Global Volatility Transmission and Portfolio Management: The Case of Saudi Arabia

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Abstract

The Saudi stock market's performance has changed considerably over the past two decades, thus strengthening this market's position in not only the Gulf Cooperation Council (GCC) region but also the Arab world. The GCC countries' financial development and Saudi Arabia's economic growth have also influenced this market. The market index, termed Tadawul All Share Index (TASI), has changed through many economic and financial crises resulting from globalisation. The Saudi stock market that commenced in 1985 is a major market in the Middle East and North Africa region, and since it has been maturing, it is defined enough to be assessed empirically.

Therefore, this thesis explores the changing patterns of the Saudi stock market volatility over time, the effects of volatility pattern changes on optimal portfolio choices and the evolution of these choices. Significantly, given the increasing globalisation and financial integration in recent years, this thesis tests a new hypothesis that the Saudi stock market's volatility is affected by global volatility spillovers (i.e. the volatility in global markets, in commodity markets during the sample periods, including the 2008 global financial crisis [GFC] and the 2014–2016 oil price shocks) with important outcomes for portfolio management. To the best knowledge of the author, this type of comprehensive analysis that offers insights on volatility origin, although critical and novel in the finance and portfolio management fields, has not been undertaken for the purpose of policy analysis in the literature and, in particular, for Saudi Arabia.

The research uses advanced econometrics: cross-correlation function (CCF) and multivariate generalised autoregressive conditional heteroscedasticity (GARCH) models (i.e. Baba, Engle, Kraft and Kroner [BEKK], constant conditional correlation [CCC] and dynamic conditional correlation [DCC] models) and high-frequency daily data for 2007–2018. The multivariate models are reliable and effective for addressing volatility transmission interactions and correlations. These models are flexible in revealing the changes in conditional variance and covariance and simplify the estimation process. These approaches are appropriate and significant in volatility origin studies. In addition, Kroner

and Ng's approach is used to determine the optimal weight and Kroner and Sultan's approach to determine the optimal hedge ratio.

The major findings and contributions of this thesis to the volatility origin area of finance and portfolio management are summarised as follows:

(i) This empirical research examines the causality relationship of the TASI with global stock markets and major commodity markets during the full and crisis/shocks periods, using daily data for determining the causality in variance movements of the TASI and stock/commodity pairs. The CCF test shows that overall, the current relationship between TASI and the global stock markets is significant but finds no link between TASI and the commodity markets for all periods except the full period in which it is obvious that TASI is unidirectionally causal to crude oil. This thesis documents bidirectional causality in variance in global stock markets between TASI and some global stock markets over certain periods.

(ii) In the second empirical analysis, the Saudi stock market's trading partner stock markets and major commodity markets are analysed to ascertain volatility transmission and correlations with TASI. This analysis, based on the estimation results of the multivariate GARCH models (BEKK, CCC and DCC), shows that the volatility transmission effect and the conditional correlation behaviours in the full and crisis/shock periods differ. The findings show that transmission channel of shock and volatility spillover varies from market to market over the three periods and that TASI also reacts differently over the three periods. Over the GFC and oil decline periods, some global equity markets influenced TASI volatility to varying degrees, as revealed by the statistically significant model coefficients. This thesis documents that TASI is more integrated with global stock markets throughout the periods of GFC and oil decline. In addition, the results show highly positive conditional correlation at least at the 5% significance levels between TASI and the international stock markets during the three sample periods.

(iii) The thesis findings for optimal portfolio weights and hedge ratios recommend that portfolio risk can be minimised without reducing portfolio efficiency by combining some indices of global stocks and commodities into a well-diversified portfolio with TASI.

Since international portfolio diversification has become more popular worldwide, investors, portfolio managers and policymakers can apply this information to make new financial investments, recommend cautious financial regulations and implement quick, efficient policy tools.

Declaration

I, [Khalil Awad Alruwaitee], declare that the PhD thesis entitled Global Volatility Transmission and Portfolio Management: The Case of Saudi Arabia is no more than 80,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work.

I have conducted my research in alignment with the Australian Code for the Responsible Conduct of Research and Victoria University's Higher Degree by Research Policy and Procedures.

Signature	Date
Khalil Awad Alruwaitee	**20/01/2021**

Dedication

This thesis is dedicated to the memory of my great beloved father who passed away in June 2015, but still lives with me every single moment of my life. His encouragement and ongoing push towards achieving success has taken me to the right path, in not only my academic journey but also over my life. To my mother, my lovely wife, my precious children and the whole of my family who support, care and pray for me all the way since the beginning of my studies. Indeed, I owe all the moments of my life to them and appreciate their love, compassion and encouragement.

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List of Abbreviations

ADF	Augmented Dickey–Fuller
ADCC	Asymmetric Dynamic Conditional Correlation
AFC	Asian Financial Crisis
ARAMCO	Arabian American Oil Company
ARCH	Autoregressive Conditional Heteroscedasticity
ARMA	Autoregressive Moving Average
BEKK	Baba, Engle, Kraft and Kroner
BRIC	Brazil, Russia, India and China
CCC	Constant Conditional Correlation
CCF	Cross-Correlation Function
CMA	Capital Market Authority
CML	Capital Market Law
DCC	Dynamic Conditional Correlation
DECO	Dynamic EquiCOrrelations
DW	Durbin Watson
EGARCH	Exponential Generalised Autoregressive Conditional Heteroscedasticity
ESIS	Electronic Securities Information System
EU	European Union
FIAPARCH	Factionally Integrated Asymmetric Power ARCH
G20	Group of Twenty
GARCH	Generalised Autoregressive Conditional Heteroscedasticity
GARCH-M	GARCH-in-Mean
GCC	Gulf Council Countries
GDP	Gross Domestic Product
GED	Generalised Error Distribution
GFC	Global Financial Crisis
GIPSI	Greece, Ireland, Portugal, Spain and Italy
JB	Jarque–Bera

KPSS	Kwiatkowski, Phillips, Schmidt and Shin
LM	Lagrange Multiplier
MCMC	Markov Chain Monte Carlo
MENA	Middle East and North Africa
MSCI	Morgan Stanley Capital International
NCFEI	National Centre for Financial and Economic Information
OLS	Ordinary Least Squares
OPEC	Organization of the Petroleum Exporting Countries
PESTLE	Political, Economic, Social, Technological, Legal and Environmental
PP	Phillips–Perron
RATS	Regression Analysis of Time Series
SAMA	Saudi Arabian Monetary Agency
TASI	Tadawul All Share Index
TGARCH	Threshold GARCH
UK	United Kingdom
US	United States
VAR	Vector Autoregression
WTI	West Texas Intermediate
WTO	World Trade Organization

Chapter 1 Introduction

1.1 Introduction

The increasing interdependency of economies worldwide has made the financial markets integrated. Financial markets are a key to a country's economic growth and development. Further, global trade, investment and finance are being strengthened in several ways, such as through technological developments, liberalised trade policies and increased government support. These factors have led to the development of making financial markets interlinked and varying degrees of price volatility. The volatility has been enhanced by the increasing interdependence of advanced and emerging stock markets in recent decades (Cardona et al., 2017; Prasad et al., 2018; Rejeb & Boughrara, 2015). Significantly, globalisation involves global volatility transmission, which has serious outcomes. Financial market volatility is influenced by market-wide shocks. The volatility of emerging stock markets is likely to be greatly affected by their financial and economic activities. Harvey (1995) argued that emerging nations' stock markets experience greater volatility compared with developed markets.

The Saudi economy has demonstrated stronger economic prospects, with the government pursuing macroeconomic policies in the form of five-year plans, which ultimately led to the consistent growth of its financial markets. After joining the World Trade Organization (WTO) in 2005, the country has improved its connections with the international community and the local and regional economies. Its tremendous economic growth has become a driving force in the entire Arab region and has led to substantial changes in local and global economies. The establishment of the Saudi stock market resulted in better economic performance in the country, characterised by growth over time that improved its financial position in relation to the rest of the world, which made the government's economic plan—Vision 2030—feasible (Saudi Arabian Monetary Agency [SAMA], 2020). These changes have not only led to the country's significant economic growth but also resulted in higher volatility transmission from global financial markets to the Saudi stock market. Since Saudi Arabia is perceived as an emerging market, its stock market, which is characterised by significant volatility of returns, attracts investors from around the world who seek to diversify their portfolios to include both domestic and international investments.

Thus, these changes call for analysis to understand the volatility transmission between the Saudi stock market and other financial markets in this era of globalisation. This investigation requires further exploration of the links between different financial markets as well as of a series of events that resulted in volatility transmission between the global stock markets of the trading partners of Saudi Arabia and major commodity markets, and the Saudi stock market. The effects of financial shocks and crises caused by changes in the prices in the global stock and major commodity markets, and the implications for the Saudi stock market in terms of volatility transmission, is a significant topic that will be explored in detail in this thesis. Moreover, the knowledge on the relationship between stocks and commodities is significant for prospective investors and other interests, who would gain information for mitigating financial risks through portfolio management.

According to the SAMA, the nation's stock market is perceived to be a leading market in both the Gulf region and the wider Arab world. Saudi Arabia's capital market has been the leader among the Arab world's capital markets for the past 10 years. In addition, the country has recently led the Middle East and North Africa (MENA) region in initial public offerings and by end-2016, the Saudi stock market achieved the leading position of the highest market capitalisation among the MENA markets with US$448.3 billion, which is equivalent to 40.4%. Saudi Arabia is currently ranked ninth among the international emerging stock markets (SAMA, 2017a). Consequently, the Saudi stock market is likely to experience volatility transmission from global markets during periods of crisis or shock. These issues are important, but to date, are yet to be studied adequately, and therefore, this research is possibly the first to address them.

The remainder of this chapter is structured as follows. first, the background is explained in Section 1.2; followed by the research objectives in Section 1.3. The research questions and hypotheses are represented in Section 1.4. The primary research contributions (the contribution to knowledge and a statement of the practical contribution) of this research are provided in Section 1.5, whereas the thesis structure is outlined in Section 1.6.

1.2 Background

Since the October 1987 crisis in the United States (US), studies on the effects of volatility have increased, which have serious financial implications. The effects of spillover were transmitted from the US to the rest of the world, owing to the strength of the US economy. According to Ng (2000), Baele (2005), Kundu and Sarkar (2016), Cardona et al. (2017) and Vo and Ellis (2018), growth in other economies (emerging markets) has led to studies on spillover and its effects on the rest of the world. These studies have shown that significant integration of the emerging markets influenced the global markets, affecting them in terms of much expected returns. The impact of the global financial crisis (GFC) and the spillovers from the oil price decline of 2014–2016 have been analysed because these analyses help to understand the impact of the respective financial crisis/shock within the market (Al-Yahyaee et al., 2019; Hemche et al., 2016; Zheng & Zuo, 2013). These analyses have resulted in a series of observations that reveal differences in the patterns between the local, regional and global financial markets.

The Saudi Arabian stock market is officially termed the Tadawul, and its major index is the Tadawul All Share Index (TASI). It is defined as open, with more financial integration between the country and other global economies. Saudi Arabia is perceived as wielding considerable influence within the Arab and the Gulf Cooperation Council (GCC) region. Awartani et al. (2013) showed the effect of spillover from the Saudi stock market to its immediate neighbours. Further, Jouini (2015) examined the integration in terms of minor volatility spillovers from 31 May 2005 to 4 March 2015 between Saudi Arabia's market and international stock markets, namely those or the US, the United Kingdom (UK), China, Mexico, Japan, South Africa and the world market index.

The Saudi stock market experienced several crises in 1986, 1990, 1993, 1994, 1998, 2006, 2008 and 2015. According to SAMA (2007, 2009, 2017), these collapses caused the Saudi stock market much damage, destroying its value to a significant extent. Efficiency in investments enhances financial growth—particularly in emerging markets that exhibit capital erosion attributed to price volatility—but this growth may be compromised or seriously impaired by stock market volatility. Financial volatilities in different markets and types of assets influence each other. The problem leads to a single asset or market causing volatility elsewhere (Bauwens et al., 2006). The exchange of Saudi Arabia is highly sensitive to sudden news, shocks and other factors and is therefore considered volatile. Some collapses that have occurred in its index are attributed to the global volatility transmission, particularly since it is now connected to the global stock markets. Consequently, it is critical to investigate the volatility of diverse markets for improved understanding and useful portfolio analysis.

1.3 Research Objectives

To construct an efficient equity portfolio, investors and other interests must understand the cross-market interactions and explore the volatility transmission between various financial markets in different contexts. Thus, the main aim of this thesis is to improve portfolio management by examining volatility transmission through an econometric analysis. Diversification through portfolio management means investing in different assets in the same market or investing in more than one nation's market to minimise risks by selecting countries whose economies are not completely linked. This strategy can help investors or portfolio managers to reduce their portfolio volatility risk (Bodie et al., 2014). Thus, in this study, the portfolio is composed of a mixture of assets derived from international financial markets (stocks and commodities). Consequently, investors and other interests benefit through investing in a broader range of securities. The primary purpose of portfolio management diversification is to boost the risk–return benefit for investors, portfolio managers and others.

Moreover, this thesis examines volatility transmission by using major specific global financial markets related to the Saudi stock market in the modelling specification. These global variables include the following: (i) major global stock markets (including the S&P 500 of the US, the DAX 30 of Germany, the NIKKEI 225 of Japan, the FTSE 100 of the UK, the SSE of China and the MSCI[1] Index); and (ii) major commodity markets, such as those for oil and precious metals (where precious metals are considered a safe haven for hedging against crises/shocks and their effects on the Saudi stock market).

[1] This abbreviation is used for Morgan Stanley Capital International.

The connection of a local market with global stock markets is crucial for investors because diversification occurs in cross-country portfolios. Therefore, portfolio diversification is measured in this thesis by seeking to identify the optimal portfolio management approach. This identification is conducted based on estimations to minimise the time-varying conditional variance and covariance of return assets using different econometric methods. The optimal amount of each asset is measured by the optimal portfolio weight to be included in the investment portfolio. Further, the hedging ratio is determined by employing the rate at a long position in one market that could be hedged by taking a short position in another market.

The study is focused on the breakdowns that occurred owing to the GFC in 2008 and the decline in oil prices in mid-2014. The GFC was selected because of the sharp fall (56%) experienced by TASI from 11,038.66 points at end-2007 to 4,802.99 points at end-2008 (SAMA, 2008). Thus, this critical period allows examining certain outcomes (Mensi, 2019). Further, the oil price decline in mid-2014 led to a gradual decline (39%) in TASI from 9,000 points in mid-2015 to 5,500 points at the start of 2016 (Investment Jadwa, 2016). However, both the GFC and the oil price collapse in 2014–2016 have not been thoroughly investigated in the context of the Saudi Arabian stock market.

The following specific issues are addressed in this thesis:

i. Distinguishing and measuring the nature and effects of volatility transmission from global stock markets and major commodity markets to the Saudi stock market during the whole sample period and during the shock and crisis periods.

ii. Using the findings for building an optimal portfolio management strategy by investigating the research variables, of which some such as precious metals may be less correlated with the Saudi stock market (Mensi, Hammoudeh, & Kang, 2015; Samontaray & Alanuzi, 2015).

Despite the studies on the effects of volatility spillover between the Saudi stock market and the other global financial markets, there exists a major literature gap regarding, first, the significance of volatility transmission from the stock markets of Saudi Arabia’s trading partners due to rising globalisation and financial integration; and second, the importance of volatility transmission from major commodity markets in view of Saudi Arabia's natural resources. According to Creti et al. (2013), Raza et al. (2016) and Bass (2017), commodity markets have recently become connected to equity markets in some manner. However, existing empirical studies on the relationship between stock and commodity markets, including a recent study by Ahmed and Huo (2020), have recently focused on emerging markets. Thus, the Arab markets have received minimal attention, resulting in knowledge deficiencies, and more knowledge is required about the volatility transmission effect from the global stocks and major commodities to the Saudi stock market. Bridging this gap will help improve the region's market performance, given the greater emphasis on the existing financial variables in this thesis. Third, this thesis compares the importance effects of the volatility transmission of the GFC in 2008 and oil price decline in 2014–2016 on the Saudi stock market.

Methodologically, this thesis employs advanced econometric techniques, namely, the cross-correlation function (CCF) and multivariate generalised autoregressive conditional heteroscedasticity (MGARCH), to calculate, for Saudi Arabia, first the global stock and commodity volatility transmission effects and, second, the associated optimal weights and hedge ratios, to enhance portfolio management and diversify portfolios. It uses updated daily data for 2007–2018 for a more current practical analysis. Specifically, these integrated concepts, econometric models and updated data with expected new improved outcomes for portfolio management have not been used in the Saudi Arabian context. Hence, the findings are expected to provide useful portfolio allocation guidance to investors and other interests.

1.4 Research Questions and Hypotheses

The study will focus on the effect of volatility transmission emerging from global stocks and major commodities to the stock market of Saudi Arabia during the full period or during the periods of financial crisis and shock so that optimal portfolio management can be achieved. The two major financial collapses that occurred in 2008 and 2014–2016 will be examined in this context. The study aims to contribute to existing literature by addressing several research questions, which are as follows:

1. Is there volatility transmission between global stock markets and the Saudi stock market?

2. Is there volatility transmission between major commodity markets and the Saudi stock market?

3. How does volatility transmission of global stock and major commodity markets impact the Saudi Arabian stock market?

4. How did the volatility of global variables influence the Saudi stock market during the collapses of 2008 and 2014–2016?

5. What is the importance of the research findings in improving optimal portfolio management to reduce risks in Saudi Arabia?

Next, the null hypotheses from those research questions for testing are as follow:

H_1: There is volatility transmission between global stock markets and the Saudi stock market.

H_{2a}: There is volatility transmission between oil prices and the Saudi stock market.

H_{2b}: There is volatility transmission between precious metals and the Saudi stock market.

H_3: There is volatility transmission occurring between global stock and major commodity markets during the major financial collapses of 2008 and 2014–2016 for Saudi Arabia's stock market.

H_4: There is an optimal weight/hedge ratio that can rebalance the financial portfolio.

1.5 Research Contributions

The primary purpose of this thesis is to reveal the comprehensive relationship between the stock market of Saudi Arabia and the global stock and major commodity markets. The assumed influence of the latter markets will be used to quantify the transmission of information. This approach places this study in the best possible position to understand the nature of the volatility transmission to the Saudi Arabian stock market by using its trading partners' stock markets indices. Further, the study intends to understand market movement and transmission volatilities arising from the GFC in 2008 and the oil price decline in 2014–2016. Comparing the results between the two events sheds more light on stock market volatility. The observed volatility transmission is believed to exert significant and immediate influence on the Saudi stock market.

This thesis's findings are based on the examination of the interaction between the Saudi stock market and global stock and major commodity markets. To this end, it employs Baba, Engle, Kraft and Kroner – GARCH (BEKK-GARCH), constant conditional correlation – GARCH (CCC-GARCH) and dynamic conditional correlation – GARCH (DCC-GARCH) models in actualising the differences in volatility transmission for these financial markets on the Saudi Arabian stock market, with their diversified portfolios. It calls for evaluation of the effects of the volatility transmission of global financial markets with a series of market behaviours over a series of periods. The purpose of this research is to provide policy implications for informed involvement in the industry, for the best strategies to be put in place. Saudi Arabia is undergoing restructuring of its financial market, with Vision 2030 as the target focus. This makes these policies significant in promoting an open economy, for investment and trade towards sustainable economic growth by being able to improve financial integration or interdependence.

