Storage Inc.	31,39	JPMorgan Chase & Co.	79,42
Atmos Energy Corporation	31,42	Host Hotels & Resorts, Inc.	79,60
Jack Henry & Associates, Inc.	32,20	Abbott Laboratories	79,76
Old Dominion Freight Line, Inc.	32,59	Autodesk, Inc.	79,77
Booking Holdings Inc.	33,19	Accenture plc (Class A)	80,31
Dexcom, Inc.	33,23	Halliburton Company	80,36
Zebra Technologies Corporation	33,54	Hasbro, Inc.	80,67
Loews Corporation	34,11	Weyerhaeuser Company	80,97
Universal Health Services, Inc.	34,28	Johnson Controls Int.	81,55
First Republic Bank	34,68	Freeport-McMoRan Inc.	82,34
Constellation Brands, Inc.	35,11	PepsiCo, Inc.	82,35
D.R. Horton, Inc.	35,16	Target Corporation	82,68
ServiceNow, Inc.	35,31	GE Aerospace	82,70
C.H. Robinson Worldwide, Inc.	35,33	Citigroup Inc.	82,83
Equifax Inc.	35,40	Baker Hughes Company	82,99
Teledyne Technologies	35,60	Campbell Soup Company	83,14
Bio-Rad Laboratories, Inc.	35,65	Waste Management, Inc.	83,45
Align Technology, Inc.	35,77	Agilent Technologies, Inc.	83,51
Molina Healthcare, Inc.	35,91	Baxter International Inc.	83,93
Signature Bank	36,36	Newmont Corporation	84,13
Live Nation Entertainment, Inc.	36,46	PG&E Corporation	84,26
Martin Marietta Materials, Inc.	36,48	State Street Corporation	84,74
Copart, Inc.	36,52	Colgate-Palmolive Company	84,78
Arch Capital Group Ltd.	36,52	Texas Instruments Inc.	85,05

Huntington Ingalls Industries Inc.	36,58	Altria Group, Inc.	85,57
Public Storage	37,42	CVS Health Corporation	86,12
Paychex, Inc.	37,87	Cisco Systems, Inc.	86,15
Evergy, Inc.	38,02	CBRE Group, Inc. (Class A)	86,24
O'Reilly Automotive, Inc.	38,64	Dow Inc. (Ordinary Shares)	86,79
CenterPoint Energy, Inc.	39,28	Johnson & Johnson	86,80
Take-Two Interactive Software	39,45	Intel Corporation	88,99
Dollar General Corporation	39,86	3M	89,79
Warner Bros. Discovery, Inc.	20,23	Microsoft Corporation	91,95

Note: Table 4 displays an overview of all the companies included in this analysis, along with their corresponding 10 year average ESG scores. The companies listed are part of the S&P 500 as of December 2022. ESG scores reflect the companies' performance in environmental, social, and governance factors.

