Examining volatility spillovers among ESG compliant large, mid, and small-cap stocks: A comparative analysis of the US and UK markets

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A thesis submitted in partial fulfillment of the requirements for the degree of

MASTER OF COMMERCE IN FINANCIAL MARKETS

In the

DEPARTMENT OF ECONOMICS AND ECONOMIC HISTORY
RHODES UNIVERSITY, MAKHANDA

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March 2025

DECLARATION

I hereby declare that the work produced in this thesis is my own work, carried out during the course of completing the degree of Master of Commerce in Financial Markets at Rhodes University. Any work I have not done myself is properly credited. I, Xolela Ndzamela, the author of this thesis, declare that this thesis has not been submitted for the award of a degree at any other university, Technikon or college.

Xolela Ndzamela

Signed……NX……….

Date……14/04/2025…

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LIST OF ABBREVIATIONS

ADF	Augmented Dickey-Fuller test
AIC	Akaike information criterion
AR	AutoRegressive
ARCH	Autoregressive conditional heteroskedasticity
ARCH LM	Autoregressive conditional heteroskedasticity Lagrange Multiplier
ARMA	AutoRegressive Moving Average
BEKK	Baba, Engle, Kraft, and Kroner
BFT	Behavioural Finance Theory
CPI	Consumer Price Index
DCC	Dynamic Conditional Correlation
DID	Difference-in-Differences
DY	Diebold-Yilmaz
EGARCH	Exponential Generalized AutoRegressive Conditional Heteroskedasticity
EMH	Efficient Market Hypothesis
ESG	Environmental, Social and governance
FEVD	Forecast Error Variance Decompositions
FPE	Final prediction error
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GARCH-M	Generalized AutoRegressive Conditional Heteroskedasticity in the Mean
GC	Granger causality
HQ	Hannan-Quinn information criterion
IRF	Impulse response function
LEGARCH	Logistic Exponential Generalized Autoregressive Conditional Heteroscedasticity
LSE	London Stock Exchange
LSEG	London Stock Exchange Group
NYSE	New York stock exchange
OLS	Ordinary Least Squares
PCA	Principal component analysis
SIC	Schwarz information criterion
TARCH	Threshold Autoregressive Conditional Heteroskedasticity
TVP-VAR	Time-Varying Parameter Vector Autoregressive
UK	United Kingdom

US	United States
VAR	Vector Autoregressive
VDC	Variance Decomposition
VECM	Vector Error Correction Model

ACKNOWLEDGEMENTS

"We Walk by Faith Not by Sight"

I would like to begin by thanking God first and foremost for his grace and guidance, which has been the firm base on which I have built all I have been able to accomplish.

While this work is a product of my efforts, it is truly a mirror of those who have influenced, shaped and inspired me in ways I could not have imagined, and others in ways no words can accurately communicate. I owe a great debt of gratitude to my supervisors Prof. Hugo Nel and Prof. Juniours Marire for their wisdom and support that played an immense part in my academic growth. Your belief in my potential and patient guidance through the uncertainties of research were the anchor by which I steadied. This work could not have been shaped without your mentorship, which has also urged me to ask better questions, go more in-depth, and trust the process. In the same breath of importance, thank you to the incoming Dr. Nwabisa Malimba for planting the seeds that helped to nurture my early research days. Additionally, I express my sincere thanks to the Economics department staff, whose assistance has been instrumental during this entire process.

Above all else, I want to express my deepest and sincerest gratitude to my parents, Mr. L. Ndzamela and Mrs. Z. Ndzamela, for their unwavering love, sacrifices, and support towards my education, which has molded me into who I am today. Additionally, I wholeheartedly thank my siblings, Mr. S. Ndzamela, Ms. A. Ndzamela, and everyone in my family for the encouragement and support they have given me, which is above what words can express.

To my study mates, James Jere and Thabo Mahoza, I am more than thankful to have taken this journey with you through the highs and the lows. Your companionship made every challenge easier and every success even more rewarding. Furthermore, to my brothers, Lutho Mbalula, Thembelani Chili, Ntikana Ramohlale, Nkosinamadla Machastella, Banoyolo Sicwebu, Sibonelelo Mdelwa, Thulebone Tsele, Ilunga Tommy Tshiunza, Aphendulwe Mbane, and Sive Busakwe—thank you for being my safety net, for your constant support and adding colour to my experience at Rhodes University. Your presence during moments of joy as well as moments of doubt, have been a true blessing.

In addition, I also extend my gratitude to the incredible friends I met in the library spaces from departments such as Chemistry, Politics, and Sociology. The exchange of knowledge, whether academic or casual, broadened my perspective and often served as a comforting relief during stressful times. Lastly, to my close friends and classmates, your support has been a guiding light. If there are two things, I hope you continue carrying with you going forward, they are humbleness and my account number! May your journeys be blessed and your careers filled with God's grace.

With deep gratitude and respect,
Xolela

DEDICATION

"TO TEACH IS TO TOUCH A LIFE FOREVER." — UNKNOWN

I dedicate this work to my former lecturer and supervisor **Professor Juniours Marire**.

ABSTRACT

Several crises have had and continue to have permanent effects on global governance and sustainable finance. These crises, however, have also raised investors' scrutiny of firms' Environmental, Social, and governance (ESG) performance when making investment decisions. These investment decisions have an impact on the overall market behaviour and stock volatility. Hence, with the assumed benefits of ESG adoption being believed to be a mitigating factor against stock crashes and hence volatility. It is no surprise that adopting sustainable practices has become a transformative trend in the financial sector, increasingly influencing investment decision-making. In an era where ESG principles are reshaping financial markets, adherence to ESG standards could reduce market volatility between firms of different sizes. This study aimed to examine the volatility spillovers among ESG compliant large, mid, and small-cap stocks in the US and UK markets.

The methodology proposed in this paper consisted of several steps to systematically investigate the directionality, magnitude, and persistence of volatility transmissions between ESG-compliant large-, mid-, and small-cap firms in US and UK markets and to shed light on diversification and risk management. Weekly closing price data of highly compliant ESG firms that covered a span of 5 years from 5 January 2018 to 30 December 2022 were used, resulting in 261 observations. The study applied rigorous econometric models such as the principal component analysis (PCA) to create the return indices (Large, Mid and small) for both the US and UK respectively. Subsequently, the GARCH-family of models that is the GARCH (2,1) & (1,1) in as well as the TARCH (1,1) were used to generate the volatility variables using the return indices. Finally, a VAR framework was employed to analyse the volatility spillover between the large, mid and small cap volatility indices for both the US and UK respectively.

The findings of the granger causality test revealed bidirectional spillovers between the large-cap and small-cap volatility index, as well as between the mid-cap and small-cap volatility index, are evident in both the US and UK markets. Unidirectional spillovers, however, differ between the two markets. In the US, the mid-cap volatility index significantly drives the large-cap volatility index. Conversely, in the UK, a top-down spillover is observed, with the large-cap volatility index influencing the mid-cap volatility index. Furthermore, the impulse response revealed that overall, in the US the midcap volatility index and in the UK the large cap volatility index has the biggest magnitude and most persistent spillover effect on

other indices, transmitting positive volatility. Finally, the variance decomposition revealed in the US that the large and small caps' variance is predominately driven by shocks emanating from the mid-cap volatility index, while the mid-caps variance is driven by its own shocks. Whereas in the UK the mid and small caps' variance is predominately driven by shocks emanating from the large-cap volatility index, while the large-caps variance is driven by its own shocks.

The implication of findings may suggest that ESG credentials genuinely guide investors into calmer financial waters. This is because the US mid-cap and UK large-cap are relatively insulated from volatility spillovers from other indices and serve as sources of self-reinforcing segments. This limited exposure to market-wide shocks means that changes in price movements in the markets that are mainly the recipients of volatility tend not to induce price movements in the markets that are drivers of volatility. With this, investors can shelter themselves from market risk exposure and achieve better diversification opportunities when they invest in these two self-reinforcing segments.

Keywords: Volatility spillover, Market capitalization, ESG-compliant stocks, GARCH models, VAR model.

CHAPTER 1
INTRODUCTION

1.1 BACKGROUND

Several crises have had and continue to have permanent effects on global governance and sustainable finance. The 2008 global financial crisis and 1997 Asian financial crisis made it evident how stock markets are vulnerable to external shocks and can intensify investors' overreaction to them. For instance, Lim et al. (2008), Luchtenberg and Vu (2015) have identified stock market volatility as a major crisis indicator in crisis induced economies. Given these high incidences of global financial crises and the serious negative side effects of the COVID 19 pandemic to the worldwide economy, corporations have become more conscious of risk management. At the same time, these crises have also heightened investors' attention to firms' Environmental, Social, and governance (ESG) performance when it comes to making investment decisions. Gao et al. (2022) add that there is a greater interest in ESG because a better ESG performance acts as a safeguard against volatility, market crashes, and stock market risk. This emphasises the key role that ESG plays in current business considerations.

It has become a major transformative trend in the financial sector for ESG considerations to be incorporated into the decision-making processes of investments. More and more investors are now realizing that a company's commitment to sustainable and socially responsible practices and strong governance is a good driver of its future performance and resilience (DesJardine et al., 2019). As a consequence, ESG factors have entered the process of portfolio construction, with the aim of aligning investment strategies with more general social goals such as international recognized principles for an ethical behaviour of a corporation (Fulton et al., 2012; Liu et al., 2023). This change towards sustainable investment practices is also further implied by Askarany and Xin (2024), who claim that investors, until now, have predominantly concentrated on financial metrics. However, Lately, the emphasis has shifted toward non-financial factors, particularly ESG ratings, which are deemed crucial in investment decisions. ESG ratings are a holistic measure of how a company is environmentally friendly and socially responsible, and how is to be governed. This gives the investor a complete picture of how that particular company might grow. ESG ratings are a means to communicate nonfinancial information to investors, thereby reducing information asymmetry and facilitating better-informed investment decisions. If properly stressed, these ratings guide and control managerial behavior, improve corporate growth quality, and reduce the risk of crises. As the literature regarding traditional financial indicators and information disclosure approaches saturation, the contribution of nonfinancial information, particularly the ESG ratings, in determining securities markets becomes substantial.

1.2 RATIONALE AND PROBLEM STATEMENT

Central to understanding the issue is the question: Are ESG credentials genuinely guiding investors into calmer financial waters, or do they merely place a green veneer over the same old waves of volatility? The answer to this question forms the foundation of this research.

Over the last few years, ESG criteria integration into investment strategies has received an unprecedented level of adoption. Sustainability issues remain of increasing importance for corporate management and the investment management industry. For instance, as Coppola (2016) points out, while only 20% of S&P 500 companies published sustainability reports in 2011, this number increased to 81% in 2016. Part of this increased emphasis on the evaluation of the performance of corporate sustainability stems from increasing empirical evidence of a largely positive and stable connection between the corporate financial performance (CFP) and the environmental, social, and governance (ESG) factors, as evidenced by Friede et al. (2015). Empirical literature further confirms this positiveness of sustainability practices by showing that firms adhering to sustainability practices have lower volatility (Liu et al.,2023).

Although empirical data have supported this trend, there have been rising concerns about greenwashing globally, as there are no international standards of ESG-related taxonomy. In the environmental context, De Silva Lokuwaduge and De Silva (2022) argue that greenwashing refers to potentially misleading disclosures and claims that would exaggerate and misrepresent 'green' credentials. For instance, De Silva Lokuwaduge and De Silva (2022) further points out that the "green" credentials might be a marketing action to make a positive impression of a company or its products. Hence the adoption of these sustainable practices can be questioned, do they merely place a green veneer over the same old waves of volatility?

In light of this existing research has extensively analysed volatility spill overs in conventional markets, where sustainability is not highly prioritized, yielding a wealth of evidence pointing to diverse spillover patterns (fully discussed in chapter 3) between different sized firms (Large, Mid and small- cap). The findings of these diverse spillover patterns lay the foundation on which the 'old waves of volatility' are conceptualized. However, there is a significant gap in understanding how these dynamics operate within and between large, mid, and small-cap ESG-compliant firms across different geographical markets. This study is not intended to present itself as a pioneering study on risk management and investment strategies in the expanding field of sustainable finance; however, its contribution is expected to provide meaningful insights into this field of study to advance understanding. The study attempts to offer evidence with empirical backing that could help investors make more judicious investment decisions and in turn, contribute to the stability and growth of ESG investment portfolios.

1.3 RESEARCH QUESTIONS AND THE GOALS OF THE STUDY

1.3.1 RESEARCH QUESTIONS

In order to fill the identified knowledge gap, the following research questions have been developed to understand:

- How do volatility spillovers flow between large-, mid-, and small-cap ESG-compliant stocks in the US and UK markets?
- How does firm size segment (large-, mid-, small-cap) influence the magnitude and persistence of volatility transmissions among ESG-compliant firms in both US and UK market environments?
- How can investors leverage knowledge of ESG volatility spillover dynamics to reducing overall portfolio risk through selective exposure to specific size segments?

1.3.2 GOALS OF THE RESEARCH

The general aims of this study following the research questions are:

- To identify the directionality of volatility transmissions between large-, mid-, and small-cap ESG compliant firms in the US and UK.
- To examine the magnitude and persistence of volatility spillovers among large-, mid-, and small-cap ESG-compliant firms in US and U.K. markets, gauging the degree to which each segment influences, and is influenced by, others.
- To make recommendations on diversification and risk mitigation by evaluating volatility interactions across market segments to inform portfolio strategies.

1.4 METHODS, PROCEDURES & TECHNIQUES

This section describes the proposed methods, procedures and techniques for accomplishing the research objectives. By applying rigorous econometric models, carefully chosen samples, and a balanced qualitative lens, the study aims to address these objectives with empirical precision—and do so responsibly, transparently, and ethically.

This study employs a post-positivist research paradigm. Weekly closing price data of highly compliant ESG firms that covers a span of 5 years from 5 January 2018 to 30 December 2022 is used, resulting in 261 observations, in designing appropriate methodologies, and ensure the feasibility of the study. The data used for the firms in the sample was extracted from the London Stock Exchange Group (LSEG) database. The time frame and sample of firms chosen are dictated by data availability and the desire to keep the sample size manageable. This study attempts to balance obtaining a sample size large enough for making inferences and addressing the practical constraints of data collection and analysis.

In gathering the sample, while only briefly lifting the curtain on the selection process which is more fully discussed in Chapter 4, the study used a non-probability sampling method known as purposive sampling. This technique can accommodate an analysis focused on firms that fulfill specific requirements (Rahi, 2017). For instance, one of the strict requirements of the study was that firms needed to meet and maintain a certain percentage of compliance as measured by the ESG score for all the years under observation to be included in the sample. A higher ESG score implies greater compliance and the opposite is also true. In light of this the study focused on identifying the most compliant large, mid and small cap stocks from the financial and real estate sector with the highest ESG scores in the UK and US. The decision to include only these two markets was primarily dictated by data availability; the UK and US had the most coverage and consistent data reported for ESG scores for firms under the period of interest.

The methodology proposed in this paper consists of several steps to systematically investigate the directionality, magnitude, and persistence of volatility transmissions between ESG-compliant large-, mid-, and small-cap firms in U.S. and U.K. markets and to shed light on diversification and risk management. The research is conducted in three stages. The first stage involved taking the selected ESG compliant firms at each market capitalization (Large, mid and small) and creating a single index at each level that captures the broad market behaviour of the firms using principal component analysis (PCA). This follows the same logic as Jalil *et al.* (2010) who constructed an index to reduce the dimensionality of the data. The advantage of this is that the smaller data sets are easier to explore and visualize and make data analysis much easier and faster for econometric modelling without extraneous variables to process, thus increasing interpretability.

The second stage involves using the constructed *return indices* (large, mid and small cap) from the PCA to model the volatility indices using carefully selected Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family of models. The theoretical motivation to use these models is that most of the financial time series appear to be heteroscedastic, which means the variance of the series varies with time (Wang et al., 2022). To estimate the time variation, GARCH models are employed primarily to investigate the stochastic properties of a financial variable. The study proposed to adopt a GARCH and Threshold Autoregressive Conditional Heteroskedasticity (TARCH) to model volatility. The econometric justification for the adoption of these models is engineered through a process where a number of GARCH-type of models are regressed and compete on an equal footing based on "specific selection criteria", thereby giving each an unbiased opportunity for consideration. The models that best satisfy these "specific selection criteria" are used in the volatility generation. The usage of the selected models (GARCH and TGARCH) is further backed up by previous literature such as that of Lin (2018) and da Silva Antunes (2021).

The last stage involves analysing the volatility spill over by using a VAR framework. Having generated the volatility indices (Large, mid and small cap) the study is able to address the goals through employing statistical tools such as the VAR Granger causality to address goal one. While the impulse response, supplemented with the variance decomposition are used to address goal two. The last goal is then addressed in the recommendations based on the results obtained from the two-processes mentioned above.

1.5 OUTLINE OF THE RESEARCH

This section outlines the research structure, demonstrating how each component logically spills over into the next. Chapter 1 provides the background, problem statement and objectives of the study. Building on that overview, Chapter 2 presents the theoretical literature which acts as a roadmap for analysing results and drawing conclusions, ensuring findings are consistent with the chosen theoretical lens. Chapter 3 synthesizes empirical literature on volatility spillovers, establishing a robust foundation. Having laid out this framework, Chapter 4 turns to the research methods employed, explaining how econometric models and other analytical tools will be utilized. Equipped with these methodological insights, Chapter 5 applies them to present and discuss the empirical findings, drawing comparisons with existing research. Finally, Chapter 6 summarizes the main findings, offers recommendations, and suggests opportunities for extending the study.

CHAPTER 2
THEORETICAL LITERATURE

2.1 INTRODUCTION

This chapter provides the theoretical foundation of the stock market volatility and its spillover effects. The theoretical section defines volatility and explains stock price volatility from the perspective of the efficient market hypothesis as well as behavioral finance. It further investigates the causes of market volatility and how volatility is transmitted in the stock markets. Finally, it also considers how the contagion theory (the main theory underpinning the study) in financial markets explains the volatility spillovers from both a broad and confined perspective.

The emergence of globalization has brought about improved interconnectedness in financial markets that have provided huge financial advantages such as improved capital flow from nations with excess savings into nations that require capital to help fuel economic growth (Bernanke et al., 2011; Matsumoto, 2022; Nguyen, 2022). Nonetheless, this integration has also presented new obstacles. As interconnection increases, markets are more likely to move simultaneously, and disturbances in one area are more likely to cause volatility to quickly propagate from one area to another (Sánchez García and Cruz Rambaud, 2023). The 2008 financial crisis exemplified how the failure of significant financial entities, such as Lehman Brothers, Bear Stearns from the US and Northern Rock, Royal Bank of Scotland from the UK precipitated extensive market upheaval, affecting assets even indirectly connected to the original crisis (Herz, 2016). Based on this discussion of interconnectedness and its relationship with volatility, the paper proceeds to the theoretical frameworks generating empirical grounds to understand the transmission of market shocks and their broader economic implications.

2.2 EXPLORING STOCK MARKET VOLATILITY

2.2.1 VOLATILITY

According to Gupta and Mishra (2024), volatility is the tendency for prices to change unpredictably. If a stock price varies widely, the stock is said to be volatile; conversely, if the price doesn't vary much, it is less volatile. This stock price volatility can be measured by using several theoretical approaches, which we can mention to begin with the beta, which is an instrument for estimating the volatility of the asset as well as its sensitivity to the market as a whole. If the beta is one, the asset's volatility is equal to that of the market. The higher the beta, the more volatile the asset is in the market. Another theoretical approach to measure volatility is the standard deviation, which measures the degree of dispersion in a data set. A higher dispersion in the data points indicates an increase in volatility. Lastly, a much more advanced volatility measurement approach, as introduced by Engle (1982), is by estimating a GARCH model; it considers the variation of errors in decline.

Stock market volatility has become a topic of increasing interest in the finance literature since the stock markets worldwide have become more integrated and volatile. In addition, financial volatility estimation is frequently employed and relied upon by policymakers to gauge a markets and an economy's sensitivity to financial volatility. For instance, Khositkulporn (2013) argues that the Federal Reserve in the United States accounted for the stock, bond, currency, and commodity volatility in formulating its monetary policy. Despite its importance in monetary policy, volatility is generally seen as unfavourable in the private investment climate because it's believed to represent uncertainty and risk. But volatility can be advantageous if the investor buys at the lows and sells at the peaks. For instance, Liu et al. (1999) argue that volatility has significant practical benefits to traders because it measures risk.

2.2.2 FACTORS AFFECTING STOCK MARKET VOLATILITY

The study of volatility has been done in several areas such as oil price volatility, exchange rate volatility and community price volatility. There are a number of factors that cause stock market volatility. For instance, numerous studies have demonstrated that stock market returns volatility is influenced by domestic economic factors. Some of these domestic factors are monetary and fiscal policies such as inflation, exchange rates and interest rates (Khositkulporn, 2013). Economic indicators, like the Consumer Price Index (CPI), real activity, money supply and industrial production also play an important role. Apart from the domestic economic factors, the volatility of the stock markets is also influenced by internal factors. These include the trade-weighted world exchange rate, the world index and oil prices (Khositkulporn, 2013). The combination of these factors has collectively and cumulatively contributed to the volatility in the stock market.

Sadraoui et al. (2016) further add to this discussion by proposing that market volatility is explained by some explanatory elements, both structural and cyclical. The Structural explanatory factors include leverage, price per share ratio and profitability. Whereas the cyclical factors include stock market anomalies, inflation and interest rate. Additionally, Ackert and Smith (1993) contend that stock price volatility can be caused by either a change in new information or a discount rate about future cash flows received by shareholders.

2.2.3 STOCK MARKET VOLATILITY TRANSMISSION

The growing sophisticated technology and extensive introduction of information processing globally have made international transactions more straightforward and cheaper than ever (Sari et al., 2017). On the other hand, capital movements and securities on the stock market have become highly liberalized. That has allowed the national stock markets to respond to new information from the international market quickly. As a result, the stock market movement can be transmitted between markets in terms of volatility. This rapid transmission is evidenced by King and Wadhwani (1990) who examined what occurred in October 1987, when all of the stock markets plummeted simultaneously, even though they were in different economic circumstances. The investigation aimed to construct a model to study the effect of 'contagion' across markets due to the actions of rational agents reacting to price change in other markets. Therefore, this can be perceived as a signal indicating that the 'mistake' on one market can be passed onto other markets through a process known as the 'contagion effect.'

2.3 EFFICIENT MARKET HYPOTHESIS: PERSPECTIVE ON VOLATILITY

The basic framework of the Efficient Market Hypothesis (EMH) provides a firm foundation for understanding volatility in stock markets. According to the EMH, markets operate efficiently, meaning stock prices and returns reflect all market information (Hussain et al., 2019). Assuming an efficient market and no time-varying risk premium, it should not be possible to forecast the value of returns for a given stock in terms of the lagged returns of a different stock (Harris and Pisedtasalasai, 2006). The presence of a spillover effect in returns implies the existence of an exploitable trading opportunity. If the trading opportunity generates higher profit than transaction costs, it will likely provide evidence against market efficiency. According to Engle et al. (1990), this inefficiency in the market may be attributed to meteor showers. Meteor showers are defined as a phenomenon of intraday volatility spillover across different markets. The reasons for the meteor showers on financial assets are that economies have a global news linkage, rational investors passively disseminate private news gradually, and policy coordination among industrialized nations occurs through a stochastic process, where a policy change or announcement in one nation triggers another nation to react resulting in volatility spillover. As Choudhry (2004) observes in their study on volatility transmission, this is experienced in countries with political rivalry elements. However, in friendly countries, there is no meteor shower effect since the governments in these countries know the impact of the policy change. So, they adjust accordingly to derive Pareto gains from the announcement or policy shift. As a result, Choudhry (2004) thus suggests deterministic coordination when establishing policies between nations in order to avoid the adverse effects of news and policy change on other countries. This is because if the markets are geographically close and have existing trade links, it is possible that errors in one market, due to noise trading, speculative trading, herding, and trends, to be transmitted to other markets when the price movements are affected.

In essence, EMH offers a theoretical starting point to describe market behaviour, but it fails to explain the practical imperfections that give rise to the spillovers in volatility. According to the Efficient Market Hypothesis (EMH), stock prices fully reflect all the available information, which should mean that there is no predictable pattern in volatility spillovers between stocks. In a perfect market, for instance, a shock to a large ESG stock would be instantaneously and fully absorbed without any spillover effect on other ESG stocks. In reality, however, markets are not perfectly efficient. The stock price may not include all information or may take time to include all, for instance, due to information lags, liquidation constraints, or investor behavior.

2.4 BEHAVIORAL FINANCE: PERSPECTIVE ON VOLATILITY

Behavioural Finance Theory (BFT) came as a response to EMH's claim of purely rational behaviour by suggesting that psychological influences also play a significant role on market decisions (Bhanu, 2023). The field of behavioural finance studies the role of psychology in the financial markets by demonstrating that the emotional behaviour of people or cognitive biases directly affect the investor behaviour, which in turn leads to market volatility (Dixit, 2024). Traditional financial theory, such as the EMH, assumes that investors are rational, spreading all available information fast and accurately and, as a result, that contributes to optimal decision-making. However, that is not always true as can be evidenced by empirical evidence; investors make decisions based on psychological factors that often cause predictable errors and market inefficiencies (Kahneman, 2011; Thaler, 2015). The integration of psychology into finance provides a more accurate description of what occurs in a market, where it is shown that investor behavior may not always be in line with the model of the rational actor, thereby causing price swings and cycles in the market, which deviate from the traditional finance models.

The pioneers of behavioural finance introduced prospect theory and loss aversion as means to reveal how irrational behaviors impact financial decision-making according to Kahneman and Tversky (1979). Several market events, including excessive market volatility and asset price bubble behavior, result from behavioral market biases. For instance, Barber and Odean (2001) point out that investors' behavior is influenced by their biases; for example, over-trading leads to market volatility, while anchoring dictates that investors hold onto certain price points and fail to react to the market fundamentals. Such insights shed light on markets' propensity to overreact to news or to not quickly respond to information, indicating that psychological biases have concrete ramifications for financial markets. These behavioral patterns explain market-related anomalies like the extreme volatility observed in case of financial crisis or long-term mispricing of the underlying assets.

Also, the study of investor psychology includes the study of how investors behave as a group of market participants. An example of this is herding behavior in which other investors follow the behavior of the majority of other investors even if it is not based on information, which amplifies market volatility and results in inflation or deflation of the asset bubbles (Shiller, 2000). Furthermore, the contagion of fear (or greed) resulting from groupthink and the bandwagon effect is direct evidence of how psychological phenomena can drive up the volatility of markets during times of high turbulence. Understanding these psychological influences is essential for practitioners who wish to predict the change in the market and policymakers who want to stabilize the financial markets. Thus, the understanding of investor psychology is of vital importance to build a more robust financial model and an adequate regulation framework focused on the inclusion of the human factor in market dynamics. Although behavioral finance can account for volatility spillovers arising from the behavior of investors, such as herding, it is difficult to observe investor sentiment and its immediate effect on spillovers empirically.

2.5 CONTAGION IN GLOBAL MARKETS

Since the 1987 Asian financial crisis, contagion has been one of the most discussed concepts in the international finance literature. However, there is no clear agreement in the literature on precisely what this concept means. Forbes and Rigobon (2002) define the contagion effect as a rise in volatility spillover between two financial markets as a result of a financial crisis. Khallouli and Sandretto (2012) offer a range of definitions: First, they define Contagion as the spreading of a crisis from one country to another or from one market to another. Secondly, Contagion is referred to as the spread of shocks above fundamentals, propagating faster than usual economic or financial channels and mechanisms amongst countries or markets. Thirdly, they consider Contagion to be the propagation of shock due to panic movements and the phenomenon of herding amongst investors. In addition, they contend that Contagion refers to the transmission of shocks via any channel, and that leads to the markets fluctuating. Finally, they argue that Contagion is a high-frequency transmission process of shocks that takes place more frequently in a crisis period compared to a tranquil period.

The World Bank Group (2009) defines financial Contagion slightly differently. First, Contagion refers to the cross-country spillover effect, which is the general cross-country transmission of shocks. Fundamental linkages are not considered as a channel of Contagion within this definition. Secondly, Contagion is defined as excess co-movement, a correlation that persists even after accounting for common and fundamentals shocks. In addition, Contagion refers only to those crisis transmissions that cannot be distinguished from observed changes in macroeconomic fundamentals. Lastly, Contagion denotes a shift and excludes the assumption of a constant high frequency of co-movement in the crisis period.

Against this background, Paas and Kuusk (2012) point out that in recent decades financial contagion has become an increasingly popular research topic. A vast amount of economic and empirical literature has investigated the idea of ‘financial contagion’ and the channels through which a financial crisis is transmitted. So, when contagion is a prevalent condition, one market transmits its massive loss to another. This is further noted by Das (2004) who asserts if the economy of one market is opened and integrated with the global economy, it can transmit a crisis in one market to another market. As a result, there are certain fundamental links among the financial markets that lead to contagion which arise when markets are connected with the international financial markets. For instance, when international institutions expand their portfolio across many markets, if one of those markets has a negative shock, the values of their assets will diminish. Consequently, international institutions will need to sell part of their asset holdings in another market that is still unaffected by the initial shock so that they can build up their reserves. The shock is then propagated to other markets.

The subprime mortgage crisis is one prime example of financial links. This crisis was caused by financial innovation that allowed investors and international institutions to invest in the US housing market through securitization and mortgage-backed securities (Karnad 2008). The high level of speculation, predatory lending and over borrowing caused these innovations to fuel the housing market bubble (Dodd, 2007). When the housing prices fell (bubble burst), delinquencies on mortgages and foreclosures in the United States skyrocketed. As a result, this crisis eventually led to a recession of the United States economy which spread around the world undermining other financial markets as well as weakening purchasing power, product activity and consumption demand (Shin, 2008). Ultimately, understanding contagion in global markets reveals how financial shocks ripple through economies, reshaping market stability and investor strategies

2.6 CONTAGION IN THE STOCK MARKETS

For this study, the contagion theory is well suited to analyzing the interplay between the spillovers of volatility of different sized stocks because it directly explains how shocks spread from one segment to another. According to Su (2021), history has repeatedly demonstrated that large stock markets tend to transfer their crises to small stock markets, which in turn infect each other, forming a domino effect that spreads very quickly across susceptible regional stock markets. As a result, many small market investors, institutions, and national stock markets have lost enormous amounts or even gone into bankruptcy. These episodes are commonly referred to as financial contagion, a self-reinforcing phenomenon, where the effects of past cases such as the Asian financial market crash, the subprime, the 1987 market crash, and the Greek debt crises continue to influence how global markets operate to a certain degree. It is a typical property of contagion risk that the collapse of a large market would cause other markets to tumble (Roll, 1988) and even fall simultaneously (Malliaris and Urrutia, 1992), although in different economic climates the smaller markets may continue to compete amongst themselves trying to survive. In addition to the economic foundation, other essential causes of contagion risk exist. According to King and Wadhwani (1990), market asset prices are not just a function of economic information but also of other market asset prices. Moreover, as argued by Dornbusch et al. (2000), contagion is the significant increase in cross-market linkages created by the shock of a particular market, and these cross-market linkages come from different channels. These channels include financial trading, information asymmetry, investor risk preference and global commercial activities.

