FM321- FINAL PROJECT

1. INTRODUCTION

In 2016, the Global Sustainable Investment Alliance (GSIA) reported \$22.89 trillion in assets under responsible investment strategies, comprising 26% of all professionally managed assets—a 25% rise from 2014 (Martini, 2021). ESG investing has since grown rapidly, driven by global commitments to sustainability and ethical practices post-COP21. This study addresses a critical gap in ESG literature, exploring the volatility dynamics of high ESG portfolios, which are often seen as less risky yet lack empirical evidence on their risk profiles. It provides valuable insights into portfolio persistence, asymmetric volatility responses, and correlation structures, aiding institutional investors, portfolio managers, and policymakers in incorporating ESG considerations while managing market risks.

While most of the existing work focuses on ESG bonds, Górka & Kuziak's (2022) work on volatility and dependence structure between ESG and conventional stock indices is one of the very closely related literature to this paper. Their use of EGARCH for modeling conditional modeling was adopted for this paper. However, the key difference between the papers is that one of their key focuses was in capturing tail dependence using copula models and one of the key focuses of this paper is in exploring how volatilities of ESG and non-ESG portfolios react to different kinds of shocks. Instead of using a time-varying approach or a rolling window, the authors have computed volatility as a static measure over 4 different windows. In contrast, the novelty of this research stems from its use of time-varying models.

The research question, "Analyzing volatility dynamics of High and Low ESG stock portfolios using DCC-EGARCH and Stress Testing," highlights the use of the DCC-EGARCH model to capture dynamic correlations and volatility clustering, crucial for understanding temporal interactions between ESG portfolios. Coupled with stress testing, the analysis provides a forward-looking assessment of portfolio performance under adverse conditions.

2. DATA

The primary data for this paper is sourced from the Center for Research in Security Prices (CRSP) via Wharton Research Data Services (WRDS). Two equally weighted portfolios with 9 stocks each were created: one with high Environmental, Social, and Governance (ESG) ratings and another with lower ESG ratings. Ratings from the MSCI World ESG Leaders Index and S&P Global ESG Score were used to make portfolios, which serve as representative indices throughout the analysis. There is nearly equal representation across key sectors of the economy, ensuring that the concentration of high-return sectors/assets in one portfolio does not distort the analysis of the ESG factor. The stocks are equally weighted in all portfolios. The study period spans 02-01-2013 to 29-12-2023. For the CAPM and Fama-French 5-factor model, the risk-free rate was sourced from FRED's Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity, with additional data from Kenneth R. French's website.

