# Addressing the Power of News in Financial Markets: Analysing Stock Returns with GARCH Models

A thesis submitted for the degree of Doctor of Philosophy by

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# Abstract

Risk management remains a paramount concern within the investment industry. Despite a wealth of literature and papers dedicated to stock volatility estimation and forecasting analysis, many experts redirected their attention to the relationship between news and stock returns.

This thesis comprises three essays investigating the impact of news (newspaper headlines) on stock return indices by applying GARCH-type models (GARCH, EGARCH, and MGARCH). The initial essay delves into the returns estimation and forecasting of the GARCH model using various distributions in a portfolio context. The subsequent essay introduces news sentiment as an additional variable in GARCH and EGARCH models to effectively explore the impact on stock return estimations. The final essay addresses the correlations between the geopolitical risk news and energy stock (renewable and non-renewable energy stock) return fluctuations, explicitly focusing on the Russian-Ukraine war period. Multivariate GARCH models are employed.

Chapter 2 seeks to assess the accuracy of the GARCH (1, 1) model in estimating and predicting portfolio returns and conditional variance for long-term investment, featuring two distinct distributions (normal and students' t distribution). Weekly data, beginning in June 2010 and ending in June 2020 for ten years, were abstracted within the BRICS market. The findings underscore the superiority of the standard distribution assumption over the Student's t-distribution with GARCH (1, 1) for estimating and predicting conditional volatility.

Chapter 3 analyses news impact on company stock returns and focuses on information within diverse industries. It evaluates news intensity, news sentiments (positive and negative news sentiment), and the VIX index (Benchmark index of the broad U.S. stock market) across individual companies and portfolio returns within selected APEC countries. Chapter 3 uses daily stock price data spanning 2017-2022 to employ analysis based on plain GARCH (1, 1) and EGARCH (1, 1) models. Models incorporating VIX log returns and varied news types as supplementary variables reveal results that diverge across industries and countries yet consistently affirm a robust correlation between the VIX index, news indexes, particularly news intensities and stock returns. The outperformance of GARCH over EGARCH becomes evident, highlighting stocks' heightened susceptibility to negative news.

Chapter 4 scrutinises the repercussions of geopolitical risk-related news on renewable and non-renewable energy stock returns, particularly during the Russian-Ukraine war period. This examination involves testing three renewable energy stock indexes alongside three indexes representative of non-renewable energy stocks on a global, European, and US scale. By collecting daily energy stock index data from 2022 to 2023, the chapter applies the MGARCH model to elucidate correlations among the stock return indexes and GPR news. The analysis shows a positive correlation between world-level, European-level and American energy stock returns. The chapter also finds that increased headlines concerning geopolitical risk correspond to heightened renewable energy prices and decreased non-renewable energy prices.

# Acknowledgements

I want to express my gratitude to all those who have supported me throughout my research journey.

My sincerest thanks go to my principal supervisor, Dr. Nicola Spagnolo. This PhD thesis would only have materialised with his patient guidance, enthusiastic encouragement, and invaluable suggestions. His illuminating instruction and unwavering support have been instrumental in turning my aspirations into reality.

I am also deeply thankful to Dr. Fabio Spagnolo, whose support allowed me to pursue my PhD at Brunel University. I appreciate the insightful comments provided by Dr. Woo-Young Kang and Dr. Matthias Winter, which greatly enriched my research.

My gratitude mainly goes to my parents, whose financial support has facilitated my academic journey. Their continuous guidance has been a beacon of strength throughout every phase of my Ph.D. life. I am equally indebted to my friends for their unwavering care and companionship.

Lastly, I wish to convey my deep appreciation to the Department of Economics and Finance at Brunel University for their support and provision of resources during my doctoral studies.

To all those mentioned above, my heartfelt thanks for your invaluable contributions and support. Your role in my journey is immeasurable and deeply cherished.

# Declaration

I hereby declare that the thesis is based on my original work, except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Brunel University or other institutions.

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# Contents

# List of tables



**Appendix B**

# List of figures



**Appendix A**

**Appendix C**

# List of abbreviations

**ARCH:** Autoregressive conditional heteroscedasticity

**GARCH:** Generalized autoregressive conditional heteroscedasticity

**VaR:** Value at risk

**EGARCH:** The exponential general autoregressive conditional heteroskedastic model

**GPR news:** Geopolitical risk news

**VIX:** Benchmark index of the broad U.S. stock market

**T-GARCH:** GARCH model with students't distribution

**N-GARCH:** GARCH model with normal distribution

**GED:** Generalized error distribution

**APEC:** The Asia pacific economic co-operation

**MGARCH:** Multivariate generalized autoregressive conditional heteroskedasticity model

**DCC:** The dynamic conditional correlation model

**CCC:** Constant conditional correlations model.

**BRICS:** Brazil, Russia, India, China and South Africa

**EWMA:** The exponential weighted moving average model

**IGARCH:** Integrated generalized autoregressive conditional heteroskedasticity model

**GJR-GARCH:** The Glosten, Jagannathan, and Runkle model

**ASEAN:** Association of Southeast Asian Nations

**BOVESPA:** IBOVESPA index, benchmark of the Brazilian stock market

**MOEX:** MICEX Index, benchmark of the Russian stock market **SENSEX:** The S&P Bombay Stock Exchange or Sensitive Index

**SSE:** Stocks index of all shares traded at the Shanghai Stock Exchange

**FTSE/JSE:** The JSE securities exchange and the Johannesburg African stockexchange

**S&P:** Standard & Poor's 500 index

**ASX:** The Australia stock market index

**SP/TSX:** The S&P/TSX composite index

**NIKEEI:** Japan's Nikkei 225 stock average

**KOSPI:** Korean composite stock price indexes

**HSC:** The Hang Seng China 50 Index

**SPGTCED:** The S&P global renewable energy index

**ERIXP:** The European Renewable Energy Index

**SPXESUP:** The S&P 500 ESG Index

**SPGOGUP:** S&P Global Oil Index

**SXEP:** STOXX Europe 600 Oil & Gas Price EUR

**USCRWTIC:** The S&P GSCI Crude Oil index

**SPGTCED:** The S&P global renewable energy index

# Chapter 1

# Introduction

In the ever-evolving landscape of financial markets, the ability to predict and understand stock price movements has been the subject of relentless scrutiny and innovation. In this information age, where data flows ceaselessly and market sentiment shifts with every headline, the interplay between news and stock prices is a pivotal yet complex relationship. This thesis embarks on a journey into the heart of this intricate nexus, aiming to shed light on the influence of news on stock returns by applying GARCH-type models.

The finance industry is constantly dealing with market unpredictability, leading investors to seek ways of minimising risks and making well-informed choices. To address this challenge, our research proposes a groundbreaking method incorporating news sentiment into the GARCH framework. By doing so, we can reveal how news stories, market sentiment, and fluctuations in stock prices are interrelated.

The core objective of this thesis is to provide a comprehensive understanding of how news sentiment impacts stock prices, enhance our comprehension of financial market dynamics, and empower investors to make more informed decisions. By examining the relationship between news sentiment and stock returns, we aspire to offer valuable insights that can contribute to more effective risk management strategies and astute investment choices.

## 1.1 Risk Management

Financial risk pertains to the possibility of financial losses or experiencing adverse consequences resulting from unpredictable future occurrences or fluctuations in market conditions. A core principle within finance encompasses various scenarios in which the realised result differs from the anticipated outcome, ultimately resulting in financial detriment. Financial risk can affect individuals, businesses, institutions, and governments. It is a critical consideration in various financial decisions and strategies (Grippa, Schmittmann and Suntheim, 2019; Zhao, Shahbaz, Dong and Dong, 2021).

Market risk, or systematic or non-diversifiable risk, pertains to the potential for encountering financial losses resulting from unfavourable shifts in financial markets. This includes elements such as fluctuations in interest rates, currency exchange rates, commodity prices, and trends in stock markets. Market risk affects all investments to varying degrees and cannot be eliminated through diversification (Leo and Maddulety, 2019).

In the realms of economic and financial development, significant attention is dedicated to the management of risks in investments. Financial risk management involves identifying, assessing, and mitigating these risks to minimise potential adverse impacts. This objective can be achieved through risk assessment models and prudent financial planning (Gurtu and Johny, 2021).

Moreover, risk can be quantified as the volatility of returns in a specific asset, which consequently affects the capital gain – the difference between the buying and selling prices (Hubbard, 2020). Therefore, estimating and forecasting the volatility of asset returns consistently holds a pivotal role in various financial applications within financial markets.

## 1.2 GARCH model analysis

Traditionally, various time series models were employed for analysing financial asset movements. Among these models, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model stands out as a statistical tool extensively used in econometrics and finance for the analysis and prediction of volatility in financial markets and time series data (So & Philip (2006), Hamid & Hasan (2016), Malik & Anjum (2019) and Sobreira & Louro (2020)). Serving as an extension of the Autoregressive Conditional Heteroskedasticity (ARCH) model, the GARCH model is specifically designed to capture the evolving levels of volatility within a time series—a common characteristic observed in financial data.

The GARCH model proves particularly valuable in the following areas:

Volatility Forecasting (Aras, 2021): The primary application of the GARCH model is to predict the future volatility of financial assets, such as stocks, bonds, currencies, and commodities. Accurate volatility forecasting is crucial for risk management and portfolio optimisation.

Risk Management (Guo, 2022): By providing precise predictions of future volatility, the GARCH model assists financial institutions, fund managers, and individual investors in evaluating investment risks. This, in turn, enables more informed decisions regarding portfolio allocation and strategies.

Portfolio Management (Ghosh, Sanyal and Jana 2021): GARCH models aid in estimating the risk associated with various assets within a portfolio. This knowledge is essential for crafting diversified portfolios that align with investors' risk preferences.

Value-at-Risk (VaR) Calculation (Kakade Jain and Mishra, 2022): VaR quantifies the maximum potential loss a portfolio could experience over a specific time frame at a given confidence level. GARCH models enhance VaR calculations by providing more accurate volatility estimates.

Market Volatility Analysis (Bonga, 2019): Researchers and analysts leverage GARCH models to examine market volatility patterns and dynamics. This analysis sheds light on how markets respond to diverse events and economic indicators.

Economic and Financial Research: Academic studies Tse & Tsung (1992), Brook & Burke (2003), Olowe (2009), Dana (2016), and Trapero, Cardos & Kourentzes (2019) employ GARCH models to investigate financial market behaviour and the influence of various economic variables on volatility.

Acknowledging GARCH models' efficacy in both volatility analysis and forecasting is imperative. However, it is fundamental to note that these models rely on certain assumptions and are subject to limitations. As such, it is essential to exercise discretion when utilising GARCH models to ensure that the results are accurate and reliable.

## 1.3 The effect of information including extreme event news

The impact of data on stock returns cannot be overstated. The financial news cycle can quickly sway investors' emotions and mental attitudes, leading to notable fluctuations in the stock market. For example, adverse reports on a company can prompt traders to reevaluate their positions and sell their holdings, ultimately causing a drop in stock values. When it comes to analysing market data, whether as investment analysts, institutional traders, or market speculators, the primary objective remains to attain significant gains.

Since 2016, the financial markets have been jolted by many extreme events. These events have caused significant shocks that have left investors reeling. It is imperative that investors remain vigilant and informed about these events to make informed decisions and mitigate risks:

Brexit Referendum (2016). The United Kingdom's vote to leave the European Union led to uncertainty regarding trade relationships, regulatory frameworks, and the economic future of the UK and the EU. As a result, financial markets experienced significant volatility, and the British pound sterling weakened.

U.S.-China Trade War (2018-present). The U.S.-China trade war, ongoing since 2018, has led to tariffs on many products, causing global trade uncertainty, supply chain disruption, and market volatility. The impacts have been felt across various sectors with significant implications for corporate profitability, investors, and other stakeholders. The long-term implications of the conflict remain unclear, necessitating vigilance from policymakers, businesses, and other stakeholders to mitigate potential risks and capitalise on emerging opportunities.

COVID-19 Pandemic (2020-present): The global pandemic caused widespread lockdowns, supply chain disruptions, and an economic contraction. Financial markets experienced significant volatility during this time, with an initial sharp decline followed by unprecedented government interventions. These interventions took the form of stimulus packages and monetary easing, all aimed at stabilising economies and markets.

Oil Price Collapse (2020): The 2020 oil price collapse was a significant and devastating event that shook the world economy. A convergence of factors, including reduced demand due to the COVID-19 pandemic and a price war between Saudi Arabia and Russia, led to historically low oil prices. The impact of this crisis was felt globally, with energy-related industries and oil-exporting economies suffering significant losses. The ripple effects of the decline in oil prices were far-reaching, affecting the financial stability of both businesses and individuals. The future of the global economy became uncertain, particularly in countries where oil exports make up a substantial portion of their GDP. This event will undoubtedly be remembered as a turning point in the energy industry's history, and its aftermath will continue to be felt for years.

Recent global events have greatly affected the markets, leading businesses, financial market actors, and policymakers to consider the economic impact carefully. Quantifying risk is a crucial aspect of this evaluation, emphasising the importance of effective risk management in financial markets. Despite the widespread use of the GARCH model by financial institutions and investors, it failed to account for the impact of news.

## 1.4 Research aim

There needs to be more knowledge regarding utilising the GARCH model for risk assessment in financial markets. Despite an extensive body of literature on the topic, more research needs to be conducted to investigate the impact of news on stock returns using GARCH estimation. This study endeavours to bridge this gap with academic rigour and practical relevance. By tackling this issue, the research aims to further academic discourse and provide valuable insights into decision-making frameworks for financial investment.

The main objective of this thesis is to examine the impact of news sentiment on stock prices by integrating it as an additional variable in the GARCH model. To achieve this, several subsidiary objectives are pursued:

Chapter 2: Apply GARCH models with different distributions in portfolio estimations and forecasting to compare the results.

Chapter 3: Incorporating news sentiment as supplementary factors in both GARCH and EGARCH models to substantially increase their precision and forecasting capabilities.

Chapter 4: Conduct a comprehensive investigation into the impact of geopolitical risk news on stock returns utilising the MGARCH model.

By systematically pursuing these objectives, this research endeavours to enrich the theoretical underpinnings of risk management using quantitative methods while providing actionable insights that can inform investors, policymakers and other financial organisations.

This research employs a comprehensive methodology integrating quantitative analysis and qualitative exploration through GARCH estimations to fulfil the stated goals. By incorporating news sentiment data and indexes, the investigation gains an empirical aspect that enhances the credibility and depth of the findings. Overall, this approach enables a complete understanding of news with GARCH estimation.

The following chapters of this thesis are structured in the following manner:

Chapter 2: The comparison of N-GARCH (1,1) and T-GARCH (1,1) in estimation and forecasting volatility in BRICS markets.

Chapter 3: Analysing news impact on APEC stock volatilities with GARCH models.

Chapter 4: The reaction of energy stocks to geopolitical news during the Russian-Ukraine conflict.

Chapter 5: Concluding remarks.

Each chapter presented in this research contributes a distinct facet to the overarching narrative, leading to a comprehensive understanding of the impact of news on stock returns. This understanding is fundamental in shaping the future of the financial industry and policy decisions. By examining the various chapters, readers will gain insights into the intricate mechanisms of the financial market and how it responds to news. Ultimately, this knowledge will enable them to make informed decisions in the fast-paced and ever-changing world of finance.

# Chapter 2

# The comparison of N-GARCH (1, 1) and T-GARCH (1, 1) in estimation and forecasting volatility in BRICS markets

## 2.1 Introduction

The bedrock of financial products lies in the concepts of risk and return. Return denotes the net gains or losses incurred during a specific investment period, while risk encapsulates the possible fluctuations in returns within an asset. Investors strive for higher returns but must also mitigate unbridled risks that can result in financial setbacks. Therefore, estimating asset return volatility is crucial in various financial applications in ever-changing markets.

The ongoing trade dispute between the United States and China that began in 2018 and the worldwide economic downturn brought on by the Coronavirus pandemic in 2020 has profoundly affected global markets. As a result, enterprises, financial market players, policymakers, and other economic actors are grappling with the challenge of comprehending the extensive implications.

Risk assessment is a critical component of this analysis, underscoring the crucial significance of return estimating and forecasting within the intricate web of financial markets. It is widely used for portfolio selection derivative pricing and offers a thorough assessment of market risk within asset portfolios.

Engle (1982) and Bollerslev (1986) developed the ARCH/GARCH models to measure the risk associated with financial instruments. The GARCH model is a widely used framework for volatility forecasting based on return time series. Notable references in this context include So & Philip (2006), Hamid & Hasan (2016), Malik & Anjum (2019), and Sobreira & Louro (2020).

GARCH-type models are employed by various organisations such as banks, regulators, portfolio managers, and investors for different error distributions. This is achieved using standard computer software to facilitate efficient risk management. By leveraging these models, organisations can analyse and evaluate financial risk in a structured manner, which in turn helps them make informed decisions. GARCH-type models provide a reliable and effective approach for organisations to manage financial risk and are a widely accepted practice in the industry.

A considerable amount of literature is dedicated to studying GARCH family models. This body of work, exemplified by the likes of Balaban (2004), Galdi & Pereira (2007), Miah & Rahman (2016), and Babikir (2018), continues to grow and explores the applications of these models under different specifications across multiple disciplines. This research aids in analysing volatility-associated portfolios consisting of bonds, exchange rates and stock markets.

Furthermore, the straightforward GARCH (1, 1) model has demonstrated its ability to capture numerous economic and financial time series dynamics effectively. Existing literature presents compelling evidence attesting to the remarkable predictive prowess of the GARCH (1, 1) model, as evidenced by Tse & Tsung (1992), Brook & Burke (2003), Olowe (2009), Dana (2016), and Trapero, Cardos & Kourentzes (2019). Given the substantial success of the GARCH (1, 1) model, the exploration of higher-order GARCH models has yet to be featured in our study.

Gulay (2019) asserts that the robust forecasting performances of models hinge upon selecting an appropriate forecasting performance measure. However, while GARCH is great for estimating volatility of just about any financial time series.

GARCH is a valuable tool for estimating financial time series volatility, yet its forecasting capability is limited by unobserved conditional volatility. To address this issue, a proxy is necessary, but this can lead to an increase in mean-squared error. Consequently, one might conclude that GARCH is no more effective than a homoscedastic benchmark model. Nonetheless, GARCH generally delivers superior results when alpha and beta exhibit high persistence.

In the context of forecasting ability, the GARCH (1, 1) model, when utilising a one-step-ahead forecast, surpasses the predictive potential of the GARCH (1, 1) model relying on a multi-step ahead forecast. Consequently, the focal point of this study predominantly revolves around the one-step-ahead forecast.

Throughout our study's findings, our attention remains directed exclusively towards the parsimonious GARCH (1, 1) model estimation. Nevertheless, it can readily be expanded and modified to accommodate the broader realm of GARCH (p, q) models, where max (p, q) > 1.

Indeed, the acronym BRIC serves as a brief abbreviation denoting the emerging economies of Brazil, Russia, India, and China. Subsequently, in December 2010, South African inclusion culminated in the group's expansion, giving rise to the acronym BRICS. While forming country groupings such as BRICS inherently entails arbitrary selection, criteria such as country size, population, and economic growth potential often serve as prevailing factors. Within this context, at least two discernible strengths intrinsic to the BRICS economies warrant thorough examination.

Taylor (2020) asserts the significance of studying the economies of the BRICS nations, emphasising several key reasons, including their rapid economic growth rates, substantial populations, and burgeoning markets for goods and capital. Notably, prognostications suggest that their collective presence in the global economy could increase twofold over the forthcoming two decades, surging from 25.6% to an estimated 40%. This rationale underscores the inherent motivations of these economies to establish a distinctive consortium or grouping, serving as a counterbalance in multilateral diplomacy, particularly in interactions with the United States and the European Union.

Consequently, a gap in the literature emerges in assessing the GARCH (1, 1) model across various distributions, particularly within portfolios spanning BRICS countries.

This chapter aims to comprehensively analyse and compare the effectiveness of two distinct variations of the GARCH (1, 1) models within the context of BRIC markets. The analysis uses weekly data and concentrates on accurately estimating and forecasting portfolio returns and volatility. The central attention is directed towards understanding the returns and volatilities associated with a pivotal composite metric encompassing stock prices, exchange rates, and bond prices.

The initial model adopts the normal distribution approach proposed by Bollerslev (1986). Conversely, the second model utilises the student's distribution, first introduced by Gosset

(1908). The two models are denoted here as the N-GARCH (1, 1) and T-GARCH (1, 1) model. Significantly, this chapter explores the forecasting accuracy inherent in these models.

The contributions of this chapter to the academic literature are two-fold:

To begin with, this chapter delves into understanding how the volatility of models can be explained using GARCH family models. This involves considering the assumptions about how data is spread out and using predictions to identify the most suitable models. The chapter also closely examines numerous earlier studies that revolve around this subject. Additionally, it highlights portfolios that carry different combinations of index weights, bringing them into focus.

In a word, this chapter aims to assess the accuracy of two GARCH (1, 1) models. These models are utilised alongside distribution assumptions during the portfolio estimation and forecasting processes. This chapter also introduces portfolios that feature varied weights assigned to stock index prices, bond prices, and exchange rates, following the approach outlined by Engel (2001). The ensuing outcomes hold the potential to encourage the integration of asymmetric distribution aspects into future predictive analyses, thereby capturing the volatility of stock returns and offering new insights to academic circles and practitioners in finance.

Notably, this chapter adds to the growing body of research on countries such as BRICS, which have garnered increased attention from researchers. This is important as volatility carries significant economic implications across international investment, risk management, remittances, and stock pricing.

This chapter comprises six well-defined sections, each with a unique objective. The first section acquaints the reader with the study's background and sets the foundation for the research. The second section delves into the theoretical framework and empirical studies that underpin the project's extension. The third section conducts a comprehensive exploration of the datasets and underlying indices. The fourth section outlines the specific econometric techniques and methodology employed in the analysis. The fifth section presents the empirical findings of the study, which are used to draw conclusions for section six. The chapter concludes with section six, providing policy or strategy recommendations and summarising the key points covered throughout the chapter.

## 2.2 Literature review

### 2.2.1 Theoretical background

To provide an information metric to measure risk, when the field of risk management and analysis was growing, the concept of "value the risk", initially presented by Bernstein (1992), has become one of the most critical statistics and an industry-standard in the area of risk management. There is a wealth of literature from the $20^{th}$ century until today, such as Jorion (1996), Butler (1999), Yamai & Yoshiba (2005), Gaye Gencer & Demiralay (2016), Ewing & Dahl (2017), Malik & Anjum (2019), Runes, Mora and Aragón (2020), and Goel & Sharma (2020) which can be found to focus on understanding and analysing risks.

Risk managment is widely embraced by financial institutions, including banks, insurance companies, regulators, and portfolio managers. This is because it enables them to anticipate potential losses in the most extreme and precise scenarios within a specific timeframe and with a predetermined level of certainty. It is beneficial and has been extensively used in portfolio management, as shown by Duffie & Pan (1997), Krokhmal, Palmquist & Uryasev (2002), Ranković, Drenovak, Urosevic & Jelic (2016), Jammazi & Nguyen (2017), Amin, Yahya, Ibrahim & Kamari (2018), and Hung, Su, Chang & Wang (2020).

Numerous models have been presented throughout the contemporary history of economic study to determine which models are most accurate for predicting stocks' volatility. For example, the EWMA model, introduced by Roberts (1959), also discussed by Muth (1960), Cox (1961), Box, Jenkins & MacGregor (1974), and others. The Stochastic Volatility (SV) model, introduced by Taylor in 1986, has significantly developed in financial modelling and volatility analysis. It was expanded upon by Taylor in 1994, Jacquier, Polson, Rossi in 1994, and Kim, Shephard, and Chib in 1998. In 1994, J.P. Morgan (the risk management group) decided to make the Risk Metrics model the universally agreed method for measuring risks in the market.

When constructing a model, assessing the mean statistical characteristics and utilising the acquired parameters in the prediction procedure is standard. Much research compares and employs various volatility models to pinpoint the most effective model for precise forecasting. Other models can lead to vastly different results in risk prediction, as shown by Galdi & Pereira

(2007), Abad, Benito & López (2014), Bui, Klein, Nguyen & Walther (2018), Makamo (2019), Bekiros, Loukeris, Eleftheriadis & Avdoulas (2019) among others.

Some papers found one particular model to be the most accurate; for example, Nilsson (2016), Chan & Grant (2016), Bui, Klein, Nguyen & Walther (2018) and Chun, Cho & Kim (2019) concluded that the SV model is the most effective. Other papers, such as Ding & Meade (2010), Lee, Nguyen & Ry (2017), Berger (2019), and Lestari (2019), claimed that an EWMA model was more effective.

However, Matei (2006), after comparing alternative models, the GARCH model proposed by Bollerslev (1986) is most effective for tracing the actual return process with large amounts of observations without considering the cost component. Similar results that the GARCH-type outperforms the others can be found in So & Philip (2006), Galdi & Pereira (2007), and Fuess, Kaiser & Adams (2007). Numerous studies, see Morimune (2007), Wang & Nishiyama (2015), Lux, Segnon & Gupta (2016), and Emenogu, Adenomon & Nweze (2020) have reported that GARCH stands out as the most accurate model because it effectively captures time-varying volatility clustering, persistence, and the asymmetric responses to not only positive but also adverse shocks of equal magnitude. As the most successful and popular model for in-sample estimating and predicting volatility, the GARCH model became the most common model to estimate and forecast volatility; see Hamid & Hasan (2016), Shiferaw (2018), Ewing, Malik & Anjum (2019), Nugroho, Kurniawati, Panjaitan, Kholil, Susanto & Sasongko (2019), and Sobreira & Louro (2020).

Since the 1990s, researchers have explored and developed extensions to the GARCH model owing to its high effectiveness and potential application in varied domains. For example, EGARCH was mentioned by Nelson (1991), Threshold GARCH produced by Glosten (1993), FGARCH in 1996, suggested by Baillie, and others such as GARCH- M, IGARCH and so on. To improve critical aspects of the GARCH model, there are numerous comparisons inside the GARCH family, and it is not surprising that the results are sometimes different. Vilauso (2002) tested that FIGARCH outperforms GARCH and IGARCH. More recently, Dritsaki (2017) found EGARCH (1, 1) with t-student provide better volatilities forecasting than GARCH (1, 1) and GJR-GARCH (1, 1) using daily stock returns from the Stockholm Stock Exchange. Ariff (2018) analysed that the EGARCH slightly outperforms the GARCH model and extended by Lin (2018) that EGARCH (1, 1) exceeds GARCH (1, 1) and TARCH (1, 1).

While more sophisticated GARCH models are available, the original GARCH (1,1) model remains a popular benchmark for practitioners to compare against. Its simplicity, effectiveness, and usefulness in risk management and financial forecasting have made it a trusted tool in the field. Robert Engle (2001) explained that the standard notion (1,1) has been described as specifying how many lags for autoregressive (ARCH terms) and moving average lags (GARCH terms) based on the GARCH (p, q) model, which was introduced by Bollerslev in 1986 and Taylor in 1986, has become a prominent tool in the field of financial modelling and risk analysis. Considerable emphasis has been placed on various statistical tests and criteria to ascertain an appropriate model. Numerous empirical findings concluded that GARCH (1, 1) is the most accurate predictive model.

Early researchers such as Tse & Tsung (1992) stated that GARCH (1, 1) models were assumed to be reacting faster to those high volatility environments. GARCH (1, 1) model has been concluded to fit many economic and financial time series superiorly; see Taylor (1994), Bekaert & Harvey (1997), Aggarwal, Inclan & Leal (1999).

Further, Brook & Burke (2003), Frimpong & Oteng (2006), Galdi & Pereira (2007) and Olowe (2009) found a similar conclusion that it is the most accurate model to describe the data and measure volatility. The forecasting ability of GARCH (1, 1) has been well explored and documented in the literature. Bollerslev (1987), McCurdy & Morgan (1987), Hsieh (1988, 1989), Baillie & Bollerslev (1989), and Sharma (1996) showed the GARCH (1, 1) model has been surprisingly successful in predicting conditional variances. Similar results can be found from Balaban (2004); results revealed that the standard GARCH (1, 1) model provides significantly better forecasts in exchange rate volatility.

Also, there is evidence in Hansen & Lunde (2005) that it is difficult to improve upon GARCH (1, 1) in terms of its forecasting ability compared to other GARCH-type models. Jafari, Bahraminasab & Norouzzadeh (2007) further explained the well-known idea that the GARCH (1, 1) model works well.

Recent papers such as Trapero, Cardos & Kourentzes (2019) stated that, for longer lead times, GARCH (1, 1) is deemed more suitable because the primary deviation of utmost significance is the autocorrelation of the variance in the forecast errors. Dana (2016) showed that the

GARCH (1, 1) models outperform EGARCH (1, 1); Rizwan & Khursheed (2018) found the GARCH (1, 1) is the most suitable for the Islamic stock index of Pakistan. Shabani, Gharneh & Esfahanipour (2017) found that the GARCH (1, 1) model has demonstrated superior performance compared to all six other univariate GARCH (p, q) models when applied to the Brent crude oil market, regardless of the loss function used for evaluation.

According to the literature above, GARCH (1, 1) is suitable for estimating conditional volatility and is thus helpful in calculating returns.

Based on most prior research, the conditional distribution of the return in GARCH (1, 1) is assumed to be typical with mean zero. The normal distribution has been a benchmark process for describing return volatilities; see Longerstaey (1995), Barndorff & Nielsen (1997), Oteng & Abayie (2006), Wilhelmsson (2009) and Jensen & Lunde (2001).

Alexander & Lazar (2006) proved that GARCH (1, 1) for normal distribution performs better than symmetric and skewed Student's t-GARCH models in modelling exchange rates. Salamat, Fu, Mohsin, Zia your Rehman & Baig (2018) conducted empirical analyses modelling the volatility of the Pakistani stock market considering five different distribution techniques, including the Normal Distribution (Norm), Student's t Distribution (Std.), Generalized Error Distribution (GED), Student's t Distribution with fixed degrees of freedom (Std. with fixed DOF), and Generalized Error Distribution with specified parameters (GED with set parameters). The results show that GARCH (1, 1) with lagged conditional variance and squared disturbance is significant in all distributions. Others, such as Frimpong, Glasserman, Pirjol & Wu (2019), support the widespread use of Gaussian density to approximate the actual prediction density.

However, others, such as Galdi & Pereira (2007), believe that the normal distribution cannot capture extremely volatile changes in a market index. Therefore, some papers began to investigate the limitation of estimating the risk for normal distribution; for example, Mikosch & Starcia (1998) emphasised that the GARCH models with typical standard errors generate a much thinner tail than observed from accurate data.

McFarland, Pettit & Sung, S. K. (1982), and Baillie & Bollerslev (1991) stated that assuming the normality of errors is not reasonable for various applications in financial economics. McNeil & Frey (2000) found that the GARCH models with a heavy-tailed error demonstrate a higher estimating and forecasting performance. Abadir, Luati & Paruolo (2018) implied that for typical values encountered in GARCH (1, 1) applications, they show that deviations of the prediction distribution from the Gaussian can be minor and hence provide some support to the widespread practice of using the Gaussian density as an approximation of the actual prediction density.

The ability of GARCH (1,1) models with different distribution assumptions, such as usual, student-t and GED, in estimating and forecasting volatility can be found in numerous studies such as Hsieh (1989), Granger & Ding (1995), Zivot (2008), Vee, Gonpot & Sookia (2011). More recently, Rahim, Zahari & Shariff (2016) attempted to examine the different error assumptions: Student-t distribution, GED, skewed Normal distribution, skewed Student-t distribution and skewed GED. They showed that the skewed error distribution assumptions outperform the non-skewed distribution. Almarashi & Khan (2019) revealed that GARCH (1, 1) with GED is the most accurate model for capturing the volatility of stock returns.

Many researchers primarily prefer the student-t distribution exhibiting heavy-tailed characteristics. Vosvrda & Zikes (2004) reported that using the GARCH model with the student- t distribution revealed better parameter estimations. Wilhelmsson (2006) believes the GARCH model estimated with Student's t distribution outperforms the other nine distributions in stock returns. Orhan & Koksal (2012) found that GARCH (1, 1) with Student's t distribution is slightly more effective at estimating volatility than the Normal in both emerging (Brazil and Turkey) and developed (Germany and the USA) markets throughout the global financial crisis.

Recently, contemporary studies used students' t distribution to improve tail modelling, which is believed to enhance conditional volatility modelling. For example, Korkpoe (2016) studied the risk of equity returns in Ghanaian markets using the student's t and normal distributions. The results highlighted that compared with a normal distribution, the students' t can provide more accurate information to describe the volatility dynamics of the market.

Abdullah, Siddiqua, Siddiquee & Hossain (2017) found that GARCH (1, 1) is considered better with Student's t-distribution residuals than the normal distribution for out-of-sample volatility forecasting accuracy in exchange rate volatility between the BDT (Bangladeshi taka) and $ (the US dollar). By comparing the values under different GARCH models, Wang and Dai (2018) found that the GARCH model under the assumption of t distribution can better reflect China's SME board market risk. Notably, this difference did not extend to portfolio estimations.

More recently, Altun, Tatlidil, Ozel & Nadarajah (2018) proposed a new generalised alpha-skew -T (GAST) distribution; they believe it outperforms others and generates the most conservative forecasts for all confidence levels and both long and short positions. Gulay & Emec (2019) specify that the GARCH (1, 1) under the truncated standard normal distribution (TSND) is more suitable than under the standard and student-t distributions in forecasting volatility. Alonso & Estrada (2019) acknowledged that the statistical power varies depending on the heteroscedasticity type and distribution under consideration.

Recent research examines which GARCH (1, 1) model, with normal and student-t distributions, is more efficient in evaluating effectiveness, but most empirical evidence has yet to offer a specific conclusion. Applying different distributions of the model is a worthy and valuable task. This study compares N-GARCH (1, 1) and T-GARCH (1, 1).

The assessment and prediction of volatility across different indices, including equities, exchange rates, bonds, and portfolio returns, have proven valuable in various financial applications within the markets. Such estimates enable businesses to make informed decisions, mitigate risks, and leverage opportunities. Accurate volatility forecasting can provide insight into market trends and aid in developing effective investment strategies. As such, volatility measurements and forecasts have become an indispensable tool for professionals in the financial industry. Countless empirical studies; see Miah & Rahman (2016), Hussain & Ali (2017), Hassan, and Mwambi & Babikir (2018) have applied GARCH and ARCH models in capturing the stock market volatility. Balaban (2004), Hanse & Lunde (2005), Galdi & Pereira (2007), Polak (2016) and Lin (2018) applied the models to exchange rate indices. Reilly (2000) used other asset indexes, such as bonds, as did Jones & Wilson (2004) and Werner & Upper (2004).

Most of the papers lead to the specific recommendation to use a portfolio with more than one asset, which is also important and considered by portfolio managers in their practical use. Engle (2001) used a portfolio which consisted of 50% of Nasdaq, 30% of Dow Jones and 20% of the bond price (a ten-year constant maturity Treasury bond). This project utilises a portfolio containing stock indices, bond prices, and exchange rates based on Engle (2001), however, to observe the variations in outcomes, we assign varying weights to different assets.

Different studies applied different frequency data. Eriksson & Strandberg (2015) tested the GARCH (1, 1) with yearly data, while Balaban (2004), Emenike (2010), Nyoni (2018), and Zeghdoudi & Amine (2019) tested the GARCH (1, 1) with monthly data. Basher & Sadorsky (2016), Katsiampa (2017), and Hamid &Hasan (2017), Mutaju & Pastory (2019) tested with daily data. However, the GARCH (1, 1) model was shown to be the most appropriate for weekly data (Akhtar & Khan, 2016), (Fufa & Zeleke, 2018).

### 2.2.1 Recent literature

Many studies covered different regions/countries. Most countries that have been chosen can be divided into two types: high-income (HI) countries such as Canada, the U.S., Denmark, Norway, Australia, Switzerland, the UK, Japan, and Europe, and emerging market economies (EMEs) such as Brazil, China, Estonia, India, Mexico, Russian Federation and Turkey.

Aouadi, Arouri &Teulon (2015) focused precisely on French stock market behaviour on the conditional volatility estimated from the GARCH (1, 1) market model. Molnár (2016) used a broad class of assets, particularly 30 individual stocks, six stock indices and simulated data from the Dow Jones Industrial Average, which represents the United States. Choudhry, Hasan & Zhang (2019) empirically estimated and forecasted the hedge ratios of four European-developed stock futures markets (Greece, Hungary, Poland and the UK) using seven versions of GARCH models.

Some compared developed and developing countries; Joshi & Pandya (2012) revealed that the GARCH (1, 1) model successfully captures the time-varying volatility of Indian and Canadian stock markets. However, the persistence of volatility in the Canadian stock market is marginally more than that of the Indian stock market. Zhang, Li & Peng (2019) revisited the analysis of daily HKD/USD exchange rates.

There is growing empirical research in which their methodologies focus on applying ARCH/ GARCH models to emerging markets to estimate and predict volatility. Rahim, Zahari &

Shariff (2016) explored ASEAN countries, including Indonesia, Singapore and Malaysia. Lin (2019) applied the GARCH model with t distribution in China. The GARCH (1, 1) model is the most accurate forecasting model for Malaysia, Indonesia, and Japanese stock markets, see Lee, Nguyen & Sy (2017). Almarashi & Khan (2019) estimated the volatility of stock returns using the GARCH model on Gaussian (standard), student's t and GED.

Recent research has placed a growing emphasis on the BRICS economic group due to its substantial size and significant growth potential across various sectors in the past two decades. Confident economists have gone as far as predicting that this group may have the potential to outpace both the United States and the European Union in terms of real GDP by the year 2050 (O'Neill, 2001; Boubakar & Raza, 2017; Mensi, 2017; Plakandaras, 2019).

Over the past decade, the returns on investments in BRIC stocks have exceeded the Standard and Poor's Index by more than four times. Furthermore, the economic growth in these countries has surpassed that of the United States by as much as four times on average. Patterson & Chen (2011), Ghosh & Saggar (2017), Bonga- Bonga (2017). The BRICS nations represented 3% of the world's trade in 1990. However, as of 2011, their collective impact has grown exponentially, accounting for 19% of worldwide exports and 16% of global imports of goods and services. This remarkable expansion in their share of international trade can be attributed to their growing significance in the worldwide economy.

China has established itself as the world's foremost exporter and the second-largest importer of merchandise goods. Russia and India also rank within the top 20 merchandise exporters and importers. While China, Russia, and Brazil boast a surplus in their merchandise trade balance, India and South Africa face deficits. Between the eurozone and the BRICS, imports and exports amounted to 551 million and 340 million euros, respectively, in 2014. These nations have witnessed substantial trade growth with the United States, primarily fuelled by their export expansion in recent years.

Bonga-Bonga (2018), Guptha & Rao (2017), Boubaker & Raza (2017), Patra & Panda (2019) and Ndlovu (2019) have undertaken the study of the volatility behaviour of BRICS in stock markets. Caporale & Spagnolo (2017), Dube (2019), Otieno (2017), Bhattacharya & Roychoudhury (2017), Rai & Kumar (2020), and Zerihun, Breitenbach & Njindan Iyke (2020) have focused on exchange rates. As for the portfolio, a limited number of studies have considered diverse portfolio weights when estimating portfolio returns.

Rombouts and Verbeek (2009) conducted a comparison of three MGARCH (Multivariate Generalized Autoregressive Conditional Heteroskedasticity) models that utilised both normal and Student-t distributions in estimating the returns of a portfolio. This portfolio was constructed using non-specific or arbitrary weightings, incorporating the Standard and Poor's 500 (S&P 500) and NASDAQ indices.

Significantly, in the study by Amato, Bonga, Nleya, Maghyereh, Moosa, and Tronzano (2018), it was discovered that a portfolio comprising both equity and currency components has the potential to mitigate the exchange rate risk associated with investing in an emerging market. Such a portfolio also offers investors a degree of safety in preserving the actual value of their investment within the equity market. They estimated returns using a portfolio that combines assets in the currency and equity markets with three different multivariate risk models in the BRICS economies. The findings suggest that portfolios with a higher allocation to cash and a lower percentage to equities represent the most effective approach for minimising potential losses when investing in BRICS countries.

There exists a very substantial gap. At the same time, many studies have concentrated on market risk modelling using GARCH models in equity and currency; few of these studies have applied GARCH (1,1) with a portfolio on emerging markets, particularly BRICS. Moreover, these studies have yet to analyse the effects of a portfolio consisting of stock price, exchange rate, and bond price in different weights for BRICS economies.

In 2018, the world's two largest economies (the US and China) broke into an unprecedented trade war. Cepni, Gabauer, Gupta & Ramabulana (2020) highlighted the trade uncertainty of emerging economies under the recent US-China trade war policy. Haidar (2012) concluded that the transmission of crisis effects can spread globally even if it starts in one specific country or region. Ruzima & Boachie (2018) addressed the importance of emerging markets in the global economy through trade linkages.

In 2019, COVID-19 caused enormous chaos since December, firstly in Wuhan, China, then spreading worldwide. Igwe (2020) noted that the global economic shock from this virus could lead to an incredibly damaging economic recession; it can increase volatility and impact many countries' economic and financial systems negatively.

Furthermore, Baker's study from 2020 discussed that the COVID-19 pandemic had a detrimental effect on stock markets. The research suggested that the repercussions of this pandemic were even more significant compared to previous infectious disease outbreaks, including the devastating 1918 Spanish Flu.

Undoubtedly, most of the world's economies and financial markets would be affected due to lockdown and social distancing. Adenomon & Maijamaa (2020) have already examined the effect of the COVID-19 outbreak on the performance of the Nigerian stock returns and high volatility using GARCH models.

The economic uncertainty can influence the emerging economies. To predict risk accurately, there will be a more significant number of discussions and arguments; Li, Ker & Rude (2019), Zhou, Fu, Jiang, Zeng & Lin (2019), and Bouri, Gkillas, Gupta & Pierdzioch (2020) examined which is the most effective implementing risk prediction financial model, leading to a proper estimation, which can help reduce the cost of investment for investors and financial institutions. Tache & Darie (2019) implied GARCH (1, 1) for the CNY/USD exchange rate and concluded that it could more effectively predict the volatility of foreign exchange markets.

According to the research conducted by Akhtar, Akhtar, Jahromi, and John (2017), it was discovered that both stocks and bonds tend to experience increased volatility when macroeconomic announcements are made. Baur & Lucey (2010) and Chan (2011) conducted research that suggests that during stock market crises, Treasury bonds possess more valuable properties as a haven than gold. Investors tend to view Treasury bonds as a more reliable option to protect their investments during market downturns than gold.

Lin's (2019) research observed that the Chinese stock market considered an emerging market with substantial potential, demonstrates distinctive characteristics in its index yield series. Specifically, this market exhibits the typical features of leptokurtic distributions, negative skewness, and fat-tailed behaviour. When extreme events happen, estimating conditional variance should use GARCH-type models, and the assumption should be skewed-t distribution instead of normal distribution in China.

As mentioned in previous literature, numerous studies have focused on modelling market risk by employing multivariate GARCH models to assess the efficacy of these two variations in estimating and predicting the stock volatility. Given the notably volatile characteristics of emerging market data, there is a specific interest in utilising GARCH models for returns estimation and portfolio selection.

The exhibit and test of GARCH models with extensions GARCH (1, 1) for two specific distributions can provide statistical evidence on many asset pricing theories and portfolio analysis. After 2010, few of these studies have compared GARCH (1, 1) with the normal distribution and the student's t distribution error assumption on BRICS, which this project focuses on. Most previous studies have only focused on exchange rates or stock indexes.

Therefore, this study constructs a portfolio comprising three assets: equities, currencies and bonds, given weights of 50%, 30%, and 20% based on Engle (2001). As stated, these studies have yet to attempt to analyse the effects of a portfolio of equity, currency and bonds with different weights to minimise the portfolio risk for BRICS economies.

In this era of the volatile global economy, how the volatilities of the portfolio in BRICS countries behave is the main issue of concern in this paper. The paper's findings should interest policymakers in BRICS for any resolution on capital market liberalisation and the international asset managers and investors seeking to diversify portfolios in the BRICS markets to predict their investment outcome.

## 2.3 Data

This chapter compares the T-GARCH (1, 1) and N-GARCH (1, 1) models using secondary weekly data from the BRICS market indices. The data covers a total period of 10 years, starting from June 2010 and ending in June 2020. All data have been obtained from the add-in Excel Data Stream and then input into the software EVIEWS11 program to calculate and construct the hypothetical historical index data.

The data was split into two: in-sample estimating data, accounting for 90%, and in-sample forecasting data, accounting for the remaining 10%. The in-sample counting part is applied to models with two error distributions separately to analyse the efficiency of the estimating data set.

To assess the precision of our predictions, we opted for in-sample prediction over out-of-sample prediction. By utilizing in-sample forecasting, we can anticipate future values within the sample by relying on parameter estimates. On the other hand, out-of-sample forecasting enables us to project the value of future occurrences that are not present in the sample.

In the context of in-sample forecasting, a comparative analysis is conducted between the actual value and the forecasting values generated by two distinct models. This approach is based on the premise that the model with the smallest distance between the actual and forecasting values is deemed more precise and reliable.

### 2.3.1 Portfolio

The selected indices, comprising stock prices, exchange rates, and bond prices, constitute a unified portfolio outlined below:

For the stock index, we collected BOVESPA, MOEX, SENSEX, SSE, and FTSE/JSE, the five national stock price indices of Brazil, Russia, India, China and South Africa, respectively.

The IBOVESPA, or BOVESPA index, is a comprehensive return index that encompasses Brazilian market leaders based on their capitalisation and trading volume. Since its inception in 1968, this index has been the benchmark for approximately 60 Brazilian companies listed on the B3 (Brazil Stock Exchange and Over-the-Counter Market) stock exchange. This index was chosen to represent the Brazilian stock market in most of the literature, see Dakhlaoui & Aloui (2016), Guptha & Rao (2017), Bonga-Bonga (2018), and Jiang & Ruan (2019).

Since its establishment in 1997, the MOEX Russia Index, formerly the MICEX Index, has been widely recognised as the leading ruble-denominated benchmark for the Russian stock market. It is a crucial indicator of the performance of the Russian economy, providing investors with valuable insights into the trends and fluctuations of the market. The MOEX Russia Index enjoys a long-standing reputation for trustworthiness and stability, which makes it a preferred choice for those seeking to invest in the Russian stock market.

The Brasil Bolsa Balcão S.A., previously known as BM&FBOVESPA, is a stock exchange in São Paulo, Brazil. Local investors typically employ RUB, whereas foreign investors use the USD-denominated RTS4 (Russia Trading System) Index.

Most of the researchers, such as Dakhlaoui & Aloui (2016), Guptha & Rao (2017), Jiang & Ruan (2019), used the MOEX index to analyse the volatility, while Tripathy (2017), Bonga-Bonga (2018) used RTS index. Meanwhile, Dakhlaoui & Aloui (2016) used MTI (Moscow Times Index), and Subedi (2018) decided to test the MSCI (Morgan Stanley Capital International) index of the Brazilian stock market.

The SENSEX index, formally known as the BSE SENSEX index or S&P Bombay Stock Exchange, has been a critical player in the Indian stock market since 1986. It's a market-weighted index that reflects the performance of the top 30 blue-chip companies across various sectors of the Indian economy. As a widely recognised barometer of India's domestic stock markets, the S&P BSE SENSEX index is a vital tool for investors seeking to track the pulse of the Indian economy.

Bonga- Bonga (2018) observed S&P CNX500, Seth & Singhania (2019) tested the NIFTY (National Index Fifty) index, and Dakhlaoui & Aloui (2016) preferred BSI (Bombay Sensex Index). However, in most of the studies, Tripathy (2017), Babu, Hariharan & Srinivasan (2016), and Seth & Singhania (2019) used the SENSEX index, which in this study follows.

The SSE Composite Index, also referred to as the SSE Index, is a widely recognised benchmark for the stock market. It encompasses all the stocks listed and traded on the Shanghai Stock Exchange, comprising A and B shares. B share stocks are generally quoted in U.S. dollars, but while calculating other indices, their prices are converted to Chinese Renminbi (RMB) using the prevailing exchange rate. The exchange rate is determined as the middle price of the U.S.

dollar on the last trading day of each week, as provided by the China Foreign Exchange Trading Centre. The exchange makes These converted prices available for reference and analysis purposes.

Lin tested the SSE Composite Index using different GARCH models in 2018 and concluded that the Index shows time carrying and clustering, along with ARCH and GARCH effects. Therefore, in this study, we used a share by analysing Babu, Hariharan & Srinivasan (2016), Tripathy (2017) and Seth & Singhania (2019).

JSE Limited, formerly known as the JSE Securities Exchange and the Johannesburg Stock Exchange, is the largest stock exchange in Africa. It is worth noting that the FTSE/JSE Africa Index Series effectively represents the South African equity market, including its various market segments, from 2000 onwards. This study chose the JSE index based on Guptha & Rao (2017) and Jiang & Ruan (2019), among others.

Trading of currency constitutes an essential part of financial investments. The high-risk rate has been involved in the foreign exchange market in the trading process. Therefore, there is a high demand to estimate the risks and, thus, a valuable application for the GARCH models. For the exchange rate index, the Brazil Real (BRL), Russian Ruble (RUB), Indian Rupee (INR), Chinese Yuan (RMB), and South African rand (R) to US Dollars were selected. In 2017, Dritsaki suggested using a British pound/US dollar for the exchange rate static procedure for better estimating and forecasting.

Treasury bonds are instruments issued by the US government that serve as a standard for other securities in the market. This means their value and performance are often used to compare other financial products, including corporate bonds. Due to their low-risk nature and stable returns, Treasury bonds are frequently favoured by investors seeking a haven for their capital.

In 2019, Trucíos, Zevallos, Hotta & Santos created four portfolios by giving weights to seven market indices. This inspired this study to change the importance of other indices in the portfolio.

There are five portfolios in this study:

Portfolio 1: 50% stock price, 30% exchange rate, 20% bond price

Portfolio 2: 30% stock price, 50% exchange rate, 20% bond price

Portfolio 3: 30% stock price, 20% exchange rate, 50% bond price

Portfolio 4: 20% stock price, 30% exchange rate, 50% bond price

Portfolio 5: 25% stock price, 25% exchange rate, 50% bond price

The essence of stock markets and foreign exchange rate volatility is highly related to risk. Therefore, for portfolios 3, 4 and 5, we gave more weight to the bond index to lower the risks.

All the index prices in these five portfolios are collected weekly from 24 June 2010 to 25 June 2020 and calculated using Microsoft Excel. There are 522 observations for each country in each portfolio.

### 2.3.2 Estimation

In the first part, the primary purpose of the data is to estimate the unknown parameters in GARCH models. After obtaining the parameters, the estimation can then be computed. The next step is using the measures we got from the first part to access the in-sample forecasting.

The returns were the overall number of gains or losses for an asset after the investigation for a specific time horizon. The measurement can be expressed in a sum of cash distribution with changes in value over the period. See Equation 1:

$$R_t = \frac{P_t - P_{t-1} + C_t}{P_t}\ , \qquad (1)$$

Where $R_t$ is the stock return at time t, $P_t$ is the stock price at time t, $P_{t-1}$ is the stock price at time t-1, and $C_t$ refers to cash received from the investment from t-1 to t, introduced by Stephen (2006).

Additionally, this study will use the following equation to calculate the returns of all the indices included. The first difference of the return is the logarithm of the ratio between the index price at time t and the index price at time t-1; due to continuous compounding, the equation is as follows:

$$R_t = \log(P_t \ / \ P_{t-1}) \ , \tag{2}$$

Where $R_t$ is the index return at time t, and $P_t$ is the index price at time t, and $P_{t-1}$ is the index price at time t-1.

For the financial index, according to Hull (2000), volatility can be presented in terms of standard deviation squared or variance over a specific time; the population variance equation is as follows:

$$\sigma_t^2 = \frac{\sum_{i=1}^{N}(x_i - \mu)^2}{N} \ , \tag{3}$$

Where $\sigma_t^2$ is the variance at time t, $x_i$ is the individual value of the $i^{th}$ element, $\mu$ is the population mean, and N is the total number of the population.

The volatility clustering in financial data, shown in the plot of returns figures as significant changes followed by minor changes, can be helpful in analysing volatility. The stock prices and return plot must be observed to decide whether GARCH (1, 1) is accurate for the whole data set. The volatility figures must show a sign that all the statistics are stationary, which means all the returns should surround the mean value (mean-reverted).

### 2.3.3 Forecasting

According to Almarashi and Khan (2019), the quantity of data utilised plays a pivotal role in producing reliable predictions. An excessive amount of data may result in a more precise estimation, but it could also lead to slower response times to dynamic changes in volatility. Conversely, more data could result in accurate analysis and forecasting. A larger dataset, however, can assist in deriving more precise conclusions regarding volatility in BRICS.

Between June 20, 2019 and June 25, 2020, 54 observations were utilised to evaluate the precision of empirical and theoretical data in forecasting.

As noted in the introduction, this chapter is primarily focused on estimation rather than forecasting due to the limitations of GARCH. To aid in understanding patterns and correlations between process parameters, we utilize visual representations of the in-sample forecasting data.

By analysing the distance between the three lines, we evaluate the forecast ability. Instead of presenting statistical data, we offer graphical evidence.

After obtaining the forecasting figures, the accuracy of N-GARCH (1,1) and T-GARCH (1,1) forecasting becomes more straightforward. The results section comprehensively displays all tables and figures that detail the estimation and forecasting results, categorised by name and discussed thoroughly.

## 2.4 Methodology

The focus of this section is to offer a comprehensive mathematical explanation of our methodology. We will begin by elaborating on the basic ARCH model that uses an autoregressive representation of the conditional variance.

The GARCH model is essential for modelling conditional variance in financial time series. It builds on the popular ARCH model by incorporating moving average components, making it a powerful way to capture volatility clustering and leverage effects. In particular, the GARCH (p, q) model combines lagged squared residuals and conditional variances with moving average terms, making it a versatile and widely used model in finance.

The GARCH (1, 1) model, a specific variant of the GARCH model, is beneficial for its simplicity and ease of interpretation. Understanding and utilising the GARCH model can significantly improve our ability to analyse and forecast financial time series.

### 2.4.1 ARCH/GARCH model

ARCH models were mentioned by Engel (1982). He introduced the concept that the conditional variance changes over time; at time t, it is decided by the squared error term at t-1. ARCH (p) model is the first generalised form of ARCH (1), which expresses conditional variance determined by the past p-squared disturbance terms.

Bollerslev introduced the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model in 1986. This model builds on the Autoregressive Conditional Heteroskedasticity (ARCH) model by including past conditional variances in the dependent variance equation. This enhancement enables the GARCH model to capture volatility clustering, a prevalent occurrence in financial data analysis. As a result of its capability to depict such trends, the GARCH model has emerged as a favoured option in empirical finance research.

The GARCH (p, q) model, which p > 0 and q ≥ 0, was suggested by Bollerslev (1986) as follows:

$$\sigma^2 = \omega + \alpha(B)\mu_t^2 + \beta(B)\sigma_t^2 \ , \tag{4}$$

Where $\omega > 0$, $\alpha(B) = \alpha_1 B + \cdots + \alpha_q B^q$ and $\beta(B) = \beta_1 B + \cdots + \beta_p B^p$, with $\alpha_i \geq 0$ for i=1, …, q and $\beta_j \geq 0$ for j=1, …, p. And it also can be described as:

$$\sigma_t^2 = \omega(1 - \beta(B))^{-1} + \alpha(B)(1 - \beta(B))^{-1}\mu_t^2 \ , \tag{5}$$

The GARCH (p, q) model is usually applied in a long-position investment, such as decades of daily data or hourly data in a year. GARCH (p, q) is a model with additional lags, which does not apply to this chapter.

Since the GARCH (1, 1) model was found to be effective for many different types of financial time series by Bollerslev (1992), this dissertation focuses on the GARCH (1, 1) model in our empirical analysis.

### 2.4.2 GARCH (1, 1) model

A univariate setting time series model GARCH (1, 1) specifications are widely used to model the conditional portfolio variance for financial historical stationary data. With only three parameters in the conditional variance equation, it can be expressed as:

$$X_t = \sigma_t Z_t \ , \tag{6}$$

Where $X_t$ is the observed financial data, $\sigma_t$ is a volatility process specified by:

$$\sigma_t^2 = \gamma V + \alpha {\mu_{t-1}}^2 + \beta {\sigma_{t-1}}^2 \ , \tag{7}$$

Where, $V_L$ is the long run variance, $\omega = \gamma V_L$ and $\gamma$ = weight of long run variance (decide the persistence), $\gamma + \alpha + \beta = 1$, $\mu_{t-1}$ is return at time t-1, $\sigma_{t-1}$ is the variance of time t-1, $\alpha$ is the weight of squared return, $\beta$ is the weight of squared variance. And $\{Z_t\}$ is an innovation process.

$$\sigma_t^2 = \omega + \alpha {\mu_{t-1}}^2 + \beta {\sigma_{t-1}}^2 \ , \tag{8}$$

Where $\sigma_t$ is todays' variance, $\alpha{\mu_{t-1}}^2$ is the squared return of the day before, and $\beta{\sigma_{t-1}}^2$ is variance on the day before. Given the many previous studies on this topic, the returns are expected to be positive and significant.

The conditional variance process is more likely to be positive and stationary when: $\omega > 0$; $\alpha > 0$; $\beta > 0$ and $\alpha + \beta < 1$. The long-run variance, $\alpha$ and $\beta$, are obtained by the computer software EVIEWS to test which model has better skills to estimate the variance of day t.

Previous empirical studies gave different, conflicting results; therefore, the outcomes of this test are difficult to predict. The results of this test are expected to be positive and significantly more likely for developed countries than emerging ones. But again, the disagreements in the literature do not permit reliable predictions to be made.

From the previous section, variance estimates for time t through GARCH (1, 1) using data on t-1. Then, estimates are made for t+1, t+2, t+3……

To predict and forecast with GARCH (1, 1) model, the equation below is used:

$$\mathrm{E}\ [\sigma_{n+t}^2] = V_L + (\alpha + \beta)^n (\sigma_t^2 - v) \ , \tag{9}$$

Where E $[\sigma_{n+t}^2]$ is the expected variance on the day n + t, which is day t plus n days forward, $V_L$ is the long-run variance, and $\sigma_t$ is the variance of time t.

The difference between variance on day t and long-run variance $\sigma_t - V_L$, which is the distance between the two variables. $(\alpha + \beta)^n is$ the persistence of the series, which needs to be less than one. The higher that $(\alpha + \beta)^n$is, the more sticker to the variance of day t and less to declaim the long-run variance.

In this part, the equation is run through EVIEWS to get the in-sample forecast of the data and then predicted results are compared with actual results to test the effectiveness of the forecasting abilities of these models.

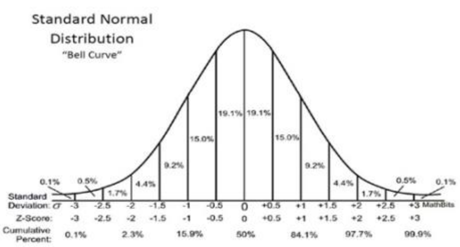
### 2.4.3 GARCH (1, 1) model with different distributions

As mentioned in Manuela and Nicolas K (2016), there are eight types of distribution of $Z_t$: the normal distribution, also named Gaussian distribution; the skewed Gaussian distribution; the Student's t distribution; the skewed Student's t distribution; the generalised error distribution, the skewed generalised error distribution, the asymmetric exponential power distribution, and the asymmetric Student's t distribution. The first six are commonly used models, and the last two are relatively new.