Kyle and Xiong (2001) further add depth to the ongoing discourse by asserting that losses in a large market induce the quick sale of assets in another market since investors sell such assets to guard their resources, irrespective of long-term economic consequences. As a result when the large markets crash, it is often observed that contagion propagates from the large markets to the small markets to offset the larger market losses. This leaves the question of whether distress in small markets impacts large markets, too. If it does, we try to understand who or who isn't affected by contagion negatively. The large and the small stock markets are connected and share in each other's successes as well as failures. Nevertheless, there exist idiosyncratic characteristics among various stock markets (large and small). For instance, as argued by Su (2021), large stock markets tend to be more complete and have a more developed and extensive diversity of industries, and they partially bear their risk among themselves and share their growth. Small stock markets are comparatively less complete and have a less deep and narrower scope of industries subject to the growth of large markets. Large stock markets supply excess amounts of capital in times of normal market conditions, which benefits small markets, but once large stock markets suffer unusually large losses during crisis periods such as the subprime crisis, this extra capital is withdrawn from small markets, causing small ones to suffer and struggle together (Su, 2021). Additionally, small stock markets that take a hit the worst channel vicious, negative feedback back onto other small or even large markets. Alternatively, the largest stock market has been noted to rally following the inflow of fight-to-safety capital back into its markets from small markets.

The theoretical literature on volatility spillover implies a great propensity for large markets to spill over to smaller markets. The contribution of mid-cap stocks to this issue remains largely neglected to some degree or is not as clear-cut from a theoretical perspective. We can, however, deduce that if mid-cap stocks are theoretically more extensive than small-cap stocks, then mid-cap stocks may also 'spill over' into smaller markets. Additionally, the theoretical framework posits that small markets may transfer negative volatility to large markets especially when market turbulence is high. Based on the theoretical framework the following hypothesis is proposed: There is a significant volatility spillover from large ESG-compliant stocks to small ESG-compliant stocks.

2.7 SUMMARY

This chapter opened by first laying the theoretical foundation necessary for understanding how interconnectedness in financial markets can impact volatility. The study then looked at defining volatility through different angles, first through the efficient market hypothesis lens. In a voyage of explanations, the study crossed disciplines to borrow partly from psychology in order to understand the behavioural finance perspective on market volatility. This therefore shed light on how human emotions and cognitive biases directly influence investor behaviour and subsequently, market volatility. Having been equipped with these crucial concepts the study looked at how stock market transmission can lead to the "contagion effect", A theory central to the studies understanding of how volatility spillovers occur.

CHAPTER 3
EMPIRICAL LITERATURE

3.1 INTRODUCTION

In the literature, it is generally accepted that financial markets are prone to contagion. For example, empirical studies have shown that risks in the global financial markets increased substantially after the outbreak of COVID-19 (Harjoto and Rossi, 2023; Zhang et al., 2020). Consequently, this resulted in the spillover effects of such risk being observed across different asset classes (Corbet et al., 2020; Goodell and Goutte, 2021; Mensi et al., 2020; Wang et al., 2021), including equity markets (Akhtaruzzaman et al., 2021; Boyer et al., 2006). In light of this, the study examines the spillover literature in two dimensions in an attempt to understand volatility transmission patterns in equity markets.

One-dimension concentrates on the traditional knowledge of volatility spillovers without taking sustainability practices into account and mainly investigates the effect of the size of a company on its stock volatility. How these spillovers play out among the large, mid and small cap stocks under different regulatory and economic landscapes is what the study initially ventures to uncover. However, the introduction of environmental, social, and governance (ESG) elements, on the second dimension of the empirical review, throws complexity into the mix, forcing academics to rethink the accepted wisdom about the connection between size and volatility, thus paving the way for a new dimension of exploration.

The second dimension explores how volatility spillover affects ESG-compliant stocks. It is well understood that the links between stock market volatility, the size of corporations, and a company's adherence to ESG standards are intricate. In a way, there is a synthesis of current literature, as certain aspects are completely in line with prior studies, while other areas are dissimilar, establishing the base for the present study.

3.2 TRADITIONAL UNDERSTANDING OF VOLATILITY SPILLOVERS

This section examines the literature regarding firm size (large, mid, and small capitalisation stocks or indexes) and volatility spillover across several markets, including the U.S., Asia, Europe, and emerging countries. The examined literature, employing various approaches, has produced a range of results about the characteristics and impacts of these volatility dynamics. The key findings of the analysed studies may be categorized into four distinct types: bidirectional spillover across stocks of varying sizes, unidirectional spillover effects from large to small stocks, unidirectional spillover effects from small to large stocks, and complex spillover effects. This categorization highlights the gaps and commonalities in the literature and stresses the need for further research, especially on the spillover effects in ESG-compliant stocks, to contribute to the knowledge in this growing field.

3.2.1 UNIDIRECTIONAL SPILLOVER EFFECTS: LARGE TO SMALL STOCKS

3.2.1.1 US STOCK MARKETS

The U.S. stock markets, for instance, the New York stock exchange (NYSE) and NASDAQ offer a robust framework for assessing the impact of volatility on other markets, owing to their substantial financial infrastructure and considerable market capitalisation. Research in this field clarifies the transmission of volatility between major and smaller stocks, providing an in-depth understanding of information flow within a prominent global financial system. For instance, Conrad et al. (1991) examines the temporal linkages that exist within size-based portfolios to determine the means by which volatility is transmitted between large and small companies in the United States. The findings of their investigation, which employs a multivariate GARCH model, indicate an asymmetric (unequal) effect in both volatility and price. The study demonstrated that shocks to larger companies affect smaller ones; the contrary is not observed.

The mechanisms of volatility spillovers inside the New York Stock Exchange (NYSE) are investigated further by Chordia et al. (2005) in their study. To investigate the persistent liquidity, return, and volatility spillovers that occur between small-cap and large-cap portfolios, their research makes use of a vector autoregression model. The research findings indicate that the small-cap sector is most influenced by disturbances in the large-cap sector. This observation aligns with the conclusions reached by Conrad et al., (1991). Additionally, the study determined that liquidity and returns in large-cap stocks may reliably predict volatility and returns in small-cap stocks; however, the reverse has not been seen. This suggests that large-cap securities ought to assume a more prominent role in the dissemination of market disruptions. This illustrates the unequal nature of these market contacts and corroborates the notion of unidirectional spillovers from large-cap stocks to small-cap shares. The research further notes that sector-specific volatility and returns can be utilised to predict sector liquidity.

In a comparable vein, da Silva Antunes (2021) investigates volatility spillovers between big and small companies operating in the U.S. stock market. This research advances knowledge of market dynamics and the interdependence of companies of different sizes within the financial environment. The study provides further understanding by using pairwise Granger causality tests in tandem with multivariate models. The results show a clear asymmetric characteristic of volatility transmission wherein bigger companies significantly influence the volatility experienced by smaller companies. This discovery emphasises the unidirectional spillover effect reported in previous studies, therefore augmenting the corpus of information already in use in the area. Particularly, it has been shown that disruptions impacting big companies predict future volatility in small companies. On the other hand, the impact of shocks coming from small companies on the volatility of big companies is negligible and mainly unimportant. Together with Chordia et al. (2005), the findings of this study help to improve and confirm the patterns already noted by Conrad et al. (1991). This emphasises a continuous pattern of asymmetric spillover effects inside the U.S. stock market, which supports the current body of knowledge on this phenomenon.

3.2.1.2 ASIAN STOCK MARKETS

Having explored the intricate mechanics of volatility spillovers in the US stock markets, it is essential that we extend our perspective to include concurrent events in the markets of Asia. Research of volatility dynamics reflects the unique economic situations and market systems of countries like Japan and South Korea. The data from these regions show throughout the several Asian nations how the volatility and return spillovers between big and small shares vary at different rates.

Pyuna et al. (2000) specifically analyses the Korean stock Exchange using the generalised autoregressive conditional heteroskedasticity (GARCH) model. The study looks at the statistical characteristics of time-varying volatility in returns and trading volume as well as the ways in which conditional variances of returns might be utilised to project information flow patterns throughout a spectrum of different size of companies. Based on study results, the volatility spillover effect from larger companies to smaller businesses is significantly more evident. Given this finding, it seems that one may forecast the volatility of small-capitalization stocks by means of shocks to the volatility of big-capitalization stocks. Conversely, the influence of small stocks on big stocks is far less significant.

In an attempt to widen the focus of analysis of Asian markets outside of South Korea, Reyes (2001) investigates the volatility spillover effects found in the Tokyo Stock Exchange. This study focusses on the connections between large-cap and small-cap stocks. The transmission of price and volatility variations between the two different stock categories is investigated in this paper using a bivariate AR(1)-EGARCH(1,1) model. The study produces clear evidence of an asymmetric spillover effect. Particularly, the volatility of small-cap stocks is greatly influenced by volatility shocks arising from large-cap equities. On the other hand, this impact is not reciprocal as small-cap equities seem to have no effect on the volatility of large-cap stocks in a comparable sense. The asymmetric effect shown in this setting emphasises the major influence large-cap stocks have on the volatility dynamics of their smaller counterparts on the Tokyo Stock Exchange.

Building on the fundamental study of Pyuna et al. (2000), who similarly examined the Korean stock market using the GARCH model, Kang and Yoon (2011) investigate this market using a bivariate GARCH-BEKK model. They assess the predictive effects and the dynamics of information flow from larger stocks to their smaller counterparts. Their results show a one-way flow of returns from big stocks to medium and small equities, therefore supporting the conclusions reached by Pyuna et al (200). Furthermore, emphasized by Kang and Yoon (2011) are asymmetric volatility transmission. They find that unfavourable news affecting the big cap stocks causes small cap stocks volatility to rise noticeably. The consistency with the past research enhances the high prevalence of the volatility spillover effect seen from bigger companies to their smaller counterparts in the Korean market.

3.2.1.3 EUROPEAN STOCK MARKETS

A closer look at European markets exposes the complex relationships among various stock sizes. Studies on the UK, Greece, and Spain help to clarify how different regulatory systems manage volatility spillovers. Harris and Pisedtasalasai (2006) investigate the UK stock market with an eye on many facets of return and volatility spillovers. Using a multivariate AR-GJR-GARCH-M model; their paper investigates the asymmetric character of spillovers and the consequences of non-synchronous trading. Large stocks to small ones show apparent asymmetric return spillovers marked by positive volatility spillovers in that direction; the feedback from small stocks to large ones is negligible. Their study emphasizes an organized flow of information in the UK market since they indicate that information often influences big stock prices before it reaches small stock pricing.

Koulakiotis et al. (2016) conducted a similar cross-sectional analysis of return and volatility spillovers on big, medium, and small stock portfolios on the Athens Stock Exchange in Greece. They studied nonsynchronous trading and the cross-over imbalance that emerged after the financial crises. Their work employs an improved multivariate VAR-EGARCH model to examine how shocks from one index will affect the returns and the volatility of other indices in a nonlinear asymmetric manner. The analyses presented in this study suggest that significant volatility spillovers exist across varying-size portfolios, but the extent is more apparent during the financial crisis. In addition, asymmetric spillover effects were found, where large market capital indices affect the small market capital indices more.

3.2.1.4 EMERGING MARKETS

Although much is known about volatility spillovers from the US, Asia, and Europe, such spillovers and associated financial systems still need to be better understood in developing economies. At the emerging markets level, volatility spillovers from Iran, Saudi Arabia, India, Malaysia, and Brazil present characteristics that are not comparable to those of developed countries. These studies reveal significant differences that explain the volatility effects of nascent and poorly developed financial structures and widely varying levels of economic development. These markets could provide more views on the spillover of large and small stocks in the world's emergent economies.

Striving to map the dynamics of the emerging markets, Alsubaie and Najand (2009) concentrate on identifying the volatility-volume connection in the context of the Saudi stock exchange adopting the GARCH model. Their work investigates how trading volume influences conditional volatility persistence and how other information flow measures, including intraday and overnight activity, affect the relation. The findings reveal the volatility of smaller firms can be inferred from the volatility of larger firms. It also shows that there is a relationship between the previous volatility of the large and small firms and the current volatility of their own firms.

In addition to the preceding examination, Righi and Ceretta (2014) engage in this discourse to analyse the volatility spillover effect between small-scale and large firms in Brazil using the multivariate GARCH models. Their results show that the stocks of big companies affect the conditional volatility of the stocks of small companies. On the other hand, the market for large company stocks continues to experience fluctuations independent of small company stocks, which also uphold a unidirectional transmission of volatilities.

There is more literature reporting the spillover effect from large- to small-cap stocks in the US and Asian markets. European and emerging markets also depict similar results, but the representation is not as extensive as revealed by the other two markets studies. In general, based on the reviewed work, all markets experience unidirectional spillover effects in the stock market, whereby large stocks apply more potent force to smaller stocks.

3.2.2 UNIDIRECTIONAL SPILLOVER EFFECTS: SMALL TO LARGE STOCKS

3.2.2.1 EMERGING MARKETS

Similarly, Abbasian et al. (2008) analyse the volatility dynamics of emerging markets in the Tehran Stock Exchange by applying the Multivariate ARMA-GARCH-M model and the VAR model to study the interdependencies in the returns and volatilities of different sizes of stocks. Their study revealed that small stocks have a higher return spillover than large stocks. However, the study also established that the spillover effect of volatility from small stock to large stock is low, which means that although small stock greatly impacts the total return of large stock, it does not impact the volatility of large stock to the same degree.

Following Alsubaie and Najand (2009), who looked at the Saudi stock market, Al-Nassar (2023) extended the analysis to look at return and volatility spillovers between large--, mid-, and small-cap indices. In a VAR asymmetric BEKK GARCH model, the study establishes that volatility spillovers are present among all the indices. Nevertheless, these are reduced when structural breaks are incorporated, especially among the mid and small-cap indices. The results suggest that portfolio rebalancing, particularly with mid and small-cap stocks, is very effective in the flow of information in periods of crisis. Contrary to the findings of unidirectional spillovers from large to small stocks of Alsubaie and Najand (2009) who also examined the Saudi stock exchange, Al-Nassar (2023) also showed that small caps generally act as net transmitters of volatility shocks to large and mid-caps because of speculative trading, which causes price inflation while the fundamentals are adjusted.

In summation there is very little empirical evidence to support the notion that small stocks influence large stocks. This is observed only in emerging markets, and there is no such evidence in the US, Asian, or European markets according to the reviewed work. This is counterintuitive because conventional thinking is that the spillover would be mostly one-way in emerging markets from the large-cap stocks to small-cap stocks, given that the emerging markets are less developed and hence more sensitive to shocks from the large-cap and developed markets.

3.2.3 BIDIRECTIONAL SPILLOVER BETWEEN DIFFERENT SIZED STOCKS

3.2.3.1 ASIAN STOCK MARKETS

Revisiting the empirical analysis of the Tokyo Stock Exchange, Hung and Lin (2013) extend the examination of the mean and volatility spillover effects between large-cap and small-cap stock indices by employing different methodologies. They use a Vector Autoregression (VAR) framework for mean spillovers, whereas, for volatility spillovers, they employ a bivariate time-varying correlation GJR GARCH model. The study identifies bidirectional volatility spillovers: Volatility in the large index is influenced by positive shocks from the small index, and positive and negative shocks in the small index are influenced by the large index shocks. This contrasts the one-way volatility spillover from large-cap to small-cap stocks seen by Reyes (2001), which indicates variations in the Japanese market results.

3.2.3.2 EUROPEAN STOCK MARKETS

Grieb and Reyes (2002) explore the temporal dynamics between large- and small-cap stock returns in the UK, focusing on the Granger-causal transmission of information between these indexes. Building on the methodologies of Darbar and Deb (1999, 2000), they use the bivariate Logistic Exponential Generalized Autoregressive Conditional Heteroscedasticity (LEGARCH) model to examine information spillovers. Their findings reveal a bidirectional flow of information, indicating that changes in large-cap and small-cap indexes influence each other's future correlations. This suggests a significant degree of interconnectedness between the two market segments.

Pardo and Torró (2007) re-examined the Spanish stock market to analyse volatility spillovers between large and small firms using a vector error correction model (VECM) and a multivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. Their study found bidirectional volatility spillovers following negative news, with shocks from small firms significantly impacting large firms and shocks from large firms affecting small firms only in the context of negative shocks. Additionally, Pardo and Torró (2007) offer a more detailed analysis by demonstrating that the magnitude and direction of spillovers vary depending on firm size and the nature of the shock.

Angelidis and Andrikopoulos (2010) extend the analysis of volatility spillovers by examining the relationships between liquidity, idiosyncratic risk, and return across time and size-based portfolios of stocks listed on the London Stock Exchange (LSE). Their study builds upon the work of Harris and Pisedtasalasai (2006), who investigated return and volatility spillovers among major LSE stock indices but did not account for the impact of liquidity on these spillovers. By extending the sample period and incorporating interactions between idiosyncratic risk, return, and liquidity within a VAR framework, Angelidis and Andrikopoulos (2010) provide a more comprehensive analysis, including both cross-sectional and time series perspectives. Contrary to Harris and Pisedtasalasai (2006), their findings reveal bidirectional transmission of volatility, with shocks from small firms significantly impacting large firms, while shocks from large firms affect small firms only in the case of negative shocks.

An investigation into volatility spillover, employing a methodology influenced by prior research, is similarly conducted by Chuliá and Torró (2011). They investigate the relationship between firm size and volatility in the Spanish stock market by employing a conditional Capital Asset Pricing Model (CAPM) combined with an asymmetric multivariate Generalized Autoregressive Conditional Heteroskedasticity in Mean (GARCH-M) model. This approach parallels that of Harris and Pisedtasalasai (2006), who used a multivariate AR-GJR-GARCH-M model to study the UK stock market and found unidirectional spillover effects from large to small stocks. The AR-GJR-GARCH-M model, while slightly more advanced, allows for a more nuanced analysis of asymmetric spillovers compared to the GARCH-M model used by Chuliá and Torró (2011). Both studies use these models to examine asymmetric spillovers and the effect of firm size. In contrast to the findings of Harris and Pisedtasalasai (2006), Chuliá and Torró (2011) provide strong evidence of bidirectional volatility spillovers and significant impacts on firm volatility following negative shocks, indicating that volatility shocks in one group of firms can substantially affect the other group.

The Spanish stock market is further examined by Miralles-Marcelo et al. (2013), who re-examine the relationships among different firms using the Large-, Medium-, and Small Cap indexes to track the performance of large, medium, and small firms, respectively. Similar to Pardo and Torró (2007), they employ multivariate GARCH models (both symmetric and asymmetric with structural changes) but extend the analysis by including the medium cap index. Their findings align with Pardo and Torró (2007), demonstrating significant bidirectional transmission of volatility and shocks among large, medium, and small firms in the Spanish stock market.

3.2.3.3 EMERGING MARKETS

Karmakar (2010) extends the exploration of volatility spillovers to the Indian stock market, employing both standard and asymmetric BEKK models. The study investigates return and volatility transmission mechanisms between large and small stocks, examining the causal and dynamic relationships between these categories. The standard BEKK model initially indicates unidirectional volatility spillovers from large to small stocks. However, this finding is questioned due to potential model misspecification, which may result in biased or unreliable results. To address this, the study incorporates the asymmetric BEKK model, which reveals bidirectional volatility spillovers between large and small stocks, including interactions between the Nifty and Nifty Jr., as well as between the Nifty and Midcap indices.

Another key piece of work in the emerging market landscape is by Wei-Chong et al. (2011), who replicate the methodology used by Harris and Pisedtasalasai (2006) to explore return and volatility spillovers between large and small stocks in Bursa Malaysia. While Harris and Pisedtasalasai's study identified significant unidirectional spillovers in the UK, Wei-Chong et al.'s (2011) findings reveal notable reciprocal spillover effects between large and small stocks in Malaysia. This indicates a bidirectional transmission of volatility, further confirming the diverse patterns of spillover dynamics observed across different emerging markets.

Sinha and Agnihotri (2014) further investigate the dynamics of volatility in India by examining the impact of volatility persistence, market asymmetry, and information inflow on stock indices (large-cap, mid-cap, and small-cap) using a bivariate GJR-GARCH model. While their methodology bears some resemblance to that of Wei-Chong et al. (2011), it is less complex. Wei-Chong et al. (2011) employs an AR-GJR-GARCH-M model, which includes an autoregressive term to account for autocorrelation and integrates conditional variance into the mean equation, capturing the relationship between risk and returns. Despite these methodological differences, Sinha and Agnihotri's study also uncovers bidirectional causality between volatility and trading volume across all three indices considered.

Evidence of bidirectional spillover effects is found across Asian, European, and emerging markets. However, the European market appears to experience the most pronounced bidirectional spillovers based on the reviewed studies. This may be attributed to the region's highly integrated financial structures, where shocks in one segment tend to trigger ripple effects that feedback into the system, amplifying the original disturbance. Overall, this body of work highlights the interconnectedness of European markets and demonstrates that volatility and information transmission are complex, reciprocal phenomena extending across various market segments and methodologies.

3.2.4 COMPLEX SPILLOVER EFFECTS.

3.2.4.1 EMERGING MARKETS

While earlier research by Karmakar (2010) in the Indian stock market indicates bidirectional volatility spillovers between large and small stocks, Jena et al. (2021) provides a more nuanced view by employing a VAR-based spillover model to explore volatility across large-, mid-, and small-cap stocks on the National Stock Exchange of India. Their findings reveal that, in the short term, large-cap stocks are net receivers of volatility from mid- and small-cap stocks. However, this dynamic shifts over the medium-to-long term, with large-cap stocks becoming net transmitters of volatility to smaller stocks. This shift highlights the intricate and evolving nature of volatility interactions, offering insights into potential strategies for portfolio diversification and risk management.

The evidence supporting the complex spillover effects is only observable in emerging markets. These findings highlight the diverse and evolving nature of volatility interactions in emerging markets, reflecting the influence of economic development and financial market maturity.

Table 3.1: Summary findings of the traditional understanding of volatility spillovers

Spillover Effects of different sized stocks across different markets			
Bilateral	**Large to small**	**Small to Large**	**Complex**
Asian markets	Asian markets	Emerging markets	Emerging markets
European markets	European markets		
Emerging markets	Emerging markets		
	US markets		

Source: Author

3.3 VOLATILITY SPILLOVER EFFECTS SPECIFICALLY IN ESG-COMPLIANT STOCKS

This section takes a slightly different approach by critically and thoroughly examining previous research to understand the nature of volatility spillovers in ESG-compliant stocks. Building on the foundation laid in the previous review, where the paper initially explored the interplay of spillovers among different-sized stocks (Large, Mid and Small) without rigorously considering ESG compliance, this study now delves deeper. By understanding how ESG-compliant stocks are affected by volatility spillovers, will allow the study to investigate the dynamics between different-sized stocks when sustainability practices are rigorously taken into account. The analysis is structured into two main themes. The first theme examines the impact of ESG performance on overall market stability and volatility. The second theme explores how ESG performance and volatility respond to news and crises effects. The study reviews both developing and developed markets to provide a comprehensive perspective.

3.3.1 IMPACT OF ESG PERFORMANCE ON VOLATILITY

Several studies have examined how ESG performance or strict adherence to sustainability practices might affect the overall market stability and stock volatility. The paper contributes to this growing body of work by addressing the central question of this research: Are ESG credentials genuinely guiding investors into calmer financial waters, or do they merely place a green veneer over the same old waves of volatility? The review of traditional volatility spillover literature revealed cases of bilateral spillovers, unidirectional (volatility flowing both from large to small stocks and vice versa), as well as more complex spillover dynamics. This raises important questions, such as whether strict adherence to sustainability practices (ESG compliance) can alter these observed spillover patterns. Specifically, does the size of highly ESG-compliant companies impact the transmission of volatility shocks? In pursuit of answers, the paper delves into a broad and diverse range of ESG-related literature. While the studies explored differ in their methodologies, the markets analysed, and the periods studied, their findings are generally consistent and close to each other. The most persistent pattern that emerged from this research indicated that strict adherence to ESG criteria tended to reduce volatility spillovers.

Ashwin Kumar et al. (2016) contributed to this pool of findings by investigating the relationship between ESG factors and the volatility of stock returns, as well as the overall financial performance of companies through assessing companies listed on the Dow Jones Sustainability Index. The methodology included the calculation of the Sharpe ratio and the Treynor ratio to assess risk-adjusted returns. The findings revealed ESG companies exhibit lower stock return volatility compared to their non-ESG counterparts, with an average reduction in volatility of 28.67% across all studied industries. Since ESG companies exhibited lower volatility compared to their non-ESG counterparts, it implies that the overall market may experience less volatility spillover from these companies. In addition, the impact of ESG factors on performance varies by industry, indicating that some sectors benefit more from ESG integration than others. While the study offers valuable findings it lacks a thorough examination of how company size (large, mid and small) proxied by market capitalization affects the relationship between ESG performance and stock volatility. Incorporating this element could shed light on whether the size of ESG-compliant companies impacts the extent of risk reduction or return enhancement within the different industries, offering more detailed insights.

An extended market perspective is offered by Jakobsson and Lundberg (2018), who examined the impact of ESG performance on total share price volatility by using two different methods of estimating historical volatility: realized volatility and a GARCH (1,1) model. Their analysis includes data from 481 firms in the S&P 500 Index, which encompasses more companies than the Dow Jones sustainability index analysed by Ashwin Kumar et al. (2016). The study also found a statistically significant negative relationship between high ESG scores and share price volatility. The negative relationship between high ESG scores and share price volatility indicated that firms with strong ESG performance may experience less volatility spillover from external market shocks. However, Jakobsson and Lundberg (2018) are able to further establish that when market conditions change (e.g., economic downturns, regulatory changes), the impact on the stock prices of firms with high ESG scores may be less pronounced compared to those with lower ESG scores. Like previous research, this study does not explore the relationship between company size and volatility, even though ESG-compliant companies of varying sizes may experience different levels of volatility reduction.

In an effort to delve deeper into the evolving ESG landscape, the paper shifts its focus to Asian markets, exploring the link between corporate ESG performance and stock price volatility. Using fixed effects and Ordinary Least Squares (OLS) regression, Xu (2023) provided fresh perspectives on this relationship. Similar to the studies done in the US markets, the findings revealed corporate ESG performance is significantly negatively correlated with stock price volatility. Specifically, as companies enhance their ESG practices, they not only lower their own stock price volatility but also potentially mitigate the transmission of volatility to other firms and the broader market. Although the findings contribute meaningfully to the expanding ESG literature, the analysis lacks depth compared to Jakobsson and Lundberg (2018). It does not fully explore how economic cycles and external shocks, such as pandemics or financial crises, influence the relationship between ESG performance and volatility. This is a crucial consideration, as crises could affect the effectiveness of ESG practices in stabilizing stock prices.

The Chinese market is revisited by Gu et al (2023) with a renewed approach, using Ordinary Least Squares (OLS) regression to investigate the causal impact of ESG performance on stock idiosyncratic volatility. This renewed analysis builds on Xu's (2023) methodology, but shifts the focus from overall volatility, as commonly studied, to idiosyncratic volatility (Company-specific risk). The study found that the ESG performance of listed companies significantly reduces stock idiosyncratic volatility. This indicates that companies with better ESG practices tend to have more stable stock prices and lower firm-specific risks which can lead to a more stable investment environment, reducing the likelihood of volatility spillover effects that can impact other stocks or sectors. Although the findings are robust, the study does not thoroughly investigate how the impact of ESG performance on idiosyncratic volatility may differ across various sectors. Sectors such as energy or finance might be more susceptible to ESG-related factors, resulting in varying degrees of volatility reduction.

Recognizing the contributions of earlier research on stock market spillovers, Liu et al. (2023) take a wider canvas to paint a more expansive picture by exploring spillover effects across a variety of financial markets, thereby extending the scope of ESG's influence far beyond the stock market. The study employed a time-Varying Parameter Vector Autoregressive (TVP-VAR) and the Diebold-Yilmaz (DY) method to explore the relationship between ESG investment and financial market stability across various financial markets, including stocks, bonds, interbank, and foreign exchange markets in China. The findings of the study indicate that ESG investment enhances the stability of the Chinese financial market by reducing total, directional, and pairwise return and volatility spillover effects across various financial sectors, suggesting a positive correlation between sustainability and financial stability. These findings are also consistent with earlier research done in the Chinese market, but the study adds a macro-financial dimension not explored in other studies focused solely on stock market spillovers.

While Chen and Ying (2023) work with a smaller canvas than Liu et al. (2023), they focus on finer details, centering their analysis on the stock market. Instead of painting broad market dynamics, they carefully examine how state-owned and non-state-owned enterprises contribute to volatility transmission employing regression analysis. The study finds a significant negative correlation between ESG ratings and stock price volatility, indicating that better ESG performance stabilizes stock prices. The study further highlighted that non-state-owned enterprises experience a stronger relationship between ESG performance and stock price stability compared to state-owned enterprises. This indicates that in markets with a significant presence of non-state-owned firms, enhancing ESG performance could lead to a more stable market environment, thereby reducing the risk of volatility spillover from these firms to others. Once again, these findings are consistent with earlier research; however, the study adds a new layer of understanding by differentiating how different companies transmit volatility —an area that many studies tend to underexplore.

Likewise, Sandu (2023) paints the relationship on a canvas of similar size to that of Chen and Ying (2023), thereby maintaining a narrow focus. The study investigates the spillover effects of ESG scores among European listed companies operating within the same industry. In addition, it examines their impact on stock return volatility using a fixed-effects model. The study found that both individual company ESG scores and industry-average ESG scores have a direct impact on stock return volatility. Higher ESG scores are associated with lower volatility, indicating that companies with better sustainability practices tend to experience more stable stock prices. There is evidence of spillover effects, where the ESG scores of one company are influenced by the average ESG scores of other companies within the same industry. This suggests that companies are subject to peer pressure regarding their ESG performance, which can affect their own scores and, consequently, their stock volatility.

Fu (2024) explores the Chinese market by analysing the relationship between ESG performance and its effects on stock returns and volatility across all A-share companies in China from 2019 to 2022.The study employs ordinary Least Squares (OLS) regression models to analyse how the combined ESG score, as well as individual scores for environmental (E), social (S), and governance (G) factors, influence stock returns and volatility. The study finds a statistically significant negative relationship between the combined ESG score and individual E and G scores with stock volatility. This implies that companies with higher ESG scores tend to have less volatile stock prices, while the social score (S) does not significantly affect stock volatility. The study not only examines the impact of the overall ESG score but also differentiates the distinct effects of the environmental, social, and governance components. It emphasizes that certain factors, such as governance, may have a more substantial influence on volatility than others—an aspect often overlooked in many studies.