FIGURE 1. HIGH ESG PORTFOLIO

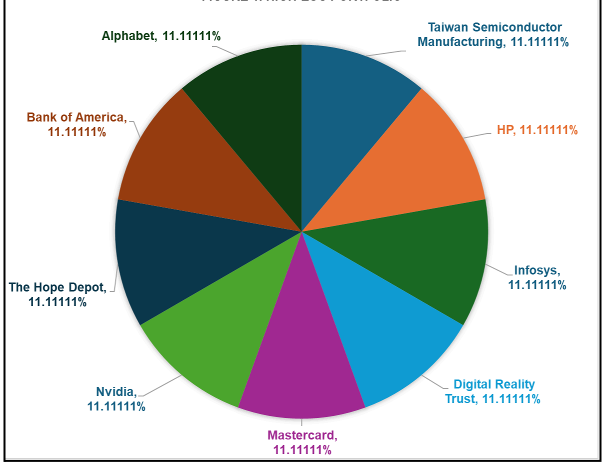


FIGURE 2. LOW ESG PORTFOLIO

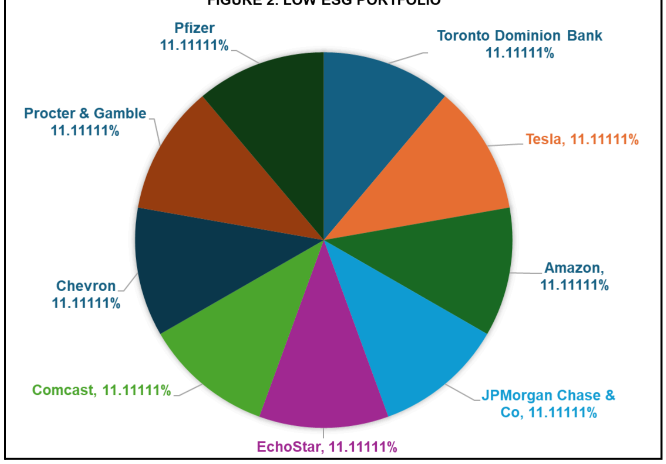


Table 1. Descriptive Analysis of ESG,non-ESG and Diversified portfolio

Portfolio	Mean_Return	Std_Dev	Skewness	Kurtosis	Max_Return	Min_Return
High-ESG	0.000918	0.0134	-0.3016	18.146	0.138	-0.145
Low-ESG	0.000704	0.0116	-0.487	13.577	0.0965	-0.105
Diversified portfolio	0.000811	0.012	-0.474	17.615	0.115	-0.125

From Table 1, one can infer that the high-ESG portfolio achieves the highest mean return and risk (standard deviation), consistent with high-rated ESG stocks, aligning with the understanding that high-rated ESG stocks often attract long-term sustainability-focused investors, who may face high risks but are compensated with higher returns. The low-ESG portfolio shows slightly lower mean returns, moderate volatility, and high skewness, indicating frequent large positive returns appealing to short-term investors. The diversified portfolio offers the lowest mean return and risk, demonstrating the benefits of diversification, although rare shocks align its negative and high kurtosis with the low-ESG portfolio.

Figure 3 shows cumulative returns for the three portfolios from 2013 to 2023. The portfolios aligned until 2016, after which the high-ESG portfolio outperformed, coinciding with the rise of responsible investing post-COP21. Returns fell sharply during COVID-19 but the high-ESG portfolio recovered strongly, driven by post-2020 preferences for sustainable investments.

3. EMPIRICAL ANALYSIS

3.1 Portfolio Volatility using DCC-EGARCH

The first empirical methodology involves applying advanced statistical models to calculate the portfolio volatility for the ESG and non-ESG portfolios. Since a portfolio includes multiple stocks, to account for time-varying correlations between the stocks and individual stock volatilities in each portfolio, the analysis is conducted using Dynamic Conditional Correlation (DCC). After computing the loglikelihood ratio of the DCC volatilities computed using standard GARCH and Exponential GARCH, EGARCH is finally chosen to be used since it has a higher loglikelihood ratio. A positive and significant gamma coefficient indicates the presence of asymmetry and the use of EGARCH is hence justified.

A Multivariate t-distribution (mvt) accounts for fat tails, improving model stability. Portfolio volatility is calculated using dynamic covariance matrices generated by DCC-EGARCH, weighted by asset allocations. The analysis is implemented in R with rugarch and rmgarch libraries, leveraging functions such as dccfit for model fitting and rcov for extracting covariance matrices.

3.2 Spillovers within and in between portfolios

Spillovers are examined within ESG and non-ESG portfolios and between them using DCC-EGARCH. The model captures time-varying correlations between asset returns, allowing us to quantify spillovers dynamically, which is crucial for understanding cross-asset impacts. EGARCH addresses leverage effects in individual asset volatility. Additionally, to analyze volatility spillover between ESG and non-ESG portfolios, the DCC-EGARCH model was extended to capture time-varying correlations and volatilities. The volatility spillover was computed as the product of the volatilities of ESG and non-ESG portfolios, weighted by their dynamic correlation.

While for computing spillovers between ESG and non-ESG portfolios, we could simply use the time-varying correlation estimates, for intra-portfolio spillovers, at each period, an average of the non-diagonal components of the matrix is used to represent the overall spillover effect. The EGARCH model is specified for each stock with parameters optimized using maximum likelihood estimation. Key functions include dccspec and dccfit for DCC-GARCH estimation and rcor for extracting dynamic correlation matrices.

3.3 Value-at-Risk (VaR) for ESG and non-ESG portfolio

To compute the Value at Risk (VaR) for ESG and non-ESG portfolios, we employ a parametric approach using the T-GARCH model to assess their downside risk. As compared to non-parametric methods like Historical Simulation, it adapts quickly to changing data and the parameters of estimation will also help to measure how ESG and non-ESG portfolios react and remember information. Daily VaR at a 99% confidence level is computed using a T-GARCH model, which adapts well to fat-tailed data and captures volatility dynamics. A 250-day rolling window approach assesses period-specific VaR. The PerformanceAnalytics package in R facilitates VaR calculation and performance analysis.