The distributions listed above are mentioned by Mover (1738), Gauss (1809), Azzalini (1985), Gosset (1908), Fernandez & Steel (1998), Subbotin (1923); Theodossiou (1998); Zhu & Zinde-Walsh (2009); Zhu & Galbraith (2010).

The normal distribution is a well-known probability distribution that exhibits unique characteristics. The curve of the standard normal distribution is shown in Figure 2.1

**Figure 2.1 Standard Normal Distribution Curve**[1]




**Notes:** In statistical analysis, the normal distribution is often used to represent various phenomena, such as test scores, weights, heights, etc. The distribution is notable for the tendency of data points to cluster around the mean, with fewer data points appearing far from it. This makes the normal distribution an invaluable tool for analysing and comprehending large data sets. It's the most commonly used distribution in statistics, represented

[1] Normal distribution is the most commonly used statistical distribution, represented by Westfall (2007).
Source: https://www.investopedia.com/terms/n/normaldistribution.asp [Accessed 1 Sep. 2018].

by Westfall (2007). Its shape is a bell curve, with the highest point denoting the mean and the curve being symmetrical around this point.

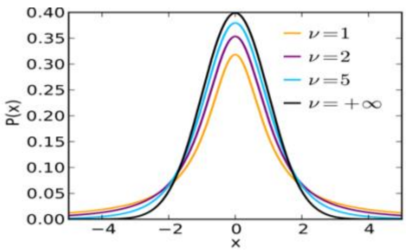
The normal distribution is best presented as follows:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2}, \tag{10}$$

where x is the value of the variables, and $f(x)$ is the probability function, $\mu$ is the mean, $\sigma$ is the standard deviation and $\pi$ is the constant pi.

Figure 2.2 shows the curve of students' distribution.

**Figure 2.2 Students' t Distribution curve[2]**




**Notes:** The student's t-distribution, also called the T distribution, was developed by Gosset (1908) under a pseudonym. It is a distribution used when specific requirements are met to estimate the mean of a normally distributed population. These requirements are as follows: 1) small sample size and 2) the population standard deviation is unknown. It is almost identical to the normal distribution curve but a bit shorter and fatter.

Under the students' t distribution, the log-likelihood is computed as follows;

$$T = \frac{\overline{x}-\mu}{\frac{s}{\sqrt{N}}}, \tag{11}$$

Where N is the sample size, ¯x is the mean of the first sample, µ is the mean of the second sample and $\frac{s}{\sqrt{N}}$ is the estimation of the standard error of the difference between the means.

[2] Roberts, D. (2018). *Standard Normal Distribution - MathBitsNotebook(A2 - CCSS Math).*

## 2.5 Results and Discussion

The EVIEWS software facilitates data analysis through tables and figures. The authors have arranged the tables and figures in this paper according to the original EVIEWS output results. The primary tables and figures are provided below; the rest can be accessed in Appendix A.

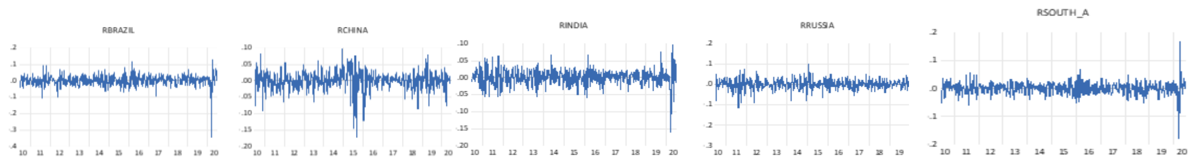
It is important to note that all observations must pertain to GARCH (1, 1). It is anticipated that the returns of each portfolio in all countries will demonstrate stationarity and mean-reversion, though this may only sometimes be the case. To accurately estimate ARCH/GARCH, it is crucial to transform them into the right states.

**Figure 2.3 Line plots of portfolio 1 prices in BRICS countries[3]**


**Notes:** Portfolio 1 prices consist of 50% stock price, 30% exchange rate and 20% bond price in each country. Portfolio 1 price clearly showed that they were not stationary and sometimes in a random walk pattern but fluctuating up and down. Notably, the Chinese portfolio price shows a different pattern from other countries; there is a massive peak from 2014-2015, then after 2015, a significant drop followed during the later years. From 12 June 2015 to early February 2016, the popping of the stock market bubble was named "The Chinese stock market turbulence". After three weeks of falling, the value continued to fall even though the government was trying to reduce it.

By conducting the first difference of return calculations as mentioned in Equation 2, the results of each Figure became stationary and mean-reverting, for example, Figure 2.4.

**Figure 2.4 Line plots of portfolio 1 return series in BRICS countries [4]**




**Notes:** All portfolio 1 returns in this figure show volatility clustering compared with the portfolio 1 prices in

[3] Figure 2.3 plots the portfolio prices for each country. All the prices in the portfolio are collected weekly from 24 June 2010 to 25 June 2020 and the portfolio prices are calculated using Microsoft Excel.
[4] Figure 2.4 shows the plots of BRICS nations' portfolio returns in portfolio 1 after calculating Equation 2.

Figure 2.3. At every terming point, the portfolio 1 returns are more volatile, which means GARCH (1, 1) would be perfect to fit them. The rest of the portfolio prices and return graphs can be found in Appendix A.

We delved into the prices and returns of various portfolios across different countries. Figure 2.3 illustrates the prices, while Figure 2.4 showcases the returns. Each portfolio is comprised of different index weights. For this section, we will concentrate on the outcomes of portfolio one. Nevertheless, Appendix A shows figures for portfolios two to five. The rationale behind transforming Figure 2.3 into Figure 2.4 is to confirm that the portfolio returns remain stationary and not in non-random walk status or excluded white noises.

Table 2.1 provides a comprehensive statistical analysis of all the portfolio returns. The table includes detailed information on the mean, median, standard deviation, skewness, and kurtosis of the returns.

**Table 2.1 The statistical description of the five portfolio returns in BRICS countries[5]**

| | *Portfolio* | *Mean* | *Std.Deviation* | *Skewness* | *Kurtosis* | *Jarque-Bera Probability* |
|---|---|---|---|---|---|---|
| ***Brazil*** | 1 | 0.000778 | 0.033845 | -1.894721 | 23.10902 | 9107.434(0.000000) |
| | 2 | 0.000778 | 0.033840 | -1.895032 | 23.11251 | 9110.588(0.000000) |
| | 3 | 0.000778 | 0.033835 | -1.895925 | 23.12375 | 9120.722(0.000000) |
| | 4 | 0.000778 | 0.033826 | -1.896760 | 23.13373 | 9129.737(0.000000) |
| | 5 | 0.000778 | 0.033831 | -1.896259 | 23.12774 | 9124.327(0.000000) |
| ***Russia*** | 1 | 0.001352 | 0.027142 | -1.097771 | 10.21253 | 1236.292(0.000000) |
| | 2 | 0.001355 | 0.026170 | -1.092827 | 9.993255 | 1167.599(0.000000) |
| | 3 | 0.001345 | 0.026838 | -1.100398 | 10.21017 | 1236.055(0.000000) |
| | 4 | 0.001344 | 0.025976 | -1.096796 | 10.03725 | 1126.657(0.000000) |
| | 5 | 0.001344 | 0.026486 | -1.099435 | 10.14309 | 1241.929(0.000000) |
| ***India*** | 1 | 0.001293 | 0.024441 | -0.886471 | 9.045094 | 863.1809(0.000000) |
| | 2 | 0.001292 | 0.024362 | -0.887858 | 9.061528 | 867.7224(0.000000) |
| | 3 | 0.001293 | 0.024426 | -0.886880 | 9.050064 | 864.5515(0.000000) |
| | 4 | 0.001291 | 0.024358 | -0.888122 | 9.055987 | 866.1879(0.000000) |
| | 5 | 0.001292 | 0.024399 | -0.887377 | 11.65844 | 1581.505(0.000000) |
| ***China*** | 1 | 0.000285 | 0.029428 | -0.905231 | 7.310833 | 475.4779(0.000000) |
| | 2 | 0.000284 | 0.029352 | -0.906031 | 7.319700 | 477.2683(0.000000) |
| | 3 | 0.000284 | 0.031384 | -0.905737 | 7.315736 | 476.4776(0.000000) |
| | 4 | 0.000283 | 0.029305 | -0.906583 | 7.324801 | 478.3145(0.000000) |
| | 5 | 0.000284 | 0.029352 | -0.906076 | 7.319367 | 477.2130(0.000000) |
| ***South Africa*** | 1 | 0.001296 | 0.023575 | -0.747870 | 17.07573 | 4357.903(0.000000) |
| | 2 | 0.001296 | 0.023564 | -0.747555 | 17.06948 | 4354.039(0.000000) |
| | 3 | 0.001295 | 0.023567 | -0.747281 | 17.06867 | 4353.505(0.000000) |
| | 4 | 0.001295 | 0.023554 | -0.746750 | 17.06046 | 4348.414(0.000000) |
| | 5 | 0.001295 | 0.023562 | -0.747069 | 17.06538 | 4351.468(0.000000) |

**Notes:** This table provides a comprehensive overview of critical statistical measures such as the mean, standard deviation, skewness, kurtosis, and probability for five distinct portfolio returns in BRICS countries. This information is essential for understanding the performance and characteristics of each portfolio. It shows that the mean of the portfolio returns are positive for all countries. Standard deviation (SD) measures the riskiness of the

[5] Table2.1 displays the mean, standard deviation, skewness, kurtosis, and probability statistics for five portfolio returns in BRICS countries.

returns; the higher the standard deviation, the higher the volatility of the market and the riskier the equity. Brazil and China have much higher SD, thus, more investment risks. The skewness of a normally distributed series should be close to zero; it points to the fact that the rate of return is not symmetric. Positive skewness is the indication of making profits from investing. In this table, they are all negative. Kurtosis is more significant than three, a standard cut-off point for a normally distributed series. This fact indicates some degree of fat-tail characteristics of the return series. Fat-tailed features are further supplemented by the value of the Jarque-Bera test with $p<0.01$, indicating that portfolio returns are non-normal.

The GARCH (1, 1) for normal distributions and students' t distribution are applied individually to all the portfolios to compare which model is more effective in estimating portfolio returns. To begin with, it must be clear that the GARCH (1, 1) model uses one lag. Table 2.2 presents the results obtained after running the regression.

**Table 2.2 The estimations of T-GARCH (1, 1) and N-GARCH (1, 1) for five portfolios**

| Portfolio | | Brazil | Russia | India | China | South Africa |
|---|---|---|---|---|---|---|
| **1** | **N-GARCH (1,1)** | | | | | |
| | ω(p) | 0.000183(0.0010) | 0.000112(0.0000) | 8.03E-05(0.0016) | 1.69E-05(0.0083) | 7.98E-05(0.0077) |
| | α(p) | 0.239389(0.0000) | 0.206544(0.0000) | 0.226395(0.0000) | 0.112534(0.0001) | 0.204919(0.0000) |
| | β(p) | 0.623536(0.0000) | 0.645615(0.0000) | 0.645925(0.0000) | 0.868386(0.0000) | 0.626652(0.0000) |
| | **T-GARCH (1,1)** | | | | | |
| | ω(p) | 0.000136(0.1459) | 8.20E-05(0.0341) | 5.09E-05(0.0564) | 2.73E-05(0.0642) | 8.64E-05(0.0020) |
| | α(p) | 0.062989(0.1484) | 0.130801(0.0083) | 0.146722(0.0039) | 0.132993(0.0011) | 0.165301(0.0015) |
| | β(p) | 0.793608(0.0000) | 0.750906(0.0000) | 0.764381(0.0000) | 0.591584(0.0000) | 0.635412(0.0000) |
| | DOF | 7.003128(0.0000) | 5.211422(0.0000) | 9.785186(0.0001) | 5.654110(0.0014) | 9.374141(0.0001) |
| **2** | **N-GARCH (1,1)** | | | | | |
| | ω(p) | 0.000183(0.0010) | 0.000104(0.0000) | 7.98E-05(0.0016) | 1.68E-05(0.0083) | 7.98E-05(0.0077) |
| | α(p) | 0.239378(0.0000) | 0.206991(0.0000) | 0.226416(0.0007) | 0.112579(0.0000) | 0.204897(0.0000) |
| | β(p) | 0.623528(0.0006) | 0.645724(0.0000) | 0.645788(0.0000) | 0.868325(0.0000) | 0.626606(0.0000) |
| | **T-GARCH (1,1)** | | | | | |
| | ω(p) | 0.000136(0.1459) | 7.52E-05(0.0330) | 5.06E-05(0.0564) | 2.71E-05(0.0641) | 8.64E-05(0.0196) |
| | α(p) | 0.062968(0.1485) | 0.132857(0.0074) | 0.146616(0.0040) | 0.133034(0.0011) | 0.165299(0.0015) |
| | β(p) | 0.793596(0.0000) | 0.750394(0.0000) | 0.764290(0.0000) | 0.839033(0.0000) | 0.635648(0.0000) |
| | DOF | 7.003388(0.0000) | 5.297905(0.00000) | 9.784261(0.0001) | 5.655580(0.0000) | 9.375366(0.0000) |
| **3** | **N-GARCH (1,1)** | | | | | |
| | ω(p) | 0.000183(0.0010) | 0.000111(0.0000) | 8.02E-05(0.0016) | 1.68E-05(0.0083) | 7.98E-05(0.0077) |
| | α(π) | 0.239375(0.0000) | 0.205682(0.0000) | 0.226398(0.0000) | 0.112505(0.0000) | 0.204889(0.0000) |
| | β(π) | 0.623518(0.0000) | 0.644969(0.0000) | 0.645812(0.0000) | 0.868415(0.0000) | 0.626657(0.0000) |
| | **T-GARCH (1,1)** | | | | | |
| | ω(π) | 0.000136(0.1460) | 8.07E-05(0.0343) | 5.08E-05(0.0564) | 2.72E-05(0.0642) | 8.64E-05(0.0197) |
| | α(π) | 0.062935(0.1487) | 0.130307(0.0085) | 0.146708(0.0040) | 0.132954(0.0011) | 0.165302(0.0015) |
| | β(π) | 0.793603(0.0000) | 0.750379(0.0000) | 0.764288(0.0000) | 0.839117(0.0000) | 0.635413(0.0000) |
| | DOF | 7.003933(0.0000) | 5.235426(0.0000) | 9.784547(0.0001) | 5.654251(0.0014) | 5.334027(0.0001) |

**Table 2.2 The estimations of T-GARCH (1, 1) and N-GARCH (1, 1) for five portfolios (Continued)**

| Portfolio | | Brazil | Russia | India | China | South Africa |
|---|---|---|---|---|---|---|
| 4 | **N-GARCH (1,1)** | | | | | |
| | ω(π) | 0.000183(0.0010) | 0.000103(0.0000) | 7.89E-05(0.0016) | 1.67E-05(0.0083) | 3.47E-05(0.0077) |
| | α(π) | 0.239360(0.0000) | 0.205500(0.0000) | 0.226415(0.0000) | 0.112524(0.0000) | 0.167114(0.0000) |
| | β(π) | 0.623502(0.0000) | 0.644898(0.0000) | 0.645653(0.0000) | 0.868385(0.0000) | 0.775121(0.0000) |
| | **T-GARCH (1,1)** | | | | | |
| | ω(π) | 0.000136(0.1461) | 7.51E-05(0.0335) | 5.06E-05(0.0564) | 2.70E-05(0.0641) | 3.08E-05(0.0197) |
| | α(π) | 0.062892(0.1489) | 0.131703(0.0078) | 0.146621(0.0040) | 0.132966(0.0011) | 0.170434(0.0015) |
| | β(π) | 0.793592(0.0000) | 0.749712(0.0000) | 0.764173(0.0000) | 0.839074(0.0000) | 0.764962(0.0000) |
| | DOF | 7.004530(0.0000) | 5.313187(0.0000) | 9.783522(0.0001) | 5.65430(0.0014) | 9.375557(0.0001) |
| 5 | **N-GARCH (1,1)** | | | | | |
| | ω(π) | 0.000183(0.0010) | 0.000108(0.0000) | 8.01E-05(0.0016) | 1.68E-05(0.0083) | 7.98E-05(0.0077) |
| | α(π) | 0.239369(0.0000) | 0.205612(0.0000) | 0.226405(0.0000) | 0.112513(0.0000) | 0.204877(0.0000) |
| | β(π) | 0.623511(0.0000) | 0.644919(0.0000) | 0.645748(0.0000) | 0.868403(0.0000) | 0.626645(0.0000) |
| | **T-GARCH (1,1)** | | | | | |
| | ω(π) | 0.001360(0.1461) | 7.84E-05(0.0340) | 5.08E-05(0.0564) | 2.71E-05(0.0642) | 8.64E-05(0.0197) |
| | α(π) | 0.062918(0.1488) | 0.130795(0.0082) | 0.146673(0.0040) | 0.132959(0.0011) | 0.165302(0.0015) |
| | β(π) | 0.793599(0.0000) | 0.750154(0.0000) | 0.764242(0.0000) | 0.839100(0.0000) | 0.635394(0.0000) |
| | DOF | 7.004171(0.0000) | 5.265882(0.0000) | 9.784146(0.0207) | 5.654721(0.0014) | 9.374907(0.0001) |

**Notes:** This table presents the results obtained after running the regression. Notice for the GARCH (1, 1) equation described previously in Equation 7 and Equation 8, there are three parts to pay attention to. First, the constant part $\alpha$, then, the weight of squared return, and the squared variance. To make sure the variance part is stationary, the following should apply $\alpha > 0$, $\beta > 0$ and $\alpha + \beta < 1$.

Upon analysing Table 2.2, we observed that all the numerical values present are more significant than zero, implying that they are positive and stationary. These results satisfy the prerequisites of GARCH (1, 1) and indicate that the data under consideration is suitable for further analysis.

Based on our analysis using N-GARCH (1, 1), the P-value for all portfolio returns is significant at a 5% level. However, we observed that when T-GARCH (1, 1) is applied, specific data points such as $P$ω for Brazil (0.1459), $P$α for Brazil (0.1484) in portfolio one, $P$ω for India (0.0564), and $P$ω for China (0.0642) are non-significant. Despite these findings, we are pleased to report that all other results were significant at a 5% level.

While Pω's value in India and China may be considered slightly insignificant at the 5% level, it is worth noting that it does hold significance at the 10% level in Brazil. Despite the portfolio used (ranging from 1 to 5), T-GARCH (1, 1) did not perform well in any of the three countries - Brazil, India, and China.

In estimating portfolio returns in BRICS countries, the N-GARCH (1, 1) model exhibits superior performance compared to the T-GARCH (1, 1) model. This suggests that N-GARCH (1, 1) may be more suitable for investors seeking to optimise their portfolio returns in this region.

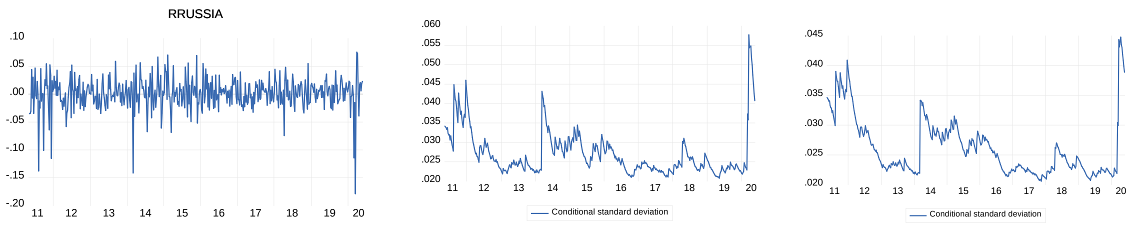
The T-GARCH analysis revealed that Brazil, India, and China exhibited poor performance in data analysis. This is due to the insignificance of their numbers, suggesting that other factors may affect the results. Specifically, Brazil's p values were found to be non-significant, indicating no evidence of a relationship between the variables being analysed.

On the other hand, India and China had significant numbers at a 10% level, meaning that there was some correlation between the variables. However, even with significant numbers, India's data still performed better than China's. These findings suggest that further investigation is needed to understand why these countries showed such variations in their performance and to determine any underlying factors that may explain the results.

Interestingly, the performance of both models remains relatively consistent even when different portfolio weightings are considered. Overall, this highlights the importance of carefully selecting an appropriate model for portfolio optimisation, mainly when investing in emerging markets such as the BRICS countries.

When assessing the potential risks associated with investment returns, it is important to look into the stability of the conditional variance. To illustrate this point, we consider the Russian portfolio one return. By plotting the conditional variance, as depicted in Figure 2.5, we can better understand its consistency over time.

**Figure 2.5 Line plots of portfolio return and conditional variance in Russia[6]**




**Notes:** This figure is an example of the previously mentioned trend, utilising the Russian market's portfolio returns and conditional variance. The middle plot showcases the conditional variance of the Russian portfolio with N-GARCH. At the same time, the story on the left depicts the dependent conflict of the Russian portfolio with T-GARCH.

One can determine its persistence by analysing the conditional variance plot. Upon careful observation of all the dependent variance figures, a common trend emerges: an increase in return corresponds to a rise in the conditional variance. The relevant findings can be found in Figure 2.5.

One effective approach to better understand the conditional variance is to examine the beta values presented in Table 2.2 meticulously. As the value of beta increases, the portfolio becomes more responsive to market shocks. This means that the portfolio's returns will be more sensitive to sudden changes in the market, and the volatility will decay faster after a large shock. In other words, a high beta value reflects a higher level of risk and potential reward, implying that the portfolio is exposed to more significant fluctuations in the market.

Table 2.2 provides us with insightful data indicating that China has a significantly high persistency percentage of the conditional variance value of β (86.83%) most of the time, whether it is N-GARCH or T-GARCH. This indicates that the forecasted future volatility of the financial instrument is highly influenced by the past volatility of the instrument. However, in portfolio 1, Brazil has the highest β (79.36%) with the student's t distribution. This means that the returns of the financial instrument in the portfolio have a higher sensitivity to the market returns.

[6] Figure2.5 compares the plots of portfolio returns and portfolio conditional variances in Russia.

The beta percentage order results for Portfolios 2, 3, and 5 are identical. However, when using N-GARCH, the sensitive order changes based on countries, with China, India, Russia, South Africa, and Brazil carrying the most risk, while T-GARCH shows China, Brazil, India, Russia, and South Africa as the countries with the highest risk. Portfolio 2 and 3 have the same weightage of 30% for stocks, but different weights for bonds and exchange rates. Portfolio 5, which has a weightage of 25% for stocks, is similar to Portfolios 2 and 3.

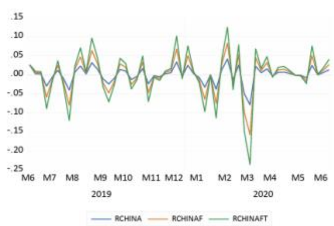
Interestingly, it appears that when a portfolio has a higher weightage of bonds and exchange rates, Asian countries like China and India carry a greater risk.

The rankings for portfolios 1 and 4 exhibit different changes. T-GARCH analysis shows that the order for portfolio 1 is Brazil, India, Russia, South Africa, and China. However, N-GARCH analysis for portfolio 4 reveals a different order of China, South Africa, India, Russia, and Brazil. A subsequent T-GARCH analysis for portfolio 1 shows yet another change to China, Brazil, South Africa, India, and Russia.

Moreover, portfolio 1 assigns the highest weight of 50% to stocks, while portfolio 4 assigns the lowest weight of 20%. This implies that any deviation from the half-weight allocation to stocks could increase the risk in Brazilian and South African markets.

When making predictions about future trends and outcomes, it's crucial to ensure that the chosen forecasting method is accurate and reliable. One way to do this is by comparing the in-sample predictions with the actual historical data. By analyzing the accuracy of the distribution, we can identify any discrepancies and make necessary adjustments to the forecasting model. Figure 2.6 illustrates how this process works in practice.

**Figure 2.6 Line plots of return and forecast series for portfolio1 in China [7]**




[7] Between June 20, 2019 and June 25, 2020, 54 observations were utilised to evaluate the precision of empirical and theoretical data in forecasting.

**Notes:** This figure showcases the accuracy of two forecasting techniques, N-GARCH and T-GARCH. The blue line indicates the actual historical values, while the red and green lines show the predicted values for N-GARCH (1, 1) and T-GARCH (1, 1), respectively. By examining the variance between the predicted and actual values, we can assess the efficacy of each forecasting method.

The variance between the predicted and actual values determines the accuracy of a forecast. The prognosis is typically less precise during instability and abrupt shifts, as the disparity between the predicted and actual values is wider. Conversely, the forecast accuracy increases when the predicted and actual values are more closely aligned.

As noted in the introduction, this chapter is primarily focused on estimation rather than forecasting due to the limitations of GARCH. To understand patterns and correlations between process parameters, we utilise visual representations of the in-sample forecasting data. We evaluate the forecast ability by analysing the distance between the three lines. Therefore, instead of presenting statistical data, we offer graphical evidence.

Figure 2.6 reveals that the disparity between the actual value and the red line is comparatively less than the difference between the actual value and the green line. This suggests that the N-GARCH (1, 1) model is more precise than the T-GARCH (1, 1) model. Nevertheless, it is essential to acknowledge that the green line exhibits more excellent responsiveness than the red line during drastic fluctuations, which should be noticed.

The entirety of the forecast-related figures has been documented in Appendix A. According to our analysis, N-GARCH (1, 1) demonstrated superior performance in estimating and forecasting portfolio returns in BRICS countries compared to T-GARCH (1, 1).

Within this chapter, an illustration of volatility modelling is presented. The accuracy of estimating and forecasting is not solely dependent on the models utilised but also on the distribution of the error term. This highlights the importance of considering both factors when performing volatility modelling.

When it comes to estimating and forecasting GARCH, the N-GARCH (1, 1) model generally demonstrates superior performance than the T-GARCH (1, 1) model in BRICS countries. If the portfolio weights are primarily allocated to the Bond and Exchange rate index, then Asian countries such as China and India tend to exhibit greater sensitivity to risk. Conversely, if the portfolio weights are placed on stocks, then Brazil, Russia, and South Africa tend to be more sensitive. When it comes to investment, China is generally regarded as a riskier option compared to other countries.

## 2.6 Conclusion

The ARCH/GARCH models have been widely used in various time series analyses and have been particularly successful in financial risk management. Financial decisions rely more on the measurements and forecasting of return and risk. Effective risk management is a crucial and intricate responsibility for financial regulators and investors. Historically, research has focused on discovering the most precise equations or models. However, more recent studies have pivoted their empirical analysis towards exploring the impact of error assumption distributions.

This project assessed the conditional variance model's estimation capability and forecasting accuracy for two distinct error term distributional assumptions within BRICS market over the past nine years. This chapter has shown that the N-GARCH (1, 1) model is a superior choice for estimating and forecasting GARCH models in BRICS countries compared to the T-GARCH (1, 1) model. The N-GARCH (1, 1) model can detect non-linear and asymmetric traits in financial data, which are often observed in developing markets such as those in the BRICS group. This insight can be beneficial for investors and risk managers seeking to accurately model financial risk in these nations.

Furthermore, the sensitivity of portfolio weights to risk varies depending on the asset class. When portfolio weights are primarily allocated to the Bond and Exchange rate index, Asian countries such as China and India tend to exhibit a higher level of sensitivity to risk. This is because the bond and currency markets in these countries are more volatile and subject to fluctuations. Conversely, when portfolio weights are placed on stocks, Brazil, Russia, and South Africa tend to be more sensitive to risk. This is because stock markets are inherently more volatile and subject to fluctuations than other financial markets.

When it comes to investment, China is generally regarded as a riskier option compared to other countries in the BRICS grouping. This is partly due to the country's political and economic environment, which is subject to greater levels of uncertainty and volatility than other countries in the group. Additionally, the volatility of the Chinese yuan and the level of government intervention in the market contribute to the perceived riskiness of investing in China. However, it should be noted that investment decisions should always be based on a thorough analysis of market conditions and a careful assessment of the associated risks and returns.

While in-sample forecasts are a popular method for predicting outcomes, out-of-sample forecasts can yield valuable insights. By evaluating and comparing alternate distributions, more precise predictions can be generated. Extending the GARCH (1, 1) model to the GARCH (p, q) model, which considers multiple lags, can enhance its accuracy. Hence, initiating the forecasting process with a GARCH (2, 2) model can be a promising strategy for an extended period.

Additionally, there is potential for further exploration and examination within this field. The findings need to determine the optimal country to employ the GARCH (1, 1) model or the most fitting portfolio. Moreover, there is no conclusive evidence regarding the efficacy of assigning varying weights to the index to form diverse portfolios. This subject warrant further investigation as a promising avenue for future research. Additionally, alternative means of assessing the precision of forecast outcomes exist, such as employing statistical back-testing instead of relying exclusively on visual interpretation of data.

Future research could compare models' performance in estimating and forecasting volatility across different periods, including pre-crisis, crisis, post-crisis, and low-volatility periods, using events such as the COVID-19 pandemic and the US-China trade war. It would also be valuable to investigate the impact of news data, explore different types of GARCH models and distributions, expand the sample of countries, and cover short-term investments. Comparing BRICS markets to larger economies could enhance the global market understanding.

# Chapter 3

# Analysing news impact on APEC stock volatilities using GARCH models

## 3.1 Introduction

The stock market is heavily influenced by the information available. Quickly digesting financial news articles can impact investors' moods and decision-making, leading to fluctuating stock prices. For example, if a company receives negative news, traders may change their minds and sell their assets, causing a decline in the corporation's stock value. Investment analysts, institutional traders, and market speculators can all earn substantial profits by analysing market information (Kalra, S. & Prasad, J.S., 2019).

In recent years, academia has shown an increasing interest in exploring the connection between news sentiment and financial price movements (Audrino, F., Sigrist, F. & Ballinari, D., 2020). Numerous research papers have delved into the impact of positive, negative, and neutral news on stock prices (Burchard, C.H., Proelss, J., Schäffer, U. & Schweizer, D., 2021).

Financial institutions and investors have long utilised the GARCH model for its effectiveness. However, it cannot consider the influence of news sentiment on stock prices. To better understand how investor sentiment impacts asset returns, it is essential to integrate additional asset pricing models containing sentiment risk factors (investor decisions) into both the mean and conditional volatility in the variance equation.

Since its introduction in 1993, the VIX Volatility Index has become crucial to the financial market toolkit. Calculated based on bid/ask quotes of S&P 500 index-linked options, the VIX indicates market expectations of future volatility in the index for the upcoming month. As such, it offers valuable insights into investor sentiment and risk aversion. (Sarwar, G., 2012).

As investors become more risk-averse, they seek options to protect their investments. The increase in demand for these options leads to a rise in implied volatility (IV) and, in turn, a corresponding increase in the value of the VIX. Essentially, as investors become more cautious, the market becomes more volatile, which can be seen in the increasing importance of the VIX. The VIX is used as an indicator of market implied volatility in studies such as (Akdağ, S., Kiliç, İ. and Yildirim, H., 2019), (Qadan, M., Kliger, D. and Chen, N., 2019), (İskenderoglu, Ö. and Akdag, S., 2020) and more.

Incorporating news as an additional variable, we integrated the recognised VIX volatility index, which the esteemed Chicago Board Options Exchange calculates. Utilising time series GARCH models, we delved into the correlation between alterations in price and risk.

The primary aim of this chapter is to analyse the correlation between the VIX index, news, and stock returns in six significant APEC nations: United States, China, Japan, Canada, South Korea, and Australia, through the application of GARCH models (GARCH (1,1) and EGARCH (1,1)). Furthermore, this study investigates the effects of both positive and negative news on the stock market. Additionally, we aim to scrutinise the impact of information on stock market volatility in various industries such as technology, energy, finance, and healthcare.

Our research has revealed that news distinctly impacts stock prices, but this impact differs based on the particular industry and region. Additionally, we discovered that the volatility of stocks is positively linked to both the intensity and sentiment of news.

Incorporating news parameters can enhance the precision of estimating stock price fluctuations, ultimately aiding in mitigating risks. Further, the inclusion of VIX changes in news variables can exert a significant impact on stock volatility changes. Negative news had a more pronounced effect on index reactions in APEC countries than positive news relative to other regions. Market capitalisation size-weighted portfolios exhibited superior performance compared to equally-weighted portfolios. GARCH (1,1) outperformed EGARCH (1,1) in terms of efficacy.

This chapter contains several valuable contributions to the existing literature. Firstly, it sheds light on the APEC countries, which have yet to be thoroughly studied despite their significant global economic impact. Secondly, it incorporates the volatility index and news as additional variables in time series models. Thirdly, it considers historical stock prices and news sentiment when estimating the time series model. Fourthly, comparing GARCH and EGARCH results in a more insightful evaluation of stock prices with the news factor. Fifthly, it delves deeper into the effects of positive and negative news sentiment by thoroughly examining it. Sixthly, it discusses news from various sectors. Lastly, we apply our findings to different portfolios.

This chapter consists of five distinct sections. The initial section serves as an introduction and is followed by an in-depth literature review. The third section thoroughly explains the data sets and each analysis step. The fourth section outlines the econometric techniques and methodology employed. Finally, the fifth and final section presents a comprehensive summary of the outcomes and concludes the chapter.

## 3.2 Literature Review

### 3.2.1 VIX Index

Determining volatility is paramount when making market-timing decisions, pricing options and derivatives, and assessing market risk and hedge ratios. As Kambouroudis and McMillan (2016) point out, the need for accurate volatility estimation is ongoing. The VIX is a benchmark for anticipating short-term market volatility and provides a predictive outlook for volatility.

The introduction of the VIX index in 1993 has contributed significantly to understanding asset markets, particularly stock market uncertainty and variance risk premium. This index, also referred to as the "fear index", provides insight into the expected volatility of the stock market and the variance risk premium, which are important considerations for investors. According to Pan, Wang, Liu and Wang (2019), the VIX index has become a widely accepted measure of market sentiment. It is now considered an essential tool for assessing the risk associated with financial investments.

The esteemed Chicago Board Options Exchange (CBOE) calculates the VIX index, utilising option prices obtained from the S&P 500 index. This index is widely recognised as the key benchmark for the U.S. equity market and is frequently employed as the underlying asset for American equity derivatives (Whaley, R.E., 2009, De la Torre-Torres, O.V., Venegas-Martínez, F. and Martínez-Torre-Enciso, M.I., 2021). Notably, the VIX leverages a model-free estimator of implied volatility, which allows it to remain independent of any specific options pricing methodology or framework.

The VIX index serves as a gauge of options traders' risk perception. Extreme values of the VIX index are often seen as trading signals. A high VIX value suggests elevated levels of fear and uncertainty in the market, with a value exceeding 30 indicating exceptionally high tension. Conversely, a meagre VIX value could indicate a potential shift away from downward price movement. The VIX offers a market-based, forward-looking projection of stock market volatility over one month (Qiao, G., Yang, J. and Li, W., 2020).

Numerous studies have scrutinised the GARCH model's capabilities in estimating and forecasting, utilising the VIX index. Kambouroudis and McMillan's (2016) research revealed that both VIX and volume augment the informational value of GARCH-type models, with VIX being more insightful than volume. Venter and Maré's (2022) study demonstrated enhanced estimation outcomes by incorporating VIX into GARCH, albeit with a student t distribution.

### 3.2.2 News

The study conducted by Mitchell and Mulherin (1994) aimed at exploring the relationship between news announcements and market prices. However, the study results revealed that the evidence available could not substantiate a strong correlation between the two variables under consideration. Additionally, market activities could not explain the pattern of news announcements. Therefore, the study failed to establish a conclusive association between news and market prices and highlights the need for further research in this area.

The financial industry has seen the rise in the importance and activity of the stock market. Accurate predictions of market volatility are crucial for investors, who rely on analysing news and utilising various models to achieve this. One such successful model was employed in 2018 by Zhang, Fu & Li, who used Thomson Reuters to analyse media news and predict the movement of a Chinese company's stock price through a VaR model. A more recent development was introduced in 2019 by Sadik, Date & Mitra. The NA-GARCH model, or news-augmented GARCH model, utilises news sentiment data in conjunction with asset time series data to predict the volatility of asset price returns.

A growing body of empirical findings and theoretical studies have run the estimations and showed a significant relationship between sentiment and stock return volatility. In 2018, Atkins, Niranjan & Gerding found that financial news predicts stock volatilities better than the close price. Cepoi (2020) investigated the stock prices related to COVID news in the most affected countries and found a positive result. Carlini, Cucinelli, Previtali & Soana (2020) showed that governance news affects corporate stocks significantly. Sun, Liu, Chen, Hao & Zhang (2020) found a positive effect on Chinese social media news and stock return. The financial news contains quantitative figures and qualitative contextual information, for example, corporate disclosures, third-party news articles and analyst reports.

"News intensity" is a phrase used to describe the level of interest that a news story garners from the public or market participants. This level is usually assessed by examining various factors, including the quantity of news articles, the number of sources reporting on the story, and the level of sophistication and nuance in the reporting.

The change in news intensity can trigger return changes for different reasons, such as the nature of news, the timing and frequency, the type of stocks and other market conditions. The correlation between changes in news intensity and stock price changes is a subject of considerable interest to investors and researchers.

Papers such as (Boudoukh, J., Feldman, R., Kogan, S. & Richardson, M., 2019), (Sun, B. and Gao, Y., 2020) (Chen, J., Tang, G., Yao, J. & Zhou, G., 2022) introduced the concept of news intensity. They also explored the relationship between news intensity and various measures of stock market performance, such as volatility (Deng, M., Nguyen, M. and Gebka, B., 2023), returns (Feng, L., Fu, T. & Shi, Y., 2022), liquidity (Carlini, F., Cucinelli, D., Previtali, D. and Soana, M.G., 2020) (Sun, B. and Gao, Y., 2020), and the cross-section of stock returns (Jeon, Y., McCurdy, T.H. and Zhao, X., 2022).

Generally, there is a positive/negative correlation or no correlation. There have been several studies that have examined this relationship. Here are some key findings: There can be cases where the correlation could be more straightforward. For instance, there may be cases where the stock market overreacts to the news, leading to a temporary spike or dip in stock prices that does not align with the company's underlying fundamentals or the broader market. Additionally, there may be times when news intensity has no discernible effect on stock prices due to market inefficiencies or other factors.

These papers provide the stock market's potential overreaction to news (Liu, C., Wu, Y. and Zhu, D., 2022) covering a range of topics, such as the impact of COVID-19 news (Ambros, M., Frenkel, M., Huynh, T.L.D. and Kilinc, M., 2021), government policy (Sunardi, S., Noviolla, C., Supramono, S. and Hermanto, Y.B., 2023), natural language processing (Luo, Y., 2020) and dividend cut announcements (Pandey, D.K. and Kumari, V., 2022) on stock prices.

However, most of the time, the increase in news intensity can affect the trading volume (Xie, D., Cui, Y. and Liu, Y., 2023). For example, suppose a company announces positive news, such as higher-than-expected earnings. In that case, the news intensity may be high, and the stock price may increase, indicating a positive correlation between the two. Studies include (Mohan, S., Mullapudi, S., Sammeta, S., Vijayvergia, P. and Anastasiu, D.C., 2019) (Duz Tan, S. and Tas, O., 2021).

Conversely, when a company releases adverse news, such as a product recall or scandal announcement, the news intensity may be high. The stock price may decrease, indicating a negative correlation (Boubaker, S., Liu, Z. and Zhai, L., 2021), (Yang, S., Liu, Z. and Wang, X., 2020), (Baek, S., Mohanty, S.K. and Glambosky, M., 2020).

Determining the correlation between news intensity and stock prices can be challenging due to the many variables that can impact them. However, our research has revealed that news intensity significantly influences stock prices. News events with higher power have been shown to trigger more significant fluctuations in stock volatility. As such, it is imperative for investors to diligently track news events and their corresponding intensity levels to stay abreast of any potential market shifts.

Sentiment analysis is a valuable tool that categorises information in a text as positive, negative, or neutral. This analysis can provide insights into the attitudes and emotions of investors towards a particular product or company. For instance, a positive sentiment score in news articles might encourage investors to purchase, while a negative score might prompt them to sell. A neutral score could result in a holding pattern.

In the recent past, there has been a growing interest among academia in the impact of news sentiment on financial price movement (Audrino, F., Sigrist, F. & Ballinari, D., 2020), Allen, D.E., McAleer, M. and Singh, A.K., 2019). Research studies have explored the human emotional responses to news articles that exhibit a positive, negative, or neutral tone. However, the findings presented by (Burchard, Proelss, Schäffer, & Schweizer, 2021) and (Souma, Vodenska, & Aoyama, 2019) demonstrate no consensus on these reactions.

Studies by Allen, McAleer & Singh (2019) and Duan, Liu & Wang (2020) suggest that neutral news updates, such as routine business updates or minor management changes, minimally impact stock prices. This is because such news does not provide significant or new information that would affect investor sentiment or demand for the company's shares (Du, H., Hao, J., He, F. and Xi, W., 2022). It is generally accepted that neutral news does not affect stock prices, as noted in the studies above, see Allen, McAleer & Singh (2019) and Duan, Liu & Wang (2020).

Disseminating positive news, such as optimistic quarterly reports and indications of stability, can entice more investors to invest in a company, increasing its stock prices. According to a study conducted by Suleman in 2012, positive political news has the potential to decrease market volatility. In contrast, negative political news can have divisive impacts, resulting in an escalation of volatility. The study utilised the Pakistan index as a crucial measure for evaluating shifts in market volatility.

Li's research in 2018 delved into the relationship between the stock returns of Chinese companies and government news. The findings indicated that positive news boosted stock performance, whereas negative information led to a decline. Similarly, Heston and Sinha conducted a study in 2017 that revealed that positive news triggered an immediate rise in stock prices, whereas negative news caused a delayed effect. Their analysis encompassed a broad range of over 900,000 news stories.

According to recent research by leading authors in the field, including Prempeh, K.B., Frimpong, J.M. and Amaning, N. (2022) and Zhao, H., Wang, D., Wang, M., He, X. and Jin, J. (2019), positive news sentiment is a critical factor impacting stock prices. The use of sentiment analysis and social media activity is rapidly gaining prominence, as observed by Rognone, L., Hyde, S. and Zhang, S.S. (2020). For instance, it is believed that good news, such as positive quarterly reports and indications of stability in a company, can attract more investors, leading to stock price increases (Li, Z., Tian, M., Ouyang, G. & Wen, F., 2021).

This chapter emphasises that news sentiment's influence on stock prices can vary depending on the country and market involved. For instance, according to the research conducted by Pérez, A., García de los Salmones, M.D.M. and López-Gutiérrez, C. (2020), the market's reaction tends to be more pronounced when negative news is disclosed across all sectors -

primary, energy, finance, goods and services. Nevertheless, it is worth mentioning that positive news can also trigger significant positive responses in the stock market, particularly in the finance and primary sectors.

On the other hand, research has uncovered a strong correlation between negative news and market volatility. For example, in 2020, Carlini, Cucinelli, Previtali, and Soana conducted a study that found negative information can affect bank stock returns. Similarly, Baek, Mohanty, and Glambosky analysed the impact of COVID-19 news on US stock prices and discovered that bad news has a more significant effect on volatility. Nerger, Huynh, and Wang also demonstrated how negative information can increase stock price volatility. Additionally, studies by Ho Chau, C., Wu, S., Liu, Y., Zou, Z., and Weng, T. H. (2022), Ajjoub, C., Walker, T., and Zhao, Y. (2021) indicate that negative news sentiment can significantly impact stock prices due to decreased investor confidence, increased uncertainty, and potential changes in market expectations.

According to a study by Carlini, Cucinelli, Previtali & Soana in 2020, negative news can significantly increase market volatility. Negative information can dramatically impact stock prices more than positive news. This was shown by various papers, such as An, Z., Chen, C., Naiker, V., and Wang, J., 2020 tested that negative news has the most potent effect on cross-sectional stock returns. Chen, C.Y.H. and Hafner, C.M., 2019 also found that bad news has a more substantial impact on volatility than good news. Others all have similar results; see, (Abou Elseoud, M.S. and Haji, A.A., 2021), (Panda, A.K., Panda, P., Nanda, S. and Parad, A., 2021), (Saranya, P.B., 2022), (Rao, K.M., 2021).

Various factors can affect the correlation between negative news sentiment and stock prices, such as the gravity and scope of the negative news, the frequency and timing of its release, and the prevailing economic and market conditions, as noted by Blaufus, Möhlmann, and Schwäbe in 2019 and by Ender and Brinckmann in 2019.

Based on our research, we have observed that news, whether positive or negative, can influence stock prices. Nonetheless, negative news appears to substantially impact stock volatilities more than positive news. It's worth highlighting, however, that the effects of information on stock prices can be unpredictable, and additional exploration might be necessary to comprehend the underlying mechanisms and factors contributing to this occurrence.

Stock prediction through market data analysis is a fascinating area of study. Researchers have utilised stock prices and news articles to craft prediction models. Nevertheless, the primary obstacle is skillfully merging technical indicators derived from stock prices with the sentiment information gleaned from textual news articles while allowing the model to intelligently learn sequential transmission within time series data. Regrettably, this challenge remains unresolved in the present research climate.

Research has shown that more than relying solely on historical data or textual information is required to accurately predict stock prices (S. Mohan, S. Mullapudi, S. Sammeta, P. Vijayvergia & D. C. Anastasiu, 2019). Consequently, incorporating both historical daily stock prices and current daily financial news (such as risk factors and investors' decisions) as inputs into the mean-variance equation is believed to result in more precise predictions of the closing stock price for a given day (Atkins, Niranjan & Gerding, 2018).

Studies have demonstrated that including news factors can enhance the precision of estimation outcomes. The estimation accuracy was substantially improved by considering positive and negative sentiment in conjunction with historical daily price data. According to Kalra and Prasad's 2019 research, accuracy rates ranged from 65.30% to 91.2%. Similarly, Jammalamadaka, Qiu, and Ning incorporated sentiment analysis in the form of polarities and emotions into an advanced multivariate Bayesian machine learning time series model, resulting in improved stock portfolio estimating.

According to Qian, Tu, and Härdle's 2019 study, the most precise method for estimating significant US market stock returns is incorporating news variables into intraday stock volatility modelling using the GARCH process with skew-t error distribution. Similarly, Liang, Tang, Li, and Wei's 2020 research examined the predictive capabilities of three sentiment indices constructed from social media, newspaper, and internet media news for forecasting realised volatility from both in and out-of-sample perspectives. Their findings highlighted a significant impact.

Various empirical and theoretical studies have utilised time series models to demonstrate a significant correlation between sentiment and stock return volatility (Chiong, R., Fan, Z., Hu, Z., Adam, M.T., Lutz, B. & Neumann, D., 2018). To illustrate, some studies have employed

Ordinary Least Square (OLS) and Quantile Regression (QR) techniques (Simon Alfano, Stefan Feuerriegel, Dirk Neumann, 2020).

Financial institutions and investors commonly rely on GARCH and EGARCH models to assess risks. However, these models only partially consider the effect of news sentiment on stock prices, as Chen and Haga (2021) noted. While many studies have attempted to adapt existing models, new approaches have emerged. For instance, Sadik, Date, and Mitra introduced the NA-GARCH (news-augmented GARCH) model in 2019, which leverages news sentiment data in conjunction with asset time series data to enhance the accuracy of asset price return volatility predictions.

Our results show that our estimating results are improved by using news intensity and sentiment as extra variables in GARCH models.

### 3.2.3 The Asia-Pacific Economic Cooperation

The global stock market can be influenced uniquely by various financial news. For instance, Shi, Ho, K & Liu (2016) conducted a study in developed countries to determine how public news sentiment affected the volatility of American stock prices. Similarly, Sadik, Date & Mitra (2019) used the news augment GARCH (1, 1) model to analyse the impact of financial information on FTSE 100 and EUROSTOXX55. Additionally, Iqbal, Manzoor & Bhatti (2021) researched the influence of news on Australian stock volatility.

Numerous studies have concentrated on examining the influence of news on stock prices in emerging economies. To illustrate, Korkpoe & Junior (2018) analysed the impact of communication on stock prices in the South African market. Emenike & Enock (2020) utilised information from Uganda to elucidate how news impacts stock return volatility. Meanwhile, Xu, Wang, Chen & Liang (2021) scrutinised the correlation between realised volatility and information throughout the Chinese market.

The existing body of literature needs to include research on the correlation between news and global market performance in an economic group of advanced and developing regions. This gap in knowledge presents an opportunity for further investigation and analysis.

The Asia-Pacific region has played a significant role in the global economy, spearheading economic growth following the tumultuous 2008-2009 Global Financial Crisis. To acknowledge the region's vital significance, Asia Pacific Economic Co-operation (APEC) was formed in 1989, taking inspiration from the fruitful chain of post-ministerial conferences first introduced by the Association of Southeast Asian Nations (ASEAN) in the mid-1980s.

APEC is the primary and most prominent economic alliance in the Asia-Pacific region. It is a platform for fostering economic cooperation to promote growth and prosperity. The annual gathering of APEC member state leaders is focused on achieving equitable, sustainable, pioneering, and secure economic expansion and accelerating regional economic integration. APEC ensures that goods, services, investments, and individuals can move freely and efficiently across borders.

APEC, which stands for the Asia-Pacific Economic Cooperation, is a diverse organisation composed of member countries along the Pacific Ocean. These nations work together to promote economic cooperation and development. The members of APEC include a wide range of countries such as the United States, Russia, China, Japan, Canada, Singapore, Australia, Taiwan, Brunei, Chile, Hong Kong, Indonesia, Korea, Malaysia, Mexico, New Zealand, Peru, Papua New Guinea, the Philippines, Thailand, and Vietnam. This organisation was established in 1989 with 12 founding members, including Canada, the United States, Australia, Japan, and the Republic of Korea. In 1991, China (Hong Kong) became a member of APEC.

With a population of 329 million people, the United States boasts the world's largest economy. The country co-founded APEC in 1989, with a GDP of USD 8.8 trillion and a per capita GDP of 36,000. Fast forward to 2020, and the real GDP has surged to 21 trillion, with a per capita GDP of 63,543. The first-ever APEC Economic Leaders' Meeting took place in the United States in 1993, with the country hosting the event again in 2011.

Canada has a population of 38 million. The real GDP of Canada increased from USD 1 trillion to 1.6 trillion, and the per capita GDP significantly rose from USD 37,000 to 43,258 from 1989 to 2020. The leaders’ meeting in Canada was hosted in 1997.

Australia is home to 26 million people. The real GDP of Australia doubled from USD 590 billion to 1.3 trillion, and the per capita GDP significantly rose from USD 35,000 to 51,812 from 1989 to 2020. The leaders' meeting in 2007 was chaired in Sydney.

With a population of 126 million people, Japan ranks as the third-largest economy in the world. In 1989, the country's GDP stood at USD 4.4 trillion, with a real per capita GDP of USD 36,000. Fast forward to 2020, and Japan's real GDP had increased to USD 5 trillion, while its per capita GDP rose to USD 39,538. It is worth noting that Japan has played host to APEC twice, first in 1995 and then in 2010, where the theme was "Change and Action."

With a population of 7 million, Hong Kong (China) is among the rapidly expanding economies globally. Since joining APEC in 1991, it has made impressive strides. Over the past three decades, Canada's real GDP has surged from $plate_number_1 billion to $347 billion, with a substantial rise in per capita GDP from USD 19,000 to 46,323 between 1989 and 2020.

With a population of 52 million, the Republic of Korea has experienced significant economic growth over the years. Its real GDP has increased from USD 330 billion to 1.6 trillion, while the per capita GDP has risen from USD 7,700 to 31,489 between 1989 and 2020. The country has also hosted two leaders' meetings, one in 1991 and the other in 2005.

Examining various nations is crucial for comprehensively analysing how news impacts stock prices worldwide. The Asia-Pacific Economic Cooperation (APEC) comprises 21 countries with unique cultural and developmental backgrounds, including the world's three largest economies: the United States, China, and Japan. APEC holds substantial economic sway (Higgott, R., 2019), establishing it as the perfect cohort to study the effects of news on stock prices.

The APEC region boasts a population of over 4 billion individuals. As of 2020, APEC's GDP was approximately 53 billion, while the world's GDP was around 84 billion. An interesting fact to consider is that APEC, with 37% of the world's population, generates 63% of the global GDP. Moreover, APEC represents nearly 55% of the world's total domestic products and roughly 44% of international trade.

Our research focused on the APEC group, which stood out as the ideal region due to its robust economic strength and active organisational initiatives. Based on their GDP value ranking, we carefully handpicked six countries from this group, namely the United States (the world's largest economy), Canada, Australia, Japan (the world's third-largest economy), Hong Kong (China) (one of the most rapidly expanding economies in the world), and South Korea.

### 3.2.4 This chapter

The effect of news on the cross-section of stock returns has recently received a great deal of attention from researchers and practitioners; however, they offer different views on the relationship between news and stock returns (Fang, L. & Peress, J., 2009). It was mentioned that firms in the same industry have co-move stock prices due to sharing common industry-specific risks (Wu & Mazouz, 2016).

Research has indicated that even seemingly minor news can notably impact specific industries. For example, a 2020 study conducted by Law, Cornelsen, Adams, Penney, Rutter, White, and Smith found that event news hurt the soft drinks industry in the UK. Similarly, a 2021 study by Nerger, Huynh, and Wang examined the effects of political reports - such as the election of Trump and his actions - on 49 industry sectors in the US. The results revealed that only one industry was affected by political news.

There is ongoing debate surrounding the feasibility of using industry-specific media coverage to anticipate stock returns. Huang and Zhang's recent findings (2021) indicate that companies with lower media exposure often outperform those with a more extensive range. Salisu and Vo (2020) have proposed that blending financial and health news can enhance the accuracy of market projections, particularly during the pandemic. The present inquiry explores the variability in news impact across diverse industry sectors.

A vast literature, such as Rizwan & Khursheed (2018) and Trapero, Cardos & Kourentzes (2019), It has been observed that the simple GARCH (1, 1) model is often sufficient for effectively modelling various economic and financial time series data. Evidence in the literature shows that GARCH (1, 1) is superior to other GARCH-type models. See Nugroho, Kurniawati, Panjaitan, Kholil, Susanto & Sasongko (2019), and Sobreira & Louro (2020).

However, others argue that EGARCH (1, 1) captures the leverage effect, which can better describe the stock returns see Naimy & Hayek (2018), Xu & Lien (2022). EGARCH (1, 1) is believed to be the most accurate model by Bonga after comparing the stock analysis results among GARCH (1, 1), GARCH-M (1, 1) and IGARCH in 2019.

Therefore, our study has yet to report using higher-order GARCH models. Nonetheless, the suggested model could be readily expanded and adapted to accommodate more comprehensive GARCH (p, q) models where the maximum of p and q exceeds 1.

It was tested that using only historical data or textual information cannot produce an accurate result when combined for predicting stock prices (S. Mohan, S. Mullapudi, S. Sammeta, P. Vijayvergia & D. C. Anastasiu, 2019). Hence, we believe taking into consideration historical daily stock prices along with current daily financial news (risk factor/investors' decision) as input into the mean-variance equation to produce present days closing stock price prediction can lead to better results (Atkins, Niranjan & Gerding, 2018).

Previous studies have utilised various sources such as social media, Twitter, financial blogs, Thomson Reuters, and news articles for collecting data (Sun, Liu, Chen, Hao & Zhang, 2020; H. Alostad & H. Davulcu, 2015; Y. Wang, D. Seyler, S. K. K. Santu & C. Zhai, 2017; Zhang, Fu & Li, 2018; H. D. Huynh, L. M. Dang & D. Duong, 2017). However, our research approach involved using financial news articles from reliable sources such as Bloomberg that were automatically labelled and selected - a method previously highlighted by Caporale, G.M., Spagnolo, F. & Spagnolo, N. (2018).

This chapter intends to provide compelling reasoning for the following assertions: 1) news has an impact on stock returns, 2) the effect of positive and negative news on the stock market varies, 3) select industries are more vulnerable to news than others, 4) news impact may differ across countries, 5) GARCH models can yield superior outcomes with the inclusion of news information as an additional parameter, and 6) integrating VIX with news variables can further augment our discoveries.

## 3.3 Data

This project included the VIX index and two types of news data: market and news data.

This study is based on extensive data gathered over five years, from November 8th, 2017 to December 8th, 2022. The analysis uses 1326 observations, incorporating information from the VIX index, market returns and news sentiment. All data is sourced from Bloomberg and processed through the EVIEWS computer program to create a hypothetical historical index. The tables and figures presented in the study focus on American indexes, while data for other countries is available in Appendix B, organized by country.

### 3.3.1 VIX index

The VIX index serves as a gauge of implied volatility for options associated with the S&P 500 index. It does not have a straightforward return calculation, such as a stock or bond. However, we can calculate returns based on changes in the VIX index level over time.

To calculate returns for the VIX index is to use log differences, also known as log returns.

After extracting the VIX daily index from 2017-2022, we input it into Eviews to calculate the log return of the VIX index between two time periods t and t-1. Firstly, we take logarithm of each variable using the equation below:

$$LVIX = \log\,(VIX)\,, \tag{12}$$

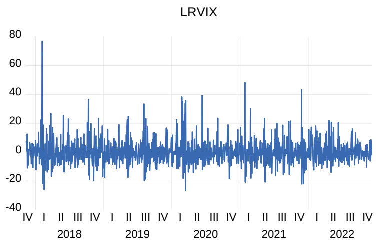
The percentage return calculation was calculated using the following equation.

$$Log\ return\ of\ VIX = 100 * \log(VIX_t) - \log(VIX_{t-1}) * 100\,, \tag{13}$$

Where $VIX_t$ represents the value of the VIX index at time t, and $VIX_{t-1}$represents the value of the VIX index at the previous time period t-1.

The statistics description of VIX index log return is included in Figure 7, we can see log return of VIX is stable, it is stationary and mean-reverting.

**Figure 3.1 Line plots of VIX log return**




**Notes:** This figure shows the log of the VIX index after applying Equation 12 and Equation 13. The VIX is a persistent time series, as its daily levels display high autocorrelation.

### 3.3.2 Market return

Using intraday data for analysis using the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) (1,1) model can be complex due to volatility seasonality throughout the trading day. As Onali (2020) highlighted, this poses a significant challenge to researchers and practitioners analysing financial data at high frequencies. To this end, the present study employs daily closing stock prices to model volatility in the time series data for the analysis of financial data.

United States, China, Japan, Canada, South Korea and Australia were selected based on the top 7 GDP ranking inside the APEC group in 2021, see **Table 3.1**.

**Table 3.1 Selected APEC countries and indexes by GDP**[8]

| Member Economy(s) | Name as used in APEC | GDP in 2020 (Millions of US$) | Index |
|---:|---:|:---:|:---|
| **United States** | The United States | 20,936,600 | S&P 500 |
| **China** | People's Republic of China | 14,722,730 | HSC 50 |
| **Japan** | Japan | 4,975,415 | NIKEEI 225 |
| **Canada** | Canada | 1,644,037 | SP TSX 300 |
| **South Korea** | Republic of Korea | 1,630,525 | KOSPI100 |
| **Australia** | Australia | 1,330,900 | ASX 200 |

**Notes:** We carefully choose a primary benchmark indicator for each market to identify the top countries. Our selected indicators include the S&P 500, ASX 200, SP TSX 300, NIKEEI 225, KOSPI100, and HSC 50.

[8] Resources: APEC Key Indicators Database StatsAPEC - Economic and social statistics for the Asia-Pacific region.