3.3.2 ESG PERFORMANCE AND VOLATILITY RESPONSE TO NEWS AND CRISES EFFECTS

Filling in some of the gaps left by previous research, Zhou and Zhou (2021) investigate the effects of crisis periods, such as the COVID-19 pandemic. The study employs the Difference-in-Differences (DID) approach to investigate the impact of ESG performance on stock price volatility during the COVID-19 pandemic on A-share listed companies in China. The findings suggest that Companies with excellent ESG performance experienced lower stock price volatility compared to those with poor ESG performance during the COVID-19 pandemic. This indicates that good ESG practices contribute to stabilizing stock prices in times of crisis. The lower volatility observed in companies with strong ESG performance during the pandemic suggests that these firms are better insulated from external shocks. This stability can prevent the volatility spillover to other firms or sectors, thereby reducing overall market volatility.

Larsson et al. (2022) temporarily shift the focus from crisis analysis to examine the effect of news by investigating the relationship between positive changes in ESG scores and the instantaneous volatility of stock prices in the European Union by Employing contingency table analysis and ordinary least squares (OLS) linear regression. The analysis revealed no significant association between the changes in ESG scores and the volatility of stock prices across different performance categories. This means that, despite the expectation that improvements in ESG scores might lead to reduced volatility (as companies with better ESG practices are often perceived as less risky), the data did not support this hypothesis strongly enough to reject the null hypothesis. The findings imply that while there is a theoretical expectation that higher ESG scores should correlate with lower volatility (due to factors like better corporate governance and reduced risk of information shocks), the empirical evidence from this study does not strongly support this in the short term.

Although the study did not find significant short-term associations, it hinted at the possibility that companies with better ESG practices might experience lower long-term volatility. This is based on the premise that such companies are likely to be more resilient and transparent, leading to a more stable business environment over time.

The effects of crisis periods, particularly the COVID-19 pandemic, are reassessed in a study by Nemoto et al. (2023), which highlights how the relationship between ESG performance and volatility can shift under varying market conditions. Focusing on the Japanese market, the study employs a firm fixed-effects panel model to explore how ESG factors impact stock returns, volatility, and liquidity during times of global crisis. The findings indicated that firms with better corporate governance experienced lower stock market volatility. This suggests that strong governance practices can act as a stabilizing force, potentially reducing the spillover of volatility from broader market fluctuations to individual stocks. During times of crisis, such as the COVID-19 pandemic, investors may perceive these firms as more resilient, leading to less drastic price movements. Interestingly, while better environmental performance was associated with higher volatility during normal market conditions, it contributed to reduced volatility during the pandemic. This dynamic suggests that the relationship between ESG factors and volatility can change depending on the market context. This context-sensitive finding is absent in studies like Ashwin Kumar et al. (2016) and Xu (2023), which focus on stable market conditions.

Sabbaghi (2023) models a multivariate DCC-EGARCH to investigate the conditional volatility risk of high ESG-rated firms in emerging and developed markets outside of the United States and Canada. The study analyses the asymmetric volatility response of these firms to news, particularly focusing on whether the impact of bad news on volatility is greater than that of good news. The findings of the study indicate that high ESG-rated firms exhibit a greater volatility impact from bad news compared to good news, supporting the hypothesis of asymmetric volatility. Specifically, the study reveals that the observed increase in volatility for high ESG-rated firms in response to bad news is lower in emerging markets compared to developed markets. Additionally, it finds that high ESG-rated firms in developed markets are more sensitive to the size of the news relative to their counterparts in emerging markets. The differential responses observed between emerging and developed markets indicate that volatility spillover may vary significantly based on the market context. In developed markets, where high ESG-rated firms are more sensitive to news, negative shocks could lead to more substantial spillover effects, potentially affecting investor sentiment and market stability more broadly.

These findings align with Nemoto et al. (2023), who also emphasize the variability of volatility spillovers depending on the market context. However, Sabbaghi (2023) offers a more comprehensive analysis by focusing on the asymmetric volatility response, rather than assuming equal response magnitudes across different market conditions, as Nemoto et al. (2023) does. Additionally, Sabbaghi (2023) extends the analysis to both developed and emerging markets, whereas Nemoto et al. (2023) confines their study to the Japanese market.

Askarany and Xin (2024) contribute to this pool of ESG-related findings by using a multivariate linear regression model to investigate the relationship between ESG ratings and stock price volatility, particularly in the context of the COVID-19 pandemic. The study analysed how ESG factors influence stock market dynamics and volatility across different sectors, with a specific focus on companies in China. The study confirms a significant negative correlation between ESG ratings and stock price volatility. Companies with higher ESG ratings tend to experience lower stock price volatility, indicating that strong ESG performance can act as a mitigating factor against market risks. Furthermore, Askarany and Xin (2024) offer essential insights that serve as a roadmap in the search for answers, arguing that company size does not moderate the relationship between ESG ratings and stock price volatility, while other studies do not directly address this factor, leaving room for further investigation. This suggests that both large and small companies with high-quality ESG ratings are equally effective in reducing stock price volatility. The study highlights that the impact of ESG ratings on stock price volatility varies across different industries. Both Askarany and Xin (2024) and Ashwin Kumar et al. (2016) emphasize that certain sectors experience greater benefits from ESG integration in terms of reduced volatility, though the extent of this impact varies by industry.

3.4 CHAPTER SUMMARY

Building on the theoretical concepts, the empirical review further augments the understanding of volatility spillover by synthesizing past findings. Thereby putting the study in a better position to understand, though limited, of whether ESG credentials are genuinely guiding investors into calmer financial waters, or they merely place a green veneer over the same old waves of volatility? The dimension investigating the traditional knowledge of volatility spillovers without taking sustainability practices into account revealed evidence of bilateral, unidirectional and complex spillover patterns among the different sized stocks. These findings are crucial as they form the foundation on which the old waves of volatility are conceptualized. An extended analysis into the volatility patterns among ESG compliant stocks, as investigated on the second dimension, revealed that companies that adhere to sustainability practices as demonstrated by high ESG scores exhibit lower volatility than those that are less compliant. While these findings are valuable, and the study acknowledges the evidence of less volatility subject to sustainability compliance, the reviewed studies fail to explore the interplay of volatility between ESG compliant stocks of different size. This lack of exploration in the interplay (as depicted in figure 3.1) of different company size and ESG compliance in understanding volatility spillovers is where the study sheds new knowledge.

Figure 3.1: Interplay of company size, ESG compliance and volatility spillovers (*the gap*)

Source: Author

Incorporating these elements could reveal the volatility spillover patterns within the "greener" financial landscape. This analysis may help uncover the theoretical implications of "greenwashing" claims or provide support for the idea that ESG credentials genuinely guide investors toward more stable financial markets.

CHAPTER 4
DATA AND METHODOLOGY

4.1 INTRODUCTION

The purpose of this chapter is to describe the formal analytical framework employed in implementing the objectives identified in Chapter One of this study. The objectives are designed to assist in addressing the research problem which aims to understand whether ESG credentials genuinely are guiding investors into calmer financial waters, or they do merely place a green veneer over the same old waves of volatility.

In addressing the objectives, we follow several authors, first we construct (*return indices*) variables building on the foundational work of Jalil et al. (2010) and Aziakpono et al. (2022) who have illuminated key aspects of this process. For modelling volatility, we follow the approaches of Desai and Joshi (2021), Lin (2018) and da Silva Antunes (2021) whose work stems from the pioneering contributions of Bollerslev (1986), Zakoian (1994) and Glosten *et al.,* (1993) in developing the GARCH family of models. Lastly, we employ a VAR framework for the spillover analysis, paralleling the work of Sanchez Garcia and Cruz Rambaud (2023), da Silva Antunes (2021), Karmakar (2010), Yonis (2011) and Chordia *et al*., (2005) whose approach has shaped the understanding of volatility spillovers.

The rest of this chapter is organised as follows. Section 4.2 describes the research paradigm. Section 4.3 outlines the research design. Section 4.4 discusses the econometric estimation techniques, while Section 4.5 concludes the chapter.

4.2 RESEARCH PARADIGM

A research paradigm is defined as the philosophical or theoretical framework underpinning the research study (Khatri, 2020). The word paradigm was first coined in the field of research by the American philosopher Thomas Kuhn in 1962 and referred to a philosophical approach. A paradigm comprises four components: epistemology, ontology, methodology, and axiology, as defined by Lincoln and Guba (1985). The ontological view refers to the nature of reality, the epistemological view describes the nature of knowledge and the relationship between the researcher and the researched, the methodological view describes the approach to systematic research, and the axiological view defines the nature of ethics (Mertens, 2010). These elements represent the research paradigm, assist in shaping its methodological decisions, and guarantee the coherence of the selected research approach with the study's objectives. In light of this, the study will follow a post-positivism research paradigm. In a post-positivism paradigm, the role of research is to forecast results, prove or disprove a theory, and identify the existence of causality, relationship, or strength in relationships between variables (Habib, 2020).

Since the study has positioned itself as following a post-positivist paradigm, the below axioms or assumptions of this paradigm automatically will guide the rest of the study. The four types of axioms as highlighted above that are applied include: epistemology, ontology, methodology, and axiology.

4.2.1 ONTOLOGY OF POST POSITIVISM

Ontology has two perspectives (subjectivism and objectivism) that can change the landscape of how the organization of a study is approached (Bryman and Bell, 2015). In this study, ontology aligns with the assumption that the spillover effects of volatility between the small, mid-, and large-cap ESG-compliant stocks are part of an *objective* financial reality. As a result, this reality can be analysed, measured and observed independently of the personal beliefs of the researcher. The study assumes that volatility spillovers in the UK and US between ESG-compliant stocks are real phenomena that can be compared and quantified, thus paving the way to objective insights into their market behaviour. The implication of this is that the objective nature of the ontology of this research promotes or encourages the goal of uncovering volatility transmission patterns between small, mid-, and large-cap ESG-compliant stocks without being subjective in the interpretation.

4.2.2 EPISTEMOLOGY OF POST-POSITIVISM

The major schools of epistemology are pragmatism, realism, interpretivism, and positivism (Saunders et al., 2009). The study's epistemological position is guided by measurement and empirical observation, allowing the study to create knowledge using a similar line of logic as that of *positivists,* emphasizing quantifying data. The study will employ quantitative measurements to capture the spillover effects. By applying statistical methods to quantify the spillover of volatility, the study can produce verifiable and objective findings as to how ESG compliant stocks spread volatility through the UK and US markets respectively. This implies that this is an epistemology rooted in empirical knowledge that can be observed. The ability to collect quantitative data free of subjective interpretation enables the verification and replication of the volatility of ESG-compliant stocks, hence enabling sound insights into the volatility spillover.

4.2.3 METHODOLOGY OF POST-POSITIVISM

Despite much literature on the classification of research, two dominant methods are the quantitative and qualitative (Rahi, 2017). The study follows a *quantitative, deductive* methodology through the application of econometric estimation techniques such as the principal component analysis (PCA), GARCH family of models and Vector Autoregressive (VAR) to investigate the spillover volatility patterns (will fully be canvased in the subsequent sections). This approach thus conforms to the positivist paradigm, in which repeatable and methodologically organised research is used to obtain generally applicable findings.

4.2.4 THE AXIOLOGY OF POST-POSITIVISM

This study remains *value neutral* by seeking to observe the effects of volatility spillover objectively without letting the personal values of the researcher taint how data is gathered and analysed. Through the commitment to objectivity and the application of statistical methods and measurable data (stock prices), the study reduces researcher bias. This has an implication that the results are credible and the purpose of the study to objectively shed light into volatility spillovers between ESG compliant stocks is reinforced. As a result, by adhering to value-neutrality, allows the study to generate findings that are driven by market behaviour rather skewed by the researchers' biases.

4.2.5 LIMITATIONS ACKNOWLEDGEMENT OF POST-POSITIVISM

The prevalent desire for the positivist paradigm to focus on quantifiable and measurable variables means the study's analysis does not consider factors such as the US and UK regulatory framework, even though they could potentially impact the market behaviour of the volatility spillover between the ESG-compliant stocks. Consequently, such contextual factors are less likely to be incorporated into a strictly quantitative framework.

However, although these contextual factors may contribute slight differences to the behaviour of spillover, the study's focus on the trends generalizable within stocks that are ESG compliant is in alignment with the objective of uncovering broader, data-driven patterns by the positivists. Since the goal primarily is to determine the dynamics of the volatility spillover rather than analysing regulatory nuances, this shortcoming is less likely to diminish the applicability and validity of the results significantly.

Table 4.1: Summary of scientific method

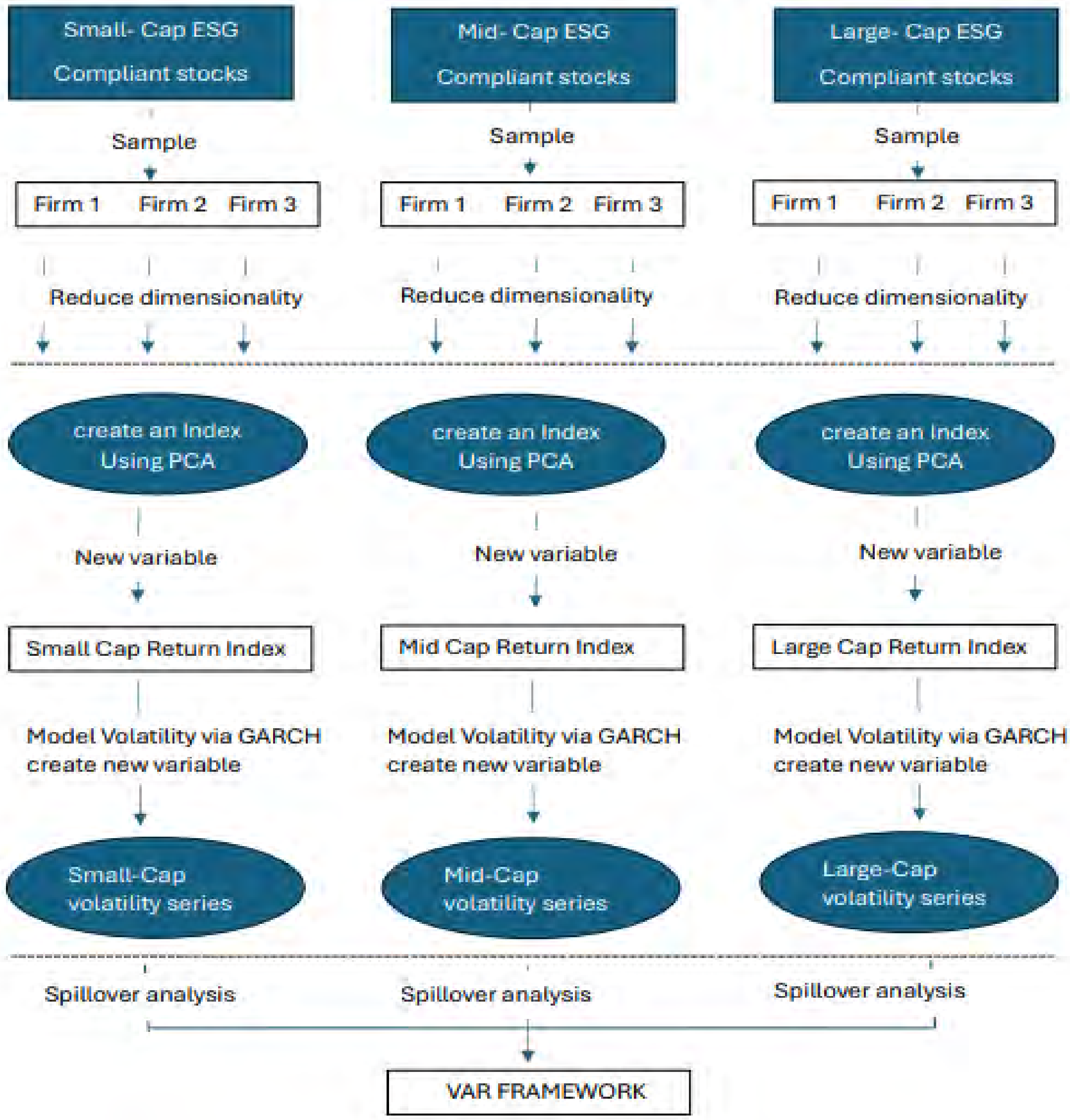
Area of research design	Chosen approach
Ontological Assumption	Objectivist
Epistemological Assumption	Positivist
Methodological Assumption	quantitative -deductive
Axiological Assumption	Value-neutrality

Source: Author

4.3 RESEARCH DESIGN

A research design is an action-orientated strategic framework designed to serve as an interface between research questions and the implementation of research strategy (Blanche et al., 2006). Additionally, Adams et al. (2014) argue that it is a blueprint or a master plan of how to collect and analyse data. As noted in the research paradigm above, the study will adopt a quantitative research design to test theories, establish facts and relationships between variables, and predict outcomes (Van der Merwe, 1996). Quantitative research relies on methods of the natural sciences, applying means to be objective, generable and reliable (Weinreib, 2009).

Figure 4.1: The methodological steps for the design process for both the US and UK



Source: Author

4.3.1 DATA COLLECTION

In line with the axiological assumption of maintaining value neutrality, the study gathers data without the researcher's personal values influencing it. Data gathering is based solely on fulfilling specific criteria (such as selecting firms with high *ESG scores*) rather than any subjective preference or appeal to the researcher. The analysis is carried out objectively using measurable secondary data, i.e., weekly closing price data of highly complaint ESG stocks. Weekly data series eliminates excessive noise and captures important activity in volatility changes, for which we are keenly interested. This is consistent with Liow (2015), who uses weekly data instead of daily data to cushion the effect of noise in the daily data and avoid the potential day-of-the-week effect.

The data is sourced from a financial database that is a highly reputable and well-established financial database. Since the London Stock Exchange database (LSEG) is more authentic and credible, all the firms' data (historical price data, market capitalization, sector classification, and ESG scores) is sourced from it. By pulling the data from one source, data integrity is maintained, and the frequency of all the variables is consistent, which, in turn, increases the accuracy and reliability of the findings. This guarantees that the patterns found in the outcome are not a product of data timing irrationalities but merely regular market movements.

The data covers the period from 5 January 2018 to 20 December 2022 (i.e., 5 years) resulting in 261 observations for the US and UK respectively. In addition, the sample range also encompasses a major global shock: the covid 19 pandemic of 2020, which caused an unprecedented shock to firms in financial markets that created extremely volatile conditions (Yarovaya *et al*., 2022; Khan *et al*., 2023). Including this timeframe in the analysis allows this study to capture the volatility pattern of one of the most stressful economic periods in contemporary history, and determine how ESG compliant firms perform during such a period. Finally, data availability limitations and the need of a reasonable sample size to draw meaningful conclusions dictate what the timeframe of the analysis and how many firms to include in the sample.

4.3.2 SAMPLING DESIGN

The sample selection was carried out systematically to increase the overall applicability of the results, minimize the impact of various biases, and improve the study's validity. Thus, this is achieved by accounting for the ontological assumption of the commitment to objectivity. In gathering the sample necessary for analyzing the volatility spillover, the study used a non-probability sampling method known as purposive sampling, which can accommodate an analysis focused on firms that fulfill specific requirements (Rahi, 2017).

First, firms were purposively selected based on their market capitalization; that is, large, mid, and small-cap firms were identified using the LSEG database. From the results obtained from the LSEG database, any firm with a market capitalization of $10 billion and above is classified as a large capitalization stock, firms with a market capitalization between $2 billion and $ 10 billion are classified as mid-capitalization stocks, and firms with a market capitalization of less than $2 billion are classified as small capitalization stocks.

Classifying ESG compliant companies by market cap was required to capture the differences in the volatility of companies of different sizes, which might provide insight into how spillovers in volatility might differ with company size, thereby helping to address the research gap. The study excluded undesirable markets, focusing on US and UK firms. As previously hinted, data availability dictated the decision of only including these two; the UK and US had the most coverage and consistent data reported for ESG scores for firms under the period of interest. In addition, the UK and US also serve as host to the largest financial institutions (London and New York Stock Exchange, amongst others) and are highly interconnected and influential in world finance. The inclusion of firms from these regions widens the generalizability and strength of the findings, so that the study can make broad and comprehensive conclusions regarding the spillover volatility beyond the confines of only one market.

The second requirement was to purposively select companies from the same sector. The study achieved this by pulling most of the firms from the financial industry, but because of ESG data limitation, the study was forced to include ESG-compliant firms from the real estate sector. This was because some small-cap firms in the US operating in the financial industry did not meet the threshold ESG score for compliance set by the study. Additionally, some small cap firms did not have ESG scores provided for some years, which meant there were data inconsistencies. The real estate sector was then added to remedy this. Despite the limitation, the study deliberately maintained a greater ratio of firms from the financial industry because they substantially influence the volatility of the economy at large. The covid 19 pandemic of 2020, global financial crisis of 2007/8 and the great depression of 1929 are some of the great examples of how financial weakness in the system can induce massive economic turbulence. The study also understands that most of these crises could not have exclusively emanated from the financial markets. However, the sector has acted as a mechanism for transmitting shocks at an amplified magnitude beyond the impact of the initial shocks.

Therefore, the inclusion of the real estate sector was selected purposively because it is a market with a solid marriage to the financial industry. (Acharya and Richardson, 2009; Huseynov, 2018). This further points to the fact that financial institutions do invest a sizeable portion of the balance sheet in property and real estate backed securities. Consequently, real estate value volatility can be directly related to the performance and stability of financial institutions. As a result, the addition of the real estate sector complements the analyses by capturing cross-sector effects of volatility spillover in passing since the two are highly interconnected.

The last requirement in assembling the sample was to select highly compliant firms based on their ESG scores. The study used the combined ESG score, a percentage, to measure compliance. This score is a percentage that can range from 0 to 100. Higher ESG scores indicate higher compliance, and the opposite is also true. By choosing these highly compliant companies, the study should gain a broader understanding of how a solid commitment to sustainability practices shapes the spillover of volatility. Critical to this selection process is the strict requirement that the firms chosen should maintain the threshold requirement as determined by the study for all years under observation; failure to do so leads to the elimination of that firm. The ESG scores, as previously stated, were also sourced from the LSEG database; as of now (2024), the data range covers a period from 2018 to 2023.

Consequently, the 2023 ESG scores have yet to be reported for most firms since they are done with a lag. In light of this, the study can only collect ESG data from 2018 up to 2022. This, therefore, confines the analysis of the study to this timeframe. However, this sample range parallels that of Sandu (2023) who investigated the spillover effects of ESG scores from companies operating in the same industry and their impact on stock return volatility and considered a sample of European listed companies from 2019 to 2022. In selecting companies based on high ESG scores, the study is aware that large-cap firms are able to better comply with the sustainability requirements due to their financial strength and extensive resources compared to mid-cap and small-cap companies. Likewise, mid-cap firms can comply better than small-cap firms for the same reasons. Kaiser (2020) further confirms this difference in compliance by firm size by observing that other things equal, firm size is positively correlated with ESG ratings, that is, larger firms are more compliant than smaller firms. As a result, the study imposed varying ESG score requirements based on these differences to ensure fairness because the small and mid-caps cannot consistently meet extremely high ESG scores.

Moreover, this is done to ensure an equal representation of firms in each cap subject to the available data. For a large cap firm to be included in the sample, an ESG score of 70 or above should be maintained for each year under observation. For a mid-cap firm, an ESG score of 60 and above was required; lastly, for the small-cap, an ESG score of 50 and above was required.

Furthermore, companies were selected by taking only "Active only," which excludes delisted firms. The "Dual-listed shares" were excluded to get the "primary issues only." Therefore, other categories of securities other than "ordinary shares" were also not included to help ensure that data only included the shares trading in public exchanges, that is the New York stock exchange for the US and the London stock exchange for the UK. The selection resulted in three firms at each market capitalization level for both the UK and US, respectively, resulting in nine firms for each country. The sample size is legitimized by methodological rigor and practical limitations.

Table 4.2: Top ESG compliant firms from the US

			ESG scores				
Company name	**Ticker symbol**	**Industry**	**2018**	**2019**	**2020**	**2021**	**2022**
Large Cap US							
Bank of America Corp	**BAC**.NY	Financials	75.68	85.52	84.21	82.43	79.91
Citigroup Inc	**C**.NY	Financials	85.80	86.28	88.28	85.5	85.1
Goldman Sachs Group Inc	**GS.** NY	Financials	70.83	82.8	88.79	87.38	86.39
Mid cap US							
Voya Financial Inc	**VOYA.**NY	Financials	75.38	77.74	75.89	71.17	61.84
Invesco Ltd	**IVZ**.NY	Financials	72.25	77.2	75.12	74.23	76.62
Comerica Inc	**CMA**.NY	Financials	70.16	70.66	70.92	70.42	71.19
Small Cap US							
Brandywine Realty Trust	**BDN**.NY	Real estate	75.17	68.81	65.37	58.42	58.92
Diamondrock Hospitality Co	**DRH**.NY	Real estate	61.62	70.35	61.44	71.8	81.04
Pebblebrook Hotel Trust	**PEB**.NY	Real estate	58.64	69.54	65.94	64.54	68.46
The (. NY) on the Ticker symbols of the firms denotes that the firm is listed on the New York Stock Exchange							

Source: London Stock Exchange (2024)

Table 4.3: Top ESG compliant firms from the UK

			ESG scores				
Company name	**Ticker symbol**	**Industry**	**2018**	**2019**	**2020**	**2021**	**2022**
Large Cap UK							
Barclays PLC	**BARC**.L	Financials	89.62	88.94	83.47	84.93	84.42
Lloyds Banking Group PLC	**LLOY**.L	Financials	74.07	79.37	83.79	81.5	84.52
Aviva PLC	**AV.** L	Financials	77.81	73.84	71.69	75.62	73.1
Mid cap UK							
Abrdn PLC	**ABDN**.L	Financials	80.19	82.78	84	83.64	85.71
Man Group PLC	**EMG.**L	Financials	65.21	66.38	69.7	70.03	76.22
Investec PLC	**INVP.**L	Financials	70.19	62.35	67.21	71.99	65.51
Small Cap UK							
Close Brothers Group PLC	**CBRO**.L	Financials	63.21	68.60	70.31	69.63	66.61
Ashmore Group PLC	**ASHM**.L	Financials	63.17	64.73	61.95	64.63	63.26
OSB Group PLC	**OSBO.**L	Financials	62.61	54.89	55.38	59.34	58.68
The (. L) on the Ticker symbols of the firms denotes that the firm is listed on the London Stock Exchange							

Source: London Stock Exchange (2024)

4.3.2.1 DATA PREPARATION

Subsequent to the identification of the firms in the sample, the research data is pre-processed through formatting and transformation before it can be used in the estimation process. The first part of the data preparation is done by logging the weekly closing historical price data for each firm in the sample. Thereafter, the data is converted from the logged weekly closing price data for each firm to weekly log returns using the formula presented below, and this is in line with previous research such as that of Alsubaie and Najand (2009), Jena *et al* (2021) and da Silva Antunes (2021).

$$R_t = Ln\left(\frac{Pt}{Pt-1}\right) = Ln\ (P_t) - Ln\ (P_{t-1}) \qquad (4.1)$$

Where:

R_t represents the returns at time t,

Ln is the natural logarithm,

P_t represents the closing price at time t,

P_{t-1} refers to the previous time periods closing price.

The formula above provides the change in percentage in price from one time period to the subsequent one in terms of logged returns. This assists in normalizing the returns and is generally applied in financial analysis to achieve comparability and consistency. The motivation for this is that the study can express the size of the fluctuations in a manner that accounts for the differences in the scale of the small, mid, and large-cap firms. For instance, a change in small and large-cap stock of 1 % may have varying price impacts in absolute terms, while the implications for investors might be the same relatively.

4.3.3 VARIABLE DEFINITION, VARIABLE JUSTIFICATION & LIMITATIONS

4.3.3.1 VARIABLE DEFINITION

The logged return price data for the three firms within the same market capitalization is then used to create a return index for each market capitalization: the large, mid, and small cap for the US and the UK respectively. These indices then become the first set of variables of interest which are used in the preliminary analysis (description statistics and correlation analysis).

Table 4.4: Description of the return variables

New variable	**Description**	**Firms included in the PCA for the construction of the variable [Firm 1, Firm 2, Firm 3]**
US: Large-Cap Return Index **&** **UK:** Large-Cap Return Index	Derived through PCA on the returns of large -cap firms in an effort to generate an index of the overall movement of large-cap companies in the US and UK respectively.	**US**: BAC, C & GS **UK**: BARC, LLOY & AV

US: Mid-Cap Return Index **&** **UK:** Mid-Cap Return Index	Derived through PCA on the returns of mid- cap firms in an effort to generate an index of the overall movement of mid-cap companies in the US and UK respectively.	**US**: VOYA, IVZ & CMA **UK**: ABDN, EMG & INVP
US: Small-Cap Return Index **&** **UK:** Small-Cap Return Index	Derived through PCA on the returns of small-cap firms in an effort to generate am index of the overall movement of small-cap companies in the US and UK respectively.	**US**: BDN, DRH & PEB **UK**: CBRO, ASHM & OSBO

Source: Author

The return indices (Large, mid and small) for both the US and UK represent the broad market behavior of the top highly compliant firms in each market cap category. The next set of variables are the volatility series (large, mid and small), these are constructed by using a GARCH model to generate the respective series for both countries.

Table 4.5: Description of the volatility variables

New variable	**Description**	**Return index transformed into volatility series**
US: Large-Cap Volatility Series **&** **UK:** Large-Cap Volatility Series	Estimates a GARCH model on the Large-cap return index (constructed from the PCA) to obtain the volatility series for the Large-cap index for both the US and UK respectively.	**US:** Large-Cap Return Index **UK:** Large-Cap Return Index
US: Mid-Cap Volatility Series **&** **UK:** Mid-Cap Volatility Series	Estimates a GARCH model on the mid-cap return index (constructed from the PCA) to obtain the volatility series for the mid-cap index for both the US and UK respectively.	**US:** Mid-Cap Return Index **UK:** Mid-Cap Return Index
US: Small-Cap Volatility Series **&** **UK:** Small-Cap Volatility Series	Estimates a GARCH model on the small-cap return index (constructed from the PCA) to obtain the volatility series for the small-cap index for both the US and UK respectively.	**US**: Small-Cap Return Index **UK:** Small-Cap Return Index

Source: Author

4.3.3.2 VARIABLE JUSTIFICATION

The return indices are the first set of variables used in the analysis to provide some preliminary statistics to understand the data properties, such as stationarity and heteroskedasticity, descriptive statistics etc and hence establish whether the need for a volatility series is justified. If there is a need for a volatility series (indicated by the *presence of heteroskedasticity*) the return indices are then further used to create the volatility variables employed to analyse the volatility spillover through the VAR framework. The decision to use the index instead of the firms individually is because, with indices, information is aggregated across numerous firms, thereby smoothing out noise and idiosyncratic shocks that could affect the individual stocks. Hence, by working with indices, the analysis can extract broader trends not affected by the specific firm factors and are more helpful in identifying volatility spillover across the different market segments.