3.4 Stress-testing two different types of hypothetical scenarios

This section of the paper involves inducing two types of shock to see how ESG and non-ESG portfolios react differently in terms of conditional volatility.

3.4.1 ESG-specific shock induced on portfolio returns

This section utilizes the eGARCH model to assess the conditional volatility of ESG and Non-ESG portfolios, before and after an ESG-specific regulatory shock. The hypothetical ESG-related shock was the introduction of a strengthened environmental regulation that penalizes polluting industries while incentivizing sustainable business practices by way of subsidies or green tax credits. Non-ESG Companies may face higher costs for compliance, which would hurt their profitability and returns and hence bringing down their portfolio returns by 15%. ESG-focused companies are likely to benefit from green subsidies or tax incentives which could lead to a slight increase in returns while still incurring slightly increased costs on carbon tax, hence in this case, it is assumed to be a 5% increase in returns. The shock was imposed on a relatively stable period of 6 months, from 01-01-2017 to 30-06-2017.

3.4.2 Systematic shock induced on volatility

The second shock was a systematic risk affecting all the companies in the economy some way or the other. The shocks were induced on each company's volatility computes using univariate eGARCH and a different multiplier was used for each company depending on the industry with tech and real estate investment funds being the most volatile, followed by the financial sector with moderate volatility, followed by consumer essentials which is the least volatile. Volatility shock is again only induced for a period of 6 months. New returns that are shocked are then generated based on shocked volatility for the stress period using a normal distribution (rnorm()).

3.5 Portfolio Behavior Analysis using CAPM and Fama-French 5-Factor Model

In the last section of this paper, portfolio behavior is analyzed using CAPM and Fama-French 5-factor models. CAPM estimates systematic risk (β) and excess returns (α) by regressing portfolio returns on market excess returns. The 5-factor model extends this with size (SMB), value (HML), profitability (RMW), and investment (CMA) factors. These models were chosen due to their widespread use in finance to assess systematic risk and factor-driven return contributions. The analysis was conducted in R using the lm() function for linear regression.

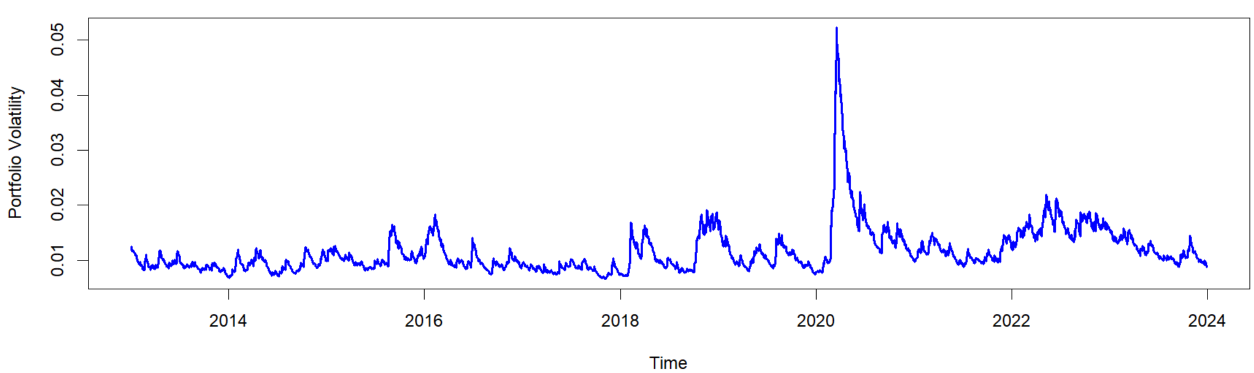
4. RESULTS

4.1 Portfolio Volatility using DCC-EGARCH

The results of the empirical analysis reveal significant insights into the behavior of ESG and non-ESG portfolios under varying market conditions. Comparing the log-likelihood values of GARCH and EGARCH models, the EGARCH model shows superior performance, with a log-likelihood of 70070.99 compared to 68380.42 for standard GARCH when fitted for the ESG portfolio. This highlights the EGARCH model's effectiveness in capturing the leverage effect and asymmetric volatility. The gamma parameter, estimated at 0.172 and 0.119 for ESG and non-ESG portfolios respectively confirms the presence of the leverage effect, and this result aligns with expectations for financial markets, where bad news generally induces more volatility than good news of the same magnitude. Interestingly, the magnitude of the gamma coefficient is higher for the ESG portfolio compared to the non-ESG portfolio, implying potential variations in how these portfolios respond to market shocks.