Economists use a classification system to group industries based on the types of activities in which workers are engaged. This system identifies five main sectors: Primary, Secondary, Tertiary, Quaternary, and Quinary. In recent years, the proportion of workers in primary sector activities has declined in both developed and developing countries. For example, in 2018, the percentage of American workers engaged in primary sector activities was only 1.8%. As a result, we have opted to exclude the primary sector from our data selection. For further information on the chosen industries across different sectors, please refer to Table 3.2.

**Table 3.2 Selection of industries from economic sectors**[9]

| Sectors | Definition | Activity | Industry selected |
|---|---|---|---|
| **Primary Sector** | Extracts or harvests products from the earth such as raw materials and basic foods. | Agriculture, mining, forestry, grazing, hunting and gathering, fishing, and quarrying. | None |
| **Secondary Sector** | Produces finished goods from the raw materials extracted by the primary economy. | Manufacturing, processing, and construction; energy utilities, breweries and bottlers, construction, and shipbuilding | Energy |
| **Tertiary Sector** | Sells the goods produced by the secondary sector and provides commercial services to both the general population and to businesses. | Retail and wholesale sales, transportation and distribution, restaurants, clerical services, media, tourism, insurance, banking, health care, and law. | Finance |
| **Quaternary Sector** | Consists of intellectual activities often associated with technological innovation. | Government, culture, libraries, scientific research, education, and information technology. | Technology |
| **Quinary Sector** | The highest levels of decision-making in a society or economy | government, science, universities, non-profits, health care, culture, and the media | Health care |

**Notes:** We have selected a diverse range of industries from various sectors, including energy from the secondary sector, finance from the tertiary sector (also referred to as the service industry), technology from the quaternary sector, and healthcare from the quinary sector.

Then, we make the stock selections based on the market capitalisation of the companies, ensuring that they are the largest within their respective industries. This approach allows us to gather robust news data points, as companies with significant market capitalisation typically receive extensive news coverage. See Table 3.3.

[9] Resources: Rosenberg, Matt. “The 5 Sectors of the Economy.” ThoughtCo, Aug. 27, 2020. https://www.thoughtco.com/sectors-of-the-economy-1435795.

## Table 3.3 Selected stocks by the market cap [10]

| | TITLE/SYMBOL | INDUSTRY | MARKET CAP |
|---|---|---|---|
| **US** | **S &P 500** | | |
| | Apple Inc (AAPL) | Technology | \$2.986T |
| | Berkshire Hathaway Inc (BRK) | Finance | \$673.128B |
| | Exxon mobil Corporate (XOM) | Energy | \$269.080B |
| | United Health Group Incorporated (UNH) | Health care | \$473.073B |
| **AU** | **ASX 200** | | |
| | Wisetech Global Ltd (WTC) | Technology | A\$15.43B |
| | Common Wealth Bank of Australia (CBA) | Finance | A\$181.82B |
| | Woodsite Petroleum Ltd (WPLCD) | Energy | A\$31.45B |
| | CSL Ltd (CSL) | Health care | A\$126.67B |
| **CD** | **SP TSX 300** | | |
| | Shopify (SHOP) | Technology | \$109.04B |
| | Royal Bank of Canada (RY) | Finance | \$194.53B |
| | Enbrudge (ENB) | Energy | \$117.65B |
| | Bausch Health (BHC) | Health care | \$10.37B |
| **JP** | **NIKKEI 225** | | |
| | SONY | Technology | JPY¥1.53T |
| | MISUBISHI (UFJ) | Finance | JPY¥9.75T |
| | MITSUI & Co (MITS) | Energy | JPY¥5.31T |
| | HOYA Crop (HOYA) | Health care | JPY¥5.13T |
| **SK** | **KOSPI 100** | | |
| | SAMSUNG (SMS) | Technology | ₩449.76T |
| | KBFinancial Group (KBF) | Finance | ₩23.016T |
| | SK Innovation (SKN) | Energy | ₩311.31K |
| | Celltrion (CTN) | Health care | ₩236.84K |
| **CH** | **HSC 50** | | |
| | Tencent (TNT) | Technology | HKD4.04T |
| | Industrial and Commercial Bank of China (ICBC) | Finance | HKD2022B |
| | WuXi Biologics (WXB) | Health care | HKD432.97B |
| | Petrochina (PTC) | Energy | HKD1195B |

**Notes:** In order to make our stock selection process more efficient, we have selected stocks based on their market capitalisation within the specific industry. We then provided each stock's corresponding symbols, such as AAPL for Apple Inc. The market capitalisation is expressed in the local currency and is denoted as K for thousand, B for billion, and T for trillion. This allows for a clear understanding of the value of each stock in relation to its market capitalisation.

Asset returns were known as an overall number of gains or losses on a day-to-day basis. There are various ways to calculate asset returns. In this project, we use the following equation after collecting the daily historical market data:

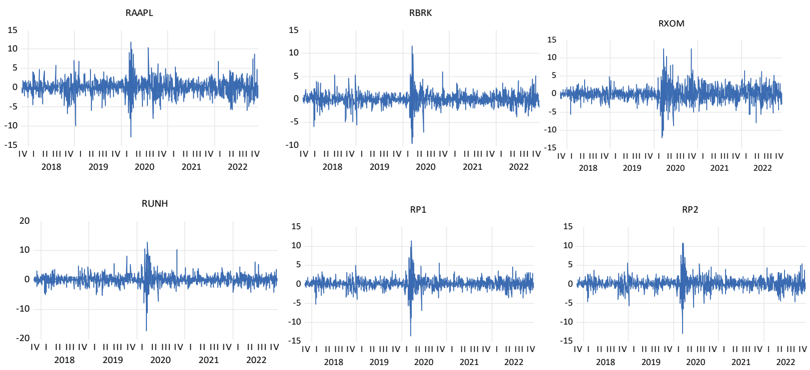
$$R_t = \left(\frac{P_t - P_{t-1}}{P_{t-1}}\right) * 100\,, \tag{14}$$

[10] Resources: : https://www.liberatedstocktrader.com/sp-500-companies/https://www.marketindex.com.au/asx-listed-companieshttps://fknol.com/ca/market-cap-tsx-composite-index.
https://www.tradingview.com/markets/stocks-korea/market-movers-large-cap
https://fknol.com/jp/stock/healthcare.phphttps://www.tradingview.com/markets/stocks-china/market-movers-large-cap/https://fknol.com/hk/stock/healthcare.php

Where $P_t$ is the stock price at time t, $P_{t-1}$ is the stock price at time t-1, $R_t$ is the stock return at time t.

Applying Equation 14 to all the stocks provides a conclusive insight into the accuracy of GARCH models. Figure 3.2 displays the volatilities of American stocks, with the remaining return volatilities exhibiting a comparable pattern. Figures of other countries' stock returns are available in Appendix C.

**Figure 3.2 Line plots of American stock returns**[11]




**Notes:** All the stock returns exhibit volatility clustering, which suggests that a GARCH model would be appropriate. In order to ascertain if GARCH (1,1) is appropriate for the complete dataset, it is imperative to analyze both the index price and return plots. The return plot must demonstrate characteristics of stationarity, signifying that all returns are aligned with the mean value and do not exhibit a pattern over time.

### 3.3.3 News input

While raw news data possesses qualitative value, models require quantitative inputs to incorporate news in an automated and direct manner. Fortunately, advancements in technology now allow for automatic news collection, extraction, aggregation, categorization, and scoring. Through the utilization of machine-learning techniques, contextual news stories can be processed and transformed into quantified news sentiment scores.

[11] This study is based on extensive data gathered over five years, from November 8th, 2017 to December 8th, 2022. The analysis uses 1326 observations, incorporating information from the VIX index, market returns and news sentiment. All data is sourced from Bloomberg and processed through the EVIEWS computer program to create a hypothetical historical index. The returns of prominent companies are represented by RAAPL for Apple Inc (AAPL), BREK for Berkshire Hathaway Inc (BRK), RXOM for Exxon Mobil Corporation (XOM), and RUNH for UnitedHealth Group Incorporated (UNH). Portfolio 1's return is denoted by RP1, while Portfolio 2's return is symbolized by RP2.

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Bloomberg Terminal is an essential resource for finance and business professionals. It provides real-time data and analytics on various assets, along with multimedia content, efficient communication tools, and electronic trading capabilities. Bloomberg offers brief and practical news with over 40 content streams for easy sorting. The bullet point format provides quick updates on critical developments, aiding investors to make informed decisions.

Bloomberg now offers easy and efficient natural language search processing for critical news. Users can combine different criteria to search for news. Bloomberg has implemented advanced techniques to efficiently recognize news stories and tweets that are specifically related to individual stock tickers.

Furthermore, Bloomberg's technology can assign a sentiment score to each story or tweet in the feed, enabling investors to better analyse and understand market trends. This innovative approach not only enhances the speed and accuracy of stock analysis but also helps investors make informed decisions based on current market sentiment. Bloomberg provided two types of sentiment analytics: story-level sentiment and company-level sentiment.

The paper presents an alternative approach to sourcing news data for analysis. Rather than relying on Bloomberg News sentiment scores, the authors opted for a methodology that involved using specific keywords as search criteria to extract the necessary quantity of news articles.

To calculate the news indexes for AAPL stock, we would tally the number of news headlines featuring keywords such as "AAPL," "AAPL Inc.," and "AAPL stocks" in the top ten newspapers worldwide, as well as in all the other primary resources available in Bloomberg terminals. With regard to news sentiment, any news that references the keywords "AAPL" along with additional keywords like "positive" and "increase" would be categorized as positive news. Conversely, news that includes keywords such as "negative" and "decline" would fall under the classification of negative news.

This novel approach not only provides a more flexible and customizable means of data collection but also allows for a more comprehensive view of the news landscape on a given topic. Our research aims to investigate the potential benefits of integrating news sentiment information into existing investment strategies to achieve higher risk-adjusted returns.

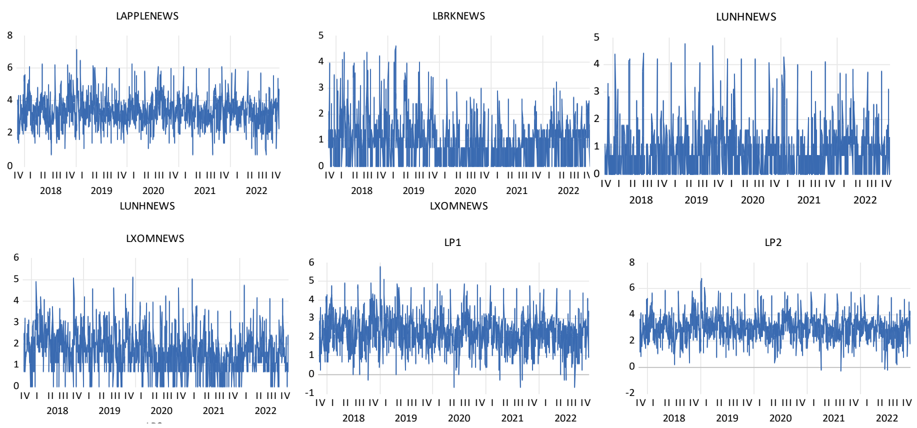
In order to determine the current impact, we take account a specific number of past time periods, referred to as the "look-back period." This period spans a duration of 24 hours, and we gather information from various sources such as Bloomberg news, web content, and select premium news wires from Bloomberg.

There are three types of news data obtained from Bloomberg in this chapter: News intensity (sum of positive news number plus numbers of negative news), which is all the news with “tones”; positive news sentiment, and negative news sentiment. To make the news data stable, we took the logarithm of the news intensity.  The equation is as follows:

$$news\ intensity = positive\ news + negative\ news\ , \tag{15}$$

$$L_t = \log\left(news\ intensity\right)\ , \tag{16}$$

**Figure 3.3 Line plots of American log news intensity**[12]




**Notes:** By utilizing Equation 15 and Equation 16, we successfully produced this table. The news intensity metric is derived from the sum of positive and negative news headlines. The plotted data exhibits stationary features, implying that the returns are uniformly distributed around the mean value, without any noticeable trends over time.

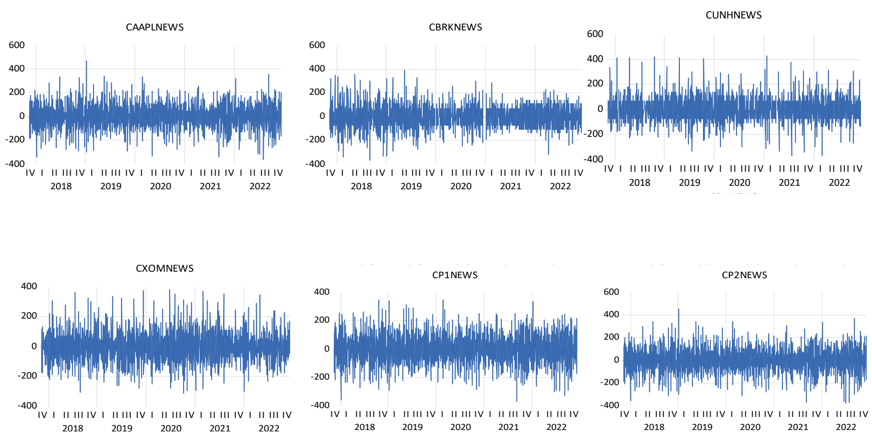
[12]Figures of other countries’ stock returns are available in Appendix C. The returns of prominent companies are represented by RAAPL for Apple Inc (AAPL), BREK for Berkshire Hathaway Inc (BRK), RXOM for Exxon Mobil Corporation (XOM), and RUNH for UnitedHealth Group Incorporated (UNH). Portfolio 1's return is denoted by RP1, while Portfolio 2's return is symbolized by RP2.

The first difference of the return is the logarithm of the ratio between the news intensity at time t and the index market price at time t-1, due to continuous compounding, the equation is as follows:

$$C_t = 100 * log\left(\frac{l_t}{l_{t-1}}\right) = 100 * L_t - 100 * L_{t-1}\,, \qquad (17)$$

Where, $c_t$ is the change of news intensity logarithm in day t, $l_t$ is the logarithm of news intensity at time t, and $l_{t-1}$is the logarithm of news intensity at time t-1.

**Figure 3.4 Line plots of American log news intensity changes[13]**




**Notes:** The metric for news intensity is determined by summing up the positive and negative headlines. By utilizing Equation 17, we were able to illustrate the changes in the intensity of American log news. Based on the plotted data, it can be observed that the returns are uniformly spread out around the mean value, and there are no notable patterns discernible over time.

The emotional sentiment conveyed in a news article can be measured through a news sentiment score, which spans from positive to negative. This introduces an additional aspect to estimating volatility. The sentiment score is confined to a defined range, with a minimal and maximal value reflecting the news article's general emotional tenor. To compute these sentiment scores, the following equations are employed:

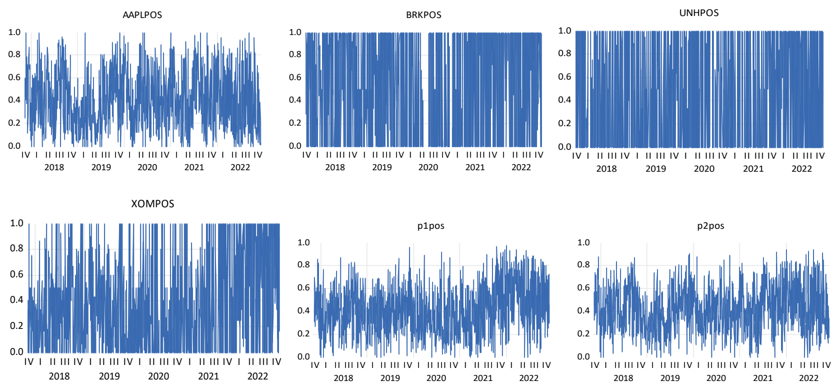
$$PN_t = \frac{positive\ news}{news\ intensity} * 100\% = \frac{positive\ news}{positivenews+negative\ news} * 100\%\,, \qquad (18)$$

[13] Figures of other countries' stock returns are available in Appendix C.

$$NN_t = \frac{negative\ news}{news\ intensity} * 100\% = \frac{negative\ news}{positivenews + negative\ news} * 100\%\ , \tag{19}$$

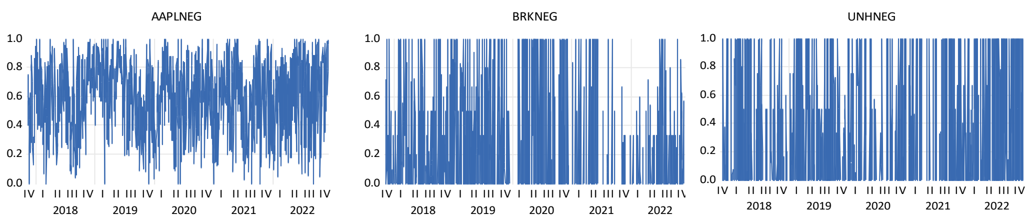
where $PN_t$ is positive sentiment score at time t, $NN_t$ is negative sentiment score at time t.

**Figure 3.5 Line plots of American positive news sentiment[14]**



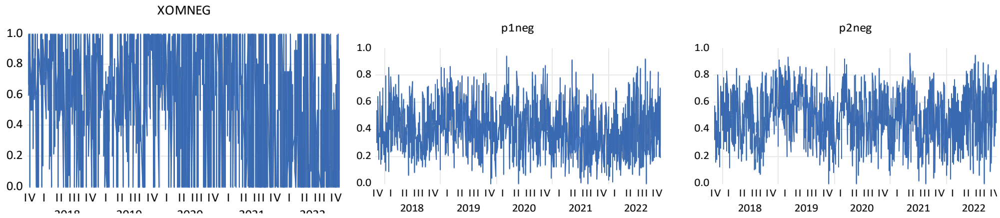

**Notes:** Using Equation 18, we can effectively showcase the degree of positivity in American news coverage. This is achieved by calculating the ratio of positive news headlines to the overall news intensity. This study is based on extensive data gathered over five years, from November 8th, 2017 to December 8th, 2022. The analysis uses 1326 observations, incorporating information from the VIX index, market returns and news sentiment. All data is sourced from Bloomberg and processed through the EVIEWS computer program to create a hypothetical historical index.

**Figure 3.6 Line plots of American negative news sentiment**




[14] Figures of other countries' stock returns are available in Appendix C.

**Figure 3.6 Line plots of American negative news sentiment (Continued)**




**Notes:** In order to better understand the negative news sentiment, we can use Equation 19. This equation calculates the ratio of negative news headlines to the overall news intensity, which is a measure of the total news coverage in a given period of time. This study is based on extensive data gathered over five years, from November 8th, 2017 to December 8th, 2022. The analysis uses 1326 observations, incorporating information from the VIX index, market returns and news sentiment. All data is sourced from Bloomberg and processed through the EVIEWS computer program to create a hypothetical historical index.

## 3.4 Methodology

This paper adapted mainly two models: GARCH (1, 1) and EGARCH (1,1). A comparison was made between these two models without news parameters, and those models with news as extra information. When incorporating news parameters, we conducted separate tests for news intensity, positive news sentiment, and negative news sentiment to obtain more information.

### 3.4.1 GARCH (1, 1)

A univariate setting time series model GARCH (1, 1) introduced by Bollerslev (1986) are widely used to model the conditional portfolio variance for financial stationary data. It can be expressed as:

$$\sigma_t^2 = \omega + \alpha_1 \mu_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \,, \tag{20}$$

Where $\sigma_t$ is today's variance, $\alpha\mu_{t-1}^2$ is the squared return of the day before, and $\beta\sigma_{t-1}^2$ is the variance on the day before. Given the many previous studies on this topic, the returns are expected to be positive and significant.

The conditional variance process is more likely to be positive and stationary when: $\omega$ > 0; $\alpha$ > 0; $\beta$ > 0 and $\alpha$+$\beta$< 1. The long-run variance, $\alpha$ and $\beta$, are obtained by the computer software EVIEWS to test which model has better skills to estimate the variance of day t.

As shown above, there is an apparent limitation in the GARCH (1, 1) model. The estimated method may violate the non-negativity conditions since the model's coefficients are probably harmful. Therefore, we introduce EGARCH (1, 1).

### 3.4.2 EGARCH (1, 1)

The EGARCH (1, 1) model, introduced by Nelson in 1991, is designed to capture the leverage effect. This effect refers to the asymmetric nature or skewness in the relationship between volatility and returns, which is driven by the inverse correlation between them when the standard GARCH model does not. EGARCH models have been demonstrated to be superior compared to other competing asymmetric conditional variances in many studies (see Alexander, 2009).

The expression for the conditional variance in the EGARCH (Exponential GARCH) model is detailed as follows:

$$log\ (\sigma_t^2) = \omega + \ \beta log\ (\sigma_{t-1}^2) + \gamma \left| \frac{\mu_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right| + \ \alpha \left| \frac{|\mu_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right|, \tag{21}$$

Where $\mu_{t-1}$= return at time t-1 and $\sigma_t^2$= the conditional variance of time t-1.

The parameters ω, α, β, and γ are to be estimated in the model. A significant advantage of EGARCH models is that, because they model the log of $\sigma_t^2$, even if the estimated parameters turn out to be negative, $\sigma_t^2$ will remain positive.

Here's a breakdown of the parameters:

The α parameter represents the magnitude effect or the symmetric effect of the model, often referred to as the "GARCH" effect.

The β parameter measures the persistence in conditional volatility, indicating how past volatility affects current volatility, regardless of market conditions or events.

The γ parameter is related to the asymmetry or leverage effect in the model, capturing how positive and negative shocks impact volatility differently, the γ parameter plays a particular significance role in measuring the asymmetry or leverage effect in the EGARCH model.

Indeed, when the γ parameter is equal to 0 in the EGARCH model, it signifies a symmetric model in which positive and negative shocks exert an equal impact on volatility. When γ is less than 0 ($\gamma < 0$), it suggests that positive shocks (good news) lead to less volatility than negative shocks (bad news). In other words, positive innovations have a dampening effect on volatility compared to negative innovations. Conversely, when γ is greater than 0 ($\gamma > 0$), it indicates that positive innovations are more destabilizing and lead to greater volatility than negative innovations.

### 3.4.3 GARCH model with news

In this part, we included the quantified news sentiment data and its impact on the movement of stock prices as an additional component.

We introduced a new variable, $z$, and we let $z_t$ equal to news intensity, positive news sentiment and negative news sentiment at time t independently. The new parameter φ represents the impact of news on stock prices, then we run the estimation and observe the P value of $\varphi$. If the P value is significant, there is a strong correlation. Otherwise, there is not enough evidence of the impact.

For GARCH (1, 1), the new equation is as shown below:

$$\sigma_t^2 = \omega + \alpha_1 \mu_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \varphi z_t^2 \,, \qquad (22)$$

Where $\sigma_t$ is today's variance, $\alpha\mu_{t-1}^2$ is the squared return of the day before, and $\beta\sigma_{t-1}^2$ is the variance on the day before. $\omega > 0$; $\alpha > 0$; $\beta > 0$ and $\alpha+\beta< 1$.

For EGARCH (1, 1), the new equation is as show below:

$$log(\sigma_t^2) = \omega + \beta\, log(\sigma_{t-1}^2) + \gamma \left| \frac{\mu_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right| + \alpha \left[ \frac{|\mu_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] + \varphi z_t^2 \,, \quad (23)$$

Where $\mu_{t-1}$= return at time t-1 and $\sigma_t^2$= the conditional variance of time t-1.

### 3.4.4 GARCH model with VIX index

In this part, we included the VIX volatility index and its impact on the movement of stock prices as an additional component.

We introduced a new variable $\mu$, and let $\mu_t$ equal the VIX index at time t independently. The new parameter $\delta$ represents the impact of the VIX index on stock prices, then we run the estimation and observe the P value of $\delta$. If the P value is significant, there is a strong correlation. Otherwise, there is not enough evidence of the impact.

For GARCH (1, 1), the new equation is as shown below:

$$\sigma_t^2 = \omega + \alpha_1 \mu_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \varphi z_t^2 + \delta\, \mu_t^2 \,, \quad (24)$$

Where Where $\sigma_t$ is today's variance, $\alpha\mu_{t-1}^2$ is the squared return of the day before, and $\beta\sigma_{t-1}^2$ is the variance on the day before. $\omega$ > 0; $\alpha$ > 0; $\beta$ > 0 and $\alpha$+$\beta$< 1.

For EGARCH (1, 1), the new equation is as follows

$$log\ (\sigma_t^2) = \omega + \beta log\ (\sigma_{t-1}^2) + \gamma \left| \frac{\mu_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right| + \alpha \left| \frac{|\mu_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right| + \varphi z_t^2 + \delta\, \mu_t^2 \,, \quad (25)$$

Where $\mu_{t-1}$= return at time t-1 and $\sigma_t^2$= the conditional variance of time t-1

### 3.4.5 Portfolios

Within the context of this chapter, two portfolios were meticulously constructed to estimate different models. The two portfolios, namely P1 and P2, utilised national-level asset indication as a basis for their construction. Both portfolios were constructed with high care and precision, ensuring they were reliable and accurate.

As part of our strategy in P1, we opted to allocate equal weights to all the stocks in our portfolio. The portfolio itself comprises six countries - namely the US, AU, CD, JP, SK, and CH - each with four stocks. This means that each individual stock was assigned a weightage of 25%. For example, the US stocks were calculated as the sum of 25% of AAPL, 25% of BRK, 25% of XOM, and 25% of UNH prices.

P2's stock weights are determined based on the market capitalization percentage of each stock in its respective country. P2 consists of six countries. For example, if AAPL has a market cap of 2.986 trillion dollars and the total market cap of the US is 4401.281 billion dollars, we divide AAPL's market cap by the total market cap of the US to calculate its weight. This weight is then multiplied by 100 to give us a percentage, which is 67.8%. Similarly, BRK, XOM, and UHN have weights of 15.3%, 6.1%, and 10.8%, respectively. In P2, the US index is calculated by multiplying AAPL prices by 67.8%, BRK prices by 15.3%, XOM prices by 6.1%, and UNH prices by 10.8%. The calculation for other countries follows the same method.

## 3.5 Result

### 3.5.1 Estimation result

EVIEWS is software that assists in analysing data and presenting results. The program provides various tools to help users extract valuable insights from the data. The results obtained can be viewed through tables and figures, which are organised by the author. To gain more detailed information, see Appendix B and C.

In our analysis, we have calculated the returns of all the stocks in all the countries, as well as the log of news intensity, changes in log news intensity, positive news sentiment and negative news sentiment. To showcase our findings, we have utilised the statistical description of log news intensity only which provides a more detailed and insightful representation of the results, the rest of the results can be found in Appendix B organised by name.

After obtaining Table 3.4, the accuracy of GARCH (1, 1) can be easily concluded.

**Table 3.4 The statistical description for the log news intensity**

| | Mean | Median | Maximum | Minimum | Std.Dev | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|
| **US** | | | | | | | |
| AAPL | 3.389137 | 3.401197 | 7.141245 | 0.000000 | 0.964034 | 0.019051 | 4.244832 |
| BRKB | 0.991999 | 1.098612 | 4.615121 | 0.000000 | 0.897428 | 1.006479 | 4.151652 |
| XOM | 1.699342 | 1.609438 | 5.123964 | 0.000000 | 0.944692 | 0.333626 | 3.140308 |
| UNH | 0.844317 | 0.693147 | 4.762174 | 0.000000 | 0.930942 | 1.504815 | 5.622559 |
| P1 | 2.368151 | 2.420368 | 5.799093 | -0.693147 | 0.894200 | -0.085201 | 3.866508 |
| P2 | 3.069859 | 3.079430 | 6.762344 | -0.302457 | 0.938261 | 0.030873 | 4.193241 |
| **AU** | | | | | | | |
| WTC | 0.162590 | 0.000000 | 3.332205 | 0.000000 | 0.443715 | 3.505839 | 17.39598 |
| CBA | 0.795058 | 0.693147 | 4.804021 | 0.000000 | 0.870322 | 1.285956 | 5.001688 |
| WPL | 0.327286 | 0.000000 | 3.401197 | 0.000000 | 0.549688 | 2.054236 | 8.219157 |
| CSL | 0.430230 | 0.000000 | 3.610918 | 0.000000 | 0.668257 | 1.946984 | 7.186788 |
| P1 | 0.625260 | 0.559616 | 3.442019 | 0.000000 | 0.559003 | 1.536260 | 6.136335 |
| P2 | 0.725134 | 0.625938 | 4.138521 | 0.000000 | 0.668882 | 1.506590 | 6.318898 |
| **CD** | | | | | | | |
| SHOP | 0.765609 | 0.693147 | 4.624973 | 0.000000 | 0.865125 | 1.267079 | 4.777863 |
| RY | 0.513192 | 0.000000 | 3.713572 | 0.000000 | 0.735059 | 1.656464 | 5.797864 |
| BHC | 0.703136 | 0.693147 | 4.744932 | 0.000000 | 0.896322 | 1.314152 | 4.171489 |
| ENG | 0.558156 | 0.000000 | 3.526361 | 0.000000 | 0.691628 | 1.154979 | 4.100029 |
| P1 | 0.852681 | 0.810930 | 3.417727 | 0.000000 | 0.669476 | 0.751231 | 3.251273 |
| P2 | 0.760127 | 0.609766 | 3.371769 | 0.000000 | 0.663944 | 1.037473 | 3.801218 |
| **JP** | | | | | | | |
| SONY | 0.772347 | 0.693147 | 5.424950 | 0.000000 | 0.966236 | 1.744977 | 6.787939 |
| UFJ | 0.493208 | 0.000000 | 3.931826 | 0.000000 | 0.772518 | 1.827972 | 6.536509 |
| MITS | 0.288042 | 0.000000 | 3.871201 | 0.000000 | 0.612729 | 2.779596 | 11.95583 |
| HOYA | 0.116282 | 0.000000 | 3.401197 | 0.000000 | 0.418811 | 4.710925 | 28.21194 |
| P1 | 0.620973 | 0.405465 | 4.060443 | 0.000000 | 0.696237 | 1.900230 | 7.443054 |
| P2 | 0.534178 | 0.350657 | 3.513335 | 0.000000 | 0.648579 | 1.813944 | 6.646398 |
| **SK** | | | | | | | |
| CTN | 0.214052 | 0.000000 | 2.772589 | 0.000000 | 0.475815 | 2.435815 | 8.742997 |
| KBF | 0.156350 | 0.000000 | 2.564949 | 0.000000 | 0.385649 | 2.801535 | 11.49488 |
| SMS | 1.806289 | 1.609438 | 5.442418 | 0.000000 | 1.009332 | 0.821718 | 4.144063 |
| SKN | 0.193953 | 0.000000 | 3.367296 | 0.000000 | 0.489484 | 3.193515 | 14.82171 |
| P1 | 1.025704 | 0.916291 | 4.069027 | 0.000000 | 0.718786 | 1.493044 | 5.756661 |
| P2 | 1.757820 | 1.585145 | 5.370173 | 0.000000 | 0.992282 | 0.870282 | 4.215774 |
| **CH** | | | | | | | |
| ICBC | 0.311400 | 0.000000 | 3.401197 | 0.000000 | 0.550046 | 2.197334 | 8.710964 |
| TNT | 1.275151 | 1.098612 | 5.036953 | 0.000000 | 1.030160 | 0.706690 | 3.126230 |
| PTC | 0.603052 | 0.693147 | 3.496508 | 0.000000 | 0.723987 | 1.225907 | 4.169741 |
| WCB | 0.144064 | 0.000000 | 3.295837 | 0.000000 | 0.429024 | 3.390169 | 15.22403 |
| P1 | 0.882665 | 0.810930 | 3.669951 | 0.000000 | 0.640805 | 1.045446 | 3.805613 |
| P2 | 1.104116 | 0.951658 | 4.407816 | 0.000000 | 0.801698 | 0.964610 | 3.805613 |

**Notes:** The table provides a comprehensive statistical analysis of the prescription for log news intensity, highlighting the stability, stationarity, and mean-reverting nature of the variables. The data in the table is presented in an organized and easy-to-understand format, making it a valuable resource for anyone seeking insights into log news intensity dynamics. The statistical description for news intensity changes, positive news and negative news are detailed in Appendix B, showing the same pattern.

In order to assess the efficacy of GARCH (1,1) across the entire data set, it is crucial to carefully examine the stock and portfolio price and return plots. The return plot should demonstrate stationary figures, with returns clustering around the mean value - or being mean-reverted. A statistical overview of the categorized stock returns by country can be found in Appendix B for reference.

Upon analysing the P-value, we can investigate the relationship between the volatility of a firm's stocks and any news relevant to the firm. Analysing the impact of positive and negative news on a particular stock can provide valuable insights into its performance. By comparing the effects of both types of news, we can gain a better understanding of how the stock is affected by different factors. When conducting statistical tests to evaluate the significance of our findings, the significance level serves as a measure of the likelihood that the observed data is not simply due to chance.

The estimation results for the GARCH model after adding different extra variables are included in the tables below. Table 3.5 shows the GARCH estimation results for the US.

**Table 3.5 GARCH estimations for US[15]**

| | Ʊ (p-value) | $\alpha$ (p-value) | $\beta$ (p-value) | γ(p-value) |
|---|---|---|---|---|
| **GARCH (1, 1)** | | | | |
| ***AAPL*** | 0.154622 (0.0000) | 0.128598 (0.0000) | 0.838660 (0.0000) | - |
| ***BRK*** | 0.078637 (0.0000) | 0.114506 (0.0000) | 0.842133 (0.0000) | - |
| ***XOM*** | 0.038824 (0.0002) | 0.097061 (0.0000) | 0.898404 (0.0000) | - |
| ***UNH*** | 0.146232 (0.0000) | 0.085040 (0.0000) | 0.861212 (0.0000) | - |
| ***P1*** | 0.065857 (0.0000) | 0.122261 (0.0000) | 0.837983 (0.0000) | - |
| ***P2*** | 0.054668 (0.0000) | 0.112245 (0.0000) | 0.863635 (0.0000) | - |
| **EGARCH (1, 1)** | | | | |
| ***AAPL*** | -0.099465 (0.0000) | 0.208244 (0.0000) | 0.954065 (0.0000) | -0.116254(0.0000) |
| ***BRK*** | -0.141996 (0.0000) | 0.221383 (0.0000) | 0.950721 (0.0000) | -0.072152(0.0000) |
| ***XOM*** | -0.132774 (0.0000) | 0.202108 (0.0000) | 0.982622 (0.0000) | -0.032242(0.0058) |
| ***UNH*** | -0.076104 (0.0000) | 0.155064 (0.0000) | 0.959348 (0.0000) | -0.123477(0.0000) |
| ***P1*** | -0.126862 (0.0000) | 0.190175 (0.0000) | 0.955193 (0.0000) | -0.127404(0.0000) |
| ***P2*** | -0.124528 (0.0000) | 0.195641 (0.0000) | 0.962910 (0.0000) | -0.101966(0.0000) |

**Notes:** A 5% significance level means that the probability of the observed result being due to chance is less than 5%. In other words, if the p-value is less than 0.05, there is strong evidence against the null hypothesis, and the result is considered statistically significant. Similarly, a p-value between 0.05 and 0.1 means that there is a 10% chance that the observed effect is due to an event. This result is still considered significant but with a lower level

[15] AAPL is short for "Apple", which was selected from the technology industry. BRK is the "Berkshire Hathaway Inc", representing the financial industry. XOM is" Exxon Mobil corporate", from the energy sector, and UNH is" United Health Group Incorporated", from the health and care industry. P1 is the equal-weighted portfolio and P2 is the market cap-weighted portfolio.

of confidence. On the other hand, if the p-value is greater than 0.1, there is a high chance that the observed result is due to an event, and the result is considered non-significant.

The statistical analysis conducted on our data set in Table 3.5 reveals that the P-values for both GARCH (1, 1) and EGARCH (1, 1) are significant at the 5% level. This indicates that these models are ideal fits for our data set. The results suggest that we can rely on the accuracy of GARCH (1, 1) and EGARCH (1, 1) in estimating outcomes based on our data. Tables for other countries see Appendix B.

The findings of GARCH estimation for the US after incorporating news intensity variables are illustrated in Table 3.6. Our analysis involved two sets of estimations. The initial set only considered news intensity variables, while the second set introduced news intensity changes as a supplementary variable to examine their effect. To calculate the news intensity changes, we determined the difference between the news volume of today and yesterday.

**Table 3.6 GARCH with log news intensity estimations for US**

| | **Ʊ (P-VALUE)** | **$\alpha$ (P-VALUE)** | **$\beta$ (P-VALUE)** | **Γ(P-VALUE)** | **NEWS INTENSITY** |
|---|---|---|---|---|---|
| **GARCH (1, 1) WITH LOG NEWS INTENSITY** | | | | | |
| ***AAPL*** | 1.443902 (0.0000) | 0.427363 (0.0000) | 0.568401 (0.0000) | - | -0.297264 (0.0000) |
| ***BRK*** | 0.052708 (0.0034) | 0.124722 (0.0000) | 0.819169 (0.0000) | - | 0.048580(0.0005) |
| ***XOM*** | 0.088176 (0.0000) | 0.128791 (0.0000) | 0.845109 (0.0000) | - | -0.032031 (0.0000) |
| ***UNH*** | 0.093399 (0.0011) | 0.092530 (0.0000) | 0.842011 (0.0000) | - | 0.105134 (0.0000) |
| ***P1*** | 0.039931 (0.1602) | 0.124135 (0.0000) | 0.832967 (0.0000) | - | 0.012927(0.3199) |
| ***P2*** | 1.017323 (0.0000) | 0.256147 (0.0000) | 0.609778 (0.0000) | - | -0.218067 (0.0000) |
| **EGARCH (1, 1) WITH LOG NEWS INTENSITY** | | | | | |
| ***AAPL*** | -0.245059 (0.0000) | 0.197691 (0.0000) | 0.947497 (0.0000) | -0.106586 (0.0000) | 0.047089 (0.0000) |
| ***BRK*** | -0.152178 (0.0000) | 0.224481(0.0000) | 0.949270 (0.0000) | -0.071357 (0.0000) | 0.008481 (0.4156) |
| ***XOM*** | -0.096711 (0.0000) | 0.211338(0.0000) | 0.978908 (0.0000) | -0.033737 (0.0065) | -0.023042 (0.0255) |
| ***UNH*** | -0.087689 (0.0000) | 0.146245 (0.0000) | 0.956110 (0.0000) | -0.130468 (0.0000) | 0.024507 (0.0065) |
| ***P1*** | -0.112841(0.0000) | 0.190677 (0.0000) | 0.955363 (0.0000) | -0.127305(0.0000) | -0.006098 (0.4112) |
| ***P2*** | -0.150732 (0.0000) | 0.190735 (0.0000) | 0.963358 (0.0000) | -0.099844 (0.0000) | 0.009631 (0.0957) |
| **GARCH (1, 1) WITH LOG NEWS INTENSITY CHANGES** | | | | | |
| ***AAPL*** | 0.204813 (0.0000) | 0.158452 (0.0000) | 0.791511 (0.0000) | - | 0.005056 (0.0000) |
| ***BRK*** | 0.079336 (0.0000) | 0.115778 (0.0000) | 0.840092 (0.0000) | - | 0.001320 (0.0000) |
| ***XOM*** | 0.042851 (0.0000) | 0.090145(0.0000) | 0.902616 (0.0000) | - | 0.001884 (0.0000) |
| ***UNH*** | 0.653350 (0.0000) | 0.171333 (0.0000) | 0.587537 (0.0000) | - | 0.006717 (0.0000) |
| ***P1*** | 0.064691 (0.0000) | 0.119936 (0.0000) | 0.840834 (0.0000) | - | 0.000765 (0.0436) |
| ***P2*** | 0.057407 (0.0000) | 0.113510 (0.0000) | 0.859992 (0.0000) | - | 0.000765 (0.0000) |
| **EGARCH (1, 1) WITH LOG NEWS INTENSITY CHANGES** | | | | | |
| ***AAPL*** | -0.109452 (0.0000) | 0.211332 (0.0000) | 0.957218 (0.0000) | -0.110859 (0.0000) | 0.002365 (0.0000) |
| ***BRK*** | -0.148316 (0.0000) | 0.229075 (0.0000) | 0.950119 (0.0000) | -0.067135 (0.0000) | 0.001379 (0.0000) |
| ***XOM*** | -0.127362 (0.0000) | 0.192135 (0.0000) | 0.984397 (0.0000) | -0.034716 (0.0043) | 0.000925 (0.0034) |
| ***UNH*** | -0.081897 (0.0000) | 0.164481 (0.0000) | 0.956692(0.0000) | -0.134135 (0.0000) | 0.002449 (0.0000) |
| ***P1*** | -0.121166 (0.0000) | 0.181941 (0.0000) | 0.957271 (0.0000) | -0.128983 (0.0000) | 0.000810 (0.0191) |
| ***P2*** | -0.123428 (0.0000) | 0.192044 (0.0000) | 0.964847 (0.0000) | -0.104844 (0.0000) | 0.109900 (0.0008) |

**Notes:** A 5% significance level means that the probability of the observed result being due to chance is less than 5%. In other words, if the p-value is less than 0.05, there is strong evidence against the null hypothesis, and the result is considered statistically significant. Similarly, a p-value between 0.05 and 0.1 means that there is a 10% chance that the observed effect is due to an event. This result is still considered significant but with a lower level of confidence. On the other hand, if the p-value is greater than 0.1, there is a high chance that the observed result is due to an event, and the result is considered non-significant.

The analysis from Table 3.6 provides valuable insights into the performance of GARCH and EGARCH estimations when changes in news intensity variables are taken into account. The results indicate that both GARCH models perform better when the changes in news intensity variables are adapted. Interestingly, Portfolio One exhibited poor performance with log news intensity. Additionally, GARCH outperformed EGARCH, as the former produced fewer significant numbers. These findings suggest that adapting news intensity variables can enhance the accuracy of GARCH models.

Table 3.7 shows the results of the GARCH and EGARCH models, which have been augmented with an extra variable representing positive news sentiment. The table offers estimates of the models, which can be used to analyse the behaviour of the data under different circumstances and scenarios. By incorporating positive news sentiment into the models, we can gain further insight into the impact of positive news on our data set.

**Table 3.7 GARCH with positive news sentiments estimations for US**

| | **Ʊ (P-VALUE)** | **$\alpha$ (P-VALUE)** | **$\beta$ (P-VALUE)** | **Γ(P-VALUE)** | **POSITIVEE NEWS** | **POSITIVE NEWS AT T-1** |
|---|---|---|---|---|---|---|
| **GARCH (1, 1) WITH POSITIVE NEWS** | | | | | | |
| ***AAPL*** | 1.101491 (0.0000) | 0.240599 (0.0000) | 0.639859 (0.0000) | - | -1.381145 (0.0000) | - |
| | 0.206860(0.0017) | 0.127996(0.0000) | 0.836114(0.0000) | - | - | 0.101801(0.2999) |
| ***BRK*** | 0.085576 (0.0000) | 0.113870 (0.0000) | 0.842845 (0.0000) | - | -0.013493(0.6305) | - |
| | 0.090694(0.0000) | 0.113820 (0.0000) | 0.843274 (0.0000) | - | - | 0.024095(0.4040) |
| ***XOM*** | 0.044415 (0.0076) | 0.096374 (0.0000) | 0.899786 (0.0000) | - | -0.023153(0.6629) | - |
| | 0.051156 (0.0011) | 0.096126 (0.0000) | 0.900586 (0.0000) | - | - | 0.048147(0.2949) |
| ***UNH*** | 0.169515 (0.0000) | 0.84998 (0.0000) | 0.860445 (0.0000) | - | -0.056593(0.3242) | - |
| | 0.329782 (0.0000) | 0.106461 (0.0000) | 0.816290 (0.0000) | - | - | 0.311827(0.0000) |
| ***P1*** | 0.114611 (0.0000) | 0.125447 (0.0000) | 0.833113 (0.0000) | - | -0.109398 (0.0420) | - |
| | 0.111966(0.0002) | 0.125644(0.0000) | 0.831615(0.0000) | - | - | 0.099264(0.0703) |
| ***P2*** | 0.135128 (0.0001) | 0.118239 (0.0000) | 0.849477 (0.0000) | - | -0.154516 (0.0160) | - |
| | 0.127784(0.0004) | 0.118609(0.0000) | 0.849042(0.0000) | - | - | 0.137418(0.0321) |
| **EGARCH (1, 1) WITH POSITIVE NEWS** | | | | | | |
| ***AAPL*** | -0.130207 (0.0000) | 0.208929 (0.0000) | 0.957869 (0.0000) | -0.125362 (0.0000) | 0.063122(0.0877) | - |
| | -0.113514 (0.0000) | 0.208234 (0.0000) | 0.956041 (0.0000) | -0.119693 (0.0000) | - | 0.028762(0.4378) |
| ***BRK*** | -0.123479(0.0000) | 0.217366 (0.0000) | 0.949737 (0.0000) | -0.073429 (0.0000) | -0.029485 (0.1378) | - |
| | -0.125758(0.0000) | 0.218308 (0.0000) | 0.949954 (0.0000) | -0.073152 (0.0000) | - | -0.026523 (0.1693) |
| ***XOM*** | -0.140398 (0.0000) | 0.202319 (0.0000) | 0.981935 (0.0000) | -0.036858 (0.0065) | 0.023028 (0.3389) | - |
| | -0.134500 (0.0000) | 0.201741 (0.0000) | 0.982496 (0.0000) | -0.033386 (0.0101) | - | 0.006053 (0.7925) |
| ***UNH*** | -0.076980 (0.0000) | 0.154513 (0.0000) | 0.959354 (0.0000) | -0.123993 (0.0000) | 0.003271 (0.8988) | - |
| | -0.069258 (0.0000) | 0.163041 (0.0000) | 0.958258 (0.0000) | -0.119230 (0.0000) | - | -0.030371 (0.2351) |
| ***P1*** | -0.103536(0.0000) | 0.192951 (0.0000) | 0.953937 (0.0000) | -0.124253 (0.0000) | -0.06041 (0.0959) | - |
| | -0.103898 (0.0000) | 0.191202 (0.0000) | 0.954311 (0.0000) | -0.125228 (0.0000) | - | -0.056882 (0.1109) |
| ***P2*** | -0.1261112(0.0000) | 0.196265 (0.0000) | 0.962299 (0.0000) | -0.101691 (0.0000) | -0.008654 (0.8533) | - |
| | -0.121319(0.00000) | 0.197677(0.0000) | 0.962191(0.0000) | -0.101448(0.0000) | - | -0.010948(0.8126) |

**Notes:** A 5% significance level means that the probability of the observed result being due to chance is less than 5%. In other words, if the p-value is less than 0.05, there is strong evidence against the null hypothesis, and the result is considered statistically significant. Similarly, a p-value between 0.05 and 0.1 means that there is a 10%

chance that the observed effect is due to an event. This result is still considered significant but with a lower level of confidence. On the other hand, if the p-value is greater than 0.1, there is a high chance that the observed result is due to an event, and the result is considered non-significant. We have tested the positive news on both day t and day t-1 due to the potential of delay effect.

Table 3.7 shows GARCH's superior effectiveness over EGARCH for positive news sentiment variables. Portfolio One's performance was subpar with positive news sentiment. Positive news has a significant impact on healthcare and technology sectors, with healthcare stock prices fluctuating on the following day, and technology stock prices changing on the same day.

Table 3.8 showcases the outcomes of the GARCH and EGARCH models, which consider negative news sentiment as an extra variable. The estimates in the table allow for a thorough analysis of the data's patterns in various circumstances. Incorporating negative news sentiment in the models enables us to gain further insights into the effects of negative news on our dataset.

**Table 3.8 GARCH with negative news sentiments estimations for US**

| | **$\omega$ (P-VALUE)** | **$\alpha$ (P-VALUE)** | **$\beta$ (P-VALUE)** | **$\Gamma$(P-VALUE)** | **NEGATIVE NEWS** | **NEGATIVE NEWS AT T-1** |
|---|---|---|---|---|---|---|
| **GARCH (1, 1) WITH NEGATIVE NEWS** | | | | | | |
| **AAPL** | 0.147084(0.0019) | 0.128474 (0.0000) | 0.838399 (0.0000) | - | 0.014720 (0.8723) | - |
| | 0.105059 (0.0313) | 0.127996 (0.0000) | 0.836115 (0.0000) | - | - | 0.101802 (0.2999) |
| **BRK** | 0.065835 (0.0000) | 0.111725 (0.0000) | 0.837418 (0.0000) | - | 0.129376 (0.0050) | - |
| | 0.065661 (0.0000) | 0.113643 (0.0000) | 0.835553 (0.0000) | - | - | 0.131334 (0.0025) |
| **XOM** | 0.100608 (0.0169) | 0.101758 (0.0000) | 0.891317(0.0000) | - | -0.089736 (0.1164) | - |
| | 0.062002 (0.1000) | 0.097952 (0.0000) | 0.896662 (0.0000) | - | - | -0.034483 (0.5011) |
| **UNH** | 0.084190 (0.0002) | 0.083115 (0.0000) | 0.858455 (0.0000) | - | 0.313421 (0.0000) | - |
| | 0.102937 (0.0000) | 0.084374 (0.0000) | 0.853971 (0.0000) | - | - | 0.265348 (0.0001) |
| **P1** | 0.003164 (0.9049) | 0.127386 (0.0000) | 0.821328 (0.0000) | - | 0.200488 (0.0078) | - |
| | 0.002902(0.9148) | 0.13408 (0.0000) | 0.815965(0.0000) | - | - | 0.225221(0.0021) |
| **P2** | 0.008179 (0.7723) | 0.117203 (0.0000) | 0.851009 (0.0000) | - | 0.123967(0.00553) | - |
| | 0.004987(0.8594) | 0.119092(0.0000) | 0.847974(0.0000) | - | - | 0.135145(0.0364) |
| **EGARCH (1, 1) WITH NEGATIVE NEWS** | | | | | | |
| **AAPL** | -0.067085 (0.0069) | 0.208929 (0.0000) | 0.957869 (0.0000) | -0.125362 (0.0000) | -0.063122 (0.0877) | - |
| | -0.084753 (0.0004) | 0.208234 (0.0000) | 0.956041 (0.0000) | -0.119693 (0.0000) | - | -0.028762 (0.4378) |
| **BRK** | -0.152060 (0.0000) | 0.211964 (0.0000) | 0.944179 (0.0000) | -0.072645 (0.0000) | 0.098122 (0.0014) | - |
| | -0.155591 (0.0000) | 0.216530 (0.0000) | 0.943040 (0.0000) | -0.073993(0.0000) | - | 0.100969 (0.0008) |
| **XOM** | -0.095799 (0.0000) | 0.212578 (0.0000) | 0.978447(0.0000) | -0.047169 (0.0019) | -0.071661 (0.0129) | - |
| | -0.106962 (0.0000) | 0.204002 (0.0000) | 0.980646 (0.0000) | -0.040940 (0.0032) | - | -0.044339 (0.0924) |
| **UNH** | -0.079388 (0.0000) | 0.155735 (0.0000) | 0.958366 (0.0000) | -0.121355 (0.0000) | 0.015164 (0.5719) | - |
| | -0.078174 (0.0000) | 0.155449 (0.0000) | 0.958633 (0.0000) | -0.121092 (0.0000) | - | 0.010051 (0.6880) |
| **P1** | -0.142246 (0.0000) | 0.192315 (0.0000) | 0.953251 (0.0000) | -0.125925 (0.0000) | 0.035686 (0.5732) | - |
| | -0.14905 (0.0000) | 0.191623 (0.0000) | 0.953585 (0.0000) | -0.126332 (0.0000) | - | 0.035528 (0.5457) |
| **P2** | -0.096590 (0.0003) | 0.191162 (0.0000) | 0.966994 (0.0000) | -0.105014 (0.0000) | -0.053597 (0.2705) | - |
| | -0.100236(0.0001) | 0.192407(0.0000) | 0.966943(0.0000) | -0.103255(0.0000) | - | -0.048416(0.3182) |

**Notes:** A 5% significance level means that if the p-value is less than 0.05, there is strong evidence against the null hypothesis. A p-value between 0.05 and 0.1 means that the observed effect is significant but with a lower level of confidence. If the p-value is greater than 0.1, the result is considered non-significant.

Table 3.8 indicates that GARCH performs better than EGARCH for negative news sentiment variables. Negative news affects the healthcare and finance sectors, and Portfolio One's poor performance is linked to negative news sentiment.

The VIX index is widely recognized as a key indicator of global volatility and is closely linked to fluctuations in stock prices. The relationship between the VIX and stock prices is particularly strong, and when the VIX index is incorporated as an additional variable in conjunction with news variables, the outcomes tend to hold significant value. This indicates a more robust connection between stocks and news.

Table 3.9 shows the GARCH and EGARCH models' results with news intensity and VIX index as additional variables. The estimates provide valuable insights into data patterns under different conditions. The VIX index helps us understand how general news indices impact our dataset.

## Table 3.9 GARCH with news intensity and VIX estimations for US

| | Ʊ (P-VALUE) | $\alpha$ (P-VALUE) | $\beta$ (P-VALUE) | Γ(P-VALUE) | NEWS INTENSITY | VIX |
|---|---|---|---|---|---|---|
| **GARCH WITH LOG NEWS INTENSITY AND VIX ESTIMATION** | | | | | | |
| ***AAPL*** | 0.095313 (0.0023) | 0.007698 (0.0000) | 0.987792 (0.0000) | - | -0.024209(0.0074) | 0.082370(0.0000) |
| ***BRK*** | 0.010241 (0.0153) | 0.017871 (0.0000) | 0.971976 (0.0000) | - | 0.002990 (0.3354) | 0.030411(0.0000) |
| ***XOM*** | 0.039777 (0.0148) | 0.046609 (0.0000) | 0.946705 (0.0000) | - | -0.010180 (0.2231) | 0.036425(0.0000) |
| ***UNH*** | 0.056866 (0.0023) | 0.065036 (0.0000) | 0.881975 (0.0000) | - | 0.096864 (0.0000) | 0.026007(0.0000) |
| ***P1*** | 0.031963 (0.0000) | 0.047907 (0.0000) | 0.930775 (0.0000) | - | -0.000429(0.2861) | 0.024439(0.0000) |
| ***P2*** | 0.034174 (0.0000) | 0.038827 (0.0000) | 0.943975 (0.7050) | - | 0.0000499(0.0000) | 0.034174 (0.0000) |
| **EGARCH WITH LOG NEWS INTENSITY AND VIX ESTIMATION** | | | | | | |
| ***AAPL*** | -0.148678(0.0000) | 0.117527 (0.0000) | 0.978609 (0.0000) | -0.033547(0.0114) | 0.023698 (0.0023) | 0.024534 (0.0000) |
| ***BRK*** | -0.015157(0.0003) | 0.019570 (0.0003) | 0.997779 (0.0000) | 0.0077622(0.2208) | 0.000611 (0.6903) | 0.026529 (0.0000) |
| ***XOM*** | 0.003171(0.5848) | -0.003844(0.5296) | 1.000883 (0.0000) | -0.021099 (0.0000) | -0.000583(0.6081) | 0.019319 (0.0000) |
| ***UNH*** | -0.034607(0.0000) | 0.050363 (0.0000) | 0.985276 (0.0000) | -0.066839 (0.0000) | 0.009264 (0.0748) | 0.018615 (0.0000) |
| ***P1*** | 0.021647(0.0000) | -0.021598(0.0021) | 0.996397 (0.0000) | -0.031437 (0.0000) | -0.000396 (0.0000) | 0.027216 (0.0000) |
| ***P2*** | -0.010163(0.1492) | 0.017241 (0.0286) | 0.998279 (0.0000) | -0.008518 (0.1734) | -0.000101 (0.0923) | 0.029297 (0.0000) |
| **GARCH WITH LOG NEWS INTENSITY CHANGES AND VIX ESTIMATION** | | | | | | |
| ***AAPL*** | 0.030785 (0.0000) | 0.015052 (0.0000) | 0.974265 (0.0000) | - | 0.003019 (0.0000) | 0.078387 (0.0000) |
| ***BRK*** | 0.028237 (0.0000) | 0.038858 (0.0000) | 0.940091 (0.0000) | - | 0.001196 (0.0000) | 0.028645 (0.0000) |
| ***XOM*** | 0.026613 (0.0000) | 0.043885 (0.0000) | 0.947305 (0.0000) | - | 0.000953 (0.0348) | 0.038656(0.0000) |
| ***UNH*** | 0.111908 (0.0000) | 0.063334 (0.0000) | 0.890686 (0.0000) | - | 0.005993 (0.0000) | 0.039693(0.0000) |
| ***P1*** | 0.028210 (0.0000) | 0.049712 (0.0000) | 0.926310 (0.0000) | - | 0.001225 (0.0000) | 0.024649(0.0000) |
| ***P2*** | 0.024358 (0.0000) | 0.039163 (0.0000) | 0.942400 (0.0000) | - | 0.001033 (0.0000) | 0.034905 (0.0000) |
| **EGARCH WITH LOG NEWS INTENSITY CHANGES AND VIX ESTIMATION** | | | | | | |
| ***AAPL*** | -0.052239(0.0000) | 0.079481 (0.0000) | 0.990711 (0.0000) | -0.004969 (0.6072) | 0.023698 (0.0023) | 0.025967 (0.0000) |
| ***BRK*** | -0.015119(0.0016) | 0.020498 (0.0010) | 0.997463 (0.0000) | 0.010356 (0.0782) | 0.001622 (0.0000) | 0.027090 (0.0000) |
| ***XOM*** | 0.003264(0.5076) | -0.006113(0.3038) | 1.001411 (0.0000) | -0.023299 (0.0000) | 0.000937 (0.0097) | 0.019472 (0.0000) |
| ***UNH*** | -0.027985(0.0004) | 0.048603 (0.0000) | 0.988041(0.0000) | -0.063257 (0.0000) | 0.003144 (0.0000) | 0.021166 (0.0000) |
| ***P1*** | -0.005265(0.2791) | 0.005593 (0.3719) | 0.995950 (0.0000) | -0.023522 (0.0000) | 0.001813 (0.0000) | 0.027340 (0.0000) |
| ***P2*** | -0.022935(0.0024) | 0.029155 (0.0029) | 0.997828 (0.0000) | -0.005402 (0.4600) | 0.029929 (0.0000) | 0.029929 (0.0000) |

**Notes:** A 5% significance level means that if the p-value is less than 0.05, there is strong evidence against the null hypothesis. A p-value between 0.05 and 0.1 means that the observed effect is significant but with a lower level of confidence. If the p-value is greater than 0.1, the result is considered non-significant.

According to the data presented in Table 3.9, the incorporation of the VIX index in conjunction with news intensity substantially enhances the estimations, ultimately resulting in outcomes with high levels of significance. The EGARCH model is known to have better estimation capabilities than the GARCH model, which results in more significant outcomes. In comparison, Portfolio 1 has been observed to perform better than Portfolio 2.

In Table 3.10, we can see the outcomes of employing GARCH and EGARCH models that factor in positive news sentiment and the VIX index as supplementary variables. The estimates presented in the table furnish a thorough examination of the data's performance under various circumstances. With the incorporation of VIX and positive news sentiment into the models, we can acquire a more profound understanding of the effects of positive news on our dataset.