On understanding the impact of spillover effects within several financial markets, investors and other stakeholders can use the information transmitted, adjust the discovery process and use new information effectively. In general, under the efficient market hypothesis market movements reflect the changes in the terms of information transmission. Understanding the transmission channel of shocks and of volatility spillover influences helps understand the genesis of volatility and drivers of important security prices, which facilitates determining the cost of capital and understanding changes in hedging strategies worldwide. These goals can be achieved through a series of decisions regarding asset allocation, which makes this study vital in terms of global portfolio optimisation for gaining diversification advantages. In addition, this study is important to policymakers who can evaluate proposals on regulations that lead to volatility transmission, which can be used to measure local economies' performance where local markets may be threatened financially.

1.5.1 Contribution to Knowledge

By analysing the above issues, the current study contributes to the literature in several significant ways (for details, see Chapter 3). These are explained briefly as follows.

First and most important is the comprehensive use of bivariate analysis for examining multiple global financial markets in portfolio management. Saudi Arabia has received little consideration in the existing literature on stock market volatility transmission in the wake of the GFC in 2008 and the 2014–2016 oil price collapse. This study will address this significant gap in the knowledge on the subject and will provide up-to-date empirical evidence for an important decade (2007–2018) in a global analysis that may yield valuable insights. This will help to capture the extent of stock market volatility transmission between international stock markets, major commodity markets and the Saudi stock market.

Second, this bivariate analysis contributes to the existing spillover literature (origin of volatility) on finance. To date, this type of topic has not been investigated in detail for Saudi Arabia. More specifically, the current literature mainly considers a limited number of markets (e.g. only commodity market and TASI, or oil and TASI), and ignores the impact of combining the global stock markets of most of Saudi Arabia's trading partners together with the major commodity markets to consider crises/shock periods. In addition, the Saudi stock market has recently adopted liberalisation policies that have allowed foreign investors to buy shares in its local market. These reforms have increased investment in the country and could therefore have strengthened integration patterns. To the best of the researcher's knowledge, few studies have tested the level of spillover effects and their transmission from two events, such as the GFC in 2008 and the oil price decline after mid-2014, in the context of the interaction of the Saudi stock market with the global stock and major commodity markets. The premise is that the intensity and length of the effects of both events can differ when the Saudi stock market is compared with the global stock and major commodity markets in general and during the 2008 GFC and oil decline in 2014–2016 in particular.

Third, the study will apply advanced econometric models, namely CCF as well as BEKK-, CCC- and DCC-GARCH models. These models will be used to measure the causality in variance and the interaction between variables to assess the volatility transmission for more accurate data-based results. These results will generate new insights into the relationship of volatility transmission between TASI and international stock markets and major commodity markets not only for the overall period but also for the crisis and shock periods. Lastly, this thesis will provide guidelines for both investors and other interests.

1.5.2 Statement of Practical Contribution Regarding Volatility Origin and Portfolio Analysis

Understanding volatility origin or the way the Saudi market interacts globally will crucially help portfolio managers to conduct portfolio allocation and hedging decisions. Consequently, this study will facilitate optimal portfolio management from the global allocation portfolio perspective. In addition, the adding of global assets in a portfolio enables investors to allocate their portfolios across cross-markets effectively (Sadorsky, 2014). It also offers a method to organise risk, based on minimising the matrices of variance and covariance through assigning different weights to each asset. This research assumes that the results will provide hedging ratios that vary daily. Time-varying hedging is deemed to be an effective approach for managing and rebalancing portfolio risk. Thus, if investors prefer more conservative approaches, for example, simple regression as their preferred strategy, they will not benefit from financial portfolio diversification. The hedging ratio is of great significance to investors and portfolio managers in mitigating any risk that may lead to increased stock market volatility (Arouri, Lahiani, & Nguyen, 2011).

1.6 Thesis Structure

This thesis consists of seven chapters and begins with the introduction chapter of the topic, which addressed the background, research objectives, research questions and hypotheses, research contributions and thesis structure.

Chapter 2 provides the background of Saudi Arabia’s legislation, regulations and financial market development, especially from 1983 onwards, its international trading status after joining the WTO, is economic transformation under its ‘five-year plan’, and its stock market development. Further, the Saudi stock market’s historical background and the current Tadawul market’s development will be discussed. This chapter also explores the effect of the global factors on the Saudi stock market’s volatility, and the reasons for the increased interdependence between this market and those of its trading countries, thus providing details of what is truly occurring in Saudi Arabia.

Chapter 3 reviews the related literature and highlights a selection of significant topics related to volatility transmission, crisis/shock and portfolio management for financial markets, and, in particular, for stocks and commodities. This chapter discusses numerous empirical studies that have analysed these topics using different methods. It begins by providing a review of various research studies from four broad perspectives as follows. First, the review discusses studies on volatility transmission and its effect on various financial markets from the perspective of developed and developing countries but with a focus on the Saudi stock market. Second, it explores the research on the relationships between the two financial markets of stocks and commodities. Third, it summarises the related studies that have analysed volatility transmission in different financial markets during periods of financial crises and shocks. Lastly, the chapter reviews the literature on the opportunity for global portfolio diversification. The analysis of the existing literature allows identifying gaps that require further research and examination. This literature review aims to focus to some extent on studies that have released findings for Saudi Arabia and its trading partners’ stock and major commodity markets. Obviously, there are many studies in this context, but this thesis focused on the literature appropriate for the subject to be examined and the methodology being implemented.

Chapter 4 presents a comprehensive review of the methodology of unit roots tests, CCF and MGARCH models and portfolio management. All the econometric techniques are considered advanced, appropriate tools that can help to investigate volatility transmission and portfolio management.

Chapter 5 discusses the first empirical analysis of the thesis on the co-movement behaviour of TASI and six global stock markets and five major commodity markets. This chapter begins with the basic description of the data and the initial analysis of the preliminary data.

Unit root tests are performed to verify the values of those markets' stationarity and/or the existence of unit root. Daily data between 2007 and 2018 for the indexes of global stock markets (S&P 500, NIKKEI 225, DAX 30, FTSE 100, SSE and MSCI) and major commodity markets (crude oil, gold, silver, palladium and platinum) are used. This chapter also discusses the causality-in-variance interactions between the Saudi stock market and the global stock and major commodity markets across not only the whole period but also two subperiods based on the CCF test.

Chapter 6 provides the results on volatility transmission, conditional correlation and portfolio management in the relationship between TASI and six global stock markets and five major commodity markets. This chapter investigates the effects of volatility spillovers to analyse the relationships between these markets by applying MGARCH models (BEKK, CCC and DCC). The aim of current study is to examine more broadly the linkages between the Saudi stock market and the global stock and major commodity markets, to address the effects of the volatility transmission and conditional correlation and then to build the optimal weight and hedge ratio portfolios for both the whole period and the two subperiods using the MGARCH models (BEKK and DCC).

Chapter 7 summarises the main results of the thesis and provides policy implications for investors and policymakers. This chapter also addresses the limitations of this study and highlights directions for future research.

Chapter 2 Saudi Arabia: Overview

2.1 Introduction

Financial securities, including stocks and commodities, are traded by investors in markets termed financial markets (Blake, 1990). Financial markets are classified into capital markets and money markets. Of the two types of financial assets traded, one is termed a long-term asset and is traded in the capital market, and the other is termed a short-term asset and is traded in the money market (Fabozzi & Modigliani, 2009). This analysis in this thesis is focused on the capital market and not the money market.

The stock market is basically a collection of markets in which over-the-counter trading is performed in the shares of publicly listed companies in an authorised way. Stock markets are critical to national economic development because they represent the investment activity in these nations and in their publicly listed companies. Local and foreign investments in companies are channelled through stock markets, which results in rising productivity. Stock markets are established through each country's financial regulations to provide opportunities for investing in the short, medium and long terms. Newly listed companies float their shares to the public through an initial public offering, which allows them to list their shares. The aim is to help companies raise equity capital and thus the start-up capital required. In this manner, companies obtain financial resources that they will not otherwise obtain if the stock market does not play a role in this process. This new issuance of shares and the raising of equity finance is channelled through the primary stock market. Conversely, the secondary stock market serves the purpose of stock trading, which refers to the buying and selling of stock between various investors. Investors have varying interests, risk aptitude and financial goals; therefore, the buying and selling of stocks takes place in the stock markets. People use their savings to invest in stocks and earn capital gain and dividend income (Pescetto, 1993).

This chapter reviews the development of the Saudi Arabian stock market along with the relevant regulations that were implemented to govern the country's stock market. Further, it reviews this market's history from its inception to the present day.

2.2 Legislation and Regulations Developed for the Saudi Stock Market

The stock market in Saudi Arabia has been developed through a long regulatory and legislative process that can be divided into two stages, namely, the regulation of the stock market by the Ministerial Committee and the Executive Committee, and the founding of the Capital Market Authority (CMA) of Saudi Arabia. Both stages have their own characteristics in which the regulatory frameworks were developed and implemented. A detailed chronology of the Saudi stock market development is provided next. First, the Council of Ministers of Saudi Arabia was formed in 1983 to establish policies regarding economics, finance, defence, education and other affairs. It was headed by the Prime Minister and representatives from many ministries, such as those for finance, investment and trade. Moreover, the head of the SAMA was part of this council. This council was responsible for making and implementing policies to promote stock trading in Saudi Arabia and the registration of Saudi companies on the stock market to enable the public to invest and trade in stocks.

SAMA implemented important measures from 1985 to 1987 in this regard to facilitate share transfers and trading. For this reason, the Saudi companies were required to be listed on the Saudi stock market. This was an important step to promote confidence among the general public and institutional investors in the stock market and to protect investors' rights. A key step by SAMA was establishing a central hall for stock trading that allowed banks to work together in the same building for better collaboration. It was an important decision because stock trading through various intermediaries posed difficulties especially when two banks were involved, and a stock's price could differ at a single time owing to currency differences. Moreover, this decision helped to increase the share transfer time and make it easier and faster. However, this mechanism was not successful because of the intermediaries' resistance since the trading volume was too small and not many companies' stocks could be traded. Therefore, banks returned to the previous trading mechanism soon after and the concept of trading in a central hall failed.

The council took more steps to improve stock trading. For this purpose, the Electronic Securities Information System (ESIS) was implemented for automatic trading of stocks with the facilitation of local Saudi banks. This system was aimed to solve the problems faced in the central hall plan that had failed. These problems included the poor transparency in stock trading, the lack of efficiency in stock ownership transfer and the inability of the intermediaries to work together in one trading hall. Therefore, ESIS was a true solution for such problems since it was automatic in nature and offered the electronic trading of stocks and quick settlement with efficient ownership transfer. Moreover, it permitted the intermediary banks to collect sufficient information about the traders. Thus, it resolved many problems in the previous central hall trading, such as poor transparency, inefficient transfer and lack of protection of traders' rights.

The ESIS, which was introduced in 1990, continued to run successfully in subsequent years. In 1997, more regulations were put in place to facilitate investors, including a mandatory condition for disclosures regarding investment details to protect investors and improve trading transparency. A key disclosure requirement concerned companies' internal issues, such as profits or losses for the period and major restructuring, merger or takeover plans. These disclosure requirements were added to protect investors from insider trading through which some investors gained from trading on the basis of 'insider' information, which put other investors at a significant disadvantage. Therefore, the board of directors of companies were made responsible for disclosing such important internal information so that investors could make informed decisions. Moreover, the investment and trading of stocks by a company's directors, employees and management were restricted by mandating certain conditions to reduce the element of insider trading.

The ESIS was further improved in 1998 through additional conditions and requirements. Earlier, share transfers were possible once a new company had been launched and registered on the stock exchange as a listed company. Companies seeking to be listed were required to disclose two years of financial statements along with budgets for this reason. New laws made it possible for two types of Saudi companies to be registered on the stock exchange—equity firms with subscription and equity firms with limited underwriting.

2.2.1 Capital Market Law

The Capital Market Law (CML) was established in 2003 for the purpose of reorganising and restructuring the Saudi financial market. This restructuring was necessary to introduce the latest financial systems to increase stock investment and trading by potential investors, and to ensure the necessary transparency and fairness in stock trading. A Royal Decree was issued to regulate and develop the capital market under which regulations were established for all the listed securities and their transactions (CMA, 2017). Under this law, CMA was formed as a government organisation having complete financial and legal independence and working under the Prime Minister. Its purpose is to regulate Tadawul, the currently operating Saudi Arabian stock exchange. CMA is responsible for regulating the capital market, protecting investors and the general public from unfair trading practices in stocks, promoting transparency in stock trading, monitoring the issuance of securities and also regulating the financial information disclosures by listed companies. Under CMA rules, the Saudi stock market experienced good growth between 2003 and 2017, and it became a leading stock exchange in the Arab world. Meanwhile, the Saudi stock market, that is, Tadawul, and the Commission for Settlement of Disputes and Financial Management were established to settle any disputes. Moreover, a Committee for Appeal was established to review the decisions made by this commission (CMA, 2009, 2017).

2.2.2 Capital Market Authority

CMA (2017) has important functions: the development and regulation of the capital market in Saudi Arabia; the development of stock trading practices and their improvement; the protection of investors from unfair trading practices; the promotion of transparency and efficiency in stock trading; the enforcement of controls for risk reduction; the regulation of initial public offers of shares and their trading along with monitoring in this regard; the regulation of proxies; the issue of licences to special purpose entities; and the regulation of information disclosures by the listed companies.

The parties subject to this authority's (CMA, 2017) supervision are as follows:

(i) Tadawul: Based on CML, the Saudi Stock Market (Tadawul) was established under Article 20 for investment and trading of shares of companies with a legal status of joint stock company. In addition, Tadawul was given full authority over share trading, and all the matters related to trading became its responsibility.

(ii) Persons authorised by CML: These individuals can trade in securities.

(iii) Listed companies: These companies are those whose shares are traded on Tadawul.

(iv) Securities Depository Center: Securities' deposits are provided by Securities Depository Center Company in Saudi Arabia.

(v) Capital market dealers/participants.

(vi) Special Purpose Entities: These were established under CMA for issuance of debt instruments.

(vii) Credit rating agencies and companies.

(viii) Investment products in the capital market.

2.2.3 CMA's Efforts in 2017 to Achieve Vision 2030

CMA has taken many steps in conjunction with Vision 2030 to develop the country's financial sector. The key aim of Vision 2030 is to reduce the reliance of the Saudi Arabian economy on oil exports and to achieve economic diversification. CMA is playing an important role in this regard. The key functions performed by CMA during 2017 in alignment with Vision 2030 are presented in Table 2.1.

Table 2.1: Strategic Plan for Achieving Vision 2030 Objectives

Number	Action	Result
1	Amending the timeframe of the transaction settlement cycle for the shares of the listed companies in TASI.	To align the share trading in Saudi Arabia with global practices, to facilitate collaboration with international stock markets and to protect traders in Saudi Arabia.
2	Establishing a parallel capital market.	To provide a new capital market as a financial channel for funding and increasing penetration in Saudi Arabia.
3	Allowing the lending of securities along with implementing the legislation for short selling in the stock market.	To attract more investment from investors and align the Saudi stock market practices with international practices.
4	Mandating that all listed companies and financial institutions in TASI should adopt International Financial Reporting Standards.	To lead towards higher transparency in financial statements, better comparability, more informed decision-making by the investors, higher confidence in the financial reports of the companies, among other outcomes. The mandatory adoption of these Standards is a major step taken by CMA.
5	Including the MSCI index in Tadawul.	To attract foreign investors. The MSCI index is important for measuring the performance of large- and mid-cap companies in the Saudi stock market. It is an internationally recognised global investment market index and makes the capital market highly attractive to foreign investors.
6	Establishing regulations for supervision and control of function for auditors for the listed companies and market institutions in TASI.	To boost investor confidence. This step is very important for boosting investors' confidence and for maintaining transparent and fair business practices. It resulted in higher confidence in global financial markets about Saudi companies owing to these companies' reliable financial statements and improved comparability with international competitors.

Table 2.1: Continued

Number	Action	Result
7	Approving the merger and acquisition regulations along with a new glossary of terms.	To facilitate mergers and acquisitions in Saudi Arabia. This step is very important in facilitating acquisitions and mergers, a tool for corporate growth, and in enhancing the capital market stability.
8	Reducing licensing requirements to promote asset management.	To develop the asset management industry in Saudi Arabia. Asset management is a significant part of capital market and provides experts with a chance to work with companies on their asset management practices.
9	Allowing non-resident foreign investors invest in the stock market through a parallel market.	To facilitate investment in the Saudi stock market. This is an important development in this regard.
10	Increasing the ranking for protection of minority investors from 63 to 10.	To protect existing investors and attract more investors. This results in attracting investors, both local and international.
11	Converting the Securities Depository Center into an independent company.	To promote stock trading efficiency. This action is crucial for working compliance alongside international markets’ listing requirement.
12	Launching an investor protection system for resolving investors’ complaints and issues they face.	To promote trading. The effectiveness and speed of resolving complaints and problems is key to boosting market participants.
13	Stipulating that market disputes are to be resolved through regulations of class action suits.	To ensure quick resolution of disputes. The speedy resolution of disputes is helpful to investors, and therefore, CMA’s legislation procedures in this regard help traders to receive any indemnity or compensations easily.

Table 2.1: Continued

Number	Action	Result
14	Amending the rules related to securities and continuing obligations along with the listing regulations.	To support the issuance of shares and also increase the penetration of the capital market of Saudi Arabia.
15	Formulating regulations for special purpose entities adopted by CMA.	To boost the performance of the Saudi Arabian capital market and also help CMA to better regulate and monitor transactions related to stocks.
16	Adopting FinTech Lab initiative.	To adopt new, sophisticated technologies. The rapid development of international stock markets has resulted in the updating of regulations and standards, which have resulted in best practices. CMA is following the same path to ensure the Saudi stock exchange is in line with the international stock markets by promoting new technologies such as FinTech.
17	Issuing a regulation for mandatory voting in general meetings of the listed companies.	To ensure shareholder attention. It is important that shareholders attend the general meetings of listed companies and participate in the decision-making of the company by building a relationship based on trust with the management. This would allow shareholders to attend to all matters that require their general opinion, such as the selection of directors.
18	Establishing a financial academy specifically for training financial sector employees.	To provide necessary skills. Qualified, skilled employees are key to financial sector success and this step is in line with the Saudi Vision 2030 that calls for the diversification of the economy.

Source: CMA (2017).

2.2.4 Saudi Stock Market

On 19 March 2007, the Saudi stock market company or Tadawul was approved its establishment as a joint stock company under CML, and under the supervision of CMA. Tadawul is the sole authority in Saudi Arabia, and it functions as the country's securities exchange. It conducts various functions, such as listing securities and maintaining a registry of securities traded. The company is also responsible for deposit, transfer, clearing and settlement. Tadawul is the most liquid stock market in the MENA region and is headquartered in Riyadh. The capital amount of Tadawul is SR1,200 million, and 120 million shares of equal value of SR10 are held by the country's public investment fund. The market capitalisation of Tadawul is three times greater than that of the exchanges of its neighbouring countries (SAMA, 2018).

Since the stock exchange is the central pillar of the Saudi economy, a key aim of Tadawul is to create an efficient and transparent stock market that will be recognised for its global exchange capacity. After its establishment, Tadawul switched to an electronic trading system that helps buyers and sellers trade on computers rather than by visiting a bank or a security exchange office. This electronic trading system also eliminated geographical restrictions. In 2008, CMA issued new rules for foreign investors by allowing them to gain indirect ownership. The Saudi stock exchange became a member of the World Federation of Exchanges in 2009. It was able to join more than 60 other global member exchanges (Tadawul, 2009). It is also responsible for fulfilling the Federation's criteria. According to these criteria, it must educate investors seeking to participate in the stock market. It is also responsible for more efficient allocation of public capital to profitable channels. Further, it must ensure that stock market transactions are transparent and safe and protect investors from market manipulations through which large investors take advantage of small investors who lack market 'savvy'. In this regard, the Saudi stock market implements a technology-based system so that market efficiency can be achieved. It ensures justice and equal treatment of investors and the completion of litigation settlements according to regulations and within specified periods.