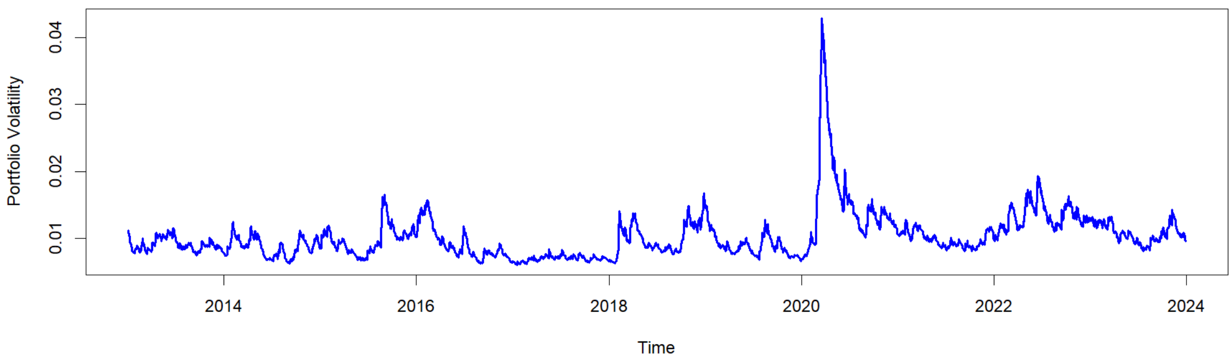
As seen in Figures 4 and 5, while the ESG portfolio had the same volatility as the non-ESG portfolio during stable periods, it showed heightened volatility during the COVID-19 crisis, with

Figure 4. Dynamic Portfolio Volatility-ESG



values of 0.052 for ESG and 0.043 for non-ESG. This divergence suggests that ESG portfolios may be more sensitive to systemic shocks, possibly due to their exposure to industries impacted by regulatory or environmental risks, while non-ESG portfolios have a diversified sectoral exposure and often adhere to fewer regulations. As a result of COVID-19, there were many changes in society including health policy changes, lockdowns, and vaccine rollouts which could have had an impact on consumer demand and societal trends for consumer-based stocks.

Figure 5. Dynamic Portfolio Volatility-non ESG



4.2 Spillover effect within and in between portfolios

The results of the spillover analysis within the portfolios reveal notable differences between ESG and non-ESG portfolios. Yet again using DCC-EGARCH, from Figures 6 and 7, we observe higher mean correlation spillovers within the ESG portfolio compared to the non-ESG portfolio, with average correlations of 0.296 and 0.264, respectively. This indicates that ESG stocks are more interconnected in terms of volatility transmission. These findings reiterate that ESG portfolios are inherently more reactive to systemic shocks, reflecting higher sensitivity within this segment. Non-ESG stocks display relatively lower internal spillovers, potentially signaling more diversified drivers of volatility or less synchronized reactions to market movements. The results align with expectations, as the growing integration of ESG factors in financial markets and similar investor behavior towards ESG assets may lead to heightened co-movement among ESG assets.