**Table 3.10 GARCH with positive news sentiment and VIX estimations for US**

| | Ʊ (P-VALUE) | $\alpha$ (P-VALUE) | $\beta$ (P-VALUE) | Γ(P-VALUE) | POSITIVE NEWS | VIX |
|---|---|---|---|---|---|---|
| **GARCH (1, 1) WITH POSITIVE NEWS AND VIX ESTIMATION** | | | | | | |
| ***AAPL*** | 0.018638 (0.0918) | 0.011634 (0.0000) | 0.984166 (0.0000) | - | 0.072829 (0.0000) | 0.081092 (0.0000) |
| ***BRK*** | 0.011141 (0.0187) | 0.016685 (0.0000) | 0.973719 (0.0000) | - | 0.002307 (0.7124) | 0.030412 (0.0000) |
| ***XOM*** | 0.030455 (0.0013) | 0.046206 (0.0000) | 0.947838 (0.0000) | - | -0.031834 (0.2623) | 0.037575 (0.0000) |
| ***UNH*** | 0.098860 (0.0000) | 0.052569 (0.0000) | 0.912480 (0.0000) | - | -0.027337 (0.0000) | 0.023294 (0.0000) |
| ***P1*** | 0.041263 (0.0000) | 0.049991 (0.0000) | 0.929724 (0.0000) | - | -0.040981 (0.0000) | 0.023986(0.0000) |
| ***P2*** | 0.025063 (0.0194) | 0.039015 (0.0000) | 0.944039 (0.0000) | - | -0.006014 (0.7756) | 0.034054 (0.0000) |
| **EGARCH (1, 1) WITH POSITIVE NEWS AND VIX ESTIMATION** | | | | | | |
| ***AAPL*** | -0.071521(0.0001) | 0.118458 (0.0000) | 0.981955 (0.0000) | -0.032983 (0.0122) | 0.000867 (0.9726) | 0.025149 (0.0000) |
| ***BRK*** | 0.000115 (0.9780) | -0.005375(0.3334) | 0.999204 (0.0000) | 0.022098 (0.00000) | 0.009719 (0.0000) | 0.026630 (0.0000) |
| ***XOM*** | 0.001326(0.7927) | -0.005781(0.3717) | 1.001247 (0.0000) | -0.024731 (0.0000) | 0.005603 (0.1317) | 0.019192 (0.0000) |
| ***UNH*** | -0.030986(0.0006) | 0.052675 (0.0000) | 0.986396(0.0000) | -0.065773 (0.0000) | 0.004002 (0.0000) | 0.018853 (0.0000) |
| ***P1*** | 0.005699 (0.2583) | -0.017852(0.0163) | 0.997777 (0.0000) | -0.017327 (0.0006) | 0.017075 (0.0000) | 0.025914 (0.0000) |
| ***P2*** | -0.021525(0.0003) | 0.013643 (0.0499) | 0.999244 (0.0000) | -0.005805 (0.2895) | 0.025151 (0.0000) | 0.027821 (0.0000) |
| **GARCH (1, 1) WITH POSITIVE NEWS AT TIME T-1 AND VIX ESTIMATION** | | | | | | |
| ***AAPL*** | 0.631879 (0.0000) | 0.113951 (0.0000) | 0.766505 (0.0000) | - | -0.674422 (0.0000) | 0.074036 (0.0000) |
| ***BRK*** | 0.012097 (0.0099) | 0.016618 (0.0000) | 0.973735 (0.0000) | - | 0.000644 (0.9123) | 0.030476(0.0000) |
| ***XOM*** | 0.034284 (0.0006) | 0.047308 (0.0000) | 0.946830 (0.0000) | - | -0.043379 (0.1210) | 0.037723 (0.0000) |
| ***UNH*** | 0.167858 (0.0000) | 0.060590 (0.0000) | 0.897665 (0.0000) | - | -0.160807 (0.0003) | 0.023034 (0.0000) |
| ***P1*** | 0.047448 (0.0000) | 0.053421 (0.0000) | 0.926602 (0.0000) | - | -0.055905 (0.0076) | 0.023936 (0.0000) |
| ***P2*** | 0.028921 (0.0111) | 0.039954 (0.0000) | 0.942632 (0.0000) | - | -0.013445 (0.5372) | 0.034048 (0.0000) |
| **EGARCH (1, 1) WITH POSITIVE NEWS AT TIME T-1 AND VIX ESTIMATION** | | | | | | |
| ***AAPL*** | -0.061800(0.0010) | 0.117543 (0.0000) | 0.980818 (0.0000) | -0.030200 (0.0228) | -0.018208 (0.4807) | 0.025149 (0.0000) |
| ***BRK*** | -0.008270(0.0487) | 0.007259 (0.2231) | 0.998848 (0.0000) | 0.017418 (0.00019) | 0.006824 (0.0034) | 0.026708 (0.0000) |
| ***XOM*** | -0.000614(0.0000) | -0.000683(0.0000) | 1.000909 (0.0000) | -0.016156 (0.0000) | 0.001124 (0.4313) | 0.019962 (0.0000) |
| ***UNH*** | -0.028425(0.0008) | 0.054342 (0.0000) | 0.986690(0.0000) | -0.063230 (0.0000) | -0.006226 (0.6276) | 0.018881 (0.0000) |
| ***P1*** | 0.007246 (0.0549) | -0.019914 (0.0001) | 0.997154 (0.0000) | -0.020256 (0.0001) | 0.017229 (0.0000) | 0.025775 (0.0000) |
| ***P2*** | -0.021427(0.0003) | 0.013581 (0.0512) | 0.999234 (0.0000) | -0.005662 (0.3022) | 0.025045 (0.0052) | 0.027794 (0.0000) |

**Notes:** A 5% significance level means that if the p-value is less than 0.05, there is strong evidence against the null hypothesis. A p-value between 0.05 and 0.1 means that the observed effect is significant but with a lower level of confidence. If the p-value is greater than 0.1, the result is considered non-significant.

The data in Table 3.10 suggests that including the VIX index with positive news intensity can greatly enhance estimations, resulting in highly significant outcomes. The EGARCH model is renowned for its superior estimation capabilities over the GARCH model, leading to more impactful results. Additionally, Portfolio 1 proved to be more successful than Portfolio 2. It's noteworthy that positive news regarding technology, finance, and healthcare significantly affects stock returns.

Table 3.11 showcases the outcomes of applying GARCH and EGARCH models that factor in negative news sentiment and the VIX index as supplementary variables. The estimates laid out in the table offer a thorough examination of the data's behavior under different scenarios. By integrating the VIX index and negative news sentiment into the models, we can attain a more profound comprehension of the influence of adverse news on our dataset.

### Table 3.11 GARCH with negative news sentiment and VIX estimations for US

| | **Ʊ (P-VALUE)** | **$\alpha$ (P-VALUE)** | **$\beta$ (P-VALUE)** | **Γ(P-VALUE)** | **NEGATIVE NEWS** | **VIX** |
|---|---|---|---|---|---|---|
| **GARCH (1, 1) WITH NEGATIVE NEWS AND VIX ESTIMATION** | | | | | | |
| ***AAPL*** | 0.054180 (0.0000) | 0.011629 (0.0000) | 0.984174 (0.0000) | - | -0.072827 (0.0020) | 0.081087 (0.0000) |
| ***BRK*** | 0.012616 (0.0000) | 0.016279 (0.0000) | 0.974185 (0.0000) | - | -0.001894 (0.8505) | 0.030471(0.0000) |
| ***XOM*** | 0.046150 (0.0296) | 0.046248 (0.0000) | 0.946450 (0.0000) | - | -0.038587 (0.2306) | 0.037092 (0.0000) |
| ***UNH*** | 0.023522 (0.0126) | 0.042288 (0.0000) | 0.923512 (0.0000) | - | 0.264230(0.0000) | 0.029701 (0.0000) |
| ***P1*** | 0.025553 (0.0824) | 0.050488 (0.0000) | 0.925904 (0.0000) | - | 0.137829 (0.0004) | 0.024525 (0.0000) |
| ***P2*** | 0.016897 (0.1867) | 0.039424 (0.0000) | 0.943362 (0.0000) | - | 0.012418 (0.6537) | 0.034033 (0.0000) |
| **EGARCH (1, 1) WITH NEGATIVE NEWS AND VIX ESTIMATION** | | | | | | |
| ***AAPL*** | -0.070619(0.0000) | 0.118392 (0.0000) | 0.981968 (0.0000) | -0.032944 (0.0122) | -0.000870 (0.9725) | 0.025145 (0.0000) |
| ***BRK*** | 0.017460 (0.0000) | -0.016837(0.0000) | 0.997499 (0.0000) | 0.017348 (0.00001) | -0.014690 (0.0001) | 0.029322 (0.0000) |
| ***XOM*** | 0.005345 (0.3996) | -0.05624 (0.3694) | 1.001114 (0.0000) | -0.023916(0.0000) | -0.003682 (0.3734) | 0.019348 (0.0000) |
| ***UNH*** | -0.031986(0.0001) | 0.053614 (0.0000) | 0.986003 (0.0000) | -0.062561 (0.0000) | 0.009418 (0.4436) | 0.018867 (0.0000) |
| ***P1*** | 0.024793 (0.0000) | -0.019764 (0.0000) | 0.996932 (0.0000) | -0.027934 (0.0000) | -0.026717 (0.0000) | 0.026838 (0.0000) |
| ***P2*** | 0.002259 (0.7946) | 0.017394 (0.0180) | 0.999393 (0.0000) | -0.014426 (0.0170) | -0.033368 (0.0148) | 0.028158 (0.0000) |
| **GARCH (1, 1) WITH NEGATIVE NEWS AT TIME T-1 AND VIX ESTIMATION** | | | | | | |
| ***AAPL*** | 0.067613 (0.0001) | 0.023735 (0.0000) | 0.969278 (0.0000) | - | -0.060392 (0.0565) | 0.098707 (0.0000) |
| ***BRK*** | 0.012498 (0.0000) | 0.016577 (0.0000) | 0.973772 (0.0000) | - | -0.000297 (0.9767) | 0.030490(0.0000) |
| ***XOM*** | 0.035502 (0.0684) | 0.044935 (0.0000) | 0.948023 (0.0000) | - | -0.022283 (0.4602) | 0.037380 (0.0000) |
| ***UNH*** | 0.035644 (0.0005) | 0.043562 (0.0000) | 0.919127 (0.0000) | - | 0.241616 (0.0000) | 0.030272 (0.0000) |
| ***P1*** | 0.022582 (0.0129) | 0.050081 (0.0000) | 0.925816 (0.0000) | - | 0.131367 (0.0009) | 0.024880 (0.0000) |
| ***P2*** | 0.014988 (0.2653) | 0.039909 (0.0000) | 0.942564 (0.0000) | - | 0.017326 (0.5627) | 0.034081 (0.0000) |
| **EGARCH (1, 1) WITH NEGATIVE NEWS AT TIME T-1 AND VIX ESTIMATION** | | | | | | |
| ***AAPL*** | -0.079990(0.0000) | 0.117518 (0.0000) | 0.980823 (0.0000) | -0.030185 (0.0228) | -0.018198 (0.4809) | 0.025420 (0.0000) |
| ***BRK*** | 0.016528 (0.0000) | -0.015789(0.0000) | 0.997751 (0.0000) | 0.018167 (0.00000) | -0.014215 (0.0001) | 0.029548 (0.0000) |
| ***XOM*** | 0.005302 (0.3966) | -0.006281(0.3006) | 1.001257 (0.0000) | -0.023562(0.0000) | -0.003092 (0.4582) | 0.019470 (0.0000) |
| ***UNH*** | -0.031574(0.0001) | 0.053613 (0.0000) | 0.986088 (0.0000) | -0.062992 (0.0000) | 0.007388 (0.5160) | 0.018868 (0.0000) |
| ***P1*** | 0.023505 (0.0000) | -0.018634(0.0013) | 0.997478 (0.0000) | -0.026530 (0.0001) | -0.026530 (0.0001) | 0.026924 (0.0000) |
| ***P2*** | 0.002581 (0.7662) | 0.017147 (0.0193) | 0.999390 (0.0000) | -0.014278 (0.0165) | -0.033628 (0.0128) | 0.028109 (0.0000) |

**Notes:** A 5% significance level means that the probability of the observed result being due to chance is less than 5%. In other words, if the p-value is less than 0.05, there is strong evidence against the null hypothesis, and the result is considered statistically significant. Similarly, a p-value between 0.05 and 0.1 means that there is a 10% chance that the observed effect is due to an event. This result is still considered significant but with a lower level of confidence. On the other hand, if the p-value is greater than 0.1, there is a high chance that the observed result is due to an event, and the result is considered non-significant. We have tested the positive news on both day t and day t-1 due to the potential of delay effect.

Based on the results outlined in Table 3.11, the integration of the VIX index in conjunction with negative news intensity can notably enhance estimations, resulting in highly significant outcomes. Notably, the EGARCH model is renowned for its superior estimation capabilities in comparison to the GARCH model, which can yield more impactful findings. Additionally, Portfolio 1 demonstrated greater success than Portfolio 2. It is noteworthy that negative news linked to technology and finance can significantly affect stock returns.

In general, GARCH outperforms EGARCH in the US when there are extra news variables. Portfolio Two (market size weighted) performed better than Portfolio One (average weighted). However, after adding the VIX index with other news variables, EGARCH performed better. Portfolio One performed better than Portfolio Two. The technology and healthcare sectors are more influenced by positive news, while finance responds to negative news faster.

After gathering data from various sources, we meticulously organized the information into detailed tables for each country. Using advanced data analysis techniques, we carefully examined the data to identify any notable trends and patterns. Finally, based on our findings, we drew meaningful conclusions that can provide valuable insights and inform future decisions.

Based on research, in Australia, GARCH is typically superior to EGARCH when extra news variables are introduced. However, when the VIX index is included with other news variables, EGARCH outperforms. Additionally, Portfolio One exhibits stronger performance than Portfolio Two. It's noteworthy that the technology and energy sectors tend to respond more favorably to positive news, whereas all other sectors demonstrate a reaction to negative news, with the exception of the energy industry.

In Canada, the GARCH model outperformed the EGARCH model with additional news variables, but EGARCH performed better when the VIX index was included. Portfolio One performed better than Portfolio Two. All sectors responded to the news, except for the energy sector, which reacted slowly to negative news.

GARCH and EGARCH are effective models used in financial analysis in Japan. Adding the VIX index with other news variables, GARCH performs better than EGARCH. Portfolio Two outperforms Portfolio One. Technology stocks respond to positive news, while finance stocks respond to negative news.

Studies have found that in South Korea, the GARCH and EGARCH models prove effective when additional news variables are taken into account. Nevertheless, when the VIX index is introduced alongside other news variables, the GARCH model outperforms the EGARCH model. Moreover, concerning portfolio performance, Portfolio One exhibits superior results compared to Portfolio Two. Additionally, it has been observed that the technology and healthcare sectors demonstrate a positive response to news developments, while the finance industry displays a negative reaction.

Studies indicate that GARCH and EGARCH models have proven to be effective in China when supplemented with supplementary news variables. Nevertheless, when the VIX index was introduced alongside other news variables, the GARCH model displayed superior performance. Furthermore, Portfolio One outperformed Portfolio Two in the same study. The research also revealed that the finance industry responds positively to news, while the energy and healthcare sectors tend to respond negatively.

Broadly speaking, GARCH estimations are more precise than EGARCH estimations in developed Western countries when taking into account supplementary news variables like news intensity and sentiment. Nevertheless, once the VIX index is incorporated, the EGARCH model outshines GARCH. Conversely, in Asian countries, both models exhibit adequate performance at first, but GARCH proves superior to EGARCH once the VIX variable is included.

This chapter has shown that news intensity affects developed Western countries differently than Asian countries. Western countries tend to be more reactive to news events, whereas Asian countries are less influenced by them. Remarkably, the healthcare industry displays a notable correlation between news and stock prices, implying that news can have a substantial impact on this sector.

It's important to recognize that news can elicit varying reactions across different industries. In particular, the healthcare sector is known to be highly responsive to both positive and negative news. Positive developments can often boost demand and returns for technology stocks, while unfavourable news related to finance and energy can lead to increased stock volatilities and decreased demand. As such, it is vital for investors to stay up-to-date on industry-specific news and trends in order to make well-informed investment decisions.

## 3.6 Conclusion

The paper sufficiently addressed the gaps in the current literature but may benefit from the inclusion of additional GARCH models and the exploration of various distributions. Furthermore, conducting tests with more lags could further enhance the paper's findings. Given that the data was collected during the COVID-19 pandemic, comparing the results before and after the pandemic would be valuable in determining its impact. This presents a promising avenue for future research.

To sum up, the effect of news on stock prices varies depending on the industry and region. However, there is a significant relationship between news intensity and stock volatility, whereby changes in news intensity can trigger changes in stock prices.

Our analysis of news sentiment among the APEC countries we selected has revealed that western developed countries tend to be more responsive to news sentiment, both positive and negative. On the other hand, Asian countries appear to be less affected by news sentiment. This suggests that cultural and societal differences may play a role in how news is perceived and its potential impact on different regions. Different stocks respond differently to news sentiments. Negative news has a greater impact than positive news.

By including general global news such as the VIX volatility index alongside specific firm news, the estimation results have shown significant improvement. And GARCH estimation outperforms EGARCH. When comparing market size weighted portfolio to even weighted portfolio, the former slightly outperforms the latter. However, this performance varies depending on the industry and region.

Overall, when factoring in news intensity and sentiment alongside other variables, GARCH estimations are typically more precise than EGARCH estimations in developed Western nations. Nevertheless, when the VIX index is considered, the EGARCH model proves to be more effective than GARCH. Conversely, in Asian countries, both models exhibit strong performance initially, but GARCH surpasses EGARCH once the VIX variable is incorporated.

The findings in this chapter reveal that news intensity impacts developed Western countries and Asian countries differently. Western countries demonstrate greater responsiveness to news events, whereas Asian countries display a comparatively lower sensitivity. Notably, the healthcare industry displays a strong correlation between news and stock prices, suggesting that news can significantly impact this sector.

It is imperative to grasp that news can elicit varying reactions across different industries. Notably, the healthcare sector tends to be significantly responsive to both positive and negative news. Positive news can drive up demand and returns for technology stocks, while unfavourable news related to finance and energy can create more stock volatility and decrease demand. Hence, investors must stay abreast of industry-specific news and trends to make well-informed investment choices.

This implies that EGARCH and Portfolio 1 could potentially be the preferred choices for investors seeking higher returns with greater significance when they compare the VIX index with other news variables in APEC countries.

It's worth noting that the technology and healthcare industries are particularly sensitive to news that portrays them in a positive light. Positive news can significantly impact these sectors, leading to increased investor confidence, greater public trust, and improved overall market performance. On the other hand, finance tends to respond more quickly to negative news. Negative news can trigger a chain of events that leads to a rapid decline in stock prices, reduced investment demand, and a general sense of unease among investors. As such, investors should closely monitor market trends and stay informed about the latest news and developments in their chosen industries to make informed investment decisions.

# Chapter 4

# The reaction of energy stocks to geopolitical risk news during the Russian-Ukrainian conflict

## 4.1 Introduction

Starting on February 24th, 2022, the military conflict between Russia and Ukraine has caused a devastating loss of life. It has created the swiftest-growing refugee crisis in Europe since World War II. It is essential to reflect on the effects of military investments, the human toll on the economy, and the obstacles of reconstructing and addressing post-war devastation (Khudaykulova, Yuanqiong and Khudaykulov, 2022).

In the aftermath of Russia's aggression towards Ukraine in February 2022, various nations, such as the US and Europe, implemented financial sanctions against Russia. These sanctions have had a significant impact on the Russian economy, but unfortunately, the repercussions of the conflict have extended beyond its borders and are felt worldwide (Huang and Lu, 2022).

The global financial market, particularly the stock markets, has been adversely affected by investor aversion to risk, given the political and economic instability worldwide. As per Hosoe's (2023) analysis, the economic consequences of the war have already transcended Russia's borders.

### 4.1.1 Russia’s war on Ukraine has brought back the energy security crisis

Throughout history, Ukraine has served as a crucial transit route for Russia's natural gas exports to Europe. However, the ongoing conflict in the region has sparked concerns regarding the dependability and stability of energy supplies and the security of energy infrastructure in the area. Incidents of gas supply disruptions and harm to energy infrastructure have negatively impacted Russia, Ukraine and European nations reliant on gas transit through Ukraine (Kumari, Kumar, and Pandey, 2023).

Russia holds a pivotal position in the global non-renewable energy market. Russia occupies a significant role in the global energy sector, being the largest producer and exporter of natural gas worldwide, the second-largest exporter of oil, and the third-largest exporter of coal to international markets. Most of these resources are directed toward supplying the European Union (U.S. Energy Information Administration 2021).

According to a report by Li and Li in 2022, the European Union and the USA have implemented substantial sanctions against Russia to decrease their dependence on Russian fossil fuels. Meanwhile, Osička and Černoch highlighted in 2022 that non-renewable energy continues to be utilised worldwide, including in European nations, despite the ongoing conflict in Ukraine.

### 4.1.2 Needs for energy diversification, such as local and renewable energy sources

The conflict between Russia and Ukraine has led to an unparalleled price surge for renewable and non-renewable energy sources, causing reverberations worldwide. This has led to a global economic downturn, cost instability, supply chain difficulties, worries about financial markets, and significant inflation (Usman and Radulescu, 2022). Consequently, numerous nations are reassessing their energy requirements.

The ongoing political tensions between Russia and Ukraine have significantly impacted global energy costs, which increased by 58.3% between December 2021 and June 2022. As of this year, Russia accounts for approximately 10% to 15% of coal, 5.4% of uranium, and roughly 8% of gas produced worldwide. It's worth noting that 60% of Russia's oil is exported to Europe and 20% to China.

Furthermore, from May to October of 2022, Russia reduced its gas exports to the European Union by over 80%, leading to a considerable energy shortfall and an urgent need for alternative energy sources. (Kumari, Kumar and Pandey, 2023).

As a result of the energy crisis, nations have been prompted to develop new energy policies that prioritise long-term energy security swiftly. Additionally, it is expected that the rise in energy costs will cause an increase in prices for goods and interest rates, to make borrowing money more expensive. This could have economic consequences for projects that require financing (Aydin, 2022).

The war in Ukraine has far-reaching consequences that can significantly impact a company's performance. It can lower the output, reduce profitability, disrupt anticipated cash flows, and decrease share values. This makes it particularly crucial for investors, portfolio managers, and regulators to understand the effects of wars on renewable energy markets. With the potential for massive disruptions in the industry, it's essential to carefully evaluate the risks and opportunities of investing in renewable energy during times of conflict (Umar, Riaz, Yousaf, 2022).

The ongoing tension between Russia and Ukraine has elevated geopolitical risks, which can significantly impact industrial stocks, especially those in the energy sector. Given the evolving global political landscape and the increasing focus on environmentally sustainable policies, it is essential to scrutinise the responses of both renewable and non-renewable energy stocks. The findings outlined in this chapter offer valuable insights into estimating energy stock prices by integrating news on geopolitical risks.

This chapter will begin with a comprehensive review and summary of the existing literature. Next, we will provide a concise overview of the model used and a detailed explanation of the data collection and processing procedures. The empirical results will then be presented in full. Lastly, we will conclude with a summary of the entire chapter, including any limitations that were encountered.

## 4.2 Existing Literature

Research has been conducted on how unexpected events affect the stock markets. This includes occurrences such as natural disasters, artificial disasters, and emergencies. In 2019, Papakyriakou, Sakkas, and Taoushianis conducted a study on the impact of terrorist attacks in G7 countries, while Liu, Manzoor, Wang, Zhang, and Manzoor examined the effect of the COVID-19 outbreak in 2020. Also, in 2020, Batten, Sowerbutts, and Tanaka investigated the impact of climate change on the financial markets.

Smales' (2017) study aimed to showcase the influence of geopolitical risks on the financial market. The findings indicated a noteworthy positive correlation between political risk and financial market uncertainty amidst the Brexit period. Conversely, Babar, Ahmad, and Yousaf's (2023) research delved into the connection between agricultural commodities and return volatilities in emerging countries amid crises like the COVID-19 pandemic and the Russian-Ukrainian conflict. Their findings suggested a limited association between the two variables.

In a study by Salisu, Cuñado and Gupta (2022), Russia's invasion of Ukraine in 2022 is viewed as a significant geopolitical threat, reflecting a resurgent competition among the world's great powers.

The genesis of this chapter is rooted in the research conducted by Caldara, Conlisk, Iacoviello, and Penn (2022), which delves into the uncertainties stemming from events like wars, terrorist acts, and conflicts between nations. The research highlights the financial implications of geopolitical risk (GPR), particularly its adverse effects on investments, such as equity returns.

Numerous studies have explored the impact of war and conflict on financial markets, with notable contributions from Thies and Baum (2020), Boubaker, Goodell, Pandey, and Kumari (2022), and Umar, Z., Polat, Choi, and Teplova (2022). Many of these studies have utilised the event study method. One such study by Ahmed, Hasan, and Kamal (2022) showed that European stock markets suffered a significant negative abnormal return following the imposition of new sanctions on Russia, as analysed through the event study approach.

The current state of political uncertainty has resulted in adverse stock price reactions during and after the crisis. This trend is reflected in the research of Yousaf, Patel, and Yarovaya (2022), who have taken a similar approach. Additionally, Kumari, Kumar, and Pandey (2023) have conducted a study that delves into the country-specific characteristics that drive abnormal returns following the Russian invasion of Ukraine. Their research involved an analysis of the leading European Union stock market index using Brown and Warner's (1985) event study method, cross-sectional analysis, and network analysis.

Lo, Marcelin, Bassene, Sene, and Lo (2022) conducted a study on the financial markets' response to the Russo-Ukrainian war. They utilised daily world stocks index data and an OLS regression model to analyse the situation. Instead of using an event study approach, they relied on the Google search volume index to measure the intensity of internet searches associated with the "Ukraine war." Their findings suggest that the military conflict in Ukraine hurts stock markets.

Le, Mettenheim, Goutte and Liu (2023) investigated the market reactions of the aerospace and defence industry and the airline industry in response to the ongoing conflict between Ukraine and Russia. They utilised sentiment analysis of war-related news articles to draw their conclusions. Their findings revealed a substantial negative impact of the competition on the airline market, while the defence market experienced a positive effect.

The energy crisis is also a geopolitical problem, yet the academic world has not fully explored its impact and the subsequent media's impact on the financial world. Thus, limited papers examine how news related to the war affects energy stock price changes, see Hasan, 2022; Kuzemko, Blondeel, Dupont and Brisbois, 2022; Vaughan, 2022.

Papers such as Al Mamun, Sohag, Shahbaz and Hammoudeh (2018), Razmi, Bajgiran, Behname, Salari and Razmi (2020), Le, Nguyen and Park (2020) have paid more attention to renewable energy than non-renewable energy in the financial market. Still, these studies mainly focus on enhancing eco-friendly growth, mitigating carbon dioxide (CO2) emissions and reducing temperature and global warming. They pointed out the energy transition and deployment instead of the environmental effects of geopolitical risks.

Non-renewable energy has always been heavily related to war. Noguera-Santaella (2016) confirmed war can trigger non-renewable energy price changes. Su, Khan, Tao and Umar (2020), the oil company stocks reacted negatively to the Russian invasion of Ukraine event. Osicka and Cernoch (2022) documented that the war caused natural gas uncertainty and will play a significant role in the future development of the European energy transition.

On the contrary, the ambitions for sustainable renewable energy sources, such as solar, wind, geothermal, whole cell, and bio-renewable fuels, emerge mainly when the war event arises. Umar, Riaz, and Yousaf delved into the repercussions of the Russian-Ukraine war on the metals, conventional energy, and renewable energy markets in their 2022 research paper. Employing an event study methodology, they assessed the impact of the conflict and discovered that Europe was among the first renewable energy markets to react to the war. The report also underscored the war's substantial impact on metals such as gold, platinum, palladium, and nickel.

Steffen and Patt (2022) show that public support for policies aimed at expanding solar and wind energy production reached the highest levels since the war. Dutta and Dutta (2022) concluded when the geopolitical risk increases, the users of crude oil tend to consider renewable energy as a substitute for non-renewable energy sources. Others see Rabbi, Popp, Máté and Kovács (2022), Tsangas, Papamichael and Zorpas (2023).

According to Nerlinger and Utz's (2022) report, the Russia-Ukraine conflict increased the demand for renewable energy in the short term. However, coal and uranium stocks remain more favourable among market participants in the long run. Regardless of the Russian-Ukrainian conflict, the existing literature has shed light on the war on different stores using the event study methodology, Tuna (2022), Li, Meng, Qi and Yang (2022), Pereira, Zhao, Symochko, Inacio, Bogunovic and Barcelo (2022).

Polyzos' (2022) proposal features an insightful case study that examines the impact of the Ukrainian War on diverse financial indices. Their findings reveal that the escalation of conflict often results in an immediate adverse reaction for European currencies and markets. Conversely, crude oil prices tend to experience a delayed negative response. The US stock markets remain mostly impervious to the war's effects. At the same time, the US Dollar demonstrates a tendency to react positively to adverse events associated with the conflict.

The literature suggests an urgent need to investigate GPR news's impact on renewable and non-renewable energy stocks. It is crucial to provide qualitative discussion and empirical evidence to understand better the potential effects of GPR news on these energy sectors. The results of this investigation could have significant implications for investors and policymakers alike.

Our objective in this chapter is to explore the correlation between news concerning geopolitics and fluctuations in energy stock prices within the context of the Russian-Ukraine conflict. Furthermore, we will examine how renewable and non-renewable energy sector stocks react to GPR news. Rather than analysing individual nations, we will investigate global, EU, and USA indices to determine if any connections exist.

To the best of the authors' knowledge, no study has investigated the relationship between the war news of Russia and Ukraine using the MGARCH model in the energy sector. This chapter aims to fill this gap in the literature.

This chapter provides fresh insights on geopolitical uncertainty news, environmental economics and energy transition. It can help geography experts, political scientists, social scholars, energy enterprises, academic scholars, energy experts, public institutes, regional organisations, international organisations, and policymakers to design policies and make decisions.

The results of this chapter are helpful for investors to better analyse and manage their assets when particular events happen. Further, it benefits the economies seeking effective energy market management and environmental performance management.

## 4.3 Methodology

Univariate GARCH models are used to model/forecast volatility of one time series. However, MGARCH (multivariate generalised autoregressive conditional heteroskedasticity) model, an extension of the well-known univariate GARCH, is an extension of the widely recognised univariate GARCH model, is a precious tool for modelling the co-movement of multivariate time series data with a covariance matrix that varies over time (Chevallier, 2012).

Among the MGARCH models, DCC (dynamic conditional correlation) is broadly applied in the volatility spillover effects between markets, especially in energy economics and finance, such as studies concerning oil prices (Filis, Degiannakis and Floros, 2011).

The Dynamic Conditional Correlation model was proposed by Engle in 2002. It is a non-linear combination of univariate GARCH models and a generalised version of the CCC (Constant Conditional Correlations) model. DCC method models the conditional variances and correlations instead of directly modelling $H_t$.

The form of Engle's DCC model is as follows:

$$H_t = D_t R_t D_t \, , \tag{26}$$

Where, $D_t$ =diag($h_{1\,1t}^{1/2}, \dots, h_{N\,Nt}^{\frac{1}{2}}$), each $h_{iit}$ is a univariance GARCH model and $R_t$ =diag($q_{1\,1t}^{1/2}, \dots, q_{N\,Nt}^{\frac{1}{2}}$) $Q_t$ diag($q_{1\,1t}^{1/2}, \dots, q_{N\,Nt}^{\frac{1}{2}}$).

The matrix $Q_t = (q_{iit})$ is the N*N symmetric positive define matrix updated by the following:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u'_{t-1} u_{t-1} + \beta Q_{t-1} , \tag{27}$$

Where $u_{it}$=$\epsilon_{it}/\sqrt{h_{iit}}$ .

Engle (2002) introduced the DCC model by allowing $R_t$, representing conditional correlations, to vary over time. Hence, $u_t$ denotes the matrix of standardised residuals. Q is the N × N matrix representing the unconditional variance matrix of $, u_t$, and α and β are non-negative scalar parameters, both less than 1.

In brief, in the first place, the conditional variance is estimated via the univariate GARCH model for each variable. The next step is to evaluate the parameters for the conditional correlation. The DCC model can make the covariance matrix positive at any point.

## 4.4 Data

### 4.4.1 Stock returns

In this chapter, we delve into the effects of geopolitical risk on energy stock returns, particularly emphasising the Russian-Ukrainian conflict. Our analysis encompasses a time frame from February 1st, 2022, to April 28th, 2023, and we gathered daily data on the closing prices of the stock index from Bloomberg. We included all the trading day data to ensure consistency and comparable analysis, resulting in 324 observations. The market data is expressed in U.S. dollars.

We meticulously crafted renewable energy stock indexes, comprising of three expertly chosen stocks that represent the global, European, and American renewable energy industry. The index features SPGTCED, ERIXP, and SPXESUP, offering investors a comprehensive view of the renewable energy market. Conversely, to offer a balanced perspective, we have handpicked three non-renewable energy stocks, namely SPGOGUP, SXEP, and USCRWTIC, based on their performance, to provide an accurate snapshot of the non-renewable energy industry.

The S&P Global Renewable Energy Index (SPGTCED Index) is a benchmark for evaluating the global performance of companies engaged in the renewable energy sector. Its primary objective is to offer investors a reliable means of monitoring the progress of renewable energy firms worldwide. The index endeavours to comprise 100 constituent companies.

The European Renewable Energy Index (ERIXP) is a stock market index that provides investors with a comprehensive overview of the renewable energy sector in Europe. The index tracks the performance of the industry's ten most extensive and most liquid stocks, focusing on companies producing biomass, geothermal, marine, solar, and water energy. By monitoring the ERIXP, investors can stay up-to-date with the latest trends and developments in the renewable energy market and make informed decisions about their investments.

The S&P 500 ESG Index (SPXESUP) is a potent instrument for investors prioritising supporting sustainable and socially responsible companies. As a market capitalization-weighted index, it meticulously evaluates securities that meet strict sustainability standards, making it a crucial gauge of companies' environmental, social, and governance performance. The index endeavours to maintain comparable overall industry group weightings as the S&P 500 while encouraging investments prioritising sustainable practices and responsible corporate behaviour.

The SPGOGUP Index (SPGOGUP Index), the S&P Global Oil Index, monitors the progress of the 120 biggest publicly traded oil and gas entities. This comprises companies that engage in all aspects of the industry, such as exploration, extraction, production, refining, marketing, and distribution. Its objective is to provide investors with a comprehensive understanding of the global oil and gas sector's overall performance.

The STOXX Europe 600 Oil & Gas Price EUR (SXEP Index) is a pivotal gauge representing the performance of companies operating within the European oil and gas sector. This index encompasses companies engaged in diverse facets of the industry, encompassing activities such as oil and gas exploration, production, refining, and marketing. It includes companies of various market capitalisations, spanning from large to mid-sized to small-cap firms across multiple European countries. The index's weighting is established through market apitalisation, which measures the relative significance of each constituent company within the index.

The S&P GSCI Crude Oil Index (USCRWTIC) is a widely used financial instrument that monitors the price movements of futures contracts for crude oil traded on various commodity exchanges. This index is a reliable and easily accessible benchmark for investors to assess their investment performance within the natural oil market. By tracking the fluctuations of crude oil futures, the USCRWTIC provides a valuable tool for investors to make informed decisions about their portfolios and stay up-to-date on the latest market trends.

### 4.4.2 GPR news

In a comprehensive study conducted by Ibar-Alonso, Quiroga-García, and Arenas-Parra (2022), an in-depth analysis of public sentiment and emotion was carried out by monitoring Twitter activity before and after a significant conflict. The researchers focused on tweets containing the term "green energy," which provided valuable insights into how this topic was discussed on social media during the conflict.

The results revealed that the conflict has significantly impacted society's perception of renewable energy, prompting countries worldwide to accelerate their transition to sustainable energy sources.

Since the introduction of the GPR index by Caldara and Iacoviello in 2022, numerous researchers have utilised it as a quantitative measure of geopolitical uncertainty. For example, Dutta and Dutta (2022) analysed how the volatility of renewable energy exchange-traded funds is impacted by geopolitical uncertainty, as represented by the GPR index. Similarly, Będowska-Sójka, Demir, and Zaremba (2022) have also employed this index. The GPR news is a text-based metric that assesses geopolitical risk by tallying the number of news articles.

In this chapter, we use the GPR news, initially collected by Dario Caldara and Matteo Iacoviello and then extracted by the author from the website, to represent the news index.
The GPR news, a daily count of global geopolitical risk news headlines, is a news indicator based on the tally of newspaper articles covering geopolitical tensions. It assesses the evolution of these tensions and their economic effects. It can be used to measure and quantify the level

of risk associated with geopolitical events and developments that may impact global politics, economies, and financial markets.

GPR news typically includes various factors such as political instability, geopolitical conflicts, trade disputes, sanctions, and other geopolitical events that may introduce uncertainty and potential risks to economic and financial stability.

The GPR news data is generated from automated text-search results obtained from the digital archives of ten prominent newspapers, including the Chicago Tribune, the Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, the Los Angeles Times, The New York Times, USA Today, The Wall Street Journal, and The Washington Post.

It measured the frequency of articles in leading newspapers focusing on wars, terrorism, and tensions between states. The keywords would be headlines containing words such as war, nuclear, and terrorism, also containing either “threat” or “act” words for each topic.

## 4.5 Empirical results

The indexes' return was calculated in Eviews using the return formula; all results are stationary and mean-revert, see Table 4.1.

**Table 4.1 The statistical description for the energy stock return series and GPR news[16]**

| *Symbol* | *Index* | *Mean* | *Median* | *Maximum* | *Minimum* | *Std.Dev* | *Skewness* | *Kurtosis* |
|---|---|---|---|---|---|---|---|---|
| ***SPGTCED*** | S&P Global Renewable Energy index | 0.017452 | -0.052652 | 7.695806 | -5.935319 | 1.871752 | 0.513042 | 4.820879 |
| ***ERIXP*** | European Renewable Energy Index | 0.024765 | 0.017811 | 10.549650 | -6.631090 | 1.980933 | 0.845256 | 7.035436 |
| ***SPXESUP*** | S&P 500 ESG Index | -0.013051 | -0.015130 | 5.592316 | -4.379399 | 1.416222 | -0.028578 | 3.710984 |
| ***SPGOGUP*** | S&P Global Oil Index | 0.025342 | 0.000000 | 5.386741 | -7.091009 | 1.789743 | -0.618380 | 5.585282 |
| ***SXEP*** | STOXX Europe 600 Oil & Gas Price EUR | 0.054264 | 0.092122 | 4.775726 | -6.700115 | 1.703476 | -0.443077 | 4.542424 |
| ***RUSCRWTIC*** | S&P GSCI Crude Oil index | -0.002342 | 0.088095 | 8.354377 | -12.12611 | 2.836653 | -0.305419 | 8.354377 |
| ***PGR NEWS*** | Geopolitical risks news | 552.1517 | 549.0000 | 787.0000 | 256.0000 | 76.90265 | 0.180239 | 4.301462 |

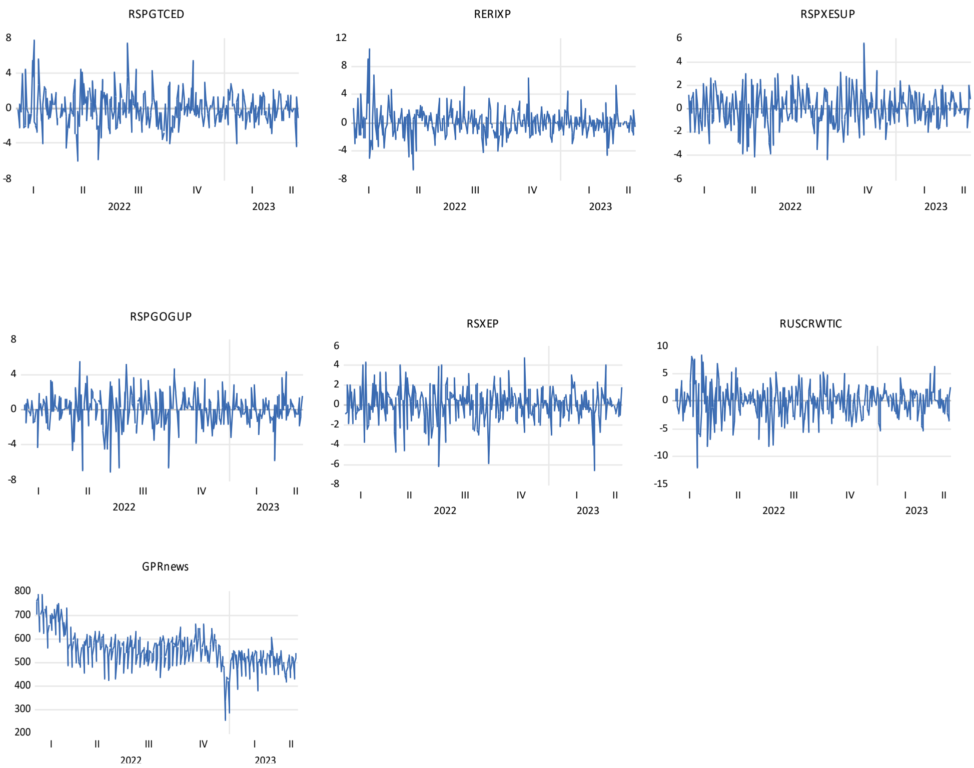
**Notes:** This table presents the basic statistical estimation description (mean, standard deviation, skewness) of the research sample used in the chapter. The symbol indicates the daily stocks used in the chapter. The study period is from 01/02/2022 to 28/04/2023.

[16] All the stocks were collected from Bloomberg, apart from PGR news, which were obtained from the website https://www.matteoiacoviello.com/gpr.htm.

In Table 4.1, PGR news (Geopolitical risk news) has different results than other stock indexes due to the raw data input instead of calculating the returns. Unlike calculating the returns, the volume of PGR news is observed to gather insights.

After obtaining Table 4.1 for all the returns, we generated Figure 4.1 from Eviews. Figure 4.1 plots the return series over time.

**Figure 4.1 Line plots of energy stock return series and GPR news[17]**




**Notes:** This Figure illustrates the time series of the indexes representing the energy stock returns and GPR news included in our sample. The study period is 01/02/2022 to 28/04/2023.

Based on the provided graphs, it can be observed that the volume of GPR news reached its peak in early 2022, resulting in notable fluctuations in the returns of SPGTCED, ERIXP, and USCRWTIC. While the remaining index returns exhibited delayed changes in volatility. As time progressed, the quantity of GPR news gradually decreased and stabilized until the conclusion of 2023.

It can be observed that when Russia invaded Ukraine, it triggered the world energy crisis. The keywords such as; “War”, “Threat”, and “Act” increased in headlines, resulting in the GPR news amount peaking in our data sample. The shortage of energy resources and the related news impacted the energy stock prices worldwide, especially in European, where renewable stock prices started to change frequently while the non-renewable energy stock prices in the US followed the same pattern.

This is against the result of Babar, Ahmad and Yousaf (2023), who believe that special events have a weak influence on the financial market. However, it supported Smales’ (2017) conclusion that the news related to war can affect the stock returns changes. We also agree with Umar, Riaz, Yousaf, 2022, Kumari, Kumar and Pandey, 2023, that the world, mainly European countries, prioritise renewable energy against non-renewable sources after the Russian and Kurian conflict. And the policies lead to the renewable energy stock returns to rapidly and significantly rise.

In our analysis, we employed the DCC-GARCH model, utilizing a two-step estimation methodology. Initially, we conducted a comprehensive evaluation of the ARCH/GARCH effect of all stock returns to ensure adherence to required standards. Once we were confident in the validity of the returns, we proceeded to the second step, which involved examining the correlations between variables.

For the first step, we gather our results in Table 4.2.

**Table 4.2 Estimations of GARCH of all stocks in DCC-GARCH-Step 1**

| | RSPGTCED | RERIXP | RSPXESUP | RSPGOGUP | RSXEP | RUSCRWTIC | PGR NEWS |
|---|---|---|---|---|---|---|---|
| $\omega$ | 0.465085 | 0.446195 | 0.013947 | 0.248069 | 1.353945 | 0.594613 | 402.6889 |
| | (0.0607) | (0.0321) | (0.06457) | (0.0741) | (0.0060) | (0.0882) | (0.0334) |
| $\alpha$ | 0.099523 | 0.110147 | 0.046568 | 0.057598 | 0.205364 | 0.108212 | 0.161116 |
| | (0.0031) | (0.0006) | (0.0366) | (0.0181) | (0.0018) | (0.0175) | (0.0003) |
| $\beta$ | 0.768325 | 0.771054 | 0.945387 | 0.866694 | 0.334176 | 0.817368 | 0.749203 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0891) | (0.0000) | (0.0000) |

**Notes:** This table displays the MARCH estimation of the research sample. ω indicates the long-run variance, and to make sure the conditional variance process is positive and stationary, $\omega$ needs to be positive; α, β are non-negative scalar parameters with α and $\beta < 1$. The study period is from 01/02/2022 to 28/04/2023. All the stocks and news were estimated in Eviews, and the author organises the results.

In Table 4.2, all the parameters are positive, and the P value is significant at 10%. Therefore, since the MGARCH model is an excellent fit for all indexes, we can proceed to analyse the correlation between different variables.

Once we confirm that all estimations are positive and significant, we move forward to examine the correlation between GPR news and the returns of renewable and non-renewable energy stocks separately.

Then we delved into the trends or any associations between renewable and non-renewable variables and GPR news. To deepen our comprehension, we broadened our investigation to encompass the connection between energy stock prices and news in various regions. This enabled us to detect any patterns that might be distinct to particular geographic locations.
Our research delivers valuable insights into the interdependence of stocks, news, and regional factors. These discoveries can assist investors in making more informed decisions and managing potential risks linked with their investment portfolios.

Each table features numerical markers 1, 2, and 3 to distinguish between the various stocks, while 4 denotes GPR news. We will furnish a comprehensive description for each numeric classification in each table.

The renewable energy stocks were tested along with the GPR news; results are shown in Table 4.3.

**Table 4.3 The correlation between renewable energy stocks and GPR news**

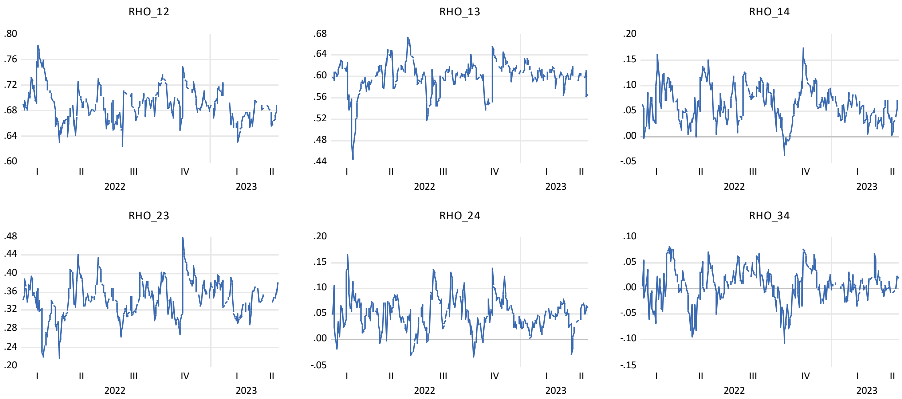
| **Renewable** | **12** | **13** | **14** | **23** | **24** | **34** |
|---|---|---|---|---|---|---|
| **correlation** | 0.690238 | 0.599243 | 0.062263 | 0.345141 | 0.049350 | 0.005240 |

**Notes:** This table shows the regional correlation of renewable energy stocks and their connection to GPR news. A positive number indicates a positive correlation, while a negative number indicates a negative relationship between the variables.

Between 01/02/2022 and 28/04/2023, multiple renewable energy indices were identified by various symbols. These symbols include symbol 1, which corresponds to the worldwide renewable energy index return referred to as "SPGTED," symbol 2, which represents the European renewable energy return index known as "ERIXP," and symbol 3, which denotes the American renewable energy index referred to as "SPXESUP." Furthermore, symbol 4 is used to indicate the GPR news.

We created Table 4.3 and then plotted Figure 4.2 to provide a more detailed representation of the correlation.

**Figure 4.2 Line plots of the correlation between renewable energy stocks and GPR news**




**Notes:** This plot shows the relationship between three renewable energy stocks and their coherence with GPR news in our sample. The study period is 01/02/2022 to 28/04/2023. These symbols include symbol 1, which corresponds to the worldwide renewable energy index return referred to as "SPGTED," symbol 2, which represents the European renewable energy return index known as "ERIXP," and symbol 3, which denotes the American renewable energy index referred to as "SPXESUP." Furthermore, symbol 4 is used to indicate the GPR news.

Steffen and Patt (2022) mentioned that public policies aimed at expanding renewable energy have reached their highest levels since the war.

Table 4.3 and Figure 4.2 analyse the geopolitical risk news relationship with renewable stock variables using values 14, 24, and 34. Furthermore, we can assess the influence of fluctuations in world energy stock prices on the renewable energy industry in Europe and the US, with a focus on values 13 and 23.

It is expected that the renewable energy stocks across the globe will witness a surge in the US and Europe, as there exists a positive correlation between the figures obtained through 13 and 23.

The positive values of 14, 24, and 34 imply a positive relationship between GPR news and renewable stock returns. This suggests that, as GPR news increases, renewable stock returns also tend to increase.

As per the findings outlined in Figure 4.1, it was observed that while the world and European renewable returns were impacted by news events, American renewable returns did not show the same pattern of behavior. Table 4.2 further illustrates this point, with the 13 and 14 values being significantly larger than the 34 numbers. These observations suggest that geopolitical news has relatively less impact on US renewable stocks as compared to their counterparts in other regions.

In addition, our research has revealed a noteworthy connection between GPR news and renewable energy stocks, with a positive correlation observed. Essentially, when the primary newspaper publishes more headlines related to the Russian-Ukrainian conflict, which tends to heighten geopolitical risks, the prices of renewable energy stocks experience an upswing. These conclusions align with those of Umar, Riaz, and Yousaf (2022), who also noted a marked impact of the war on renewable energy markets, particularly in Europe. Investing in renewable energy has been on the rise and the correlation we have identified only adds to the evidence that the trend is favorable. This presents an opportune moment for investors to take notice and make the most of the potential financial gains.

The non-renewable energy stocks were tested alongside GPR news. The findings of these tests are presented in detail in Table 4.4 and Figure 4.3.

**Table 4.4 The correlation between non-renewable energy stocks and GPR news**

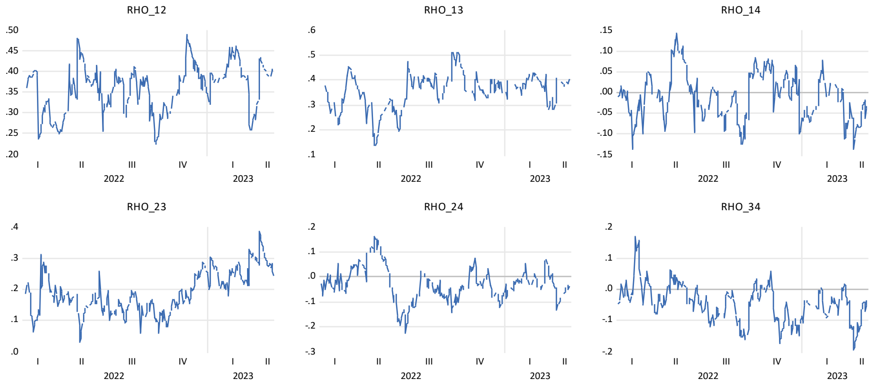
| Non-renewable | 12 | 13 | 14 | 23 | 24 | 34 |
|---|---|---|---|---|---|---|
| Correlation | 0.359362 | 0.356408 | -0.009867 | 0.189197 | -0.028425 | -0.045260 |

**Notes:** This table shows the regional correlation of non-renewable energy stocks and their connection to GPR news. A positive number indicates a positive correlation, while a negative number indicates a negative relationship between the variables.

Between 01/02/2022 and 28/04/2023, multiple non-renewable energy indices were identified by various symbols. Symbol 1 indicates the world none-green energy index return “SPGOGUP”, symbol 2 is the European none-green energy return index “SXEP”, and the American none-green energy index “USCRWTIC “are represented as symbol 3. Number 4 shows the GPR news.

We created Table 4.4 and then plotted Figure 4.3 to provide a more detailed representation of the correlation.

**Figure 4.4 Line plots of the correlation between none-renewable energy stocks and GPR news**




**Notes:** This plot shows the relationship between three non-renewable energy stocks and their coherence with GPR news in our sample. The study period is 01/02/2022 to 28/04/2023. These symbols include Symbol 1, which indicates the world none-green energy index return “SPGOGUP”; Symbol 2 is the European none-green energy return index “SXEP”, and the American none-green energy index “USCRWTIC “represented as symbol 3. Number 4 shows the GPR news.

In this analysis, we delve into the correlation between the quantity of news about geopolitical risks and the stock of non-renewable resources, as illustrated in Table 4.4 and Figure 4.3. Our investigation employs values of 14, 24, and 34 to establish this relationship. Furthermore, we scrutinize the effect of changes in worldwide energy stock prices on the non-renewable energy sector in Europe and the US, with a particular emphasis on values 13 and 23.

Investment in non-renewable energy stocks in the US and Europe is likely to result in a surge in their figures if the global prices increase. This is due to a clear and positive correlation between these regions, which is shown from 13 and 23.

The data analysis suggests a negative correlation between GPR news and non-renewable stock returns, as indicated by the negative values of 14, 24, and 34. This implies that an increase in GPR news results in decreased returns on non-renewable stocks.

The findings also imply that investors tend to shift their focus towards renewable energy stocks as more attention is given to GPR news. Thus, the negative correlation between GPR news and the non-renewable energy index can be deemed as an inverse correlation. The obtained results can be used to make informed investment decisions and to gain a better understanding of the relationship between GPR news and non-renewable energy stocks' performance.

Therefore, we agree with Osicka and Cernoch (2022) and Noguera-Santaella (2016) that the supply of non-renewable energy in Europe has been dramatically affected by the uncertainty caused by war. Su, Khan, Tao and Umar (2020) have corroborated this claim through their research, emphasising how the Russian invasion of Ukraine has resulted in unfavourable stock news for non-renewable energy.

Additionally, we tested the relationship between renewable and non-renewable energy stocks and the news index using the DCC-GARCH model. Our analysis began with an initial test of global stocks, focusing on SPGTCED for renewable supplies and SPGOGUP for non-renewable reserves. To refine our findings, we conducted a second test, incorporating European stocks with ERIXP for renewable and SXEP for non-renewable. Finally, we completed a comprehensive analysis by integrating American stocks, using SPXESUP for renewable and USCRWTIC for non-renewable. The results are as follows.

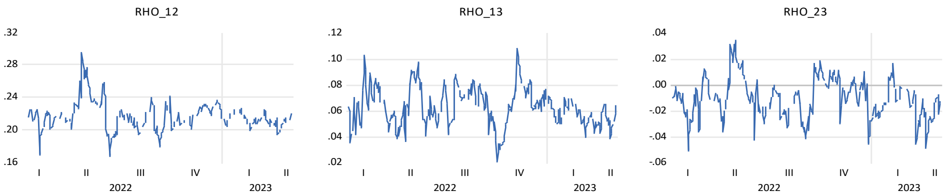
For the world-level comparison, see Table 4.5 and Figure 4.4.

**Table 4.5 The correlation between world energy stocks and GPR news**

| | **12** | **13** | **23** |
|---|---|---|---|
| **Correlation** | 0.217256 | 0.062690 | -0.010349 |

**Notes:** This table shows the correlation between renewable and non-renewable energy stocks and their connection to GPR news. A positive number indicates a positive correlation, while a negative number indicates a negative relationship between the variables. Between 01/02/2022 and 28/04/2023, multiple energy stocks were identified by various symbols. Symbol 1 indicates the world green energy index return “SPGTCED”, symbol 2 is the world none-green energy return index “SPGOGUP”, Number 3 shows the GPR news.

## Figure 4.4 Line plots of the correlation between world energy stocks and GPR news




**Notes:** This figure shows the correlation between renewable and non-renewable energy stocks and their connection to GPR news. The study period is 01/02/2022 to 28/04/2023. Symbol 1 indicates the world green energy index return “SPGTCED”, symbol 2 is the world none-green energy return index “SPGOGUP”, Number 3 shows the GPR news.

We can observe that renewable energy prices tend to rise in response to increased GPR news. In contrast, non-renewable energy prices decrease due to a rise in uncertainty or risk-related news.

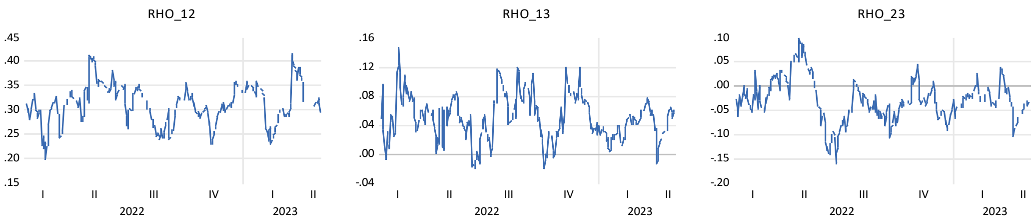
For the European-level comparison, see Table 4.6 and Figure 4.5.

### Table 4.6 The correlation between European energy stocks and GPR news

| | **12** | **13** | **23** |
|---|---|---|---|
| **Correlation** | 0.312321 | 0.049269 | -0.028557 |

**Notes:** This table shows the correlation between renewable and non-renewable energy stocks and their connection to GPR news. A positive number indicates a positive correlation, while a negative number indicates a negative relationship between the variables. Between 01/02/2022 and 28/04/2023, multiple energy stocks were identified by various symbols. Symbol 1 indicates the European green energy index return “ERIXP”, symbol 2 is the European none-green energy return index “SXEP”, Number 3 shows the GPR news.

## Figure 4.5 Line plots of the correlation between European energy stocks and GPR news




**Notes:** This plot shows the correlation between renewable and non-renewable energy stocks and their connection to GPR news. The study period is 01/02/2022 to 28/04/2023. Symbol 1 indicates the European green energy index return “ERIXP”, symbol 2 is the European none-green energy return index “SXEP”, Number 3 shows the GPR news.

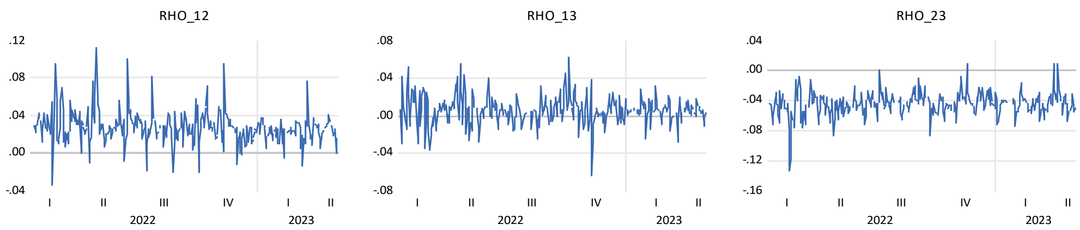
For the US-level comparison, see Table 4.7 and Figure 4.6.

**Table 4.7 The correlation between US energy stocks and GPR news**

| | **12** | **13** | **23** |
|---|---|---|---|
| **Correlation** | 0.027424 | 0.005380 | -0.044343 |

**Notes:** This table shows the correlation between renewable and non-renewable energy stocks and their connection to GPR news. A positive number indicates a positive correlation, while a negative number indicates a negative relationship between the variables. Between 01/02/2022 and 28/04/2023, multiple energy stocks were identified by various symbols. Symbol 1 indicates the American green energy index return “SPXESUP”, symbol 2 is the American none-green energy return index “USCRWTIC”, Number 3 shows the GPR news.