2.2.5 Corporate Governance

CMA passed corporate governance regulations on 12 November 2006 (CMA, 2009). These regulations are applicable to all the companies listed on the Saudi stock market. The regulations were initially not mandatory; however, in 2009, CMA directed that companies must comply with certain rules to enhance transparency and protect their shareholders' interests. As per the new CMA regulations for listed companies, CMA reviews the prospectus and internal organisational regulations prior to a company being listed on the Saudi stock exchange. CMA requires full disclosure of their board of directors from listed companies. If the board composition changes, affected companies should provide full information before and after board members' nomination. Further, the companies are required to provide information on the compensation and remuneration paid to board members. CMA has also specified the information to be provided on non-executive and independent board members.

Further, companies listed with CMA are required to comply with the best corporate governance regulations. CMA conducts a supervisory visit to check the corporate governance practices of listed companies and provides them with recommendations to ensure investors are protected and have the confidence to participate in trading on the stock market. However, if a company fails to comply with the corporate governance regulations, CMA imposes a penalty. For example, it imposed a fine of SR50,000 on a listed company that failed to include the board's information in its report. CMA also aims to educate and advise new companies listed on stock exchange regarding governance practices (CMA, 2017).

2.3 History of the Saudi Stock Market

The Saudi Arabian stock market, or Tadawul, and its index, the TASI, is supervised by CMA of Saudi Arabia. Currently, it is considered the largest stock market in the GCC and MENA regions. Its history dates to the 1930s when the Arab Automobile Company was founded as a joint stock company in Saudi Arabia. It was the first company of its kind. In the 1930s, Saudi Arabia was not an oil-rich country and still very far from the developed economy that it is today. The country faced many challenges, and these were mainly related to the scarcity of financial resources.

Later, in 1943, Arabian American Oil Company (ARAMCO) was in full control of oil exploration in Saudi Arabia. From 1949 to 1954, the oil production doubled from 500,000 to 1 million barrels per day. However, in 1950, the Saudi government began to increase its share in ARAMCO, and later, signed an agreement with ARAMCO to share profits equally. The Saudi government started imposing taxes on ARAMCO to increase government revenues. Over time, the government started to reduce the oil exploration area of ARAMCO, and by 1982, the area fell from 930,000 to 220,000 square kilometres. By 1988, the Saudi government bought all the shares of ARAMCO, and it officially became the national oil company of Saudi Arabia. Subsequently, the number of public listed companies, such as the Riyadh Bank, began increasing significantly. This institution became one of the first listed banks in Saudi Arabia, and its initial equity was SR50 million.

Over time, more companies started to list on the Saudi stock exchange. Further, there was an increasing trend to develop joint venture companies, such as the Arabian Petroleum Supply Company established in 1961as a joint venture between US Exxon Mobil Company and HAACO Company Saudi Arabia. By 1964, the number of listed companies in Saudi Arabia reached 17 with a combined capital of SR2 billion. The listed companies Saudi Arabia were increasing rapidly but there was no overarching authority that could regulate these businesses. At that time, more than 20 million shares were available in the market but because of the absence of a regulatory authority, the public was uncertain about the trading activities of such joint stock companies. For this reason, the Saudi government passed the Companies Act in 1965 to regulate the joint stock companies operating in the country.

With the increase in oil prices in 1973 from $3 per barrel to $12 per barrel, the revenue of the Saudi government also rose, and the Saudi economy grew even more. The gross domestic product (GDP) increased from $15 billion to $184 billion during 1973–1981. The number of listed companies rose in tandem with the increase in government revenues from oil production and export and reached 97 by the end of 1980 with a total of 186.6 million shares. The public learned to understand market trading and showed interest in both short- and long-term investments. An increase in trade activities resulted in the establishment of financial intermediaries that served as the agents between transacting parties and facilitated the buying and selling of stocks.

The economic boom that the country was experiencing increased individual wealth and savings, which resulted in increased stock market activity. In 1981, about 150,000 transactions were recorded in a single month. Since listed companies were paying dividends regularly, people's interest in shares increased and they started to shift their real estate investments to the stock market. Owing to the increase in trade activities, the companies began offering more capital to the public, which, in turn, further enhanced trade activities. For example, in 1983, the Saudi Arabian Basic Industries Corporation (SABIC)—the largest listed Saudi company on the stock exchange before ARAMCO listed in the market—offered 30% of its capital to investors.

In the 1980s, Saudi Arabia's oil production reached 10 billion barrels per day; however, in these same years, new oil discoveries (in Mexico, the North Sea and the Soviet Union) by countries that were not part of the Organization of the Petroleum Exporting Countries (OPEC) severely affected Saudi Arabian revenues. The oil share of non–OPEC countries increased from 48% to 71% in 1975–1985, which caused oil supply to increase, the demand for oil reduced, and therefore, the other OPEC countries pressurised Saud Arabia to halve its oil production. The reduction of oil production severely affected its oil exports and revenues, and since the government budget mostly depended on oil exports, the end result was a budget deficit. This, in turn, forced the government to curtail its expenses and find ways to diversify the Saudi economy.

In the 1970s, despite the increasing number of listed companies in Saudi Arabia, there was no regulatory authority, and therefore, informal agencies started to play a role as intermediaries or brokers. These brokers were mainly real estate agencies and currency exchange offices. They facilitated the buying and selling of stock and securities. Since these intermediaries were not regulated, the market suffered from illegal practices. However, in the early 1980s a regulated market for trading was implemented; further, in 1984, a Ministerial Committee was formed to regulate and develop the stock market. To protect investors and ensure stock market efficiency, many rules and regulations were issued by the Ministerial Committee. It also regulated that the public could trade stocks only through commercial banks and not real estate agencies and currency exchange centres. The committee also played a key role at the time of the stock market crash in neighbouring countries, such as in 1982, when the Kuwait stock market badly crashed, which affected its neighbouring countries, including Saudi Arabia. At the time of the crash, the committee played a key role, prohibited forward transactions and opened central trading units in Riyadh.

2.3.1 The Saudi Stock Market: General Index

The National Centre for Financial and Economic Information (NCFEI) introduced indices for the Saudi stock market in 1985 for the first time. The general index for the market was set at 1,000 points, and 4 million shares were traded by end-1985. At that time, more than 30% of trade transactions were via informal agencies, but banks were also involved in share trading. Since a formal agency or authority and proper communication channels were lacking, share trading was not performed properly. Each bank quoted different prices of each share, and when they were asked to match the prices of a certain share, it sometimes took them three weeks to do so. For share trading, the informal agencies charged low commissions despite the Ministerial Committee's policies that prohibited this practice.

In 1986, the stock market did not grow as expected, and instead, it dropped to 630 points. To centralise stock trading, the Saudi government took measures and developed a trading hall. SAMA was in charge of operating it, and SAMA opened the hall to the public in May 1987. SAMA allowed only banks to trade in that trading hall and did not permit informal agencies to trade there. These revolutionary measures taken by the Saudi government to centralise the stock market failed to grow the market. The major reason behind this failure was that more than 30% of the stock was traded by the informal agencies, which were not allowed to operate in the trading hall. To grow the stock market, the government decided to trade the stock with the old system; this decision worked well in 1988—the index went up by 22%, and in that year 41,951 transactions were executed.

The Saudi Arabian stock exchange saw continuous growth by 1988. The total market value of securities traded in the stock exchange was SR107 billion, and therefore, the NCFEI index reached 1,000 points. SAMA moved towards an automated system of security trading—the first of its kind in the Arab world. It was designed to eliminate the need for manual share transfers and provided updated and quick information about the markets and share price bids. The introduction of this system highly increased the number of securities traded, and thus, the NCFEI index went up to 1,590 points by 1990. However, the significant political turmoil in the region due to the first Gulf war in September 1990 halted the fast progress of the Saudi stock market. Yet, the effect was felt only in the short term, and the NCFEI index entered a strong bullish trend from the end of 1990 until April 1992, when it reached a new record of 2,338 points with SR239 billion worth of trading.

Mutual funds are a significant component of the capital market considering that these funds take investments from the general public and invest on their behalf in a portfolio of investments. Therefore, this type of investment carries less risks for investors and offers relatively stable returns. In 1992, SAMA allowed the formation of mutual funds in Saudi Arabia, which boosted share trading. This fast-paced growth led analysts to believe that shares had become overpriced. Therefore, SAMA had to raise the interest rate to make the public increase savings and to reduce liquidity to avoid a stock market collapse. Moreover, price ceilings levels were introduced to control unexplained rises and falls in share prices beyond 50% of the price at any given time. This measure resulted in the fall of the stock market index to 1,890 points at the end of 1992. This fall was partly due to the decline in the oil price, which reduced the government's oil export revenues, and the government approved a deficit budget for that year.

The decline in the NCFEI index continued throughout 1993, and the index reached 1,800 points by year end. The bearish trend continued in the next year, and the index reached 1,280 points by end-1994. This trend caused a significant decline and led the stock exchange to lose SR100 billion in that year. This bearish trend was noted in 1995 as well; however, it slowed down, and the index finally reached 1,150 points by May 1995. Afterwards, the NCFEI index started recovering, entered a bullish trend and reached 1,370 points by the end of 1995. The Saudi stock market began to recover quickly in 1996 when all the industrial sectors grew, and the budget deficit was strongly cut; the country's GDP increased in the same year.

In 1997, the Saudi American Bank was authorised to allow all foreigners to invest in the Saudi stock market; they were allowed to invest through banks in the Saudi Arabian Investment Fund, which managed to raise funds amounting to SR1 billion. However, as soon as this fund that was designed to attract foreigners and raise the stock market index was launched, the Asian Financial Crisis (AFC) of 1997–1998 occurred and caused a significant drop in oil prices from $20.61 in 1997 to $14.42 in 1998. This fall led to a strong stock market decline, by nearly 30%, and the trading volume at the end of 1998 reached SR52 billion. SAMA took necessary actions to reverse these trends and allowed foreigners to invest in the Saudi stock market through mutual funds. These actions following the end of the AFC resulted in an increase in the stock market activities and enabled the index to reach 1,500 points in 1999.

The year 2001 was important in the history of the Saudi stock market because Tadawul was implemented for the first time, and it then replaced the previous electronic system for securities trading. Tadawul is supervised by CMA, and the introduction of TASI resulted in better efficiency and handling of a higher stock trading volume. In 2003, CMA established market monitoring and regulations for Tadawul. These changes resulted in improving investors' confidence, smoothing the market's liberalisation and making available more finance-related products in Tadawul—for instance, exchange traded funds—which increased the share trading volume, value and capitalisation of the market.

The period until 2006 was one of significant growth for Tadawul, which allowed it to sign a contract with a Swedish company for redesigning its trading system, one that would allow trading in larger volumes and same-day settlement options. TASI recorded its highest close ever at 20,634.86 points by 25 February 2006 (see Table 2.3). This was an increase of 365% compared with what the index points closed in the end of 2003. The total market capitalisation recorded was SR3,000 billion in 2006. However, by the end of 2006 the stock market collapsed, causing the index to fall by 12,701.57 points. Therefore, 2006 was a highly turbulent year for TASI when the market reached its peak and then crashed by 61.6% in the same year and closed at 7,933.29 points. This event resulted in huge financial losses for many investors. CMA intervened and fined the alleged market manipulators who had compromised the market for short-term gains. However, the turbulent stock market behaviour recurred in 2007, when the market rose and recovered its losses. It reached 11,175.96 points, which was an increase of 3,242.67 points compared with the previous year (Tadawul, 2007).

The period 2005–2008 was marked by a significant increase in the number of investors entering the Saudi stock market. This fact led to the emergence of businesses such as portfolio management, financial analysts and other securities-related businesses. In 2008, the foreign capital in the Saudi stock market was estimated to have reached 22.4% of the total trading volume. In comparison to the previous year, the bullish trend continued in 2009 and reached 6,122 points, marking a 50% increase, and market capitalisation reached SR1,195 billion. Afterwards, Tadawul exhibited a stable pattern owing to CMA actions to stabilise the stock market and prevent undue influence by large investors. In 2010 and 2011, the market remained at around 6,000 points. By the end of 2011, it had reached 6,417 points (SAMA, 2011).

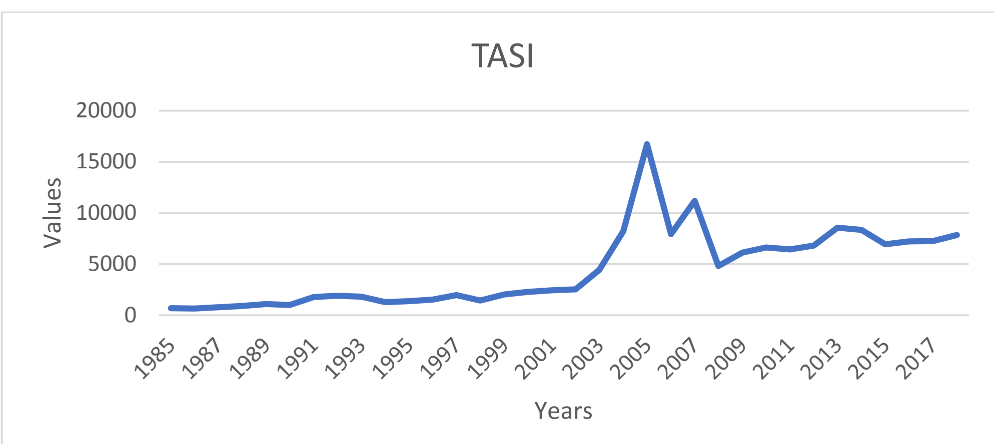
Moreover, Tadawul rose during the period 2013–2018 in which it recorded the highest close at 10,851 points on 2 October 2014. This was followed by a sharp decline to 8,289 points by 8 January 2015. This pattern shows that the volatile movement in TASI has been a key characteristic of trading and despite the steps taken by CMA, external forces push the stock market index up and down. TASI had fluctuated in a range of 7,200–7,800 index points between 2016–2018 (Tadawul, 2018).

Table 2.2: Tadawul All Share Index (TASI) 1985–2018 Main Market

Year	TASI	Change (%)	Year	TASI	Change (%)
1985	690.88		**2002**	2,518.08	3.62%
1986	646.03	−6.49%	**2003**	4,437.58	76.23%
1987	780.64	20.84%	**2004**	8,206.23	84.93%
1988	892.00	14.27%	**2005**	16,712.64	103.66%
1989	1,086.83	21.84%	**2006**	7,933.29	−52.53%
1990	979.77	−9.85%	**2007**	11,175.96	40.87%
1991	1,765.24	80.17%	**2008**	4,802.99	−56.49%
1992	1,888.65	6.99%	**2009**	6,121.76	27.46%
1993	1,793.30	−5.05%	**2010**	6,620.75	8.15%
1994	1,282.87	−28.46%	**2011**	6,417.73	−3.07%
1995	1,367.60	6.60%	**2012**	6,801.22	5.98%
1996	1,531.00	11.95%	**2013**	8,535.60	25.50%
1997	1,957.80	27.88%	**2014**	8,333.30	−2.37%
1998	1,413.10	−27.82%	**2015**	6,911.76	−17.06%
1999	2,028.53	43.55%	**2016**	7,210.43	4.32%
2000	2,258.29	11.33%	**2017**	7,226.32	0.22%
2001	2,430.11	7.61%	**2018**	7,826.73	8.31%

Source: Tadawul (2007, 2018) and SAMA (2018).

Figure 2.1: Tadawul All Share Index (TASI) 1985–2018 Main Market



2.3.2 Tadawul: Performance Remark

In this thesis, the behaviour changes of Saudi Arabia's stock market have been highlighted and explained over the 34-year period, that is, 1985–2018 using statistical analysis. This period is divided into two: 1985–1999 and 2000–2018. In the first period, the stock market was relatively stable except during the Gulf War in 1991 and the AFC in 1997–1998. However, in the second period, there was a rapid increase in stock prices followed by a strong bearish trend after 2006, the 2008 GFC and the 2014–2016 oil price decline.

2.3.2.1 Industrial Sectors in the Saudi Stock Market

The industrial sectors traded on TASI have continuously increased, and by 2018, a total of 190 companies were listed on Tadawul. This number was 75 and 146 in 2000 and 2010, respectively. The introduction of more regulations and government control led to an increase in stock market functionality in Saudi Arabia. Once the stock market was regulated by CML, new sectors were introduced to the Saudi stock exchange in 2008 and 2016, and this led to a total of 16 and 20 sectors, respectively. The policies adopted by CML led to many family-based and closed companies going public and listing on the Saudi stock exchange. As shown in Table 2.4, this provided great opportunities for local and foreign investors to invest in a portfolio of companies and diversify their investment risks.

Further, in terms of share volume traded, in 2018 a total of 9.05 billion shares of companies in the Materials group were traded, and this proved to be the most active industry group in the Saudi stock exchange during that year. Moreover, the number of shares traded for the Banks industry group was about 8.40 billion, and of the Real Estate Management & Development industry group was 8.10 billion. The highest value of shares traded during 2018 was also that of Materials at SR273.48 billion, followed by Banks at SR221.67 billion and Real Estate Management & Development at SR98.92 billion (Tadawul, 2018).

Table 2.3: Sectors Operating in the Saudi Stock Market

Number	Sectors before 5/4/2008	Sectors between 5/4/2008 and December 2016	Sectors after 2017
1	Banking	Banks & Financial Services	Energy
2	Industry	Petrochemical Industries	Materials
3	Cement	Cement	Capital Goods
4	Services	Retail	Commercial & Professional Services
5	Electricity	Energy & Utilities	Transport
6	Telecommunication	Agriculture & Food Industries	Consumer Durables & Apparel
7	Insurance	Telecommunications & Information Technology	Consumer Services
8	Agriculture	Insurance	Media
9		Multi-Investment	Retailing
10		Industrial Investment	Food & Staples Retailing
11		Building & Construction	Food & Beverages
12		Real Estate Development	Health Care Equipment & Services
13		Transport	Pharma, Biotech & Life Science
14		Media and Publishing	Banks
15		Hotel & Tourism	Diversified Financials
16		Real Estate Investment Trusts	Insurance
17			Telecommunication Services
18			Utilities

Table 2.3: Continued

Number	Sectors before 5/4/2008	Sectors between 5/4/2008 and December 2016	Sectors after 2017
19			Real Estate Investment Trusts
20			Real Estate Management & Development

Source: CMA (2008, 2017).

2.3.2.2 The Number of Listed Companies

The number of companies listed on the Saudi stock market over the decades has been increasing. There were 46, 146 and 190 listed companies in 1986, 2010 and 2018, respectively (SAMA, 2018). The data show that the trend of privatisation of companies and getting them listed has significantly risen in recent years, given that share listing allows them to raise equity finance and expand their operations. The increase in the number of listed companies in 1986–2005 was very slow, and only 31 new companies were listed; however, the pace picked up after 2005 because of the favourable CMA policies. The years between 2005 and 2018 saw considerable increase in the number of listed companies on the Saudi stock market.