Table 5: Summary Statistics for HESG Companies

Company	N	Min	Mean	Max	SD	Skewness	Kurtosis
LEIDOS HOLDINGS	2517	-20,340496	0,0601533	10,2306301	1,77512734	-1,5012265	21,0119272
HP	2517	-18,96439	0,05448026	15,7840311	2,19919163	-0,5879031	14,5517224
KELLANOVA	2517	-11,562949	0,00892267	10,1162421	1,29835683	-0,4708551	14,0602473
FORD MOTOR	2517	-13,152403	-0,0050309	21,0596335	2,1214146	0,13686676	11,2993213
PHILIP MORRIS INTL.	2517	-16,931503	0,00612962	9,56246947	1,44986566	-1,4506172	20,4376392
S&P GLOBAL	2517	-16,474868	0,07125991	12,9762257	1,65328577	-0,7298726	16,7630949
DOMINION ENERGY	2517	-13,139875	0,00585319	15,8987574	1,3720652	-0,5782165	24,5915978
AIR PRDS.& CHEMS.	2517	-13,472281	0,05390261	12,8598258	1,51281043	-0,187406	13,2955926
EXXON MOBIL	2517	-13,039102	0,0086544	11,9442143	1,69428038	-0,1615898	10,6154504
CHEVRON	2517	-25,006226	0,01931267	20,4903701	1,83472144	-0,9876623	31,7067558
HUMANA	2517	-21,53152	0,07996575	18,4924522	1,87597294	-0,1333128	21,6428137
BEST BUY	2517	-33,66852	0,07611051	19,4575928	2,53656585	-0,7339074	22,8050568
WALMART	2517	-12,076476	0,02847706	11,0720884	1,29584109	-0,1598151	19,7204568
BECTON DICKINSON	2517	-12,553619	0,04622117	10,7723948	1,34767756	-0,5175799	11,9826745
LINDE (NYS)	2517	-10,85131	0,042264	11,0599269	1,40591662	-0,0447956	10,0200204
MOTOROLA SOLUTIONS	2517	-13,13273	0,06050529	13,2086664	1,55976846	-0,3032403	13,4242982
JOHNSON CONTROLS INTL.	2517	-14,294793	0,0319369	11,0089195	1,60341285	-0,5025969	9,54215083
FREEPORT-MCMORAN	2517	-22,731119	0,0030748	25,9935171	3,37137429	0,03809335	9,1519004
PEPSICO	2517	-12,135811	0,03805082	12,1656406	1,15388973	-0,5736643	26,2557118
TARGET	2517	-28,675348	0,03693813	18,5861797	1,85865327	-1,3962245	36,7129987
GE AEROSPACE	2517	-16,439316	-0,026706	13,7408199	2,11217779	-0,1209478	10,5805832
CITIGROUP	2517	-21,441413	0,00365949	16,5381219	2,03359882	-0,487128	17,9404887
BAKER HUGHES A	2517	-25,184762	0,00024589	18,7133114	2,48329301	-0,2162527	12,2381692
THE CAMPBELL S COMPANY	2517	-13,200273	0,01817089	9,62970095	1,4837605	-0,5212601	12,4234681
WASTE MANAGEMENT	2517	-11,789671	0,06078679	8,66358936	1,16718677	-0,5838761	16,3196193
AGILENT TECHS.	2517	-11,666539	0,06391908	9,38490105	1,62593017	-0,3674284	8,02386554
BAXTER INTL.	2517	-12,36497	0,01299386	11,7705409	1,42860227	-0,851266	13,8369126
NEWMONT	2517	-14,193398	0,00025333	13,1188275	2,3258113	-0,1569968	6,86550049
PG&E	2517	-74,148264	-0,0365942	55,7288748	3,77379331	-3,0384002	101,09817
STATE STREET	2517	-20,981115	0,01880553	20,1463852	2,02106466	-0,2929541	15,3988418
COLGATE-PALM.	2517	-10,295146	0,01563663	11,8745037	1,18548944	-0,0416666	13,9925445
TEXAS INSTRUMENTS	2517	-12,585495	0,06483517	12,6891752	1,71784891	-0,1551838	8,79192437
ALTRIA GROUP	2517	-10,568995	0,01350207	9,55098503	1,40786301	-1,0567983	10,5902067
CVS HEALTH	2517	-13,133012	0,02499158	10,3446639	1,55630597	-0,726019	12,3759361
CISCO SYSTEMS	2517	-14,76924	0,0338134	12,5517439	1,60379014	-0,5498867	15,8773912
CBRE GROUP CLASS A	2517	-18,881087	0,05282931	15,5320955	2,01020913	-0,2810104	13,7903907
JOHNSON & JOHNSON	2517	-10,578148	0,036303	7,69399903	1,119249	-0,4605132	13,0256941
INTEL	2517	-19,895742	0,00842447	17,8324412	1,95149398	-0,6704338	17,3330509
3M	2517	-13,863059	0,00934709	11,8659155	1,39625626	-0,8281455	14,4822016
MICROSOFT	2517	-15,945339	0,08587002	13,2928953	1,70488556	-0,2703977	12,1291519
AUTODESK	2517	-17,268747	0,06440676	15,0130003	2,26493533	-0,1265833	10,5350026
ABBOTT LABORATORIES	2517	-10,298191	0,04891825	10,3783341	1,47542202	-0,4137121	9,89899703
HOST HOTELS & RESORTS REIT	2517	-17,06459	-0,0002222	26,3060988	2,07672314	0,69536753	19,2671817
JP MORGAN CHASE & CO.	2517	-16,210576	0,04368326	16,5620305	1,68919015	-0,0605597	16,7031841
INTL.FLAVORS & FRAG.	2517	-17,372078	0,01699618	14,6801646	1,66117346	-0,7702415	17,1726385
HEALTHPEAK PROPERTIES	2517	-25,921607	-0,0199845	13,8792212	1,81038531	-1,7214956	30,3401437
ACCENTURE CLASS A	2517	-10,866245	0,05370178	12,0954278	1,51452465	-0,1493501	10,5302203
HALLIBURTON	2517	-47,23016	0,00385639	23,5283306	2,88352955	-2,0177826	40,5069878
HASBRO	2517	-20,705234	0,02115739	19,6138647	1,93321991	-0,3414833	23,3090116
WEYERHAEUSER	2517	-25,713163	0,00244467	22,5664499	1,98611803	-0,9745903	32,7902891
Average	2517	-18,286218	0,02846455	15,3605238	1,80648047	-0,5680504	18,355184

Note: Table 5 summarizes key financial statistics for the 50 highest-scoring ESG companies (HESG) in the S&P 500 as of December 2022. The variables include Min, Mean, Max and Standard Deviation