**Figure 4.6 Line plot of the correlation between US energy stocks and GPR news**




**Notes:** This figure shows the correlation between renewable and non-renewable energy stocks and their connection to GPR news. The study period is 01/02/2022 to 28/04/2023. Symbol 1 indicates the American green energy index return “SPXESUP”, symbol 2 is the American none-green energy return index “USCRWTIC”, Number 3 shows the GPR news.

The correlation between the world energy index and energy prices in Europe and the US remains consistent, regardless of whether the energy source is renewable or non-renewable. Essentially, as the world energy index rises, energy prices in these regions also increase.

Additionally, the performance of renewable and non-renewable energy company stocks reveals an intriguing trend. During periods of heightened geopolitical risk, renewable energy stocks typically experience a boost in returns, whereas non-renewable energy stocks decline. This indicates that investors may be more inclined to support sustainable energy solutions when global political conditions are uncertain.

The evidence shared in this chapter bolsters the findings outlined in prominent recent publications, including Ibar-Alonso, Quiroga-García, and Arenas-Parra (2022), Rabbi, Popp, Máté, and Kovács (2022), Tsangas, Papamichael, and Zorpas (2023), and Dutta and Dutta (2022). These studies indicate that escalating geopolitical risks related to war could hasten the shift towards sustainable energy solutions.

Our analysis shows that EU stocks generally react unfavourably to an uptick in GPR news, aligning with Polyzos' (2022) insights. However, we have diverged from Polyzos' findings regarding the US market. Contrary to their suggestion that the US market remains unaffected by such developments, we have discovered that stock prices are indeed impacted, with shifts in direction contingent on the specific energy stocks affected by the news.

## 4.6 Conclusion

The Russian military intervention in Ukraine sparked a global energy crisis that caught the international community by surprise. Many countries are forced to seek alternative energy sources than non-renewable ones. A thorough analysis of news headlines at the time showed a surge in keywords like "war," "threat," and "act," highlighting the severity of the situation.

Our data demonstrated a significant rise in GPR news coverage, emphasizing the crisis's magnitude and geopolitical importance. This points to the importance of anticipating potential ripple effects from conflicts involving major powers and the need for greater vigilance and foresight as they can greatly impact the global economy and security landscape.

The depletion of energy resources and the associated news has caused a ripple effect on the energy stock market around the globe. The prices of renewable energy stocks in the European region have been subject to frequent changes, often influenced by market fluctuations, environmental regulations, and government policies aimed at promoting green energy. Meanwhile, in the US, non-renewable energy stocks have been following a similar pattern, responding to the same market forces and uncertainties. The energy sector remains highly dynamic and volatile, with many factors impacting the stock prices and investment choices of companies and individuals alike.

The limited availability of energy resources and the consequential news coverage have had a profound impact on the stock prices of energy companies worldwide. The European region has witnessed a remarkable shift in the prices of renewable energy stocks, with frequent and significant fluctuations. Conversely, non-renewable energy stocks in the United States have exhibited a similar pattern, indicating the pervasive influence of market conditions on the energy sector. The observed trends underscore the need for diligent monitoring of stock prices, particularly in the energy sector, which is known for its volatility. Stakeholders in the industry must remain vigilant and respond proactively to market changes, ensuring long-term sustainability and growth.

We analysed economics using the multivariance GARCH (DCC-GARCH model) estimation. This approach allows the examination of co-movements between renewable and non-renewable energy stocks and GPR news. Data were collected specifically from the start of the Russian-Ukraine war conflict to include more war-related information. Correlations were observed during and after the sanction as well.

We have handpicked six energy stocks that represent a global perspective, including European and American regions. In addition, we are using the GPR news headline count as a reliable indicator to provide up-to-date information in the energy sector.

Our outcomes suggest that energy stocks are sensitive to worldwide geopolitical uncertainty. There is a positive influence of geopolitical risk news on renewable-energy prices increasing. However, the geopolitical risk news significantly reduces non-renewable energy prices in the short run. Thus, based on the findings, renewable energy consumption can be a valuable tool to mitigate geopolitical risks.

Consequently, we propose the policymakers reducing the carbon footprint of businesses and societies, publish more strict environmental regulations, and aiming at promoting green energy. There is also need to encourage the adoption of renewable energy technologies through investment in research and development, tax incentives, and funding for renewable energy projects. By adopting cleaner energy sources, businesses can reduce their energy costs and carbon emissions.

By reducing our reliance on traditional energy resources, we can mitigate the negative effects of war-related news and help ease any resulting panic. This approach will not only improve our resilience but also demonstrate our commitment to responsible and sustainable practices.

To make informed investment decisions and manage potential risks associated with their portfolios, investors and risk managers should analyse geopolitical news, including military conflicts. Our research suggests that investors tend to shift their attention towards renewable energy stocks when there's an uptick in geopolitical news. By incorporating GPR news analyses, investors can adjust their decisions in line with the pace of energy stocks' response.

The findings of our research work serve to emphasize the critical importance of diligent monitoring of stock prices, particularly in the energy sector, which is widely acknowledged for its volatility. It is incumbent upon all stakeholders in the industry to remain vigilant and respond proactively to market changes, in order to ensure the long-term sustainability and growth of their businesses. In light of the dynamic nature of the industry, it is essential that all relevant parties stay abreast of ongoing developments, and take timely and informed actions to mitigate risks and seize opportunities.This chapter adds empirical evidence to the news effect of stock returns during special events and highlights the war's impact on the energy industry.

This study has certain limitations that should be acknowledged. Firstly, it solely explores the impact of GPR news on energy stocks in the short term. It is recommended that a follow-up investigation be conducted to estimate and analyse the post-war period or a long-term investment period.

Alongside DCC-GARCH, there are several other dynamic MGARCH models available, such as VEC-GARCH, BEKK-GARCH, and CCC-GARCH. Out of these, BEKK and DCC are the most popularly utilized models. This work could involve additional scrutiny of model comparisons, as well as exploration of their diagnostics and forecasting.

In the realm of empirical research, there is potential for further exploration of alternative distributions, such as the student t distribution, as opposed to the standard normal distribution.

Moreover, there may be merit in conducting estimations on a monthly and weekly basis in order to obtain more granular insights.

Multiple energy indices exist to evaluate the performance of renewable energy businesses. One such index is the RENIXX, a worldwide stock index that monitors the 30 largest companies in the renewable energy industry based on their market capitalization. Typical stock indices are grouped by coal, gas, oil, and other categories, and each category may possess different indices. The World Economic Forum (WEF) created the Global Energy Transition Index (ETI) as another energy index to gauge countries' advancement in moving toward renewable energy sources.

To enhance the news index, it may be beneficial to incorporate news headlines that feature specific keywords such as "energy", "green energy", "renewable", and "non-renewable". By doing so, the search criteria will be more comprehensive, and there will be a greater likelihood of capturing relevant news articles. Additionally, it could be worthwhile to examine the effect of news sentiment on the overall index. By analysing the tone of the articles and determining whether they are positive, negative, or neutral, one can gain valuable insights into how the news is being perceived by the public and how it may be impacting various industries.

# Chapter 5

# Concluding Remarks

Managing risks is of utmost importance in the world of investments. It is crucial to ensure that potential losses are minimised and that the investment has the potential for long-term success. Therefore, developing strategies that can help mitigate risks and maximise returns is necessary. While much literature is available on stock volatility estimation and forecasting analysis, industry experts have explored the correlation between news and stock returns.

Our study aims to explore the impact of news on stock returns estimation. We examined various types of news, including news intensity, changes in intensity, sentiment (positive and negative), specific company and industry news, and geopolitical risk news. We applied the GARCH, EGARCH, and MGARCH models to conduct our research. We aim to offer valuable insights into news-based investment strategies for investors and clarify the mechanisms that drive the stock market's response to news.

Our research shows that news's influence on stock prices varies depending on the industry, region, and nature of the news. Our findings suggest incorporating news related to specific companies can significantly enhance estimation outcomes. We have observed a robust relationship between the intensity of news coverage and stock volatility, indicating that shifts in news coverage can stimulate adjustments in stock returns. Further, negative news has a more pronounced effect than positive news.

Geopolitical events and news have a noteworthy impact on the prices of renewable and non-renewable energy sources. The findings suggest that the returns of renewable energy increase in the presence of geopolitical risk news, whereas the returns of non-renewable energy significantly decrease in the short run. These results indicate that renewable energy consumption can be crucial in mitigating geopolitical risks and ensuring sustainable energy security.

Chapter 2 explores the estimation and forecasting of stock returns using the GARCH model and two distributions (normal distribution and student's t distribution) in a portfolio context.

Although utilised in numerous time series analyses, ARCH/GARCH models have achieved a notable triumph in financial risk management (Malik & Anjum, 2019; Sobreira & Louro, 2020). The precision and forecasting of return and risk play a crucial role in financial decision-making, placing the onus of efficient risk management on investors and regulators.

Throughout its history, research has primarily been concerned with uncovering the most accurate equations or models, as noted by Balaban (2004), Galdi & Pereira (2007), Miah & Rahman (2016), and Babikir (2018). However, contemporary studies have shifted their empirical analysis towards examining the effects of error assumption distributions, as explored by Vee, Gonpot & Sookia (2011) and Cepni, Gabauer, Gupta & Ramabulana (2020).

The objective of Chapter 2 is to assess the ability of the GARCH (1, 1) model to estimate and predict portfolio returns for long-term investment using two distinct distributions (normal and student's t distribution). The study utilised weekly data from the BRICS market over the last decade to evaluate the model's capacity to accurately forecast and estimate the conditional variance while considering two separate error term distributional assumptions.

Researchers like Abdullah, Siddiqua, Siddiquee & Hossain (2017) and Korkpoe (2016) compared the efficiency of normal and student-t distributed GARCH (1, 1) models, but empirical evidence still needs to be conclusive. Comparing the N-GARCH (1, 1) and T-GARCH (1, 1) estimation results is a worthy and valuable task. The findings of Chapter 2 underscore the superiority of the standard distribution assumption over the Student's t-distribution with GARCH (1, 1) for estimating and predicting conditional volatility in BRICS countries.

Consequently, Chapter 2 fulfilled a gap in the literature in assessing the GARCH (1, 1) model across various distributions, particularly within portfolios spanning BRICS countries. Additionally, it highlights portfolios that carry different combinations of index weights, bringing them into focus.

There are some limitations to Chapter 2. For example, extending the GARCH (1, 1) model to the GARCH (p, q) model, which considers multiple lags, can enhance its accuracy. The analyses of this study may provide an extension of many models with different types of distributions. While in-sample forecasts are a popular method for predicting outcomes, out-of-sample forecasts can yield valuable insights.

Future research could compare models' performance in estimating and forecasting volatility across different periods, including pre-crisis, crisis, post-crisis, and low-volatility periods, using events such as the COVID-19 pandemic and the US-China trade war. It would also be valuable to investigate the impact of news data, explore different types of GARCH models, expand the sample of countries, and cover short-term investments.

In Chapter 3, a new approach exploring the impact of news on stock return estimations is introduced. This is achieved by incorporating news as an additional variable in the GARCH and EGARCH models. This approach aims to provide a more effective means of analysing the relationship between news and stock returns.

Financial institutions and investors have long utilised the GARCH model for its effectiveness. Nevertheless, the model needs to consider the impact of news sentiment on stock prices. To better understand how investor sentiment affects asset returns, it's imperative to integrate GARCH models with sentiment risk factors (investor decisions) in both the mean and conditional volatility of the variance equation.

The academic community has recently displayed a growing curiosity in investigating the correlation between news sentiment and financial price fluctuations (Audrino, F., Sigrist, F. & Ballinari, D., 2020). Several research papers have delved into positive, negative, and neutral news effects on stock returns (Burchard, C.H., Proelss, J., Schäffer, U. & Schweizer, D., 2021).

The primary aim of Chapter 3 is to analyse the correlation between news (news intensity, news sentiment and general news index) and stock returns in top APEC nations through the application of GARCH (1,1) and EGARCH (1,1) models. Furthermore, this study investigates the effects of both positive and negative news on the stock market. Additionally, we aim to scrutinise the impact of information on stock market volatility in various industries such as technology, energy, finance, and healthcare.

Chapter 3 incorporated news intensity, news sentiments (positive and negative news sentiment), and the VIX index (Benchmark index of the broad U.S. stock market) across individual companies as extra variables besides the stock returns and portfolio returns. The stocks were carefully selected among the top APEC countries. Daily stock returns spanning 2017-2022 were input into plain GARCH (1, 1) and EGARCH (1, 1) models.

Chapter 3 concluded that the effect of the news on stock prices varies depending on the industry and region. However, there is a significant relationship between news intensity and stock volatility, whereby changes in news intensity can trigger changes in stock prices. Our analysis of news sentiment among the APEC countries we selected suggested that cultural and societal differences influence how news is perceived and its potential impact on different regions.

Different stocks respond differently to news sentiments. However, negative information has a more significant effect than positive news. The estimation results have shown considerable improvement by including general global news, such as the VIX volatility index, alongside specific firm information. And GARCH estimation outperforms EGARCH. The former slightly exceeds the latter when comparing a market-size-weighted portfolio to an even-weighted portfolio. However, this performance varies depending on the industry and region.

Chapter 3 offers significant contributions to the current literature by shedding light on the APEC countries, which have yet to receive thorough research attention despite their considerable global economic impact. Additionally, this chapter introduces supplementary variables like the VIX index and news in time series models, incorporating historical stock prices and news sentiment in the estimation process. This chapter also provides a more insightful assessment of stock prices with the news factor by comparing GARCH and EGARCH results and delving deeper into the effects of positive and negative news sentiment. Furthermore, the chapter examines news from various sectors and applies the findings to different portfolios.

Chapter 4 explores the relationship between geopolitical risk news and fluctuations in renewable and non-renewable energy stock returns during the Russian-Ukraine war. The study utilises multivariate GARCH models.

The ongoing conflict between Russia and Ukraine has had far-reaching consequences, significantly impacting global geopolitical risk (Khudaykulova, Yuanqiong and Khudaykulov, 2022), (Kumari, Kumar, and Pandey, 2023). In addition, the conflict has resulted in an energy crisis, particularly for European countries that have traditionally relied on non-renewable energy sources. As a result, many of these countries have been compelled to explore alternative options for meeting their energy needs, such as renewable energy sources like solar, wind, and hydroelectric power (Usman and Radulescu, 2022), (Huang and Lu, 2022).

Companies may face severe consequences due to the war in Ukraine, resulting in decreased output, profitability, cash flow disruption, and a decline in share values. This underscores the importance for investors, portfolio managers, and regulators to grasp the impact of wars on renewable energy markets (Aydin, 2022). Assessing the risks and opportunities of investing in renewable energy during times of conflict is critical, as the industry may experience significant disruptions. Proceeding cautiously and making informed decisions is essential (Umar, Riaz, Yousaf, 2022).

The current political unrest between Russia and Ukraine has heightened geopolitical uncertainties, consequently affecting industrial stocks, particularly those in the energy sector. Given the evolving global political climate and the amplified focus on eco-friendly policies, it's crucial to carefully scrutinise the reactions of both renewable and non-renewable energy stocks. The findings outlined in this chapter offer valuable insights into estimating energy stock prices by integrating news on geopolitical risks.

Numerous studies have examined the impact of unexpected events on the stock market, with notable contributions from Smales (2017), Babar, Ahmad, and Yousaf (2023), and Salisu, Cuñado, and Gupta (2022). In addition, several studies have explored the effects of war and conflict on financial markets, including Thies and Baum (2020), Boubaker, Goodell, Pandey, and Kumari (2022), Umar, Z., Polat, Choi, and Teplova (2022), and Kumari, Kumar, and Pandey (2023). However, all of these papers utilised the event study method. To fill this gap in the literature, this chapter aims to investigate the connection between the war news of Russia and Ukraine in the energy sector using the MGARCH model.

Therefore, Chapter 4 scrutinises the repercussions of geopolitical risk-related news on renewable and non-renewable energy stock returns, particularly during the Russian-Ukraine war period. By collecting daily energy stock index data from 2022 to 2023, the chapter applies the multivariance GARCH (DCC-GARCH model) to elucidate correlations between the stock return indexes and GPR news.

This approach allows the examination of co-movements between renewable and non-renewable energy stocks and GPR news. Data were collected specifically from the start of the Russian-Ukraine war conflict to include more war-related information. Correlations were observed during and after the sanction as well. We have handpicked six energy stocks. In addition, we are using the GPR news headline count as a reliable indicator to provide up-to-date information in the energy sector.

Our analysis indicates a clear correlation between the returns of global, European, and American energy stocks. Interestingly, our study suggests that when headlines about geopolitical risks increase, renewable energy prices rise while non-renewable energy prices decrease in the short term. These results indicate that energy stocks are indeed sensitive to geopolitical uncertainty. As a result, our findings suggest that using renewable energy can be a valuable tool in mitigating these risks.

Chapter 4 presents empirical evidence for the impact of news on stock market returns during special events and highlights the effects of the war on the energy industry. However, this chapter is limited. It solely examined the immediate effects of GPR news on energy stocks without exploring the post-war era.

To enhance future research, it is recommended that alternative dynamic MGARCH models, such as BEKK, be utilised. Moreover, it is suggested that other distributions, such as the student t distribution, be examined in addition to the normal distribution. Estimating data on a monthly and weekly basis is also advised. Lastly, analysing the national index and corporate stocks is recommended to gain a more comprehensive understanding.

As a result, we recommend that policymakers reduce carbon-based energy consumption. Additionally, we advise investors and risk managers to incorporate GPR news and military conflict analyses to adjust their decision-making in response to the volatility of energy stocks.

All in all, the impact of news on stock prices has been a subject of great interest in both academic and industry circles. The correlation between the two has been studied extensively, but still, unanswered questions require additional exploration and analysis. Researchers delve deeper into this topic and discover new insights that shed light on the intricate relationship between news and stock market performance.

The thesis findings imply a notable positive relationship between news and stock returns. The accuracy of estimation results can be enhanced by integrating information as supplementary variables in time series analysis. Nevertheless, there is scope for additional research to predict stock returns better.

As the importance of textual information continues to grow, more researchers are expected to devote their efforts to quantifying it. Meanwhile, exploring and refining econometric models will be an ongoing process, leading to the emergence of new and improved models and technologies that will facilitate the progress of social and academic research.

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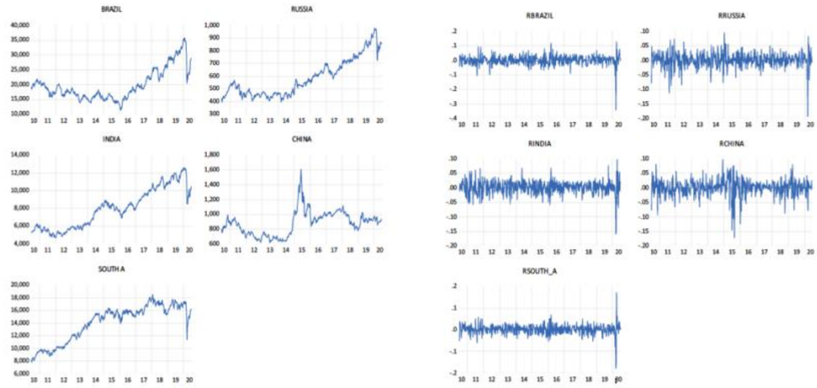
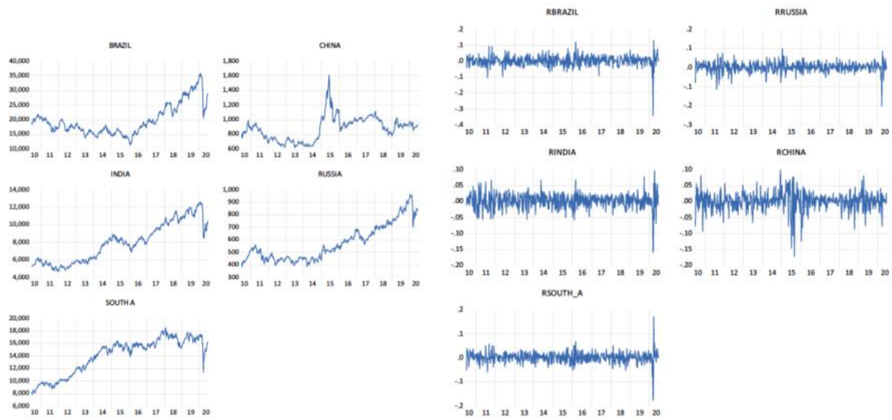
# Appendix A

### Figure A1 Line plots of portfolio 2 prices and return series in BRICS countries



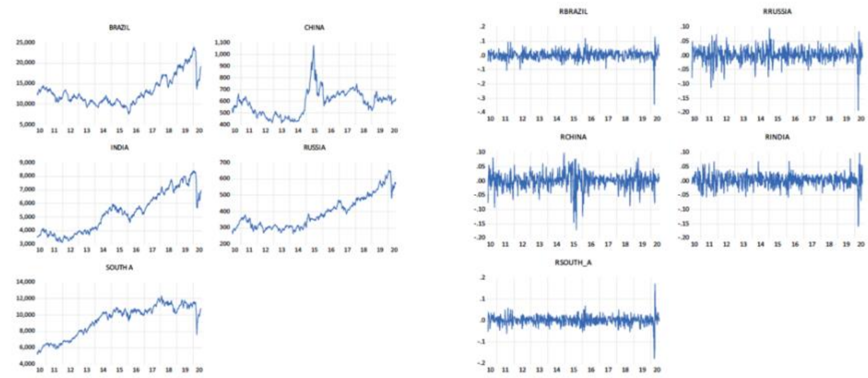

**Notes:** Portfolio 2 prices consist of 30% stock price, 50% exchange rate and 20% bond price in each country. The portfolio 2 prices on the left side clearly showed that they were not stationary and sometimes in a random walk pattern but fluctuating up and down. All portfolio 2 returns on the right side then show volatility clustering after adjusting. At every terming point, the portfolio one returns are more volatile, which means GARCH (1, 1) would be perfect to fit them. All the index prices in these five portfolios are collected weekly from 24 June 2010 to 25 June 2020 and calculated using Microsoft Excel. There are 522 observations for each country in each portfolio.

### Figure A2 Line plots of portfolio 3 prices and return series in BRICS countries



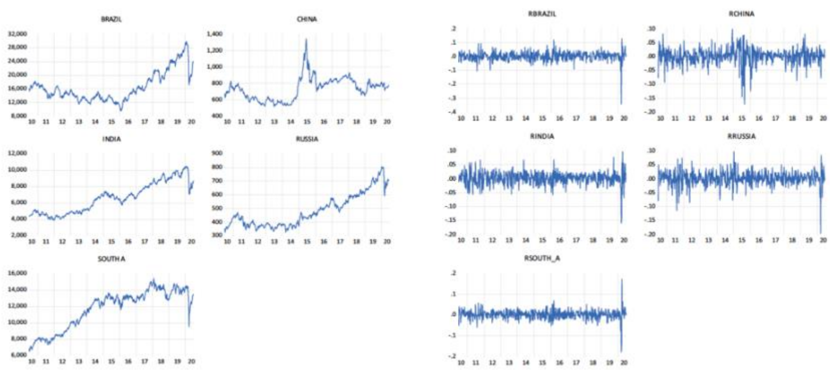

**Notes:** Portfolio 3 prices consist of 30% stock price, 20% exchange rate and 50% bond price in each country. The portfolio 3 prices on the left side clearly showed that they were not stationary and sometimes in a random walk pattern but fluctuating up and down. All portfolio 2 returns on the right side then show volatility clustering after adjusting. At every terming point, the portfolio one returns are more volatile, which means GARCH (1, 1) would be perfect to fit them. All the index prices in these five portfolios are collected weekly from 24 June 2010 to 25 June 2020 and calculated using Microsoft Excel. There are 522 observations for each country in each portfolio.

## Figure A3 Line plots of portfolio 4 prices and return series in BRICS countries



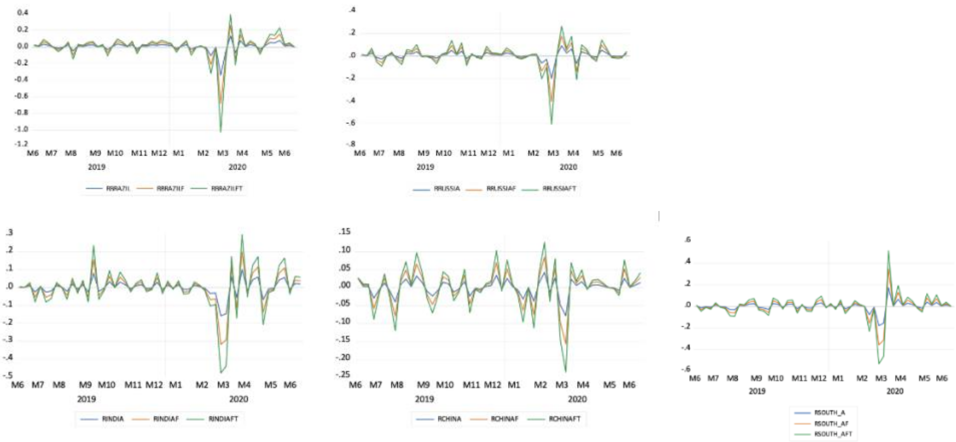
**Notes:** Portfolio 4 prices consist of 20% stock price, 30% exchange rate and 50% bond price in each country. The portfolio 4 prices on the left side clearly showed that they were not stationary and sometimes in a random walk pattern but fluctuating up and down. All portfolio 2 returns on the right side then show volatility clustering after adjusting. At every terming point, the portfolio one returns are more volatile, which means GARCH (1, 1) would be perfect to fit them. All the index prices in these five portfolios are collected weekly from 24 June 2010 to 25 June 2020 and calculated using Microsoft Excel. There are 522 observations for each country in each portfolio.

## Figure A4 Line plots of portfolio 5 prices and return series in BRICS countries



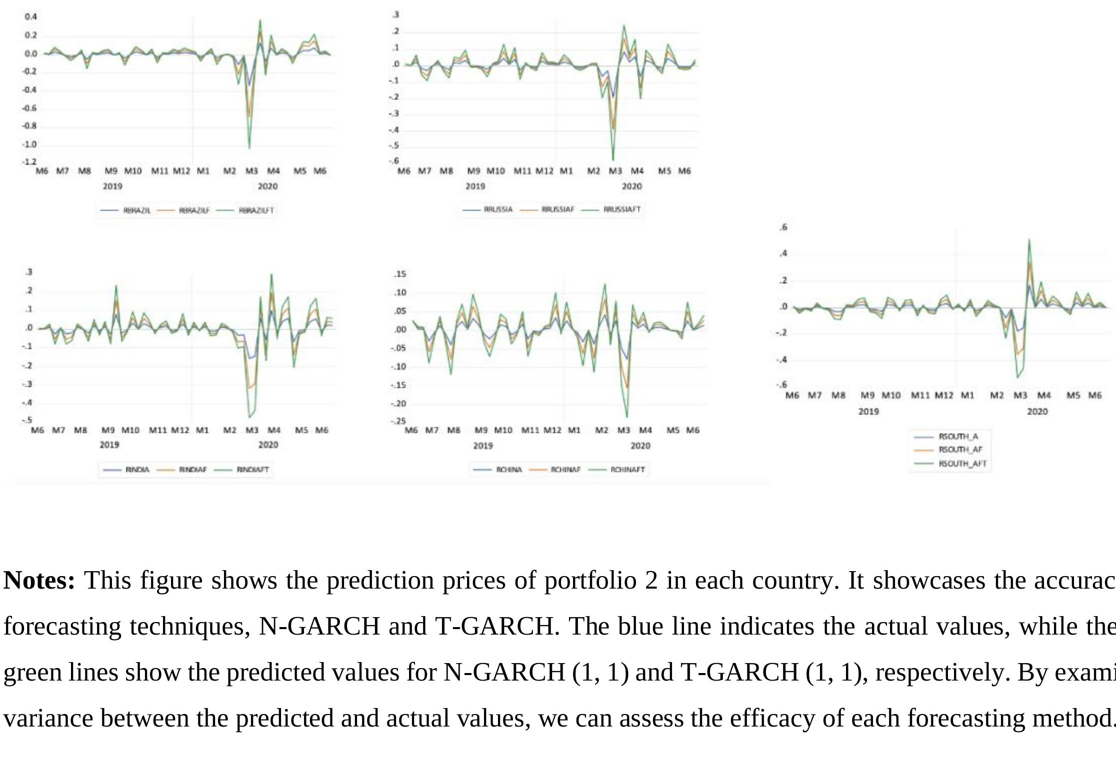
**Notes:** Portfolio 5 prices consist of 25% stock price, 25% exchange rate and 50% bond price in each country. The portfolio 4 prices on the left side clearly showed that they were not stationary and sometimes in a random walk pattern but fluctuating up and down. All portfolio 2 returns on the right side then show volatility clustering after adjusting. At every terming point, the portfolio one returns are more volatile, which means GARCH (1, 1) would be perfect to fit them. All the index prices in these five portfolios are collected weekly from 24 June 2010 to 25 June 2020 and calculated using Microsoft Excel. There are 522 observations for each country in each portfolio.

## Figure A5 The forecast and actual return of portfolio1 in BRICS countries



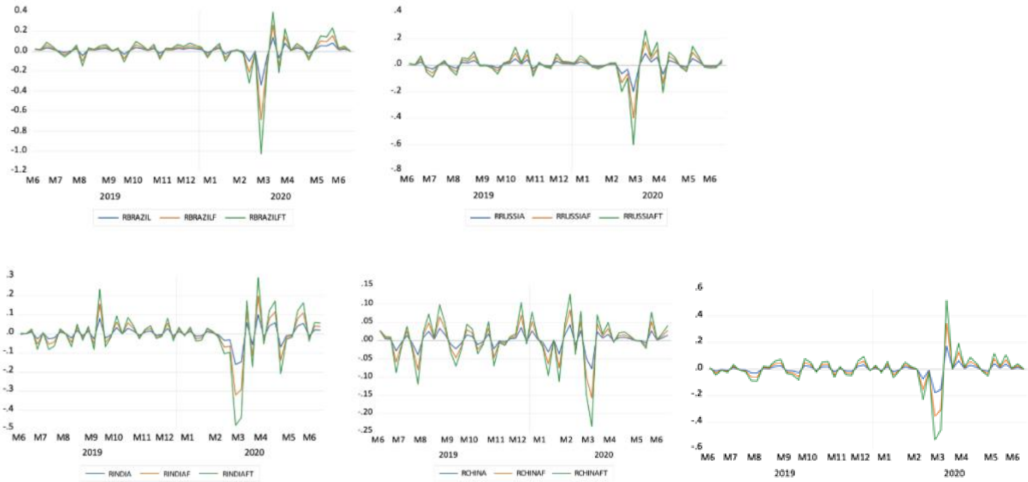
**Notes:** This figure shows the prediction prices of portfolio 1 in each country. It showcases the accuracy of two forecasting techniques, N-GARCH and T-GARCH. The blue line indicates the actual values, while the red and green lines show the predicted values for N-GARCH (1, 1) and T-GARCH (1, 1), respectively. By examining the variance between the predicted and actual values, we can assess the efficacy of each forecasting method.

## Figure A6 The forecast and actual return of portfolio2 in BRICS countries



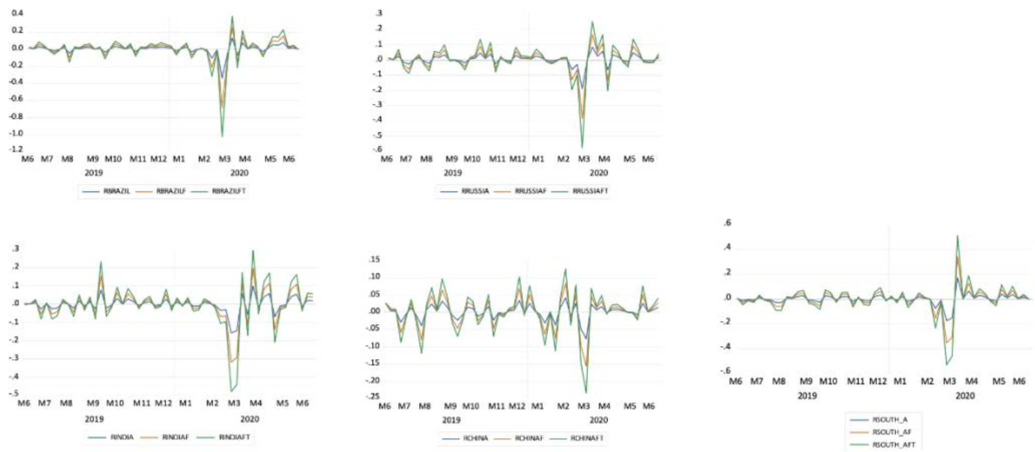
**Notes:** This figure shows the prediction prices of portfolio 2 in each country. It showcases the accuracy of two forecasting techniques, N-GARCH and T-GARCH. The blue line indicates the actual values, while the red and green lines show the predicted values for N-GARCH (1, 1) and T-GARCH (1, 1), respectively. By examining the variance between the predicted and actual values, we can assess the efficacy of each forecasting method.

## Figure A7 The forecast and actual return of portfolio3 in BRICS countries



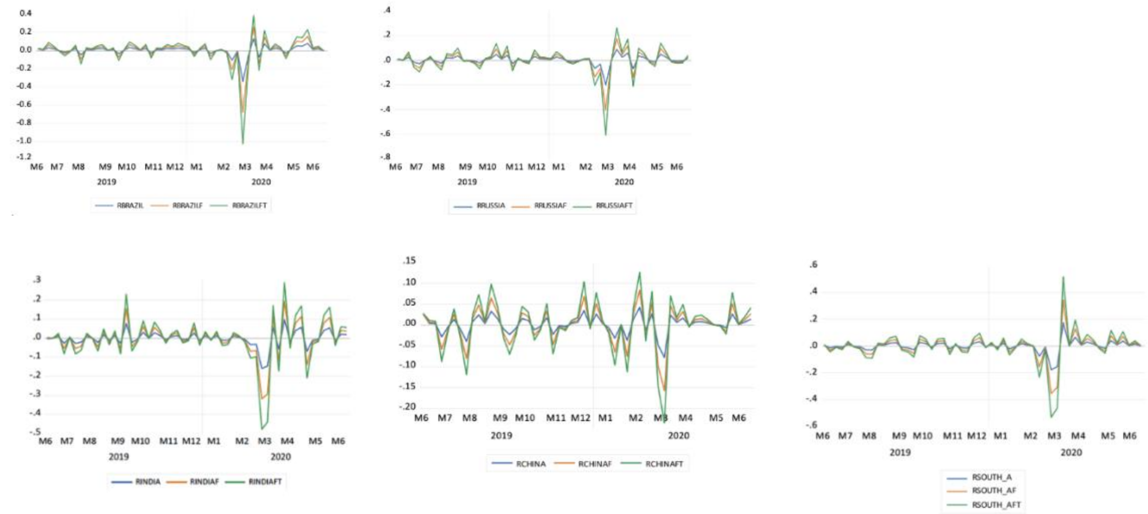
**Notes:** This figure shows the prediction prices of portfolio 3 in each country. It showcases the accuracy of two forecasting techniques, N-GARCH and T-GARCH. The blue line indicates the actual values, while the red and green lines show the predicted values for N-GARCH (1, 1) and T-GARCH (1, 1), respectively. By examining the variance between the predicted and actual values, we can assess the efficacy of each forecasting method.

## Figure A8 The forecast and actual return of portfolio4 in BRICS countries



**Notes:** This figure shows the prediction prices of portfolio 4 in each country. It showcases the accuracy of two forecasting techniques, N-GARCH and T-GARCH. The blue line indicates the actual values, while the red and green lines show the predicted values for N-GARCH (1, 1) and T-GARCH (1, 1), respectively. By examining the variance between the predicted and actual values, we can assess the efficacy of each forecasting method.

## Figure A9 The forecast and actual return of portfolio5 in BRICS countries




**Notes:** This figure shows the prediction prices of portfolio 5 in each country. It showcases the accuracy of two forecasting techniques, N-GARCH and T-GARCH. The blue line indicates the actual values, while the red and green lines show the predicted values for N-GARCH (1, 1) and T-GARCH (1, 1), respectively. By examining the variance between the predicted and actual values, we can assess the efficacy of each forecasting method.

# Appendix B

## Table B1 Statistical description of the stock returns in selected APEC countries [18]

| | Mean | Median | Maximum | Minimum | Std.Dev | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|
| **US** | | | | | | | |
| **AAPL** | 0.109313 | 0.020431 | 11.98073 | -12.86461 | 2.050258 | -0.011026 | 7.907809 |
| **BRKB** | 0.048168 | 0.027014 | 11.60993 | -9.592067 | 1.424657 | -0.016401 | 13.46527 |
| **XOM** | 0.038318 | 0.000000 | 12.68680 | -12.22479 | 2.081210 | 0.53171 | 8.339570 |
| **UNH** | 0.088740 | 0.057085 | 12.79893 | -17.27687 | 1.832064 | -0.083126 | 15.92121 |
| **P1** | 0.066413 | 0.058866 | 11.38881 | -13.57514 | 1.440016 | -0.425237 | 18.15954 |
| **P2** | 0.078614 | 0.072208 | 10.74153 | -13.05134 | 1.534367 | -0.248279 | 13.67595 |
| **AU** | | | | | | | |
| **WTC** | 0.175705 | 0.062408 | 33.92600 | -27.30978 | 3.600122 | 0.781904 | 18.90971 |
| **CBA** | 0.031962 | 0.000000 | 13.62189 | -10.00603 | 1.515117 | 0.252774 | 15.29827 |
| **WPL** | 0.068115 | 0.021381 | 12.02350 | -10.35274 | 1.646324 | 0.206055 | 10.94997 |
| **CSL** | 0.025306 | 0.000000 | 9.848088 | -18.34723 | 2.032842 | -0.672924 | 11.86647 |
| **P1** | 0.054885 | 0.050138 | 11.49897 | -10.16467 | 1.389270 | 0.028310 | 13.96322 |
| **P2** | 0.050507 | 0.039695 | 11.70220 | -10.28749 | 1.371242 | 0.036353 | 14.70937 |
| **CD** | | | | | | | |
| **SHOP** | 0.180393 | 0.152845 | 16.47115 | -17.10282 | 3.803248 | -0.040606 | 5.213087 |
| **RY** | 0.027619 | 0.055180 | 14.89632 | -10.53830 | 1.262619 | 0.611020 | 38.37445 |
| **BHC** | 0.020087 | 0.000000 | 19.36508 | -37.16338 | 3.559370 | -1.019634 | 18.10785 |
| **ENG** | 0.023772 | 0.075680 | 19.18037 | -16.50372 | 1.669461 | -0.367010 | 35.99943 |
| **P1** | 0.037583 | 0.028764 | 14.04433 | -11.62214 | 1.630551 | 0.003112 | 15.60245 |
| **P2** | 0.035960 | 0.021211 | 13.97377 | -11.28548 | 1.434537 | 0.260041 | 22.40554 |
| **JP** | | | | | | | |
| **SONY** | 0.069626 | 0.000000 | 9.980110 | -12.78988 | 1.920304 | 0.023020 | 5.739742 |
| **UFJ** | 0.010446 | 0.000000 | 11.19031 | -11.28437 | 1.533202 | 0.062940 | 8.259596 |
| **MITS** | 0.011364 | 0.000000 | 6.420198 | -8.028967 | 1.396558 | -0.017725 | 5.739742 |
| **HOYA** | 0.076867 | 0.000000 | 10.19523 | -7.770219 | 1.947626 | 0.183753 | 5.586412 |
| **P1** | 0.052590 | 0.000000 | 7.217425 | -8.297375 | 1.469671 | -0.008143 | 5.950601 |
| **P2** | 0.048014 | 0.000000 | 8.081750 | -6.377481 | 1.466051 | 0.108737 | 5.950601 |
| **SK** | | | | | | | |
| **CTN** | 0.055479 | 0.000000 | 23.78414 | -13.53745 | 2.992044 | 0.577193 | 9.498869 |
| **KBF** | 0.009560 | 0.000000 | 18.42610 | -10.37277 | 1.976275 | 0.712560 | 11.27421 |
| **SMS** | 0.015802 | 0.000000 | 10.47059 | -6.387665 | 1.593063 | 0.431230 | 5.501157 |
| **SKN** | 0.018897 | 0.000000 | 24.99965 | -19.18179 | 2.837946 | 1.611498 | 16.72734 |
| **P1** | 0.012472 | 0.000000 | 12.40874 | -11.98619 | 1.873683 | 0.289777 | 9.306906 |
| **P2** | 0.013228 | 0.000000 | 10.22491 | -6.321594 | 1.496762 | 0.405662 | 5.907962 |
| **CH** | | | | | | | |
| **ICBC** | -0.026605 | 0.000000 | 5.811623 | -7.258065 | 1.379754 | 0.018637 | 6.122007 |
| **TNT** | 0.017301 | 0.000000 | 23.15436 | -11.42612 | 2.452802 | 0.854109 | 11.28406 |
| **PTC** | -0.015321 | 0.000000 | 13.16872 | -9.634551 | 1.992289 | 0.364665 | 7.029726 |
| **WCB** | 0.168681 | 0.000000 | 19.78836 | -22.76675 | 3.614995 | -0.288907 | 7.099513 |
| **P1** | 0.024170 | 0.000000 | 21.72259 | -10.64629 | 2.379782 | 0.758042 | 10.38999 |
| **P2** | 0.017576 | 0.000000 | 22.79527 | -11.24731 | 2.426687 | 0.840858 | 11.14300 |

**Notes:** The table provides a comprehensive statistical analysis of the prescription for all the stock returns, highlighting the stability, stationarity, and mean-reverting nature of the variables. The data in the table is presented in an organised and easy-to-understand format, making it a valuable resource for anyone seeking insights into stock return dynamics.

[18] There are 1326 observations included. And it starts from 8/11/2017 to 8/12/2022.

**Table B2 Statistical description of the log news intensity changes in selected APEC countries**

| | Mean | Median | Maximum | Minimum | Std.Dev | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|
| **US** | | | | | | | |
| **AAPL** | 0.040648 | -7.155042 | 479.0612 | -387.1201 | 114.4248 | 0.059445 | 3.710248 |
| **BRK** | -0.073969 | 0.000000 | 395.1244 | -371.3572 | 99.18878 | 0.134832 | 3.991270 |
| **XOM** | 0.015134 | 0.000000 | 378.4190 | -313.5494 | 107.5726 | 0.246573 | 3.578957 |
| **UNH** | 0.021695 | 0.000000 | 427.6666 | -366.3562 | 102.7334 | 0.359634 | 4.770973 |
| **P1** | 0.029289 | -3.672921 | 346.5736 | -370.5409 | 107.4686 | 0.051024 | 3.338613 |
| **P2** | 0.037980 | -6.289940 | 454.9920 | -372.8521 | 111.4484 | 0.058803 | 3.624275 |
| **AU** | | | | | | | |
| **WTC** | 0.000000 | 0.00000 | 333.2205 | -283.3213 | 54.19867 | 0.551190 | 11.06809 |
| **CBA** | -0.242751 | 0.00000 | 472.7388 | -263.9057 | 101.7014 | 0.541280 | 4.218576 |
| **WPL** | 0.052274 | 0.00000 | 340.1197 | -283.3213 | 66.70296 | 0.446166 | 6.765955 |
| **CSL** | -76.47694 | 0.000000 | 352.6361 | -3380.278 | 322.6637 | -5.299018 | 37.79021 |
| **P1** | -0.129922 | 0.000000 | 314.4152 | -192.0377 | 66.99607 | 0.646563 | 0.639395 |
| **P2** | -0.171626 | 0.000000 | 375.5025 | -220.2710 | 78.61815 | 0.639395 | 4.892307 |
| **CD** | | | | | | | |
| **SHOP** | 0.069102 | 0.000000 | 358.3519 | -393.1829 | 93.34865 | -0.155221 | 3.984657 |
| **RY** | 0.030578 | 0.000000 | 352.6361 | -321.8876 | 77.88549 | 0.298388 | 6.165735 |
| **BHC** | -0.305564 | 0.000000 | 329.5837 | -366.3562 | 75.14103 | 0.292998 | 6.015632 |
| **ENG** | -0.030578 | 0.000000 | 336.7296 | -333.2205 | 82.33534 | 0.081859 | 4.837553 |
| **P1** | -0.174896 | 0.000000 | 232.7278 | -267.4149 | 70.48651 | -0.096009 | 3.585316 |
| **P2** | -0.043007 | 0.000000 | 263.3327 | -267.5527 | 72.77694 | -0.096149 | 3.921390 |
| **JP** | | | | | | | |
| **SONY** | -0.030578 | 0.000000 | 485.2030 | -435.6709 | 112.9517 | 0.227075 | 4.611282 |
| **UFJ** | -0.000021 | 0.000000 | 387.1201 | -313.5494 | 73.76224 | 0.736864 | 8.660613 |
| **MITS** | 0.113430 | 0.000000 | 387.1201 | -313.5494 | 73.76224 | 0.736864 | 8.660613 |
| **HOYA** | -24.93917 | 0.000000 | 340.1197 | -2900.000 | 206.2940 | -8.478460 | 87.28849 |
| **P1** | 0.046685 | 0.000000 | 358.3519 | -336.7296 | 78.67416 | 0.299400 | 5.335422 |
| **P2** | 0.058310 | 0.000000 | 344.5676 | -308.7856 | 75.67200 | 0.369744 | 5.519226 |
| **SK** | | | | | | | |
| **CTN** | -0.104547 | 0.000000 | 277.2589 | -277.2589 | 62.72834 | 0.218668 | 6.514203 |
| **KBF** | -0.052274 | 0.000000 | 256.4949 | -194.5910 | 48.22198 | 0.582056 | 7.498162 |
| **SMS** | -0.121375 | 0.000000 | 504.9856 | -444.2651 | 114.1402 | 0.447076 | 4.214595 |
| **SKN** | 0.000086 | 0.000000 | 336.7296 | -289.0372 | 63.10726 | 0.394866 | 9.844215 |
| **P1** | -0.092291 | 0.000000 | 344.6808 | -309.1042 | 81.44614 | 0.590907 | 5.273757 |
| **P2** | -0.119796 | -0.516797 | 491.9843 | -437.0966 | 112.1104 | 0.457175 | 4.279832 |
| **CH** | | | | | | | |
| **ICBC** | 0.052274 | 0.000000 | 313.5494 | -263.9057 | 67.07539 | 0.508562 | 5.922531 |
| **TNT** | -0.182532 | 0.000000 | 325.8097 | -304.4522 | 102.6538 | 0.221735 | 3.037467 |
| **PTC** | -0.000021 | 0.000000 | 336.7296 | -349.6508 | 84.90238 | 0.125617 | 3.970452 |
| **WCB** | 0.0000422 | 0.000000 | 230.2585 | -277.2589 | 48.49282 | 0.048640 | 11.10209 |
| **P1** | -0.135125 | 0.000000 | 241.7188 | -221.5574 | 63.04876 | 0.106845 | 3.534905 |
| **P2** | -0.161688 | -2.057140 | 264.0833 | -236.4426 | 78.30013 | 0.156276 | 3.298825 |
| **VIX** | 0.062127 | -0.685308 | 76.82450 | -26.62276 | 8.297115 | 1.558903 | 11.57118 |

**Notes:** The table provides a comprehensive statistical analysis of the prescription for all the changes of news intensity, highlighting the stability, stationarity, and mean-reverting nature of the variables. The data in the table is presented in an organised and easy-to-understand format, making it a valuable resource for anyone seeking insights into the changes of log news intensity dynamics.

## Table B3 Statistical description of positive news sentiment in selected APEC countries

| | Mean | Median | Maximum | Minimum | Std.Dev | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|
| **US** | | | | | | | |
| **AAPL** | 0.404743 | 0.379310 | 1.000000 | 0.000000 | 0.249647 | 0.328054 | 2.169253 |
| **BRK** | 0.520918 | 0.571429 | 1.000000 | 0.000000 | 0.453121 | -0.103565 | 1.189207 |
| **XOM** | 0.351418 | 0.250000 | 1.000000 | 0.000000 | 0.350241 | 0.618112 | 2.055167 |
| **UNH** | 0.387097 | 0.000000 | 1.000000 | 0.000000 | 0.445274 | 0.437841 | 1.363600 |
| **P1** | 0.416044 | 0.410311 | 0.977124 | 0.000000 | 0.210206 | 0.186886 | 2.450431 |
| **P2** | 0.417359 | 0.403097 | 0.941700 | 0.000000 | 0.197884 | 0.198591 | 2.489126 |
| **AU** | | | | | | | |
| **WTC** | 0.101287 | 0.000000 | 1.000000 | 0.000000 | 0.293920 | 2.631775 | 8.051024 |
| **CBA** | 0.202308 | 0.000000 | 1.000000 | 0.000000 | 0.362054 | 1.493289 | 3.531974 |
| **CSL** | 0.201456 | 0.000000 | 1.000000 | 0.000000 | 0.386730 | 1.476969 | 3.287072 |
| **WDS** | 0.204889 | 0.000000 | 1.000000 | 0.000000 | 0.382398 | 1.464329 | 3.295305 |
| **P1** | 0.177485 | 0.166667 | 1.000000 | 0.000000 | 0.183840 | 0.873086 | 3.254193 |
| **P2** | 0.198193 | 0.090000 | 1.000000 | 0.000000 | 0.238381 | 1.061028 | 3.222409 |
| **CD** | | | | | | | |
| **SHOP** | 0.358531 | 0.000000 | 1.000000 | 0.000000 | 0.428506 | 0.574079 | 1.562623 |
| **RY** | 0.217930 | 0.000000 | 1.000000 | 0.000000 | 0.379014 | 1.333540 | 3.005521 |
| **BHC** | 0.314153 | 0.000000 | 1.000000 | 0.000000 | 0.413890 | 0.754031 | 1.804501 |
| **ENG** | 0.259192 | 0.000000 | 1.000000 | 0.000000 | 0.410275 | 1.087109 | 2.345057 |
| **P1** | 0.287451 | 0.250000 | 1.000000 | 0.000000 | 0.253985 | 0.754312 | 2.887340 |
| **P2** | 0.267108 | 0.250000 | 1.000000 | 0.000000 | 0.270709 | 0.873614 | 2.868411 |
| **JP** | | | | | | | |
| **SONY** | 0.341848 | 0.000000 | 1.000000 | 0.000000 | 0.441314 | 0.652846 | 1.567003 |
| **UFJ** | 0.288795 | 0.000000 | 1.000000 | 0.000000 | 0.395915 | 1.272731 | 2.770806 |
| **MITS** | 0.132413 | 0.000000 | 1.000000 | 0.000000 | 0.325358 | 2.157686 | 5.822544 |
| **HOYA** | 0.077146 | 0.000000 | 1.000000 | 0.000000 | 0.264021 | 3.163406 | 11.06534 |
| **P1** | 0.195050 | 0.208333 | 1.000000 | 0.000000 | 0.202910 | 0.873014 | 3.166467 |
| **P2** | 0.177181 | 0.070000 | 1.000000 | 0.000000 | 0.223724 | 1.133290 | 3.215437 |
| **SK** | | | | | | | |
| **CTN** | 0.145074 | 0.000000 | 1.000000 | 0.000000 | 0.343953 | 2.008412 | 5.123202 |
| **KBF** | 0.102812 | 0.000000 | 1.000000 | 0.000000 | 0.297881 | 2.604703 | 7.874204 |
| **SMS** | 0.394281 | 0.333333 | 1.000000 | 0.000000 | 0.347727 | 0.406966 | 1.868902 |
| **SKN** | 0.081208 | 0.000000 | 1.000000 | 0.000000 | 0.258900 | 3.056402 | 10.67526 |
| **P1** | 0.180844 | 0.156452 | 0.937500 | 0.000000 | 0.161526 | 0.915617 | 3.629207 |
| **P2** | 0.374085 | 0.320000 | 0.990000 | 0.000000 | 0.324387 | 0.398741 | 1.860299 |
| **CH** | | | | | | | |
| **ICBC** | 0.155337 | 0.000000 | 1.000000 | 0.000000 | 0.351649 | 1.883864 | 4.646297 |
| **TNT** | 0.429588 | 0.333333 | 1.000000 | 0.000000 | 0.422500 | 0.276631 | 1.375973 |
| **PTC** | 0.307081 | 0.000000 | 1.000000 | 0.000000 | 0.191725 | 0.622014 | 3.137501 |
| **WCB** | 0.092238 | 0.000000 | 1.000000 | 0.000000 | 0.284549 | 2.806549 | 8.956216 |
| **P1** | 0.246061 | 0.250000 | 1.000000 | 0.000000 | 0.191725 | 0.622014 | 3.137501 |
| **P2** | 0.322736 | 0.291587 | 1.010000 | 0.000000 | 0.252656 | 0.304110 | 2.050346 |

**Notes:** The table provides a comprehensive statistical analysis of the prescription for all the positive news sentiment, highlighting the stability, stationarity, and mean-reverting nature of the variables. The data in the table is presented in an organised and easy-to-understand format, making it a valuable resource for anyone seeking insights into positive news dynamics.

### Table B4 Statistical description of negative news sentiment in selected APEC countries

| | Mean | Median | Maximum | Minimum | Std.Dev | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|
| **US** | | | | | | | |
| **AAPL** | 0.595257 | 0.620690 | 1.000000 | 0.000000 | 0.249647 | -0.328054 | 2.169253 |
| **BRK** | 0.190461 | 0.000000 | 1.000000 | 0.000000 | 0.331466 | 1.544750 | 3.905234 |
| **XOM** | 0.570210 | 0.666667 | 1.000000 | 0.000000 | 0.373937 | -0.344206 | 1.676468 |
| **UNH** | 0.243649 | 0.000000 | 1.000000 | 0.000000 | 0.381130 | 1.195194 | 2.735064 |
| **P1** | 0.399894 | 0.388690 | 0.943376 | 0.000000 | 0.180674 | 0.278390 | 2.616950 |
| **P2** | 0.399894 | 0.388690 | 0.943376 | 0.000000 | 0.180674 | 0.278390 | 2.616950 |
| **AU** | | | | | | | |
| **WTC** | 0.055471 | 0.000000 | 1.000000 | 0.000000 | 0.218470 | 3.890778 | 16.53602 |
| **CBA** | 0.396790 | 0.000000 | 1.000000 | 0.000000 | 0.457315 | 0.399309 | 1.284166 |
| **CSL** | 0.129352 | 0.000000 | 1.000000 | 0.000000 | 0.318253 | 2.214100 | 6.128564 |
| **WDS** | 0.187747 | 0.000000 | 1.000000 | 0.000000 | 0.368540 | 1.580389 | 3.666660 |
| **P1** | 0.192781 | 0.250000 | 1.000000 | 0.000000 | 0.182470 | 0.782895 | 3.331720 |
| **P2** | 0.268380 | 0.190000 | 1.000000 | 0.000000 | 0.267644 | 0.523456 | 2.127822 |
| **CD** | | | | | | | |
| **SHOP** | 0.210421 | 0.000000 | 1.000000 | 0.000000 | 0.346016 | 1.354175 | 3.296973 |
| **RY** | 0.210857 | 0.000000 | 1.000000 | 0.000000 | 0.373642 | 1.415725 | 3.252839 |
| **BHC** | 0.195267 | 0.000000 | 1.000000 | 0.000000 | 0.336063 | 1.510854 | 3.781407 |
| **ENG** | 0.214809 | 0.000000 | 1.000000 | 0.000000 | 0.380739 | 1.380586 | 3.122445 |
| **P1** | 0.207839 | 0.153846 | 1.000000 | 0.000000 | 0.223581 | 1.126685 | 3.819908 |
| **P2** | 0.205507 | 0.900000 | 1.000000 | 0.000000 | 0.249249 | 1.169007 | 3.500289 |
| **JP** | | | | | | | |
| **SONY** | 0.213540 | 0.000000 | 1.000000 | 0.000000 | 0.371036 | 1.387937 | 3.191816 |
| **UFJ** | 0.151010 | 0.000000 | 1.000000 | 0.000000 | 0.329349 | 1.945556 | 5.089953 |
| **MITS** | 0.116269 | 0.000000 | 1.000000 | 0.000000 | 0.306136 | 2.392620 | 6.937798 |
| **HOYA** | 0.023833 | 0.000000 | 1.000000 | 0.000000 | 0.147451 | 6.263992 | 40.81432 |
| **P1** | 0.126163 | 0.000000 | 0.750000 | 0.000000 | 0.156707 | 1.105458 | 3.746080 |
| **P2** | 0.116527 | 0.000000 | 0.930000 | 0.000000 | 0.178177 | 1.572066 | 4.597162 |
| **SK** | | | | | | | |
| **CTN** | 0.056885 | 0.000000 | 1.000000 | 0.000000 | 0.218797 | 3.826796 | 16.15941 |
| **KBF** | 0.065990 | 0.000000 | 1.000000 | 0.000000 | 0.241045 | 3.508975 | 13.52272 |
| **SMS** | 0.552215 | 0.600000 | 1.000000 | 0.000000 | 0.359682 | -0.244375 | 1.707345 |
| **SKN** | 0.096637 | 0.000000 | 1.000000 | 0.000000 | 0.282353 | 2.717821 | 8.625600 |
| **P1** | 0.192932 | 0.187500 | 0.750000 | 0.000000 | 0.139645 | 0.675502 | 3.325497 |
| **P2** | 0.518395 | 0.558000 | 0.990000 | 0.000000 | 0.334857 | -0.243431 | 1.712953 |
| **CH** | | | | | | | |
| **ICBC** | 0.156645 | 0.000000 | 1.000000 | 0.000000 | 0.352927 | 1.903031 | 4.721454 |
| **TNT** | 0.348860 | 0.125000 | 1.000000 | 0.000000 | 0.400759 | 0.591370 | 1.696987 |
| **PTC** | 0.214396 | 0.000000 | 1.000000 | 0.000000 | 0.382730 | 1.389060 | 3.122114 |
| **WCB** | 0.032102 | 0.000000 | 1.000000 | 0.000000 | 0.168138 | 5.340369 | 30.14779 |
| **P1** | 0.188001 | 0.175000 | 1.000000 | 0.000000 | 0.178777 | 0.856629 | 3.373833 |
| **P2** | 0.261853 | 0.246667 | 1.010000 | 0.000000 | 0.246588 | 0.608745 | 2.375132 |

**Notes:** The table provides a comprehensive statistical analysis of the prescription for all the negative news, highlighting the stability, stationarity, and mean-reverting nature of the variables. The data in the table is presented in an organised and easy-to-understand format, making it a valuable resource for anyone seeking insights into the changes in negative news dynamics.