Moreover, conducting a VAR analysis on individual firms could be highly computationally demanding, mainly when working with datasets containing many variables (firms), hence the application of indices is helpful in reducing the data dimensionality. Most importantly, the motivation to use indices stems from a need to be consistent with past research. For instance, Al-Nassar (2023), Sinha and Agnihotri (2014), Kang and Yoon (2011) and Karmakar (2010) studied the volatility spillover using the indices as a proxy for different market cap tiers (large, mid, and small). Their study further employs a VAR to probe the volatility transmission between the market cap tiers. It follows that using indices in a VAR for volatility spillover is consequently both feasible and theoretically substantiated; the study can achieve accurate, generalizable, and interpretable findings across various market segments while conforming to prior research methodology for analysis.

4.3.3.3 LIMITATIONS

The study is aware of the fact that excluding the individual firm prices entails the loss of information where individual volatility profiles of such firms might be obscured within the index by the averaging, and it recognizes that even in the presence of such loss, aggregation serves as an essential alternative source of information. Nevertheless, this is favourable, as this study aims to learn about average trends in volatility spillovers across the different market cap tiers as opposed to specific idiosyncrasies.

4.4 ECONOMETRIC ESTIMATION TECHNIQUES

As highlighted in the methodological assumption of the research paradigm, the study follows a quantitative and deductive methodology through the application of econometric methods to address the research objectives such as the principal component analysis (PCA), GARCH family of models, and Vector Autoregressive (VAR), which ensure the study produces replicable and structured methods of research that yield generalizable findings.

4.4.1 PRINCIPAL COMPONENT ANALYSIS: CONSTRUCTION OF RETURN INDICES

A novel feature of this study is to use a principal component that combines the price data of three ESG compliant firms in each market capitalization level (large, mid and small) to create an index. This follows the same logic as Jalil et al. (2010) who constructed an index using three variables. The fundamental purpose of Principal component analysis is to decrease the dimensionality or the number of variables in a data set, yet maintain as much information as possible (Wang et al., 2014). Principal components are new variables obtained by constructing linear combination or a mixture of the original variables (Huang and Wang, 2018). The use of a PCA for the study offers several advantages in the sense that smaller data sets are easier to explore and visually interpret, and data analysis, in general, is much easier, faster, and less demanding for modeling econometrics on the smaller data sets without redundant variables to process. This, in turn, allows us to have less information loss yet increase interpretability. In view of this, as noted by Aziakpono et al. (2022) the principal component problem can be formulated as

$$P = AX \tag{4.2}$$

where P: are principal components or a vector of orthogonal factors and they are a linear combination of the original variables.

X: is the m observed sets of variables.

A: is a matrix of coefficients or factor loadings with each coefficient representing the weight of the corresponding original variable in the relevant principal component (PC).

Steps involved in the construction of the return

The first step the study will take in constructing the variables (indices) is to perform the initial extraction of the components. The PCs extracted are equal to the number of variables being analysed. The 1st PC typically accounts for a relatively sizeable total variance. The subsequent PCs will account progressively for smaller amounts of variance. The variables can be transformed by using either a correlation or covariance matrix (Lee, 2017). Since the scales of the variables are different, the correlation matrix is particularly advantageous to use; it is mean centered (Jolliffe, 2002) and it is commonly used. In order to evaluate the explanatory power of each of the PCs, two conventional methods will be used: the eigenvalue and cumulative R^2. The second step is to determine how many PCs to retain. The study will use the Kaiser Rule, which states that PCs with an eigenvalue more significant than one should be retained (Kaiser, 1960). The third step involves rotation to reach a final solution. The most popular method is VARIMAX Rotation. As recommended by Jolliffe (2002) the study will use a varimax rotation, which is an orthogonal rotation, giving uncorrelated components. Finally, the rotated solution is interpreted. In other words, this entails defining what is being measured by the retained components. The return indices (Large, Mid & small cap) in the US and UK are generated using these retained principal components.

4.4.2 MODELING VOLATILITY: CONSTRUCTION OF VOLATILITY SERIES

In traditional econometrics, it is assumed that the variance of random variable is constant. However, in reality, most of the financial time series appear to be heteroscedastic, which means the variance of the series varies with time (Wang et al., 2022). To estimate the time variation, GARCH models are employed primarily to investigate the stochastic properties of a financial variable, as well as to capture volatility clustering, leptokurtosis, and skewness, which are the three most essential characteristics in data of stock returns (Theodossiou and Lee, 1993; Kim and Rui, 1999). This has in turn attracted a great deal of attention on how news of one market affects the volatility process of another market. Some of the early papers on this area of study include Koutmos and Booth (1995), Hamao et al. (1990), Lin et al. (1994) in the US and the UK. The GARCH type models are used in all these studies to investigate the volatility transmissions between markets.

Although the usage of the GARCH-type models is beneficial, considering the context (non-constant variance), the selection of the appropriate model from the family of GARCH-type models in most studies is conventionally influenced by previous research. While that approach does offer a great theoretical foundation and justification for adopting a model, it also can result in a poor model selection process. In consideration of this, the study is conscious of the fact that this can lead to subjectivity because the variable or data properties such as heteroskedasticity, non-normality, volatility clustering, and fat tails, etc., are most likely to be neglected to fit a model with considerable coverage in literature, which might not necessarily be the best model. The study mitigates this by following a much more thorough and systemic process. As a result, the overarching voice on which models to use in generating the volatility variables comes from this process. The study introduces an objectivity angle, which involves stricter and more structured selection criteria, thereby eliminating subjectivity. The systematic process begins by taking each return index (variable) constructed from the PCA and running it on a selected number of GARCH-type models (ARCH, GARCH, TARCH, EGARCH). The results for each GARCH model are evaluated based on satisfying certain conditions. The process is repeated, but the models are made to account for the IN-MEAN (IM) risk-return tradeoff in financial data. The study delves more profoundly in the segment below on how the procedure is carefully carried out.

Steps involved in the selection process of the appropriate GARCH model

The following steps are performed to determine the appropriate volatility model for each return variable: the large, mid, and small-cap index generated using PCA for both the US and UK. A mean equation is specified and estimated for each return variable. The results are tested for autocorrelation; if it is present, a lag of the dependent variable is added to correct it. Subsequently, an ARCH effect test is performed on the return variable; if there is evidence of the ARCH effect, it means that the variance of the return variable is heteroskedastic. Therefore, the usage of the GARCH-family type of models which can handle heteroskedastic variables will be appropriate. In essence this first part entails identifying the issue (heteroskedasticity) and perhaps finding a remedy (GARCH models) for it. After that, the estimation of the GARCH models can occur, meaning the equations for the alternative conditional variance should be specified.

In order to ensure the issue (heteroskedasticity) has been remedied, the study should revisit the test after estimating a GARCH model and determine whether the ARCH effect has been eliminated if that condition is met. The following checkpoint is to determine if the stationarity and non-negativity constraints are satisfied for that particular GARCH model. The study will further test for asymmetric effects using the (EGARCH and TARCH). The abovementioned process will be repeated for all models with the incorporated IN-MEAN term. If a model shows evidence of asymmetric effects and has a significant IN-MEAN term, it is considered superior to alternatives. This is simply because these models are able to provide us with more information compared to models that lack those characteristics. However, if two models equally fulfill the above-specified criteria, the information criteria are used to determine the superior model. Finally, the superior model is used to generate the conditional variance series, which is then used to analyze the behavior of the volatility spillover in a VAR framework. The table that is used to evaluate the suitable appropriate GARCH model from the rest of the family is presented below.

Table 4.6: The model selection process table

Model:	ARCH effect	Stationarity	Non-negativity	Asymmetry (EGARCH; TARCH)	In-Mean	HIC	SIC	RMSE
ARCH				No asymmetry	No IM			
GARCH				No asymmetry	No IM			
TARCH					No IM			
EGARCH					No IM			
ARCH IM				No asymmetry				
GARCH IM				No asymmetry				
TARCH IM								
EGARCH IM								
HIC: Hannan-Quinn criteria; SIC: Schwarz criterion; RMSE: Root means squared error								
For each model a tick is awarded in each box for every conditioned satisfied								

Source:Author

From following the above systematic process and keeping the analyzing process impartial, two models, the GARCH (p,q) and TARCH, were deemed suitable for generating the volatility series for each return variable. Consequently, this provides a rationale for using these models in data analysis. In addition, these models' application is backed by prior research such as that of Desai and Joshi (2021), Lin (2018) and da Silva Antunes (2021), who have also employed similar methods. Hence, based on the previous studies, the present work confirms the value of the selected models at theoretical and empirical levels and assures the coherence of the obtained results with the other contributions in the respective field. The specifications of the selected models are discussed below.

4.4.2.1 SYMMETRIC GARCH MODEL: GARCH (p,q)

The ARCH model offers a concise and practical analysis approach to explaining the volatility, which generally varies according to a financial time series (Lin, 2018). While other conventional econometric models expect the variance to be the same at all points in time, ARCH models allow for time-varying conditional variance (Bollerslev, 1986). However, for empirical works, the ARCH model often uses a larger order and thus needs more parameters to be estimated, which causes problems such as the multicollinearity of the independent variables (Asteriou and Hall, 2011). In an effort to correct some of the shortcomings of the ARCH model, Bollerslev (1986) extended it by including an autoregressive term in order to obtain the GARCH model. This extension of the ARCH model in its most basic form can be presented as a GARCH (1,1).

$$R_t = a_0 + a_1 R_{t-1} + \varepsilon_t \tag{4.3}$$

$$\varepsilon_t \sim i.i.d. N(0, \sigma_t^2) \quad (4.4)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (4.5)$$

The exogenous variables mean equation is presented as equation 1, followed by the mean of error equation. The third equation is the specification of the conditional volatility, which is a function of three terms that explain the varying volatility over time. The first term is a constant [α_0], the second term is the ARCH part, which represents the previous period's volatility [ε_{t-1}^2] and lastly, the final term is the GARCH part which represents the last period's variance prediction [σ_{t-1}^2]. While [σ_t^2] is the conditional variance, this represents the estimated variance based on the previous period's information. In addition, in a GARCH (1,1), the first "1" in the brackets refers to the GARCH Component of order 1, and the second "1" in backets refers to the ARCH component of order 1. This model can be adapted to explain higher orders of both terms. The notation for the higher order of the GARCH model is as GARCH (p,q) where the "p" or "q" is a value more than 1. The variance equation can be specified as follows:

$$\sigma_t^2 = \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \quad (4.6)$$

Where the GARCH component and ARCH component are denoted as "p" and "q" respectively (p≥0, q>0). $\alpha_i \geq 0$ (i= 1,2, 3..., q), $\beta_j > 0$ (j = 1,2,3…, p), $\alpha_0 > 0$ and $\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j$ is the coefficient of attenuation which measures the amount of persistence in volatility. When $\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j < 1$, stationarity is said to be achieved in a GARCH process. Overall, the GARCH(p,q) has provided satisfactory simulation for the implied volatility sequence and asset yield sequence. However, they do not incorporate long-term memory and volatility asymmetry and long-term memory is prevalent within the forex and stock market.

4.4.2.2 ASYMMETRIC GARCH MODEL: Threshold GARCH (TARCH)

There is a tendency for an upsurge in the prices of assets to be associated with a steeper degree of decline in the prices, which is well observed in the financial markets. In an attempt to rationalize such occurrences, Engle and Ng (1993) have, with the help of asymmetric information curves distinguished between the impact of good and bad news. The asymmetric effect is the simplest form of how the market responds to shocks. It is also referred to as the "leverage effect" which is a property of many financial instruments. In the capital market, for example, through the movement of stock prices, market analysts have discovered that there is also a phenomenon of asymmetric effects. That is, while stocks are affected by negative shocks their volatility is significantly higher than that caused by positive shocks. Since a large fall in the stock price erodes shareholders interest, ramping up the risk associated with owning the stock in a company. There are two primary models that capture such shocks: TARCH and EGARCH.

In order to identify the leverage effect in the financial market, Zakoian (1994) and Glosten et al., (1993) developed the threshold GARCH model. In an effort to account for this, a multiplicative dummy variable is added to the variance equation in a bid to test if, when shocks are negative, there is any statistically significant difference. It is on this presumption that information on sometimes unexpected shocks might influence the volatility in stock returns. The model can be specified in this form:

$$R_t = a + bR_{t-1} + \varepsilon_t \quad (4.7)$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-i}^2 d_{t-1} + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \quad (4.8)$$

d_t= 1 when $\varepsilon_t < 0$ otherwise d_t= 0. The coefficient y measures the response to positive shocks, coefficients y + α measure the response to adverse shocks. As a result, when α is greater than 0, the "bad news" effect is greater than the "good news" thus evidencing the presence of asymmetric effects. And if α is equal 0 there is no evidence of the leverage effect. The TGARCH (1,1) can be specified as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_i \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-i}^2 d_{t-1} + \beta_j \sigma_{t-1}^2 \quad (4.9)$$

By applying the systematic process to select volatility models, the study can produce several volatility series for each variable (indices) that reflect the data set's features. In a later analysis, the volatility series determines the spillover effects between the different indices (Large, Mid, and small) for the UK and US markets. These analyses are then done using a VAR; the general specifications and the theoretical underpinnings of the model are outlined below.

4.4.3 VECTOR AUTOREGRESSIVE (VAR) MODEL

This study provides evidence of the cross-market contagion risk between large, mid and small ESG compliant stock indices by employing vector autoregression (VAR). The analysis of transmission of volatility between large-, mid-, and small-cap ESG-compliant stocks by this approach stems from the VAR models by Sims (1980). This model helps model the interactions between multiple macroeconomic variables where the relationships can be assumed linear. The main strength of VAR models lies in their ability to produce forecasts (Nyopa and Khumalo, 2022). In addition, they do not require the researcher to determine the endogenous variables as would be needed with the structural models with simultaneous equations (Sims, 1980). Thus, its use is justified because it helps measure the degree of interdependence among the variables' volatility to distinguish the source and the recipient of the spillover effect. This analysis of spillover through a VAR framework also accords with the previous research by Sanchez Garcia and Cruz Rambaud (2023), da Silva Antunes (2021), Karmakar (2010), Yonis (2011) and Chordia *et al*., (2005) as such, does receive a lot of backing from existing literature. While a VAR is deemed appropriate for the achievement of the objectives by the study, a much more advanced similar model (time-varying parameter VAR) was also taken into consideration, however its application was of limited usage since they require large sample sizes and may introduce estimation complexity. Moreover, estimation and inference in a TVP-VAR is highly complex since the model is fundamentally nonlinear due to the time variation in the coefficients and in the covariance matrix of the error term (Lubik and Matthes, 2015).

Although the VAR framework is a good theoretical concept, it has some shortcomings. Since the innovations are orthogonalized by a Cholesky decomposition, FEVDs derived from the Cholesky factorization are very sensitive to variable ordering. An important part of this is that the order of variables does not create any correlation between the forecast errors nor lead to erroneous and unrealistic conclusions (Dekker et al., 2001). In accounting for this possible drawback, the study posits that the rationality of the economic classification of large-cap, mid-cap, and small-cap indices is evident. They are ranked based on the size and liquidity of stocks, whereas large-cap stocks dominate logically. With a proper data arrangement, suitable diagnostic tests, and tools for analysis, the analysis is relatively sound and highly relevant for identifying volatility spillovers. Therefore, the effects of the VAR's sensitivity to variable ordering are reasonably well-contained. As Sánchez García and Cruz Rambaud (2023) point out, the VAR processes are of the form:

$$\gamma_t = A_1\gamma_{t-1} + A_2\gamma_{t-2} + \cdots + A_p\gamma_{t-p} + \varepsilon_t \qquad (4.10)$$

where $\gamma_t = (\gamma_{1t}, \gamma_{2t}, \dots, \gamma_{kt})$ is the vector of the k endogenous variables,

$A_1, A_2, \dots, A_p$ are the k × k coefficient matrices,

t is the vector of error terms, which follows a white noise.

Therefore, the model specification for investigating the spillover effects between large (Y), mid (X) and small cap (Z) takes this form:

$$\gamma_t = A_{10} + A_{11}\gamma_{t-p} + A_{12}x_{t-p} + A_{13}z_{t-p} + \varepsilon_{yt} \qquad (4.11)$$

$$x_t = A_{20} + A_{21}x_{t-p} + A_{22}y_{t-p} + A_{23}z_{t-p} + \varepsilon_{xt} \quad (4.12)$$

$$z_t = A_{30} + A_{31}z_{t-p} + A_{32}x_{t-p} + A_p\gamma_{t-p} + \varepsilon_{xt} \quad (4.13)$$

4.4.3.1 STATIONARITY CHECK

For the VAR approach, the time series should be stationary (da Silva Antunes,2021; Pinho. and Maldonado, 2022). When non-stationary variables are regressed over the other, the estimated parameters and degree of association may be inaccurately represented (Karmakar, 2010). As a result, the order of integration of each variable has to be determined. The augmented Dickey-Fuller test (ADF) developed by Dickey and Fuller (1979) will be used in the current study to determine the level of integration of the variables in the model. The Augmented Dickey–Fuller regression can be expressed as follows:

$$\Delta x_t = \rho_0 + \rho x_{t-1} + \sum_{i=1}^{n} \delta_i \, \Delta x_{t-i} + \varepsilon_t \quad (4.14)$$

Where:

x_t = the variable,

ρ_0 = a drift or constant,

p= $(\alpha - 1)$,

Δ = the first difference operator,

ε_t =a pure white noise error term and

$\Delta x_{t-1} = (x_{t-1} - x_{t-2})$, $\Delta x_{t-2} = \Delta x_{t-2} - \Delta x_{t-3}$, etc. i=1 to n is number of lagged difference terms which is determined empirically to remove any autocorrelation in error term ε_t. In the test the null hypothesis is that ρ = 0. If ρ = 0, then α = 1, that is we have a unit root, implying that the time series being investigated is non-stationary. However, if α is less than one then ρ must be negative and stationarity must be true. In order to ensure a robust conclusion about the level of stationarity of the variables, the study will make further use of the Phillips-Perron (PP) test to determine their order of integration. Developed by Phillips and Perron (1988), the PP test is designed to test for the presence of a unit root while controlling for serial correlation, thereby providing more reliable results.

4.4.3.2 THE OPTIMAL LAG LENGTH

After determining the variables are stationary, the study will investigate the most appropriate lag to employ in the VAR model. Gredenhoff and Karlsson (1999) have pointed out that lag length selection is an essential step for estimating the VAR model and has serious consequences for inference. Therefore, the choice of the lag length frequently determines whether to accept or reject a null hypothesis (Hsiao, 1979;1981). In practice, many VAR models are estimated with symmetric lag structures (i.e., the same lag length is used for all variables and equations in any single model). Ozcicek and Douglas Mcmillin (1999) have shown that this lag length is often selected using an explicit statistical criterion such as the Akaike information criterion (AIC) or Schwarz information criterion (SIC). The study will consider three more criteria that is: Likelihood ratio (LR), Final prediction error (FPE) and Hannan-Quinn information criterion (HQ) in an effort to improve the robustness of the VAR model and the accuracy of the inferences made by the model with respect to the chosen lag length.

4.4.4 DIAGNOSTIC CHECKS

The VAR model is tested for adequacy and reliability by various diagnostic tests like serial correlation LM, heteroskedasticity, normality, and stability tests.

4.4.4.1 VAR RESIDUAL SERIAL CORRELATION LM TEST

Autocorrelation (also termed serial correlation) is the correlation of the error terms at different observations (i.e., time series data) of the study (Gujarati, 2004). After fitting a VAR model, the residuals should generally have no autocorrelation and be white noise. If there is autocorrelation in the residuals, it implies that there was some information not accounted for by the model, perhaps not enough lags. The Breusch–Godfrey LM test is applied to test the null hypothesis $\rho = 0$ of no autocorrelation against the alternative hypothesis $\rho \neq 0$ of autocorrelation. If the p-value of the chi-square is greater than alpha ($\alpha = 0.05$), then we fail to reject the null hypothesis of no autocorrelation, which means that error terms are not serially correlated.

4.4.4.2 VAR RESIDUAL HETEROSKEDASTICITY TESTS

Heteroscedasticity refers to the condition in which the error terms do not have a constant variance across the observations of the study (Gujarati and Porter, 2009). In order to detect heteroscedasticity in the residuals, the study will use the Breusch-Pagan-Godfrey test. The null hypothesis for the test is that the residuals are not heteroscedastic (Var (μt) $\neq \delta^2$), and the alternative hypothesis is that the residuals are heteroscedastic (Var (μt) = δ^2). If the p-value from the chi-square test is greater than alpha (α = 0.05), then we cannot reject the null hypothesis that there is no heteroscedasticity, meaning that the residuals are homoscedastic.

4.4.4.3 NORMALITY TEST

A normality test is used to determine if the data for the study is normally distributed. Therefore, following the study by Jarque and Bera (1987), the null hypothesis and the alternative hypothesis deduced for this study are as follows:

H_0: Error term is normally distributed

H_1: Error term is not normally distributed

As a result, we will reject the null hypothesis and determine that the error terms are not normally distributed if the P value is smaller than 5%. On the other hand, if the P value is greater than 5%, then we will not reject the null hypothesis, and we will be able to conclude that error terms follow normal distribution.

4.4.4.4 STABILITY TEST

As noted by Glaister (1984), before one can validly perform an impulse response analysis or variance decomposition, the VAR stability condition must be satisfied. For the purpose of this study the model stability is evaluated using a Roots of Characteristic Polynomial test. The VAR is said to be stable (stationary) if the roots all have modulus less than one and lie within the unit circle (Lütkepohl and Poskitt, 1991). In case where the VAR is not stable, some of the results (for instance, impulse response standard errors) can be invalid (Xiong et al., 2022).

4.4.5 GRANGER CAUSALITY TESTS

In achieving the first objective, determining the direction of spillover, the study uses a Granger causality (GC) method to yield observable findings. The Granger (1969) causality test is most commonly used to assess the statistical causality among financial markets. In this test, the idea is to see whether a fluctuation in one market impacts another. The study will model the casual relationships between three variables, say, X_t (Large cap volatility), Y_t (mid cap volatility) and Z_t (small cap volatility) for both the US and UK. The GC test can be completed by running the following trivariate regressions:

$$x_t = \omega_1 + \sum_{i=1}^{p} \alpha_i x_{t-i} + \sum_{i=1}^{p} \beta_i \gamma_{t-i} + \sum_{i=1}^{p} \delta_i Z_{t-i} + \boldsymbol{\varepsilon_t} \quad (4.15)$$

$$\gamma_t = \omega_2 + \sum_{i=1}^{p} \alpha_i \gamma_{t-i} + \sum_{i=1}^{p} \beta_i x_{t-i} + \sum_{i=1}^{p} \delta_i Z_{t-i} + \boldsymbol{\varepsilon_t} \quad (4.16)$$

$$Z_t = \omega_3 + \sum_{i=1}^{p} \delta_i Z_{t-i} + \sum_{i=1}^{p} \alpha_i \gamma_{t-i} + \sum_{i=1}^{p} \beta_i x_{t-i} + \boldsymbol{\varepsilon_t} \quad (4.17)$$

Where:

ω_i: Constant term in each equation

p: Number of lags used in the model (determined by lag selection criteria like AIC or BIC)

β_i, α_i, δ_i : Coefficients of the lagged values of X_t, Y_t, Z_t respectively.

$\boldsymbol{\varepsilon_t}$**:** Error term for equation

Where for example, x_t (γ_t, Z_t) is assumed to be a function of past values of itself and past and contemporaneous values of γ_t and Z_t. The standard F-test is used to examine Granger-causality between variables in the VAR system. If the F-test rejects the null hypothesis that the lag coefficients of variable y, Z_t are jointly zero, we then can say that variable γ and Z_t Granger causes variable x. Similarly, if the F-test rejects the null hypothesis that the lag coefficients of variable x and $Z_t$are jointly zero, the variable x and Z_tGranger causes variable γ. The same test is also applied for the Z_t variable.

4.4.6 VARIANCE DECOMPOSITION AND IMPULSE RESPONSE FUNCTIONS

After the VAR model is estimated, the study will perform two short-run dynamic analyses: variance decomposition (VDC) and impulse response function (IRF). With the application of these two methods, the study will be able to address objective two, i.e., to assess the magnitude and volatility persistence among the volatility indices. In addition, this VD and IFR will also direct the study to analyse the behaviour of these different variables in reaction to shocks, thereby shedding light on objective three. As a result, that will help to understand risk mitigation and portfolio diversification opportunities.

These forecast error variance decompositions (FEVDs) inform us how important different shocks are in driving fluctuations of a set of economic variables in a VAR; equivalently, they show what shock has the most influence on the forecast error variance of each variable within a given time horizon (Lütkepohl, 2010; Zaefarian, 2022). In contrast, Impulse Response Functions (IRFs) are employed to analyse the shocks or impulse effects in a VAR. They trace out the impulse of one unit or one standard deviation shock of an endogenous variable to another endogenous variable and all other endogenous variables in a VAR, holding all other variables and shocks constant (Baumeister and Peersman, 2013). IRFs are a very important tool for empirical causal analysis and policy effectiveness analysis.

4.5 CHAPTER SUMMARY

This chapter initially presents the research paradigm applied in this study from a post-positivism perspective. That is followed by a description of the research design, which focuses on defining and justifying variables and how the data collection and operationalized sampling design was accomplished. Subsequently, the econometric estimation techniques are explained in detail, these are important for validating economic theories and addressing the objectives.

In order to achieve the objectives three different econometric models are applied to the estimation process. The first step consists of constructing return indices via principal component analysis (PCA) in line with the study's quantitative approach. In econometric modelling, adopting PCA is beneficial because it decreases the number of variables to explore and visually analyse, saving time and resources for data analysis and minimizing the time spent on processing extraneous variables.

The second quantitative approach is a further development of the first, in which the indices developed based on PCA are further built by selecting appropriate GARCH models for each index to get the volatility variables. This study systematically selected GARCH and TARCH as suitable models for generating the volatility process. Finally, a VAR model will be used to supply evidence for cross market contagion risk between ESG compliant stock indices.

CHAPTER 5
EMPIRICAL AND DISCUSSION OF RESULTS

5.1 INTRODUCTION

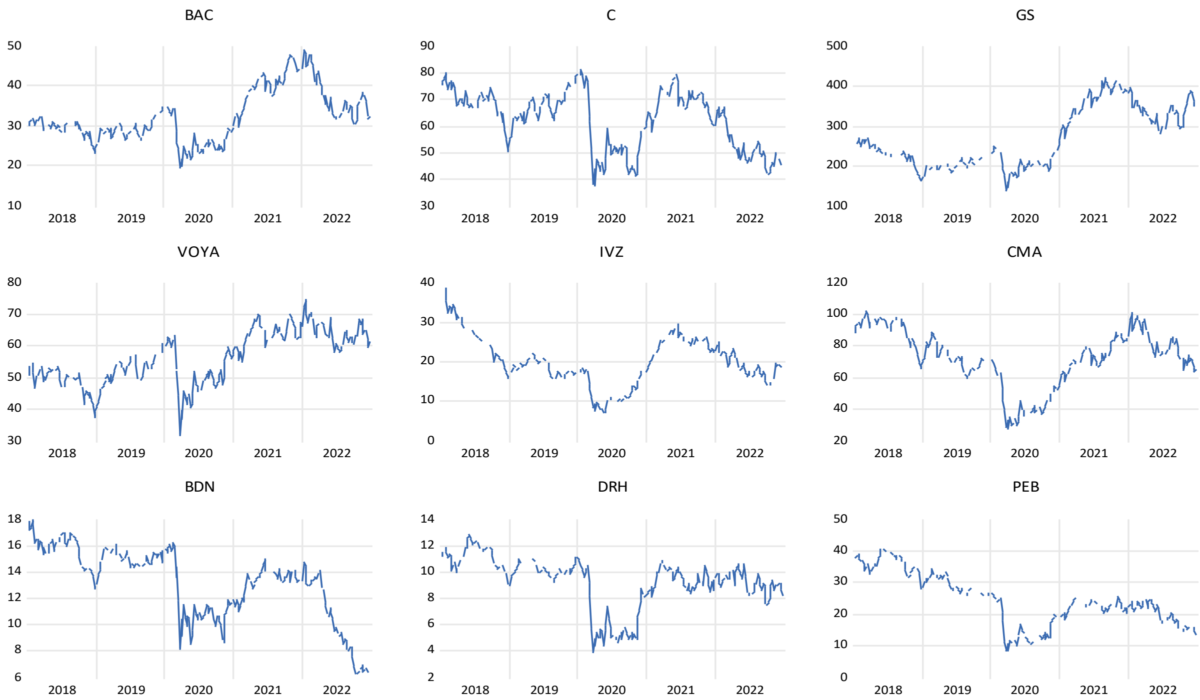
This chapter uses the analytical framework outlined in Chapter Four to present and analyse the results of volatility spillover between the indices, derived from the tests and models discussed previously, in accordance with the set objectives. The structure of the chapter is as follows: Section 5.2 discusses the trend analysis of the firms in the sample, while section 5.3 develops return indices using principal component analysis. In Section 5.4, we give an interpretation of the visual plots of the return indices. Descriptive statistics for these indices are provided in Section 5.5, and their correlations are explored in Section 5.6. Subsequently, Section 5.7 then carries out a unit root test to determine whether the data is appropriate for modelling. In Section 5.8, after suitability has been established, volatility is modelled through GARCH models. Section 5.9 presents the visual inspection of the volatility series.

Section 5.11 finally discusses the estimation of a VAR model, including the determination of the optimal lag length and diagnostic checks. It then proceeds to Granger causality tests, which are aimed at addressing Objective One. In addition, the section also includes the estimation of Impulse Response Functions (IRF) and Variance Decomposition, which helps to satisfy Objective Two and to a greater extent to achieve Objective Three. Section 5.12 bridges the gap by contrasting the findings of this study to previous work, followed by section 5.13, which concludes the chapter.

5.2 TREND ANALYSIS

The study begins by performing a visual analysis on the firms included in the sample. The preliminary analysis assists to recognize variations in trend strength and volatility stabilization. This process holds great importance when selecting models that account for possible non-stationarity and structural breaks. The visual plots of the US firms are presented in the below figure 5.1.