2.3.2.3 The Number of Shares Traded

The increasing number of listed companies, especially during the past 12 years, 2007–2018, has led to a significant increase in the number of traded shares as well. This is because local and foreign investors have multiple options from various industries to invest in and thereby reduce their systematic risk, or beta. Moreover, the number of shares traded from 1985 to 201grew significantly 8 (see Table 2.5). The only periods when the number of shares traded fell were during the GFC and the oil price decline, and these crises cover the years 2008, 2009, 2010 and 2015. This means that the years 2007, 2009, 2010, 2013, 2015, 2017 and 2018 were, in fact, the exceptions. Tadawul has played a very strong role in attracting new investments, especially between 2002 and 2006. Moreover, the advanced share trading technology and the quick same-day transfer are the key reasons for the increase in the number of shares traded in that time. Nevertheless, in 2007–2018, the number of shares traded has fluctuated from year to year.

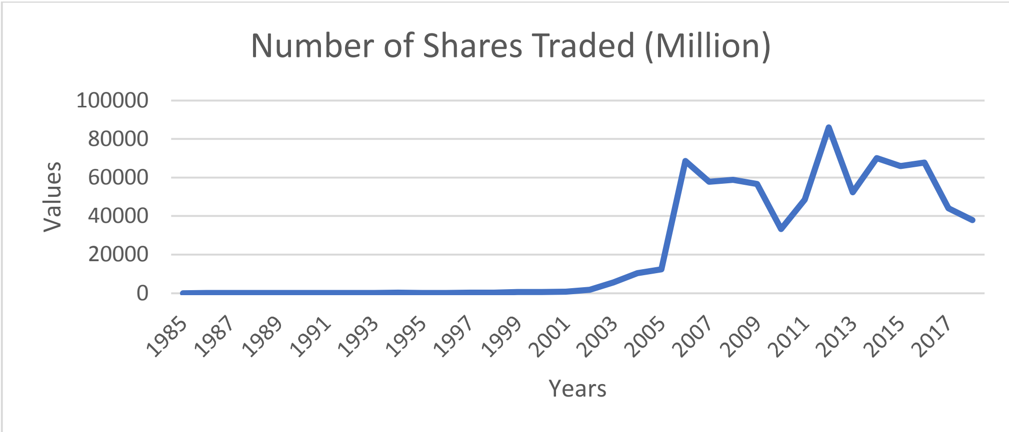
Table 2.4: Number of Shares Traded

Year	Number of Shares Traded (Million)	Change (%)	Year	Number of Shares Traded (Million)	Change (%)
1985	4		**2002**	1,736	150.91
1986	5	24.09	**2003**	5,566	220.64
1987	14	184.63	**2004**	10,298	85.03
1988	15	5.31	**2005**	12,281	19.26
1989	15	4.31	**2006**	68,515	457.88
1990	17	10.91	**2007**	57,829	−15.60
1991	34	98.50	**2008**	58,727	1.55
1992	34	1.82	**2009**	56,686	−3.48
1993	60	76.16	**2010**	33,255	−41.33
1994	152	152.19	**2011**	48,545	45.98
1995	117	−23.32	**2012**	86,006	77.17
1996	138	18.19	**2013**	52,306	−39.18
1997	314	127.79	**2014**	70,118	34.05
1998	295	−6.16	**2015**	65,920	−5.99
1999	528	79.04	**2016**	67,729	2.74
2000	555	5.20	**2017**	43,969	−35.08
2001	692	24.67	**2018**	37,820	−12.65

Source: Tadawul (2007, 2018) and SAMA (2018).

A total of 37.8 billion shares were traded in 2018, and this was below the 2016 level of 67.7 billion shares. A significant decline was observed during 2017, namely, 35.1% reduction in shares traded, and the total traded was 43.9 billion shares. The number of shares trade witnessed almost continuous growth from 1985 to 1995, from 4 million to 152 million shares. This number reached 528 million shares in 1999 and 555 million in 2000. The total shares traded grew consistently in 2003–2005, reaching 68.5 billion shares in 2006. A notable decline to 57.8 billion occurred in 2007 followed by a small rise of 59.7 billion in 2008. In 2009, it fell again to 56.7 billion shares, and a strong decline was evident in 2010 when the total shares traded was 33.25 billion.

Figure 2.2: Number of Shares Traded



2.3.2.4 The Value of Shares Traded

The value of shares traded has also increased significantly since 1985 (see Table 2.6), corresponding to the rising share price. Money has been flowing into the Saudi stock market, and investors are willing to pay more to buy the shares of companies listed on this market. People invest only when they expect future capital gain and dividend income. However, these investors' confidence is shaken during periods of turmoil or financial crisis, and when these occur, capital flows out of the stock market. That is why the TASI fell significantly during the AFC and GFC and the value of shares also fell.

Figure 2.3: Value of Shares Traded

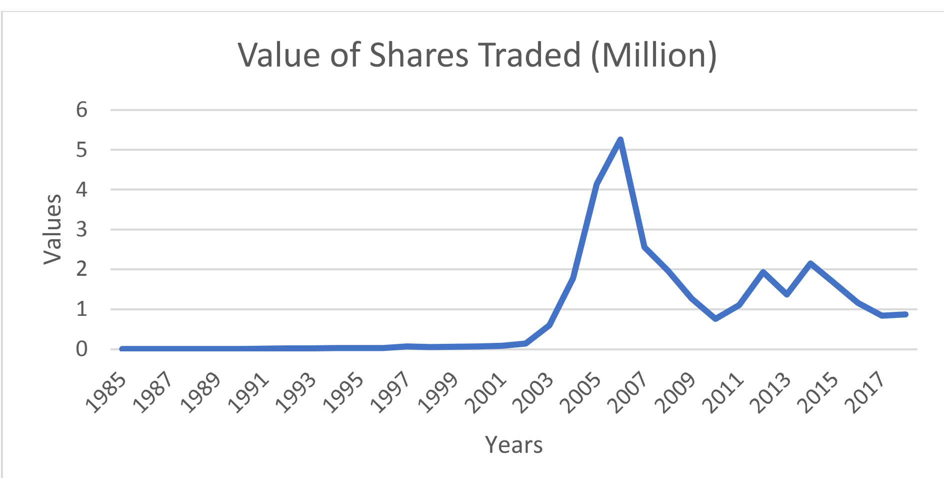


Table 2.5: Value of Shares Traded

Year	Value of Shares Traded (Million)	Change (%)	Year	Value of Shares Traded (Million)	Change (%)
1985	760		**2002**	133,787	60.03
1986	831	9.31	**2003**	596,510	345.87
1987	1,686	102.89	**2004**	1,773,859	197.37
1988	2,098	24.47	**2005**	4,138,696	133.32
1989	3,364	60.33	**2006**	5,261,851	27.14
1990	4,403	30.91	**2007**	2,557,713	−51.39
1991	8,527	93.66	**2008**	1,962,946	−23.25
1992	13,699	60.65	**2009**	1,264,011	−35.61
1993	17,360	26.73	**2010**	759,184	−39.94
1994	24,871	43.27	**2011**	1,098,836	44.74
1995	23,227	−6.61	**2012**	1,929,318	75.58
1996	25,397	9.35	**2013**	1,369,666	−29.01
1997	62,060	144.36	**2014**	2,146,512	56.72
1998	51,509	−17.00	**2015**	1,660,622	−22.64
1999	56,579	9.84	**2016**	1,156,987	−30.33
2000	65,293	15.40	**2017**	836,275	−27.72
2001	83,601	28.04	**2018**	870,869	4.14

Source: Tadawul (2007, 2018) and SAMA (2018).

In 2018, the total share value of the Saudi stock exchange was approximately SR870,869 million, up from SR836,275 billion in 2017, and this meant the overall market capitalisation grew by about 4%. Prior to the 21st century, considerable share price growth was evident. During 1985, the value of shares traded on the Saudi stock exchange was SR760 million, and this increased to SR24.9 billion in 1994, falling slightly to SR23.2 billion in 1995. However, in 1997, the value of shares grew by 144% compared with the value in the previous year and reached SR62 billion. Later, the value dropped because of the AFC. In 1999, the total value was SR56.6 billion, which was higher than that in 1998. In 2003, the value of shares reached SR597 billion compared with SR134 billion in 2002.

This was the biggest rise (346%) in the value of shares traded in the history of the Saudi stock market. After 2006, the value of shares took a downward turn and reduced consistently in 2007, 2008, 2009 and 2010 by 51.4%, 23.3%, 35.6% and 39.94%, respectively.

2.3.2.5 Tadawul's 2006 Collapse

The 2006 crash was the biggest in the history of the Saudi stock market. The origins of this event date to 2003 when the stock market started to go bullish exponentially, and TASI rose 4,437.6 points in that year. According to the SAMA annual reports, the economy was growing, new companies and new industries were being listed in Tadawul and all the factors were positive for stock market growth. This led to local and foreign investors having much more confidence in gaining higher earnings. Companies were earning profits and paid higher dividends. Therefore, the year 2004 saw a big boost in the stock market index, and it rose to 8,206 points that year and by 16,712 points in 2005; this represented 103.7% growth compared with the previous year. This finally led to the highest index point in the history of the stock exchange: 20,634.86 points by February 2006 (see Figure 2.1). As explained, many reasons drove the stock market index higher, such as favourable economic conditions, more investors, higher investor confidence, higher stock returns, more companies listing, share split, incomes for small investors and a new, more efficient and reliable trading system. Investing in the stock market became so popular that more than half of the Saudi people invested in it.

Figure 2.4: Daily Price of TASI, July 2004 – December 2006

Source: Tadawul (2007).

SAMA annual reports indicate that the Saudi people took SR50.5 billion loans to invest in the stock market. People took loans against collateral such as real estate, equipment and goods and also took lines of credit. These loans increased to SR137 billion by the end of 2005. All this money was going into investments in the stock market in the expectation of making very high profits. Many risk-averse investors had become strong risk takers on noticing the huge profits. However, TASI's bubble started to burst at the end of February 2006 and it then fell sharply. For a few weeks, it remained stable at around 15,000 points during 2006; however, it started to fall again and continued to do so until year end. It had lost more than half of its index points (52%) by then. This trend continued in the next couple of years as well.

2.3.2.6 Saudi Stock Market's Ranking in the Arab World

The Saudi stock market has led the Arab world with a market capitalisation of $451 billion, and it accounted for 39.71% of the total market capital capitalisation of Arab stock markets by the end of 2017 (see Table 2.7). Conversely, the number of listed companies in other Arab stock exchanges was more than that in Tadawul and it is ranked the fourth largest in the Arab world. The stock markets of Egypt, Kuwait and Jordan had more companies listed, at 257, 216 and 194, respectively. However, the average size of companies listed in Tadawul was higher than that in all other Arab countries. The average value of companies listed on Tadawul was $2.4 billion compared with the average of $0.647 billion for other stock exchanges in the Arab world. Therefore, the companies listed in Tadawul are larger than those of other Arab countries. Moreover, the value of shares traded in Tadawul totalled $61.2 billion by the end of 2017, comprising 69% of the total share value traded on the Arab stock markets. The size of Tadawul in the GDP of the Saudi economy was 66% while the average was 39.8% for other Arab countries' stock exchanges (Table 2.7). The Saudi stock market is more liquid and attracts a larger number and size of investors compared when other Arab stock markets (SAMA, 2018).

Table 2.6: Key Indicators of Arab Capital Markets by the End of 2017

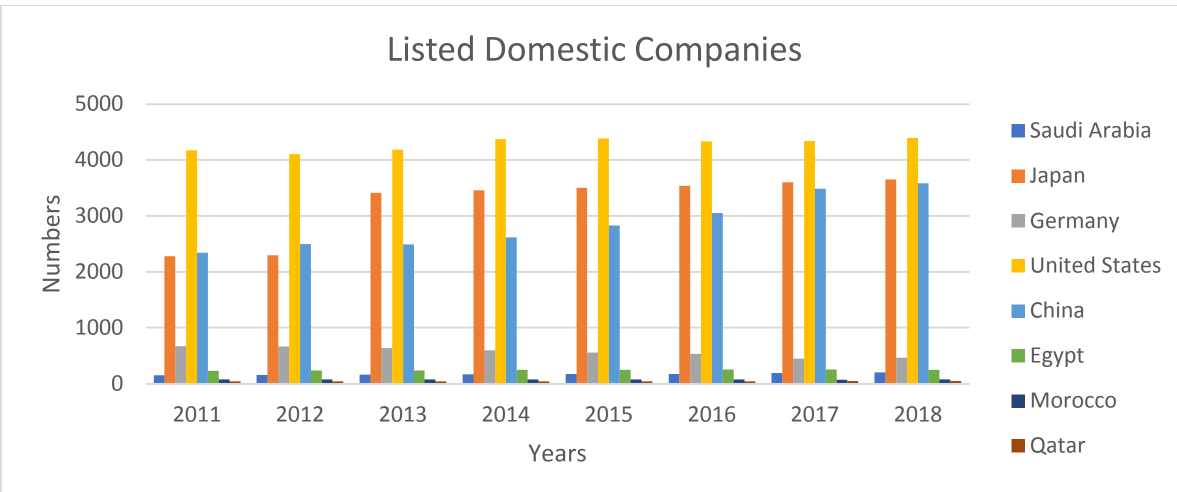
	Market Capitalisation (Million $)	No. of Listed Companies	Average Company Size (Million $)	Market Depth (%)*
Saudi Arabia	451,150	188	2,400	66
Kuwait	92,578	216	429	77
Egypt	44,433	257	173	19
Morocco	67,098	74	907	61
Bahrain	21,603	43	502	62
Jordan	23,938	194	123	59
Oman	46,625	131	356	63
Tunisia	8,854	81	109	22
Lebanon	11,473	30	382	22
Abu Dhabi	124,529	67	1,859	33
Algeria	85	2	42	0
Dubai	107,289	65	1,651	28
Sudan	3,077	67	46	5
Palestine	3,891	48	81	--
Average	71,902	105	647	39.8

Source: Arab Monetary Fund (2017). * Market capitalisation to GDP. -- represents not available.

2.3.2.7 Comparison of Saudi Stock Market to the Arab and world stock markets

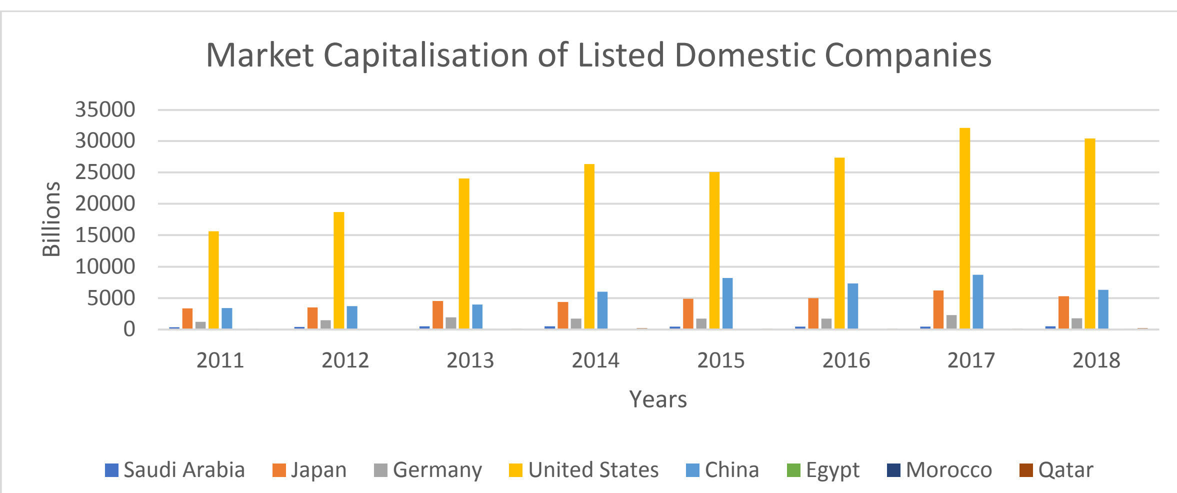
This subsection looks at the performance of the Saudi stock market compared to regional and international markets. On a geographic scale, the Tadawul is ahead of its competitors in MENA region. This is significant in the context of how other regional markets compare, since Saudi Arabia is considerably deeper in the Middle East markets and is in several ways much more liquid. It is seen as being a growing market and little recognized as a local investor, as far as the major advanced stock markets are concerned, but it holds potential if perceived from a developing economy, such as Europe and Asia or America. These tables demonstrate that, in the Arab world, the Saudi stock market has surpassed all other capital markets to the top position in the eight years from 2011 to 2018. Saudi Arabia leads the Arab stock markets in terms of market capitalisation; however, it is behinds the advanced stock markets as well as China in terms of the market capitalisation and in terms of list domestic companies, too (See Figure 2.5 and 2.6).

Figure 2.5: Listed Domestic Companies, 2011 – 2018.



Source: World Bank Database

Figure 2.6: Market Capitalisation of Listed Domestic Companies, 2011 – 2018.



Source: World Bank Database

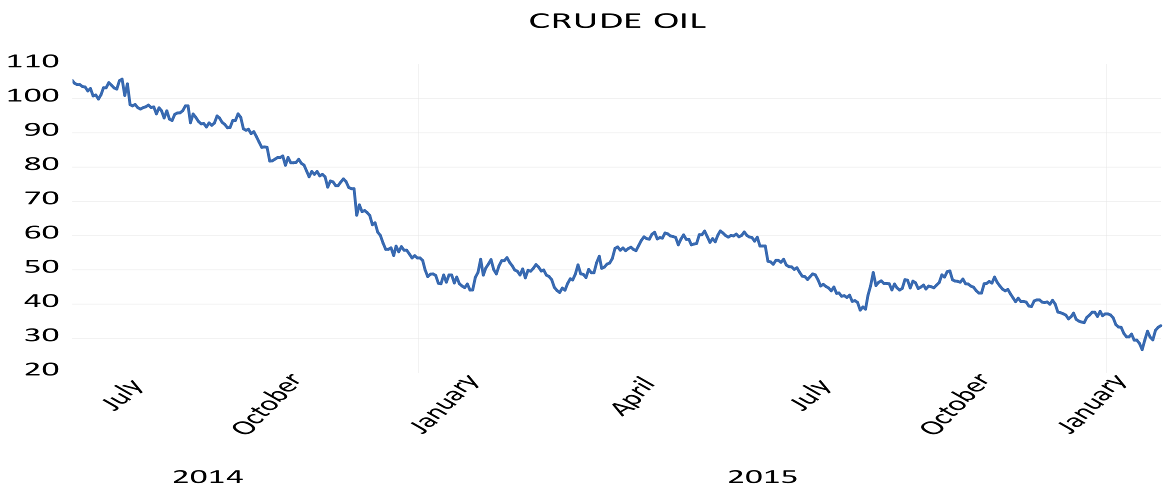
2.4 Effect of Global Factors on Saudi Stock Market Volatility

2.4.1 Oil Price

According to Cunado and Perez de Gracia (2005) and Yıldırım et al. (2018), the effect of changes in oil prices on price movement depends on many factors. These generally include factors such as the country's economic and institutional structures, its current account balance and its economic development status. Oil price volatility is a systematic risk factor that must be addressed in finalising investment portfolios (N. F. Chen et al., 1986; Mensi, Hammoudeh, Shahzad, & Shahbaz, 2017). Moreover, the oil price plays a crucial role in their economy for some countries, and Saudi Arabia is a prime example. It has been traditionally dependent on oil exports, to the extent that 67.5% of government revenues in 2018 were derived from the oil industry (SAMA, 2020).

As an oil-based economy that has few exports other than oil, the Saudi Arabian economy uses its oil revenues to import all that it needs, such as raw materials and food items. All aspects of the economy, such as government spending and GDP, depend on oil export revenues. Although rising oil prices provide more money for the government and increase the share prices of the oil sector, these can negatively affect other industries. Moreover, it leads to higher inflation and interest rates and declining stock prices. Therefore, an oil price rise has both positive and negative effects on the Saudi Arabian economy. One aim of this research is to analyse the effects of oil price volatility on TASI and to establish whether oil price changes determine stock market volatility during the full period or the subperiods covered in this research. There is an emphasis on the recent period witnessing declining oil prices starting from mid-2014 until the beginning of 2016 (see Figure 2.2).