# Table B5 The GARCH estimation results in Australia

| | ℧ (p-VALUE) | $\alpha$ (p-value) | $\beta$ (p-value) | γ(p-value) | News intensity |
|---|---|---|---|---|---|
| **GARCH (1, 1)** | | | | | |
| **WTC** | 7.590339 (0.0001) | 0.249407 (0.0000) | 0.183498 (0.0000) | | |
| **CBA** | 0.150455 (0.0000) | 0.144646 (0.0000) | 0.776672 (0.0000) | | |
| **CSL** | 0.223919 (0.0000) | 0.125789 (0.0000) | 0.780389 (0.0000) | | |
| **WDS** | 0.101150 (0.0000) | 0.100087 (0.0000) | 0.878431 (0.0000) | | |
| **P1** | 0.083992 (0.0000) | 0.099348 (0.0000) | 0.846766 (0.0000) | | |
| **P2** | 0.090673 (0.0000) | 0.107602 (0.0000) | 0.831408 (0.0000) | | |
| **EGARCH (1, 1)** | | | | | |
| **WTC** | 1.101871 (0.0000) | 0.373735 (0.0000) | 0.029687 (0.1797) | 0.455373(0.0000) | |
| **CBA** | -0.151187 (0.0000) | 0.237198 (0.0000) | 0.947674 (0.0000) | -0.055823(0.0000) | |
| **CSL** | -0.105396 (0.0000) | 0.203922 (0.0000) | 0.938124 (0.0000) | -0.097408(0.0000) | |
| **WDS** | -0.107149 (0.0000) | 0.190128 (0.0000) | 0.971672 (0.0000) | -0.056208(0.0000) | |
| **P1** | -0.105069 (0.0000) | 0.160754 (0.0000) | 0.958599 (0.0000) | -0.093987(0.0000) | |
| **P2** | -0.116177 (0.0000) | 0.173887 (0.0000) | 0.955621 (0.0000) | -0.089754 (0.0000) | |
| **GARCH (1, 1) WITH LOG NEWS INTENSITY** | | | | | |
| | **℧ (p-VALUE)** | **$\alpha$ (p-value)** | **$\beta$ (p-value)** | **γ(p-value)** | **News intensity** |
| ***WTC*** | 3.926046 (0.0000) | 0.178052 (0.0000) | 0.226514 (0.0000) | - | 17.82995 (0.0000) |
| ***CBA*** | 0.123062 (0.0007) | 0.178055 (0.0000) | 0.692040 (0.0000) | - | 0.152508 (0.0000) |
| ***CSL*** | 0.411827 (0.0000) | 0.203751 (0.0000) | 0.491629 (0.0000) | - | 0.921297 (0.0000) |
| ***WDS*** | 0.045448 (0.0784) | 0.110637 (0.0000) | 0.828021 (0.0000) | - | 0.476402 (0.0000) |
| ***P1*** | 0.038520 (0.0341) | 0.095717 (0.0000) | 0.848675 (0.0000) | - | 0.076242 (0.0002) |
| ***P2*** | 0.062732 (0.0030) | 0.106987 (0.0000) | 0.829454 (0.0000) | - | 0.043185 (0.0139) |
| **EGARCH (1, 1) WITH LOG NEWS INTENSITY** | | | | | |
| ***WTC*** | 0.767412 (0.0000) | 0.359659 (0.0000) | 0.448324 (0.0000) | -0.040446 (0.1611) | 0.978965 (0.0000) |
| ***CBA*** | -0.194006 (0.0000) | 0.265869(0.0000) | 0.933817 (0.0000) | -0.051986(0.0000) | 0.034507 (0.0000) |
| ***CSL*** | -0.223148 (0.0000) | 0.398880(0.0000) | 0.715323 (0.0000) | -0.127169(0.0000) | 0.375672 (0.0000) |
| ***WDS*** | -0.153013 (0.0000) | 0.225623 (0.0000) | 0.919885 (0.0000) | -0.058529(0.0000) | 0.171794 (0.0000) |
| ***P1*** | -0.136534(0.0000) | 0.149793 (0.0000) | 0.954079 (0.0000) | -0.101956 (0.0000) | 0.065263 (0.0000) |
| ***P2*** | -0.137580 (0.0000) | 0.167127 (0.0000) | 0.954110 (0.0000) | -0.095993 (0.0000) | 0.036672 (0.0025) |
| **GARCH (1, 1) WITH NEWS INTENSITY CHANGES** | | | | | |
| ***WTC*** | 0.253410 (0.0000) | 0.025245 (0.0000) | 0.947472 (0.0000) | - | 0.147444 (0.0000) |
| ***CBA*** | 0.162615 (0.0000) | 0.156117 (0.0000) | 0.750812 (0.0000) | - | 0.002321 (0.0000) |
| ***CSL*** | 0.162615 (0.0000) | 0.156117(0.0000) | 0.750812 (0.0000) | - | 0.002321 (0.0000) |
| ***WDS*** | 0.095993 (0.0000) | 0.097737 (0.0000) | 0.880385 (0.0000) | - | 0.000075 (0.4779) |
| ***P1*** | 0.068587 (0.0000) | 0.087774 (0.0000) | 0.866467 (0.0000) | - | 0.004266 (0.0000) |
| ***P2*** | 0.080013 (0.0000) | 0.102347 (0.0000) | 0.842699 (0.0000) | - | 0.003112 (0.0000) |
| **EGARCH (1, 1) WITH NEWS INTENSITY CHANGES** | | | | | |
| ***WTC*** | -0.042282 (0.0080) | 0.135807 (0.0000) | 0.973120 (0.0000) | -0.031217 (0.0032) | 0.009964(0.0000) |
| ***CBA*** | -0.136069 (0.0000) | 0.199201 (0.0000) | 0.966210 (0.0000) | -0.042899 (0.0000) | 0.003478 (0.0000) |
| ***CSL*** | -0.136069 (0.0000) | 0.199201 (0.0000) | 0.966210 (0.0000) | -0.042899 (0.0000) | 0.003478 (0.0000) |
| ***WDS*** | -0.106752 (0.0000) | 0.188285 (0.0000) | 0.971701 (0.0000) | -0.055808 (0.0000) | 0.000012 (0.7333) |
| ***P1*** | -0.088253 (0.0000) | 0.133898 (0.0000) | 0.963946(0.0000) | -0.100807 (0.0000) | 0.004446 (0.0000) |
| ***P2*** | -0.100799 (0.0000) | 0.149356 (0.0000) | 0.962118 (0.0000) | -0.092118 (0.0000) | 0.003496 (0.0000) |

**Notes:** This table shows the GARCH estimation results in Australia. The estimation results for the GARCH model after adding the VIX index as an extra variable are included in the tables. 5% significance level means that the probability of the observed result being due to chance is less than 5%.

WTC is short for "Wisetech Global Ltd", which was selected from the technology industry. CBA is the "Common Wealth Bank of Australia", representing the financial industry. WDS is" Woodside Energy Group Ltd", from the energy sector, and CSL is" CSL Limited", from the health and care industry. P1 is the equal-weighted portfolio and P2 is the market cap-weighted portfolio.

# Table B5 The GARCH estimation results in Australia (Continued)

| | ℧ (p-VALUE) | *α* (p-value) | *β* (p-value) | γ(p-value) | Positive news | Positive news at t-1 |
|---|---|---|---|---|---|---|
| **GARCH (1, 1) WITH POSITIVE NEWS** | | | | | | |
| ***WTC*** | 4.981633 (0.0000) | 0.239891 (0.0000) | 0.159619(0.0000) | - | 34.81189 (0.0000) | |
| | 6.987868 (0.0000) | 0.251507 (0.0000) | 0.196629 (0.0000) | | - | 4.700875 (0.0000) |
| ***CBA*** | 0.116710 (0.0000) | 0.144601 (0.0000) | 0.769811(0.0000) | - | 0.226703(0.0000) | |
| | 0.170631 (0.0000) | 0.149108 (0.0000) | 0.768414(0.0000) | | | -0.064479(0.2141) |
| ***CSL*** | 0.327774 (0.0000) | 0.188980 (0.0000) | 0.608071 (0.0000) | - | 0.819946 (0.0000) | |
| | 0.273515(0.0000) | 0.153346(0.0000) | 0.715750(0.0000) | | | 0.207951(0.0003) |
| ***WDS*** | 0.089998(0.0000) | 0.107631 (0.0000) | 0.861899(0.0000) | - | 0.238317(0.0039) | |
| | 0.097695(0.0000) | 0.100717(0.0000) | 0.876202 (0.0000) | | | 0.048318 (0.4635) |
| ***P1*** | 0.074870 (0.0000) | 0.101581 (0.0000) | 0.842947 (0.0000) | - | 0.067326(0.3048) | |
| | 0.089758 (0.0000) | 0.099016 (0.0000) | 0.847610 (0.0000) | | | -0.0.037328(0.527) |
| ***P2*** | 0.075167 (0.0000) | 0.113635(0.0000) | 0.820551 (0.0000) | - | 0.118269(0.0351) | |
| | 0.088803 (0.0000) | 0.108056(0.0000) | 0.830352(0.0000) | | | 0.013992 (0.7666) |
| **EGARCH (1, 1) WITH POSITIVE NEWS** | | | | | | |
| ***WTC*** | 1.162587 (0.0000) | 0.389359 (0.0000) | 0.322189(0.0000) | -0.007913 (0.7834) | 1.549526(0.0000) | |
| | 1.124343 (0.0000) | 0.373633 (0.0000) | 0.438908(0.0000) | 0.030212 (0.1715) | | 0.170433 (0.0000) |
| ***CBA*** | -0.165064(0.0000) | 0.235750 (0.0000) | 0.947383 (0.0000) | -0.064902 (0.0000) | 0.073288(0.0105) | |
| | -0.149982(0.0000) | 0.239213(0.0000) | 0.947062(0.0000) | -0.053945(0.0000) | | -0.011931(0.6467) |
| ***CSL*** | -0.170722(0.0000) | 0.279823 (0.0000) | 0.882472 (0.0000) | -0.121721 (0.0000) | 0.238272(0.0000) | |
| | -0.0112130(0.0000) | 0.206284 (0.0000) | 0.934714(0.0000) | -0.099994(0.0000) | | 0.036585(0.0000) |
| ***WDS*** | -0.113971(0.0000) | 0.193799 (0.0000) | 0.961981 (0.0000) | -0.071828 (0.0000) | 0.072741(0.0043) | |
| | -0.107655(0.0000) | 0.189506(0.0000) | 0.970622(0.0000) | -0.058262(0.1039) | | 0.010511(0.6571) |
| ***P1*** | -0.099545 (0.0000) | 0.159732 (0.0000) | 0.959309 (0.0000) | -0.093692(0.0000) | -0.026440(0.5651) | |
| | -0.091081(0.0000) | 0.161712(0.0000) | 0.959425(0.0000) | -0.0959425 (0.0000) | | -0.082526(0.0577) |
| ***P2*** | -0.117652 (0.0000) | 0.174156 (0.0000) | 0.955385(0.0000) | -0.090087 (0.0000) | 0.006728(0.8686) | |
| | -0.107872(0.0000) | 0.17991(0.0000) | 0.956332(0.0000) | -0.088840(0.0000) | | -0.042951(0.2590) |
| **GARCH (1, 1) WITH NEGATIVE NEWS** | | | | | | |
| **WTC** | 5.450830 (0.0000) | 0.182729 (0.0000) | 0.071182 (0.0000) | - | 186.7294 (0.0000) | |
| | 8.421864 (0.0000) | 0.234367(0.0000) | 0.088996(0.0000) | | | 9.6994033(0.0034) |
| **CBA** | 0.148194 (0.0000) | 0.145273 (0.0000) | 0.775311 (0.0000) | - | 0.009098(0.0000) | |
| | 0.153589 (0.0000) | 0.143239(0.0000) | 0.779811(0.0000) | | | -0.015838 (0.5926) |
| **CSL** | 0.372827 (0.0000) | 0.172805 (0.0000) | 0.639483 (0.0000) | - | 0.596957 (0.0000) | |
| | 0.222345(0.0000) | 0.125490(0.0000) | 0.780158(0.0000) | | | 0.020870(0.7015) |
| **WDS** | 0.017323 (0.2835) | 0.087968(0.0000) | 0.876458 (0.0000) | - | 0.716994(0.0000) | |
| | 0.029814 (0.0858) | 0.084001(0.0000) | 0.888000(0.0000) | | | 0.501569(0.0000) |
| **P1** | 0.046541 (0.0154) | 0.097045(0.0000) | 0.839652(0.0000) | - | 0.266887 (0.0003) | |
| | 0.073790 (0.0006) | 0.096326(0.0000) | 0.850738(0.0000) | | | 0.044566(0.4432) |
| **P2** | 0.083075 (0.0002) | 0.106403 (0.0000) | 0.832745 (0.0000) | - | 0.027067(0.4408) | |
| | 0.106549 (0.0000) | 0.112791(0.0000) | 0.822828(0.0000) | | | -0.039428(0.2049) |
| **EGARCH (1, 1) WITH NEGATIVE NEWS** | | | | | | |
| **WTC** | 1.069352 (0.0000) | 0.331344 (0.0000) | 0.010375 (0.7012) | 0.388859 (0.0000) | 2.484636 (0.0000) | |
| | 1.024884 (0.0000) | 0.285086 (0.0000) | 0.022169(0.0000) | 0.498390(0.0000) | | 0.490213(0.0004) |
| **CBA** | -0.133253 (0.0000) | 0.226372 (0.0000) | 0.951760 (0.0003) | -0.062161(0.0000) | -0.029508(0.1663) | |
| | -0.123797(0.0000) | 0.220651(0.0000) | 0.953792(0.0000) | -0.065604(0.0000) | | -0.0045294 (0.0178) |
| **CSL** | -0.110620 (0.0000) | 0.209931 (0.0000) | 0.932401 (0.0000) | -0.098268 (0.0000) | 0.037854 (0.0000) | |
| | -0.104722 (0.000) | 0.203940(0.0000) | 0.938919(0.0000) | -0.097549(0.0000) | | -0.010070(0.6346) |
| **WDS** | -0.121555 (0.0000) | 0.178044 (0.0000) | 0.958320 (0.0000) | -0.026653(0.0274) | 0.197514(0.0000) | |
| | -0.108402 (0.0000) | 0.174633 (0.0000) | 0.966902 (0.0000) | -0.041852(0.0000) | | 0.095158 (0.0072) |
| **P1** | -0.135032(0.0000) | 0.153441 (0.0000) | 0.947854(0.0000) | -0.0947854(0.0000) | 0.200298(0.0000) | |
| | -0.114202(0.0000) | 0.151632(0.0000) | 0.955664(0.0000) | -0.094903 (0.0000) | | 0.088904 (0.0267) |
| **P2** | -0.124035 (0.0000) | 0.169681(0.0000) | 0.954880(0.0000) | -0.090754 (0.0000) | 0.041631 (0.1043) | |
| | -0.116478(0.0000) | 0.173520 (0.0000) | 0.955638(0.0000) | -0.089793 (0.0000) | | 0.002139 (0.9341) |

**Notes:** This table shows the GARCH estimation results in Australia. The estimation results for the GARCH model after adding the VIX index as an extra variable are included in the tables. 5% significance level means that the probability of the observed result being due to chance is less than 5.

WTC is short for "Wisetech Global Ltd", which was selected from the technology industry. CBA is the "Common Wealth Bank of Australia", representing the financial industry. WDS is" Woodside Energy Group Ltd", from the energy sector, and CSL is" CSL Limited", from the health and care industry. P1 is the equal-weighted portfolio and P2 is the market cap-weighted portfolio.

## Table B5 The GARCH estimation results in Australia (Continued)

| | ʊ (p-VALUE) | $\alpha$ (p-value) | $\beta$ (p-value) | γ(p-value) | News intensity | VIX |
|---|---|---|---|---|---|---|
| **GARCH (1, 1) WITH LOG NEWS INTENSITY AND VIX** | | | | | | |
| ***WTC*** | 4.061125 (0.0000) | 0.180029 (0.0000) | 0.208239 (0.0000) | - | 18.20061 (0.0000) | -0.029181(0.1913) |
| ***CBA*** | 0.073353 (0.0030) | 0.150468 (0.0000) | 0.764168 (0.0000) | - | 0.112877 (0.0000) | 0.014652(0.0001) |
| ***CSL*** | 0.313240 (0.0000) | 0.170518 (0.0000) | 0.584128 (0.0000) | - | 0.765339 (0.0000) | 0.036023 (0.0000) |
| ***WDS*** | 0.059729 (0.0025) | 0.076198 (0.0000) | 0.874832 (0.0000) | - | 0.264756 (0.0000) | 0.038418 (0.0000) |
| ***P1*** | 0.070553 (0.0000) | 0.110012 (0.0000) | 0.838887 (0.0000) | - | 0.012591 (0.0444) | 0.028633(0.0000) |
| ***P2*** | 0.027962 (0.0038) | 0.057026 (0.0000) | 0.914413 (0.0000) | - | 0.005930 (0.0174) | 0.026444 (0.0000) |
| **EGARCH (1, 1) WITH LOG NEWS INTENSITY AND VIX** | | | | | | |
| ***WTC*** | 0.817635 (0.0000) | 0.363851 (0.0000) | 0.422955 (0.0000) | -0.037862 (0.2005) | 0.989199 (0.0000) | -0.004263(0.2420) |
| ***CBA*** | -0.017893(0.0002) | 0.025117 (0.0004) | 0.994260 (0.0000) | 0.007999 (0.2238) | 0.002206 (0.4698) | 0.018729 (0.0000) |
| ***CSL*** | -0.232605(0.0000) | 0.366271 (0.0000) | 0.786792 (0.0000) | -0.117016 (0.0000) | 0.307555 (0.0000) | 0.017028 (0.0000) |
| ***WDS*** | -0.016953(0.0000) | 0.019840 (0.0005) | 0.996353 (0.0000) | -0.009987 (0.0954) | 0.013391 (0.0193) | 0.017338 (0.0000) |
| ***P1*** | -0.057918(0.0000) | 0.065246 (0.0000) | 0.989605 (0.0000) | -0.017082 (0.1510) | 0.007899 (0.0000) | 0.019900 (0.0000) |
| ***P2*** | -0.054783(0.0000) | 0.067050 (0.0000) | 0.991462 (0.0000) | -0.009831 (0.3256) | 0.002911 (0.0567) | 0.019682 (0.0000) |
| **GARCH (1, 1) WITH LOG NEWS INTENSITY CHANGES AND VIX** | | | | | | |
| ***WTC*** | 1.762248 (0.0000) | 0.077047 (0.0000) | 0.705288 (0.0000) | - | 0.066276 (0.0000) | 0.090112 (0.0000) |
| ***CBA*** | 0.085864 (0.0000) | 0.087673 (0.0000) | 0.859018(0.0000) | - | 0.002418 (0.0000) | 0.020182 (0.0000) |
| ***CSL*** | 1.273675 (0.0000) | 0.128271 (0.0000) | 0.416998 (0.0000) | - | 0.009684 (0.0000) | 0.036945 (0.0000) |
| ***WDS*** | 2.980107 (0.0000) | 0.122259 (0.0019) | 0.488935 (0.0000) | - | 0.001942 (0.0000) | 0.050891(0.0000) |
| ***P1*** | 0.091345 (0.0000) | 0.114338 (0.0000) | 0.825115 (0.0000) | - | 0.003742 (0.0000) | 0.021571(0.0000) |
| ***P2*** | 0.023007 (0.0000) | 0.187417 (0.0000) | 0.616808 (0.0000) | - | 0.002837 (0.0000) | 0.024835 (0.0000) |
| **EGARCH (1, 1) WITH LOG NEWS INTENSITY CHANGES AND VIX** | | | | | | |
| ***WTC*** | -0.016481(0.1257) | 0.056006 (0.0000) | 0.987825 (0.0000) | 0.000882 (0.9321) | 0.010747 (0.0000) | 0.014756 (0.0000) |
| ***CBA*** | -0.024633(0.0009) | 0.035476 (0.0004) | 0.993457 (0.0000) | 0.000748 (0.9146) | 0.003893 (0.0000) | 0.019736 (0.0000) |
| ***CSL*** | -0.059268(0.0000) | 0.086405 (0.0000) | 0.986445 (0.0000) | -0.017165 (0.1997) | 0.006350 (0.0000) | 0.018061 (0.0000) |
| ***WDS*** | -0.020723(0.0000) | 0.028067 (0.0000) | 0.998266(0.0000) | -0.006833 (0.2655) | 0.000015 (0.5374) | 0.018382 (0.0000) |
| ***P1*** | 0.003058 (0.5749) | -0.003058 (0.6002) | 0.997852 (0.0000) | 0.018390 (0.0007) | 0.005488 (0.0000) | 0.019675 (0.0000) |
| ***P2*** | 0.014427 (0.0000) | -0.018555 (0.0000) | 0.998160 (0.0000) | 0.018660 (0.0002) | 0.004443 (0.0000) | 0.020219 (0.0000) |

**Notes:** This table shows the GARCH estimation results in Australia. The estimation results for the GARCH model after adding the VIX index as an extra variable are included in the tables. 5% significance level means that the probability of the observed result being due to chance is less than 5%. In other words, if the p-value is less than 0.05, there is strong evidence against the null hypothesis, and the result is considered statistically significant. Similarly, a p-value between 0.05 and 0.1 means that there is a 10% chance that the observed effect is due to an event. This result is still considered significant but with a lower level of confidence. On the other hand, if the p-value is greater than 0.1, there is a high chance that the observed result is due to an event, and the result is considered non-significant.

WTC is short for “Wisetech Global Ltd”, which was selected from the technology industry. CBA is the “Common Wealth Bank of Australia”, representing the financial industry. WDS is” Woodside Energy Group Ltd”, from the energy sector, and CSL is” CSL Limited”, from the health and care industry. P1 is the equal-weighted portfolio and P2 is the market cap-weighted portfolio.

## Table B5 The GARCH estimation results in Australia (Continued)

| | Ʊ (p-VALUE) | $\alpha$ (p-value) | $\beta$ (p-value) | γ(p-value) | Positive news | VIX |
|---|---|---|---|---|---|---|
| **GARCH (1, 1) WITH POSITIVE NEWS AND VIX ESTIMATION** | | | | | | |
| ***WTC*** | 5.077107 (0.0000) | 0.239469 (0.0000) | 0.150164 (0.0000) | - | 35.22671 (0.0000) | -0.012318 (0.6186) |
| ***CBA*** | 0.072599(0.0000) | 0.121545 (0.0000) | 0.817930 (0.0000) | - | 0.211032 (0.0000) | 0.013805 (0.0000) |
| ***CSL*** | 0.135775(0.0000) | 0.130216 (0.0000) | 0.773283 (0.0000) | - | 0.474970 (0.0000) | 0.033377 (0.0000) |
| ***WDS*** | 0.082051 (0.0000) | 0.063497 (0.0000) | 0.904766 (0.0000) | - | 0.149270 (0.0051) | 0.045063 (0.0000) |
| ***P1*** | 0.081200 (0.0000) | 0.100613 (0.0000) | 0.843213 (0.0000) | - | 0.012752 (0.8001) | 0.030222 (0.0000) |
| ***P2*** | 0.044403 (0.0000) | 0.062953 (0.0000) | 0.898702 (0.0000) | - | 0.040697 (0.2223) | 0.021589 (0.0000) |
| **EGARCH (1, 1) WITH POSITIVE NEWS AND VIX ESTIMATION** | | | | | | |
| ***WTC*** | 1.394246 (0.0000) | 0.381663 (0.0000) | 0.223065 (0.0000) | 0.002035 (0.9463) | 1.598769 (0.0000) | -0.009620(0.0010) |
| ***CBA*** | -0.021728(0.0001) | 0.031444 (0.0001) | 0.993290 (0.0000) | 0.002639 (0.06918) | 0.006256 (0.3023) | 0.018276 (0.0000) |
| ***CSL*** | -0.04079 (0.0000) | 0.065353 (0.0000) | 0.982420 (0.0000) | -0.026056 (0.0052) | 0.033198 (0.0075) | 0.018062 (0.0000) |
| ***WDS*** | -0.033652(0.0000) | 0.050203 (0.0000) | 0.995172(0.0000) | -0.006930 (0.3864) | 0.003846 (0.6881) | 0.019072 (0.0000) |
| ***P1*** | -0.042365(0.0000) | 0.058242 (0.0000) | 0.997777 (0.0000) | -0.002858 (0.7923) | -0.001309(0.9486) | 0.020830 (0.0000) |
| ***P2*** | -0.041624(0.0001) | 0.058744 (0.0000) | 0.991190 (0.0000) | -0.001847 (0.8566) | -0.005123 (0.7481) | 0.019145 (0.0000) |
| **GARCH (1, 1) WITH POSITIVE NEWS AT TIME T-1 AND VIX ESTIMATION** | | | | | | |
| ***WTC*** | 7.609019 (0.0000) | 0.269940 (0.0000) | 0.135241 (0.0007) | - | 4.670561 (0.0000) | -0.077335 (0.0022) |
| ***CBA*** | 0.110570 (0.0000) | 0.118711 (0.0000) | 0.829109 (0.0000) | - | -0.050274 (0.2236) | 0.015711 (0.0000) |
| ***CSL*** | 0.109860 (0.0000) | 0.080146 (0.0000) | 0.862526 (0.0000) | - | 0.103728 (0.0012) | 0.037829 (0.0000) |
| ***WDS*** | 0.093644 (0.0000) | 0.066622(0.0000) | 0.903476 (0.0000) | - | 0.060159 (0.3589) | 0.041566 (0.0000) |
| ***P1*** | 0.106303 (0.0000) | 0.131031 (0.0000) | 0.773031 (0.0000) | - | 0.160264 (0.0122) | 0.027929 (0.0000) |
| ***P2*** | 0.045401 (0.0000) | 0.061724 (0.0000) | 0.901146 (0.0000) | - | 0.026985 (0.4164) | 0.021616 (0.0000) |
| **EGARCH (1, 1) WITH POSITIVE NEWS AT TIME T-1 AND VIX ESTIMATION** | | | | | | |
| ***WTC*** | 1.485358 (0.0000) | 0.400279 (0.0000) | 0.283937 (0.0000) | 0.047687 (0.0433) | 0.196161 (0.0000) | -0.011776 (0.0000) |
| ***CBA*** | -0.020139 (0.0002) | 0.030419 (0.0002) | 0.993481 (0.0000) | 0.003636 (0.5704) | 0.001781 (0.7621) | 0.018333 (0.0000) |
| ***CSL*** | -0.034007(0.0000) | 0.053836 (0.0000) | 0.986353 (0.0000) | -0.017489 (0.0000) | 0.013049 (0.1692) | 0.018292 (0.0000) |
| ***WDS*** | -0.034329(0.0000) | 0.051595 (0.0000) | 0.995231 (0.0000) | -0.006041 (0.4512) | 0.001672 (0.8634) | 0.019117 (0.0000) |
| ***P1*** | -0.042088 (0.0000 | 0.060600 (0.0000) | 0.991711 (0.0000) | -0.004027 (0.7182) | -0.012836(0.5245) | 0.020870 (0.0000) |
| ***P2*** | -0.041644(0.0001) | 0.058762 (0.0000) | 0.991185 (0.0000) | -0.001874 (0.8550) | -0.005086 (0.7575) | 0.019147 (0.0000) |
| **GARCH (1, 1) WITH NEGATIVE NEWS AND VIX ESTIMATION** | | | | | | |
| ***WTC*** | 5.471581 (0.0000) | 0.183648 (0.0000) | 0.066477 (0.0000) | - | 191.9284 (0.0000) | -0.048965 (0.0000) |
| ***CBA*** | 0.798491 (0.0000) | 0.198336 (0.0000) | 0.514512 (0.0000) | - | -0.632406 (0.0000) | 0 .031220 (0.0000) |
| ***CSL*** | 0.189420 (0.0000) | 0.109772 (0.0000) | 0.791922 (0.0000) | - | 0.296147 (0.0013) | 0.038192 (0.0000) |
| ***WDS*** | 0.066905 (0.0007) | 0.069571(0.0000) | 0.895630 (0.0000) | - | 0.322449 (0.0030) | 0.035313 (0.0000) |
| ***P1*** | 0.058392 (0.0001) | 0.060780 (0.0000) | 0.889984 (0.0000) | - | -0.015923 (0.7570) | 0.024520 (0.0000) |
| ***P2*** | 0.071922 (0.0001) | 0.067070 (0.0000) | 0.892625 (0.0000) | - | -0.063107 (0.0684) | 0.020974 (0.0000) |
| **EGARCH (1, 1) WITH NEGATIVE NEWS AND VIX ESTIMATION** | | | | | | |
| ***WTC*** | 1.210665 (0.0000) | 0.364413 (0.0000) | 0.315970 (0.0000) | 0.029034 (0.2713) | 2.560217 (0.0000) | -0.013068 (0.0001) |
| ***CBA*** | -0.025802(0.0003) | 0.044927 (0.0001) | 0.991447 (0.0000) | -0.005104 (0.5663) | -0.009996 (0.1501) | 0.017466 (0.0000) |
| ***CSL*** | -0.015090(0.0042) | 0.032336 (0.0000) | 0.991795 (0.0000) | -0.007656 (0.1599) | -0.032524 (0.0000) | 0.019043 (0.0000) |
| ***WDS*** | -0.033833(0.0000) | 0.043962 (0.0000) | 0.991208 (0.0000) | 0.007717 (0.3855) | 0.053106 (0.0045) | 0.018408 (0.0000) |
| ***P1*** | -0.045085(0.0000) | 0.066991 (0.0000) | 0.990145 (0.0000) | -0.000698 (0.9517) | -0.017656 (0.0000) | 0.020270 (0.0000) |
| ***P2*** | -0.040796(0.0000) | 0.063264 (0.0000) | 0.990541 (0.0000) | 0.001197 (0.9078) | -0.019098 (0.2426) | 0.019555 (0.0000) |
| **GARCH (1, 1) WITH NEGATIVE NEWS AT TIME T-1 AND VIX ESTIMATION** | | | | | | |
| ***WTC*** | 9.542385 (0.0000) | 0.280968 (0.0000) | 0.029466 (0.2763) | - | 11.26024 (0.0001) | -0.103616 (0.0000) |
| ***CBA*** | 0.103854 (0.0000) | 0.109733 (0.0000) | 0.841263 (0.0000) | - | -0.027456 (0.2991) | 0.014895 (0.0000) |
| ***CSL*** | 0.049213 (0.0000) | 0.021653 (0.0000) | 0.960885 (0.0000) | - | -0.102335 (0.0000) | 0.040684 (0.0000) |
| ***WDS*** | 0.055537 (0.0075) | 0.074088 (0.0000) | 0.889018 (0.0000) | - | 0.443828 (0.0000) | 0.033464 (0.0000) |
| ***P1*** | 0.053494 (0.0002) | 0.060273 (0.0000) | 0.900641 (0.0000) | - | 0.009602 (0.8453) | 0.024732 (0.0000) |
| ***P2*** | 0.061682 (0.0003) | 0.062417 (0.0000) | 0.900173 (0.0000) | - | -0.040275 (0.2259) | 0.021242 (0.0000) |
| **EGARCH (1, 1) WITH NEGATIVE NEWS AT TIME T-1 AND VIX ESTIMATION** | | | | | | |
| ***WTC*** | 1.277375 (0.0000) | 0.338246 (0.0000) | 0.383010(0.0000) | 0.030436 (0.1884) | 0.427995 (0.0007) | -0.007863 (0.0096) |
| ***CBA*** | -0.029418(0.0002) | 0.053132(0.0000) | 0.990226 (0.3528) | -0.008922 (0.00000) | -0.015044 (0.0552) | 0.017044 (0.0000) |
| ***CSL*** | -0.016315(0.0025) | 0.035050 (0.0000) | 0.991289 (0.0000) | -0.009036 (0.1197) | -0.036520 (0.0000) | 0.019127 (0.0000) |
| ***WDS*** | -0.036051(0.0000) | 0.046557 (0.0000) | 0.990203 (0.0000) | 0.009474 (0.2956) | 0.060452 (0.0016) | 0.018394 (0.0000) |
| ***P1*** | -0.045370(0.0000) | 0.066613 (0.0000) | 0.990069 (0.0000) | -0.001095 (0.9240) | -0.014571 (0.5954) | 0.020201 (0.0000) |
| ***P2*** | -0.040438(0.0000) | 0.061825 (0.0000) | 0.990757 (0.0000) | 0.001132 (0.9109) | -0.016536 (0.2959) | 0.019481 (0.0000) |

**Notes:** This table shows the GARCH estimation results in Australia. The estimation results for the GARCH model after adding the VIX index as an extra variable are included in the tables. 5% significance level means that the probability of the observed result being due to chance is less than 5. WTC is short for "Wisetech Global Ltd", which was selected from the technology industry. CBA is the "Common Wealth Bank of Australia", representing the financial industry. WDS is" Woodside Energy Group Ltd", from the energy sector, and CSL is" CSL Limited", from the health and care industry. P1 is the equal-weighted portfolio and P2 is the market cap-weighted portfolio.

## Table B6 The GARCH estimation results in Canada

| GARCH (1, 1) | | | | | |
|---|---|---|---|---|---|
| | **Ʊ (p-VALUE)** | **$\alpha$ (p-value)** | **$\beta$ (p-value)** | **γ(p-value)** | |
| ***SHOP*** | 0.221532 (0.0001) | 0.075771 (0.0000) | 0.910552 (0.0000) | | |
| ***RY*** | 0.054007 (0.0000) | 0.199022 (0.0000) | 0.758656 (0.0000) | | |
| ***BHC*** | 0.154041 (0.0000) | 0.048411 (0.0000) | 0.941310 (0.0000) | | |
| ***ENG*** | 0.143059 (0.0000) | 0.235622 (0.0000) | 0.728133 (0.0000) | | |
| ***P1*** | 0.030516 (0.0012) | 0.119918 (0.0000) | 0.873235 (0.0000) | | |
| ***P2*** | 0.020211 (0.0010) | 0.138214 (0.0000) | 0.860015 (0.0000) | | |
| **EGARCH (1, 1)** | | | | | |
| ***SHOP*** | -0.043872 (0.0063) | 0.132331 (0.0000) | 0.977863 (0.0000) | -0.069507(0.0000) | |
| ***RY*** | -0.142059 (0.0000) | 0.185407 (0.0000) | 0.971563 (0.0000) | -0.089761(0.0000) | |
| ***BHC*** | -0.036040 (0.0000) | 0.087896 (0.0000) | 0.989841 (0.0000) | -0.046763(0.0000) | |
| ***ENG*** | -0.200660 (0.0000) | 0.327249 (0.0000) | 0.937442 (0.0000) | -0.030460(0.0000) | |
| ***P1*** | -0.124975 (0.0000) | 0.183372 (0.0000) | 0.973316 (0.0000) | -0.103653(0.0000) | |
| ***P2*** | -0.144335 (0.0000) | 0.198558 (0.0000) | 0.974475 (0.0000) | -0.121531 (0.0000) | |
| **GARCH (1, 1) WITH LOG NEWS INTENSITY** | | | | | |
| ***SHOP*** | 0.121948 (0.0903) | 0.077906 (0.0000) | 0.896033 (0.0000) | - | 0.364681 (0.0015) |
| ***RY*** | 0.042301 (0.0000) | 0.240505 (0.0000) | 0.676301 (0.0000) | - | 0.107666 (0.0000) |
| ***BHC*** | 0.117402 (0.0000) | 0.051579 (0.0000) | 0.932101 (0.0000) | - | 0.163133 (0.0000) |
| ***ENG*** | 0.096347 (0.0000) | 0.263944 (0.0000) | 0.697883 (0.0000) | - | 0.120920 (0.0000) |
| ***P1*** | 0.016562 (0.2035) | 0.119251 (0.0000) | 0.873903 (0.0000) | - | 0.016792 (0.1545) |
| ***P2*** | 0.013186 (0.1230) | 0.138816 (0.0000) | 0.856992 (0.0000) | - | 0.013913 (0.2400) |
| **EGARCH (1, 1) WITH LOG NEWS INTENSITY** | | | | | |
| ***SHOP*** | -0.037388 (0.0292) | 0.128797 (0.0000) | 0.968254 (0.0000) | -0.070836 (0.0000) | 0.025592 (0.0000) |
| ***RY*** | -0.197099 (0.0000) | 0.222477(0.0000) | 0.957237 (0.0000) | -0.0088141(0.0000) | 0.043601 (0.0000) |
| ***BHC*** | -0.024916 (0.0000) | 0.059795(0.0000) | 0.990121 (0.0000) | -0.063715 (0.0000) | 0.009917 (0.0000) |
| ***ENG*** | -0.226600 (0.0000) | 0.337018 (0.0000) | 0.934288 (0.0000) | -0.032559 (0.0000) | 0.035834 (0.0106) |
| ***P1*** | -0.122040(0.0000) | 0.183231 (0.0000) | 0.973356 (0.0000) | -0.103976 (0.0000) | -0.003410 (0.6842) |
| ***P2*** | -0.137394 (0.0000) | 0.197345 (0.0000) | 0.975587 (0.0000) | -0.122490 (0.0000) | -0.008211 (0.4411 |
| **GARCH (1, 1) WITH NEWS INTENSITY CHANGES** | | | | | |
| ***SHOP*** | 0.249374 (0.0006) | 0.074470 (0.0000) | 0.908588 (0.0000) | - | 0.023215 (0.0000) |
| ***RY*** | 0.033496 (0.0000) | 0.149084 (0.0000) | 0.822399 (0.0000) | - | 0.001668 (0.0000) |
| ***BHC*** | 0.121173 (0.0000) | 0.066832(0.0000) | 0.926020 (0.0000) | - | 0.018292 (0.0000) |
| ***ENG*** | 0.103495 (0.0000) | 0.216628 (0.0000) | 0.764763 (0.0000) | - | 0.002686 (0.0000) |
| ***P1*** | 0.035869 (0.0006) | 0.125860 (0.0000) | 0.864690 (0.0000) | - | 0.001128 (0.0282) |
| ***P2*** | 0.024788 (0.0004) | 0.142250 (0.0000) | 0.852229 (0.0000) | - | 0.001383 (0.0034) |
| **EGARCH (1, 1) WITH NEWS INTENSITY CHANGES** | | | | | |
| ***SHOP*** | -0.042394 (0.0000) | 0.123035 (0.0000) | 0.979580 (0.0000) | -0.069281(0.0000) | 0.002695 (0.0000) |
| ***RY*** | -0.143152 (0.0000) | 0.184992 (0.0000) | 0.975323 (0.0000) | -0.086312(0.0000) | 0.003734 (0.0000) |
| ***BHC*** | -0.071027 (0.0000) | 0.143755 (0.0000) | 0.987129 (0.0000) | -0.044194(0.0000) | 0.005049 (0.0000) |
| ***ENG*** | -0.201808 (0.0000) | 0.320637 (0.0000) | 0.947201 (0.0000) | -0.027550(0.0000) | 0.001891 (0.0000) |
| ***P1*** | -0.129380 (0.0000) | 0.189864 (0.0000) | 0.971987 (0.0000) | -0.104938(0.0000) | 0.001504 (0.0046) |
| ***P2*** | -0.149184 (0.0000) | 0.204516 (0.0000) | 0.973691 (0.0000) | -0.121641(0.0000) | 0.001794 (0.0009) |

**Notes:** This table shows the GARCH estimation results in Canada. The estimation results for the GARCH model after adding the VIX index as an extra variable are included in the tables. 5% significance level means that the probability of the observed result being due to chance is less than 5%. SHOP is short for "Shopify", which was selected from the technology industry. RY is the "Royal Bank of Canada", representing the financial industry. ENB is" Enbridge", from the energy sector, and BHC is" Bausch Health", from the health and care industry. P1 is the equal-weighted portfolio and P2 is the market cap-weighted portfolio.

## Table B6 The GARCH estimation results in Canada (Continued)

| | ℧ (p-VALUE) | $\alpha$ (p-value) | $\beta$ (p-value) | γ(p-value) | Positive news | Positive news at t-1 |
|---|---|---|---|---|---|---|
| **GARCH (1, 1) WITH POSITIVE NEWS** | | | | | | |
| ***SHOP*** | 0.067280 (0.4357) | 0.076360 (0.0000) | 0.909175(0.0000) | - | 0.464353 (0.0245) | |
| | 0.084447 (0.3286) | 0.075857 (0.0000) | 0.910182(0.0000) | | - | 0.398142 (0.0548) |
| ***RY*** | 0.033606 (0.0001) | 0.213738 (0.0000) | 0.730638(0.0000) | - | 0.164510 (0.0000) | |
| | 0.041840 (0.0000) | 0.198491 (0.0000) | 0.749351(0.0000) | | | 0.094219(0.0000) |
| ***BHC*** | 0.111818 (0.0000) | 0.047188 (0.0000) | 0.940566 (0.0000) | - | 0.195723(0.0004) | |
| | 0.122404(0.0000) | 0.046358(0.0000) | 0.942251(0.0000) | | | 0.127509(0.0090) |
| ***ENG*** | 0.166189(0.0000) | 0.230088 (0.0000) | 0.729421(0.0000) | - | -0.070755(0.0761) | |
| | 0.161472(0.0000) | 0.231708(0.0000) | 0.729824(0.0000) | | | -0.062180(0.1035) |
| ***P1*** | 0.005844 (0.6540) | 0.114962 (0.0000) | 0.874999 (0.0000) | - | 0.148684(0.039) | |
| | 0.011981(0.3625) | 0.114260(0.0000) | 0.875406(0.0000) | | | 0.172883(0.0011) |
| ***P2*** | 0.000686 (0.9298) | 0.138642(0.0000) | 0.851984 (0.0000) | - | 0.1113007(0.0038) | |
| | 0.007033(0.3812) | 0.135557(0.0000) | 0.857568(0.0000) | | | 0.073350(0.0488) |
| **EGARCH (1, 1) WITH POSITIVE NEWS** | | | | | | |
| ***SHOP*** | -0.061197(0.0009) | 0.134144 (0.0000) | 0.976572(0.0000) | -0.074500 (0.0000) | 0.052439(0.0113) | |
| | -0.057476(0.0015) | 0.132364 (0.0000) | 0.977324(0.0000) | -0.072867 (0.0000) | | 0.040870(0.0425) |
| ***RY*** | -0.172850(0.0000) | 0.200102 (0.0000) | 0.965935 (0.0000) | -0.093322 (0.0000) | 0.080537(0.0001) | |
| | -0.155775(0.0000) | 0.187693(0.0000) | 0.969301(0.0000) | -0.091745(0.0000) | | 0.05053290.0047) |
| ***BHC*** | -0.032620(0.0000) | 0.066204 (0.0000) | 0.991436 (0.0000) | -0.051808 (0.0000) | 0.023255 (0.0000) | |
| | -0.031625(0.0000) | 0.064785(0.0000) | 0.991650(0.0000) | -0.051365(0.0000) | | 0.021699(0.0000) |
| ***ENG*** | -0.192129(0.0000) | 0.331256 (0.0000) | 0.934654 (0.0000) | -0.025832 (0.1361) | -0.037889(0.1656) | |
| | -0.195107(0.0000) | 0.329304(0.0000) | 0.936065(0.0000) | -0.028072(0.1039) | | -0.024089(0.3443) |
| ***P1*** | -0.135855 (0.0000) | 0.182998 (0.0000) | 0.972842 (0.0000) | -0.101695(0.0000) | 0.038697 (0.1535) | |
| | -0.137226(0.0000) | 0.183181(0.0000) | 0.972842(0.0000) | -0.101120(0.0000) | | 0.042620(0.1211) |
| ***P2*** | -0.157481 (0.0000) | 0.199997 (0.0000) | 0.972536(0.0000) | -0.121991 (0.0101) | 0.045135(0.1421) | |
| | -0.151597(0.0000) | 0.198322(0.0000) | 0.973432(0.0000) | -0.121363(0.0000) | | 0.028009(0.3340) |
| **GARCH (1, 1) WITH NEGATIVE NEWS** | | | | | | |
| **SHOP** | 0.192597(0.0032) | 0.071197 (0.0000) | 0.899994 (0.0000) | - | 1.150001 (0.0016) | |
| | 0.188106(0.0026) | 0.070116(0.0000) | 0.904360(0.0000) | | | 0.950936(0.0061) |
| **RY** | 0.050815 (0.0000) | 0.203309 (0.0000) | 0.728330 (0.0000) | - | 0.121685(0.0000) | |
| | 0.046183(0.0000) | 0.186356(0.0000) | 0.763786(0.0000) | | | 0.058356(0.0014) |
| **BHC** | 0.065827 (0.0000) | 0.112692 (0.0000) | 0.737962 (0.0000) | - | 6.512108 (0.0000) | |
| | 0.129512(0.0000) | 0.046363(0.0000) | 0.933538(0.0000) | | | 0.699262(0.0000) |
| **ENG** | 0.091150 (0.0000) | 0.256774 (0.0000) | 0.699534 (0.0000) | - | 0.388837(0.0000) | |
| | 0.112216(0.0000) | 0.239867(0.0000) | 0.715244(0.0000) | | | 0.240539(0.0003) |
| **P1** | 0.015533 (0.1902) | 0.121738 (0.0000) | 0.866608(0.0000) | - | 0.121175 (0.0353) | |
| | 0.014904(0.2107) | 0.124358(0.0000) | 0.861782(0.0000) | | | 0.145409(0.0136) |
| **P2** | 0.012415 (0.0983) | 0.138710 (0.0000) | 0.856319 (0.0000) | - | 0.059764(0.0738) | |
| | 0.017220(0.0156) | 0.137711(0.0000) | 0.859607(0.0000) | | | 0.017220(0.5818) |
| **EGARCH (1, 1) WITH NEGATIVE NEWS** | | | | | | |
| **SHOP** | -0.028518(0.1001) | 0.127340 (0.0000) | 0.967788 (0.0000) | -0.063179 (0.0000) | 0.062657 (0.0235) | |
| | -0.031157(0.0658) | 0.126843(0.0000) | 0.970170(0.0000) | -0.064739(0.0000) | | 0.049386(0.0622) |
| **RY** | -0.162909 (0.0000) | 0.194842 (0.0000) | 0.964967 (0.0000) | -0.087738(0.0000) | 0.054581(0.0014) | |
| | -0.153510(0.0000) | 0.189517(0.0000) | 0.967927(0.0000) | -0.089164(0.0000) | | 0.033845(0.0381) |
| **BHC** | -0.011460 (0.2391) | 0.093197 (0.0000) | 0.963831 (0.0000) | -0.071959 (0.0000) | 0.155240 (0.0000) | |
| | -0.018683(0.076) | 0.068862(0.0000) | 0.981045(0.0000) | -0.061740(0.0000) | | 0.078936(0.0000) |
| **ENG** | -0.236522 (0.0000) | 0.348009 (0.0000) | 0.928233 (0.0000) | -0.018979(0.2986) | 0.119320(0.0009) | |
| | -0.213663(0.0000) | 0.331713(0.0000) | 0.934364(0.0000) | -0.0027048(0.1214) | | 0.052770(0.1129) |
| **P1** | -0.127299 (0.0000) | 0.182559 (0.0000) | 0.973096(0.0000) | -0.103135 (0.0000) | 0.014003 (0.6401) | |
| | -0.133478(0.0000) | 0.185687(0.0000) | 0.971610(0.0000) | -0.102809(0.0000) | | 0.035980(0.2329) |
| **P2** | -0.141699 (0.0000) | 0.197553 (0.0000) | 0.974935(0.0000) | -0.122115 (0.0000) | -0.009493(0.6952) | |
| | -0.137530(0.0000) | 0.196498(0.0000) | 0.975703(0.0000) | -0.122923(0.0000) | | -0.026735(0.2731) |

**Notes:** This table shows the GARCH estimation results in Canada. The estimation results for the GARCH model after adding the VIX index as an extra variable are included in the tables. 5% significance level means that the probability of the observed result being due to chance is less than 5%. SHOP is short for “Shopify”, which was selected from the technology industry. RY is the “Royal Bank of Canada”, representing the financial industry. ENB is” Enbridge”, from the energy sector, and BHC is” Bausch Health”, from the health and care industry. P1 is the equal-weighted portfolio and P2 is the market cap-weighted portfolio.

## Table B6 The GARCH estimation results in Canada (Continued)

| | Ʊ (p-VALUE) | $\alpha$ (p-value) | $\beta$ (p-value) | γ(p-value) | News intensity | VIX |
|---|---|---|---|---|---|---|
| **GARCH (1, 1) WITH LOG NEWS INTENSITY AND VIX** | | | | | | |
| ***BHC*** | 0.052762 (0.0000) | 0.024845(0.0000) | 0.966196 (0.0000) | - | 0.076042 (0.0000) | 0.121980 (0.0000) |
| ***RY*** | 0.026522 (0.0000) | 0.092787 (0.0000) | 0.844992 (0.0000) | - | 0.043312 (0.0000) | 0.014458 (0.0000) |
| ***ENG*** | 0.083363 (0.0000) | 0.138689 (0.0000) | 0.814619 (0.0000) | - | 0.038374 (0.0314) | 0.028876 (0.0000) |
| ***SHOP*** | 0.100944 (0.0000) | 0.159772 (0.0000) | 0.800293 (0.0000) | - | 0.013932 (0.4175) | 0.028118 (0.0000) |
| ***P1*** | 0.015068 (0.0537) | 0.068117 (0.0000) | 0.917791 (0.0000) | - | 0.013453 (0.0986) | 0.028250 (0.0000) |
| ***P2*** | 0.009220 (0.1024) | 0.069122 (0.0000) | 0.913360 (0.0505) | - | 0.016893 (0.0000) | 0.019708 (0.0000) |
| **EGARCH (1, 1) WITH LOG NEWS INTENSITY AND VIX** | | | | | | |
| ***BHC*** | -0.014659(0.0000) | 0.025759 (0.0000) | 0.997171 (0.0000) | -0.044529 (0.0000) | 0.004084 (0.0000) | 0.010016 (0.0000) |
| ***RY*** | -0.038463(0.0000) | 0.038463 (0.0000) | 0.995787 (0.0000) | -0.007521 (0.3733) | 0.005592 (0.0032) | 0.028103 (0.0000) |
| ***ENG*** | -0.151030(0.0000) | 0.227098 (0.0000) | 0.962977 (0.0000) | -0.021099 (0.0000) | 0.002789 (0.7983) | 0.029907 (0.0000) |
| ***SHOP*** | -0.131416(0.0000) | 0.209998 (0.0000) | 0.965784 (0.0000) | 0.029998 (0.0000) | -0.008695 (0.4020) | 0.025268 (0.0000) |
| ***P1*** | -0.054468(0.0000) | 0.075735 (0.0000) | 0.995787 (0.0000) | 0.002596 (0.0000) | -0.003107 (0.0000) | 0.024445 (0.0000) |
| ***P2*** | -0.051137(0.0000) | 0.067710 (0.0000) | 0.997731 (0.0000) | -0.004449 (0.6810) | -0.002071 (0.6305) | 0.026145 (0.0000) |
| **GARCH (1, 1) WITH LOG NEWS INTENSITY CHANGES AND VIX** | | | | | | |
| ***BHC*** | 0.087170 (0.0000) | 0.040536 (0.0000) | 0.951174 (0.0000) | - | 0.017355 (0.0000) | 0.100497 (0.0000) |
| ***RY*** | 0.026227 (0.0000) | 0.071309 (0.0000) | 0.892018 (0.0000) | - | 0.001242 (0.0000) | 0.012917 (0.0000) |
| ***ENG*** | 0.112072 (0.0000) | 0.133611 (0.0000) | 0.816768 (0.0000) | - | 0.002775 (0.0000) | 0.028828 (0.0000) |
| ***SHOP*** | 0.080199 (0.0009) | 0.024921 (0.0000) | 0.968396(0.0000) | - | 0.025518 (0.0000) | 0.164381(0.0000) |
| ***P1*** | 0.272407 (0.0000) | 0.244946 (0.0000) | 0.605663 (0.0000) | - | 0.004295 (0.0000) | 0.026015(0.0000) |
| ***P2*** | 0.019886 (0.0000) | 0.063946 (0.0000) | 0.918728 (0.0000) | - | 0.001207 (0.0000) | 0.019033 (0.0000) |
| **EGARCH (1, 1) WITH LOG NEWS INTENSITY CHANGES AND VIX** | | | | | | |
| ***BHC*** | -0.068190(0.0000) | 0.113308 (0.0000) | 0.994982 (0.0000) | -0.014596 (0.0266) | 0.005091 (0.0000) | 0.011682 (0.0000) |
| ***RY*** | -0.035828(0.0001) | 0.044161 (0.0001) | 0.996850 (0.0000) | -0.011859 (0.1499) | 0.003949 (0.0000) | 0.027558 (0.0000) |
| ***ENG*** | -0.116939(0.0000) | 0.176466 (0.0000) | 0.973646 (0.0000) | 0 .026898 (0.0000) | 0.002243 (0.0000) | 0.024523 (0.0000) |
| ***SHOP*** | -0.024494(0.0123) | 0.049863 (0.0001) | 0.994212 (0.0000) | -0.033799 (0.0000) | 0.002916 (0.0000) | 0.013915 (0.0000) |
| ***P1*** | -0.005068(0.0000) | 0.070935 (0.0000) | 0.995763 (0.0000) | 0.009417 (0.4182) | 0.002160 (0.0000) | 0.025490 (0.0000) |
| ***P2*** | -0.035863(0.0000) | 0.045909 (0.0000) | 0.998243 (0.0000) | 0.007002 (0.4082) | 0.002928 (0.0000) | 0.027431 (0.0000) |

**Notes:** This table shows the GARCH estimation results in Canada. The estimation results for the GARCH model after adding the VIX index as an extra variable are included in the tables. 5% significance level means that the probability of the observed result being due to chance is less than 5%.

SHOP is short for “Shopify”, which was selected from the technology industry. RY is the “Royal Bank of Canada”, representing the financial industry. ENB is” Enbridge”, from the energy sector, and BHC is” Bausch Health”, from the health and care industry. P1 is the equal-weighted portfolio and P2 is the market cap-weighted portfolio.

# Table B6 The GARCH estimation results in Canada (Continued)

| | Ʊ (p-VALUE) | $\alpha$ (p-value) | $\beta$ (p-value) | γ(p-value) | Positive news | VIX |
|---|---|---|---|---|---|---|
| **GARCH (1, 1) WITH POSITIVE NEWS AND VIX** | | | | | | |
| ***BHC*** | 0.022264 (0.0045) | 0.017234 (0.0000) | 0.977120 (0.0000) | - | 0.124215 (0.0000) | 0.122790 (0.0000) |
| ***RY*** | 0.024794 (0.0000) | 0.091685 (0.0000) | 0.859429 (0.0000) | - | 0.062445 (0.0000) | 0.014306 (0.0000) |
| ***ENG*** | 0.135897 (0.0000) | 0.156685 (0.0000) | 0.793806 (0.0000) | - | -0.050221 (0.0000) | 0.027842 (0.0000) |
| ***SHOP*** | 0.032246 (0.4876) | 0.042797 (0.0000) | 0.948120 (0.0000) | - | 0.448487 (0.0000) | 0.130510 (0.0000) |
| ***P1*** | 0.003281 (0.7239) | 0.060961 (0.0000) | 0.925239 (0.0000) | - | 0.114643 (0.0018) | 0.025562 (0.0000) |
| ***P2*** | 0.008395 (0.1469) | 0.071837 (0.0000) | 0.909997 (0.0000) | - | 0.054655 (0.0483) | 0.018084 (0.0000) |
| **EGARCH (1, 1) WITH POSITIVE NEWS AND VIX** | | | | | | |
| ***BHC*** | -0.008518(0.0096) | 0.011601 (0.0002) | 0.998866 (0.0000) | -0.035460 (0.0000) | 0.008730 (0.0000) | 0.011374 (0.0000) |
| ***RY*** | -0.033246(0.0000) | 0.038184 (0.0000) | 0.996238 (0.0000) | -0.010181(0.2257) | 0.010892 (0.0000) | 0.027798 (0.0000) |
| ***ENG*** | -0.120638(0.0000) | 0.205652 (0.0000) | 0.964452 (0.0000) | 0.034179 (0.0043) | -0.046441(0.0219) | 0.025865 (0.0000) |
| ***SHOP*** | -0.025170(0.0067) | 0.043639 (0.0001) | 0.992545 (0.0000) | -0.033774 (0.0000) | 0.031503 (0.0006) | 0.014212 (0.0000) |
| ***P1*** | -0.065194(0.0000) | 0.080822 (0.0000) | 0.992137 (0.0000) | -0.001331 (09221) | 0.023516 (0.0619) | 0.022326 (0.0000) |
| ***P2*** | -0.054713(0.0000) | 0.067589 (0.0000) | 0.996810 (0.0000) | -0.000128 (0.9905) | 0.008328 (0.4188) | 0.026441 (0.0000) |
| **GARCH (1, 1) WITH POSITIVE NEWS AT TIME T-1 AND VIX** | | | | | | |
| ***BHC*** | 0.022443 (0.0039) | 0.016741 (0.0000) | 0.977924 (0.0000) | - | 0.122307 (0.0000) | 0.124130 (0.0000) |
| ***RY*** | 0.027522 (0.0000) | 0.090003 (0.0000) | 0.863411 (0.0000) | - | 0.041606 (0.0000) | 0.014842(0.0000) |
| ***ENG*** | 0.142034 (0.0000) | 0.158713 (0.0000) | 0.790181 (0.0000) | - | -0.060290 (0.0383) | 0.027950 (0.0000) |
| ***SHOP*** | 0.022143 (0.0000) | 0.043881 (0.0000) | 0.946814 (0.0000) | - | 0.429225 (0.0010) | 0.128489 (0.0000) |
| ***P1*** | 0.006238 (0.5022) | 0.061806 (0.0000) | 0.924256 (0.0000) | - | 0.127187 (0.0007) | 0.025370 (0.0000) |
| ***P2*** | 0.012187 (0.0273) | 0.071098 (0.0000) | 0.912005 (0.0000) | - | 0.033643 (0.1979) | 0.018373 (0.0000) |
| **EGARCH (1, 1) WITH POSITIVE NEWS AT TIME T-1 AND VIX** | | | | | | |
| ***BHC*** | -0.008054(0.0134) | 0.010905 (0.0003) | 0.998922 (0.0000) | -0.035574 (0.0000) | 0.008404 (0.0000) | 0.011385 (0.0000) |
| ***RY*** | -0.032390(0.0000) | 0.037552 (0.0000) | 0.996315 (0.0000) | -0.010291 (0.0000) | 0.009314 (0.0269) | 0.027784 (0.0000) |
| ***ENG*** | -0.117472(0.0000) | 0.202605 (0.0000) | 0.964870 (0.0000) | 0.034306 (0.0000) | -0.051140 (0.0182) | 0.026130 (0.0000) |
| ***SHOP*** | -0.025046(0.0075) | 0.042542 (0.0001) | 0.992710 (0.0000) | -0.033468 (0.0000) | 0.029559 (0.0008) | 0.014150 (0.0000) |
| ***P1*** | -0.065339(0.0000) | 0.081056 (0.0000) | 0.992133 (0.0000) | -0.001545 (0.9085) | 0.023397 (0.0630) | 0.022264 (0.0000) |
| ***P2*** | -0.053955(0.0000) | 0.067609 (0.0000) | 0.997014 (0.0000) | -0.000938 (0.9303) | 0.005333 (0.6009) | 0.026385 (0.0000) |
| **GARCH (1, 1) WITH NEGATIVE NEWS AND VIX** | | | | | | |
| ***BHC*** | 0.065027 (0.0000) | 0.026393 (0.0000) | 0.956699 (0.0000) | - | 0.695037 (0.0000) | 0.130411 (0.0000) |
| ***RY*** | 0.028478 (0.0000) | 0.081509 (0.0000) | 0.867674 (0.0000) | - | 0.050122 (0.0000) | 0.015086 (0.0000) |
| ***ENG*** | 0.085217 (0.0000) | 0.164898 (0.0000) | 0.795088 (0.0000) | - | 0.127346 (0.0026) | 0.026976 (0.0000) |
| ***SHOP*** | 0.043633 (0.1452) | 0.023702 (0.0000) | 0.959030 (0.0000) | - | 0.961720 (0.0000) | 0.147288 (0.0000) |
| ***P1*** | 0.013522 (0.0868) | 0.064232 (0.0000) | 0.922725 (0.0000) | - | 0.071962 (0.0547) | 0.027017 (0.0000) |
| ***P2*** | 0.012255 (0.0052) | 0.069310 (0.0000) | 0.913483 (0.0000) | - | 0.045560 (0.0370) | 0.020131 (0.0000) |
| **EGARCH (1, 1) WITH NEGATIVE NEWS AND VIX** | | | | | | |
| ***BHC*** | -0.017234(0.0011) | 0.044910 (0.0000) | 0.988898 (0.0000) | -0.044935 (0.0000) | 0.056419 (0.0000) | 0.009141 (0.0000) |
| ***RY*** | -0.033436(0.0000) | 0.037041 (0.0000) | 0.995521 (0.0000) | -0.007225 (0.0001) | 0.014892 (0.0022) | 0.028204 (0.0000) |
| ***ENG*** | -0.142093(0.0000) | 0.212221 (0.0000) | 0.965389 (0.0000) | 0.028562 (0.0000) | 0.020423 (0.3745) | 0.024963 (0.0000) |
| ***SHOP*** | -0.010401(0.2941) | 0.049894 (0.0000) | 0.985889 (0.0000) | -0.031619 (0.0000) | 0.035458 (0.0176) | 0.012959 (0.0000) |
| ***P1*** | -0.060018(0.0000) | 0.081997 (0.0000) | 0.992642 (0.0000) | -0.009671 (0.4478) | 0.001788 (0.0000) | 0.021577 (0.0000) |
| ***P2*** | -0.048880 (0.0000) | 0.064864 (0.0000) | 0.997873 (0.0000) | -0.004708 (0.6595) | -0.008151(0.4170) | 0.026145 (0.0000) |
| **GARCH (1, 1) WITH NEGATIVE NEWS AT TIME T-1 AND VIX** | | | | | | |
| ***BHC*** | 0.062828 (0.0000) | 0.024766 (0.0000) | 0.962866 (0.0000) | - | 0.428774 (0.0000) | 0.131122 (0.0000) |
| ***RY*** | 0.026268 (0.0000) | 0.075552 (0.0000) | 0.878803(0.0000) | - | 0.040715 (0.0000) | 0.015256 (0.0000) |
| ***ENG*** | 0.093140 (0.0000) | 0.159779 (0.0000) | 0.801144 (0.0000) | - | 0.068925 (0.0737) | 0.027250 (0.0000) |
| ***SHOP*** | 0.048695 (0.1298) | 0.025899 (0.0000) | 0.955576 (0.0000) | - | 1.020912 (0.0000) | 0.146920 (0.0000) |
| ***P1*** | 0.011941 (0.1259) | 0.063677 (0.0000) | 0.923019 (0.0000) | - | 0.081654 (0.0259) | 0.026941 (0.0000) |
| ***P2*** | 0.013161 (0.0028) | 0.068819 (0.0000) | 0.914764 (0.0000) | - | 0.036189 (0.0897) | 0.019988 (0.0000) |
| **EGARCH (1, 1) WITH NEGATIVE NEWS AT TIME T-1 AND VIX ESTIMATION** | | | | | | |
| ***BHC*** | -0.016632(0.0003) | 0.037205 (0.0000) | 0.992744 (0.0000) | -0.042989 (0.0000) | 0.036320 (0.0000) | 0.009570 (0.0000) |
| ***RY*** | -0.032549(0.0000) | 0.036291 (0.0000) | 0.995660 (0.0000) | -0.007543 (0.0000) | 0.013638 (0.0042) | 0.028207 (0.0000) |
| ***ENG*** | -0.138798(0.0000) | 0.212204 (0.0000) | 0.965588 (0.0000) | 0.028142 (0.0209) | 0.004771 (0.8346) | 0.025041 (0.0000) |
| ***SHOP*** | -0.010396(0.3088) | 0.051845 (0.0002) | 0.984923 (0.0000) | -0.031411 (0.0000) | 0.039727 (0.0097) | 0.012997 (0.0000) |
| ***P1*** | -0.060789 (0.0000) | 0.082527 (0.0000) | 0.992481 (0.0000) | -0.094480 (0.0000) | 0.003995 (0.7830) | 0.021596 (0.0000) |
| ***P2*** | -0.047607 (0.0000) | 0.063989 (0.0000) | 0.998050 (0.0000) | -0.005603 (0.5987) | -0.011259 (0.2593) | 0.026071 (0.0000) |

**Notes:** This table shows the GARCH estimation results in Canada. The estimation results for the GARCH model after adding the VIX index as an extra variable are included in the tables. 5% significance level means that the probability of the observed result being due to chance is less than 5%.