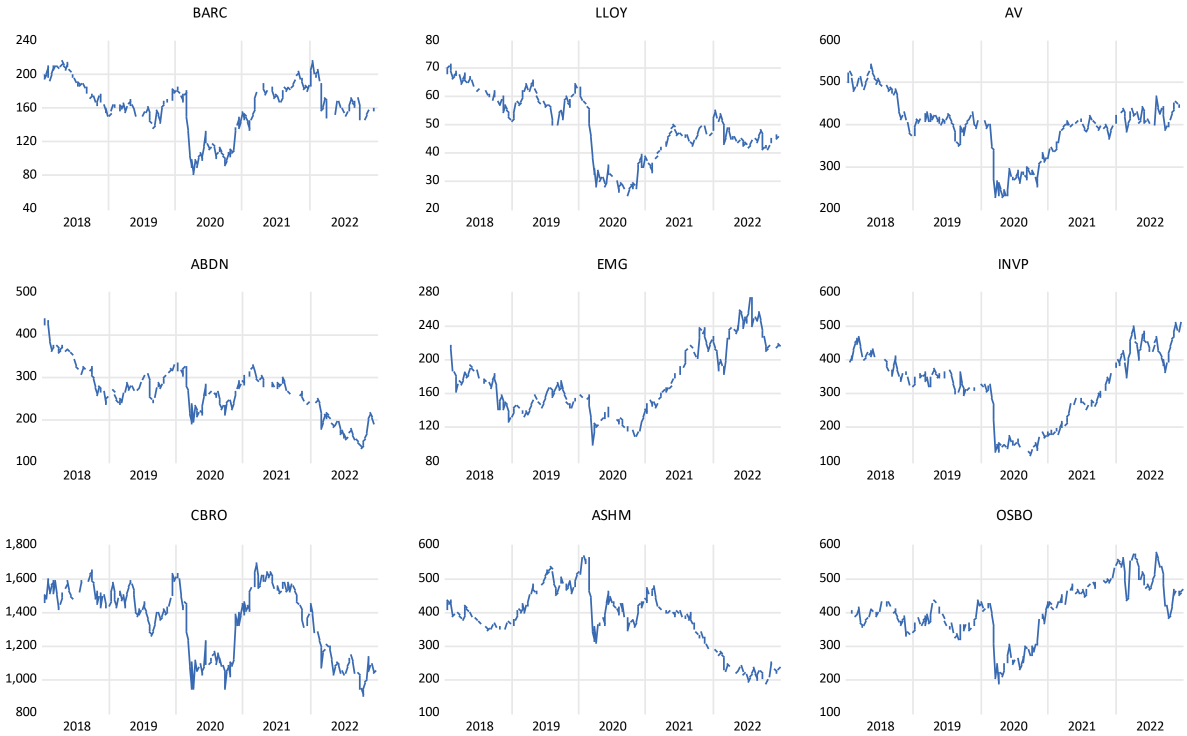
Figure 5.1: Visual plots of the US ESG compliant firms



Source: Prepared by Author based on the Eviews12.0 program

The analysis of large-cap, mid-cap, and small-cap stocks offers critical observations into their trends, volatility, and stationarity, potentially providing guidance for model selection. Large-cap ESG compliant stocks generally exhibit upward trends interrupted by the 2020 pandemic, with recoveries that vary in strength. For example, BAC achieves a smooth recovery exceeding pre-2020 levels, while C's recovery is uneven, stabilizing by 2021 without sustained upward momentum. Mid-cap ESG compliant stocks show more varied patterns, such as VOYA regaining its trajectory by 2022 despite an uneven recovery, whereas IVZ experiences inconsistent recoveries with persistent high volatility. Small-cap ESG compliant stocks are more prone to structural breaks, with sharp declines in 2020 and weak recoveries. For instance, DRH and PEB fail to return to pre-2020 levels, marked by high volatility and instability. The fluctuations in trend and variance indicate potential non-stationarity for most large-cap, mid-cap and small cap ESG compliant firms. Following a similar logic of analysis as in the US, the UK firms are investigated. The visual plots of the UK ESG compliant firms are presented in figure 5.2 below.

Figure 5.2: Visual plots of the UK ESG compliant firms



Source: Prepared by Author based on the Eviews12.0 program

Contrary to the pattern observed in the US the large-cap stocks in the UK generally exhibit significant declines during the 2020 pandemic, followed by varied recovery patterns. While some stocks, such as AV, achieve strong recoveries surpassing pre-pandemic levels, others, like LLOY, stabilize below pre-2020 levels. The volatility decreases during the recovery phase following the 2020 downturn. Mid-cap stocks display more diverse recovery patterns, with some, like INVP and EMG, showing robust upward trends post-recovery, while others, such as ABDN, exhibit inconsistent recoveries with persistent volatility. Similar to the patterns observed in the US, the small-cap stocks in the UK are more vulnerable to structural breaks, with sharp 2020 declines and weaker recoveries. For instance, CBRO and ASHM stabilize below pre-pandemic levels, reflecting limited resilience. The visible trend changes in all ESG compliant stocks indicate the potential of non-stationarity. These preliminary findings highlight the importance of selecting models that account for non-stationarity and structural breaks across all segments while recognizing variations in trend strength and volatility stabilization.

5.3 PRINCIPAL COMPONENT ANALYSIS: CONSTRUCTION OF THE RETURN INDICES

Due to the broad and varied trends observed within each market capitalization segment as seen in the trend analysis section, a principal component analysis (PCA) is employed to extract the dominant trends across the series. This approach consolidates the diverse patterns in returns, such as the sharp declines and uneven recoveries seen in mid-cap stocks or the persistent instability in small-cap stocks, into a set of principal components that capture the underlying variance. By focusing on these broad trends, PCA facilitates a more streamlined analysis, reducing dimensionality while preserving the essential characteristics of the data. This enables more robust modelling of volatility dynamics and spillover effects across market segments, ensuring that the analysis reflects the most significant and systemic behaviours within each group. The capturing of the dominant trends leads to the construction of a new set of variables (return indices) which are derived through the application of the principal components analysis.

As previously highlighted in the methodology chapter, the study pointed out that the number of extracted principal components equals the number of variables included in the analysis. For all the market capitalization levels (large, mid and small), three variables (firms) are being studied, and thus, there are also three main PCs (1, 2, 3) extracted, as can be seen from the tables (5.1 & 5.2). The next important step is determining how many principal components should be retained at each market capitalization level. The Kaiser criterion is used in this study to exclude any PC with an eigenvalue of less than one. The below tables present the results of the principal component analysis of the US.

Table 5.1: PCA results for the US

Principal Component	**Eigenvalues**	**% of Variance**	**Cumulative %**
Large Cap Firms: US			
1	2.723759	0.9079	0.9079
2	0.164271	0.0548	0.9627
3	0.111970	0.0373	1.0000
Mid Cap Firms: US			
1	2.515780	0.8386	0.8386
2	0.274868	0.0916	0.9302
3	0.209352	0.0698	1.0000
Small Cap Firms			
1	2.616344	0.8721	0.8721
2	0.290085	0.0967	0.9688
3	0.093572	0.0312	0.9688

Source: Prepared by Author based on the Eviews12.0 program

For the US as seen in table 5.1 the large, mid, and small-cap categories only have 1 PC with an eigenvalue that is above one, that is: 2.723, 2.515780, and 2.616344, respectively. As a result, only one PC will be retained for all categories, which is the first one, because PC1 has an eigenvalue exceeding one. Consequently, these retained PCs are used as the new aggregates for each market capitalization level. Also, for the large, mid, and small-cap firms, PC 1 explains most of the total variance, which is 90.79%, 83.86%, and 87.21%, respectively. This means that PC1 can effectively capture the overall market dynamics, which is the most critical factor prompting change across the firms. The large, mid, and small-cap firms index is computed using the first principal component. A similar analysis is undertaken in the UK firms to obtain the broad market trends of the different sized ESG firms. The results are presented in the table below.

Table 5.2: PCA results for the UK

Principal Component	Eigenvalues	% of Variance	Cumulative %
Large Cap Firms: UK			
1	2.557789	0.8526	**0.8526**
2	0.302263	0.1008	**0.9534**
3	0.139948	0.0466	**1.0000**
Mid Cap Firms: UK			
1	1.874704	0.6249	0.6249
2	0.768281	0.2561	0.8810
3	0.357015	0.1190	1.0000
Small Cap Firms: UK			
1	2.335030	0.7783	0.7783
2	0.420722	0.1402	0.9186
3	0.244248	0.0814	1.0000

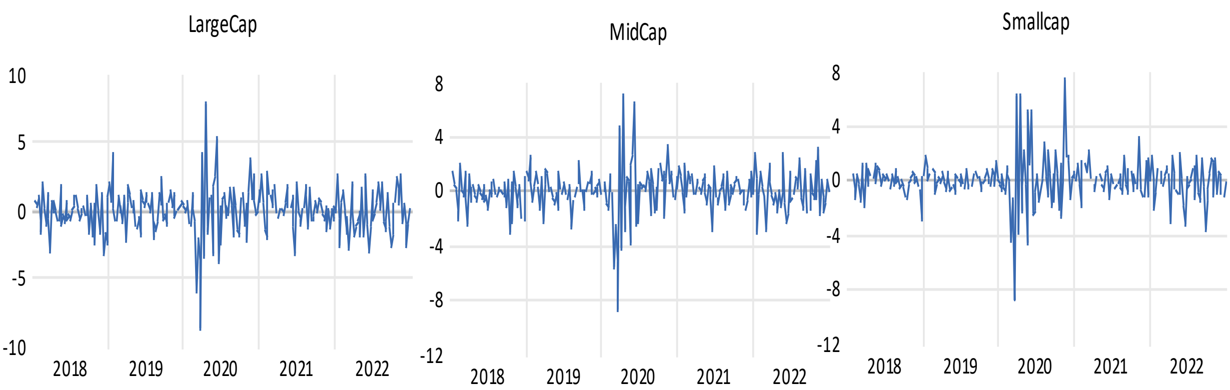
Source: Prepared by Author based on the Eviews12.0 program

As seen in the table 5.2, the analysis of the principal components in the UK revealed similar patterns to those in the US. From the large, mid, and small-cap categories, only one PC will be retained, which is the first one, because PC1 for all the caps has a higher eigenvalue than one, which is as follows: 2.557789, 1.874704, and 2.335030, respectively. Also, for the large, mid, and small-cap firms, PC 1 explains most of the total variance, which is 85.26%, 83.86%, and 87.21%, respectively. Again, this suggests that PC1 can adequately capture the market trends, which is the most critical driver of change across the firms. The Large, mid, and small-cap firms index is calculated based on the first principal component.

5.4 VISUAL PLOTS OF THE RETURN INDICES

The extracted return indices through PCA are subsequently visually scanned to develop an appreciation of the nature of the return variable, such as periods of low or high variability indicating changes in economic conditions or the state of the market. The study acknowledges the analysis by visual inspection introduces some limitations because different observers are likely to come up with different interpretations of what they see, partly because of their personal bias, experience, or whether or not they consume carrots for lunch, which is known to improve vision (Ikram, 2024). The graphical analysis is a valuable approach for pattern and outlier detection. However, the findings are laden with a degree of subjectivity and based solely on visual judgment. The visual plots for the large, mid and small cap return index for the US are presented in figure 5.3.

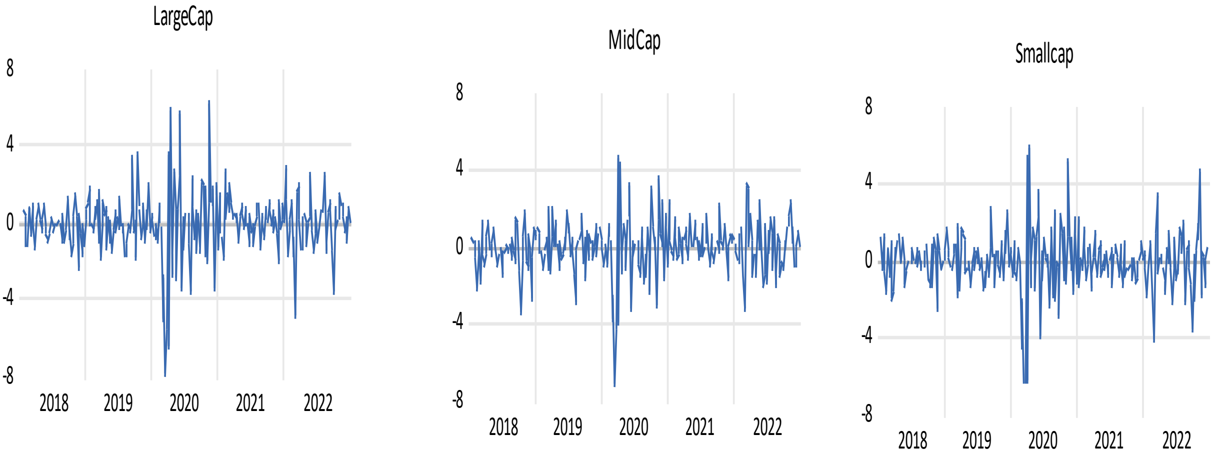
Figure 5.3: Visual plots of the US return indices



Source: Prepared by Author based on the Eviews12.0 program

The following observations are made regarding the behaviour of the return indices in the US. The large-cap index shows greater volatile returns compared to the other indices. The returns fluctuate on a wider range of 5 to -5 on average, with occasional sudden drops and increases; the most significant can be observed in 2020. The mid-cap index exhibits lesser volatility in the returns than the large-cap and small-cap, and there are also periodic large fluctuations, especially around 2020, implying high responsiveness to market fluctuations. The small-cap shows higher volatility relative to the mid-cap, characterized by frequent high fluctuations in both directions. The great volatility observed around 2020 for all three categories may be attributed to the effect of the global market disruption by the COVID-19 pandemic. Nevertheless, the large-cap index is recognized to be the most sensitive to fluctuation. On the other hand, a probe into the behaviour of the returns in the UK also leads to interesting conclusions. The visual plots for the large-, mid-, and small cap index are presented in figure 5.4.

Figure 5.4: Visual plots of the UK return indices



Source: Prepared by Author based on the Eviews12.0 program

The large cap is more volatile than other indices and witnesses more significant swings and unstable returns, particularly in 2020. The mid cap index demonstrates the least fluctuation compared to the other two indices. It has moderate to low return volatility, thus signifying relative stability compared to the large and small cap. The small cap is relatively more stable than the large cap while at the same time fluctuating more than the mid cap, thereby taking the middle ground when it comes to risk and movement in the market. Likewise, the extreme volatility demonstrated in 2020 by all categories corresponds to the effects of the COVID-19 pandemic observed in the global market. Overall, the patterns observed in the US markets are also evident in the UK market further highlighting similarities of these two markets.

5.5 DESCRIPTIVE STATISTICS

The graphical analysis of the return indices as performed in the previous segment helped the study develop an appreciation of the underlying trends and patterns; however, it can be potentially plagued with some subjectivity. To address this, the study will now transition to employing quantitative techniques, such as descriptive statistics, to ensure a more objective and reliable analysis.

Descriptive statistics are the numerical procedures that help organize and describe a given sample's characteristics (Fisher and Marshall, 2009). The study will use the mean, standard deviation, skewness, kurtosis, and the Jarque Bera statistics to perform the descriptive statistics on the analysis. The average performance is shown by the mean, and the standard deviation indicates the level of volatility within each segment. Skewness and kurtosis are used to show asymmetries and the likelihood of extreme returns, which are crucial for analyzing the nature of volatility spillovers. Finally, the Jarque-Bera test is used to determine whether the return distributions deviate from normality, and hence provide further detail on the dynamics of spillover effects across different market capitalizations. The results for the descriptive statistics for the US and UK Indices are presented in the table below.

Table 5.3: Descriptive statistics for the US and UK return indices

	US			UK		
	LARGECAP	**MIDCAP**	**SMALLCAP**	**LARGECAP**	**MIDCAP**	**SMALLCAP**
Mean	4.53E-17	1.91E-17	-5.58E-17	5.42E-17	-1.35E-16	0.000000
Median	0.155938	0.046183	0.011076	0.095125	0.054683	0.053258
Maximum	7.936083	7.087703	7.589695	6.331288	4.677491	5.887788
Minimum	-8.689009	-8.845461	-9.033775	-7.869300	-7.215923	-6.446516
Std. Dev.	1.653565	1.589180	1.620631	1.602393	1.371839	1.531028
Skewness	-0.231501	-0.44889	-0.475255	-0.442783	-0.575900	-0.368522
Kurtosis	7.819914	9.102701	12.82993	8.153561	6.732770	7.502215
Jarque-Bera	253.9977	412.1974	1056.585	296.2204	165.3190	225.4760
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	1.45E-14	2.00E-14	-1.79E-14	2.50E-14	-2.98E-14	7.77E-16
Sum Sq.	708.1774	654.1028	680.2494	665.0250	487.4230	607.1078
Sum Sq. Dev	708.1774	654.1028	680.2494	665.0250	487.4230	607.1078
Observations	260	260	260	260	260	260

Source: Prepared by Author based on the Eviews12.0 program

The descriptive statistics for the US large cap, mid cap, and small cap indices reveal significant characteristics in their return distributions. The mean returns for all indices are close to zero, indicating minimal average returns over the observation period. Among the indices, the large-cap index exhibits the highest volatility with a standard deviation of 1.65, compared to 1.59 for mid-cap and 1.62 for small cap stocks, highlighting slightly greater variability in large-cap returns. All indices display negative skewness, with small caps (−0.48) showing the most pronounced skew, indicating a higher likelihood of extreme negative returns. Kurtosis is notably high (K>3) across the indices suggesting that the returns are leptokurtic, particularly for small caps (12.83), pointing to frequent extreme returns and heavy tails in the distribution. The Jarque-Bera test confirms significant deviations from normality for all indices (p-value = 0.0000), driven by their skewness and kurtosis. Overall, while volatility levels are generally comparable, the large-cap index is the most volatile, and small caps exhibit the greatest risk of extreme negative returns, emphasizing the importance of using models that account for these characteristics in financial analysis.

Similarly, the return indices for the UK are investigated to understand their statistical properties. The mean returns for all UK indices are close to zero, consistent with the minimal average returns observed in the US indices. Volatility is highest for UK large cap stocks (1.60), like the US where large caps also had the highest standard deviation, albeit slightly higher at 1.65. UK mid-cap stocks have the lowest volatility (1.37), contrasting with the more uniform volatility levels across market caps in the US.

All UK indices exhibit negative skewness, with mid-caps (−0.58) showing the most pronounced skewness, comparable to the US's small caps (−0.48), which were the most negatively skewed in their market segment. UK indices also display high kurtosis, particularly in large caps (8.15), reflecting frequent extreme returns. This is slightly lower than the US, where small caps showed the highest kurtosis (12.83). The Jarque-Bera test confirms significant deviations from normality across UK indices (p-value = 0.0000), a result also seen in the US, driven by heavy tails and asymmetry. One way the study lessened the effect of non-normality was to transform the data or the variables in the model. For example, the study used logarithmic transformations, to reduce skewness and make the data more symmetric. These transformations can improve the validity of statistical tests and the efficiency of parameter estimates in econometric models. However, they may not fully address non-normality in the presence of heavy-tailed distributions or outliers. Overall, while both markets exhibit heavy-tailed distributions and negative skewness, the UK indices demonstrate relatively lower kurtosis, indicating fewer extreme events compared to their US counterparts.

5.6 CORRELATION ANALYSIS

The application of statistical approaches, such as central tendency (mean) and dispersion (standard deviation) are limited to analyzing a single variable or statistical analysis. It is necessary to uncover relationships between two or more statistical series. The correlation is a statistical technique for determining the relationship between two variables (Gogtay and Thatte, 2017). When two variables move in the same direction, i.e., when one increases the other also increases and vice-versa, then such a relation is called a positive Correlation. while when two variables move in opposite directions, i.e., when one increases the other decreases, and vice-versa, then such a relation is called a negative Correlation. The coefficient of correlation, used to measure the degree of co-movement, lies between +1 and -1 (Gogtay and

Thatte, 2017). Through this quantitative approach the study is able to measure the degree of co-movement in returns between ESG-compliant large, mid, and small-cap indices. This might potentially give a hint of how volatility in one market segment might influence another, shedding light on the interconnectedness and potential channels for volatility spillovers across different market capitalizations. The results for the Correlation Matrix of the US and UK are presented in in the table below.

Table 5.4: Correlation analysis for the US and UK return indices

US			
	LARGECAP	MIDCAP	SMALLCAP
LARGECAP	1		
MIDCAP	0.918684522635319 (0.0000)	1	
SMALLCAP	0.7429531371886709 (0.0000)	0.7912530675118464 (0.0000)	1
UK			
	LARGECAP	MIDCAP	SMALLCAP
LARGECAP	1		
MIDCAP	0.8153688842868476 (0.0000)	1	
SMALLCAP	0.8494381498473139 (0.0000)	0.8320574137835686 (0.0000)	1
The probability value is in brackets (.)			

Source: Prepared by Author based on the Eviews12.0 program

The correlation matrix for the US indices shows strong significant positive relationships across all categories. Large cap and mid cap have the highest correlation, indicating closely aligned movements. SmallCap is also positively correlated with both large cap and mid cap, but the correlations are weaker compared to the large cap – mid cap relationship, reflecting some divergence in their market behavior. These results suggest interconnectedness among the indices, with variations in strength reflecting differences in market capitalization dynamics.

In a similar vein the UK market indices are explored to study the co-movement in the return indices. The findings reveal that the correlation matrix for the UK indices demonstrates strong positive relationships across all market segments, with the highest correlation observed between SmallCap and large cap, suggesting a significant alignment in their movements. Midcap also exhibits strong correlations with both large cap and small cap, though slightly lower, reflecting its intermediary role in the market. This closely interconnected structure aligns with the US indices, where all categories similarly exhibit positive relationships. However, a divergence is noted: in the US, the strongest relationship is between large cap and mid cap, whereas in the UK, small cap and large cap show the closest alignment. These differences highlight regional variations in market dynamics, although both markets share a cohesive structure characterized by strong interdependence across indices. Such variations emphasize how unique market structures shape the interactions between segments.

5.7 UNIT ROOT TEST FOR THE RETURN INDICES

After conducting descriptive statistics and correlation analysis to understand the basic properties and relationships within the data, transitioning to a unit root test is a critical step to further ensure the variables are suitable for further modelling. It is important to note while the descriptive statistics and the correlation analysis are informative, these methods alone do not address the potential for non-stationarity in the data. Performing a unit root test is essential to determine whether the series are stationary meaning their statistical properties such as mean and variance do not change over time, as non-stationary data can lead to spurious results and unreliable inferences (Baumohl and Lyocsa , 2009). Stationarity is a key requirement for many econometric models especially time-series models like Vector Autoregression (VAR). By confirming stationarity or identifying and correcting for non-stationarity through differencing or other methods, the analysis ensures that subsequent modelling and forecasts are based on solid statistical foundations. The US unit root and structural break results are presented below.

Table 5.5: Return indices unit root and structural break test results for the US

Unit root test results (ADF)					
The Null Hypothesis: The "time series" has a unit root					
Variables	Model	**ADF** Level form	**PP** Level form	**Structural Break** Level form	Order of Integration
Large-Cap return Index	Intercept	-16.44098***	-16.43717***		I(0)
	Trend and intercept	-16.41073***	-16.40759***	-18.28341***	
	No trend, No intercept	-16.47290***	-16.46836***		
Mid-Cap return Index	Intercept	-10.24318***	-17.28453***		I(0)
	Trend and intercept	-10.24931***	-17.27212***	-20.04490***	
	No trend, No intercept	-10.26295***	-17.31803***		
Small-Cap return Index	Intercept	-16.74335***	-16.81992***		I(0)
	Trend and intercept	-16.71450***	-16.79003***	-19.71318***	
	No trend, No intercept	-16.77589***	-16.85462***		
Note: (***) significant at 1%; (**) Significant at the 5% & (*) Significant at the 10%					

Source: Prepared by Author based on the Eviews12.0 program

The ADF and PP unit root test results for the US indices indicate that the large cap, mid cap, and SmallCap return indices are stationary at their level forms, as the null hypothesis of a unit root is rejected across all model specifications (intercept, trend and intercept, and no trend/no intercept). This stationarity at I(0) suggests that the statistical properties of these indices, such as the mean, remain constant over time, making them suitable for further analysis without the need for differencing.

The structural break test results for the US indices reveal that the null hypothesis of a unit root is also rejected when accounting for potential structural breaks in the data. This indicates that despite potential disruptions, such as market shocks or economic events, the large cap, mid cap, and SmallCap indices remain stationary at their level forms (I(0)). Incorporating structural breaks strengthens the conclusion of stationarity, ensuring that observed patterns are not artifacts of unaccounted events, further validating the indices' suitability for time series analysis. Subsequently the unit root test is performed on the return indices for the UK. The results are presented in the table below.

Table 5.6: Return indices unit root and structural break test results for the UK

Unit root test results (ADF)					
The Null Hypothesis: The "time series" has a unit root					
Variables	Model	**ADF** Level form	**PP** Level form	**Structural Break** Level form	Order of Integration
Large-Cap return Index	Intercept	-16.93800 ***	-16.92181***		I(0)
	Trend and intercept	-16.94716***	-16.93117***	-18.29586***	
	No trend, No intercept	-16.97090***	-16.95392***		
Mid-Cap return Index	Intercept	-16.18744***	-16.24158***		I(0)
	Trend and intercept	-16.24043***	-16.33604***	-17.70587***	
	No trend, No intercept	-16.21889***	-16.27552***		
Small-Cap return Index	Intercept	-18.35967***	-18.27670***		I(0)
	Trend and intercept	-18.32714***	-18.24641***	-20.10150***	
	No trend, No intercept	-18.39522***	-18.31078***		
Note: (***) significant at 1%; (**) Significant at the 5% & (*) Significant at the 10% T-statistics are used to decide order of integration					

Source: Prepared by Author based on the Eviews12.0 program

The ADF and PP unit root test results for the UK indices indicate that the large cap, mid cap, and small cap indices are stationary at their level forms, as the null hypothesis of a unit root is rejected across all model specifications (intercept, trend and intercept, and no trend/no intercept). This stationarity at I(0) implies that the statistical properties of these indices, such as mean , remain constant over time, making them suitable for further time series analysis without requiring differencing. Additionally, the inclusion of structural break tests confirms that the indices remain stationary even when accounting for potential disruptions, ensuring that the observed patterns are robust and not influenced by unaccounted events.

5.8 MODELLING OF VOLATILITY: GARCH MODELS

Determining the presence of the arch effect

Before modelling volatility, the *return indices* are tested for the presence of the ARCH EFFECT. If the ARCH effect exists, then the series is heteroskedastic, which is a prerequisite for conducting the actual GARCH model regression. The presence of ARCH effect is observed from the residuals of the return variables (large, mid and small cap) for both the US and UK. The results are presented in Table 5.7.

Table 5.7: Heteroskedasticity test for the return indices for the US and UK

Heteroskedasticity Test: ARCH LM		
Null hypothesis: Homoskedasticity		
Variable	Prob. F statistic	Outcome
USA: Large cap return index	0.0002***	Variable is heteroskedastic
USA: Mid cap return index	0.0000***	Variable is heteroskedastic
USA: Small cap return index	0.0000***	Variable is heteroskedastic
Null hypothesis: Homoskedasticity		
UK: Large cap return index	0.0000***	Variable is heteroskedastic
UK: Mid cap return index	0.0000***	Variable is heteroskedastic
UK: Small cap return index	0.0000***	Variable is heteroskedastic
Note: (***) significant at 1*; (**) Significant at the 5% & (*) Significant at the 10%		

Source: Prepared by Author based on the Eviews12.0 program

The null hypothesis of a constant variance (Homoskedasticity) is rejected across all variables, as a result this call for models that can account for heteroskedasticity. Since GARCH-type of models can account for such properties in the data, their application is justified. The study then adopted an objective approach to selecting the appropriate GARCH model to estimate volatility for each variable. A systematic process was employed, ensuring all models competed on equal footing based on specific selection criteria, thereby giving each an unbiased opportunity for consideration. The volatility models listed in the table below were identified as outperforming the alternatives. Consequently, the volatility series for each *return index* will be generated using the model that aligns most effectively with the specific data properties of that index. The selected volatility models for the US return indices are presented below.

Table 5.8: The estimated coefficients for the volatility models in the US

	GARCH (2,1)	**TARCH (1,1)**	**GARCH (2,1)**
	Large cap return Index: US	Mid cap return Index: US	Small cap return Index: US
Constant	0.551803** [0.265958]	0.276684*** [0.083179]	0.307307*** [0.084718]
ARCH 1 term	0.051252 [0.105300]	0.002253 [0.043882]	0.124524** [0.057471]
ARCH 2 term	0.264099* [0.155693]	-	0.487174*** [0.105054]
GARCH term	0.473072** [0.197928]	0.738186*** [0.076586]	0.339246*** [0.103958]
ARCH LM (5) test	0.1069	0.2496	0.6273
Stationarity: ARCH + GARCH < 1	0.788423<1	0.740439<1	0.950944<1
Non-negativity: ARCH> 0 & GARCH> 0	Satisfied	Satisfied	Satisfied
Asymmetry term	-	0.228728** [0.092039]	-
Note: (***) significant at 1%; (**) Significant at the 5% & (*) Significant at the 10% Standard error [ ]			

Source: Prepared by Author based on the Eviews12.0 program

The estimated coefficients for the US indices' volatility models meet all necessary conditions for validity, providing a robust framework for analysing volatility dynamics. *Stationarity* is satisfied across all indices, with the sum of ARCH and GARCH terms less than 1 (LargeCap: 0.788423, MidCap: 0.740439, SmallCap: 0.950944), ensuring stable variance processes. Small cap's higher value suggests greater volatility persistence. *Non-negativity* is also fulfilled, with all ARCH and GARCH coefficients positive, ensuring that variance remains realistic and non-negative. The *ARCH effect* is insignificant for all indices, as indicated by the ARCH LM (5) test (LargeCap: 0.1069, MidCap: 0.2496, small-cap: 0.6273), showing that the models have adequately accounted for time-dependent variance, ensuring there is no evidence of heteroskedasticity. The *asymmetry condition* is addressed only for the mid-cap, with a significant asymmetry term (0.228728) capturing the stronger effect of negative shocks. These results demonstrate that the models effectively capture the unique volatility behaviors of each market segment while satisfying key statistical requirements. Extending the analysis to the UK, a rigorous and objective process was applied to identify the models best suited to capture the volatility dynamics of its market indices, as detailed in the table below.