Table 6: Summary Statistics for LESG Companies

Company	N	Min	Mean	Max	SD	Skewness	Kurtosis
CORPAY	2517	-12,742808	0,04777889	14,7946351	1,97638084	0,14445062	9,76843528
NETFLIX	2517	-43,257875	0,12358283	35,2231609	2,99932761	-0,4400058	34,0452104
CHARTER COMMS.CL.A	2517	-17,894481	0,05433459	13,2699236	1,8419036	-0,4216273	12,6513464
ROLLINS	2517	-11,435642	0,06713602	9,57148129	1,50681873	-0,6563544	12,5665045
BERKSHIRE HATHAWAY 'B'	2517	-10,083817	0,04760705	10,983987	1,21657886	-0,238611	13,9712722
LKQ	2517	-21,379178	0,03478967	19,896879	2,10392155	-0,8017289	24,3453024
GLOBAL PAYMENT TECHS.	2517	-424,84952	-0,1465586	219,722458	19,3080097	-3,62115	117,788257
LENNAR A A	2517	-21,8339	0,03324089	19,3053092	2,30465012	-0,1190783	12,8086493
NVR	2517	-23,003	0,06361613	19,1281298	1,93317881	-0,2069815	22,7478572
EXPEDIA GROUP	2517	-32,00156	0,01293945	21,9670888	2,66823419	-1,4698489	29,7048452
TRANSDIGM GROUP	2517	-24,812687	0,05973467	21,8355673	2,12649313	-0,8605365	26,3605802
MONSTER BEVERAGE	2517	-15,594072	0,06856365	26,6064585	1,87258194	1,28919665	25,8088818
COTERRA ENERGY	2517	-12,862638	-7,27E-05	14,5220237	2,36797531	0,03147441	6,49972458
GENERAC HOLDINGS	2517	-29,225005	0,04174424	15,9917915	2,60029904	-0,5534616	13,158776
MONOLITHIC PWR.SYS.	2517	-22,665287	0,1088645	15,7304197	2,46136815	-0,2834906	11,0486057
GENUINE PARTS	2517	-15,003848	0,03891708	18,9947999	1,56739839	-0,0887165	23,4153144
FISERV	2517	-18,236023	0,06373491	11,8071594	1,5560348	-0,7754624	16,7995516
EXTRA SPACE STRG.	2517	-16,805234	0,05501791	7,85965758	1,55626726	-0,9665039	12,995959
ATMOS ENERGY	2517	-13,348789	0,04537204	14,3079494	1,34123757	-0,0401372	17,2844128
JACK HENRY AND ASS.	2517	-13,782624	0,05792904	9,29155241	1,34296803	-0,6983857	13,7180037
OLD DOMINION FGT.LINES	2517	-13,895077	0,0986607	12,0364524	1,80882317	-0,2962558	7,7024363
BOOKING HOLDINGS	2517	-14,525361	0,04567138	17,1867665	2,0163997	-0,285898	11,1901501
DEXCOM	2517	-39,529028	0,13855855	26,7332879	3,00570695	-0,1681466	24,9477548
ZEBRA TECHNOLOGIES 'A'	2517	-27,241093	0,07287173	15,8832932	2,38627847	-0,8274294	18,2748305
LOEWS	2517	-17,985794	0,01349624	12,6191136	1,5910587	-0,9410986	25,0530776
UNIVERSAL HEALTH SVS.'B'	2517	-25,176312	0,04140547	22,5828671	2,1044948	-0,7242499	23,85444
FIRST REPUBLIC BANK	2517	-17,951987	0,05173128	12,1154096	1,82183195	-0,674079	15,9314702
CONSTELLATION BRANDS 'A'	2517	-19,098806	0,07229716	31,6512759	1,76744991	1,41624608	58,210245
D R HORTON	2517	-22,601025	0,05860801	13,6754258	2,26780821	-0,4005656	11,0683514
SERVICENOW	2517	-17,026766	0,1014644	14,2693176	2,59622258	-0,0771646	6,9516154
CH ROBINSON WWD.	2517	-16,072698	0,01475261	8,91891531	1,57720709	-1,2505339	14,6440629
EQUIFAX	2517	-15,993192	0,05034237	13,9244936	1,72530739	-0,7127408	16,3804214
TELEDYNE TECHS.	2517	-25,989845	0,07118133	12,5038035	1,69749074	-1,5844234	30,608097
BIO-RAD LABORATORIES 'A'	2517	-10,388519	0,0542035	18,6507109	1,739519	0,70338608	14,3862453
ALIGN TECHNOLOGY	2517	-31,454511	0,07965812	29,9853901	2,80496708	-0,2942592	23,011233
MOLINA HEALTHCARE	2517	-21,569704	0,09973136	16,2272836	2,35188424	-0,330615	15,2658575
SIGNATURE BANK	2517	-16,393982	0,01838868	25,3694322	2,33556547	0,11809127	14,2451952
LIVE NATION ENTM.	2517	-18,128952	0,07841397	16,8646526	2,36583744	-0,0701873	13,3797571
MARTIN MRTA.MATS.	2517	-14,55872	0,04959671	14,126409	2,00550026	0,03667272	9,68272367
COPART	2517	-15,151093	0,0825963	16,0014947	1,67828663	-0,3495132	14,9267222
ARCH CAP.GP.	2517	-18,482698	0,05742798	14,2867535	1,58494904	-0,8426186	23,3488508
HNTGTN.INGALLS INDS.	2517	-13,111896	0,06577192	10,8089139	1,71266098	-0,4834263	9,34980531
PUBLIC STORAGE	2517	-12,252003	0,02587385	6,167033	1,37218745	-0,839247	9,92579066
PAYCHEX	2517	-21,666653	0,05120193	16,7191465	1,47643344	-1,0760216	33,8730054
EVERGY	2517	-17,507087	0,03018151	14,8837048	1,43049166	-0,950036	32,1632983
O REILLY AUTOMOTIVE	2517	-20,938938	0,08898784	12,2733695	1,68244558	-1,2107828	24,8769466
CENTERPOINT EN.	2517	-21,993328	0,01685795	16,0312973	1,67147445	-1,5057501	35,2776134
TAKE TWO INTACT.SFTW.	2517	-14,800253	0,08760563	16,7753141	2,22405521	-0,2186116	9,74467937
DOLLAR GENERAL	2517	-19,391481	0,0694084	12,8521166	1,63989242	-0,5503061	19,2981091
WARNER BROS	2517	-32,083752	-0,0500938	15,5926485	2,52217091	-1,1536945	17,0510384
Average	2517	-27,875571	0,05230251	20,5705305	2,31232057	-0,5264043	20,8422263