## Table B7 The GARCH estimation results in Japan

| | ℧ (p-VALUE) | $\alpha$ (p-value) | $\beta$ (p-value) | γ(p-value) | News intensity |
|---|---|---|---|---|---|
| **GARCH (1, 1) ESTIMATION RESULT** | | | | | |
| ***SONY*** | 0.351305 (0.0001) | 0.053912 (0.0000) | 0.850872 (0.0000) | | |
| ***UFJ*** | 0.234897 (0.0000) | 0.114286 (0.0000) | 0.781730 (0.0000) | | |
| ***MITS*** | 0.102270 (0.0000) | 0.098532 (0.0000) | 0.848517 (0.0000) | | |
| ***HOYA*** | 0.385306 (0.0000) | 0.084360 (0.0000) | 0.813190 (0.0000) | | |
| ***P1*** | 0.085515 (0.0000) | 0.060467 (0.0000) | 0.900122 (0.0000) | | |
| ***P2*** | 0.109529 (0.0000) | 0.075024 (0.0000) | 0.874260(0.0000) | | |
| **EGARCH (1, 1) ESTIMATION RESULT** | | | | | |
| ***SONY*** | 0.008260 (0.6602) | 0.073102 (0.0000) | 0.952173 (0.0000) | -0.052377(0.0000) | |
| ***UFJ*** | -0.079858 (0.0000) | 0.180183 (0.0000) | 0.932145 (0.0000) | -0.024730(0.0000) | |
| ***MITS*** | -0.101222 (0.0000) | 0.171886 (0.0000) | 0.955157 (0.0000) | -0.027407(0.0000) | |
| ***HOYA*** | 0.008427 (0.0000) | 0.075220 (0.0000) | 0.950136 (0.0000) | -0.121967 (0.0000) | |
| ***P1*** | -0.014935 (0.2348) | 0.056187 (0.0000) | 0.963110 (0.0000) | -0.116294(0.0000) | |
| ***P2*** | -0.031026 (0.0118) | 0.076359 (0.0000) | 0.963411 (0.0000) | -0.113340 (0.0000) | |
| **GARCH (1, 1) WITH LOG NEWS INTENSITY ESTIMATION** | | | | | |
| | **℧ (p-VALUE)** | **$\alpha$ (p-value)** | **$\beta$ (p-value)** | **γ(p-value)** | **News intensity** |
| ***SONY*** | 2.384595 (0.0000) | 0.043645 (0.0534) | 0.042654 (0.6390) | - | 1.175688 (0.0000) |
| ***UFJ*** | 0.240675 (0.0000) | 0.110284 (0.0000) | 0.796571(0.0000) | - | -0.061282 (0.0518) |
| ***MITS*** | 0.104111 (0.0000) | 0.101140 (0.0000) | 0.838647 (0.0000) | - | 0.039994 (0.1946) |
| ***HOYA*** | 0.371271 (0.0000) | 0.089503 (0.0000) | 0.801688 (0.0000) | - | 0.346271 (0.0000) |
| ***P1*** | 0.088167 (0.0041) | 0.059234 (0.0000) | 0.902433 (0.0000) | - | -0.008183 (0.7512) |
| ***P2*** | 0.130620 (0.0001) | 0.070170 (0.0000) | 0.881024 (0.0000) | - | -0.049016 (0.1390) |
| **EGARCH (1, 1) WITH LOG NEWS INTENSITY ESTIMATION** | | | | | |
| ***SONY*** | 0.908016 (0.0000) | 0.029770 (0.4717) | 0.028693 (0.7369) | -0.067035 (0.0321) | 0.333537 (0.0000) |
| ***UFJ*** | -0.069302 (0.0000) | 0.178577(0.0000) | 0.937591 (0.0000) | -0.025182(0.0000) | -0.027680 (0.0000) |
| ***MITS*** | -0.103204 (0.0000) | 0.172900(0.0000) | 0.953693 (0.0000) | -0.027827(0.0119) | 0.007025 (0.0000) |
| ***HOYA*** | -0.000814 (0.9539) | 0.079650 (0.0000) | 0.947798 (0.0000) | -0.130122 (0.0000) | 0.074280 (0.0026) |
| ***P1*** | -0.001217 (0.9310) | 0.047231 (0.0000) | 0.965701 (0.0000) | -0.113609 (0.0000) | -0.014294 (0.1386) |
| ***P2*** | 0.029233 (0.0158) | 0.023645 (0.0356) | 0.974549 (0.0000) | -0.105647 (0.0000) | -0.052793(0.0000) |
| **GARCH (1, 1) WITH NEWS INTENSITY CHANGES ESTIMATION** | | | | | |
| ***SONY*** | 0.204277 (0.0021) | 0.036114 (0.0000) | 0.905679 (0.0000) | - | 0.010776 (0.0000) |
| ***UFJ*** | 0.233396 (0.0000) | 0.115595 (0.0000) | 0.781416 (0.0000) | - | 0.000773 (0.3456) |
| ***MITS*** | 0.089436 (0.0000) | 0.090954(0.0000) | 0.862505 (0.0000) | - | 0.003457 (0.0010) |
| ***HOYA*** | 0.384717 (0.0000) | 0.085382 (0.0000) | 0.814439 (0.0000) | - | 0.000326 (0.2232) |
| ***P1*** | 0.074096 (0.0000) | 0.058113 (0.0000) | 0.907827 (0.0000) | - | 0.004032 (0.0000) |
| ***P2*** | 0.097361 (0.0001) | 0.071707 (0.0000) | 0.883509 (0.0000) | - | 0.002876 (0.0026) |
| **EGARCH (1, 1) WITH NEWS INTENSITY CHANGES ESTIMATION** | | | | | |
| ***SONY*** | 0.022859 (0.1193) | 0.035896 (0.0251) | 0.958339 (0.0000) | -0.082910 (0.0000) | 0.003612 (0.0000) |
| ***UFJ*** | -0.080293 (0.0000) | 0.178326 (0.0000) | 0.934458 (0.0000) | -0.026057 (0.0000) | 0.000385 (0.3358) |
| ***MITS*** | -0.096211 (0.0000) | 0.159948 (0.0000) | 0.960736 (0.0000) | -0.024839 (0.0142) | 0.002078 (0.0001) |
| ***HOYA*** | 0.008378 (0.5430) | 0.075732 (0.0000) | 0.950052 (0.0000) | -0.121970 (0.0000) | 0.000089 (0.8261) |
| ***P1*** | -0.020452 (0.1152) | 0.059995 (0.0003) | 0.965762(0.0000) | -0.113536 (0.0000) | 0.002116 (0.0000) |
| ***P2*** | -0.034615 (0.0075) | 0.079320 (0.0000) | 0.964784 (0.0000) | -0.112609 (0.0000) | 0.001493 (0.0017) |

**Notes:** This table shows the GARCH estimation results in Japan. The estimation results for the GARCH model after adding the VIX index as an extra variable are included in the tables. 5% significance level means that the probability of the observed result being due to chance is less than 5%. In other words, if the p-value is less than 0.05, there is strong evidence against the null hypothesis, and the result is considered statistically significant. Similarly, a p-value between 0.05 and 0.1 means that there is a 10% chance that the observed effect is due to an event. This result is still considered significant but with a lower level of confidence. On the other hand, if the p-value is greater than 0.1, there is a high chance that the observed result is due to an event, and the result is considered non-significant.

SONY is short for “SONY”, which was selected from the technology industry. UFJ is the “MISUBISHI”, representing the financial industry. MITS is” MITSUI &Co”, from the energy sector, and HOYA is” HOYA Crop”, from the health and care industry. P1 is the equal-weighted portfolio and P2 is the market cap-weighted portfolio.

## Table B7 The GARCH estimation results in Japan (Continued)

| GARCH (1, 1) WITH POSITIVE NEWS ESTIMATION | | | | | | |
|---|---|---|---|---|---|---|
| | **Ʊ (p-VALUE)** | **α (p-value)** | **β (p-value)** | **γ(p-value)** | **Positive news** | **Positive news at t-1** |
| ***SONY*** | 0.652546 (0.0000) | 0.064906 (0.0000) | 0.696363 (0.0000) | - | 0.651939 (0.0000) | |
| | 0.346727 (0.0000) | 0.053562 (0.0000) | 0.853562 (0.0000) | | - | -0.011639 (0.8794) |
| ***UFJ*** | 0.255168 (0.0000) | 0.115517 (0.0000) | 0.784049(0.0000) | - | -0.12204 (0.0888) | |
| | 0.246139 (0.0000) | 0.114455 (0.0000) | 0.787425(0.0000) | | | -0.102268(0.1503) |
| ***MITS*** | 0.101357 (0.0001) | 0.098323 (0.0000) | 0.848778 (0.0000) | - | 0.005965 (0.9272) | |
| | 0.114472 (0.0001) | 0.101991(0.0000) | 0.842693(0.0000) | | | -0.056740(0.3512) |
| ***HOYA*** | 0.323073(0.0000) | 0.081939 (0.0000) | 0.824227(0.0000) | - | 0.399617(0.0514) | |
| | 0.406766(0.0000) | 0.085985(0.0000) | 0.808563(0.0000) | | | -0.129870 (0.5259) |
| ***P1*** | 0.123905 (0.0018) | 0.057626 (0.0000) | 0.900898 (0.0000) | - | -0.176126(0.0730) | |
| | 0.143976 (0.0004) | 0.059122 (0.0000) | 0.896410 (0.0000) | | | -0.246371 (0.0102) |
| ***P2*** | 0.151078 (0.0004) | 0.066973(0.0000) | 0.881273 (0.0000) | - | -0.229327(0.0223) | |
| | 0.159275 (0.0001) | 0.067011(0.0000) | 0.880060(0.0000) | | | -0.262682 (0.0032) |
| **EGARCH (1, 1) WITH POSITIVE NEWS ESTIMATION** | | | | | | |
| ***SONY*** | 0.067055 (0.0775) | 0.123360 (0.0000) | 0.839874(0.0000) | -0.005669 (0.0119) | 0.138324(0.0000) | |
| | 0.007252 (0.7075) | 0.072748 (0.0000) | 0.952085 (0.0000) | -0.052334 (0.0001) | | 0.004020 (0.7564) |
| ***UFJ*** | -0.071864(0.0000) | 0.180472 (0.0000) | 0.934435 (0.0000) | -0.022545 (0.0000) | -0.043201(0.1643) | |
| | -0.072818(0.0000) | 0.177738(0.0000) | 0.936060(0.0000) | -0.023487(0.0234) | | -0.035606 (0.2404) |
| ***MITS*** | -0.102570(0.0000) | 0.170422 (0.0000) | 0.955484 (0.0000) | -0.028993 (0.0193) | 0.016977 (0.6612) | |
| | -0.098190(0.0000) | 0.171269 (0.0000) | 0.955332 (0.0000) | -0.028818(0.0153) | | -0.012050 (0.7440) |
| ***HOYA*** | -0.001516(0.9074) | 0.067829 (0.0000) | 0.955351 (0.0000) | -0.121465 (0.0000) | 0.110040(0.0076) | |
| | 0.004997 (0.7089) | 0.070626(0.0000) | 0.953060(0.0000) | -0.120213(0.0000) | | 0.039997 (0.2982) |
| ***P1*** | 0.013641 (0.3473) | 0.040752 (0.0067) | 0.962356 (0.0000) | -0.119432(0.0000) | -0.085073 (0.0157) | |
| | 0.020177 (0.1454) | 0.038862 (0.0099) | 0.961456(0.0000) | -0.121514 (0.0000) | | -0.108447(0.0021) |
| ***P2*** | 0.015326 (0.2638) | 0.043851 (0.0000) | 0.964840(0.0000) | -0.111564 (0.0000) | -0.129211 (0.0005) | |
| | 0.019787 (0.1334) | 0.042154 (0.0020) | 0.964261(0.0000) | -0.112117(0.0000) | | -0.145291 (0.0001) |
| **GARCH (1, 1) WITH NEGATIVE NEWS ESTIMATION** | | | | | | |
| | **Ʊ (p-VALUE)** | **α (p-value)** | **β (p-value)** | **γ(p-value)** | **negative news** | **negative news at t-1** |
| **SONY** | 0.353640 (0.0001) | 0.055567 (0.0000) | 0.844235 (0.0000) | - | 0.077419 (0.4916) | |
| | 0.349933 (0.0000) | 0.054040(0.0000) | 0.850347(0.0000) | | | 0.013648 (0.8855) |
| **UFJ** | 0.264728 (0.0000) | 0.117612 (0.0000) | 0.780394 (0.0000) | - | -0.219671 (0.0161) | |
| | 0.266228 (0.0000) | 0.121089(0.0000) | 0.775893(0.0000) | | | -0.205776 (0.0505) |
| **MITS** | 0.102955 (0.0000) | 0.098824 (0.0000) | 0.849395 (0.0000) | - | -0.023933 (0.7487) | |
| | 0.103754(0.0000) | 0.098841(0.0000) | 0.851697(0.0000) | | | -0.067045(0.3336) |
| **HOYA** | 0.380974 (0.0000) | 0.082863(0.0000) | 0.816493 (0.0000) | - | -0.119715(0.6386) | |
| | 0.375813 (0.0000) | 0.082230 (0.0000) | 0.818636 (0.0000) | | | -0.141558 (0.0000) |
| **P1** | 0.074639 (0.0106) | 0.065076(0.0000) | 0.885676(0.0000) | - | 0.254925(0.1088) | |
| | 0.074395 (0.0111) | 0.063299(0.0000) | 0.890019(0.0000) | | | 0.212962 (0.1521) |
| **P2** | 0.106209 (0.0002) | 0.074858 (0.0000) | 0.874319 (0.0000) | - | 0.030413 (0.8207) | |
| | 0.103477 (0.0004) | 0.074238(0.0000) | 0.875203 (0.0000) | | | 0.048550 (0.7266) |
| **EGARCH (1, 1) WITH NEGATIVE NEWS ESTIMATION** | | | | | | |
| **SONY** | 0.010729 (0.5581) | 0.071605 (0.0000) | 0.956525 (0.0000) | -0.054983 (0.0000) | -0.033100 (0.1007) | |
| | 0.010809 (0.5586) | 0.072548 (0.0000) | 0.956074(0.0000) | -0.054747(0.0000) | | -0.034116(0.0633) |
| **UFJ** | -0.071544 (0.0000) | 0.18818 (0.0000) | 0.929295 (0.0003) | -0.030705(0.0052) | -0.085672 (0.0675) | |
| | -0.075306(0.0000) | 0.184499(0.0000) | 0.931472(0.0000) | -0.028619(0.0000) | | -0.049101 (0.3089) |
| **MITS** | -0.098212 (0.0000) | 0.170099 (0.0000) | 0.958500 (0.0000) | -0.028357(0.0090) | -0.030257 (0.3802) | |
| | -0.096205 (0.000) | 0.168627(0.0000) | 0.960272(0.0000) | -0.028320(0.0081) | | -0.046737(0.1459) |
| **HOYA** | 0.013207 (0.3011) | 0.058467 (0.0000) | 0.958073 (0.0000) | -0.117295(0.0000) | -0.101552(0.0158) | |
| | 0.013568 (0.2870) | 0.057879 (0.0000) | 0.958302 (0.0000) | -0.117264 (0.0000) | | -0.108880 (0.0161) |
| **P1** | -0.005263(0.7103) | 0.050399 (0.0018) | 0.965999( 0.0000) | -0.117126 (0.0000) | -0.058219 (0.0000) | |
| | -0.003739(0.7874) | 0.049581 (0.0019) | 0.966483(0.0000) | -0.117189 (0.0000) | | -0.068428 (0.1388) |
| **P2** | -0.013797 (0.3262) | 0.065417 (0.0000) | 0.966540 (0.0000) | -0.116801 (0.0000) | -0.096765 (0.0691) | |
| | -0.016246 (0.2535) | 0.067081 (0.0000) | 0.966225 (0.0000) | -0.115990 (0.0000) | | -0.084593 (0.1275) |

**Notes:** This table shows the GARCH estimation results in Japan. The estimation results for the GARCH model after adding the VIX index as an extra variable are included in the tables. 5% significance level means that the probability of the observed result being due to chance is less than 5%. SONY is short for "SONY", which was selected from the technology industry. UFJ is the "MISUBISHI", representing the financial industry. MITS is" MITSUI &Co", from the energy sector, and HOYA is" HOYA Crop", from the health and care industry. P1 is the equal-weighted portfolio and P2 is the market cap-weighted portfolio.

# Table B7 The GARCH estimation results in Japan (Continued)

| | | | | | | |
|---|---|---|---|---|---|---|
| **GARCH (1, 1) WITH LOG NEWS INTENSITY AND VIX** | | | | | | |
| | **ʊ (p-VALUE)** | **$\alpha$ (p-value)** | **$\beta$ (p-value)** | **γ(p-value)** | **News intensity** | **VIX** |
| ***SONY*** | 2.102831 (0.0000) | 0.045576 (0.0000) | 0.132842 (0.1684) | - | 1.098283 (0.0000) | 0.033663 (0.0000) |
| ***UFJ*** | 0.038521 (0.0039) | 0.021751 (0.0000) | 0.964361 (0.0000) | - | -0.021810 (0.1131) | 0.028246 (0.0000) |
| ***MITS*** | 0.026331 (0.0028) | 0.042429 (0.0000) | 0.941810 (0.0000) | - | 0.006715(0.6587) | 0.019500 (0.0000) |
| ***HOYA*** | 0.061417 (0.0066) | 0.018901 (0.0000) | 0.969005 (0.0000) | - | 0.076082 (0.2533) | 0.041983 (0.0000) |
| ***P1*** | 0.035247 (0.0000) | 0.000186 (0.0000) | 0.994330 (0.0000) | - | -0.038501 (0.0000) | 0.025972 (0.0000) |
| ***P2*** | 0.032649 (0.0000) | 0.006164 (0.0000) | 0.992030 (0.0000) | - | -0.045311 (0.0000) | 0.023674 (0.0000) |
| **EGARCH (1, 1) WITH LOG NEWS INTENSITY AND VIX** | | | | | | |
| ***SONY*** | 0.767410 (0.0000) | 0.045682 (0.2749) | 0.138393 (0.0000) | -0.073226 (0.0319) | 0.138393 (0.1260) | 0.319320 (0.0000) |
| ***UFJ*** | 0.001725 (0.5508) | -0.007344 (0.0324) | 1.000411 (0.0000) | 0.028444 (0.0000) | 0.008504 (0.0000) | 0.018384 (0.0000) |
| ***MITS*** | -0.058083(0.0000) | 0.090724 (0.0000) | 0.984729 (0.0000) | 0.017499 (0.0000) | -0.004866 (0.6065) | 0.015340 (0.0000) |
| ***HOYA*** | -0.004366(0.6738) | 0.038270 (0.0000) | 0.978461 (0.0000) | -0.068414 (0.0000) | 0.017239 (0.3806) | 0.011505 (0.0000) |
| ***P1*** | 0.003299(0.7746) | 0.0025700 (0.0318) | 0.983354 (0.0000) | -0.046851 (0.0008) | -0.020438 (0.0000) | 0.013512 (0.0000) |
| ***P2*** | 0.027839(0.0111) | 0.004284 (0.6575) | 0.986488 (0.0000) | -0.049387 (0.0000) | -0.043727 (0.0000) | 0.012887 (0.0000) |
| **GARCH (1, 1) WITH LOG NEWS INTENSITY CHANGES AND VIX** | | | | | | |
| | **ʊ (p-VALUE)** | **$\alpha$ (p-value)** | **$\beta$ (p-value)** | **γ(p-value)** | **News intensity changes** | **VIX** |
| ***SONY*** | 0.107778 (0.0026) | 0.013281 (0.0054) | 0.954786 (0.0000) | - | 0.010803 (0.0000) | 0.034388 (0.0000) |
| ***UFJ*** | 0.020442 (0.0005) | 0.018000 (0.0000) | 0.971574 (0.0000) | - | 0.000887 (0.1901) | 0.029198 (0.0000) |
| ***MITS*** | 0.038595 (0.0002) | 0.048645 (0.0000) | 0.929399 (0.0000) | - | 0.003202 (0.0000) | 0.018194 (0.0000) |
| ***HOYA*** | 0.059850 (0.0019) | 0.015824 (0.0004) | 0.966678 (0.0000) | - | 0.000025 (0.8545) | 0.043083 (0.0000) |
| ***P1*** | 0.034121 (0.0012) | 0.018148 (0.0020) | 0.963974 (0.0000) | - | 0.003064 (0.0000) | 0.027743(0.0000) |
| ***P2*** | 0.030813 (0.0006) | 0.020073 (0.0000) | 0.963560 (0.0000) | - | 0.001963 (0.0378) | 0.028448 (0.0000) |
| **EGARCH (1, 1) WITH LOG NEWS INTENSITY CHANGES AND VIX** | | | | | | |
| ***SONY*** | 0.008443(0.5257) | 0.028068 (0.0358) | 0.973913 (0.0000) | -0.039805 (0.0095) | 0.003660 (0.0000) | 0.010300 (0.0000) |
| ***UFJ*** | 0.004026(0.3968) | 0.010838 (0.0915) | 0.994367 (0.0000) | 0.024340 (0.0000) | 0.000657 (0.0750) | 0.017856 (0.0000) |
| ***MITS*** | 0.057868(0.0000) | 0.088214 (0.0000) | 0.984286 (0.0000) | 0.018760 (0.0000) | 0.002385 (0.0000) | 0.015602 (0.0000) |
| ***HOYA*** | -0.001994(0.8457) | 0.035781 (0.0056) | 0.979425 (0.0000) | -0.065215(0.0000) | -0.000012 (0.7698) | 0.011678 (0.0000) |
| ***P1*** | -0.018812(0.0778) | 0.038392 (0.0045) | 0.982523 (0.0000) | -0.052051(0.0000) | 0.002232 (0.0000) | 0.013685 (0.0000) |
| ***P2*** | -0.027649(0.0118) | 0.047746 (0.0007) | 0.985217 (0.0000) | -0.047746 (0.0007) | 0.001365 (0.0137) | 0.014421 (0.0000) |

**Notes:** This table shows the GARCH estimation results in Japan. The estimation results for the GARCH model after adding the VIX index as an extra variable are included in the tables. 5% significance level means that the probability of the observed result being due to chance is less than 5%.

SONY is short for “SONY”, which was selected from the technology industry. UFJ is the “MISUBISHI”, representing the financial industry. MITS is” MITSUI &Co”, from the energy sector, and HOYA is” HOYA Crop”, from the health and care industry. P1 is the equal-weighted portfolio and P2 is the market cap-weighted portfolio.

## Table B7 The GARCH estimation results in Japan (Continued)

| | | | | | | |
|---|---|---|---|---|---|---|
| **GARCH (1, 1) WITH POSITIVE NEWS AND VIX** | | | | | | |
| | **℧(p-VALUE)** | ***α* (p-value)** | ***β* (p-value)** | **γ(p-value)** | **Positive news** | **VIX** |
| ***SONY*** | 0.535973(0.0001) | 0.059562 (0.0003) | 0.739892 (0.0000) | - | 0.567002 (0.0000) | 0.038893 (0.0000) |
| ***UFJ*** | 0.029038(0.0000) | 0.019773 (0.0000) | 0.967840 (0.0000) | - | -0.018529 (0.4148) | 0.028507 (0.0000) |
| ***MITS*** | 0.028168(0.0029) | 0.042922 (0.0000) | 0.941545 (0.0000) | - | -0.002438 (0.9444) | 0.019491 (0.0000) |
| ***HOYA*** | 0.034960(0.0444) | 0.011768 (0.0016) | 0.973300 (0.0000) | - | 0.211122 (0.0017) | 0.042078 (0.0000) |
| ***P1*** | 0.058602(0.0003) | 0.007853 (0.0157) | 0.974418 (0.0000) | - | -0.121750(0.0033) | 0.031640 (0.0000) |
| ***P2*** | 0.051432(0.0000) | 0.008037 (0.0100) | 0.975442 (0.0000) | - | -0.109940 (0.0006) | 0.029746 (0.0000) |
| **EGARCH (1, 1) WITH POSITIVE NEWS AND VIX** | | | | | | |
| ***SONY*** | -0.001517(0.9095) | 0.049091 (0.0001) | 0.972246 (0.0000) | -0.017601 (0.1337) | 0.000291 (0.9760) | 0.010319(0.0000) |
| ***UFJ*** | -0.004321(0.3798) | 0.012939 (0.0727) | 0.993731 (0.0000) | 0.023071 (0.0000) | -0.003680 (0.6422) | 0.017634 (0.0000) |
| ***MITS*** | -0.056256(0.0000) | 0.090553 (0.0000) | 0.984461 (0.0000) | 0.020212 (0.0797) | -0.022248 (0.3736) | 0.015560 (0.0000) |
| ***HOYA*** | -0.006384(0.5087) | 0.031303 (0.0094) | 0.981069 (0.0000) | -0.064883 (0.0000) | 0.075187 (0.0050) | 0.011171 (0.0000) |
| ***P1*** | 0.018073(0.2060) | 0.019123 (0.1464) | 0.975880 (0.0000) | -0.062291 (0.0001) | -0.091825 (0.0030) | 0.014292 (0.0000) |
| ***P2*** | 0.012011(0.3650) | 0.024151 (0.0660) | 0.978690 (0.0000) | -0.059444 (0.0000) | -0.100086 (0.0007) | 0.014054 (0.0000) |
| **GARCH (1, 1) WITH POSITIVE NEWS AT TIME T-1 AND VIX** | | | | | | |
| | **℧ (p-VALUE)** | ***α* (p-value)** | ***β* (p-value)** | **γ(p-value)** | **Positive news(t-1)** | **VIX** |
| ***SONY*** | 0.129548 (0.0003) | 0.018064 (0.0001) | 0.954209 (0.0000) | - | -0.090214 (0.0133) | 0.039890 (0.0000) |
| ***UFJ*** | 0.028677 (0.0082) | 0.019608 (0.0000) | 0.968125 (0.0000) | - | -0.018104 (0.4166) | 0.028517 (0.0000) |
| ***MITS*** | 0.031071 (0.0014) | 0.044220 (0.0000) | 0.939790 (0.0000) | - | -0.017450 (0.5961) | 0.019479 (0.0000) |
| ***HOYA*** | 0.042018 (0.0241) | 0.011921 (0.0013) | 0.973463 (0.0000) | - | 0.105534 (0.0827) | 0.042737 (0.0000) |
| ***P1*** | 0.065068 (0.0002) | 0.008094 (0.0177) | 0.972820 (0.0000) | - | -0.140748 (0.0016) | 0.032033 (0.0000) |
| ***P2*** | 0.053798 (0.0000) | 0.008038 (0.0097) | 0.975021 (0.0000) | - | -0.118544 (0.0002) | 0.029856 (0.0000) |
| **EGARCH (1, 1) WITH POSITIVE NEWS AT TIME T-1 AND VIX** | | | | | | |
| ***SONY*** | 0.003519 (0.7896) | 0.047180 (0.0001) | 0.973244 (0.0000) | -0.015801 (0.1685) | -0.014199 (0.1422) | 0.010848 (0.0000) |
| ***UFJ*** | -0.004327(0.3809) | 0.013077 (0.0717) | 0.993689 (0.0000) | 0.022946 (0.0000) | -0.003991 (0.6183) | 0.017619 (0.0000) |
| ***MITS*** | -0.054818(0.0000) | 0.090780 (0.0000) | 0.984465 (0.0000) | 0.021723 (0.0545) | -0.034399 (0.1588) | 0.015668 (0.0000) |
| ***HOYA*** | -0.004488(0.6346) | 0.031200 (0.0101) | 0.981375 (0.0000) | -0.062365 (0.0000) | 0.048314 (0.0592) | 0.011347 (0.0000) |
| ***P1*** | 0.024412 (0.0878) | 0.016521 (0.2201) | 0.974297 (0.0000) | -0.066368 (0.0000) | -0.109548 (0.0005) | 0.014431 (0.0000) |
| ***P2*** | 0.016689 (0.2072) | 0.022102 (0.0959) | 0.977445 (0.0000) | -0.062702 (0.0000) | -0.113601 (0.0001) | 0.014011 (0.0000) |

**Notes:** This table shows the GARCH estimation results in Japan. The estimation results for the GARCH model after adding the VIX index as an extra variable are included in the tables. 5% significance level means that the probability of the observed result being due to chance is less than 5%. SONY is short for “SONY”, which was selected from the technology industry. UFJ is the “MISUBISHI”, representing the financial industry. MITS is” MITSUI &Co”, from the energy sector, and HOYA is” HOYA Crop”, from the health and care industry. P1 is the equal-weighted portfolio and P2 is the market cap-weighted portfolio.

## Table B7 The GARCH estimation results in Japan (Continued)

| | | | | | | |
|---|---|---|---|---|---|---|
| **GARCH (1, 1) WITH NEGATIVE NEWS AND VIX** | | | | | | |
| | **Ʊ (p-VALUE)** | **$\alpha$ (p-value)** | **$\beta$ (p-value)** | **γ(p-value)** | **Negative news** | **VIX** |
| ***SONY*** | 0.111467 (0.0019) | 0.018557 (0.0001) | 0.950205 (0.0000) | - | -0.001369 (0.9796) | 0.038551 (0.0000) |
| ***UFJ*** | 0.045430 (0.0004) | 0.021425 (0.0000) | 0.963552 (0.0000) | - | -0.103406 (0.0059) | 0.030097 (0.0000) |
| ***MITS*** | 0.029470 (0.0005) | 0.042993 (0.0000) | 0.942759 (0.0000) | - | -0.035003 (0.3007) | 0.019535 (0.0000) |
| ***HOYA*** | 0.042234 (0.0007) | 0.007134 (0.0111) | 0.981607 (0.0000) | - | -0.198985 (0.0000) | 0.044941 (0.0000) |
| ***P1*** | 0.032424 (0.0004) | 0.013586 (0.0013) | 0.972744 (0.0000) | - | -0.051639 (0.2561) | 0.029200 (0.0000) |
| ***P2*** | 0.018082 (0.0000) | 0.003971 (0.0000) | 0.972949 (0.0000) | - | -0.136681 (0.0000) | 0.023857 (0.0000) |
| **EGARCH (1, 1) WITH NEGATIVE NEWS AND VIX** | | | | | | |
| ***SONY*** | 0.000546 (0.9681) | 0.050693 (0.0001) | 0.972007 (0.0000) | -0.019950 (0.1119) | -0.013543 (0.4302) | 0.010201 (0.0000) |
| ***UFJ*** | 0.005173 (0.1672) | -0.009142 (0.0252) | 0.998571 (0.0000) | 0.029453 (0.0000) | 0.029010 (0.0000) | 0.018001 (0.0000) |
| ***MITS*** | -0.052965(0.0000) | 0.084892 (0.0000) | 0.987310 (0.0000) | 0.017438 (0.0978) | -0.030871 (0.1173) | 0.015437 (0.0000) |
| ***HOYA*** | 0.012071 (0.0987) | 0.008445 (0.2570) | 0.987067 (0.0000) | -0.054568 (0.0000) | -0.133430 (0.0000) | 0.011454 (0.0000) |
| ***P1*** | 0.000447 (0.0000) | 0.024018 (0.0000) | 0.989465 (0.0000) | -0.042842 (0.0013) | -0.100816 (0.0001) | 0.013565 (0.0000) |
| ***P2*** | 0.022832 (0.0034) | -0.014904(0.0800) | 0.998034 (0.0000) | -0.005250 (0.5003) | -0.008151(0.4170) | 0.015172 (0.0000) |
| **GARCH (1, 1) WITH NEGATIVE NEWS AT TIME T-1 AND VIX** | | | | | | |
| | **Ʊ (p-VALUE)** | **$\alpha$ (p-value)** | **$\beta$ (p-value)** | **γ(p-value)** | **Negative news(t-1)** | **VIX** |
| ***SONY*** | 0.109715 (0.0020) | 0.018471 (0.0001) | 0.950463 (0.0000) | - | 0.004030 (0.9392) | 0.038550 (0.0000) |
| ***UFJ*** | 0.043145 (0.0004) | 0.020934 (0.0000) | 0.964628 (0.0000) | - | -0.096067 (0.0072) | 0.030001 (0.0000) |
| ***MITS*** | 0.031313 (0.0003) | 0.044033 (0.0000) | 0.941663 (0.0000) | - | -0.050290 (0.1212) | 0.019386 (0.0000) |
| ***HOYA*** | 0.041085 (0.0007) | 0.006376 (0.0226) | 0.982816 (0.0000) | - | -0.219599 (0.0000) | 0.045108 (0.0000) |
| ***P1*** | 0.033025 (0.0003) | 0.013208 (0.0016) | 0.973392 (0.0000) | - | -0.061173 (0.1720) | 0.029182 (0.0000) |
| ***P2*** | 0.019606 (0.0000) | 0.003611 (0.0000) | 0.982204 (0.0000) | - | -0.144606 (0.0000) | 0.024225 (0.0000) |
| **EGARCH (1, 1) WITH NEGATIVE NEWS AT TIME T-1 AND VIX** | | | | | | |
| ***SONY*** | 0.000576(0.9662) | 0.050805 (0.0001) | 0.971898 (0.0000) | -0.019829 (0.1056) | -0.013457 (0.4075) | 0.010200 (0.0000) |
| ***UFJ*** | 0.004868(0.1843) | -0.08847 (0.0254) | 0.998513 (0.0000) | 0.029467 (0.0000) | 0.029715 (0.0000) | 0.017886 (0.0000) |
| ***MITS*** | -0.051524(0.0000) | 0.083871 (0.0000) | 0.987813 (0.0000) | 0.017914 (0.0880) | -0.039229 (0.0385) | 0.015441 (0.0000) |
| ***P1*** | 0.003376 (0.6962) | 0.020422 (0.0426) | 0.991028 (0.0000) | -0.039731 (0.0014) | -0.111283 (0.0000) | 0.013523 (0.0000) |
| ***P2*** | 0.023194 (0.0043) | -0.015193 (0.0876) | 0.997879 (0.0000) | -0.003422 (0.6639) | -0.095130 (0.0000) | 0.015277 (0.0000) |

**Notes:** This table shows the GARCH estimation results in Japan. The estimation results for the GARCH model after adding the VIX index as an extra variable are included in the tables. 5% significance level means that the probability of the observed result being due to chance is less than 5%. SONY is short for “SONY”, which was selected from the technology industry. UFJ is the “MISUBISHI”, representing the financial industry. MITS is” MITSUI &Co”, from the energy sector, and HOYA is” HOYA Crop”, from the health and care industry. P1 is the equal-weighted portfolio and P2 is the market cap-weighted portfolio.

# Table B8 The GARCH estimation results in Korea

| | | | | | |
|---|---|---|---|---|---|
| **GARCH (1, 1)** | | | | | |
| | **Ʊ (p-VALUE)** | ***α*** **(p-value)** | ***β*** **(p-value)** | **γ(p-value)** | |
| ***CTN*** | 0.392182 (0.0000) | 0.079853 (0.0000) | 0.876457 (0.0000) | | |
| ***KBF*** | 0.155233 (0.0000) | 0.067036 (0.0000) | 0.890082 (0.0000) | | |
| ***SMS*** | 0.098421 (0.0000) | 0.048528 (0.0000) | 0.912577 (0.0000) | | |
| ***SKN*** | 0.029384 (0.0002) | 0.038224 (0.0000) | 0.959036 (0.0000) | | |
| ***P1*** | 0.085232 (0.0000) | 0.070670 (0.0000) | 0.905177 (0.0000) | | |
| ***P2*** | 0.097524 (0.0000) | 0.051763 (0.0000) | 0.903675 (0.0000) | | |
| **EGARCH (1, 1)** | | | | | |
| ***CTN*** | -0.064718 (0.0001) | 0.196355 (0.0000) | 0.196355 (0.0000) | -0.023990(0.0190) | |
| ***KBF*** | -0.064289 (0.0000) | 0.142160 (0.0000) | 0.968136 (0.0000) | -0.053842(0.0000) | |
| ***SMS*** | -0.051673 (0.0001) | 0.117605 (0.0000) | 0.960979 (0.0000) | -0.034615(0.0010) | |
| ***SKN*** | -0.059949 (0.0000) | 0.083312 (0.0000) | 1.001731 (0.0000) | -0.035457 (0.0000) | |
| ***P1*** | -0.093571 (0.0000) | 0.166169 (0.0000) | 0.975169 (0.0000) | -0.004932(0.0000) | |
| ***P2*** | -0.058630 (0.0000) | 0.129833 (0.0000) | 0.950564 (0.0000) | -0.036966 (0.0010) | |
| **GARCH (1, 1) WITH LOG NEWS INTENSITY** | | | | | |
| | **Ʊ (p-VALUE)** | ***α*** **(p-value)** | ***β*** **(p-value)** | **γ(p-value)** | **News intensity** |
| ***CTN*** | 2.831782 (0.0000) | 0.115502 (0.0000) | 0.308441 (0.0000) | - | 11.21617 (0.0000) |
| ***KBF*** | 0.167538 (0.0000) | 0.071613 (0.0000) | 0.875894(0.0000) | - | 0.141579 (0.2785) |
| ***SMS*** | 0.066485 (0.0788) | 0.047416(0.0000) | 0.913760 (0.0000) | - | 0.017578 (0.3566) |
| ***SKN*** | 0.552108 (0.0000) | 0.146151 (0.0000) | 0.727536 (0.0000) | - | 2.393254 (0.0000) |
| ***P1*** | 0.032966 (0.3319) | 0.082386 (0.0000) | 0.880118 (0.0000) | - | 0.094635 (0.0082) |
| ***P2*** | 0.076882 (0.0337) | 0.051388 (0.0000) | 0.904172 (0.0000) | - | 0.011621 (0.5068) |
| **EGARCH (1, 1) WITH LOG NEWS INTENSITY** | | | | | |
| ***CTN*** | 0.699121 (0.0000) | 0.299395 (0.0000) | 0.452352 (0.0000) | -0.070372 (0.036) | 0.882428 (0.0000) |
| ***KBF*** | -0.065093 (0.0000) | 0.147740(0.0000) | 0.962544 (0.0000) | -0.055689(0.0000) | 0.021892 (0.0000) |
| ***SMS*** | -0.052415 (0.0068) | 0.117497 (0.0000) | 0.960901 (0.0000) | -0.034550 (0.0014) | 0.000491 (0.9547) |
| ***SKN*** | -0.054134 (0.0000) | 0.074099 (0.0000) | 1.003146 (0.0000) | -0.038403 (0.0000) | -0.009896 (0.1217) |
| ***P1*** | -0.126601 (0.0000) | 0.180206 (0.0000) | 0.965293 (0.0000) | -0.008209 (0.0000) | 0.032408 (0.0045) |
| ***P2*** | -0.052725 (0.0150) | 0.128721 (0.0000) | 0.950927 (0.0000) | -0.035919 (0.0000) | -0.003314(0.7264) |
| **GARCH (1, 1) WITH NEWS INTENSITY CHANGES** | | | | | |
| ***CTN*** | 0.356524 (0.0000) | 0.0064348(0.0000) | 0.892112 (0.0000) | - | 0.056078 (0.0000) |
| ***KBF*** | 0.189474 (0.0000) | 0.070597 (0.0000) | 0.876584 (0.0000) | - | 0.007802 (0.0176) |
| ***SMS*** | 0.103364 (0.0000) | 0.049376(0.0000) | 0.909759 (0.0000) | - | 0.000033 (0.9583) |
| ***SKN*** | 0.049815 (0.0000) | 0.043409 (0.0000) | 0.951327 (0.0000) | - | 0.037238 (0.0000) |
| ***P1*** | 0.082238 (0.0000) | 0.066795 (0.0000) | 0.910327 (0.0000) | - | 0.007235 (0.0000) |
| ***P2*** | 0.102752 (0.0000) | 0.052770 (0.0000) | 0.900284 (0.0000) | - | 0.000168 (0.7855) |
| **EGARCH (1, 1) WITH NEWS INTENSITY CHANGES** | | | | | |
| ***CTN*** | -0.068884 (0.0000) | 0.174177 (0.0000) | 0.972407 (0.0000) | -0.025500 (0.0051) | 0.006981 (0.0000) |
| ***KBF*** | -0.065526 (0.0000) | 0.153689 (0.0000) | 0.961916 (0.0000) | -0.056521 (0.0000) | 0.002967 (0.0013) |
| ***SMS*** | -0.050996 (0.0002) | 0.119989 (0.0000) | 0.958291 (0.0000) | -0.035592 (0.0014) | -0.000123 (0.6838) |
| ***SKN*** | -0.067872 (0.0000) | 0.097423 (0.0000) | 1.000191 (0.0000) | -0.036454 (0.0000) | 0.006173 (0.0000) |
| ***P1*** | -0.092418 (0.0000) | 0.159267 (0.0000) | 0.978507 (0.0000) | -0.003496 (0.6785) | 0.002148 (0.0001) |
| ***P2*** | -0.057984 (0.0001) | 0.132484 (0.0000) | 0.947113 (0.0000) | -0.038023 (0.0014) | 0.000065 (0.8427) |

**Notes:** This table shows the GARCH estimation results in Korea. The estimation results for the GARCH model after adding the VIX index as an extra variable are included in the tables. 5% significance level means that the probability of the observed result being due to chance is less than 5.

SMS is short for “SAMSUNG”, which was selected from the technology industry. KBF is the “KBF Financial group”, representing the financial industry. SKN is” SKINNOVATION”, from the energy sector, and CTN is” Celltrion”, from the health and care industry. P1 is the equal-weighted portfolio and P2 is the market cap-weighted portfolio.

# Table B8 The GARCH estimation results in Korea (Continued)

| | ℧ (p-VALUE) | $\alpha$ (p-value) | $\beta$ (p-value) | γ(p-value) | Positive news | Positive news at t-1 |
|---|---|---|---|---|---|---|
| **GARCH (1, 1) WITH POSITIVE NEWS** | | | | | | |
| ***CTN*** | 0.841759(0.0000) | 0.118916 (0.0000) | 0.712459 (0.0000) | - | 4.531617 (0.0000) | |
| | 0.463912 (0.0000) | 0.084803 (0.0000) | 0.835539 (0.0000) | | - | 1.665888 (0.0000) |
| ***KBF*** | 0.160793 (0.0000) | 0.066970 (0.0000) | 0.889912(0.0000) | - | -0.048964 (0.7072) | |
| | 0.165529 (0.0000) | 0.067218 (0.0000) | 0.889110(0.0000) | | | -0.07700(0.5264) |
| ***SMS*** | 0.107959 (0.0050) | 0.049010 (0.0000) | 0.910218 (0.0000) | - | -0.012506 (0.7837) | |
| | 0.093771 (0.0151) | 0.048979 (0.0000) | 0.912052(0.0000) | | | 0.01257 (0.7771) |
| ***SKN*** | 0.028160 (0.0022) | 0.039393 (0.0000) | 0.958825(0.0000) | - | 0.020075(0.7489) | |
| | 0.032785 (0.0005) | 0.038943(0.0000) | 0.959334(0.0000) | | | -0.047460 (0.3925) |
| ***P1*** | 0.037675 (0.1114) | 0.075231 (0.0000) | 0.883592 (0.0000) | - | 0.561622(0.0026) | |
| | 0.045258 (0.0353) | 0.068244 (0.0000) | 0.903692 (0.0000) | | | 0.287373 (0.0539) |
| ***P2*** | 0.113943 (0.0021) | 0.052927(0.0000) | 0.898739 (0.0000) | - | -0.022358(0.6229) | |
| | 0.096064 (0.0095) | 0.052381(0.0000) | 0.902113(0.0000) | | | 0.009570 (0.8299) |
| **EGARCH (1, 1) WITH POSITIVE NEWS** | | | | | | |
| ***CTN*** | -0.003255 (0.9047) | 0.226275 (0.0000) | 0.887361 0.0000) | -0.059425 (0.0000) | 0.495483(0.0000) | |
| | -0.051667 (0.0031) | 0.192091(0.0000) | 0.946027 (0.0000) | -0.040106 (0.0005) | | 0.190298 (0.0000) |
| ***KBF*** | -0.061498(0.0000) | 0.141909(0.0000) | 0.970210 (0.0000) | -0.052348 (0.0000) | -0.050277(0.1477) | |
| | -0.060652(0.0000) | 0.144065(0.0000) | 0.969565(0.0000) | -0.052799 (0.0000) | | -0.066422(0.0482) |
| ***SMS*** | -0.058566 0.0000) | 0.116027 (0.0000) | 0.964346(0.0000) | -0.035839 (0.0015) | 0.012998 (0.4706) | |
| | -0.060634(0.0001) | 0.118027 (0.0000) | 0.963049 (0.0000) | -0.036770 (0.0013) | | 0.017588 (0.3411) |
| ***SKN*** | -0.051072(0.0000) | 0.072233 (0.0000) | 1.002563 (0.0000) | -0.039284 (0.0000) | -0.033403(0.0024) | |
| | -0.049303 (0.0000) | 0.071957(0.0000) | 1.002474 (0.0000) | -0.039750(0.0000) | | -0.051581 (0.0000) |
| ***P1*** | -0.142010 (0.0000) | 0.188927 (0.0000) | 0.941954 (0.0000) | -0.031301(0.0054) | 0.373418 (0.0000) | |
| | -0.109291(0.0000) | 0.163329 (0.0000) | 0.969707(0.0000) | -0.011986 (0.0000) | | 0.130912(0.0200) |
| ***P2*** | -0.061943 (0.0001) | 0.129022 (0.0000) | 0.952107(0.0000) | -0.037549 (0.0016) | 0.007458 (0.7266) | |
| | -0.065116 (0.0001) | 0.131104 (0.0000) | 0.950384(0.0000) | -0.038988(0.0000) | | 0.015418 (0.4816) |
| **GARCH (1, 1) WITH NEGATIVE NEWS** | | | | | | |
| | **℧(p-VALUE)** | **$\alpha$ (p-value)** | **$\beta$ (p-value)** | **γ(p-value)** | **negative news** | **negative news at t-1** |
| **CTN** | 0.705089 (0.0001) | 0.097644 (0.0000) | 0.789870 (0.0000) | - | 5.245852 (0.0000) | |
| | 0.408135 (0.0000) | 0.078405(0.0000) | 0.868568(0.0000) | | | 1.154541 (0.0417) |
| **KBF** | 0.222388 (0.0000) | 0.078568 (0.0000) | 0.846580 (0.0000) | - | 0.671226 (0.0136) | |
| | 0.157335 (0.0000) | 0.067720 (0.0000) | 0.886915 (0.0000) | | | -0.098279 (0.6066) |
| **SMS** | 0.090223 (0.0003) | 0.050433 (0.0000) | 0.903106 (0.0000) | - | 0.048581 (0.3259) | |
| | 0.100458 (0.0000) | 0.050067(0.0000) | 0.905958 (0.0000) | | | 0.019104 (0.6942) |
| **SKN** | 0.024619 (0.0096) | 0.039572(0.0000) | 0.957776 (0.0000) | - | 0.117859 (0.2482) | |
| | 0.033111 (0.0007) | 0.039428 (0.0000) | 0.959384 (0.0000) | | | -0.077319 (0.4397) |
| **P1** | 0.096613 (0.0076) | 0.068551(0.0000) | 0. 909459(0.0000) | - | -0.096858(0.5950) | |
| | 0.139337 (0.0000) | 0.066309(0.0000) | 0.916687(0.0000) | | | -0.399841 (0.0209) |
| **P2** | 0.088960 (0.0006) | 0.054411 (0.0000) | 0.892134 (0.0000) | - | 0.053249 (0.2773) | |
| | 0.079976 (0.0043) | 0.055524 (0.0000 | 0.888191 (0.0000) | | | 0.082613 (0.1023) |
| **EGARCH (1, 1) WITH NEGATIVE NEWS** | | | | | | |
| **CTN** | -0.019747 (0.3198) | 0.213294 (0.0000) | 0.927508 (0.0000) | -0.018242 (0.1228) | 0.334187 (0.0000) | |
| | -0.064060 (0.0001) | 0.196141 (0.0000) | 0.964401(0.0000) | -0.023727(0.0245) | | 0.005489(0.9165) |
| **KBF** | -0.065196 (0.0000) | 0.160363 (0.0000) | 0.949907(0.0000) | -0.059623 (0.0000) | -0.141546 (0.0153) | |
| | -0.064224 (0.0000) | 0.143341 (0.0000) | 0.965853(0.0000) | -0.054749(0.0000) | | 0.027571 (0.5740) |
| **SMS** | -0.051779 (0.0031) | 0.117644 (0.0000) | 0.960897 (0.0000) | -0.034589(0.0026) | 0.000271 (0.9886) | |
| | -0.049276 (0.0000) | 0.119068 (0.0000) | 0.960082(0.0000) | -0.035510(0.0024) | | -0.004725 (0.8103) |
| **SKN** | -0.061420 (0.0000) | 0.086018 (0.0000) | 1.000951 (0.0000) | -0.034538(0.0000) | 0.009994 (0.3223) | |
| | -0.059703 (0.0000) | 0.002854 (0.0000) | 1.001894 (0.0000) | -0.035639 (0.0000) | | -0.002240 (0.8241) |
| **P1** | -0.089812 (0.0000) | 0.165072 (0.0000) | 0.976123(0.0000) | -0.004975 (0.5760) | -0.020839 (0.7552) | |
| | -0.078818 (0.0000) | 0.163220 (0.0000) | 0.978675 (0.0000) | -0.005237 (0.5484) | | -0.085589 (0.1830) |
| **P2** | -0.061208 (0.0011) | 0.130469 (0.0000) | 0.949227 (0.0000) | -0.036515 (0.0023) | 0.005942 (0.7895) | |
| | -0.065276 (0.0008) | 0.131608 (0.0000) | 0.947128 (0.0000) | -0.035947(0.0033) | | 0.015084 (0.5230) |

**Notes:** This table shows the GARCH estimation results in Korea. The estimation results for the GARCH model after adding the VIX index as an extra variable are included in the tables. 5% significance level means that the probability of the observed result being due to chance is less than 5. SMS is short for "SAMSUNG", which was selected from the technology industry. KBF is the "KBF Financial group", representing the financial industry. SKN is" SKINNOVATION", from the energy sector, and CTN is" Celltrion", from the health and care industry. P1 is the equal-weighted portfolio and P2 is the market cap-weighted portfolio.

## Table B8 The GARCH estimation results in Korea (Continued)

| | ℧ (p-VALUE) | $\alpha$ (p-value) | $\beta$ (p-value) | γ(p-value) | News intensity | VIX |
|---|---|---|---|---|---|---|
| **GARCH (1, 1) WITH LOG NEWS INTENSITY AND VIX** | | | | | | |
| ***CTN*** | 0.266362 (0.0002) | 0.031281 (0.0000) | 0.951068 (0.0000) | - | 0.072490 (0.0495) | 0.122884 (0.0000) |
| ***KBF*** | 0.062982 (0.0009) | 0.033690 (0.0000) | 0.943330 (0.0000) | - | 0.092875 (0.2697) | 0.038530 (0.0000) |
| ***SMS*** | 0.056832 (0.0934) | 0.035812 (0.0000) | 0.933108 (0.0000) | - | 0.010822(0.5381) | 0.024276 (0.0000) |
| ***SKN*** | 0.499752 (0.0000) | 0.135638 (0.0000) | 0.747179 (0.0000) | - | 2.189308 (0.0000) | 0.034567 (0.0032) |
| ***P1*** | 0.048908 (0.0476) | 0.042038 (0.0000) | 0.940611 (0.0000) | - | 0.005434 (0.8315) | 0.043362 (0.0000) |
| ***P2*** | 0.009266 (0.7716) | 0.041212 (0.0000) | 0.924394 (0.0000) | - | 0.047208 (0.0034) | 0.022342 (0.0000) |
| **EGARCH (1, 1) WITH LOG NEWS INTENSITY AND VIX** | | | | | | |
| ***CTN*** | -0.007979 (0.3904) | 0.052856 (0.0000) | 0.988656 (0.0000) | 0.014993 (0.0090) | -0.004453 (0.2558) | 0.015376 (0.0000) |
| ***KBF*** | -0.024642(0.0056) | 0.035597 (0.0029) | 0.993696 (0.0000) | -0.008669 (0.2588) | 0.033408 (0.0921) | 0.014453 (0.0000) |
| ***SMS*** | 0.285841 (0.0053) | 0.273534 (0.0000) | -0.261673(0.0000) | -0.025347 (0.1421 | 0.329265 (0.0000) | 0.000720 (0.8114) |
| ***SKN*** | -0.039397(0.0000) | 0.049427 (0.0000) | 0.975191 (0.0000) | -0.025795 (0.0000) | -0.021355 (0.0000) | 0.009756 (0.0000) |
| ***P1*** | -0.007908(0.4571) | 0.032086 (0.0037) | 0.988337 (0.0000) | 0.058945 (0.0000) | -0.003938 (0.4687) | 0.019651 (0.0000) |
| ***P2*** | 0.106962 (0.2639) | 0.297187 (0.0000) | -0.207806 (0.0000) | -0.043366 (0.0000) | 0.315045 (0.0000) | 0.000437 (0.8830) |
| **GARCH (1, 1) WITH LOG NEWS INTENSITY CHANGES AND VIX** | | | | | | |
| ***CTN*** | 0.133487 (0.0000) | 0.020069 (0.0000) | 0.961791 (0.0000) | - | 0.070329 (0.0000) | 0.102360 (0.0000) |
| ***KBF*** | 0.080106 (0.0000) | 0.035734 (0.0000) | 0.940410 (0.0000) | - | 0.004354 (0.0985) | 0.037522 (0.0000) |
| ***SMS*** | 0.056832 (0.0934) | 0.035812 (0.0000) | 0.933108 (0.0000) | - | 0.010822 (0.5381) | 0.024276 (0.0000) |
| ***SKN*** | 0.499752 (0.0000) | 0.135638 (0.0000) | 0.747179 (0.0000) | - | 2.189308 (0.0000) | 0.034567 (0.0000) |
| ***P1*** | 0.059782 (0.0000) | 0.041200 (0.0000) | 0.939786 (0.0000) | - | 0.005872 (0.0000) | 0.044012 (0.0000) |
| ***P2*** | 0.092911 (0.0000) | 0.043171 (0.0000) | 0.908400 (0.0000) | - | 0.005325 (0.0000) | 0.022995 (0.0000) |
| **EGARCH (1, 1) WITH LOG NEWS INTENSITY CHANGES AND VIX** | | | | | | |
| ***CTN*** | -0.014247(0.1315) | 0.051265 (0.0000) | 0.987866 (0.0000) | 0.010767 (0.0760) | 0.007082 (0.0000) | 0.013492 (0.0000) |
| ***KBF*** | -0.037039(0.0002) | 0.058437 (0.0000) | 0.994547(0.0000) | -0.012481 (0.1328) | 0.001896 (0.0233) | 0.013383 (0.0000) |
| ***SMS*** | -0.037233(0.0351) | 0.090191 (0.0000) | 0.970171 (0.0000) | -0.002603 (0.8078) | -0.002264(0.7638) | 0.010348 (0.0000) |
| ***SKN*** | -0.039397 (0.0000) | 0.049427 (0.0000) | 0.975191 (0.0000) | -0.025795 (0.0000) | -0.021355 (0.0000) | 0.009756 (0.0000) |
| ***P1*** | -0.012781(0.1838) | 0.032495 (0.0032) | 0.988759 (0.0000) | 0.057492 (0.0000) | 0.002353 (0.0000) | 0.019583 (0.0000) |
| ***P2*** | -0.051562 (0.0003) | 0.088742 (0.0000) | 0.977199 (0.0000) | 0.002326 (0.8419) | 0.003267 (0.0000) | 0.012228 (0.0000) |

**Notes:** This table shows the GARCH estimation results in Korea. The estimation results for the GARCH model after adding the VIX index as an extra variable are included in the tables. 5% significance level means that the probability of the observed result being due to chance is less than 5.