Table 5.9: The estimated coefficients for the volatility models in the UK

	TARCH (1,1)	**GARCH (1,1)**	**TARCH (1,1)**
	Large cap return Index: UK	Mid cap return Index: UK	Small cap return Index: UK
Constant term	0.141152*** [0.051385]	0.331538*** [0.125480]	0.095965*** [0.028627]
ARCH term	0.033277 [0.041389]	0.261473*** [0.065801]	0.004640 [0.055225]
GARCH term	0.798617*** [0.053290]	0.547229*** [0.120093]	0.822588*** [0.051038]
ARCH LM (5) test	0.7712	0.1244	0.6557
Stationarity: ARCH + GARCH < 1	0.831894 < 1	0.808702 < 1	0.827228< 1
Non- negativity: ARCH> 0 & GARCH> 0	Satisfied	Satisfied	Satisfied
Asymmetry term	0.218444*** [0.077922]	-	0.267836*** [0.084521]
Note: (***) significant at 1%; (**) Significant at the 5% & (*) Significant at the 10% Standard error [ ]			

Source: Prepared by Author based on the Eviews12.0 program

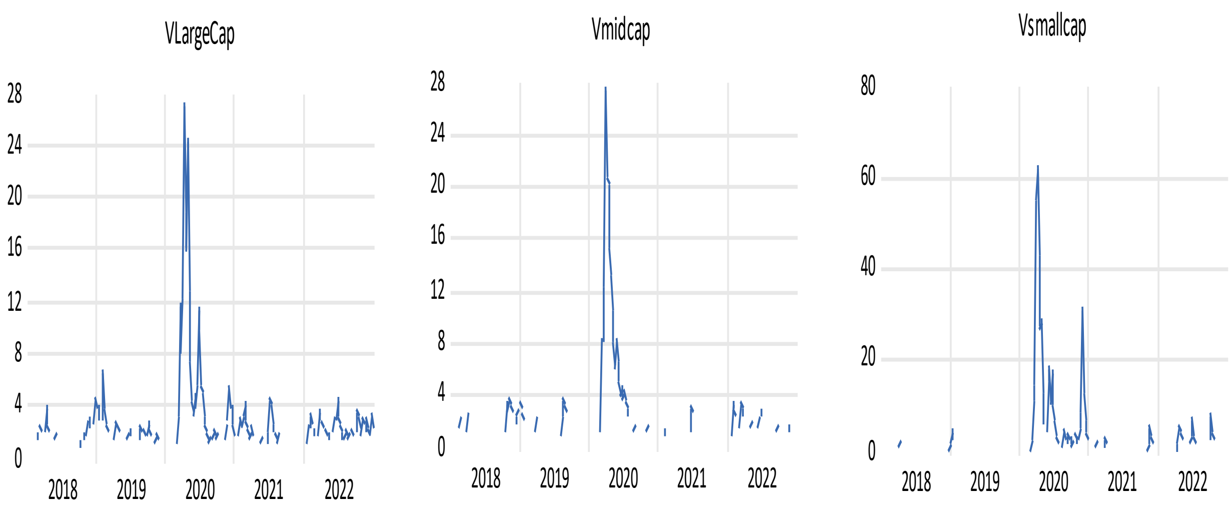
The estimated coefficients for the UK indices' volatility models meet all required conditions, demonstrating their robustness and suitability for capturing volatility dynamics. *Stationarit*y is satisfied across all indices, with the sum of ARCH and GARCH terms less than 1 (LargeCap: 0.831894, MidCap: 0.808702, SmallCap: 0.827228), ensuring stable variance processes. The values suggest similar volatility persistence across segments. *Non-negativity* is also met, with all ARCH and GARCH coefficients positive, confirming that the models generate realistic, non-negative variances. The *ARCH effect* is insignificant for all indices, as shown by the ARCH LM (5) test (LargeCap: 0.7712, MidCap: 0.1244, SmallCap: 0.6557), indicating that the models adequately account for time-dependent variance, ensuring again there is no evidence of heteroskedasticity. The *asymmetry condition* is addressed for both LargeCap (0.218444) and SmallCap (0.267836), capturing the differential impact of negative and positive shocks, while it is not included for Midcap.

The volatility models for both the UK and US indices satisfy key conditions such as stationarity and non-negativity, with each model adequately accounting for ARCH effects. Asymmetry is addressed differently, with the US focusing on mid-caps and the UK on large and small caps, reflecting regional variations in response to market shocks. Both sets of models demonstrate robustness, effectively capturing the unique volatility characteristics of their respective market segments.

5.9 VISUAL PLOTS OF THE VOLATILITY SERIES

With the effectiveness of the volatility models for both markets established and their ability to capture market-specific dynamics confirmed by the respective GARCH models. Visualizing the volatility series, similar to the approach taken with the return indices, represents an essential next step in the analysis. These plots offer a clear, contextualized view of how volatility evolves over time, allowing us to verify the patterns suggested by the models and to better understand the behavior of large, mid, and small-cap indices within the scope of the study. The visual plots of the US indices are presented in figure 5.5.

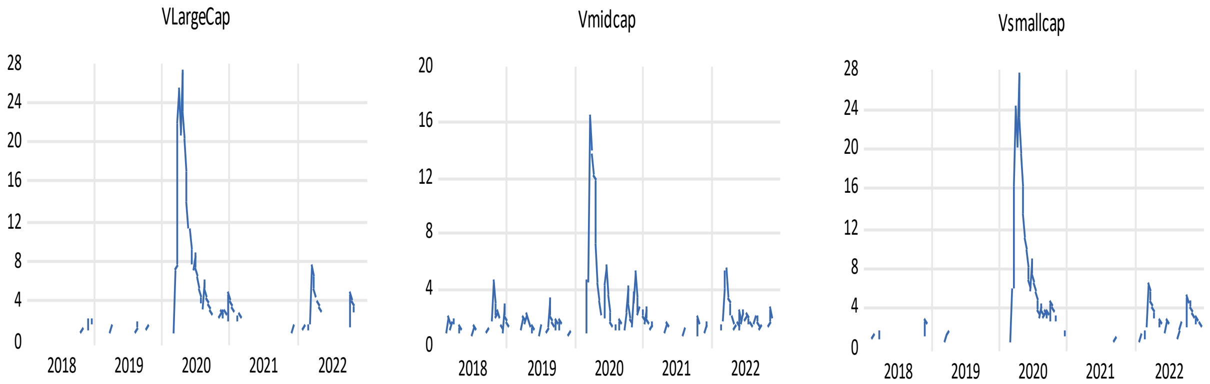
Figure 5.5: Volatility plots for the US indices



Source: Prepared by Author based on the Eviews12.0 program

The volatility series reveals common patterns across indices, with all experiencing noticeable spikes during significant market events, particularly around 2020. This indicates that major economic events and policy changes drive volatility across all categories, with the level of impact varying based on market capitalization and sector dynamics. In a comparable manner, the volatility series for the UK shows common patterns to that of US indices. The visual plots for the UK volatility indices are presented in figure 5.6 below.

Figure 5.6: Volatility plots for the UK indices



Source: Prepared by Author based on the Eviews12.0 program

All categories in the UK market experience spikes during significant events, particularly around 2020, likely reflecting the global impact of the COVID-19 pandemic. However, the magnitude of volatility differs between the two markets. In the UK, large cap, mid cap, and small cap volatility levels appear more similar, with less pronounced disparities. In contrast, the US shows greater variability, with small cap exhibiting significantly higher and more erratic volatility compared to large cap and mid cap. These differences suggest that while systemic factors influence both markets, the degree of sensitivity and the spillover dynamics vary across market capitalizations and regions.

5.10 UNIT ROOT TEST FOR THE VOLATILITY SERIES

After visually examining the volatility indices — large cap, mid cap, and small cap — they are examined for stationarity, in order to establish suitability for further modelling in the spillover analysis within a VAR framework. However, since stationarity is a strict requirement for VAR models, a unit root test is conducted to assess the suitability of these variables. The results of the unit root tests for the US are presented below.

Table 5.10: Volatility indices unit root test results for the US.

Unit root test results (ADF)					
The Null Hypothesis: The "time series" has a unit root					
Variables	Model	**ADF** Level form	**PP** Level form	**Structural Break** Level form	Order of Integration
Large-Cap Volatility Index	Intercept	-3.590348***	-5.261951***		I(0)
	Trend and intercept	-3.581855**	-5.250834***	-6.498163***	
	No trend, No intercept	-2.204631**	-3.587741***		
Mid-Cap Volatility Index	Intercept	-5.008401***	-4.195253***		I(0)
	Trend and intercept	-5.008436**	-4.194923***	-10.33934***	
	No trend, No intercept	-2.919669***	-3.160017***		
Small-Cap Volatility Index	Intercept	-5.822932***	-5.361883***		I(0)
	Trend and intercept	-5.813690***	-5.354534***	-9.217205***	
	No trend, No intercept	-5.263855***	-4.889860***		
Note: (***) significant at 1%; (**) Significant at the 5% & (*) Significant at the 10% T-statistics are used to decide order of integration					

Source: Prepared by Author based on the Eviews12.0 program

The ADF and PP test results confirm that all volatility series (Large-Cap, Mid-Cap, Small-Cap) are stationary at the level I(0), as the null hypothesis of a unit root is rejected at the 1% and 5% significance levels. Significant test statistics across model specifications (intercept, trend and intercept, no trend) support this conclusion. The structural break test further reinforces stationarity, indicating that the series remain robust even after accounting for potential structural changes. For example, the t-statistics for the structural break model are -6.54 for the Large-Cap Index, -10.34 for the Mid-Cap Index, and -9.32 for the Small-Cap Index, confirming that external shocks or structural shifts do not affect the stationarity of these volatility series. With the unit root test results for the US established, attention now shifts to the UK, enabling a broader understanding of stationarity in volatility variables across both markets.

Table 5.11: Volatility indices unit root test results for the UK

Unit root test results (ADF)					
The Null Hypothesis: The "time series" has a unit root					
Variables	Model	**ADF** Level form	**PP** Level form	**Structural Break** Level form	Order of Integration
Large-Cap Volatility Index	Intercept	-4.807155***	-3.536920***		I(0)
	Trend and intercept	-4.794587***	-3.525091***	-6.432216***	
	No trend, No intercept	-3.131193***	-2.858276***		
Mid-Cap Volatility Index	Intercept	-5.589463***	-5.039784***		I(0)
	Trend and intercept	-5.576401***	-5.029659***	-7.967667***	
	No trend, No intercept	-3.798435***	-3.521542***		
Small-Cap Volatility Index	Intercept	-3.922680***	-3.585053***		I(0)
	Trend and intercept	-3.915124**	-3.581141**	-5.335510**	
	No trend, No intercept	-3.086788***	-2.938002***		
Note: (***) significant at 1%; (**) Significant at the 5% & (*) Significant at the 10% T-statistics are used to decide order of integration					

Source: Prepared by Author based on the Eviews12.0 program

The ADF and PP test findings demonstrate that all volatility series (large-cap, mid-cap, small-cap) in the UK market are stationary at the level I(0), as the null hypothesis of a unit root is rejected at both the 1% and 5% levels of significance. This conclusion is supported by the consistent results across different model specifications—intercept, trend and intercept, and no trend or intercept. The results from the structural break test further validate the stationarity of these series, showing that they remain stable even when accounting for structural changes. For example, the t-statistics in the structural break model are -6.43 for the Large-Cap Index, -7.97 for the mid-cap Index, and -5.34 for the small-cap Index, confirming that these volatility series are unaffected by external disruptions or structural shifts. This evidence highlights the stability of the series under various model conditions and adjustments for structural breaks.

The UK and US volatility series for large-cap, mid-cap, and small-cap volatility indices are stationary at I(0), rejecting the unit root null across models. US volatility indices exhibit slightly stronger stationarity under structural break models compared to the UK, indicating greater resilience to structural changes.

5.11 VECTOR AUTOREGRESSIVE (VAR) ANALYSIS

With stationarity established, a VAR was performed for both markets, the results can be found in appendix A1 and A2. The analysis in this segment aims to provide evidence of the volatility spillover connections, starting by determining the appropriate lag length for the VAR model and conducting diagnostic tests to ensure model robustness. Furthermore, Granger causality, impulse response functions, and variance decomposition are used to dissect and understand the volatility transmission between volatility indices.

5.11.1 VAR LAG LENGTH SELECTION

The study progresses to determining the optimal lag length, a critical step for accurately capturing the temporal dependencies within the data. Lütkepohl (1993) points out that overfitting (choosing a higher order lag length than the actual lag length) may lead to an increase in mean-square forecast errors of the VAR model and that underfitting the lag length mostly likely can result in autocorrelated errors. The appropriate lag structure ensures that the VAR model can effectively trace the spillover dynamics, reflecting how changes in one variable influence others over time without introducing bias from overfitting or underfitting. The results of the lag length for the US are presented in the table below.

Table 5.12: Lag length selection for the US.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1752.440	NA	225.5261	13.93207	13.97408	13.94897
1	-1388.164	716.9888	13.44743	11.11241	11.28048	11.18004
2	-1365.352	44.35691	12.05167	11.00279	11.29691	11.12114
3	-1333.465	61.24250	10.05073	10.82115	11.24132	10.99022
4	-1276.685	107.7014	6.879808	10.44195	10.98817	10.66174
5	-1235.998	76.20721	5.351333	10.19046	10.86274*	10.46097*
6	-1220.810	28.08647	5.096624	10.14135	10.93967	10.46258
7	-1211.105	17.71478	5.070619	10.13576	11.06013	10.50771
8	-1195.260	28.54692*	4.805503*	10.08143*	11.13185	10.50410

Source: Prepared by Author based on the Eviews12.0 program

For the US, a lag length of 5 was selected based on its ability to balance model adequacy and simplicity. The selection aligns with the SC and HQ which minimizes at lag 5, while the AIC, FPE and LR suggest slightly higher lag lengths. The residual diagnostics at lag 5 confirm that the residuals exhibit no significant autocorrelation, indicating that the chosen lag length adequately captures the dynamics of the system without leaving important information unexplained. This ensures reliable forecasts and avoids the pitfalls of overfitting, providing a parsimonious yet robust representation of the system. Having determined the optimal lag length for the US, the study further explores the corresponding dynamics within the UK market indices. The results of the lag length selection criteria are presented in the table below.

Table 5.13: Lag length selection for the UK

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1299.251	NA	6.182317	10.33532	10.37734	10.35223
1	-823.5428	936.3143	0.152235	6.631292	6.799360	6.698919
2	-771.2586	101.6637	0.107979	6.287767	6.581886	6.406114
3	-744.0133	52.32829	0.093430	6.142963	6.563133	6.312030
4	-711.2947	62.06153	0.077410	5.954720	6.500941*	6.174508*
5	-697.8040	25.26820*	0.074718*	5.919080*	6.591352	6.189588
6	-691.7351	11.22263	0.076503	5.942342	6.740666	6.263571
7	-684.1744	13.80133	0.077419	5.953765	6.878139	6.325714
8	-678.6935	9.874303	0.079661	5.981695	7.032120	6.404364

Source: Prepared by Author based on the Eviews12.0 program

For the UK, a lag length of 5 was determined to be optimal. This selection was based on the minimization of the Final Prediction Error (FPE) and the Akaike Information Criterion (AIC), both of which identified lag 5 as the most appropriate choice for the analysis. Residual adequacy tests confirm that this lag length eliminates significant serial correlation, indicating that the dynamics between variables are well captured. By striking a balance between parsimony and explanatory power, the selection of lag 5 provides a reliable framework for analyzing the interactions in the UK system without introducing unnecessary complexity.

The choice of lag 5 for both the US and UK VAR models reflects a careful consideration of statistical criteria, residual adequacy, and model stability. This approach ensures that the models are both theoretically sound and empirically reliable, enabling robust analysis of the underlying dynamics in each context.

5.11.2 DIAGNOSTIC CHECKS

Subsequent to the determination of an appropriate lag structure, the VAR model is estimated to examine the interconnectedness among the volatility indices (large cap, mid cap, and small cap). This comprehensive model lays the groundwork for investigating how fluctuations in one volatility index systematically affect others over time, effectively mapping out the volatility spillover mechanisms across different market segments. To affirm the robustness and reliability of the VAR model, diagnostic tests are conducted to identify issues such as serial correlation, heteroskedasticity, and model stability, which are indispensable for validating the underlying assumptions of the model's accuracy.

5.11.2.1 VAR RESIDUAL SERIAL CORRELATION LM TESTS

A residual correlation LM test is conducted for the US and UK respectively to evaluate serial correlation, with the null hypothesis stating that there is no serial correlation at lag $h = 5$. The test results for the US and UK are summarized in the table below.

Table 5.14: Residual Serial Correlation results for the US and UK

US						
Lag	LRE* stat	Df	Prob.	Rao F-stat	df	Prob.
1	29.08105	9	0.0006	3.294366	(9, 569.6)	0.0006
2	28.36035	9	0.0008	3.210687	(9, 569.6)	0.0008
3	46.60098	9	0.0000	5.361270	(9, 569.6)	0.0000
4	28.35385	9	0.0008	3.209933	(9, 569.6)	0.0008
5	8.553813	9	0.4794	0.951704	(9, 569.6)	0.4795
UK						
Lag	LRE* stat	Df	Prob.	Rao F-stat	df	Prob.
1	9.413226	9	0.4000	1.048110	(9, 569.6)	0.4001
2	9.834293	9	0.3641	1.095397	(9, 569.6)	0.3641
3	7.560947	9	0.5789	0.840507	(9, 569.6)	0.5789
4	12.11591	9	0.2069	1.352234	(9, 569.6)	0.2069
5	12.82582	9	0.1706	1.432355	(9, 569.6)	0.1707

Source: Prepared by Author based on the Eviews12.0 program

At the selected lag length of 5, both the US and the UK, the diagnostic test for serial correlation in the VAR model reveals a p-value of 0.4794 and 0.1707 respectively. Since this value exceeds the significance threshold of 0.050, the null hypothesis of no serial correlation cannot be rejected. This outcome suggests that residuals at lag 5 do not exhibit serial correlation, indicating the model is adequately specified at this lag. Therefore, the selected lag length of 5 is appropriate for the US and UK model in terms of residual diagnostics, supporting its reliability for further analysis. In summation, the diagnostic tests for serial correlation at lag 5 confirm that both the US and UK VAR models are well-specified, with p-values exceeding the significance threshold, indicating no evidence of serial correlation. This suggests that the chosen lag length effectively captures the dynamics of the data in both cases, ensuring reliable model performance. The consistency in results across both countries supports the validity of the selected lag length for further analysis.

5.11.2.2 VAR RESIDUAL HETEROSKEDASTICITY TESTS

The VAR Residual Heteroskedasticity Tests for both the US and UK are conducted to evaluate whether the residuals exhibit homoskedasticity, as assumed under the null hypothesis. The results are presented in the table for both US and UK.

Table 5.15: Residual Heteroskedasticity Tests for the US and UK

US		
Joint test:		
Chi-sq	Df	Prob.
481.4368	180	0.0000
UK		
Joint test:		
Chi-sq	Df	Prob.
351.3713	180	0.0000

Source: Prepared by Author based on the Eviews12.0 program

The VAR residual heteroskedasticity test for both the US and UK dataset strongly rejects the null hypothesis of homoskedasticity (p-value = 0.0000), indicating variability in the residuals' variance. This result suggests that volatility in the US and UK market exhibits dynamic patterns, which may influence the transmission of shocks across large, mid, and small-cap ESG-compliant stocks. The presence of heteroskedasticity in both the US and UK datasets reflects the dynamic nature of volatility in these markets. Understanding these patterns provides valuable insights for analysing spillover dynamics among large, mid, and small-cap ESG-compliant companies.

5.11.2.3 VAR RESIDUAL NORMALITY TESTS

The VAR Residual Normality Tests for the US and UK are performed to determine whether the residuals align with the null hypothesis of multivariate normality. The results are summarized in the table below.

Table 5.16: VAR Residual Normality Tests for the US and UK

US			
Component	Jarque-Bera	Df	Prob.
1	732.4482	2	0.0000
2	29025.32	2	0.0000
3	17596.82	2	0.0000
Joint	47354.58	6	0.0000
UK			
Component	Jarque-Bera	Df	Prob.
1	36004.52	2	0.0000
2	335.2912	2	0.0000
3	434.0235	2	0.0000
Joint	36773.84	6	0.0000

Source: Prepared by Author based on the Eviews12.0 program

The VAR residual normality test for both the US and UK dataset strongly rejects the null hypothesis that residuals are multivariate normal, as evidenced by the highly significant p-values for each component and the joint test (p-value = 0.0000). This indicates that the residuals deviate from normality, reflecting potential asymmetries or heavy tails in the data, which are common in financial time series. The rejection of residual normality in both the US and UK datasets highlights the presence of non-normal features, such as skewness or kurtosis, in the volatility spillover dynamics. While non-normality is a common characteristic in financial time series (Karoglou, 2010), these results provide important context for interpreting the underlying market behavior and adapting models to account for these distributional properties.

5.11.2.4 ROOTS OF CHARACTERISTIC POLYNOMIAL

As depicted by the results in the appendix B1 and B2, the roots of the characteristic polynomial for both the US and UK dataset all lie within the unit circle, confirming that the VAR model satisfies the stability condition. This indicates that the model's dynamic behaviour is well-defined, and the shocks to the system dissipate over time rather than growing uncontrollably. This stability allows the study to confidently analyse the direction, magnitude, and persistence of volatility spillovers, enhancing the reliability of the findings.

5.11.3 GRANGER CAUSALITY TESTS

With a robust VAR model in place, the study employs granger causality tests to address the first objective by probing the potential causal relationships or rather directional influences among the volatility indices (large cap, mid cap, and small cap). These tests are instrumental in determining whether changes in one volatility index can predict changes in another, thereby illuminating the nature of spillovers and interactions within the data and revealing the dynamics of volatility transmission (contagion effect). The results for the Granger causality test for the US which aim to investigate the null hypothesis that stipulates the excluded variable does not granger-cause the dependent variable is presented in the table below.

Table 5.17: VAR Granger Causality/Block Exogeneity Wald Tests for the US

Dependent variable: VLARGECAP			
Excluded	Chi-sq	Df	Prob.
VMIDCAP	404.0633	5	0.0000
VSMALLCAP	34.89545	5	0.0000
All	707.7491	10	0.0000
Dependent variable: VMIDCAP			
Excluded	Chi-sq	Df	Prob.
VLARGECAP	6.354700	5	0.2732
VSMALLCAP	18.04336	5	0.0029
All	26.84970	10	0.0028
Dependent variable: VSMALLCAP			
Excluded	Chi-sq	Df	Prob.
VLARGECAP	11.53577	5	0.0417
VMIDCAP	74.36386	5	0.0000
All	119.2482	10	0.0000

Source: Prepared by Author based on the Eviews12.0 program

Bidirectional spillover

Bidirectional spillovers are observed between the large-cap and small-cap volatility index, as well as between the mid-cap and small-cap volatility index. The small-cap volatility index significantly granger-cause the large-cap volatility index (Chi-sq = 34.89545, p-value = 0.0000), suggesting an upward transmission of volatility from smaller, more volatile firms to the largest market segment. Conversely, the large-cap volatility index granger-cause the small-cap volatility index with a weaker but still significant effect (Chi-sq = 11.53577, p-value = 0.0417). This reciprocal relationship hints mutual dependence of these segments, where volatility shocks in one segment might propagate to the other, creating a feedback loop. Similarly, the mid-cap and small-cap volatility index exhibit a strong bidirectional spillover relationship. While the small-cap volatility index significantly influences the mid-cap volatility index (Chi-sq = 18.04336, p-value = 0.0029), the mid-cap volatility index exerts a much stronger effect on small-cap volatility index (Chi-sq = 74.36386, p-value = 0.0000). These dynamics seemingly indicate a more dominant role of the mid-cap volatility in driving small-cap volatility while small-cap stocks appear to provide moderate feedback to mid-cap stocks.

Unidirectional spillover

Unidirectional spillovers are evident in the relationship between the mid-cap and large-cap volatility index. The mid-cap volatility index significantly granger-cause the large-cap volatility index (Chi-sq = 404.0633, p-value = 0.0000), hinting their role as transmitters of volatility to the largest market segment. However, there is seemingly no evidence of significant spillovers in the reverse direction, as the large-cap volatility does not granger-cause the mid-cap volatility (Chi-sq = 6.354700, p-value = 0.2732). This absence suggests a segmentation between these markets, where the mid-cap volatility index is apparently insulated from direct volatility shocks originating from the large-cap volatility index.

Following the analysis of the VAR Granger Causality/Block Exogeneity Wald Test results for the US, the study proceeds to investigate the corresponding findings for the UK, offering a comparative examination of causal dynamics between the two markets. The results for the granger causality for the UK are presented in the table below.

Table 5.18: VAR Granger Causality/Block Exogeneity Wald Tests for the UK

Dependent variable: VLARGECAP			
Excluded	Chi-sq	Df	Prob.
VMIDCAP	5.589385	5	0.3482
VSMALLCAP	26.02660	5	0.0001
All	42.23466	10	0.0000
Dependent variable: VMIDCAP			
Excluded	Chi-sq	Df	Prob.
VLARGECAP	20.36702	5	0.0011
VSMALLCAP	12.58208	5	0.0276
All	35.68095	10	0.0001
Dependent variable: VSMALLCAP			
VLARGECAP	11.58317	5	0.0001
VMIDCAP	73.86109	5	0.0006
All	93.53249	10	0.0000

Source: Prepared by Author based on the Eviews12.0 program

Bidirectional spillover

Bidirectional spillovers are observed between the large-cap and small-cap volatility index, as well as between the mid-cap and small-cap volatility index. The small-cap volatility index significantly granger-cause the large-cap volatility index (Chi-sq = 26.02660, p-value = 0.0001), suggesting an upward transmission of volatility from smaller, more volatile firms to the largest segment. Conversely, the large-cap volatility index granger-cause the small-cap volatility index, though with a weaker effect (Chi-sq = 25.31997, p-value = 0.0001). This reciprocal relationship seemingly implies mutual dependence between these segments, where shocks in either segment can propagate to the other, creating a feedback loop. Similarly, there is a strong bidirectional relationship between the mid-cap and small-cap volatility index. The small-cap volatility index significantly influences the mid-cap volatility index (Chi-sq =

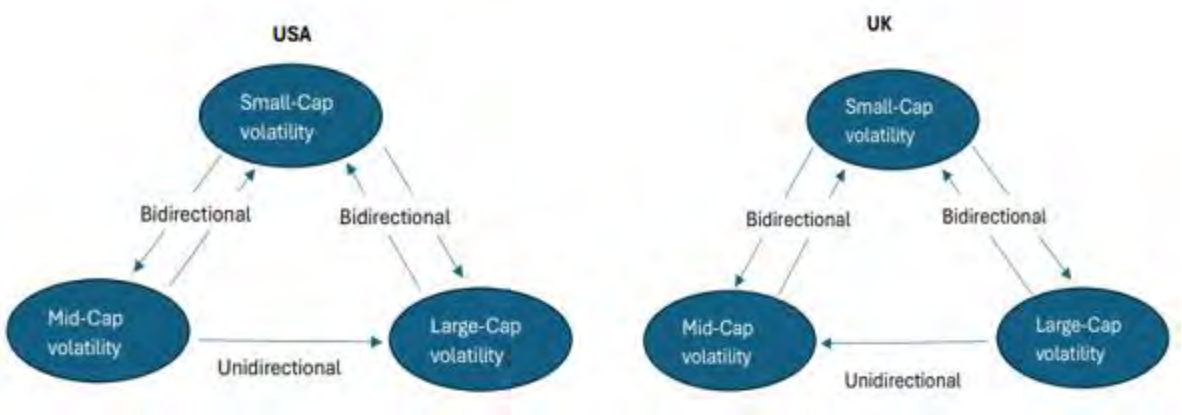
12.58208, p-value = 0.0276), while the mid-cap volatility index exerts a much lesser effect on the small-cap volatility index (Chi-sq = 21.61692, p-value = 0.0006).

Unidirectional spillover

A unidirectional spillover is evident from the large-cap to mid-cap volatility index. The Large-cap volatility index significantly granger-cause the mid-cap volatility index (Chi-sq = 20.36702, p-value = 0.0011), hinting a top-down transmission of volatility. This finding suggests that the large-cap volatility index, typically more stable and influential, drive volatility in mid-tier companies. However, there is no evidence of spillovers in the reverse direction, as the mid-cap volatility does not significantly granger-cause the large-cap volatility index (Chi-sq = 5.589385, p-value = 0.3482). This absence indicates a directional asymmetry and possible structural segmentation between these two markets.

The Granger causality results reveal both similarities and differences in volatility spillover dynamics between the US and UK markets. The figure 5.7 below shows a summarised depiction of the spillover dynamics in each market.

Figure 5.7: Summary of the granger causality results for both the US and UK.



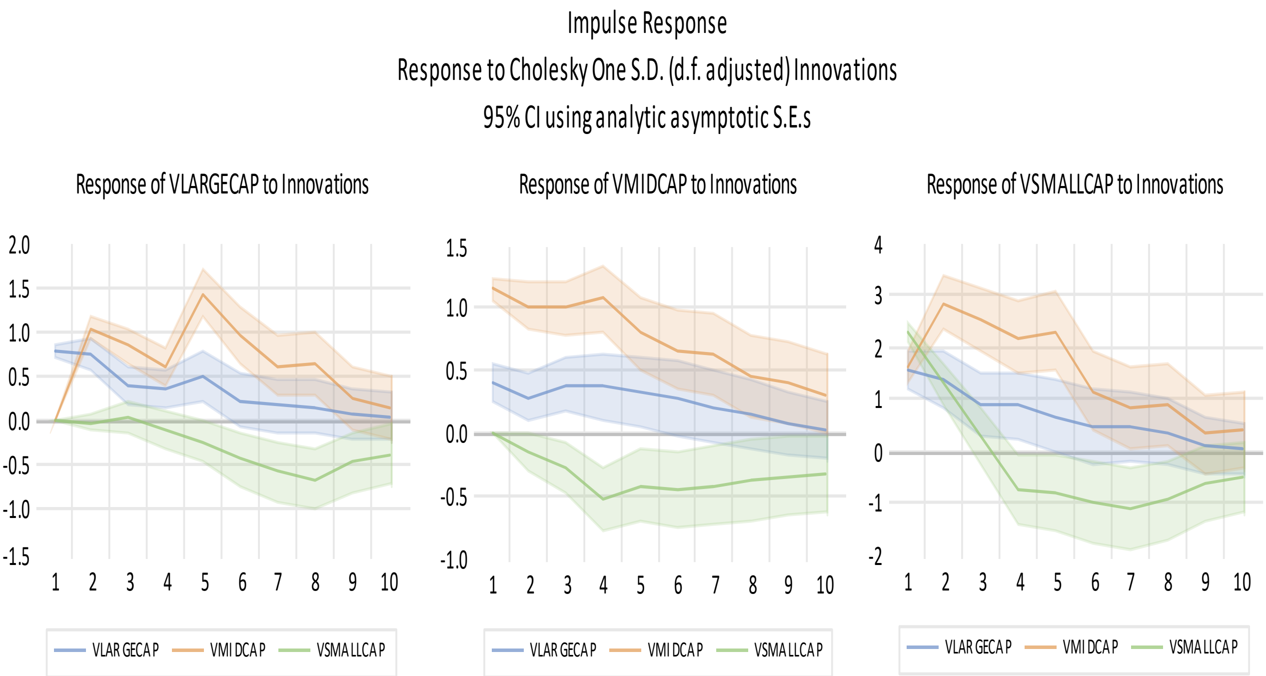
Source: Author

Bidirectional spillovers between the large-cap and small-cap volatility index, as well as between the mid-cap and small-cap volatility index, are evident in both markets, suggesting mutual dependence and feedback loops across these segments. Unidirectional spillovers, however, differ between the two markets. In the US, the mid-cap volatility index significantly drives the large-cap volatility index, implying a bottom-up transmission of volatility. Conversely, in the UK, a top-down spillover is observed, with the large-cap volatility index influencing the mid-cap volatility index. This divergence suggests structural differences, where the US market emphasizes the role of mid-tier firms as key transmitters, while the UK market exhibits a more hierarchical structure, with large-cap stocks driving mid-cap volatility. Despite these differences, both markets highlight the pivotal role of the mid-cap and large-cap volatility index in volatility propagation across ESG-compliant investments.