Figure 6. Within portfolio Spillover Measure- Average Correlation-ESG

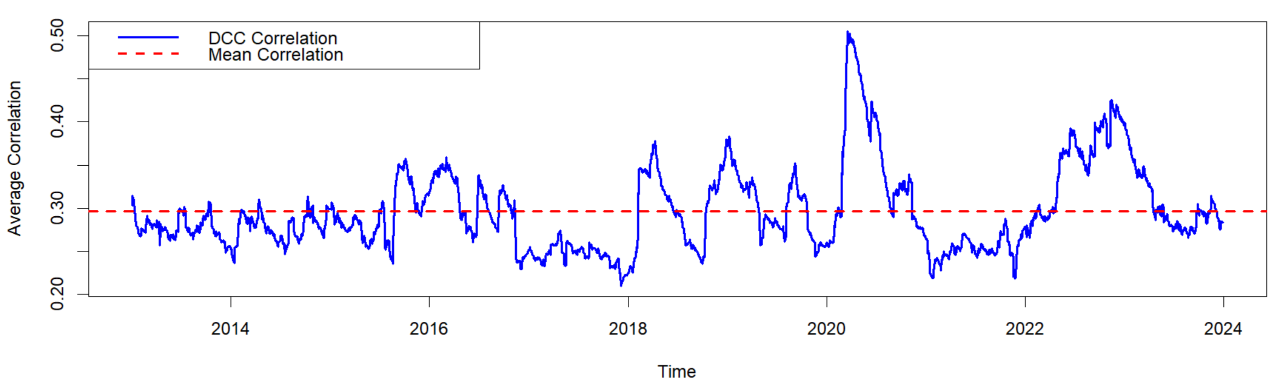
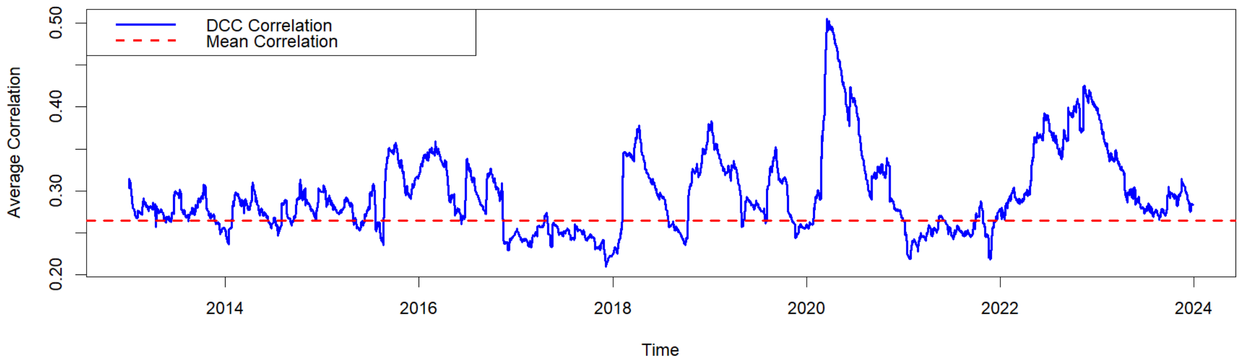


Figure 7. Within portfolio Spillover Measure- Average Correlation-non ESG



Spillover analysis, as shown in Figure 8 shows a strong correlation of 0.737 between the ESG and non-ESG portfolios, emphasizing significant spillovers between the two groups. This significant cross-portfolio spillover suggests that external shocks or systemic events affecting one portfolio are likely to have considerable impacts on the other. The volatility spillover analysis as depicted in Figure 9 indicates negligible spillover between ESG and non-ESG portfolios, suggesting that the volatilities of the two portfolios are largely independent. It implies that ESG factors may not significantly influence the volatility dynamics of traditional investments in the sample. A famous concept in finance, non-linear dependence can be observed in both cases wherein the correlation between and within the portfolios significantly increases during times of stress (COVID-19).