Figure 2.7: Daily Price of Crude Oil, July 2014 – January 2016



Source: DataStream Database.

2.4.2 Interdependence between the Selected Markets

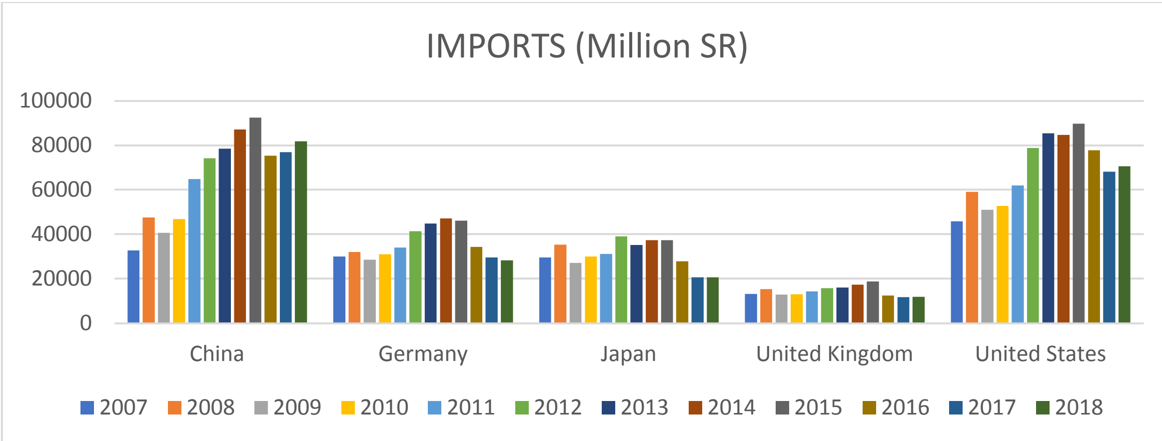
Wälti (2011) and Cai et al. (2017) have studied the joint trade involving both supply and demand sectors of the economy. The increase in demand for goods and services in one country results in exports from another country, and therefore, the output of the exporting country increases. This results in the synchronising of business cycles in various countries. If the demand for goods and services in a country declines, then the exports from the other country also fall; thus, the overall economic output decreases. Therefore, the stock market indexes of both countries would suffer. An increase in trade between various countries leads to greater stock market volatility.

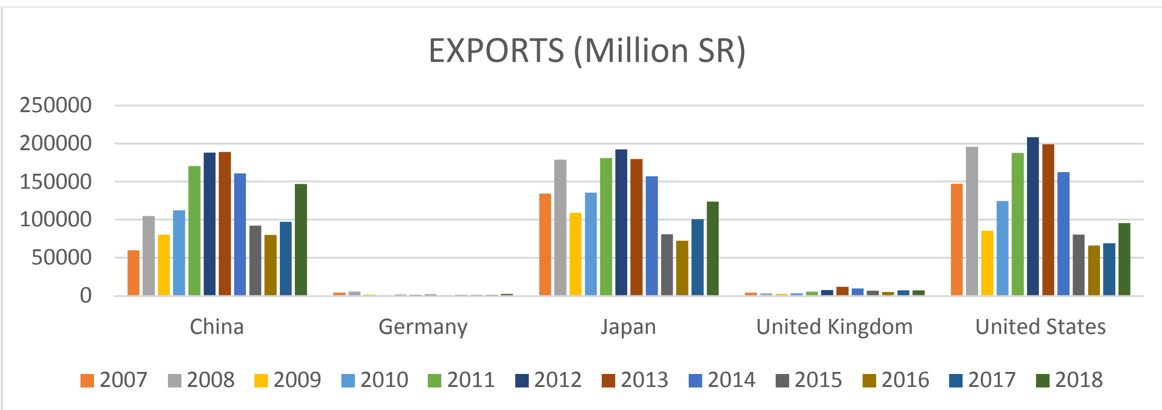
2.4.2.1 Bilateral Trade

In the modern business world, bilateral trade between countries results in increased economic activity and much more interdependent economies. It explains why various economic forums, such as BRIC (Brazil, Russia, India and China), have increased their bilateral trade by reducing national/domestic market regulations such as protectionism and tariffs. Since Saudi Arabia is a member of the GCC, the G20, the World Bank and the International Monetary Fund, it is imperative for it to move forward in bilateral trade and economic integration with other countries. As economies become interdependent, their stock markets are more closely associated with each other in terms of performance. Scholars have shown particular interest in analysing this link between the economic integration and the stock market relationships of various countries (Büttner & Hayo, 2011; Chambet & Gibson, 2008; Joyo & Lefen, 2019; Paramati et al., 2016; Pretorius, 2002; Tavares, 2009). The literature has highlighted the strong interdependent link between bilateral trade and stock market interdependence, and these relationships have been characterised as real links between various economies. Most scholars have concluded that economic cooperation through regional economic integration leads to the interdependence of stock markets (Glick & Rose, 1999; Jung & Maderitsch, 2014; Masih & Masih, 2001; Morana, 2008; Paas & Kuusk, 2012).

This thesis analyses the most important bilateral trading partners of Saudi Arabia in its study sample: the US, the European countries (mainly Germany and the UK), Japan and China (see Figure 2.3). China has been the most significant trading partner of Saudi Arabia in that it imports 15.3% of materials from China and exports 11.7% to China. The US is the second largest trading partner of Saudi Arabia in that 13.5% of its imports are from the US whereas 8.3% of its exports are to the US. The European Union (EU) is the third largest trading partner for Saudi Arabia, accounting for 8.1% of Saudi imports and 1.3% of exports. Japan is the fourth largest trading partner for Saudi Arabia with 4.1% imports and 12.1% of exports. These figures are indicative of the higher level of interdependence expected between TASI and the stock markets of these bilateral trading countries. This thesis will examine the transmission of volatility spillover between the stock markets of the bilateral trading partners of Saudi Arabia and the Saudi stock market (SAMA, 2018).

Figure 2.8: Imports and Exports Between Saudi Arabia and its Major Trading Partners in 2007–2018





Source: SAMA (2018).

2.4.2.2 Event or Crisis

The external environments of all countries affect the stock markets, and that is why these markets show changes in the PESTLE, or the 'Political, Economic, Social, Technological, Legal and Environmental' aspects, of a country and that of a foreign market. When the external market is positive, the stock market usually rises, and when external conditions are unfavourable, the stock market declines. When the external environment becomes unstable, the stock market volatility increases. Thus, the reason that the 2008 GFC affected all stock markets severely is that the financial situation had become extremely uncertain worldwide. Investors could not determine how many companies would be bankrupt and which financial institutions would default, and this uncertainty shook their confidence. The AFC in the late 1990s, which wiped out more than $500 billion from the Asian stock markets, had similar effects. Therefore, financial crises have serious effects on the stock markets, and a financial crisis in one country will spread to others because of the interconnectedness of the global economy.

The effects of the 2008 GFC spread to Tadawul as well, making share prices fall sharply; overall, the market index was significantly down. However, this financial crisis did not affect the Saudi people since they were already suffering from the 2006 GCC stock market collapse. TASI had declined significantly and closed at 4,803 index points; it had been 11,038.66 points in the previous year. The market recovered and by the start of 2008, it was at 11,697 points with a market capitalisation of SR924 billion. The total shares traded in 2008 were 59.68 billion, while 61.73 billion shares were traded in the previous year. Similarly, the transactions in Tadawul had decreased by 20.6%, and the number of transactions had also fallen in 2008 in comparison to the previous year. These factors have determined the selection of the financial market for this study. This study expects to find a correlation and dependence between the reported markets where the effect of the GFC of 2008 are taken into account.

2.5 Conclusion

The performance of Tadawul and its historical development were focused on in this chapter. First, the regulatory framework and legal history were discussed. Next, the historical performance of the Saudi stock market was analysed. Although the stock market was volatile many times in the period under study, the overall trend remained positive and share values rose. The Saudi stock market was most volatile in 2006, and the GCC stock market collapse that year affected it more than the 2008 GFC did. The Saudi authorities have regularly updated the stock market regulations for establishing a more stable financial market. These efforts have shown positive results over time. These regulatory changes have been so successful that they warded off the major impact of the GFC, unlike in the case of the US and European stock markets. However, more analysis is required on the topic of stock market volatility to confirm this conclusion.

Chapter 3 Literature Review

3.1 Introduction

This chapter presents an extensive review of the recent literature on the effects of volatility transmission as observed between various financial markets as well as the co-movement in related markets (Ahmed & Huo, 2020). Volatility is synonymous with risk assessment in financial literature. The literature on the transmission of shocks and volatility spillovers has investigated whether additional information in the form of conditional volatility in other markets influences conditional volatility in stock returns on a particular market (Engle et al., 1990). Specifically, a line of important questions in this thesis has been explored, such as the following: (a) Is there volatility transmission between global stock markets and the Saudi stock market? (b) Is there volatility transmission between major commodity markets and the Saudi stock market? (c) How does volatility transmission of global stock and major commodity markets impact the Saudi Arabian stock market? (d) How did the volatility of global variables influence the Saudi stock market during the collapses of 2008 and 2014–2016? (e) What is the importance of the research findings in improving optimal portfolio management to reduce risks in Saudi Arabia?

Portfolio managers/investors and policymakers alike would need answers to these questions, which would provide them with substantive information to ensure financial stability, retain investors' trust, predict and mitigate any existing risks and benefit from diversification advantages, as well as to make informed investment decisions. In this regard, a comprehensive literature analysis demonstrates that transmission effects do exist within developed markets themselves (Ji et al., 2018; King & Wadhwani, 1990; Li, 2020) and within developed and emerging markets as well (Cardona et al., 2017; Syriopoulos et al., 2015). This chapter is organised into the following sections. Section 3.2 presents an intensive review on the literature examining the effect of volatility transmission between interdependent stock markets. Then, empirical studies, mainly those on the relationship between stock and commodity markets, are reviewed critically in Section 3.3. Section 3.4 provides empirical proof about the effect of volatility transmission between stock and commodity markets during a financial crisis/decline (including the GFC and oil decline periods). Section 3.5 analyses the empirical literature on portfolio diversification opportunities. Section 3.6 discusses the literature gap, focusing on a review of related studies, to justify the significance of the current research. Lastly, in Section 3.7, the main topics explored in this chapter are concluded and summarised.

3.2 Effect of Volatility Transmission between Interdependent Stock Markets

Market prices and volatility are the two key information transmission pathways, while globalisation and financial liberalisation lead to enhanced opportunities for local markets to respond swiftly to updated information relayed through international markets. This, in turn, increases the co-movement of international markets. Financial assets are often characterised by their returns and volatilities. Their prices are realistic indicators of the information available in efficient markets (Fama, 1970; Kristoufek & Vosvrda, 2016). Accordingly, market prices may fluctuate to reflect the integration of new information. Ross (1989), Degiannakis and Filis (2017) and Aloui et al. (2018) suggested that financial asset price volatility demonstrates the flow of information; it is linked directly to the rapidness of information fed to the market. This view implies that for information transmission, volatility holds greater significance than do price changes.

The co-movement of stock prices is reinforced owing to particular ties, including financial links, free capital movements, related movements in national incomes and dual lists of companies, which allow an implied relationship between international stock markets (Ripley, 1973). This is exemplified by Eun and Shim's (1989) investigation regarding the global transmission mechanism of stock market movements. Their study sought to estimate the vector autoregression (VAR) system and demonstrated that deviations in the US market affected nine other markets. Such results make it evident that the US stock market dictates the behaviours of other markets and may be perceived as the most influential source of information.

3.2.1 Developed Stock Markets

Hamao et al. (1990) investigated the daily volatility transmission in the New York, London and Tokyo markets by implementing the GARCH-in-mean (GARCH-M) model. In particular, they saw that the US and UK markets had strong spillover effects on the Japanese market, but the opposite was not true: The Japanese market exerted only weak spillover effects on the US and UK markets, suggesting that Japan is the more vulnerable of the three. Regarding the persistence of return spillover, their results indicated that a spillover effect of positive return was present from the US (London) to Japan (New York).

King and Wadhwani (1990) investigated the curious case of nearly all global markets crashing at the same time as the US market in 1987. They suggested that a 'mistake' occurring in one market might also occur in others, and that 'unexpected' events of financial distress in a country may also carry over to other markets, causing an increased spillover or contagion in financial markets. Similarly, Theodossiou and Lee (1993) studied stock markets of American, Japanese, British, Canadian and German. They observed that the US's effect on the UK, Canada and Germany stock markets had a weak mean spillover and that Japan also had a weak spillover effect on Germany. Conversely, strong transmission effects were observed from the US to all those markets considered, from the UK to Canadian market and from German market to Japan. It was apparent that the stock market of Germany was the least integrated one then, and that the US market's conditional volatility affected the stock markets of the UK and Canada. However, the significance of conditional volatility for the expected return was not observed.

W. L. Lin et al. (1994) employed intra-day data and a signal extraction framework to find the general trend that Tokyo (New York) daytime returns were significantly related to the New York (Tokyo) overnight returns, suggesting that news within one market during trading hours may influence other markets globally. Susmel and Engle (1994) investigated for spillover between the US and the UK markets. They observed that there was no mean spillover during non-overlapping periods, but they found two-way weak volatility spillover effects between them for short periods, particularly during the New York opening time.

In addition, Koutmos and Booth (1995), who sought to study the transmissions of volatility between the US, Japanese and the UK stock markets, implemented a multivariate exponential generalised autoregressive conditional heteroscedasticity (EGARCH) model. They suggested that asymmetric volatility spillovers did exist and that these were more prominent for bad news than for good news. Further, the three markets were more closely tied after the 1987 crash of the US stock market—their interdependence became more evident. Another bivariate GARCH model was implemented by Karolyi (1995) to investigate the direction of returns and volatility in the US and Canada. The study observed that shocks in a particular market swiftly translated to shocks in another market. However, as of the late 1980s, the effect of New York shocks transmitting to Canadian markets changed and diminished over time, as observed through the cross-market spillovers in returns and volatilities. Karolyi (1995) also found evidence of the different effects of American innovations on portfolios with inter-listed stocks and non-inter-listed stocks. This finding prompted the idea that analysing the investment environment is key to understanding the dynamic interdependence between markets. Further, Booth et al. (1997) used the extended multivariate EGARCH framework to uncover substantial weak volatility spillovers between the Danish, Norwegian, Swedish and Finnish stock markets.

Savva et al. (2009) studied volatility spillovers in the context of the US and major developed European markets, focusing primarily on the London, Frankfurt and Paris markets. They employed the 1990–2004 sampling period and obtained data on the daily pseudo-closing prices at London time. Using an asymmetric DCC type of the EGARCH model, they observed that after the euro period, there was considerable two-way volatility spillover between the stock markets of Frankfurt and Paris. They also revealed that the volatility spillovers from the European stock markets to the US stock markets were more significant than those in the reverse case. The presence of asymmetry revealed that these correlations were higher for negative returns than for positive ones. In a similar vein, Tanizaki and Hamori (2009) studied the transmission of volatility between the three developed markets of Japan, the UK and the US. They implemented a Bayesian procedure through a Markov Chain Monte Carlo (MCMC) model, as previously suggested by others, to study these interrelationships. They hypothesised that the stock market volatility of the US and the UK would affect the Japan market, and their conclusions supported this notion. They also observed that the UK's stock market transmitted volatility to the Japanese market, and the spillover effect of the US was larger than that from Japan.

The present study also explores the more recent studies that have analysed volatility spillovers between developed markets. Xiao and Dhesi (2010) examined volatility transmission between the US and European stock markets in 2004–2009. They used two MGARCH models—the BEKK and the DCC—to study a financial time series. They found significant transmission of volatility between these stock markets, with the US acting as the dominant volatility transmitter. They also revealed that the New York market transmits volatility to other global markets. Karunanayake et al. (2010) explored the interrelationship between stock market volatilities of various countries by considering the specific case of the US, UK, Australia and Singapore. Their sampling period was 1992–2009, and they focused on the AFC in 1997–1998 and GFC in 2008–2009. They analysed weekly data for the sampling period using a multivariate GARCH model. They found that although both crisis periods did not have a significant effect on each market's returns, the volatilities of all four markets increased considerably. Specifically, it was shown that as predicted, the US stock market was the greatest transmitter of volatility to other countries. There was a one-way volatility spillover from the US and UK markets to those of Australia and Singapore.

Further, Tsai (2014) conducted a comprehensive analysis of volatility spillovers in five developed countries, the US, UK, Germany, France and Japan and considered various periods to identify the effects on stock markets. The study revealed that the effects of volatility transmission became more prominent after 1998. It identified Germany and the US as primary transmitters of volatility to other stock markets, with the former dominating the French market and the latter dominating many international markets. The prime periods of the US stock market transmitting volatility to others were identified as the period before 1997, from 2000 to 2002 and, during the GFC, from 2007 to 2008. In addition, Antonakakis and Badinger (2016) investigated economic growth, volatility and spillovers between the G7 countries by considering monthly sampling periods from 1958 to 2013. They used a VAR framework and concluded that the volatility relationships were largely interlinked and were exacerbated during periods of a financial crisis. For most cases, the US was the primary transmitter of volatility to other markets. Volatility shocks were observed to adversely affect economic growth.

The case of the interconnectedness of the G7 markets and the US was similarly explored by Ji et al. (2018), who considered time-dependent copulas with Markov-switching using data covering more than 100 years. They focused on risk spillover in the New York stock market and other G7 markets. They used a conditional value-at-risk model, and their results revealed that there were definite volatility transmission effects between these markets. However, the spillovers resulting from the US to other markets were more dominant than spillovers transmitted from other markets to the US. The values of upside risk spillover were greater than those of downside risk spillover. BenSaïda (2019) further explored the volatility spillovers of G7 stock markets, focusing on the asymmetric interconnection between the stock market indices. The major developed financial markets were scrutinised for the presence of good and bad volatility shocks and corresponding spillovers. In this vein, risk transmission and the issue of time-dependent asymmetry were also explored. It was observed that time-dependent variations existed in the volatility spillovers, both for good and bad shocks. It was also observed that for the duration of the GFC and the sovereign debt crisis, negative shock spillovers were more dominant compared with the transmission of positive shocks.

Li (2020) explored volatility spillovers in European markets under the shadow of Brexit uncertainty. This study used a multivariate GARCH model to analyse the time-dependent behaviour of European stock markets. Its results demonstrated that there were significant interactions between the markets. The net volatility spillover values showed that while the UK wielded considerable influence on other countries' markets in the period immediately after the 2016 Brexit referendum, this influence reduced later, as evidenced by the smaller spillover values. Although the unexpected referendum results did increase market volatility, the effects on market co-movements varied. The uncertain future trade agreements between the UK and the EU also suggest long-lasting dynamics between markets. Thus, to summarise, several quantitative studies were conducted in the 1990s, 2000s and 2010s and they concluded as follows: (a) Stock markets' volatility is time-dependent. (b) For cases with high volatility, the price changes in major stock markets have a strong correlation. (c) The crisis/decline of the stock markets affected correlations in volatilities and prices for other markets. (d) Major markets have spillover effects for returns and volatilities. Concluding this discussion, which was focused solely on developed markets, next, the present study seeks to explore the volatility transmission between developed and emerging markets, as demonstrated in the following section. It will consider the specific case of the Saudi stock market in Section 3.2.3.