5.11.4 IMPULSE RESPONSE FUNCTIONS (IRF)

The spillover analysis is further enhanced through the application of impulse response functions (IRFs). The IRFs track the effect of a shock to one volatility index on the entire system over time. Put differently, assuming, you apply a one-time shock (one standard deviation shock) to one of the variables in the VAR, the IFR traces out the effect of that shock on all the variables in the system over time. The IRFs add a new dimension to the analysis not revealed by the granger causality, they provide information on the magnitude and duration of these effects and can highlight whether the effect is positive or negative and how it evolves over time. In doing so the second objective is addressed by illustrating how disturbances propagate dynamically through the large cap, mid cap, and small cap volatility indices, highlighting the magnitude and persistence of spillovers. The IRF analysis relies on numerical data provided in Appendix D1 for the US and Appendix D2 for the UK. The visual plots are made to assist with the conceptualization of the spillovers. The impulse response functions for the US are presented in figure 5.8 below.

Figure 5.8: Impulse response results for the US market



Source: Prepared by Author based on the Eviews12.0 program

Response of VLARGE-CAP to innovations

The impulse response function reveals the large cap volatility index seemingly exhibits strong positive self-reinforcement in period 1, however the effect gradually dies off, by the 10^{th} period the impact of large cap volatility to its own shocks is almost close to zero, thereby converging back to a state of equilibrium. Conversely the midcap volatility index significantly positively influences the large cap volatility index and has the greatest and most persistent impact over time. This potentially suggests a much more central role by the mid cap volatility index in driving volatility upward to the larger segment. The small cap volatility index is associated with a much weaker influence on the large cap volatility index, with mostly negative spillovers in later periods. While the Granger causality results show that the small cap volatility index granger-causes the large cap volatility index, its impact is seemingly limited and largely dissipates over time.

Response of VMID-CAP to innovations

The mid cap volatility index seemingly demonstrates substantial positive self-reinforcement, with its own shocks dominating its volatility dynamics across all periods. The influence of the large cap volatility index appears to be positive on the midcap volatility index but minimal, as indicated by the granger causality results, which suggest no significant causation from the large cap to midcap volatility index. In contrast, the small cap volatility index exerts a noticeable influence on the midcap volatility index, introducing consistent negative spillovers in the impulse response analysis.

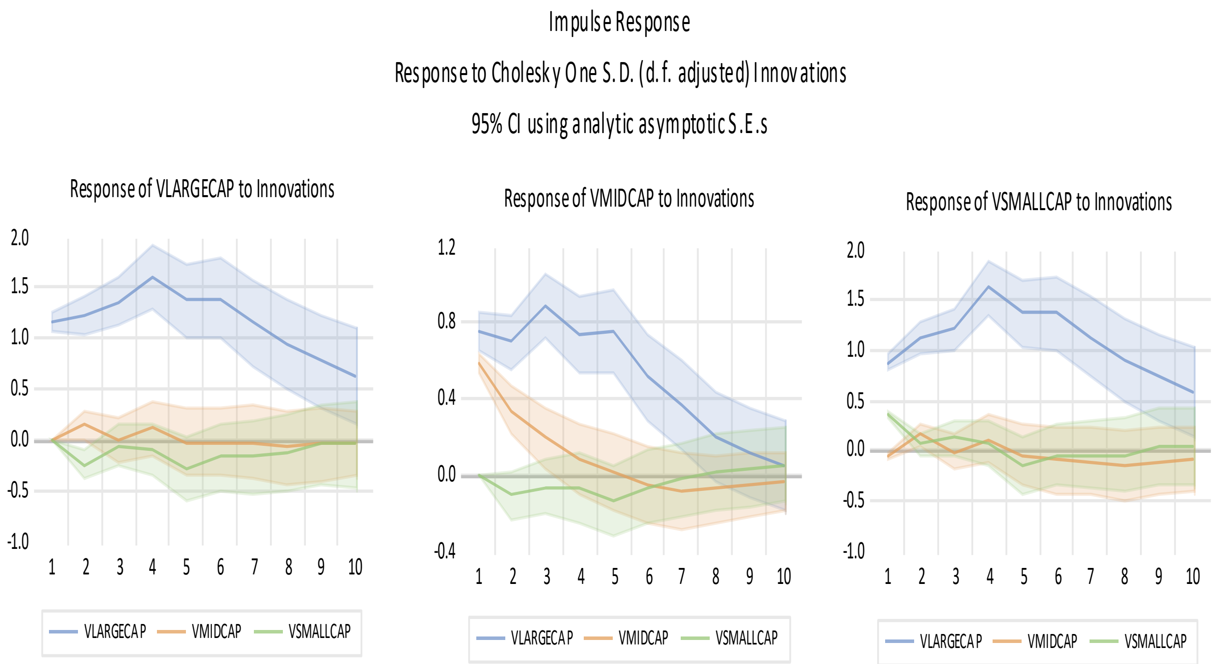
Response of VSMALL-CAP to innovations

The small cap volatility index shows strong self-reinforcement, with its own shocks dominating its volatility in period 1. However, its influence on other indices is relatively weak, as seen in its largely negative and diminishing spillovers in the impulse response analysis. Both the large cap and midcap volatility index significantly positively influence the small cap, with the midcap volatility index exerting the strongest and most persistent impact. This dynamic aligns with the Granger causality results, which show that both the large cap and midcap volatility index granger-cause the small cap, further highlighting small cap's role as primarily a recipient of volatility from larger indices.

Overall, the midcap volatility index has the biggest magnitude and most persistent spillover effect on other indices, transmitting positive volatility to both the large cap and small cap while being influenced by small cap's negative spillovers. The small cap, while initially self-reinforcing, plays a limited role in transmitting volatility upward and serves largely as a recipient of spillovers from larger indices. These findings highlight the interconnected yet asymmetric relationships among the indices.

In a like manner, the impulse response analyses are employed in the UK to investigate how disturbances propagate dynamically through the large cap, mid cap, and small cap volatility indices, thereby unveiling the magnitude and persistence of spillovers. The impulse response results for the UK are presented in figure 5.9

Figure 5.9: Impulse response functions for the UK



Source: Prepared by Author based on the Eviews12.0 program

Response of VLARGE-CAP to innovations

The large cap volatility index appears to demonstrate a strong positive self-reinforcing behaviour, with its own shocks exhibiting high magnitude and persistence, peaking in the earlier periods and gradually declining over time. The influence of the mid cap volatility index is minimal, with responses close to zero throughout, reflecting the granger causality result that the mid cap volatility index does not significantly granger-cause the large cap volatility index. The small cap volatility index has a more noticeable impact, introducing initial negative spillovers that dissipate quickly, consistent with the granger causality finding that the small cap volatility index significantly influences the large cap volatility index.

Response of VMID-CAP to innovations

The midcap volatility index positively responds strongly to its own shocks, which gradually decrease in magnitude over time, indicating high initial self-reinforcement followed by stabilization. The large cap volatility index exerts a consistently significant positive influence on the mid cap volatility index, with spillovers persisting over time, reinforcing its dominant role in driving mid cap volatility. This aligns with the granger causality results, showing a significant causal relationship from the large cap to mid-cap volatility index. The small cap volatility index has a smaller, transient influence on the midcap volatility index, introducing moderate spillovers that dissipate quickly, as supported by the granger causality findings.

Response of VSMALL-CAP to innovations

The small cap volatility index shows moderate self-reinforcement, with its own shocks peaking early and gradually diminishing over time. The large cap volatility index has the most substantial and persistent positive influence on small cap volatility index, with spillovers maintaining a strong presence throughout the periods, reflecting its dominant role in transmitting volatility to smaller indices. The mid cap also impacts small cap, but its spillovers are weaker and diminish more quickly.

In summary, the large-cap volatility index exhibits strong self-reinforcement. It is dominant in positively influencing both the mid and small-cap volatility indices. The mid-cap volatility index has minimal influence on the large-cap, while the small-cap volatility index initially has a negative impact on the large-cap that quickly dissipates. Overall, the large-cap index has the most substantial and persistent influence across all indices in the UK.

5.11.5 VARIANCE DECOMPOSITION (VD)

Finally, variance decomposition is employed to complement the IRF results by quantifying the extent to which each volatility index contributes to the forecast error variances of others within the system. In essence, IRFs give you the dynamic story of how shocks affect the system, while variance decomposition gives you a breakdown of how much each shock contributes to the variability of the variables over time. This analytical approach is vital for pinpointing which variables' shocks are most influential in driving the variability of a particular variable. Through this process of identifying and quantifying the major drivers of volatility, the study can gain insights on diversification and risk mitigation opportunities by evaluating volatility interactions across market segments to inform portfolio strategies. Thereby addressing objective three which is fully discussed in the segment below (bridging the gap). The results of the variance decomposition are presented in appendix:

Variance decomposition of Large- cap volatility

The variance decomposition results for the US market provide a compelling narrative of interconnected spillover dynamics among large-cap, mid-cap, and small-cap volatility indices, which enhance the granger causality findings to some extent. Initially, the variance of the large cap volatility index is driven entirely by its own shocks, but by the 10th period, over 68% of its variance is attributed to the mid-cap volatility index. This reinforces the notion of unidirectional spillover from the mid-cap to large-cap volatility index, as confirmed by Granger causality results. The influence of the mid-cap on the large cap volatility index highlights their pivotal role in driving volatility within the broader market.

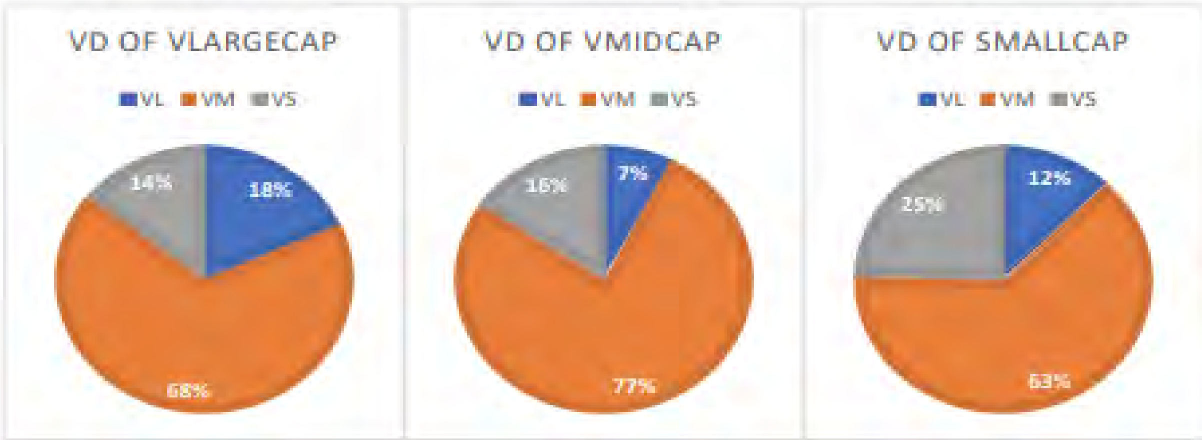
Variance decomposition of Mid- cap volatility

The mid cap's variance is predominantly driven by its own shocks, accounting for over 91% initially and gradually decreasing to 77% by Period 10. The small cap's volatility index influence steadily grows, contributing around 16% by the final period, reflecting its role in transmitting volatility to mid-cap volatility index. The large cap's impact remains minimal, consistently below 10%, this provides further justification of the granger causality results. Which show no significant causal relationship from the large cap to mid-cap volatility index but a strong influence from small cap volatility index. These findings highlight mid cap's strong self-reinforcement and its position as a recipient of increasing spillovers from small cap.

Variance decomposition of small- cap volatility

The variance decomposition of the small cap volatility index shows its variance is initially dominated by its own shocks (51%), with the mid cap and large cap volatility index contributing 27% and 23%, respectively. Over time, the mid cap volatility index becomes the largest contributor, explaining 63% of small cap's variance by the 10th period, reflecting the bidirectional spillover between the small-cap and mid-cap volatility index**.** The large cap's contribution rises to 12%, aligning with the bidirectional spillover between the large-cap and small-cap volatility index**.** By the final period, small cap's own shocks explain just 25%, emphasizing its strong dependence on external influences, particularly from mid-caps, while also playing a reciprocal role in volatility transmission across segments. A summary visual perspective is presented in figure 5.10 below to show the variable with the most influence by the 10th period on the volatility of other indices in each market segment.

Figure 5.10: Drivers of volatility in each market capitalization level for the US



VL- Large cap Volatility, VM - Mid Cap Volatility & VS – Small Cap Volatility

Source: Author

Overall, the large and small caps' variance is predominately driven by shocks emanating from the mid-cap volatility index, while the mid-caps variance is driven by its own shocks. These findings provide a deeper understanding of the volatility transmission mechanisms and dynamic relationships within the equity market, offering important implications for investors in risk mitigation and asset diversification field.

The variance decomposition analysis for the UK market offers a detailed understanding of the volatility dynamics among large-cap, mid-cap, and small-cap stocks. These findings not only highlight the distinct roles each segment plays in the volatility network but also corroborate the Granger causality results, reinforcing the interconnected relationships and spillover patterns observed within the market.

Variance decomposition of Large- cap volatility

The large cap is overwhelmingly driven by its own shocks, accounting for nearly 100% of its variance in the initial periods and maintaining dominance throughout the analysis. Mid cap and small cap contribute minimally, with small cap's impact increasing slightly over time but remaining below 2% by the tenth period. These results also lend credence to the Granger causality findings, where small cap Granger-causes large cap, albeit with a weaker effect, while mid cap does not significantly influence large cap. This suggests that large cap is relatively insulated from volatility spillovers, acting as a self-reinforcing segment.

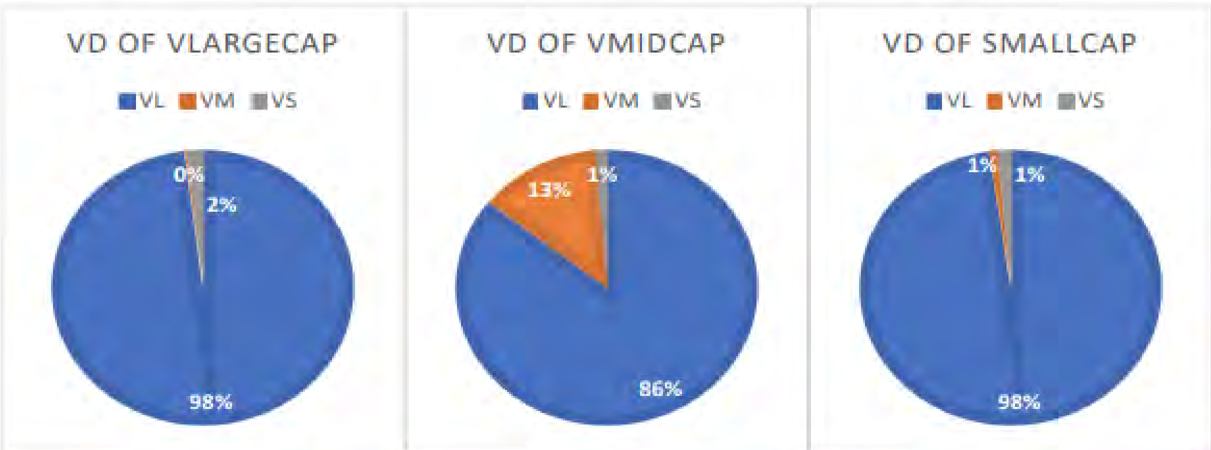
Variance decomposition of Mid- cap volatility

The Midcap's variance is primarily driven by large cap, which explains 63% of the variance in the initial period and increases to 86% by Period 10. This highlights Large Cap's dominant influence on mid cap over time. Small cap's contribution remains minimal, peaking at around 1.3% by the final period. These findings further substantiate the Granger causality results, which show that Large Cap significantly Granger-causes Mid cap, while SmallCap exerts a weaker but notable influence.

Variance decomposition of Small- cap volatility

Small cap's variance is strongly influenced by large cap, which accounts for 85% of its variance in the first period and rises to nearly 98% by Period 10. Mid cap's contribution is negligible, staying below 1% throughout. Small cap's own shocks account for a declining share of its variance, dropping from 14% initially to just over 1% by the final period. This dynamic is supported by the Granger causality results, which confirm significant causation from both Large Cap and Mid Cap to SmallCap, emphasizing small cap's role as a recipient of volatility spillovers. Likewise, the biggest sources of volatility by the 10th period for each index can be summarised as presented in figure 5.11 below.

Figure 5.11: Drivers of volatility in each capitalization level for the UK



VL- Large cap Volatility, VM - Mid Cap Volatility & VS – Small Cap Volatility

Source: Author

In summation in the UK, the mid and small caps' variance is predominately driven by shocks emanating from the large-cap volatility index, while the large-caps variance is driven by its own shocks. These findings highlight the self-reinforcing nature of the large-cap volatility index and the dominant influence of the large-cap on the mid-cap and small-cap volatility index.

5.12 BRIDGING THE GAP: CONTRASTS AND PARALLELS WITH PRIOR WORK

The study opened with a broad thought-provoking question that is: Are ESG credentials genuinely guiding investors into calmer financial waters, or do they merely place a green veneer over the same waves of volatility? In getting to the bottom of this question the study develops three research objectives aimed at providing answers. These objectives are then explored to their logical extents, where the study uncovers interesting volatility patterns within the ESG landscape. Subsequently these green volatility patterns are then compared with the old waves of volatility uncovered in the empirical review section where sustainability compliance is not heavily prioritized. The table presented below shows areas of convergence and divergence in the findings, with a particular focus on the US and UK markets.

Table 5.19: Comparison of the key findings with prior work

Previous research Findings "*Old waves of volatility*"			
Bilateral	**Large to small**	**Small to Large**	**Complex**
Asian markets	Asian markets	Emerging markets	Emerging markets
European markets **[UK]**	European markets **[UK]**		
Emerging markets	Emerging markets		
	US markets **[US]**		
The current study's Findings "*ESG landscape volatility patterns*"			
Bilateral	**Large to Mid**	**Mid to Large**	**Complex**
[US]		**[US]**	
[UK]	**[UK]**		

Source: Author

As it is shown in table 5.19, in the US the study found bilateral volatility patterns between the small cap and mid cap volatility index, as well as between the small cap and the large cap volatility index. These patterns are absolutely not observable in the US reviewed work such as that of Conrad et al., (1991) who found a unidirectional volatility spillover pattern from large to small cap stocks. In addition, despite the use of similar methodologies, such as that of Chordia et al. (2005) who also employed a Vector autoregressive model and da Silva Antunes (2021) who also used Granger causality tests in tandem with multivariate models their findings still accord with those of Conrad et al., (1991) who found unidirectional spillovers. Consistent with the expectations of the contagion theory in the stock markets, this unidirectional spilllover effect suggests that Large "less compliant firms" in the US play a major role in dissipating market shocks to their smaller counterparts. However, in an interesting turn of events, the ESG landscape volatility patterns reveal a limited role of the large cap volatility index in dissipating market shocks to both the small cap and mid cap volatility index in the US. This limited role is further enhanced by the findings that show a unidirectional spillover but from the mid-cap to large-cap volatility index. The mid-cap significantly drives large-cap volatility index, reflecting a bottom-up transmission of volatility. Nevertheless, there is no evidence of spillovers in the reverse direction, indicating that the volatility index of the mid cap index is insulated from direct volatility shocks emanating from the large cap volatility index.

These findings may suggest that ESG credentials genuinely guide investors into calmer financial waters. This is because Su (2021) notes in his analysis of the contagion theory that capital has a tendency to return to larger markets during crisis periods. Consequently, this shift generates cross-market contagion, which makes smaller stock markets encounter similar difficulties and struggles. Therefore, this lack of influence from the large- cap volatility index in the ESG landscape provides evidence in support of the notion that adoption of sustainability practices guides ESG investors into calmer financial waters. This further anchor the findings in the US of the studies that investigated the relationship between ESG performance and volatility. Which found ESG companies exhibited lower stock return volatility, as demonstrated by Ashwin Kumar et al. (2016) and Jakobsson and Lundberg (2018).

On a comparable scale, the analysis of the ESG volatility patterns in the UK bears some resemblance to the findings of the US though to a limited extent. Similar to the US ESG volatility patterns, the study also found evidence of bilateral spillovers in the UK between the small cap and mid cap volatility index, as well as between the small cap and the large cap volatility index. In some measure these findings are consistent with the earlier research done in the UK such as that of Grieb and Reyes (2002) who found bidirectional spillovers between the large-cap and small-cap index using a LEGARCH. Furthermore, Angelidis and Andrikopoulos (2010) employ a methodology that parallels that of the study and found bidirectional transmission of volatility between the small and large firms using a VAR framework.

An additional pattern identified by the study revealed evidence of unidirectional spillover from the large cap to the mid cap volatility index. Interestingly this finding diverges from the unidirectional spillover pattern uncovered by the study in the US where the direction of spillover runs in the opposite manner, from the mid cap to the large cap volatility index. However, despite this difference, this unidirectional spillover in the UK from the large cap to the mid cap index does receive some support from earlier research “partially”. Harris and Pisedtasalasai (2006) using a multivariate AR-GJR-GARCH-M model investigate the UK stock market and found positive volatility spillovers from large stocks to small stocks. while Harris and Pisedtasalasai (2006) do not directly lend support to the unidirectional spillover observed from the large to the midcap, their analyses confirm the broader findings of the study in the UK. For instance, the impulse response functions analyses revealed that the large cap serves as the primary source of spillovers, significantly influencing both the mid cap and small cap with persistent effects, the mid cap and small cap have a minimal effect on the large cap. Moreover, the variance decomposition revealed the Midcap’s and small cap’s variance is primarily driven by the large cap volatility index. This suggests that the large cap is relatively insulated from volatility spillovers, acting as a self-reinforcing segment. The dominant influence of the large-cap on the mid-cap and small-cap volatility index aligns with theoretical expectations of the contagion theory which argues that the large stock markets often project their crises onto small markets.

This therefore leads the study to believe that the adoption of ESG factors in the UK does not have a strong impact in guiding investors into calmer financial waters. This is because as identified in the theoretical foundation. It is a typical property of contagion risk that the collapse of a large market would cause other markets to tumble (Roll, 1988). As a result, the mid-cap and small-cap volatility indices are vulnerable to shocks emanating from the large-cap volatility index since in theory it is regarded as a source of market turmoil. However, on the brighter side, the lack of spillover from the mid cap and small cap volatility index does suggest a calming effect of volatility to the large cap index. Therefore, to a lesser degree as compared to the US, the adoption of the ESG factors may bring investor into calmer financial waters, because the bidirectional effect of volatility is less pronounced. Finally, it is worth noting that the reviewed studies in the US and UK do not incorporate the mid-cap index in their analyses. As a result, their findings may be limited, potentially overlooking critical insights that could be derived from a more comprehensive analysis that includes mid-cap stock.

While the study observed bilateral and unidirectional spillovers in both the US and UK respectively, the magnitude and persistency of these spillovers differ. Consequently, these differences give rise to diversification and risk mitigation opportunities, thereby putting the study in a position to shed light on the third objective. The markets that are insulated from receiving volatility spillovers offer safer investment opportunities and better diversification benefits due to their limited exposure to market wide shocks. In the US the mid cap volatility index has the most persistent and greatest effect on the volatility of other indices, therefore suggesting that this market is insulated from spillovers from the other markets. The same can be said in the UK where the large cap volatility index has the most influential impact on the volatility of other markets. With the adoption of ESG practices, and incorporating companies of varying market capitalization the study is able to provide evidence against the argument of Askarany and Xin (2024) who offered essential insights that served as a roadmap in the search for answers, arguing that company size does not significantly influence the relationship between ESG ratings and stock price volatility. On the contrary, the study noted that the mid cap volatility index had the most significant influence in dissipating market shocks in the US while in the UK it was the large cap volatility index. This suggests that large, mid and small companies with high-quality ESG ratings are not equally effective in reducing stock price volatility. These findings not only bridge the gap between earlier work on market capitalization and volatility spillovers but also contribute to the growing body of research emphasizing the importance of sustainability in financial markets.

5.13 CHAPTER SUMMARY

This chapter presented and discussed the empirical analysis according to the volatility spillover framework put forth in Chapter Four. The chapter began by performing a visual analysis on the firms included in the sample for both the US and UK. The analysis revealed all the ESG compliant stocks generally exhibited upward and downward trends interrupted by the 2020 pandemic, with recoveries that vary in strength. The fluctuations in trend and variance indicated non-stationarity. Due to the broad and varied trends observed within each market capitalization segment, a principal component analysis (PCA) is employed to extract the dominant trends across the series. For both the US and UK the PCA results indicated that from the large, mid, and small-cap categories, only one PC should be retained, which is the first one, because PC1 for all the caps has a higher eigenvalue than one. This means that PC1 can effectively capture the overall market dynamics, which is the most critical factor prompting change across the firms. The Large, mid, and small-cap firms index is computed using the first principal component.

The extracted return indices through PCA are subsequently visually scanned to develop an appreciation of the nature of the return variable, such as periods of low or high variability indicating changes in economic conditions or the state of the market. In the US it appears the mid-cap index exhibits lesser volatility in the returns than the large-cap and small-cap. The small-cap shows the high volatility relative to the mid-cap, while the large-cap index is recognized to be the most sensitive to fluctuation. While in the UK also the mid cap index demonstrates the least fluctuation compared to the other two indices. The small cap is relatively more stable than the large cap while at the same time fluctuating more than the mid cap, thereby taking the middle ground when it comes to risk and movement in the market.

The study was able to develop an appreciation of the underlying trends and patterns through the graphical analysis of the return indices, however analysis by visual inspection can be prone to some subjectivity. To avoid potential bias, the study supplemented the analysis with a quantitative analysis that is the descriptive statistics to make the analysis more objective and reliable. The descriptive statistics results indicated that volatility is highest for the large cap stocks in the UK (1.60), which is also true for US large caps, but slightly higher (1.65).

The application of statistical approaches, is extended to include the corelation analysis. The findings revealed the correlation matrix for the US indices shows strong positive relationships across all categories. In addition, in the US the correlation between large cap and mid cap was found to be the highest, signifying close movements. Like the US, the correlation matrix of the UK indices shows a strong positive correlation across all market segments, but the highest correlation was between the small and large-cap indices. In an attempt to further ensure the variables are suitable for further modelling, transitioning to a unit root test was a critical step after conducting the descriptive statistics and correlation analysis to understand the basic properties and relationships within the data. The unit root test revealed that for both the US and UK the large, mid and small cap return indices were found to be stationary at level terms I(0), even after accounting for structural breaks.

From the unit root test, the statistical properties of the return indices were confirmed as suitable for time series analysis, the study advanced to model volatility using the GARCH models. A GARCH (2,1) was used to model the US large- and small-cap volatility, and it captured volatility clustering, stationarity, and non-negativity. The US mid-cap volatility was modelled using a TARCH (1,1) that included an asymmetry term to take into account differential responses to positive and negative shocks. For the UK, the large and small cap volatility was modelled by a TARCH (1,1) that addressed volatility clustering, stationarity, and non-negativity and incorporates an asymmetry term. A GARCH (1,1) was used to estimate the mid-cap volatility, which addressed the ARCH effect, stationarity, and non-negativity but without asymmetry term. Having established the effectiveness of the volatility models for both markets, visualizing the volatility series, as done with the return indices, was a crucial next step in the analysis. For both the US and UK The volatility series reveals common patterns across indices, with all experiencing noticeable spikes during significant market events, particularly around 2020.

After visually examining the volatility indices — large cap, mid cap, and small cap — they are examined for stationarity, in order to establish suitability for further modelling in the spillover analysis within a VAR framework. For both the US and UK the ADF test results confirm that all volatility series (Large-Cap, Mid-Cap, Small-Cap) are stationary at the level I(0), With stationarity established, a VAR analysis was performed for both markets. The Granger causality results reveal that there are bidirectional spillovers between the large-cap and small-cap volatility index as well as between the mid-cap and small-cap volatility index in both markets, thus indicating mutual dependence and feedback loops between these segments. However, there were differences in the unidirectional spillovers between the two markets. The large cap volatility index is driven by the mid-cap volatility index in the US, which represents a bottom-up transmission of volatility.

The spillover analysis was further enhanced through the application of impulse response functions (IRFs). The findings revealed for the US the large- and small -cap volatility index is primarily positively influenced by the midcap. The midcap volatility index has the most significant and persistent influence in transmitting volatility to both the large cap and SmallCap. while being influenced by small cap's negative spillovers. On the other hand, the UK impulse response analysis showed that the large-cap index has the most significant and longest-lasting influence over all indices, with positive spillovers to both markets.

In addition, the variance decomposition was used to complement the IRF results and quantify the degree to which each volatility index affects the forecast error variances of the other variables in the system. Overall, the US mid-cap volatility index is found to be a key driver of volatility in the US, while in the UK, the Large-cap volatility index is driven by its own shocks with little influence from the mid-cap and small-cap volatility index. Lastly, the study addressed the gap by comparing and contrasting its findings with previous research there were areas of convergence and divergence. Overall, it was found that the adoption of ESG practices in the US may suggest that ESG credentials genuinely guide investors into calmer financial waters. While in the UK, to a lesser degree as compared to the US, the adoption of the ESG factors may bring investor into calmer financial waters, because the bidirectional effect of volatility is less pronounced.

CHAPTER 6
CONCLUSION

6.1 INTRODUCTION

The paper investigates the volatility spillovers among ESG compliant large, mid and small cap stocks in the US and UK markets. In doing so, the research sheds light on an essential question regarding the authenticity of ESG credentials directing investors to favourable, stable financial outcomes compared to a mere way of covering up the old waves of volatility. As noted by Coppola (2016), there has been an important change regarding integrating Environmental, Social, and Governance (ESG) criteria into investment strategies at the corporate and investment management levels. In part, the increased attention to a firm’s sustainability performance reflects the empirical finding that the relationship between ESG compliance and corporate financial performance is generally stable and positive over time (Friede et al., 2015). However, despite this positive outlook a growing trend in sustainability reporting brings about a fear of greenwashing without established standardized ESG frameworks. Consequently, this lack of consistent reporting standards casts doubts over the effectiveness of ESG adoption; given this, the study built a case for the research gap around this problem.

In response to the identified problem, the research objectives are to (1) establish the direction of volatility transmissions between different-sized ESG stocks, (2) measure the magnitude and persistence of volatility spillovers among large-, mid-, and small-cap ESG compliant stocks in U.S. and U.K. markets, and (3) offer recommendations on diversification and risk mitigation by examining the volatility interactions between market segments to guide portfolio strategies.

6.2 SUMMARY OF THE STUDY

The study begins in Chapter One with the background of the research. It reveals essential information about the study topic, including highlighting and supplementing previous foundational studies, depicting important historical events, and elaborating on the specific reason and manner by which the research problem of interest comes about. This is followed by an explanation of the rationale and a problem statement, which helps to create a clear cut through the dense forest of potential research topics. Subsequently, following the thorough discussion of the research problem, the goals of the study are outlined to fill the gap. Finally, a brief layout of the proposed methods, procedures, and techniques for achieving the research objectives is offered before concluding with the research outline. The second chapter examined the theoretical work concerning the stock market volatility and spillover effects. Chapter Three built a solid foundation for reviewing the empirical literature on volatility spillovers. Chapter four described the formal analytical framework upon which the objectives set out in Chapter One of this study must be achieved. Chapter Five reported and discussed the findings of the research. Finally, Chapter Six concludes the study.