Figure 8. Time-varying DCC Correlation between ESG and Non-ESG Portfolio

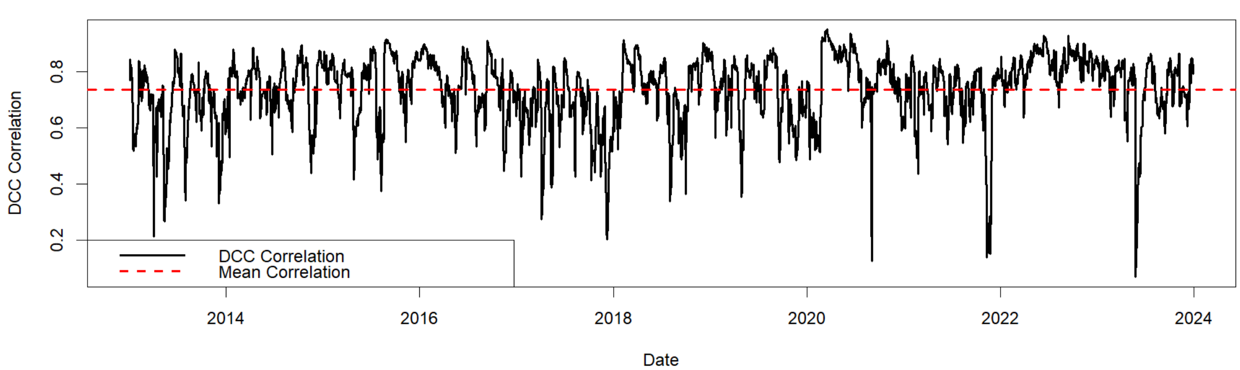
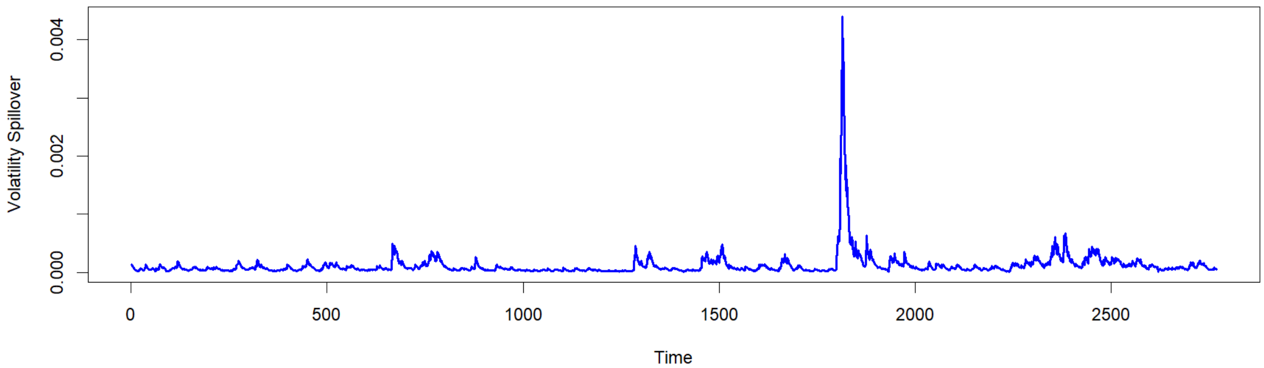


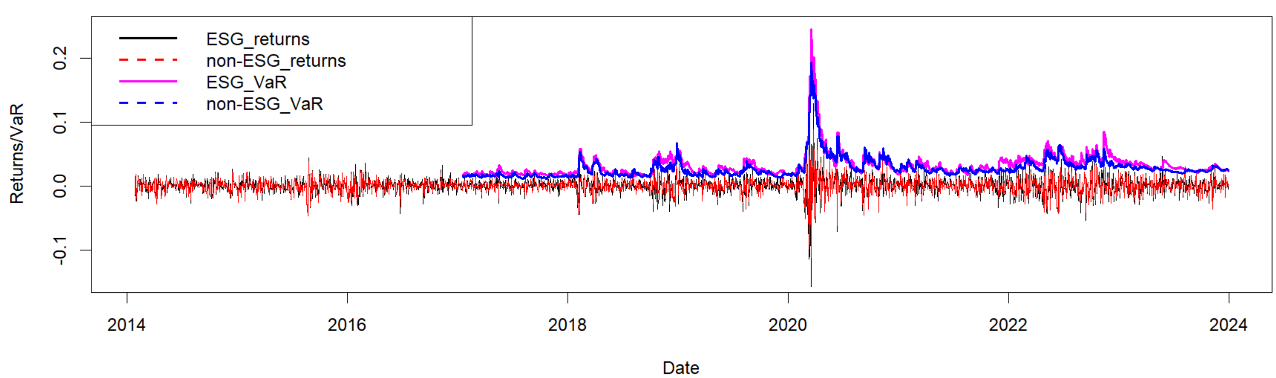
Figure 9. Volatility Spillover between ESG and Non-ESG Portfolios



4.3 Value-at-Risk (VaR) for ESG and non-ESG portfolio

VaR calculated on 29-30-2024 with a portfolio of $1000 indicates that there is a 1% chance that the daily loss from the ESG portfolio could exceed $78.75 and $70.53, implying the ESG portfolio is slightly riskier. It is evident from Figure 10 that while VaR is slightly higher for the ESG portfolio, systemic events like COVID-19 drastically increase the VaR estimate for both portfolios. Often, this is also because ESG firms are in industries disproportionately impacted by such events. This can also be attributed to the higher gamma coefficient of ESG portfolio as compared to non-ESG portfolio which means volatility of ESG portfolio reacts more drastically to negative news as compared to non-ESG portfolio.