3.2.2 Emerging Stock Markets

Financial liberalisation and globalisation have led to emerging markets becoming key components of the global economy, which prompts researchers and investors to explore the correlation between developed and emerging markets. Numerous studies have focused on the spillover of volatility from advanced to developing markets. Hu et al. (1997) adopted a causality-in-variance test to study the effects of volatility spillover in the South China region, which includes Hong Kong (a 'Special Administrative Region' of China), Taiwan, Shanghai and Shenzhen. They observed that the volatility of these four markets was contemporaneously related to the US stock market's return volatility. Further, the stock markets of Shanghai and Shenzhen had a greater correlation with the US and Japanese markets, compared with Hong Kong and Taiwan. The study's results demonstrated that for less open markets, such as Shanghai and Shenzhen, global factors had a significant impact, but geographic relationships did not account for substantial volatility interactions between stock markets.

Y. A. Liu and Pan (1997) adopted a two–stage GARCH approach to investigate the return and volatility transmission from the US and Japan to several Asian markets. They observed that during their sample period, the spillover effects of return and volatility transmission were unstable and became more pronounced following the 1987 US stock market crash. For both return and volatility transmission, the US stock market exerted greater influence on the chosen Asian markets, compared with Japan's stock market. Next, Ng (2000) considered three separate channels of shocks and developed a new framework of volatility spillover. The three types of shocks were local idiosyncratic, regional (Japan) and world (US). These were used to study the relative significance of larger stock markets for numerous Pacific-Basin markets. The study revealed that local and global factors both serve to describe the volatility in the markets in the Pacific-Basin area, and the US is particularly influential in this regard.

To examine volatility transmission, Gallo and Otranto (2008) introduced a new model based on the Markov-switching framework. They showed that the Hong Kong market exhibited long-term volatility spillovers on the stock markets of both South Korea and Thailand. Their results for Hong Kong also revealed a correlation with Malaysia and

Singapore. This finding led to the idea that Hong Kong dictates the changes in the region's stock markets. Yu and Hassan (2008) implemented an EGARCH-M framework to study the interconnectedness of the MENA financial markets. Their findings demonstrated that the New York stock market was particularly influential in forecasting volatilities for most of the MENA markets, although its own-volatility spillovers were usually greater than the cross-volatility spillovers. They observed that there was an enhanced long-term equilibrium between countries outside the GCC and the US stock market due to the rapid advances in financial liberalisation in the MENA area.

P. Singh et al. (2010), who concluded that most Asian markets under consideration were impacted by the lagged returns on the stock markets of the US and Europe, examined information transmission in diverse North American, European and Asian stock markets. There was a contradiction when the result of the same day was registered, which suggested spillover returns from the US to Japan and South Korea. In comparison, Japan and South Korea's returns influenced the stock markets of Malaysia, Taiwan and Singapore on the same day. Quantitative results demonstrated that Asia's most prominent markets were Japan, Singapore and Hong Kong, whereas the UK and Germany were particularly dominant in Europe. The US remained the most dominant market globally.

Recent literature analyses have also concentrated on the volatility spillovers in developing markets. For example, Rejeb and Boughrara (2015) researched the volatility interdependence between emerging and developed markets in peaceful and financial crises periods. They concluded that volatility transmission has significance across financial markets and that geographical location and financial liberalisation determine transmission intensity. Similarly, Balli et al. (2015) explored the transmission of volatility from developed stock markets (the US, Europe and Japan) to those of emerging countries (Asia and MENA regions). Trends for spillover models revealed significant volatility transmission from developed markets to developing ones, and the quantitative variance ratios showed that the US stock market was most dominant in transmitting volatility shocks to all considered emerging markets, although the extent of spillovers varied between countries.

Syriopoulos et al. (2015) studied time-dependent dynamic correlations and volatility spillover effects for the US and the BRIC equity markets. Their quantitative analyses, using VAR-GARCH models, showed strong returns and volatility spillovers between the US and BRIC nations. The US sectors strongly influenced shocks and volatilities, and the US market shocks affected the stock markets of Brazil, India and Russia. In addition, volatility in the US industrial sector strongly affected the industrial sector volatility of all BRIC countries except China.

Güloğlu et al. (2016) focused on Latin American stock markets, specifically emerging country markets. Five major markets in the region were considered in the presence of structural breaks. Using a DCG GARCH model, dynamic correlations revealed varying volatility transmission effects between the markets. Overall, the results revealed interdependence between the markets but there was limited statistical evidence to suggest that contagion effects were dominant. Moreover, Kundu and Sarkar (2016) examined the daily stock returns of two developed countries (the US and the UK) and four developing countries (BRIC) using a VAR-threshold GARCH-M (VAR-TGARCH-M) framework. They explored two distinct stock market scenarios, termed the 'up and down' market conditions. They found evidence of volatility transmission effects from a market in the 'up' state to a market in the 'down' state.

Yarovaya et al. (2016) demonstrated, through quantitative evidence, the existence of information transmission patterns across selected emerging and developed countries from 2005 to 2014 in Asia, Europe, Africa and the Americas. Analysing return and volatility spillovers, they showed that markets were more vulnerable to domestic and regional volatility shocks compared with international information transmission. Meanwhile, Yavas and Dedi (2016) considered the volatility linkages between selected European and emerging stock markets, namely, Austria, Germany, Poland, Russia and Turkey. Using autoregressive moving average (ARMA)-MGARCH models, they found evidence of considerable co-movement for returns of the selected markets. Volatilities were greatest for Russia and Turkey compared with other countries. All markets were susceptible to volatility spillovers from other markets except Turkey.

In a similar vein, Cardona et al. (2017) studied the effects of volatility transmission in 1993–2013 between the stock markets of the US and six South American markets, namely those of Argentina, Brazil, Chile, Columbia, Mexico and Peru. They applied an MGARCH-BEKK framework to daily frequency data. They showed that there was volatility transmission from the US stock market to the Latin American stock markets but not vice versa. However, they found some evidence that among these countries, only Brazil displayed limited volatility spillovers to the US stock market. Recently, Prasad et al. (2018) studied the time-dependent volatility spillovers between several emerging and developed markets, such as China, India, UK, US and Brazil. Evidence from their empirical analyses suggested that volatility spillovers were enhanced after crises similar to the 2008 GFC and the European debt crisis. The US dominated as a volatility transmitter to other markets. The relative level of volatility in one market was considered a key determinant in transmitting volatility to other markets.

The spillover of volatility from China's stock market to E7 (top seven emerging) and G7 (top seven developed) stock markets were investigated by Uludag and Khurshid (2019), who used GARCH models to study daily stock data on national stock indices between 1995 and 2015. Their analysis results showed there were considerable volatility spillovers from China's stock market to E7 and G7 markets, and, specifically, high transmission for countries located in the same geographical area as China. Among G7 countries, the greatest volatility transmission effects were observed to occur between China and Japan.

To summarise, quantitative data revealed transmissions of volatility between the advanced and other key developing stock markets. The interdependence between stock markets was observed to have increased, especially after the 1987 US stock market crash. Volatility spillovers were observed to be time-dependent, and the extent of integration between mature and emerging markets seems to have increased over time. Globally, the US stock market, and in Asia, the Japanese stock market, have played varying roles in transmitting information. Concluding the discussion on developed and emerging stock markets, this section reviewed the literature on volatility transmissions in several global markets in the context of the qualitative evidence provided. The present analysis concentrates on the Saudi stock market and its interrelations with developed and developing countries' stock markets, as presented in the following section.

3.2.3 Saudi Stock Market

Kalyanaraman (2014) used a univariate GARCH model to conduct a thorough study of Saudi stock market volatility. The market's conditional volatility and volatility spillovers were modelled through GARCH frameworks to analyse daily data of stock returns in 2004–2013. In particular, a linear GARCH model was used to estimate the TASI volatility. The study's quantitative results demonstrated volatility clustering in the Saudi stock market, which was described by a non-normal distribution. In addition, time-dependent volatility was observed to be persistent and predictable. The market was said to be vulnerable to market fluctuations, and the results were proven to have helped investors make informed decisions.

Alotaibi and Mishra (2015) considered the volatility transmission in 2005–2013 from regional and global players to the GCC markets. Saudi Arabia was identified as the key regional player, while the US was considered a major global transmitter of volatility. Bivariate GARCH models were used to this end, and the frameworks considered cases both with and without asymmetric effects. The analysis revealed that considerable positive volatility spillovers were transmitted from Saudi Arabia to the GCC stock markets, but there were also significant spillovers from other GCC markets to the TASI market. Cross-border trade and intra-regional political situations were observed to affect these volatility spillover patterns.

Yet another study, that of Kumar (2015), investigated the effects of volatility spillover between the GIPSI countries (Greece, Ireland, Portugal, Spain and Italy) and Egypt, Saudi Arabia and Turkey. Using asymmetric dynamic conditional correlation (ADCC)-GARCH models with structural breaks, the study revealed that portfolio strategies for the time-dependent correlations yielded higher returns for the considered markets. Two-way interdependencies were established, with volatility spillovers predominantly occurring from European markets to the TASI market, although limited evidence of the reverse occurring was obtained. The significance of this study lies in its utilisation of quantitative models to establish a correlation between the volatility spillovers of European and TASI markets, where many others have focused solely on Asian and GCC country market relationships.

In a similar vein, Jouini (2015) explored the financial integration of the Saudi Arabian stock market with other global stock markets. Using the AGDCC-GARCH model, the study aimed to identify time-dependent conditional correlations between 2005 and 2015. Daily data were analysed to demonstrate that the conditional correlations declined during the GFC period. The cross-market integration of TASI and various other countries demonstrated that interdependencies were weak during periods of turbulence, which contradicts the findings obtained by several other authors. The results were observed to be valid for data frequency, day of the week and econometric methodology.

Alqahtani et al. (2019) studied the interdependence between the GCC countries' stock markets and the US stock market. They focused on the shifts in economic policies and the resulting volatility spillovers in the considered markets. They observed that shifts in GCC economic policy did not hold major implications for the New York market, but following shifts in US economic policies, the corresponding volatility spillovers somewhat affected the GCC stock markets (Oman, Qatar, Kuwait, Saudi Arabia, the United Arab Emirates and Bahrain), particularly those of Saudi Arabia and Oman. These results were based upon quantitative observations derived from return coefficients for causality tests.

The interdependence of stock markets and the corresponding volatility transmission between African and Middle Eastern stock markets were studied by Panda et al. (2019). The countries considered included Botswana, Egypt, Ghana, Jordan, Kuwait and Saudi Arabia. The MSCI was used for the world market. The authors relied on a combination of testing methods, including the Granger causality test, the VAR framework, the vector error correction model and multivariate GARCH-BEKK framework. Since it is a key Middle East player, emphasis was placed on the Saudi Arabian market and its correlations with other economies. They found no particular links between the African and TASI stock markets, but significant interrelationships between the markets of South Africa and Jordan, and that all the markets considered had long-run equilibrium interrelationships.

Shaik and Syed (2019) studied stock market volatility by reviewing TASI stocks using data for October 2017 – May 2018 at a 5-minute frequency. To achieve this purpose, symmetric and asymmetric GARCH models were implemented. The former showed a significant positive relationship between risk and return, while the latter demonstrated negative and significant estimates. The sum of ARCH and GARCH coefficients showed an explosive persistence in volatility shocks for the Saudi market. The GARCH (1,1) models were the most appropriate symmetric model for TASI. Asymmetric results indicated that the existence of negative shocks does not justify greater future volatilities.

With a view to predict economic and financial environments, many authors have focused on the future market returns of the Saudi stock market. Domestic market volatility and global indicators hold implications for forecasting future stock returns. In this regard, W. Zhang et al. (2019) investigated the spatial connectedness of volatility transmission in the G20 stock markets. Using a GARCH-BEKK model, they constructed volatility networks and their empirical study's results demonstrated the special connectedness to be time-dependent, with a period of turmoil serving to intensify volatility spillovers. Lastly, a four-block club model was used to group different volatilities in blocks, and it was observed that volatility risks eventually spread to the US market from other stock markets, including the TASI, Italian and Russian markets.

Table 3.1 presents a summary of some recent studies on the volatility transmission between stock markets. It shows the samples examined, the period and data, the type of methodology and the main results for each study. Thus, following the detailed discussion in this chapter on the transmission channel of volatility spillovers between TASI and, in particular, developed and emerging markets, it is prudent to consider how periods of interrelation between the stock and commodity markets have different outcomes. The next section presents a comprehensive analysis from this perspective.

Table 3.1: Summary of Some Recent Studies on Volatility Transmission Between Stock Markets

Author(s)	Sample	Data Period	Methodology	Main Findings
Cardona et al. (2017)	The US, Argentina, Brazil, Chile, Mexico, Colombia and Peru.	Daily data; March 1993 – March 2013	MGARCH models (diagonal VEC, BEKK, CCC and DCC)	1. Volatility transmission from the US to the Latin markets is strong. 2. Brazil is the regional leader.
Ji et al. (2018)	The US, Japan, Germany, the UK Canada, France and Italy.	Monthly data; January 1915 – February 2017	CoVaR and Markov-switching time-varying copula models	1. Abnormal spikes of dynamic CoVaR. 2. The spillover risk magnitudes from the other G7 countries to the US are greater than those from the US to these G7 markets.
Prasad et al. (2018)	The US, Japan, Germany, the UK, China, Australia, Canada, Brazil, Korea, Taiwan, India, France, Switzerland, Spain, Mexico and Hong Kong.	Daily data; 6 January 2000 – 13 June 2014	Diebold and Yilmaz methodology	1. Evidence of volatility transmission from one develop market to developing market. 2. After 2006, many emerging markets contribute to global spillovers.
W. Zhang et al. (2019)	G20 stock market indexes.	Daily data; 2 January 2006 – 31 December 2018	GARCH-BEKK model	Evidence of time-varying spatial connectedness.

3.3 Relationship between Stock and Commodity Markets

Various financial variables dictate the relationships between stock and commodity markets, and these relationships are often predicted to be low and negative. Hence, investors may gain several diversification benefits on adding such commodities to their portfolios, as suggested by Hammoudeh et al. (2014). Many experts have studied the types of relationships between stock and commodity markets to ascertain whether commodity markets provide significant diversification and hedging value for conventional assets (Daskalaki & Skiadopoulos, 2011; Gorton & Rouwenhorst, 2006).

Investors have increasingly shown interest in commodities, such as oil and precious metals (Jiang, Jiang et al., 2019; Junttila et al., 2018). Crude oil prices have strongly influenced stock prices owing to their direct influence on volatility. Recently, several experts have weighed in on the quantitative interaction between the movements of stock markets and oil price. Studies such as these that were conducted earlier in the US had signalled significant interrelations between stock markets and oil prices (Hamilton, 1983; Kling, 1985). Several recent studies have confirmed that volatility transmission occurs between stock markets and oil prices in various countries, including the GCC countries, the US and Europe, where oil prices influence stock market returns considerably (Bouri et al., 2020; Diaz et al., 2016; Ewing & Malik, 2016; Mensi, 2019; Thorbecke, 2019; X. Wang & Wang, 2019).

These studies have been conducted in various countries. For instance, Jones and Kaul (1996) suggested that oil price variations have influenced the output and stock returns in several countries, including the US, Japan, Canada and the UK, in the post-war period. However, the theoretical predictions made were only observed for the US and Canada stock markets. Sadorsky (1999) demonstrated that shifts in oil prices lead to corresponding changes in returns of stock market and oil prices' positive variations reduce the real returns of stock market.

Basher and Sadorsky (2006) studied the influence of oil price variations on the stocks of 21 emerging markets for the 1992–2005 sample period. They revealed through conditional and unconditional risk analyses that oil price risk significantly influences stock returns of emerging markets. The effects of oil prices were dominant for equity markets and other commodity markets, with empirical evidence pointing towards co-movement in oil and non-energy markets. Such increasing trends may be explained by the increased reliance on biofuels as opposed to fossil fuels and hedging against oil price rise (Ji & Fan, 2012).

In the following subsections, two types of commodity interactions are critically reviewed. Crude oil prices and precious metals and their relationship with both developing and developed stock markets as well as with each other are presented along with a review of the empirical literature of transmission channel of volatility spillovers.

3.3.1 Oil Prices

Numerous studies have sought to examine the connection between the stock and commodity markets. One of the most valuable commodities worldwide, oil, as a natural and non-renewable energy source, is of much concern to portfolio managers, investors and policymakers. The oil market has considerable influence on a country's financial markets and on the performance of its stock market. For example, significant rises in oil prices may increase a country's inflation rate and cause an economic recession. The theoretical roots of the links between oil and stock markets are well-established. In this regard, the standard economic theory suggests that stock market returns are directly dependent on anticipated cash flows and are indirectly dependent on the discount rate formulae for stock pricing. These two are considered essential parameters that are intricately related to oil prices and explain the link between the stock markets and oil prices. Several quantitative studies have focused on the link between stock markets and shifts in oil prices. Hamilton (1983) began his work in the field through a well-known economics-based topic focused on statistical linkages between oil price shocks and the macro-economy for the US economy. Using quantitative analyses, the author observed that nearly 7–8% of the post-war era recession periods in the US had occurred after a substantial increase in crude oil prices.

The literature has recognised the significance of oil prices for not only macroeconomic factors but also financial systems. For example, Kling (1985) studied the relationship between the returns of crude oil prices in 1973–1982 and the US stock markets. This study revealed that after 1972, the stock market was able to expect oil price shifts. Further, there was a lag before these shifts affected the stock prices for sectors such as air transport, automobiles and local oil industries. These oil price shifts were often followed by decreasing stock prices for the aforementioned sectors, albeit at a delayed pace. Jones and Kaul (1996) showed that oil price shifts in the post-war period also held serious implications for the output and real stock returns of many economies, including Canada, Japan, the US and the UK. However, they could only theoretically confirm that the oil prices' variations and returns of stock market for the US and Canada were inversely correlated. They suggested that the effects of oil price variations on stock markets may be detailed through the influences on contemporaneous and future real cash flows.

A VAR approach was adopted by Sadorsky (1999), who sought to assess how shifts in prices of oil prices and the US stock markets returns were related. The study demonstrated that the oil prices and their volatilities both played a crucial role in regulating the real stock returns. Shifts in oil prices caused shifts in stock returns and, more specifically, positive shocks in oil prices caused negative variations in real stock returns. After 1986, depending on the expected error variance, the returns of real stock returns may be described more readily through oil price changes than through interest rates. In particular, a majority of the industrial production and real stock returns of the forecast error variance is explained by positive variations, rather than negative shocks, in oil prices. This result signals that the oil price shocks had asymmetric effects on the economy. Ciner (2001) also focused on the non-linear relationships between oil prices and the stock market and revealed empirical evidence for considerable two-way non-linear Granger causality between the returns of oil and stock index. These were in line with the noted influence of oil prices on the economy. Indications of linear Granger causality between the two were not found.

In another study, the specific cases of China and Vietnam were considered to analyse the market integration of oil prices and stock returns using a parametric and nonparametric approach (Nguyen & Bhatti, 2012). It demonstrated that there was a left tail dependence structure between the two in Vietnam, suggesting that the stock market would reproduce the decreasing trend in the oil sector. Such a dependence structure was not evident in the case of China. Jammazi and Nguyen (2015) suggested that oil price shocks during stable periods are likely to hold greater implications for stock returns than those during turbulent periods. These findings would exist particularly while testing for non-linearity in the oil price and the integration of stock market returns for the US, the UK, Germany and Canada. In the same vein, Salisu and Oloko (2015) also modelled the association between the US stock market and oil prices by employing a VARMA-BEKK-AGARCH model. They modified the framework to include structural breaks and computed optimal portfolio weights and hedge ratios for the oil price and the US stock market returns through sampling data. Their results confirmed volatility spillover from the oil market to stock market of the US, which became more pronounced after the GFC. They identified that there were two-way shock spillovers between these markets.