6.3 SUMMARY OF THE MAIN EMPIRICAL FINDINGS

As highlighted in the methodological assumption of the research paradigm, the study follows a quantitative and deductive methodology through the application of econometric methods to address the research objectives. In addressing objective one the study employed a granger causality test.

The results from the granger causality indicate that the large-cap and small-cap volatility index, as well as the mid-cap and small-cap volatility index, have bidirectional spillover in both the US and UK, meaning there is a feedback loop and mutual dependence between these segments. However, unidirectional spillovers behave differently in the two markets. The large cap volatility index is significantly driven by the mid-cap volatility index in the US which is consistent with a bottom–up transmission of volatility. On the contrary, in the UK, a top down spillover was observed, where the large cap volatility index is driving the mid cap volatility index. This divergence can be attributed to structural differences, as the US market gives more importance to the mid-cap volatility as key transmitters. In contrast, the UK market has a more hierarchical structure, where large-cap stocks drive mid-cap volatility. While there are differences in both markets, they reveal the importance of the mid-cap and large cap volatility index in the transmission of volatility across ESG compliant investments.

The spillover analysis is further enhanced through the application of impulse response functions (IRFs) this aided with the achievement of objective two. The IRFs track the effect of a shock to one volatility index on the entire system over time (Chordia et al, 2006). The IRFs add a new dimension to the analysis not revealed by the granger causality, they provide information on the magnitude and duration of these effects and can highlight whether the effect is positive or negative and how it evolves over time. In the US the IRF's findings reveal that the midcap exerts the biggest magnitude and most persistent spillover effects–on the other indices. In addition, it transmitted mainly positive volatility to both the large cap and small-cap while being weakly influenced by small cap's negative spillovers. Moreover, the small cap plays a rather limited role in driving volatility upwards and is mostly a recipient of volatility spillovers from larger indices. On the other hand, the UK impulse response analysis showed that the large cap volatility index exhibits strong self-reinforcement effects. It exerts a dominant positive spillover effect on both the mid and small cap volatility indices. The large-cap volatility index remains almost unaffected by the mid-cap, and the small-cap volatility index first produces a negative effect on the large-cap that diminishes quickly. Overall, across all the indices, the influence of the large-cap index is the most significant and persistent.

In an attempt to complement the IRF results, the variance decomposition was employed to quantify how much each volatility index contributes to the forecast error variances of the other indices in the system. With this process, the study was able to improve understanding of diversification and risk mitigation opportunities by determining the volatility interactions within the market segments to inform portfolio strategies. In the US, the variance decomposition results showed that the volatility index of the mid-cap was the pivotal driver of volatility and contributed significantly to explaining the volatility of the indexes for large and small caps. While in the UK the large-cap volatility index is predominantly driven by its own shocks, the mid-cap volatility index is primarily influenced by the large-cap, while small-cap is significantly impacted by large-cap, with the mid-cap playing a negligible role.

In light of these findings, the study was able to revisit and address a foundational question regarding the authenticity of ESG credentials directing investors to favourable, stable financial outcomes compared to a mere way of covering up the old waves of volatility. Drawing from the findings it was observed in the US, the mid-cap volatility index significantly drove the large-cap and small-cap volatility index and had the strongest and most persistent positive spillover effects on them. These findings may suggest that ESG credentials genuinely guide investors into calmer financial waters. This is because Su (2021) notes in his analysis of the contagion theory that capital has a tendency to return to larger markets during crisis periods. Consequently, this shift generates cross-market contagion, which makes smaller stock markets encounter similar difficulties and struggles. Therefore, this lack of influence from the large-cap volatility index (source of turmoil) in the ESG landscape suggests a segmentation between these markets. Where the mid-cap volatility index is insulated from direct volatility shocks originating from the large-cap volatility index. As a result, this provides evidence in support of the notion that adoption of sustainability practices guides ESG investors into calmer financial waters.

As for the UK, the evidence showed strong persistent positive spillovers flow from the large cap index to the other volatility indices. The dominant influence of the large-cap on the mid-cap and small-cap volatility index aligns with theoretical expectations of the contagion theory which contends that the large stock markets tend to export their crises to the small stock markets. This therefore leads the study to believe that the adoption of ESG factors in the UK does not have a strong impact in guiding investors into calmer financial waters. The reason for this is because, as described in the theoretical foundation, the inability of a large market to remain stable would lead to the collapse of other markets (Roll, 1988), and even worse, the markets are subjected to simultaneous failure (Malliaris and Urrutia, 1992). As a result, the mid-cap and small-cap volatility indices are vulnerable to shocks emanating from the large-cap volatility index since in theory it is regarded as a source of market turmoil.

6.4 RISK MITIGATION & PORTFOLIO DIVERSIFICATION IMPLICATIONS

Regarding stocks, there are limitless possibilities when it comes to diversification. Investors can diversify by the size of the companies (large, medium, or small-cap), geography (domestic or international), industry, and sector. Our findings in this study have implications for risk mitigation and portfolio diversification and thus suggest how diversity in terms of size can be achieved.

According to Markowitz (1952) and further elaborated by Sharpe (1963), one fundamental principle that must be fulfilled for diversification to bring economic benefits to potential investors is that of the reduction of the level of cointegration and co-movement between different stocks and stock markets. This is in accordance with portfolio theory. Based on this logic of thinking, the study found that the US mid-cap and the UK large-cap volatility index have the highest magnitude and most persistent spillover effects on other indices. Furthermore, they proved to be a key driver of volatility respectively. This implies that the US mid-cap and UK large-cap are relatively insulated from volatility spillovers from other indices and serve as sources of self-reinforcing segments.

This limited exposure to market-wide shocks means that changes in price movements in the markets that are mainly the recipients of volatility tend not to induce price movements in the markets that are drivers of volatility. With this, investors can shelter themselves from market risk exposure and achieve better diversification opportunities when they invest in these two self-reinforcing segments. This is because these markets (US mid-cap and UK large-cap index) can be perceived as defensive since other markets do not significantly influence their price movements. The lack of co-movement between the markets that are transmitters of volatility and those that are recipients allows the realization of economic benefits to potential investors from diversification.

While these recommendations are entirely predicated on the outcomes of this study, the practical application of such an investment strategy would need to consider many aspects beyond the determination of the degree of cointegration and co-movement among different stocks and stock markets. For example, other factors that should be assessed before making any investment commitment are the evaluation of political risk, taxation policies, legal and institutional factors, industry growth prospects, etc., which are beyond the focus of this study. Hence, on the basis of the findings of this study alone, it is not possible to thoroughly appreciate the long-term prospects of such diversification benefits.

It is equally important to note that this risk mitigation and diversification guidance is offered in alignment with the results that suggest that the mid-cap volatility index in the USA and the large-cap volatility index in the UK serve as significant channels for volatility spillovers. However, these conclusions must be viewed within the context of certain limitations. The sample was selected using a purposive approach based on ESG score criteria, leading to a relatively small and specific group of firms that may not fully represent broader market behavior. Additionally, the use of GARCH and TARCH models relies on assumptions such as stationarity, non-negativity, and homoscedasticity—assumptions that, if violated, could affect the reliability of the volatility estimates.

Furthermore, while the study provides quantitative evidence on volatility spillovers, the policy recommendations and risk mitigation strategies derived herein should be considered with caution. External factors such as regulatory differences (e.g., the implications of US financial regulations versus post-Brexit changes in the UK) and geopolitical risks (including the impact of the COVID-19 pandemic and other global political uncertainties) may further influence market dynamics in ways that are not fully captured by the current model. Thus, investors and policymakers should interpret these recommendations as indicative rather than definitive, with the understanding that a more comprehensive analysis incorporating these external elements would be beneficial for more robust decision-making.

6.5 AREAS FOR FUTURE RESEARCH

A major challenge of this study relates to data availability. The study has a relatively limited sample size and covers a short period from January 5, 2018, to December 30, 2022. The main reason for these limitations, especially within the financial field, comes from the lack of ESG-"*consistently highly*" compliant firms. Partly, the poor adoption of ESG standards in this sector may be due to the perceived compliance costs that might discourage firms from going out of their way to align with ESG standards. Although this constrains the generalizability of the findings, the chosen sample provides an interesting point of view on the emerging and important interaction between ESG compliance and financial market volatility. Depending on the availability of ESG data, future research could be extended over a longer period to collect broader market volatility dynamics in the face of different market conditions.

While indirectly implemented by this study, another area for future research is to include additional sectors, like technology, energy, industrial and healthcare and the real estate sector. Although this study did include the real estate sector, it was predominantly done to address data inconsistencies in the financial industry rather than by design. Nevertheless, volatility reduction could be impacted differently depending on which industries we consider, e.g., energy, could be more likely to respond to ESG-related factors than other sectors. Additionally, considering more countries in the research could give a broader scope of ESG initiatives' effectiveness based on different regulatory frameworks. Hence, the success of ESG depends on its good implementation and the involvement of all key stakeholders. In conclusion, as an adaptation of the saying: The grass is always greener where you water it, the study believes that ESG outcomes are most likely to be successful (greener) when regulatory support, corporate responsibility, and sustainable practices are cultivated.

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APPENDICES

VAR REGRESSION RESULTS: APPENDIX A

Appendix A1: Vector Autoregressive Estimates for the US

Vector Autoregression Estimates			
Included observations: 255 after adjustments			
Standard errors in ( ) & t-statistics in [ ]			
	VLARGECAP	VMIDCAP	VSMALLCAP
VLARGECAP(-1)	0.484722 (0.06460) [7.50334]	-0.006752 (0.09869) [-0.06842]	-0.266196 (0.25775) [-1.03277]
VLARGECAP(-2)	-0.142316 (0.06230) [-2.28433]	0.200708 (0.09518) [2.10870]	0.140891 (0.24857) [0.56680]
VLARGECAP(-3)	0.082167 (0.05817) [1.41257]	-0.038169 (0.08887) [-0.42951]	0.196800 (0.23208) [0.84797]
VLARGECAP(-4)	-0.130151 (0.05599) [-2.32464]	-0.005575 (0.08554) [-0.06518]	-0.525301 (0.22338) [-2.35155]
VLARGECAP(-5)	0.023227 (0.04597) [0.50523]	-0.038153 (0.07024) [-0.54320]	0.393475 (0.18343) [2.14508]
VMIDCAP(-1)	0.921721 (0.05387) [17.1094]	0.983870 (0.08230) [11.9541]	1.664547 (0.21494) [7.74412]
VMIDCAP(-2)	-0.635390 (0.08123) [-7.82198]	0.205388 (0.12410) [1.65499]	-0.331428 (0.32410) [-1.02260]
VMIDCAP(-3)	-0.131117 (0.08550) [-1.53346]	0.022256 (0.13063) [0.17037]	-0.004412 (0.34115) [-0.01293]
VMIDCAP(-4)	0.655731 (0.08182) [8.01399]	-0.304610 (0.12501) [-2.43675]	-0.277281 (0.32647) [-0.84934]
VMIDCAP(-5)	-0.250844 (0.07399) [-3.39005]	0.092390 (0.11305) [0.81728]	0.036029 (0.29523) [0.12204]
VSMALLCAP(-1)	-0.007696 (0.02196) [-0.35045]	-0.068672 (0.03355) [-2.04670]	0.567494 (0.08762) [6.47643]
VSMALLCAP(-2)	0.094050 (0.02661) [3.53450]	-0.022637 (0.04065) [-0.55685]	-0.083340 (0.10617) [-0.78498]
VSMALLCAP(-3)	-0.027636 (0.02761) [-1.00085]	-0.068808 (0.04219) [-1.63110]	-0.158191 (0.11017) [-1.43588]
VSMALLCAP(-4)	0.047884	0.082828	0.257646

	(0.02713) [1.76516]	(0.04144) [1.99852]	(0.10824) [2.38042]
VSMALLCAP(-5)	-0.088296 (0.02287) [-3.86156]	-0.051512 (0.03493) [-1.47461]	-0.206795 (0.09123) [-2.26674]
C	0.501786 (0.11132) [4.50779]	0.075141 (0.17006) [0.44184]	-0.512423 (0.44414) [-1.15375]
R-squared	0.933400	0.833426	0.796726
Adj. R-squared	0.929220	0.822972	0.783968
Sum sq. resids	151.3310	353.2167	2409.067
S.E. equation	0.795729	1.215687	3.174867
F-statistic	223.3070	79.71987	62.45018
Log likelihood	-295.3006	-403.3711	-648.1601
Akaike AIC	2.441573	3.289185	5.209099
Schwarz SC	2.663770	3.511382	5.431295
Mean dependent	2.701987	2.298725	2.927128
S.D. dependent	2.990963	2.889350	6.830722
Determinant resid covariance (dof adj.)		4.351892	
Determinant resid covariance		3.583037	
Log likelihood		-1248.205	
Akaike information criterion		10.16631	
Schwarz criterion		10.83290	
Number of coefficients		48	

Appendix A2: Vector Autoregressive Estimates for the UK

Vector Autoregression Estimates			
Included observations: 255 after adjustments			
Standard errors in ( ) & t-statistics in [ ]			
	VLARGECAP	VMIDCAP	VSMALLCAP
VLARGECAP(-1)	1.468757 (0.19770) [7.42909]	0.474250 (0.16200) [2.92754]	0.661314 (0.16173) [4.08910]
VLARGECAP(-2)	-0.478276 (0.24813) [-1.92749]	-0.043936 (0.20332) [-0.21610]	-0.436468 (0.20298) [-2.15031]
VLARGECAP(-3)	0.080485 (0.25360) [0.31737]	-0.246017 (0.20779) [-1.18394]	0.162973 (0.20745) [0.78561]
VLARGECAP(-4)	0.373873 (0.24828) [1.50588]	0.393588 (0.20343) [1.93472]	0.203668 (0.20310) [1.00282]
VLARGECAP(-5)	-0.504105 (0.18854) [-2.67367]	-0.488104 (0.15449) [-3.15944]	-0.458010 (0.15423) [-2.96959]
VMIDCAP(-1)	0.170727 (0.12667)	0.551523 (0.10379)	0.274830 (0.10362)

	[1.34782]	[5.31380]	[2.65233]
VMIDCAP(-2)	-0.190275 (0.14293) [-1.33120]	0.009007 (0.11712) [0.07691]	-0.296801 (0.11692) [-2.53842]
VMIDCAP(-3)	0.075977 (0.14471) [0.52502]	-0.116285 (0.11857) [-0.98070]	0.139020 (0.11838) [1.17438]
VMIDCAP(-4)	-0.179658 (0.13617) [-1.31935]	-0.002464 (0.11158) [-0.02208]	-0.276495 (0.11139) [-2.48217]
VMIDCAP(-5)	0.066248 (0.11765) [0.56308]	-0.075072 (0.09640) [-0.77872]	0.048649 (0.09624) [0.50548]
VSMALLCAP(-1)	-0.686790 (0.20585) [-3.33640]	-0.310517 (0.16867) [-1.84098]	0.163923 (0.16839) [0.97349]
VSMALLCAP(-2)	1.025728 (0.24555) [4.17728]	0.354769 (0.20120) [1.76327]	0.855533 (0.20086) [4.25925]
VSMALLCAP(-3)	-0.339953 (0.25248) [-1.34645]	0.001285 (0.20688) [0.00621]	-0.263382 (0.20653) [-1.27524]
VSMALLCAP(-4)	-0.555231 (0.25440) [-2.18248]	-0.414485 (0.20846) [-1.98836]	-0.416436 (0.20811) [-2.00105]
VSMALLCAP(-5)	0.557427 (0.18570) [3.00174]	0.464445 (0.15216) [3.05232]	0.500853 (0.15191) [3.29709]
C	0.260617 (0.14687) [1.77445]	0.690376 (0.12034) [5.73665]	0.239894 (0.12014) [1.99671]
R-squared	0.912559	0.772925	0.935225
Adj. R-squared	0.907071	0.758673	0.931160
Sum sq. resids	324.4656	217.8446	217.1199
S.E. equation	1.165160	0.954717	0.953127
F-statistic	166.2851	54.23436	230.0468
Log likelihood	-392.5461	-341.7504	-341.3255
Akaike AIC	3.204283	2.805886	2.802553
Schwarz SC	3.426480	3.028083	3.024750
Mean dependent	2.665320	1.833166	2.437162
S.D. dependent	3.822173	1.943443	3.632700

Determinant resid covariance (dof adj.)	0.060923
Determinant resid covariance	0.050160
Log likelihood	-703.9390
Akaike information criterion	5.897561
Schwarz criterion	6.564152
Number of coefficients	48

ROOTS OF CHARACTERISTIC POLYNOMIAL: APPENDIX B

Appendix B1: Roots of Characteristic Polynomial for the US

Roots of Characteristic Polynomial	
Root	Modulus
0.843167 - 0.179812i	0.862127
0.843167 + 0.179812i	0.862127
0.615257 - 0.563631i	0.834399
0.615257 + 0.563631i	0.834399
-0.530267 - 0.625126i	0.819735
-0.530267 + 0.625126i	0.819735
-0.717991 - 0.196574i	0.744414
-0.717991 + 0.196574i	0.744414
-0.183983 - 0.721240i	0.744336
-0.183983 + 0.721240i	0.744336
0.144259 - 0.682962i	0.698031
0.144259 + 0.682962i	0.698031
0.624455 - 0.201358i	0.656117
0.624455 + 0.201358i	0.656117
0.446293	0.446293
No root lies outside the unit circle. VAR satisfies the stability condition.	

Appendix B2: Roots of Characteristic Polynomial for the UK

Roots of Characteristic Polynomial	
Root	Modulus
0.897656	0.897656
0.820215 - 0.115283i	0.828277
0.820215 + 0.115283i	0.828277
0.684161 - 0.381716i	0.783443
0.684161 + 0.381716i	0.783443
-0.480494 - 0.526939i	0.713119
-0.480494 + 0.526939i	0.713119
0.126800 - 0.625452i	0.638176
0.126800 + 0.625452i	0.638176
-0.576755 - 0.123874i	0.589908
-0.576755 + 0.123874i	0.589908
0.110503 - 0.332332i	0.350223
0.110503 + 0.332332i	0.350223
-0.041156 - 0.108291i	0.115848
-0.041156 + 0.108291i	0.115848
No root lies outside the unit circle. VAR satisfies the stability condition.	

VARIANCE DECOMPOSITION: APPENDIX C

Appendix C1: Variance Decomposition for the US

Variance Decomposition of VLARGECAP (US):			
Period	S.E.	VLARGECAP	VMIDCAP
1	0.795729	100.0000 (0.00000)	0.000000 (0.00000)
2	1.501051	50.44447 (0.04115)	49.54210 (0.04662)
3	1.765790	40.64188 (0.07262)	59.26432 (0.07646)
4	1.893878	38.36738 (0.11022)	61.33955 (0.11634)
5	2.443614	26.51933 (0.13876)	72.45325 (0.16471)
6	2.669035	22.75281 (0.16611)	73.88123 (0.22311)
7	2.801270	20.96263 (0.19350)	71.80231 (0.30001)
8	2.953765	19.07221 (0.22003)	69.44585 (0.38681)
9	3.001265	18.52777 (0.24745)	68.04348 (0.48826)
10	3.028688	18.21805 (0.27583)	67.06634 (0.59799)

Variance Decomposition of VMIDCAP (US):			
Period	S.E.	VLARGECAP	VMIDCAP
1	1.215687	8.962449 (0.03413)	91.03755 (0.03413)
2	1.619348	7.410887 (0.04717)	91.67045 (0.07257)
3	1.962817	8.298774 (0.06265)	88.86533 (0.13165)
4	2.327574	7.906924 (0.07586)	84.94950 (0.20293)
5	2.516562	8.167682 (0.08713)	82.85290 (0.29550)
6	2.656752	8.250410 (0.09757)	80.68413 (0.40316)
7	2.769385	8.063457 (0.10703)	79.45999 (0.52199)
8	2.833697	7.906813 (0.11604)	78.38650 (0.65319)
9	2.884968	7.679472 (0.12516)	77.64399 (0.79276)
10	2.919079	7.502402 (0.13485)	76.92368 (0.93989)

Variance Decomposition of VSMALLCAP (US):			
Period	S.E.	VLARGECAP	VMIDCAP
1	3.174867	22.73050 (0.04614)	26.58990 (0.04247)
2	4.633948	17.98098 (0.06590)	50.56837 (0.07158)
3	5.349329	15.73876 (0.07621)	60.37462 (0.09121)
4	5.882950	14.75636 (0.08648)	63.85701 (0.12375)
5	6.404173	13.27166 (0.09700)	67.02421 (0.17575)
6	6.601082	12.88448 (0.10806)	66.22483 (0.24545)
7	6.753535	12.68357 (0.12048)	64.72557 (0.32748)
8	6.886368	12.44084 (0.13400)	63.91398 (0.41634)
9	6.923719	12.31830 (0.14849)	63.43165 (0.51159)
10	6.951565	12.22483 (0.16419)	63.21968 (0.61047)

Appendix C2: Variance Decomposition for the UK

Variance Decomposition of VLARGECAP (UK):				
Period	S.E.	VLARGECAP	VMIDCAP	VSMALLCAP
1	1.165160	100.0000 (0.00000)	0.000000 (0.00000)	0.000000 (0.00000)
2	1.722891	97.23702 (1.64804)	0.670686 (0.81052)	2.092292 (1.30033)
3	2.198768	98.24096 (1.34322)	0.414270 (0.67290)	1.344771 (1.07396)
4	2.725515	98.55386 (1.58197)	0.440800 (0.92039)	1.005341 (1.10926)
5	3.064022	97.99445 (2.32636)	0.354340 (1.00201)	1.651205 (1.95592)
6	3.368394	98.08293 (2.65459)	0.298486 (1.19295)	1.618580 (2.27150)
7	3.565621	98.02764 (3.07882)	0.276250 (1.44218)	1.696105 (2.68199)
8	3.690756	97.97037 (3.47497)	0.309160 (1.76616)	1.720474 (3.04574)
9	3.772215	98.02257 (3.76391)	0.314272 (2.06089)	1.663162 (3.24668)
10	3.824266	98.04677 (4.06030)	0.316221 (2.29525)	1.637008 (3.46639)

Variance Decomposition of VMIDCAP (UK):				
Period	S.E.	VLARGECAP	VMIDCAP	VSMALLCAP
1	0.954717	62.60846 (3.76878)	37.39154 (3.76878)	0.000000 (0.00000)
2	1.234879	69.20536 (4.07758)	29.96209 (3.88732)	0.832552 (1.12801)
3	1.535481	78.31182 (4.00004)	20.94146 (3.70469)	0.746721 (1.21939)
4	1.707394	82.02458 (4.27178)	17.19689 (3.82310)	0.778537 (1.55573)
5	1.869990	84.48218 (4.29033)	14.34312 (3.59377)	1.174699 (2.03748)
6	1.941543	85.40468 (4.37959)	13.37559 (3.51983)	1.219730 (2.46329)
7	1.978647	85.73527 (4.42949)	13.07017 (3.49294)	1.194553 (2.72277)
8	1.989821	85.73040 (4.52945)	13.08243 (3.58645)	1.187166 (2.89954)
9	1.994072	85.67644 (4.61987)	13.11767 (3.66918)	1.205894 (3.05420)
10	1.995599	85.60297 (4.70132)	13.12766 (3.70996)	1.269364 (3.17788)

Variance Decomposition of VSMALLCAP (UK):				
Period	S.E.	VLARGECAP	VMIDCAP	VSMALLCAP
1	0.953127	85.10549 (1.72636)	0.400518 (0.28104)	14.49399 (1.69632)
2	1.481277	92.63895 (1.13541)	1.198889 (0.88144)	6.162163 (0.89875)
3	1.918303	95.18543 (1.11680)	0.719626 (0.63574)	4.094943 (1.01330)
4	2.515851	96.95902 (1.15261)	0.597513 (0.89427)	2.443472 (0.85247)
5	2.869829	97.36775 (1.33452)	0.493503 (0.91237)	2.138746 (0.89095)
6	3.181866	97.72981 (1.62874)	0.510658 (1.14036)	1.759535 (1.09911)
7	3.378755	97.86553 (2.03983)	0.554335 (1.49071)	1.580134 (1.36445)
8	3.500775	97.79992 (2.54122)	0.710367 (1.95314)	1.489717 (1.65558)
9	3.577728	97.77287 (2.99288)	0.788114 (2.35302)	1.439015 (1.85639)
10	3.625023	97.75691 (3.40966)	0.833962 (2.65989)	1.409131 (2.09335)

IMPUSE RESPONSE: APPENDIX D

Appendix D1: Impulse response for the US

Response of VLARGECAP:			
Period	VLARGECAP	VMIDCAP	VSMALLCAP
1	0.795729 (0.03524)	0.000000 (0.00000)	0.000000 (0.00000)
2	0.709512 (0.08648)	1.056532 (0.06926)	-0.017395 (0.04964)
3	0.361425 (0.10176)	0.855342 (0.10330)	0.051206 (0.09369)
4	0.330048 (0.10501)	0.593499 (0.11435)	-0.087104 (0.11038)
5	0.455394 (0.14040)	1.458167 (0.13383)	-0.225474 (0.11862)
6	0.193178 (0.15254)	0.967857 (0.15938)	-0.422413 (0.15256)
7	0.155273 (0.15282)	0.609344 (0.17105)	-0.572678 (0.16553)
8	0.137976 (0.15126)	0.651577 (0.17820)	-0.658806 (0.17022)
9	0.070051 (0.14457)	0.264796 (0.17973)	-0.455894 (0.16932)
10	0.047182 (0.13177)	0.151267 (0.17684)	-0.374496 (0.16845)

Response of VMIDCAP:			
Period	VLARGECAP	VMIDCAP	VSMALLCAP
1	0.363944 (0.07440)	1.159930 (0.05136)	0.000000 (0.00000)
2	0.248755 (0.09642)	1.028797 (0.09086)	-0.155210 (0.07614)
3	0.354102 (0.11233)	1.009856 (0.11402)	-0.291834 (0.10190)
4	0.329610 (0.13504)	1.085612 (0.13642)	-0.527023 (0.12517)
5	0.298163 (0.14405)	0.803070 (0.15186)	-0.426221 (0.14669)
6	0.255098 (0.14967)	0.669183 (0.16193)	-0.460828 (0.15625)
7	0.189961 (0.14871)	0.631843 (0.16785)	-0.419346 (0.16376)
8	0.128368 (0.14003)	0.447361 (0.16976)	-0.379127 (0.16605)
9	0.065279 (0.12746)	0.409918 (0.16861)	-0.347720 (0.16296)
10	0.010752 (0.11415)	0.303877 (0.16218)	-0.324843 (0.15502)

Response of VSMALLCAP:			
Period	VLARGECAP	VMIDCAP	VSMALLCAP
1	1.513666 (0.18718)	1.637133 (0.15902)	2.260175 (0.10008)
2	1.252979 (0.27428)	2.859823 (0.25297)	1.282636 (0.20603)
3	0.801596 (0.30636)	2.533298 (0.31724)	0.285803 (0.28950)
4	0.776753 (0.33277)	2.196348 (0.35225)	-0.752654 (0.33629)
5	0.579758 (0.36093)	2.321335 (0.37985)	-0.824391 (0.36819)
6	0.413714 (0.35960)	1.169642 (0.39677)	-1.010755 (0.39248)
7	0.413143 (0.33811)	0.815165 (0.39880)	-1.095800 (0.39870)
8	0.338669 (0.30998)	0.887603 (0.39551)	-0.953564 (0.38723)
9	0.073664 (0.27895)	0.313797 (0.38672)	-0.641823 (0.36257)
10	0.049271 (0.23935)	0.377691 (0.36910)	-0.491215 (0.34092)

Appendix D2: Impulse response for the UK

Response of VLARGECAP:			
Period	VLARGECAP	VMIDCAP	VSMALLCAP
1	1.165160 (0.05159)	0.000000 (0.00000)	0.000000 (0.00000)
2	1.236424 (0.09379)	0.141097 (0.07511)	-0.249212 (0.07551)
3	1.364990 (0.12465)	-0.010949 (0.10934)	-0.053920 (0.10424)
4	1.603580 (0.15514)	0.112766 (0.13699)	-0.098321 (0.13108)
5	1.370744 (0.18183)	-0.022842 (0.16672)	-0.283439 (0.15726)
6	1.388749 (0.20198)	-0.024500 (0.17483)	-0.169194 (0.16643)
7	1.155131 (0.21828)	-0.035426 (0.18514)	-0.178862 (0.18260)
8	0.939313 (0.22830)	-0.083613 (0.18365)	-0.136823 (0.19541)
9	0.776541 (0.23194)	-0.051059 (0.17923)	-0.047999 (0.20568)
10	0.625399 (0.23499)	-0.039086 (0.16787)	-0.052452 (0.21131)

Response of VMIDCAP:			
Period	VLARGECAP	VMIDCAP	VSMALLCAP
1	0.755424 (0.04955)	0.583796 (0.02585)	0.000000 (0.00000)
2	0.696178 (0.07164)	0.340708 (0.06225)	-0.112676 (0.06141)
3	0.889398 (0.08825)	0.191932 (0.07884)	-0.070069 (0.07377)
4	0.738117 (0.10128)	0.087095 (0.09515)	-0.071347 (0.09142)
5	0.750367 (0.11129)	0.015384 (0.10295)	-0.135579 (0.09582)
6	0.514955 (0.11612)	-0.051431 (0.10141)	-0.070008 (0.09815)
7	0.370363 (0.11927)	-0.086594 (0.10041)	-0.028080 (0.10034)
8	0.194485 (0.12025)	-0.079253 (0.09355)	0.015402 (0.10219)
9	0.111239 (0.11753)	-0.060139 (0.08607)	0.030753 (0.10204)
10	0.047884 (0.11687)	-0.034599 (0.07728)	0.051001 (0.10059)

Response of VSMALLCAP:			
Period	VLARGECAP	VMIDCAP	VSMALLCAP
1	0.879285 (0.04524)	-0.060320 (0.02288)	0.362865 (0.01607)
2	1.122285 (0.07898)	0.150557 (0.06037)	0.059482 (0.06116)
3	1.212456 (0.10829)	-0.013251 (0.09424)	0.124419 (0.09024)
4	1.623057 (0.14030)	0.106481 (0.11973)	0.063012 (0.11450)
5	1.371896 (0.16942)	-0.053149 (0.15396)	-0.146580 (0.14682)
6	1.369416 (0.19067)	-0.105147 (0.16661)	-0.044661 (0.15777)
7	1.130435 (0.20729)	-0.107622 (0.17785)	-0.047411 (0.17390)
8	0.901935 (0.21739)	-0.154194 (0.17784)	-0.046726 (0.18547)
9	0.727504 (0.22114)	-0.117563 (0.17330)	0.040309 (0.19477)
10	0.575300 (0.22353)	-0.093325 (0.16275)	0.031226 (0.20018)