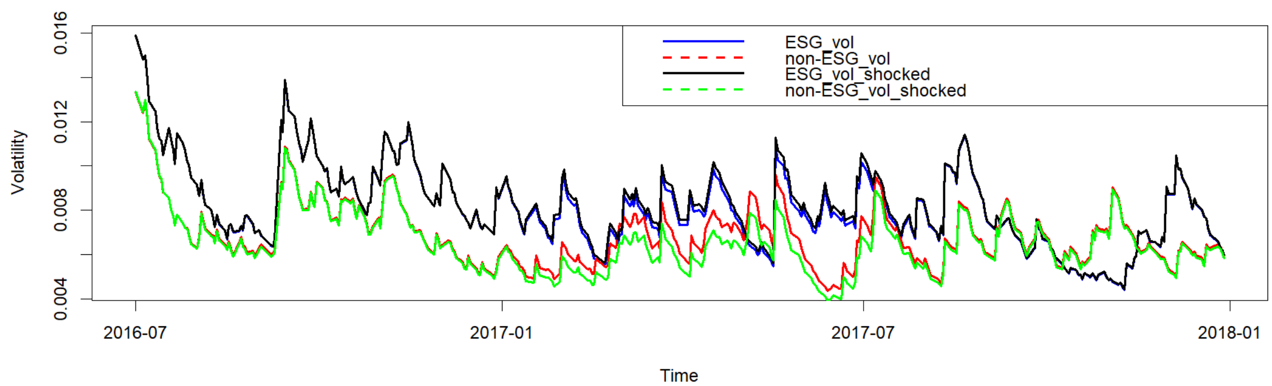
Figure 10. Returns and VaR estimates



4.4.1 ESG-specific shock induced on portfolio returns

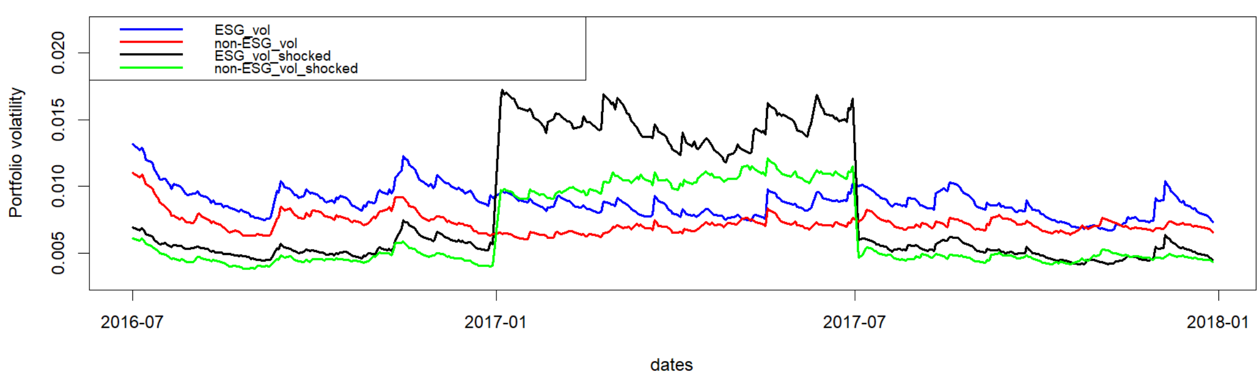
In Figure 11, we can observe that once the shock was introduced on 01-01-2017, the shocked volatility of the non-ESG portfolio (green) significantly moved away from the original volatility (red). Whereas, the shocked volatility line of the ESG portfolio (black) and the original volatility line (blue) stay very close to each other. This implies that the ESG portfolio's volatility was not greatly affected by this ESG-specific shock in the form of regulations. This reiterates the findings from the previous sections, ESG portfolio reacts drastically to systemic shocks and shows a great amount of resilience when it comes to sector-specific shocks

Figure 11.Conditional Volatility before and after shock 1



4.4.2 Systemic shock induced on volatility

Figure 12. Conditional Volatility before and after shock 2



With interest rate spike being the hypothetical systemic shock induced on conditional volatility, we can observe in Figure 12 that before and after the shock, shocked volatility seems to be higher than normal volatility. This difference is because while normal volatility was computed using individual stock's original data, shocked volatility was computed on simulated volatility which had a higher overall volatility due to the shock induced. However, this does not affect our analysis and we can assume them to be the same before and after the stress period. In contrast to the previous case of ESG-specific shock wherein the ESG portfolio's volatility was much less reactive, in this case, the gap between the original volatility (blue) and stressed volatility (black) of the ESG portfolio during the stress period is higher than the gap between the original (green) and shock-induced volatility (red) of the non-ESG portfolio. This yet again proves that ESG portfolios are highly sensitive to systemic shocks, especially to negative ones.