Boldanov et al. (2016) considered the time-dependent relationship between the volatility of the oil and stock markets for several oil-importing (the US, Japan and China) and oil-exporting countries (Norway, Canada and Russia). Using a diagonal BEKK framework and the sampling period of 2000–2014, they suggested that there were positive and negative variations between the oil and stock markets, which were sensitive to major geopolitical events. Thus, they concluded that time-dependent correlations varied depending on the nature of the country, namely, whether an oil-importing or oil-exporting country. Further, Diaz et al. (2016) analysed the relationship between the volatility of oil price and stock market returns in the G7 countries using monthly data for 1970–2014. To measure oil price volatility, they considered alternative specifications for oil prices and a VAR model with certain specified variables, namely, economic activity, interest rate, stock returns and oil prices. They found that increases in oil price volatility adversely affected the G7 economies after 1986, suggesting that these volatility spillovers were considerable for stock markets compared with national oil prices.

Ewing and Malik (2016) investigated the volatility spillover from the oil price to the US stock market prices using univariate and bivariate GARCH models with daily data between 1996 and 2013. Estimations of the volatility dynamics of the two sectors revealed that there were no volatility transmission effects between the two markets when structural breaks were ignored but were present on accounting for structural breaks. Volatility in both markets was affected by information and volatility in their own market. Thorbecke (2019) studied the spillover in 1990–2018 between the US stock market and oil prices. The sampling period was divided into pre- and post-shale revolution periods, the pre-period ranges between 1990–2007 and the post-period ranges between 2010–2018. The study results revealed that oil price increases adversely affected US stock returns between 1990 and 2007, but this effect was more subdued and even reversed between 2010 and 2018. The view that oil prices affect the entire US stock market was considered outdated, and it was deemed necessary to consider sectors that benefitted from the shale revolution.

X. Wang and Wang (2019) considered the interdependence and volatility transmission pattern between crude oil and China's stock market by accounting for sectoral stock indices. They found evidence that suggested volatility spillovers were mainly due to short-term transmission effects. Net spillovers due to the oil market were nearly all positive and caused by short-term considerations. They identified that crude oil price variations had long-term effects on certain sector indices depending upon the oil utilisation in those sectors. Bouri et al. (2020) studied how sovereign risk was influenced by the oil market situation in the MENA region, focusing on oil-exporting and oil-importing countries. For the sampling period 2011–2018, they found that sovereign risk relied on oil price and volatility spillovers. The Saudi government budget had a significant deficit because of lower oil prices. The effects of volatility spillovers originating in the oil sector had implications for stock market functionality.

Some literature reviews about Saudi Arabia study the oil price impact on its stock market. For example, recently, Ashfaq et al. (2019) considered the volatility transmission between world oil prices and the main Asian energy economies, including Saudi Arabia, the United Arab Emirates, Iraq, China, Japan, India and South Korea. They implemented various GARCH models to capture volatility transmission patterns and suggested that there was bidirectional transmission between the oil market and the Saudi stock market, South Korea and Iraq. The effect of oil price was more significant for oil-exporting countries, and oil shocks were also more strongly felt in these markets. In particular, the results showed bidirectional transmission of volatility between the Saudi stock market and oil prices.

Moreover, Hamdi et al. (2019) considered the level of interdependence between oil price and sectoral stock markets in oil-exporting countries in the GCC, including Saudi Arabia. They found that oil price and all other sectors were interdependent in the sampling period of 2006–2017, except for the banking and insurance sectors. The spillovers of volatility were mostly observed from oil markets to stock markets. In a similar vein, Mensi (2019) examined the oil price co-movements with the TASI sectors from 6 January 2007 to 6 February 2017. Their results showed weak co-movements over time frequencies between the crude oil and TASI markets.

3.3.2 Precious Metals

Currently, index fund dealing is being developed swiftly to accommodate commodities and allocate more investments to commodity markets, which enable their seamless integration with stock markets. For these benefits, the downside of not having diversification may be compromised (Tang & Xiong, 2012). Most literature sources have agreed that the diversification benefits afforded by commodities are numerous, but these sources have displayed conflicting results.

Empirical evidence, such as that found by Gorton and Rouwenhorst (2006), has suggested that investing in commodity markets may be useful in diversifying portfolio risks effectively. They demonstrated that commodity markets performed better in periods of unexpected inflation and that during the sampling period of 1959–2004, commodity markets and equity/bond markets had a negative interrelationship. Lucey and Li (2015) sought to uncover the types of precious metals that act as safe havens and the conditions for this behaviour by focusing on the US economy. They considered four precious metals, namely gold, silver, platinum and palladium, under a time-dependent model to uncover their spillover effects for stock markets. They observed that cross-market interactions were significant, suggesting that periods of economic turmoil may impact stock markets but have little effect on precious metal markets. In particular, platinum and palladium were the safest hedges, while shifts in gold prices may affect stock markets to a certain degree.

Bouri, Jain et al. (2017) considered interrelationships between the Indian stock market and the commodity markets of gold and oil by using implied volatility indices. Since gold and oil are the main imports of India, their prices would significantly affect the stock market. They revealed that volatility spillovers from the gold sector had implications for the crude oil and stock markets, while they observed no such phenomenon from the stock market to the other two markets. These results are essential for investors, who can invest in gold and oil to hedge against stock market risk, and gold to hedge against oil sector risk. Following the GFC, investors have become more cautious about risk and prefer gold even during periods of mild market uncertainty.

Lau et al. (2017) investigated the relationship between precious metals, oil, gold and global equity markets. They applied the EGARCH model to study the existence of volatility spillovers. Many different channels for volatility transmission between the selected markets were observed, with gold having a particularly dominant role in dictating the direction of these spillovers. Gold was the key transmitter to the silver, platinum and palladium markets, with oil and equity having smaller effects on the prices of white precious metals. Further, volatility clustering was present for palladium more so than it was for silver and platinum.

Mensi, Al-Yahyaee and Hoon Kang (2017) considered the time-dependent volatility transmission between the stock market and those of precious metals by considering gold, silver, palladium and platinum as well as the major stock markets of the US, Europe, Japan and Asia. Their analysis results suggested that volatility spillovers from the precious metal markets affected the stock market and that during unstable periods, the precious metal markets were net receivers of volatility: Stock market volatility affected these markets. Analysing hedging strategies, they suggested that investors need to add precious metals to their stock portfolio to diversify and improve the portfolio performance.

Mensi, Hammoudeh, Al-Jarrah et al. (2017) studied the dynamic risk spillover patterns between the gold, oil and Islamic stock markets by adopting a dynamic equicorrelations and fractionally integrated asymmetric power ARCH (DECO-FIAPARCH) approach. Using the sampling period 1998–2015, they showed that time-dependent spillovers among the stock and commodity markets occurred, whereby the gold, oil and energy sectors were net receivers of spillovers. Gold was deemed to offer the best diversification benefits for portfolio rebalancing and was considered superior to oil in this regard. Mei-Se et al. (2018) studied the time-dependent integration between oil and the metals silver, copper and gold for the sampling period 1980–2017. Quantitative evidence suggested that gold price had spillover effects on the copper and silver markets, whereas the link between the oil and gold markets was less clear. Further, during economic crisis periods, gold and the other markets had a greater volatility spillover pattern and were more integrated. Based on these conclusions, investors may consider gold a safe haven to curtail any portfolio risks.

Mensi et al. (2018) studied the time-dependent interrelation between gold and oil prices for the BRIC countries. Statistical tests on the daily returns of the stock markets, crude oil and gold return series suggested that Russia's stock market was the most vulnerable to risk and the Indian market was the least vulnerable. Among commodity sectors, crude oil was more volatile than gold. Volatility clustering was also observed for stock returns. There was little transmission of volatility from the BRIC stock markets to gold, reaffirming the utility of gold as a safe-haven asset to mitigate stock market risks.

C. Zhang et al. (2018) considered the case of China's stock market, the oil market and the gold and platinum markets as precious metal markets. As an emerging economy, China offers fierce competition to developed economies, and its vulnerability to transmission of volatility between stock and commodity markets is of significance. The authors employed an ARMA-GARCH model to this end and observed that precious metal markets transmitted volatility to stock markets, but the transmission in the opposite direction was nearly negligible. Volatility spillover effects among the precious metal markets were also observed, and there was some evidence to suggest that these may be permanent and not susceptible to crisis period variations.

Y. Chen and Qu (2019) investigated the leverage effect and dynamic interrelationships between China's precious metal markets (i.e. gold, silver and platinum) and the global oil market for the sample period 2006–2018. They used the copula method and the DCC model to investigate correlations. Their analysis results suggested that the gold and silver markets were particularly sensitive to the flow of positive information, but the crude oil market is more sensitive to negative information. A positive relationship was present between the precious metals of China and the global crude oil.

Dutta et al. (2019) studied the non-linear interrelationships between the implied volatilities of crude oil and certain precious metals, namely, gold, silver and gold miners. They implemented non-linear autoregressive distributed lag model and investigated the long-term relationships between the oil market and the precious metal markets. They found evidence of bidirectional volatility transmission between the markets of oil and gold. Overall, the two markets interacted in a non-linear manner. These results were suggested to be valuable for investors seeking new financial tools for hedging against volatility risks. Husain et al. (2019) considered the relationship between the crude oil, stock and metal markets for the US, using 1990–2017 as the sampling period. They identified numerous channels through which volatility spillovers occurred between the markets. The stock market was observed to have a marginal effect on the other two markets, but precious metals were strong transmitters of price volatility to the stock and oil markets. They concluded that oil, steel and titanium were net receivers of volatility and gold was the key transmitter. These results reaffirmed the usability of precious metals for hedging purposes.

The asymmetric relationships between precious metals and global equity markets were studied in the context of commodity markets serving as preferred asset classes for investors. Various forms of the GARCH model were used for this purpose. Volatility persistence and clustering were both observed for the considered markets, and it was generally concluded that for the case of gold and silver, negative information decreased conditional volatility more so than positive information. This finding suggested that the precious metal markets and stock markets both reacted asymmetrically to information inflows. Volatility transmission effects were observed to be weaker during peaceful periods than they were during times of financial crisis, in which volatility spillovers increased sharply (Urom et al., 2019).

The existing literature on the linkages of the stock market with precious metal markets and other commodity markets contains several strands. These strands have concentrated on different markets and sampling times of varying data levels, using specific econometric methods, and analysing their findings from different viewpoints. In particular, the Saudi Arabian stock market was explored by Mensi, Hammoudeh and Kang (2015), who employed a bivariate DCC-FIAPARCH model. They conducted analyses both with and without structural breaks. The precious metals they considered were gold and silver. Dynamic links between the aforementioned markets were considered. Insignificant correlations were observed for most commodities except for the silver – TASI stock market pair. This pair was susceptible to volatility shocks between the markets.

The usefulness of Sharia stock and gold markets as safe havens for the oil-based GCC markets was also studied. This study employed a multivariate GARCH approach to study the stock markets of six GCC countries and the interrelationships with the markets of oil and precious metals in each economy. The analysis results suggested that the role of crisis periods was imperative in determining correlations between the markets, particularly after the oil price decline of 2014 that the Saudi economy, to a great extent, was able to ride out. Investors in GCC markets stand to lower their risk by including precious metals in their portfolios because spillovers from the oil and stock markets are unlikely to significantly affect these markets (Mensi, Hammoudeh et al., 2015).

Afsal and Haque (2016) conducted a comprehensive study of the gold and stock markets for Saudi Arabia. Relevant to this study, GARCH models were employed to identify the volatility levels in the markets. To study the spillover pattern, a series of models were implemented, including GARCH (p,q) specification, EGARCH and GARCH-M models. The diagonal BEKK model was also used, and data on daily closing prices in the TASI market were employed. The results showed that volatility spillovers between the two markets were barely present, which was attributed to changes in one market being offset by similar but opposite changes in the other market to yield a net-zero effect. The GARCH family estimations were observed to have modelled volatility spillovers accurately.

The volatility spillovers between energy, precious metals and the stock markets of GCC countries were the subject of yet another study, that of Al-Yahyaee et al. (2019), who sought to investigate dynamic risk spillovers. They employed an MGARCH model and found that periods of financial crises significantly enhanced the dynamic interrelationships between the precious metal markets and the stock markets of GCC countries. Further, the gold, silver and stock markets of Oman, Bahrain and Saudi Arabia were net recipients of volatility shocks, and the transmitters were the remaining GCC markets. Precious metal markets were effective in hedging against energy for all GCC markets. Elsewhere, Tissaoui and Azibi (2019) considered the dynamic conditional correlations and predictability between the Saudi stock market and international volatility indices. They implemented a DCC-GARCH model to demonstrate volatility shocks. It was observed that for forecasting Saudi market returns, the US stock index volatility is the most dominant among all countries for the Saudi index. Further, shocks originating from the Saudi stock market had a high potential to spread to international financial markets.

Table 3.2 presents a summary of some recent studies on the volatility transmission between the stock and commodity markets. The table shows the samples examined, the period and data, the type of methodology and the main results for each study. The findings discussed in this section relate the specific case of precious metal markets to several others, including the stock markets of several specific countries as well as the oil sector. A general trend has been observed to suggest that precious metals are safe havens for investors seeking to diversify their portfolios, although this view may shift based upon the current market trend. Periods of financial turbulence often affect the relationship between the commodity and stock markets. The next section discusses the specific relationship between the stock and commodity markets during the GFC and oil decline periods.

Table 3.2: Summary of Some Recent Studies on Volatility Transmission between Stocks and Commodities

Author(s)	Sample	Data Period	Methodology	Main Findings
Mensi, Hammoudeh, and Kang (2015)	TASI, crude oil (WTI), precious metals (gold and silver) and agricultural commodities (wheat, corn and rice).	Daily data; 1 June 2005 – 13 August 2014	DCC-FIAPARCH model	1. Dynamic conditional correlation is insignificant between TASI and mentioned commodities except for silver. 2. Strong diversification benefits and hedging effectiveness for mixed commodity–stock portfolios are observed.
Mensi, Hammoudeh, Al-Jarrah et al. (2017)	Indices of S&P 500, STOXX 600, TSX, NIKKEI 225, DJASIA, gold, silver, palladium and platinum.	Daily data; 4 January 2000 – 5 May 2016	Framework of spillover index and DECO-FIGARCH model	1. Volatility spillovers are observed between precious metal and stock markets. 2. Evidence of volatility spillovers source and receipt. 3. Asset allocation, cross-market hedging and hedging effectiveness are observed.
Mensi et al. (2018)	Stock markets of BRICS (Brazil, Russia, India, China and South Africa), and prices of gold and two types of crude oil (WTI) and (Europe Brent).	Daily data; 29 September 1997 – 4 March 2016	Wavelet decomposition method and value-at-risk (VaR)	1. The relationship between crude oil price (WTI) and BRICS indices in terms of co-movement is low. 2. No relationship between gold and BRICS indices in terms of co-movement is observed.
Al-Yahyaee et al. (2019)	Stock markets of GCC countries (Saudi Arabia, Dubai, Abu Dhabi, Bahrain, Kuwait, Oman and Qatar), energy commodities (WTI crude oil, gasoline and heating oil) and precious metals (gold, palladium, platinum and silver).	Daily data; 30 September 2005 – 24 October 2016	Framework of spillover index and DECO-FIGARCH model	1. The risk of spillovers is observed between the commodities and the stock markets of GCC countries. 2. The net transmitters to stock markets are silver, platinum and energy. 3. Evidence of portfolio management for mixed commodity–stock portfolios.

Table 3.2: Continued

Author(s)	Sample	Data Period	Methodology	Main Findings
Y. Chen and Qu (2019)	The indices of precious metals (Gold, silver and platinum) and crude oil.	Daily data; November 2006 – April 2018.	Copula-DCC-GARCH and DCC-GJR-GARCH models	The dynamic correlation relationship between crude oil and precious metals is positive in normal time and negative in crisis time.
Hamdi et al. (2019)	12 sectoral indices of GCC countries and Brent crude oil.	Monthly data; 2006–2017.	Quantile regression analysis	An interdependence relationship between the 12 GCC sectors and oil prices volatility is observed.
Mensi (2019)	WTI of crude oil, TASI and 15 sectors of Saudi market.	Daily data; 6 January 2007 – 6 February 2017.	Wavelet approach and VaR	1. The co-movement between crude oil and stock market sectors is strong. 2. There is a higher dynamic of the risk analysis.
Thorbecke (2019)	Stock prices of the US and crude oil (WTI).	Daily data; January 1990 – September 2018.	ARMA-VAR model and multi-factor asset pricing model	The increase in oil prices after 2010 in the US stock market has a benefit.
Urom et al. (2019)	Gold, silver, S&P 500, bond, VIX, oil prices, Eurodollar, Term spread and default spread.	Daily data; 20 September 2000 – 20 September 2018.	DCC-GARCH and ADCC-GARCH models	1. The results of conditional variance indicate strong evidence of asymmetry. 2. Evidence of higher correlations among these assets.
Bouri et al. (2020)	Credit default swap indices of three oil-exporters (Abu Dhabi, Dubai, and Bahrain) and three oil-importers (Lebanon, Egypt and Morocco), brent crude oil, crude oil and OVX.	Daily data; 14 February 2011 – 23 November 2018.	Cross-quantilogram approach	1. Asymmetric impact of oil returns. 2. Evidence that volatility takes place in a very short period. 3. Useful implication on portfolio management for policymakers and investors.

3.4 Effect of Volatility Transmission on Financial Crisis/Decline

Instances of financial crises faced by economies are often marked by sharp asset price decrease and increased market volatility. It has been observed that along with volatility, financial crises can also be transmitted between markets. In such cases, the public loses confidence in the financial market and a downward momentum is observed in the economy. The theory of information transmission may be used to explain such volatility spillovers. Studies such as that of King and Wadhwani (1990) have examined the cause and effect of the transmission of volatility in financial crises, and more recent analyses have discussed the financial crisis/shock in terms of volatility transmission (Bampinas & Panagiotidis, 2017; Vardar et al., 2018; W. Xu et al., 2019).

Ross (1989) suggested that market volatility is a direct result of the rate of information transmission between markets. King and Wadhwani (1990) suggested that such volatility is mainly transmitted owing to selective information flows. Not having complete information makes investors uncertain about the exact extent of financial crises/shocks in a specific economy or a country and its possible implications for their own country. For example, two countries' markets may be completely independent of one another but if investors mistakenly assume that a financial crisis in another country will affect their own market, they will take steps to counter this, which would lead to volatility spillovers observed in their own market. This scenario would have been avoidable if investors had access to complete information. In this way, the financial crisis in one country may have serious implications for the market of another country, prompting investors to sell assets, apply for loans or halt lending practices.

Baele (2005) studied the spillovers of volatility originating in the US and aggregate EU markets to 13 local European stock markets by employing a regime-switching model. The study also presented considerable evidence for enhanced shock spillovers originating in the US and affecting the aggregate European markets. Increased spillover effect of the EU due to close trade ties, swift stock market evolution and increased inflation rates were also observed. This spillover effect that originated in the US market went on to affect several European markets in high volatility periods.

This section provides an overview of the link between stock and commodity markets during the two examined periods: the GFC and the 2014–2016 oil price decline. It discusses the research on stock markets and commodity interconnection actions throughout the phases of volatility. For both periods, this section discusses the literature on volatility transmissions not only for stock markets or commodity markets singly, but also for both. It also discusses the literature on volatility transmissions within the Saudi stock market.