SMS is short for "SAMSUNG", which was selected from the technology industry. KBF is the "KBF Financial group", representing the financial industry. SKN is" SKINNOVATION", from the energy sector, and CTN is" Celltrion", from the health and care industry. P1 is the equal-weighted portfolio and P2 is the market cap-weighted portfolio.

## Table B8 The GARCH estimation results in Korea (Continued)

| | | | | | | |
|---|---|---|---|---|---|---|
| **GARCH (1, 1) WITH POSITIVE NEWS AND VIX** | | | | | | |
| | **Ʊ (p-VALUE)** | ***α*** **(p-value)** | ***β*** **(p-value)** | **γ(p-value)** | **Positive news** | **VIX** |
| ***CTN*** | 0.135066 (0.0002) | 0.029467 (0.0000) | 0.933089 (0.0000) | - | 1.186417 (0.0000) | 0.139533 (0.0000) |
| ***KBF*** | 0.065879(0.0000) | 0.032971 (0.0000) | 0.946356 (0.0000) | - | 0.033688 (0.6774) | 0.037808 (0.0000) |
| ***SMS*** | 0.044431(0.0799) | 0.034052 (0.0000) | 0.941737 (0.0000) | - | 0.038623 (0.2140) | 0.024592 (0.0000) |
| ***SKN*** | 0.034499 (0.0000) | 0.016070 (0.0000) | 0.980705 (0.0000) | - | -0.201385 (0.0000) | 0.067904 (0.0000) |
| ***P1*** | 0.024467 (0.0808) | 0.037102 (0.0000) | 0.938866 (0.0000) | - | 0.268839 (0.0041) | 0.041867 (0.0000) |
| ***P2*** | 0.048342 (0.0205) | 0.035170 (0.0000) | 0.938216 (0.0000) | - | 0.021624 (0.4710) | 0.022640 (0.0000) |
| **EGARCH (1, 1) WITH POSITIVE NEWS AND VIX** | | | | | | |
| ***CTN*** | -0.025081(0.2369) | 0.181173 (0.0000) | 0.919201 (0.0000) | -0.034650 (0.0084) | 0.405464 (0.0000) | 0.0112225(0.0000) |
| ***KBF*** | -0.003155(0.0005) | 0.049217 (0.0001) | 0.995824 (0.0000) | -0.010031 (0.2057) | -0.002058 (0.9017) | 0.013679 (0.0000) |
| ***SMS*** | -0.045264(0.0021) | 0.089484 (0.0000) | 0.971352 (0.0000) | -0.003803 (0.7442) | 0.008741 (0.5769) | 0.010218 (0.0000) |
| ***SKN*** | -0.004895(0.1366) | 0.001744 (0.6601) | 0.981069 (0.0000) | -0.042918 (0.0000) | -0.075575 (0.0050) | 0.012445 (0.0000) |
| ***P1*** | -0.012483(0.2313) | 0.016680 (0.1617) | 0.982793 (0.0000) | 0.058106 (0.0000) | 0.095603 (0.0001) | 0.021091 (0.0000) |
| ***P2*** | -0.048442(0.0015) | 0.088832 (0.0000) | 0.970378 (0.0000) | 0.004472 (0.0000) | 0.008394 (0.6117) | 0.012826 (0.0000) |
| **GARCH (1, 1) WITH POSITIVE NEWS AT TIME T-1 AND VIX** | | | | | | |
| | **Ʊ (p-VALUE)** | ***α*** **(p-value)** | ***β*** **(p-value)** | **γ(p-value)** | **Positive news(t-1)** | **VIX** |
| ***CTN*** | 0.106394 (0.0000) | 0.019657 (0.0000) | 0.955803 (0.0000) | - | 0.583841 (0.0000) | 0.135660 (0.0000) |
| ***KBF*** | 0.066190 (0.0002) | 0.032978 (0.0000) | 0.946399 (0.0000) | - | 0.029022 (0.7096) | 0.037838 (0.0000) |
| ***SMS*** | 0.035669 (0.1366) | 0.033998 (0.0000) | 0.943457 (0.0000) | - | 0.050814 (0.0837) | 0.024726 (0.0000) |
| ***SKN*** | 0.037905 (0.0000) | 0.016228 (0.0000) | 0.980543 (0.0000) | - | -0.243820(0.0000) | 0.070065 (0.0000) |
| ***P1*** | 0.027031 (0.0559) | 0.037062 (0.0000) | 0.941582 (0.0000) | - | 0.212128 (0.0210) | 0.042281 (0.0000) |
| ***P2*** | 0.047676 (0.0259) | 0.035070 (0.0000) | 0.938774 (0.0000) | - | 0.020939 (0.4693) | 0.022647 (0.0000) |
| **EGARCH (1, 1) WITH POSITIVE NEWS AT TIME T-1 AND VIX** | | | | | | |
| ***CTN*** | 0.004662 (0.5456) | 0.019786 (0.0114) | 0.984990 (0.0000) | 0.001034 (0.8630) | 0.066681 (0.0000) | 0.016200 (0.0000) |
| ***KBF*** | -0.003915(0.0005) | 0.050152 (0.0001) | 0.995874 (0.0000) | -0.010097 (0.2032) | -0.005702 (0.7263) | 0.013637 (0.0000) |
| ***SMS*** | -0.046868(0.0017) | 0.089571 (0.0000) | 0.971857(0.0000) | -0.004246 (0.7141) | 0.011543 (0.4646) | 0.010181 (0.0000) |
| ***SKN*** | -0.004638(0.1643) | 0.002467 (0.5428) | 0.984780 (0.0000) | -0.040258 (0.0000) | -0.079340 (0.0000) | 0.013281 (0.0000) |
| ***P1*** | -0.008940 (0.3633) | 0.015391 (0.1818) | 0.984000 (0.0000) | 0.059380 (0.0000) | 0.075176 (0.0008) | 0.020840 (0.0000) |
| ***P2*** | -0.045869 (0.0025) | 0.088834 (0.0000) | 0.969730 (0.0000) | 0.005181 (0.6640) | 0.002767 (0.8650) | 0.012883 (0.0000) |
| **GARCH (1, 1) WITH NEGATIVE NEWS AND VIX** | | | | | | |
| | **Ʊ (p-VALUE)** | ***α*** **(p-value)** | ***β*** **(p-value)** | **γ(p-value)** | **Negative news** | **VIX** |
| ***CTN*** | 0.376205 (0.0000) | 0.063090 (0.0000) | 0.876078 (0.0000) | - | 2.497384 (0.0000) | 0.099762 (0.0000) |
| ***KBF*** | 0.076456 (0.0004) | 0.037801 (0.0000) | 0.934162 (0.0000) | - | 0.275563 (0.0469) | 0.038946 (0.0000) |
| ***SMS*** | 0.078170 (0.0000) | 0.034087 (0.0000) | 0.940296 (0.0000) | - | -0.027484 (0.3926) | 0.024538 (0.0000) |
| ***SKN*** | 0.027058 (0.0001) | 0.021093 (0.0000) | 0.974324 (0.7950) | - | 0.019947 (0.0000) | 0.052511 (0.0000) |
| ***P1*** | 0.088657 (0.0003) | 0.037675 (0.0000) | 0.946825 (0.0000) | - | -0.213870 (0.0572) | 0.041496 (0.0000) |
| ***P2*** | 0.062424 (0.0000) | 0.036958 (0.0000) | 0.932735 (0.0000) | - | 0.003611 (0.9122) | 0.022748 (0.0000) |
| **EGARCH (1, 1) WITH NEGATIVE NEWS AND VIX** | | | | | | |
| ***CTN*** | -0.006435 (0.5850) | 0.048996 (0.0000) | 0.984076 (0.0000) | 0.019762 (0.0033) | 0.042328 (0.1494) | 0.015681 (0.0000) |
| ***KBF*** | -0.032883 (0.0007) | 0.049807 (0.0001) | 0.993449 (0.0000) | 0.049807 (0.0001) | 0.051160 (0.0476) | 0.014168 (0.0000) |
| ***SMS*** | -0.038889 (0.0148) | 0.089382 (0.0000) | 0.970710 (0.0000) | -0.03100 (0.7877) | -0.004178 (0.7878) | 0.010290 (0.0000) |
| ***SKN*** | -0.047805 (0.0000) | 0.062433 (0.0000) | 0.981856 (0.0000) | -0.013749 (0.0227) | 0.007562 (0.3770) | 0.010346 (0.0000) |
| ***P1*** | 0.004876 (0.0000) | 0.026415 (0.0000) | 0.989094 (0.0000) | 0.059685 (0.0000) | -0.070052 (0.0086) | 0.019709 (0.0000) |
| ***P2*** | -0.045478 (0.0066) | 0.089165 (0.0000) | 0.968998 (0.0000) | 0.005750 (0.6251) | 0.001785 (0.9147) | 0.012933 (0.0000) |
| **GARCH (1, 1) WITH NEGATIVE NEWS AT TIME T-1 AND VIX** | | | | | | |
| | **Ʊ (p-VALUE)** | ***α*** **(p-value)** | ***β*** **(p-value)** | **γ(p-value)** | **Negative news(t-1)** | **VIX** |
| ***CTN*** | 0.132555 (0.0000) | 0.026423 (0.0000) | 0.958160 (0.0000) | - | -0.335853 (0.0883) | 0.124421 (0.0000) |
| ***KBF*** | 0.065344 (0.0007) | 0.032679 (0.0000) | 0.945446 (0.0000) | - | 0.120216 (0.2959) | 0.038656 (0.0000) |
| ***SMS*** | 0.081046 (0.0000) | 0.033257 (0.0000) | 0.944032 (0.0000) | - | -0.045384 (0.1220) | 0.024837 (0.0000) |
| ***SKN*** | 0.033810 (0.0000) | 0.021825 (0.0000) | 0.974201 (0.0000) | - | -0.092464 (0.2207) | 0.051622 (0.0000) |
| ***P1*** | 0.105056 (0.0000) | 0.038152 (0.0000) | 0.946588 (0.0000) | - | -0.302817 (0.0074) | 0.040555 (0.0000) |
| ***P2*** | 0.064796 (0.0000) | 0.034960 (0.0000) | 0.938359 (0.5925) | - | -0.015845 (0.5925) | 0.022716 (0.0000) |
| **EGARCH (1, 1) WITH NEGATIVE NEWS AT TIME T-1 AND VIX** | | | | | | |
| ***CTN*** | -0.020636(0.0659) | 0.054097 (0.0000) | 0.992019 (0.0000) | 0.010232 (0.1547) | -0.055209 (0.0620) | 0.015313 (0.0000) |
| ***KBF*** | -0.030114(0.0009) | 0.045507 (0.0002) | 0.994567 (0.0000) | -0.009228 (0.2449) | 0.037582 (0.1035) | 0.014175 (0.0000) |
| ***SMS*** | -0.037413(0.0168) | 0.088978 (0.0000) | 0.971691 (0.0000) | -0.003687 (0.7490) | -0.007845 (0.6176) | 0.010247 (0.0000) |
| ***SKN*** | -0.047730(0.0000) | 0.061851 (0.0000) | 0.982456 (0.0000) | -0.015331 (0.0095) | -0.000075 (0.9929) | 0.010165 (0.0000) |
| ***P1*** | 0.005908 (0.5312) | 0.027420 (0.0076) | 0.989121 (0.0000) | 0.059523 (0.0000) | -0.079428 (0.0037) | 0.019708 (0.0000) |
| ***P2*** | -0.043439 (0.0079) | 0.088617 (0.0000) | 0.969805 (0.0000) | 0.005266 (0.6518) | -0.002486 (0.8763) | 0.012894 (0.0000) |

**Notes:** This table shows the GARCH estimation results in Korea. The estimation results for the GARCH model after adding the VIX index as an extra variable are included in the tables. 5% significance level means that the probability of the observed result being due to chance is less than 5. SMS is short for "SAMSUNG", which was selected from the technology industry. KBF is the "KBF Financial group", representing the financial industry. SKN is" SKINNOVATION", from the energy sector, and CTN is" Celltrion", from the health and care industry. P1 is the equal-weighted portfolio and P2 is the market cap-weighted portfolio.

# Table B9 The GARCH estimation results in China

| GARCH (1, 1) | | | | | |
|---|---|---|---|---|---|
| | **Ʊ (p-VALUE)** | ***α* (p-value)** | ***β* (p-value)** | **γ(p-value)** | |
| ***ICBC*** | 0.125596 (0.0010) | 0.043887 (0.0000) | 0.890224 (0.0000) | | |
| ***TNT*** | 0.200369 (0.0001) | 0.111328 (0.0000) | 0.860201 (0.0000) | | |
| ***PTC*** | 0.072657 (0.0002) | 0.034361 (0.0000) | 0.947622 (0.0000) | | |
| ***WCB*** | 0.080302 (0.0010) | 0.031516 (0.0000) | 0.963931 (0.0000) | | |
| ***P1*** | 0.188202 (0.0001) | 0.109920 (0.0000) | 0.861073 (0.0000) | | |
| ***P2*** | 0.197443 (0.0001) | 0.111126 (0.0000) | 0.860068 (0.0000) | | |
| **EGARCH (1, 1)** | | | | | |
| ***ICBC*** | -0.035053 (0.0000) | 0.078557 (0.0000) | 0.003667 (0.6871) | 0.966946 (0.0000) | |
| ***TNT*** | -0.092972 (0.0000) | 0.215994 (0.0000) | 0.959566 (0.0000) | -0.082088(0.0000) | |
| ***PTC*** | -0.031574 (0.0000) | 0.088025 (0.0000) | 0.977168 (0.0000) | 0.000533 (0.9446) | |
| ***WCB*** | -0.001719 (0.9067) | 0.085302 (0.0000) | 0.975272 (0.0000) | -0.076238 (0.0000) | |
| ***P1*** | -0.089056 (0.0000) | 0.212137 (0.0000) | 0.956872 (0.0000) | -0.0083529(0.0000) | |
| ***P2*** | -0.093759 (0.0000) | 0.216080 (0.0000) | 0.959430 (0.0000) | -0.081624 (0.0000) | |
| **GARCH (1, 1) WITH LOG NEWS INTENSITY** | | | | | |
| | **Ʊ (p-VALUE)** | ***α* (p-value)** | ***β* (p-value)** | **γ(p-value)** | **News intensity** |
| ***ICBC*** | 0.139162 (0.0018) | 0.052921 (0.0000) | 0.855451 (0.0000) | - | 0.114869 (0.0007) |
| ***TNT*** | 0.277122 (0.0070) | 0.155406 (0.0000) | 0.651074(0.0000) | - | 0.664700 (0.0000) |
| ***PTC*** | 0.084383 (0.0001) | 0.032435(0.0000) | 0.956217 (0.0000) | - | -0.060760 (0.0128) |
| ***WCB*** | 2.669385 (0.0000) | 0.175483 (0.0000) | 0.546828 (0.0000) | - | 7.500636 (0.0000) |
| ***P1*** | 0.051217 (0.4916) | 0.125422 (0.0000) | 0.779460 (0.0000) | - | 0.546566 (0.0000) |
| ***P2*** | 0.125180 (0.1675) | 0.142818 (0.0000) | 0.690917 (0.0000) | - | 0.741218 (0.0000) |
| **EGARCH (1, 1) WITH LOG NEWS INTENSITY** | | | | | |
| ***ICBC*** | -0.049407 (0.0000) | 0.108641 (0.0000) | 0.007353 (0.0000) | 0.935045 (0.0000) | 0.039155 (0.0110) |
| ***TNT*** | -0.090877 (0.0005) | 0.231389 (0.0000) | 0.890037 (0.0000) | -0.101455(0.0000) | 0.074351 (0.0000) |
| ***PTC*** | -0.025544 (0.0001) | 0.083696 (0.0000) | 0.986376 (0.0000) | 0.001776 (0.8110) | -0.024956 (0.0025) |
| ***WCB*** | 0.504604 (0.0000) | 0.287638 (0.0000) | 0.678431 (0.0000) | -0.123284 (0.0000) | 0.458565 (0.0000) |
| ***P1*** | -0.104162 (0.0000) | 0.220243 (0.0000) | 0.919006 (0.0000) | -0.089859 (0.0000) | 0.074643 (0.0000) |
| ***P2*** | -0.100373 (0.0002) | 0.234612 (0.0000) | 0.883805 (0.0000) | -0.099499 (0.0000) | 0.099997 (0.0000) |
| **GARCH (1, 1) WITH NEWS INTENSITY CHANGES** | | | | | |
| ***ICBC*** | 0.112879(0.0008) | 0.036931(0.0000) | 0.903346 (0.0000) | - | 0.003543 (0.0000) |
| ***TNT*** | 2.164669 (0.0000) | 0.170423 (0.0000) | 0.435716 (0.0000) | - | 0.013865 (0.0000) |
| ***PTC*** | 0.062359 (0.0004) | 0.034165(0.0000) | 0.950604 (0.0000) | - | 0.003080 (0.0031) |
| ***WCB*** | 0.373434 (0.0000) | 0.052503 (0.0000) | 0.918560 (0.0000) | - | 0.097866 (0.0000) |
| ***P1*** | 2.295455 (0.0000) | 0.156726 (0.0000) | 0.442228 (0.0000) | - | 0.024851 (0.0000) |
| ***P2*** | 3.276360 (0.0000) | 0.127501 (0.0000) | 0.454380 (0.0000) | - | 0.026418 (0.0000) |
| **EGARCH (1, 1) WITH NEWS INTENSITY CHANGES** | | | | | |
| ***ICBC*** | -0.030769 (0.0000) | 0.069548 (0.0000) | 0.969718 (0.0000) | 0.006869 (0.4132) | 0.002179 (0.0000) |
| ***TNT*** | -0.079128 (0.0000) | 0.190635 (0.0000) | 0.957984 (0.0000) | -0.075245 (0.0000) | 0.004013 (0.0000) |
| ***PTC*** | -0.033856 (0.0000) | 0.087089 (0.0000) | 0.979365 (0.0000) | -0.002009 (0.7857) | 0.000929 (0.0026) |
| ***WCB*** | 0.044813(0.1463) | 0.175128 (0.0000) | 0.925216 (0.0000) | -0.106134 (0.0000) | 0.007985 (0.0000) |
| ***P1*** | -0.084693(0.0000) | 0.193996 (0.0000) | 0.959265 (0.0000) | -0.073030 (0.0000) | 0.005448 (0.0000) |
| ***P2*** | -0.082056 (0.0000) | 0.188965 (0.0000) | 0.960624 (0.0000) | -0.070439 (0.0000) | 0.004977 (0.0000) |

**Notes:** This table shows the GARCH estimation results in China. The estimation results for the GARCH model after adding the VIX index as an extra variable are included in the tables. 5% significance level means that the probability of the observed result being due to chance is less than 5%.

TNT is short for “Tencent”, which was selected from the technology industry. ICBC is the “Industrial and Commercial Bank of China”, representing the financial industry. PTC is “Petro China”, from the energy sector, and WCB is “WUXI Biologics”, from the health and care industry. P1 is the equal-weighted portfolio and P2 is the market cap-weighted portfolio.

## Table B9 The GARCH estimation results in China (Continued)

| | $\mho$ (p-VALUE) | $\alpha$ (p-value) | $\beta$ (p-value) | γ(p-value) | Positive news | Positive news at t-1 |
|---|---|---|---|---|---|---|
| **GARCH (1, 1) WITH POSITIVE NEWS** | | | | | | |
| ***ICBC*** | 0.124179(0.0009) | 0.043132 (0.0000) | 0.892777 (0.0000) | - | -0.013075 (0.7927) | |
| | 0.124518 (0.0006) | 0.039387 (0.0000) | 0.901942 (0.0000) | | - | -0.084005 (0.0512) |
| ***TNT*** | 0.250931 (0.0005) | 0.111299 (0.0000) | 0.859833(0.0000) | - | -0.112558 (0.3131) | |
| | 0.363690 (0.0000) | 0.119969 (0.0000) | 0.846014(0.0000) | | | -0.296314(0.0124) |
| ***PTC*** | 0.081238 (0.0001) | 0.034042 (0.0000) | 0.949674 (0.0000) | - | -0.048625 (0.1655) | |
| | 0.077823 (0.0003) | 0.033943 (0.0000) | 0.949860(0.0000) | | | -0.039033 (0.2694) |
| ***WCB*** | 0.106466 (0.0005) | 0.032845 (0.0000) | 0.962385(0.0000) | - | -0.239341 (0.2044) | |
| | 0.140166 (0.0001) | 0.037060(0.0000) | 0.957029 (0.0000) | | | -0.410536 (0.0243) |
| ***P1*** | 0.213870 (0.0034) | 0.108926 (0.0000) | 0.862764 (0.0000) | - | -0.120920(0.6190) | |
| | 0.308841 (0.0002) | 0.110503 (0.0000) | 0.859841 (0.0000) | | | -0.478300 (0.0537) |
| ***P2*** | 0.233479 (0.0026) | 0.110252(0.0000) | 0.861334 (0.0000) | - | -0.119474(0.5207) | |
| | 0.362516 (0.0001) | 0.116084(0.0000) | 0.851232(0.0000) | | | -0.439767 (0.0221) |
| **EGARCH (1, 1) WITH POSITIVE NEWS** | | | | | | |
| ***ICBC*** | 0.547256 (0.0000) | 0.073639 (0.0742) | - 0.049523(0.8124) | -0.014795 (0.6165) | 0.406830(0.0000) | |
| | -0.020589 (0.0007) | 0.058723 (0.0000) | 0.981476 (0.0000) | 0.007375 (0.3353) | | -0.060619 (0.0004) |
| ***TNT*** | -0.099897(0.0000) | 0.216796(0.0000) | 0.958988 (0.0000) | -0.085215 (0.0000) | 0.017184 (0.5271) | |
| | -0.083771(0.0002) | 0.217716(0.0000) | 0.958799(0.0000) | -0.078884(0.0000) | | -0.021908(0.4176) |
| ***PTC*** | -0.023696(0.0000) | 0.086904 (0.0000) | 0.980557 (0.0000) | 0.010441 (0.0000) | -0.038288 (0.0063) | |
| | -0.024370(0.0012) | 0.086298 (0.0000) | 0.980887 (0.0000) | 0.009110 (0.3449) | | -0.036199 (0.0102) |
| ***WCB*** | -0.000695(0.9644) | 0.091876 (0.0000) | 0.973667 (0.0000) | -0.075225(0.0000) | -0.021446(0.4749) | |
| | 0.006372 (0.7334) | 0.111954(0.0000) | 0.966743 (0.0000) | -0.076294(0.0000) | | -0.075454 (0.0228) |
| ***P1*** | -0.080731(0.0006) | 0.209682 (0.0000) | 0.958860 (0.0000) | -0.080873(0.0000) | -0.039713 (0.5135) | |
| | -0.063180 (0.0086) | 0.209843 (0.0000) | 0.959841(0.0000) | -0.077222 (0.0000) | | -0.118737(0.0513) |
| ***P2*** | -0.099820 (0.0000) | 0.217694 (0.0000) | 0.958380(0.0000) | -0.083627 (0.0000) | 0.020493 (0.6558) | |
| | -0.077283 (0.0012) | 0.216384 (0.0000) | 0.959728(0.0000) | -0.077380(0.0000) | | -0.053965 (0.2307) |
| **GARCH (1, 1) WITH NEGATIVE NEWS** | | | | | | |
| | **$\mho$(p-VALUE)** | **$\alpha$ (p-value)** | **$\beta$ (p-value)** | **γ(p-value)** | **negative news** | **negative news at t-1** |
| **ICBC** | 0.126179 (0.0025) | 0.047421 (0.0000) | 0.879499 (0.0000) | - | 0.084750 (0.0000) | |
| | 0.127860 (0.0028) | 0.047533(0.0000) | 0.878656(0.0000) | | | 0.082836 (0.0545) |
| **TNT** | 0.150497 (0.0187) | 0.116330 (0.0000) | 0.825240 (0.0000) | - | 0.613558 (0.0005) | |
| | 0.157983 (0.0092) | 0.114757 (0.0000) | 0.839106 (0.0000) | | | 0.402939 (0.0154) |
| **PTC** | 0.077879 (0.0001) | 0.033306 (0.0000) | 0.951476 (0.0000) | - | -0.074159 (0.0764) | |
| | 0.0076233 (0.0001) | 0.032906(0.0000) | 0.953100 (0.0000) | | | -0.088285 (0.0282) |
| **WCB** | 2.526976 (0.0000) | 0.160417 (0.0000) | 0.577349 (0.0000) | - | 31.89232 (0.0000) | |
| | 0.088738 (0.0014) | 0.037526 (0.0000) | 0.960604 (0.0000) | | | -1.277928 (0.0784) |
| **P1** | 0.076830 (0.2505) | 0.117633(0.0000) | 0.821740(0.0000) | - | 1.471788(0.0001) | |
| | 0.116997 (0.0834) | 0.118220(0.0000) | 0.829417(0.0000) | | | 1.037713 (0.0037) |
| **P2** | 0.092745 (0.1811) | 0.116789 (0.0000) | 0.819526 (0.0000) | - | 1.115045 (0.0001) | |
| | 0.117678 (0.0986) | 0.120155 (0.0000 | 0.822709 (0.0000) | | | 0.903499 (0.0015) |
| **EGARCH (1, 1) WITH NEGATIVE NEWS** | | | | | | |
| **ICBC** | -0.041419(0.0000) | 0.090858 (0.0000) | 0.956386(0.0000) | 0.006100 (0.5558) | 0.0256666 (0.2164) | |
| | -0.042076(0.0000) | 0.092736 (0.0000) | 0.954717(0.0000) | 0.006124 (0.5605) | | 0.027769(0.1966) |
| **TNT** | -0.095415 (0.0000) | 0.216478 (0.0000) | 0.955903(0.0000) | -0.079971 (0.0000) | 0.022374 (0.4742) | |
| | -0.093777 (0.0000) | 0.216085 (0.0000) | 0.958226 (0.0000) | -0.081385(0.0000) | | 0.008168 (0.7859) |
| **PTC** | -0.029246 (0.0000) | 0.085626 (0.0000) | 0.982218 (0.0000) | -0.004684(0.0000) | -0.033221 (0.0205) | |
| | -0.029259 (0.0000) | 0.084811 (0.0000) | 0.983119 (0.0000) | -0.005527(0.4516) | | -0.036103 (0.0103) |
| **WCB** | 0.379512(0.0000) | 0.290754 (0.0000) | 0.731058 (0.0000) | -0.082115(0.0046) | 1.522077 (0.0000) | |
| | -0.019013 (0.2698) | 0.108352(0.0000) | 0.978211 (0.0000) | -0.091730 (0.0000) | | -0.225235 (0.0007) |
| **P1** | -0.100002 (0.0000) | 0.216367 (0.0000) | 0.948480 0.0000) | -0.078113 (0.0000) | 0.108026 (0.1613) | |
| | -0.092960 (0.0000) | 0.213777 (0.0000) | 0.953705 (0.0000) | -0.081841 (0.0000) | | 0.039899 (0.5919) |
| **P2** | -0.102225 (0.0000) | 0.218610 (0.0000) | 0.951818 (0.0000) | -0.076819 (0.0000) | 0.069732 (0.2297) | |
| | -0.097660 (0.0000) | 0.217487 (0.0000) | 0.955751 (0.0000) | -0.079692(0.0000) | | 0.032769 (0.5632) |

**Notes:** This table shows the GARCH estimation results in China. The estimation results for the GARCH model after adding the VIX index as an extra variable are included in the tables. 5% significance level means that the probability of the observed result being due to chance is less than 5%. TNT is short for “Tencent”, which was selected from the technology industry. ICBC is the “Industrial and Commercial Bank of China”, representing the financial industry. PTC is “Petro China”, from the energy sector, and WCB is “WUXI Biologics”, from the health and care industry. P1 is the equal-weighted portfolio and P2 is the market cap-weighted portfolio.

# Table B9 The GARCH estimation results in China (Continued)

| | ℧ (p-VALUE) | $\alpha$ (p-value) | $\beta$ (p-value) | γ(p-value) | News intensity | VIX |
|---|---|---|---|---|---|---|
| **GARCH (1, 1) WITH LOG NEWS INTENSITY AND VIX** | | | | | | |
| ***ICBC*** | 0.005300 (0.1209) | 0.008449 (0.0000) | 0.987497 (0.0000) | - | 0.038211 (0.0000) | 0.022345 (0.0000) |
| ***PTC*** | 1.777132 (0.0000) | 0.070456 (0.0014) | 0.006242 (0.8802) | - | 3.036369 (0.0000) | 0.018541 (0.0513) |
| ***TNT*** | 0.096781 (0.1527) | 0.112874 (0.0000) | 0.802876 (0.0000) | - | 0.310423(0.0000) | 0.030167 (0.0056) |
| ***WCB*** | 2.474860 (0.0000) | 0.168816 (0.0000) | 0.569562 (0.0000) | - | 7.225950 (0.0000) | 0.089202 (0.0057) |
| ***P1*** | 0.004087 (0.9376) | 0.091137 (0.0000) | 0.864944 (0.0000) | - | 0.277644 (0.0001) | 0.036741 (0.0004) |
| ***P2*** | 0.046387 (0.4925) | 0.113866 (0.0000) | 0.796019 (0.0000) | - | 0.422719 (0.0000) | 0.028190 (0.0090) |
| **EGARCH (1, 1) WITH LOG NEWS INTENSITY AND VIX** | | | | | | |
| ***ICBC*** | -0.026611 (0.0000) | 0.036756 (0.0000) | 0.988948 (0.0000) | 0.008304 (0.1840) | 0.021570 (0.0070) | 0.009946 (0.0000) |
| ***PTC*** | 0.647702 (0.0000) | 0.182837 (0.0000) | -0.041084(0.4682) | -0.023507(0.3734) | 0.787463 (0.0000) | 0.005382 (0.0786) |
| ***TNT*** | -0.106009(0.0000) | 0.213975 (0.0000) | 0.922444 (0.0000) | -0.085919 (0.0000) | 0.054784 (0.0000) | 0.007290 (0.0022) |
| ***WCB*** | 0.489631 (0.0000) | 0.289237 (0.0000) | 0.683326 (0.0000) | -0.118291 (0.0001) | 0.460278 (0.0000) | 0.006526 (0.0190) |
| ***P1*** | -0.111403 (0.0000) | 0.198916 (0.0000) | 0.945849 (0.0000) | -0.072673 (0.0000) | 0.052282 (0.0004) | 0.008138 (0.0000) |
| ***P2*** | -0.115178 (0.0000) | 0.215403 (0.0000) | 0.919751 (0.0000) | -0.082227 (0.0000) | 0.073011 (0.0000) | 0.007394 (0.0022) |
| **GARCH (1, 1) WITH LOG NEWS INTENSITY CHANGES AND VIX** | | | | | | |
| | **℧ (p-VALUE)** | **$\alpha$ (p-value)** | **$\beta$ (p-value)** | **γ(p-value)** | **News intensity changes** | **VIX** |
| ***ICBC*** | 0.018696 (0.0080) | 0.010152 (0.0001) | 0.979250 (0.0000) | - | 0.004144 (0.0000) | 0.019368 (0.0000) |
| ***PTC*** | 0.052774 (0.0000) | 0.011361 (0.0000) | 0.973616 (0.0000) | - | 0.025682 (0.0000) | 0.021225 (0.0000) |
| ***TNT*** | 2.445510 (0.0000) | 0.153351 (0.0000) | 0.440524 (0.0000) | - | 0.015767 (0.0000) | 0.008982 (0.5765) |
| ***WCB*** | 7.351708 (0.0000) | 0.023152 (0.0031) | 0.413394 (0.0000) | - | 0.062134 (0.0000 | 0.027500 (0.4989) |
| ***P1*** | 2.280512 (0.0000) | 0.157165 (0.0000) | 0.443171 (0.0000) | - | 0.024681 (0.0000) | 0.000329 (0.9809) |
| ***P2*** | 3.262676 (0.0000) | 0.123981 (0.0000) | 0.452157 (0.0000) | - | 0.026495 (0.0000) | 0.019763 (0.4602) |
| **EGARCH (1, 1) WITH LOG NEWS INTENSITY CHANGES AND VIX E** | | | | | | |
| ***ICBC*** | -0.018676(0.0001) | 0.036392 (0.0000) | 0.986922 (0.0000) | 0.008000 (0.2050) | 0.002443 (0.0000) | 0.009440 (0.0000) |
| ***PTC*** | -0.022635(0.0017) | 0.045030 (0.0000) | 0.990510 (0.0000) | 0.014948 (0.1317) | 0.007204 (0.0000) | 0.010546 (0.0000) |
| ***TNT*** | -0.082436(0.0000) | 0.173292 (0.0000) | 0.968173 (0.0000) | -0.063832 (0.0000) | 0.003946 (0.0000) | 0.006867 (0.0027) |
| ***WCB*** | -0.024847(0.0909) | 0.098831 (0.0000) | 0.978328 (0.0000) | -0.055516 (0.0001) | 0.008004 (0.0000) | 0.009233 (0.0000) |
| ***P1*** | -0.088386(0.0000) | 0.175899 (0.0000) | 0.970164 (0.0000) | -0.059640(0.0000) | 0.005312 (0.0000) | 0.006848 (0.0031) |
| ***P2*** | -0.085222(0.0000) | 0.173604 (0.0000) | 0.969698 (0.0000) | -0.059964 (0.0000) | 0.004871 (0.0000) | 0.006338 (0.0065) |

**Notes:** This table shows the GARCH estimation results in Korea. The estimation results for the GARCH model after adding the VIX index as an extra variable are included in the tables. 5% significance level means that the probability of the observed result being due to chance is less than 5.

SMS is short for "SAMSUNG", which was selected from the technology industry. KBF is the "KBF Financial group", representing the financial industry. SKN is" SKINNOVATION", from the energy sector, and CTN is" Celltrion", from the health and care industry. P1 is the equal-weighted portfolio and P2 is the market cap-weighted portfolio.

## Table B9 The GARCH estimation results in China (Continued)

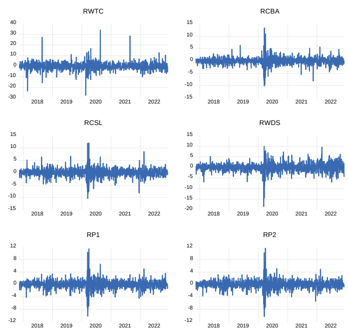
| | ℧ (p-VALUE) | $\alpha$ (p-value) | $\beta$ (p-value) | γ(p-value) | Positive news | VIX |
|---|---|---|---|---|---|---|
| **GARCH (1, 1) WITH POSITIVE NEWS AND VIX** | | | | | | |
| ***ICBC*** | 0.011028 (0.0369) | 0.011200 (0.0000) | 0.982266 (0.0000) | - | 0.002441 (0.8938) | 0.019681 (0.0000) |
| ***PTC*** | 0.630529(0.0000) | 0.094907 (0.0000) | 0.608911 (0.0000) | - | 1.748551 (0.0000) | 0.045019 (0.0000) |
| ***TNT*** | 0.194179(0.0015) | 0.094776 (0.0000) | 0.882341 (0.0000) | - | -0.091933 (0.3140) | 0.047374 (0.0000) |
| ***WCB*** | 0.056164 (0.0270) | 0.023252 (0.0000) | 0.973508 (0.0000) | - | -0.062910 (0.6869) | 0.072873 (0.0000) |
| ***P1*** | 0.150076 (0.0149) | 0.088939 (0.0000) | 0.890717 (0.0000) | - | -0.087765 (0.6732) | 0.046074 (0.0000) |
| ***P2*** | 0.177956 (0.0061) | 0.093660 (0.0000) | 0.884151 (0.0000) | - | -0.095603 (0.5292) | 0.046874 (0.0000) |
| **EGARCH (1, 1) WITH POSITIVE NEWS AND VIX** | | | | | | |
| ***ICBC*** | 0.624426 (0.0000) | 0.063331 (0.1280) | -0.161234 (0.3744) | -0.015839 (0.5897) | 0.406206 (0.0000) | -0.004325(0.0782) |
| ***PTC*** | 0.319353 (0.0000) | 0.208653 (0.0000) | 0.495845 (0.0000) | -0.071340 (0.0102) | 0.618313 (0.0000) | 0.014674 (0.0000) |
| ***TNT*** | -0.102533(0.0000) | 0.201868 (0.0000) | 0.967751 (0.0000) | -0.073340 (0.0000) | 0.011177 (0.6537) | 0.008206 (0.0004) |
| ***WCB*** | -0.021087(0.0185) | 0.050372 (0.0000) | 0.992641 (0.0000) | -0.044911 (0.0000) | 0.014591 (0.4287) | 0.008282 (0.0000) |
| ***P1*** | -0.087905(0.0000) | 0.192571 (0.0000) | 0.969106 (0.0000) | -0.067350 (0.0000) | -0.030915(0.5800) | 0.008499 (0.0002) |
| ***P2*** | -0.103711(0.0000) | 0.201922 (0.0000) | 0.967517 (0.0000) | -0.072338 (0.0000) | 0.01776 (0.6687) | 0.008313 (0.0003) |
| **GARCH (1, 1) WITH POSITIVE NEWS AT TIME T-1 AND VIX** | | | | | | |
| | **℧ (p-VALUE)** | **$\alpha$ (p-value)** | **$\beta$ (p-value)** | **γ(p-value)** | **Positive news(t-1)** | **VIX** |
| ***ICBC*** | 0.013401 (0.0159) | 0.011088 (0.0000) | 0.982260 (0.0000) | - | -0.011554 (0.5168) | 0.019259 (0.0000) |
| ***PTC*** | 0.011801 (0.0000) | 0.002416 (0.0000) | 0.963208 (0.0000) | - | -0.052597 (0.0000) | 0.052191 (0.0000) |
| ***TNT*** | 0.266480 (0.0002) | 0.099486 (0.0000) | 0.874512 (0.0000) | - | -0.215980 (0.0291) | 0.046996 (0.0000) |
| ***WCB*** | 0.085012 (0.0030) | 0.027186 (0.0000) | 0.968781 (0.0000) | - | -0.235624 (0.1130) | 0.078248 (0.0000) |
| ***P1*** | 1.281810 (0.0000) | 0.151333(0.0000) | 0.708460 (0.0000) | - | -2.258027 (0.0000) | 0.016064 (0.0407) |
| ***P2*** | 0.261052 (0.0004) | 0.096900 (0.0000) | 0.878570 (0.0000) | - | -0.310761 (0.0505) | 0.046431 (0.0000) |
| **EGARCH (1, 1) WITH POSITIVE NEWS AT TIME T-1 AND VIX** | | | | | | |
| ***ICBC*** | -0.015924 (0.0006) | 0.036064 (0.0000) | 0.990891 (0.0000) | 0.006257 (0.3022) | -0.029555 (0.0226) | 0.008634 (0.0000) |
| ***PTC*** | 0.006882 (0.0899) | 0.009200 (0.1290) | 0.995639 (0.0000) | 0.029793 (0.0000) | -0.028575 (0.0000) | 0.014800 (0.0000) |
| ***TNT*** | -0.087775 (0.0000) | 0.203289 (0.0000) | 0.967139 (0.0000) | -0.067405 (0.0000) | -0.023688 (0.3433) | 0.008326 (0.0003) |
| ***WCB*** | -0.022145 (0.0223) | 0.057055 (0.0000) | 0.991783 (0.0000) | -0.043426 (0.0000) | -0.004914 (0.7975) | 0.008157 (0.0000) |
| ***P1*** | -0.071440 (0.0011) | 0.193743 (0.0000) | 0.969199 (0.0000) | -0.064849 (0.0000) | -0.102171 (0.0702) | 0.008330 (0.0002) |
| ***P2*** | -0.083018 (0.0002) | 0.201678 (0.0000) | 0.967884 (0.0000) | -0.066959 (0.0000) | -0.048113 (0.2464) | 0.008209 (0.0003) |
| **GARCH (1, 1) WITH NEGATIVE NEWS AT TIME T-1 AND VIX** | | | | | | |
| | **℧ (p-VALUE)** | **$\alpha$ (p-value)** | **$\beta$ (p-value)** | **γ(p-value)** | **Negative news(t-1)** | **VIX** |
| ***ICBC*** | 0.002545 (0.5166) | 0.008187 (0.0000) | 0.988500 (0.0000) | - | 0.049785 (0.0016) | 0.020276 (0.0000) |
| ***PTC*** | 0.019094 (0.0000) | 0.007457 (0.0000) | 0.990511 (0.0000) | - | -0.063579 (0.0000) | 0.042491 (0.0000) |
| ***TNT*** | 0.115830 (0.0169) | 0.095531 (0.0000) | 0.873268 (0.0000) | - | 0.241327 (0.0939) | 0.044225 (0.0001) |
| ***WCB*** | 0.037730 (0.0475) | 0.023961 (0.0000) | 0.975720 (0.0000) | - | -0.778186 (0.1522) | 0.070095 (0.0000) |
| ***P1*** | 0.066771 (0.1751) | 0.090365 (0.0000) | 0.880299 (0.0000) | - | 0.574011 (0.0446) | 0.044862 (0.0000) |
| ***P2*** | 0.075476 (0.1745) | 0.096655 (0.0000) | 0.867639 (0.0000) | - | 0.552157 (0.0250) | 0.044518 (0.0001) |
| **EGARCH (1, 1) WITH NEGATIVE NEWS AT TIME T-1 AND VIX** | | | | | | |
| ***ICBC*** | 0.794871(0.0000) | 0.048299 (0.2401) | -0.281029 (0.3544) | -0.018315 (0.5141) | -0.054685 (0.4260) | -0.005407(0.0512) |
| ***PTC*** | -0.007950(0.1250) | 0.028633 (0.0003) | 0.994784 (0.0000) | 0.014685 (0.0257) | -0.027652 (0.0001) | 0.012996 (0.0000) |
| ***TNT*** | -0.096704(0.0000) | 0.201581 (0.0000) | 0.967448 (0.0000) | -0.072730 (0.0000) | 0.001659 (0.9523) | 0.008008 (0.0004) |
| ***WCB*** | -0.034792(0.0003) | 0.060418 (0.0000) | 0.997675 (0.0000) | -0.053601 (0.0000) | -0.143241 (0.0024) | 0.008026 (0.0000) |
| ***P1*** | -0.097548(0.0000) | 0.194393 (0.0000) | 0.966708 (0.0000) | -0.067518 (0.0000) | 0.023110 (0.7382) | 0.008621 (0.0001) |
| ***P2*** | -0.101316(0.0000) | 0.201705 (0.0000) | 0.965729 (0.0000) | -0.068981 (0.0000) | 0.023628 (0.6562) | 0.008308 (0.0003) |

**Notes:** This table shows the GARCH estimation results in Korea. The estimation results for the GARCH model after adding the VIX index as an extra variable are included in the tables. 5% significance level means that the probability of the observed result being due to chance is less than 5.

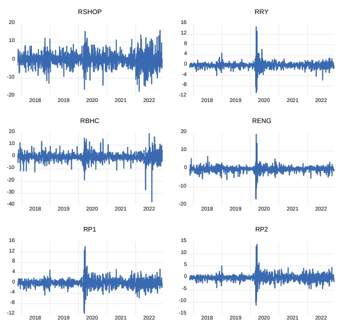
SMS is short for “SAMSUNG”, which was selected from the technology industry. KBF is the “KBF Financial group”, representing the financial industry. SKN is” SKINNOVATION”, from the energy sector, and CTN is” Celltrion”, from the health and care industry.

# Appendix C

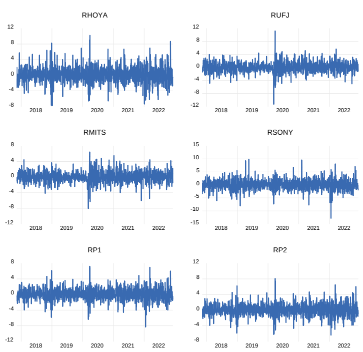
## Figure C1 Line plots stock returns for Australia, Canada, Japan, Korea and China



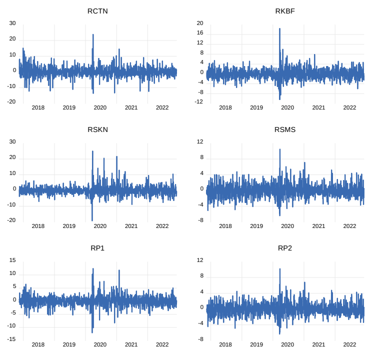

Australia



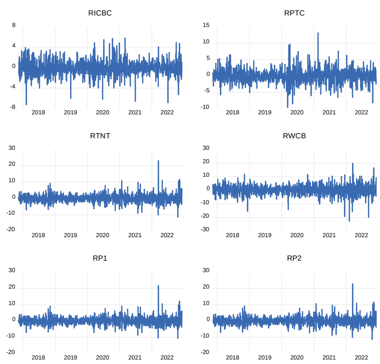

Canada




Japan



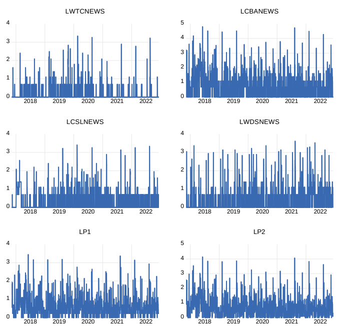

Korea



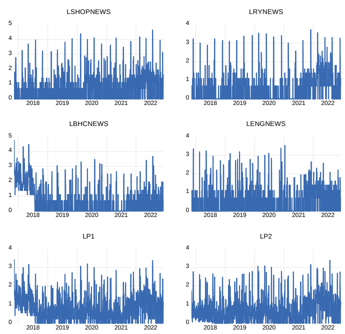

China

**Notes:** All the stock returns exhibit volatility clustering, which suggests that a GARCH model would be appropriate. In order to ascertain if GARCH (1,1) is appropriate for the complete dataset, it is imperative to analyze both the index price and return plots. The return plot must demonstrate characteristics of stationarity, signifying that all returns are aligned with the mean value and do not exhibit a pattern over time. The plot of returns is shown in this figure by country order (Australia, Canada, Japan, South Korea and China)

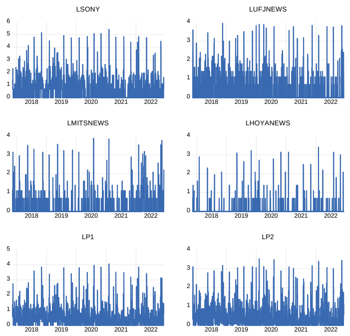
## Figure C2 Line plots of log news intensity for Australia, Canada, Japan, Korea and China



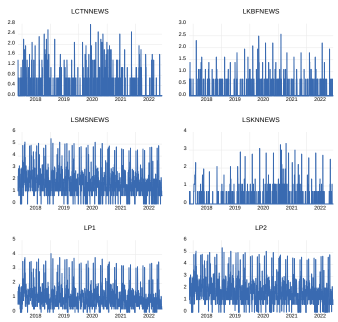

Australia



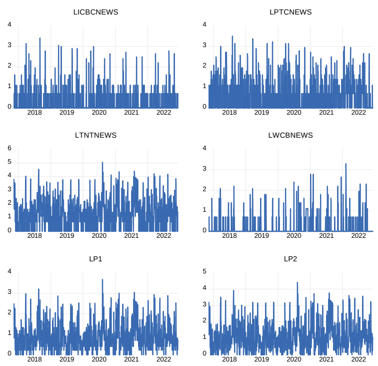

Canada




Japan



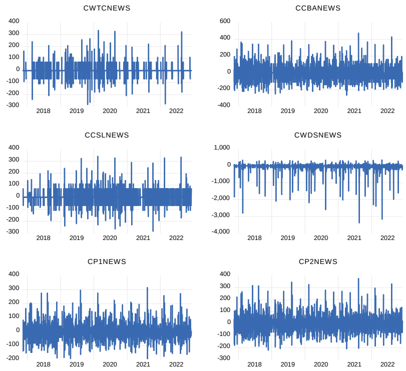

Korea



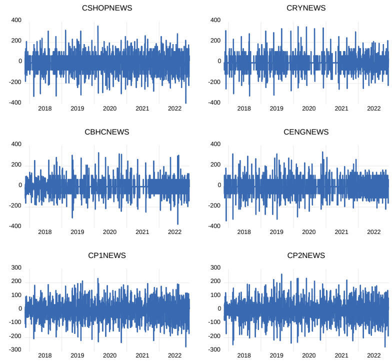

China

**Notes:** By utilizing Equation 15 and Equation 16, we successfully produced this table. The news intensity metric is derived from the sum of positive and negative news headlines. The plotted data exhibits stationary features, implying that the returns are uniformly distributed around the mean value, without any noticeable trends over time. The plot of news sentiment is shown in this figure by country order (Australia, Canada, Japan, South Korea and China)

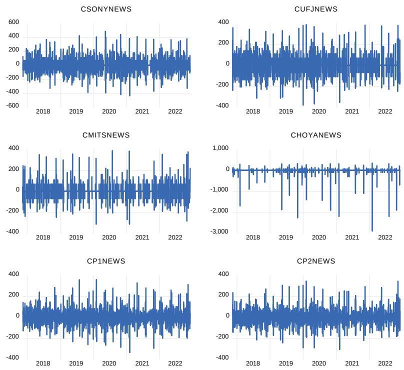
## Figure C3 Line plots of log news intensity changes for Australia, Canada, Japan, Korea and China



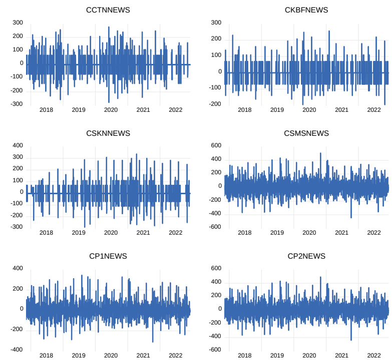

Australia



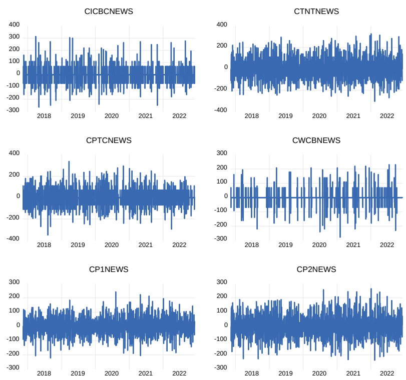

Canada




Japan



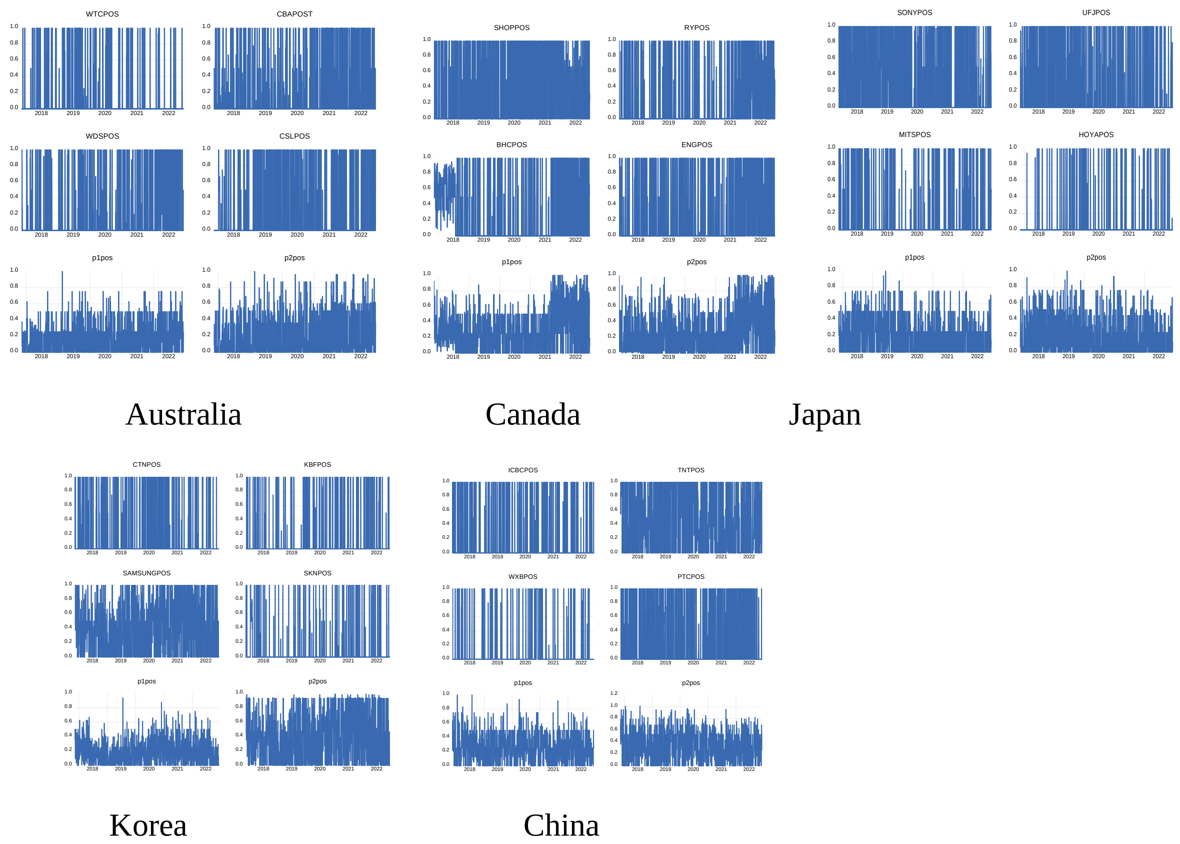

Korea




China

**Notes:** The metric for news intensity is determined by summing up the positive and negative headlines. By utilizing Equation 17, we were able to illustrate the changes in the intensity of log news. Based on the plotted data, it can be observed that the returns are uniformly spread out around the mean value, and there are no notable patterns discernible over time. The plot of news intensity changes is shown in this figure by country order (Australia, Canada, Japan, South Korea and China)

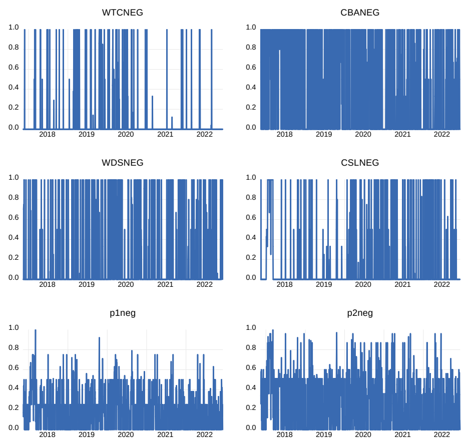
## Figure C4 Line plots of positive news sentiment



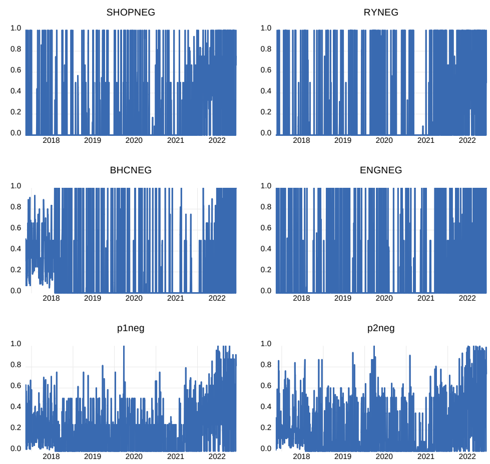

**Notes:** In order to better understand the positive news sentiment, we can use Equation 17. This equation calculates the ratio of positive news headlines to the overall news intensity, which is a measure of the total news coverage in a given period of time. The plot of negative news sentiment is shown in this figure by country order (Australia, Canada, Japan, South Korea and China)

This study is based on extensive data gathered over five years, from November 8th, 2017 to December 8th, 2022. The analysis uses 1326 observations, incorporating information from the VIX index, market returns and news sentiment. All data is sourced from Bloomberg and processed through the EVIEWS computer program to create a hypothetical historical index.

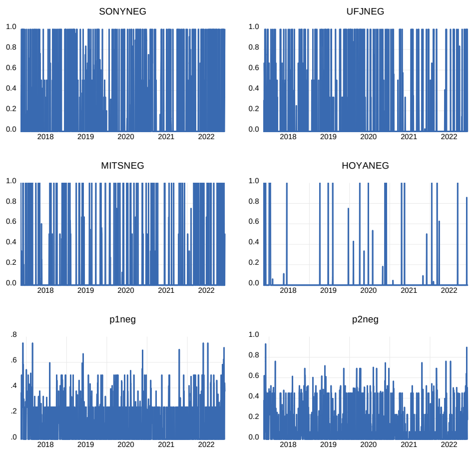
**Figure C5 Plots of negative news sentiment for Australia, Canada, Japan, Korea and China**



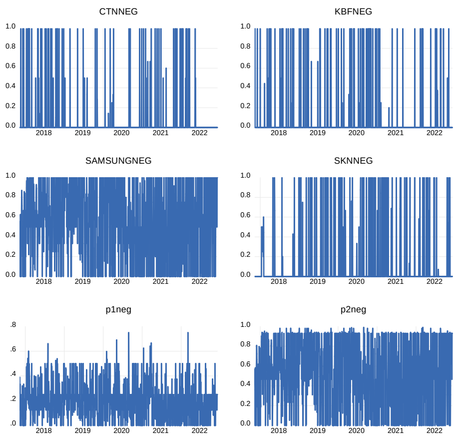

Australia



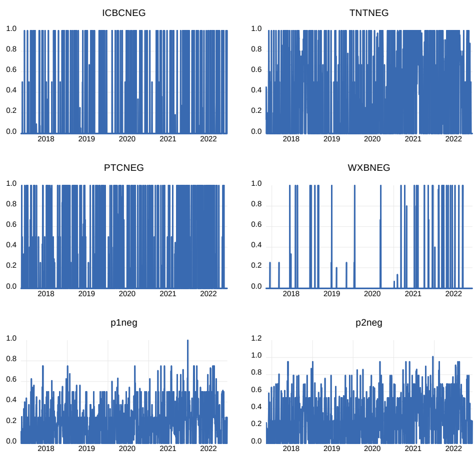

Canada




Japan




Korea




China

**Notes:** In order to better understand the negative news sentiment, we can use Equation 19. This equation calculates the ratio of negative news headlines to the overall news intensity, which is a measure of the total news coverage in a given period of time. The plot of negative news sentiment is shown in this figure by country order (Australia, Canada, Japan, South Korea and China)

This study is based on extensive data gathered over five years, from November 8th, 2017 to December 8th, 2022. The analysis uses 1326 observations, incorporating information from the VIX index, market returns and news sentiment. All data is sourced from Bloomberg and processed through the EVIEWS computer program to create a hypothetical historical index.