4.5 Portfolio Behavior Analysis using CAPM and Fama-French 5-Factor Model

Table 3. Estimates of CAPM and Fama-French 5-Factor Model

	CAPM		Fama-French 5-factor					
	Alpha	Beta	Alpha	Beta	SMB	HML	RMW	CMA
ESG	0.0003336*	1.1193453*	0.000354*	1.101*	-0.000191	0.001591*	-0.000227	-0.002114*
non-ESG	0.0002021*	0.009351*	0.000234*	0.009284*	-0.000496*	0.002443*	-0.001125*	-0.001057*
* Indicates statistically significant at 5% significance level								

The Alpha values indicating abnormal returns are statistically significant and higher for the ESG portfolio in both models, indicating that the ESG portfolio has significantly outperformed its expected return. This can be attributed to positive public perception and the concept of "green premium" which reflects investors' willingness to accept lower returns due to non-financial considerations, such as environmental, social, or governance goals. Paradoxically, strong demand can lead to higher prices and, in some cases, temporarily boost returns, resulting in a higher alpha. The Beta coefficient indicating a portfolio's relationship with market returns is significantly high for the ESG portfolio, aligning with our results in the previous sections wherein we had observed that an ESG portfolio is more sensitive to systemic shocks as compared to the non-ESG portfolio.

5. ANALYSIS

The findings of this paper provide valuable insights for institutional investors and policymakers navigating ESG finance. For traders, the higher correlation within ESG portfolios indicates the need to account for synchronized movements during market stress, while the relatively independent volatility of ESG and non-ESG portfolios offers opportunities for strategic hedging. Stress testing results highlight the importance of anticipating how ESG and non-ESG portfolios respond differently to hypothetical shocks, suggesting a need for proactive hedging strategies, especially for sectors exposed to regulatory and environmental risks. The resilience of ESG portfolios to sector-specific shocks makes them attractive for diversification during stable periods.

Investment fund managers can leverage these findings to design portfolios with optimal risk-return trade-offs. ESG portfolios' higher alpha values, driven by the "green premium" and public perception, highlight their potential for above-market returns. However, higher beta coefficients necessitate active risk monitoring and portfolio rebalancing to manage systemic risk exposure. The significant cross-portfolio spillovers between ESG and non-ESG portfolios emphasize the interconnected nature of financial markets and the potential for systemic risks to propagate across asset classes. Policymakers can use these insights to strengthen financial stability through targeted regulations like stress testing mandates and enhanced disclosures, mitigating systemic risks for industries heavily represented in ESG investments.

The integration of stress testing provides a forward-looking framework for evaluating portfolio behavior under adverse conditions. Institutional investors should prioritize stress testing, given ESG portfolios' unique volatility dynamics during systemic shocks. This research enhances the understanding of ESG's role in diversification and risk mitigation, offering actionable insights for stakeholders aiming to integrate ESG considerations into risk management and investment strategies, ultimately contributing to sustainable financial systems.

6. CONCLUSION

This paper analyzes the volatility dynamics of ESG stocks with the help of a representative portfolio using multivariate time-varying techniques such as DCC-EGARCH, rolling window VaR and stress-testing different types of shocks. We observe that the ESG portfolios are often riskier as compared to non-ESG portfolios and a higher volatility sensitivity to economic-wide shocks can be one of the reasons. However, ESG portfolios also show higher resilience and can handle ESG-specific shocks well as compared to non-ESG portfolios which is an advantage considering today's constantly evolving policies in favor of ESG. High spillovers within the ESG portfolio owing to a shared mindset can be concerning during times of crisis. While volatility spillover is insignificant, there is a significant correlation spillover between the two portfolios which also needs to be taken into account while creating hedging strategies. ESG portfolio's significantly higher cumulative returns, lower skewness and abnormal returns owing to green premium need to be taken advantage of by today's investors if they wish to earn high returns in the long term and diversify their portfolios while contributing to the environment.

7. BIBLIOGRAPHY

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