Note: Table 6 summarizes key financial statistics for the 50 lowest-scoring ESG companies (LESG) in the S&P 500 as of December 2022. The variables include Min, Mean, Max and Standard Deviation

Table 7: Summary of COVOL Responses for HESG and LESG Assets (3+/3- days Event Window)

Election Event	Group	Mean Estimation COVOL	Mean Event COVOL	CAC	HESG vs. LESG
US Election 2016	HESG	0,5532	1,7169	***1,1637	0,3675
	LESG	0,5249	1,3212	0,7962	
Brexit 2016	HESG	0,5448	1,5098	0,9650	0,1246
	LESG	0,5364	1,3668	0,8404	
US Election 2020	HESG	0,7123	1,0569	0,3446	
	LESG	0,6796	1,3013	0,6216	0,2770
EU Elections 2019	HESG	0,5396	0,4465	-0,0895	
	LESG	0,5663	0,2651	-0,2976	
Paris 2016	HESG	0,546	1,3379	*0,7919	
	LESG	0,5207	1,5037	*0,9831	0,1912

Note: Table 7 presents the results of the event study analyzing the impact of major political events on the cumulative abnormal COVOL (CAC) of HESG and LESG assets. The CAC column measures the excess volatility during the event window compared to the estimation window. In the last column ("HESG vs. LESG"), the value represents the absolute difference between the CAC values of HESG and LESG. A number is shown only for the group with the higher CAC, indicating the extent to which one group exhibited stronger volatility compared to the other. Statistical significance levels are indicated by asterisks: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Summary of COVOL Responses for HESG and LESG Assets (3+ Event Window)

Election Event	Group	Mean Estimation COVOL	Mean Event COVOL	CAC	HESG vs. LESG
US Election 2016	HESG	0,5532	1,7498	*1.1966	0,3063
	LESG	0,5249	1.4154	0.8903	
Brexit 2016	HESG	0,5448	2.6387	2.0939	
	LESG	0,5364	0.5264	*2.3885	0,2946
US Election 2020	HESG	0,7123	1.1203	0.4080	
	LESG	0,6796	1.4461	0.7665	0,3585
EU Elections 2019	HESG	0,5373	0.7778	0.2418	0,3441
	LESG	0,5663	0.4603	-0.1023	
Paris 2016	HESG	0,5460	1,9776	**1,4315	0,4239
	LESG	0,5207	1,5283	1,0076	

Note: Table 8 presents the results of the event study analyzing the impact of major political events on the cumulative abnormal COVOL (CAC) of HESG and LESG assets. The CAC column measures the excess volatility during the event window compared to the estimation window. In the last column ("HESG vs. LESG"), the value represents the absolute difference between the CAC values of HESG and LESG. A number is shown only for the group with the higher CAC, indicating the extent to which one group exhibited stronger volatility compared to the other. Statistical significance levels are indicated by asterisks: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.