3.4.1 Global Financial Crisis of 2008

The GFC of 2008 was marked by the subprime mortgage, which started in the US and swiftly spread to other global markets. When Lehman Brothers, who were the fourth largest investment bank in the world, collapsed in 2008, the entire international banking system also crashed. It has previously been suggested that financial crises originating in major developed stock markets rapidly spread to other markets, and the crisis of 2008 caused significant crashes or huge volatilities in the asset prices of global markets. This financial crisis was followed by a period of extended global fear of spillovers, causing considerable shifts in the interdependencies between global stock markets.

This review of the literature focuses on the relationship of stock markets during the GFC. Experts have attempted to uncover the unique effects of the GFC on market interdependencies by relying on several econometric models. Yiu et al. (2010) used the model of asymmetric DCC to study the interrelation of the US market with 11 Asian financial markets during the crisis period. The analysis showed evidence that the contagion impact was transmitted to the financial markets in Asia during the crisis time of 2007 from the US; however, the same effect was not observed for the AFC. On this note, Samarakoon (2011) developed a novel shock empirical method to examine the effects of shocks in periods of stability and turmoil. The author provided evidence to suggest that there was an interdependence between the US markets and Asian financial markets during the GFC. Several regional discrepancies were observed, and bidirectional and asymmetric correlations between the markets were also observed. The interdependence between the markets was based more upon the shocks of the US, while the contagion effect relied more on the shocks of the emerging markets; hence, the GFC of 2008 was more due to market interrelations.

Dimitriou et al. (2013) studied the GFC contagion effects for the BRIC countries and the US, employing the multivariate DCC-FIAPARCH framework. They showed that during the initial period of the GFC, the contagion effect was not observed for most of the BRIC countries, but these effects were particularly dominant following the Lehman Brothers collapse. This shifting pattern exemplified investors' shifting risk appetite. Nevertheless, the greatest interdependence between the US and the BRIC was observed for the post-crisis period after 2009, pointing to an increased correlation in the bullish period compared with the bearish period. They demonstrated that the trade and economic behaviours common to all BRIC countries do not explain the contagion effect pattern, which can serve as useful information for investors and policymakers. On the same note, Dungey and Gajurel (2014) used a latent factor framework to study the contagion effect transmitted from the US stock market to those of both developed and emerging economies in the crisis period. They showed that the contagion effect was dominant both in developed and emerging markets, which testified to the influence of the GFC period on market volatility. In contrast, the contagion effect was not principally linked to financial markets, suggesting that international integration and contagion were not related, as exemplified by the study.

Hemche et al. (2016) used a DCC-GARCH model to examine the contagion effect between the US market and 10 global markets. They observed a trend of increasing interdependence between the US and other markets, and a contagion effect for the US and France, Italy, UK and Mexico during the GFC. The contagion effect was not observed for the US, China, Japan, Morocco, Tunisia and Egypt, but interdependencies were present. Similarly, Mollah et al. (2016) showed that there was a contagion effect for both developed and developing markets during the GFC and the Eurozone crisis, demonstrating the spread of contagion from the US to other global markets. Latin American markets were observed to be particularly influenced. Conversely, emerging Asian markets were mildly influenced during the GFC and completely unaffected during the Eurozone crisis. The Middle Eastern markets were mildly affected by the Eurozone crisis and were completely unaffected by the GFC. The conclusions from the study suggested that bank risk transmission between the US and the other global markets was essential for cross-country information spillover.

Rejeb (2017) considered the spillover of volatility between Islamic (Arab and Asian) and conventional stock markets to investigate their degree of correlation. A quantile regression based on the GARCH model was implemented to consider non-standard distributions. Emphasis was placed on the financial crisis periods to conclude that the Islamic stock markets were not unaffected by such global market turbulence. Volatility spillovers were significant, with conventional markets showing greater spillover patterns than Islamic markets. There were strong interrelations among the Islamic markets during peaceful and crisis periods. On the same note, Shahzad et al. (2017), who considered the link between the global stock markets of the US, UK and Japan and Islamic stock markets for the 1996–2016 period, adopted a unique approach. They conducted their empirical analysis by implementing the TGARCH framework to reproduce the asymmetry in conditional variance. Information transmission was observed from Islamic stock markets to conventional stock markets, and volatility spillovers were noted to have increased following the GFC. Contradictory evidence was obtained for the claim that Islamic investments offer diversification benefits. Nevertheless, the Islamic stock market was not immune to risks that plagued other conventional financial markets.

Meanwhile, the following literature review presents how only the commodity markets across the GFC period are connected. The case of emerging stock markets, such as Jakarta and Kuala Lumpur, was considered by Nobi and Lee (2017) in the context of their respective financial and commodities (oil and natural gas) industries, particularly for the GFC, European debt crisis and the oil price decline. The sampling period of 2000–2014 was chosen to investigate the financial status of both stock and commodities markets during the crises. Average correlations showed a downward trend, except for the crisis periods where the threshold value for the financial state of each index was particularly volatile. It was generally concluded that indices are more reactive during crisis periods and that hedging strategies considering oil and natural gas as commodities to serve as safe havens may be developed.

China's commodity markets (petrochemicals, energy and oil) and global oil sectors were studied for their interlinkages through a DCC-GJR-GARCH analysis. Dynamic correlations highlighted significant fluctuations during the GFC of 2008, and it was recognised that the crisis had a significant effect on the oil and commodity sectors. It was suggested that portfolio diversification would help combat risks arising from the oil–commodity sector fluctuations, which were observed to be aggravated during crisis periods. The addition of oil–commodity sectors to an investor's portfolio would help reduce commodity sector downturns (Jiang, Jiang et al., 2019).

D. Zhang and Broadstock (2020) assessed the rising interconnectedness between global commodity markets (crude oil, energy and precious metals) during and after the GFC. Their empirical evidence showed a drastic increase in the intensity and nature of market interconnectedness following the GFC of 2008. Seven major classes of commodities were taken into consideration, including crude oil, energy and non-energy sectors, and the interdependence in price change increased from about 15% to 50% following the GFC. The crude oil market mirrored uncertainty in the global macro-economy, and its spillovers inevitable affected precious metal markets, so hedging based on oil would be the safest alternative for investors who wish to resist volatility risks.

In terms of the corresponding effect of the GFC period on the relationship between stock and commodity markets, Bouri (2015) studied oil price volatility and its linkages with the Lebanese stock market with particular emphasis on crisis periods. By using a VAR-GARCH model, the author considered the 1998–2014 sampling period. The study results revealed that contrary to previous findings of bidirectional volatility transmission between oil prices and stock markets, there was weak unidirectional volatility transmission from the oil sector to the Lebanese stock market. This was less stringent following the GFC of 2008 for the post-crisis period when compared with the crisis period. For the latter, volatility transmissions were considerable between the two sectors, originating from oil and spread to stock.

Raza et al. (2016) studied the asymmetric influence of the prices of gold and oil and their volatility spillovers on the stock markets of several developing markets in the BRIC countries. They used monthly data and the 2008–2015 sampling period, which included the crisis and post-crisis period for the GFC. Their quantitative findings suggested that oil prices had an adverse effect on the stock markets of all emerging countries, which were stated to be more vulnerable to bad news compared with good news. G.-J. Wang et al.

(2016) analysed the risk spillovers in global gold markets by considering the specific cases of Tokyo, Shanghai, New York and London for the GFC period. To achieve this, the ARMA-TGARCH model was employed. Volatility clustering in all four gold markets was considerable, with higher values obtained for the Asian markets than their European counterparts and the highest value observed for Tokyo. Spillover was more extreme during the crisis period. The importance of gold as a safe-haven asset was recognised, and it was suggested that investors should hold gold assets in markets that are sources of spillover effects in gold markets.

The stock and oil markets of the US and emerging countries (Mexico and Thailand) were considered for volatility spillovers before and after the crisis periods. The effects of financial shocks for market interlinkages between crude oil and stock markets were studied for four main crisis periods. Volatility transmission from stock to oil markets were weaker during the GFC than in all other crisis periods. Interestingly, shifting patterns of volatility spillovers marked the GFC. The idea that oil and stock markets behaved in the same way was negated through this finding, and oil was recognised as a hedge against stock markets by adding it to an investor's portfolio for diversification (Bampinas & Panagiotidis, 2017).

Öztek and Öcal (2017) searched for possible upward trends in correlations for two commodity subindices: those for agricultural commodities and precious metals with respect to the stock market. The former was found to display an increasing trend as demonstrated by empirical results: Periods of financial crises were marked by high volatility. Agricultural commodities served for portfolio diversification during calm periods. The precious metals subindex demonstrated a high correlation with stock markets during volatile periods and was considered to offer better portfolio diversification benefits during crisis periods. Financial crisis situations, such as the GFC, were seen to enhance the prevailing trends observed.

The topic of using crude oil and gold as a commodity market hedging tool against the risk of the stock market in periods of financial crises, particularly the GFC and oil price decline following 2014, was investigated by Junttila et al. (2018) for the sampling period 1989–2016. They used a GARCH framework for empirical analyses. Considering the aggregate US market, their results showed that the link between crude oil and gold increased during times of crises. Gold futures were suggested as a good option for cross-hedging during crises periods. In their analysis, Vardar et al. (2018) employed a VAR-BEKK-GARCH framework to measure the effects of shock and volatility spillover between advanced stock markets (the US, Japan, Germany, the UK and France), emerging stock markets (Turkey, China, South Korea, South Africa and India) and commodity markets (crude oil, natural gas and precious metals of gold, silver and platinum) in 2005–2016. The findings revealed a bidirectional interrelationship between the stock and commodity markets, which was persistent during the GFC period and post-GFC period. The trends were similar for both developed and emerging markets; shock transmission and volatility spillovers were the new normal following the GFC. The authors concluded that an effective hedging strategy would be to invest in stocks and commodities by considering spillover directions.

Cakan et al. (2019) examined the specific case of stock and oil markets for Russia, Brazil and Turkey. They used a novel strategy to study the connections between speculation in the oil market and the corresponding hedging behaviour by investors in the stock market. The information-based herding in these markets was observed to be particularly significant for the 2008 GFC and the oil price decline after 2014. The global oil market was observed to considerably dictate investor behaviour in Russia and Brazil markets and had implications for portfolio hedging strategies.

W. Xu et al. (2019) considered the asymmetric volatility transmission between the oil and stock markets of the US and China in 2007–2016, adopting a quantitative methodology using the asymmetric GARCH model. They observed that these spillovers were time-dependent and the oil and stock markets were more interrelated during the GFC. They identified the asymmetric effects of good and bad volatility spillovers. These findings were observed to be valuable for investors exposed to the oil and stock markets. Adding oil to a stock portfolio would reduce the negative effect on investors because of stock markets volatility spillovers.

By using the following models—GO-GARCH, VAR-BEKK-GARCH, DCC-GARCH and cDCC-GARCH—Z. Liu et al. (2020) examined the dynamic correlation and the transmission of volatility relationship between the US stock and oil markets in 2007–2018. They revealed that the correlation between the volatility of stock returns and oil is positive and significant. Thus, during the GFC, this correlation increased greatly. Further, they ascertained a significant bidirectional volatility spillover between the two markets. The results could be valuable to researchers interested in energy risk reduction and asset valuation analysis.

Studies have attempted to describe the relationship of TASI with other markets: stock or commodity. Mohanty et al. (2018) examined the asymmetric effect of oil shocks on TASI, using an industry-level analysis as well as a country-level analysis. They demonstrated that oil prices had an asymmetric impact on four of 15 sectors (petrochemicals, insurance, etc.). They identified a positive interrelationship between the oil and stock market sensitivity and suggested that corporate managers in Saudi Arabia could hedge against risk by selling and buying oil contracts based on rises and falls in prices.

Azar and Chopurian (2018) studied the interdependence of commodity markets (oil and natural gas) and the stock market for the GCC countries, including Saudi Arabia. The link between oil and commodity markets was evident, although it was observed to be waning, as in recent times. Theoretically, if commodity markets are reactive to shocks such as oil shocks, a positive interdependence should be observed. Based on empirical observations, the authors demonstrated that the risk–return trade-off was favourable and crisis events, such as the GFC, increased this interdependence. Among the GCC stock markets, the Saudi market was considered a safe haven for investors.

Bildirici and Sonustun (2018) studied the effect of oil and gold prices for oil-exporting countries, focusing on Canada, Saudi Arabia and the US, among others. Using a VAR method, they tested the degree of volatility spillovers between the oil and stock markets in these countries. They concluded that oil price fluctuations had serious effects on the business systems of oil-exporting countries and that there was significant volatility spillover between the oil and stock markets. Similarly, Finta et al. (2019) explored volatility spillovers in oil and stock markets with a particular emphasis on Saudi Arabia and the US. They observed asymmetry in the contemporaneous spillover effects, and that the volatility transmission from the US stock market to the Saudi Arabian stock market was higher than that from the Saudi market to the US market. This trend was exaggerated following the GFC. Risk managers were recommended to consider both direct and indirect volatility transmission for better hedging strategies involving oil as a commodity.

Since Saudi Arabia is a major oil exporter, it is particularly vulnerable to oil price shocks. Mensi (2019) considered the interdependence between the oil and the stock markets in Saudi Arabia during the GFC. As observed for various stock markets, the Saudi market was observed to have increased correlations between the stock and oil markets during the GFC period of 2008–2009. Further, 15 sectors were affected by the crisis, with the petrochemical sector being most severely affected. Surprisingly, the Saudi Arabian banking sector remained unaffected. Investors were advised to look to the petrochemical sector for hedging against fluctuating oil prices.

To sum up, the effects of the GFC were observed to originate in one region and rapidly spread across the globe, causing adverse effects for many international markets. The presence of direct and indirect ties with the financial system means there are significant symmetric risks. The dynamic relationship between stock markets was noted to greatly depend on time. Many studies have shown that both financial crises caused increasing interdependencies between the stock markets, demonstrating the transmission channel of volatility spillover effects. The dominant position held by the major global stock markets in dictating the behaviours of other stock markets was recognised.

3.4.2 Oil Price Decline after mid-2014 to January 2016

The oil price decline of 2014 is often classified as an international crisis because of the reliance of key international economies on the oil market for export and national energy production purposes. Many oil-exporting countries experienced slow growth because of the oil price decline, and this was particularly true for smaller oil-exporting countries (Grigoli et al., 2019). The effects of this decline were felt by developed and emerging countries alike.

In a study on the stock market volatility during the declining impact of oil, Jarrett et al. (2019) considered 44 countries primarily in the context of the oil price decline of 2014 and its effect on stock markets. They focused on 11 oil-rich countries (including Qatar, Oman, Kuwait and Mexico) and 20 countries that perform poorly in terms of financial growth. They revealed that volatility spillovers and market interconnectedness increased during crisis periods, such as those because of oil price shocks. Hedging strategies that incorporate oil and commodity prices into investors' portfolios would allow for better risk-adjusted returns in oil-exporting countries.

Some studies have focused on commodity market volatility in the oil decline period. For example, Luo and Ji (2018) studied the interrelationship between the US and Chinese crude oil and agricultural markets. They quantified time-dependent volatility spillovers through a multivariate DCC-GARCH model and concluded that there was volatility transmission between the US crude oil and China's agricultural sector. Moreover, they observed that the overall volatility connectedness between these markets increased following the oil price decline of 2014. These results suggested that it is increasingly necessary for Chinese local investors to hedge oil price risks, which they can achieve through a diversified portfolio consisting of commodities, such as precious metals and agricultural commodities.

Commodity volatility shocks and oil market interdependence structures for the BRIC countries were investigated using a GARCH-quantile approach (Bouri et al., 2019). This study focused on the periods before and after the oil decline of 2014, that is, 2010–2016 as its sampling period, and found evidence of volatility interdependence. For Brazil and Russia, the commodity and energy market interdependence served to shape the sovereign risk. Volatility spillovers increased in both India and Brazil after the oil decline of 2014. These results were useful to investors in constructing hedging strategies by considering the volatility of energy commodities and adjusting their portfolio weights accordingly.

However, most recent studies have mainly focused on the interconnections between the stock and commodity markets across the oil decline period. For instance, Bass (2017) explored the dependence structure of the stock market and oil prices in Russia through a bivariate GARCH-in-mean approach for the period 2003–2017. The study defined the uncertain aspect of oil prices to reveal that these prices (considered in US dollars) showed that this behaviour in oil prices was statistically significant and had a positive impact on stock market patterns. Positive shocks in the oil market yielded positive volatility spillovers on the stock market in Russia. Consequently, the stock market sensitivity to negative oil price changes increased, such as to the oil decline of 2014, where the oil price uncertainty was not accounted for.

The volatility transmission between commodity markets (energy, agriculture, precious metals and base/industrial metals) in 17 emerging countries and six frontier countries was examined by Bouri, de Boyrie and Pavlova (2017). They comprehensively analysed the 17 emerging global economies for specific oil and commodity market interrelationships in the 2010–2016 sampling period, adopting the Lagrange multiplier (LM) approach to model the time-dependent nature of the series appropriately. Their analysis revealed that volatility transmission effects between the two sectors were significant for most of these emerging economies and were exaggerated under oil price fluctuations. However, some countries that were less reliant on oil showed more rigidity to the shifting volatility spillover patterns. They concluded that investors in these economies could invest in the oil sector for risk-adjusted returns and hedging properties.

Tule et al. (2017) considered the specific case of oil price shocks and stock market interdependence in the Nigerian economy by employing a VARMA-AGARCH model. Using the 2011–2016 sampling period, they focused particularly on the oil price decline that caused structural shifts in sector relationships. Their study revealed that there was considerable cross-market volatility spillover between the oil and stock markets and that the effectiveness of hedging strategies may be misleadingly exaggerated on ignoring structural breaks.

Antonakakis et al. (2018) considered volatility spillovers between the crude oil of WTI and 12 out 25 of the top global oil and gas firms listed in the largest stock markets. They quantitatively estimated volatility spillovers in the context of the GFC and the oil decline of 2014 using the DCC model. They observed that there was considerable volatility spillover from the crude oil to volatility stocks of oil/gas firm companies. They determined the optimal weights strategy as the most effective hedging strategy, with the inclusion of oil stocks aimed to diversify an investor's portfolio against stock market risk. Recently, Bagirov and Mateus (2019) relied on evidence from European countries (Austria, Italy, Belgium, Germany and France) to assess the performance of the volatility spillovers between stock markets and oil prices. The effect of oil price variations on the listed firms of oil and gas performance in Western Europe, including the sharp decline of 2014, was adverse and volatility transmission effects were observed. Thus, it is essential for investors to hedge their portfolios against risk by including risk-adjusted returns from other commodity sectors.

Sun et al. (2020) studied spillovers between sovereign credit default swap, stock and commodity markets using a VAR-based spillover methodology. Representative G7 developed countries and emerging BRIC countries were chosen in the sample. They highlighted the role of various markets during different financial phases. Commodity markets were particularly important during the oil decline of 2014 when spillovers from commodity to other markets were considerable. They suggested that recognising net spillovers among markets would help develop a more diversified portfolio. Dominant assets, such as the stock market for this study, would help hedge against risk and maintain stability within the market.

Recent evidence from the GCC markets or, in particular, TASI, regarding the oil price decline period was studied by Trabelsi (2017), who explored the specific case of the asymmetric interdependence between the oil price shocks and various other industries (petrochemicals, agriculture, food and oil) in Saudi Arabia. The ARMA-GARCH margins served as dependence measures for the chosen study period of 2007–2016. Again, an empirical approach was adopted to establish nonparametric testing methods for establishing interrelationships between the considered markets. The responses of sector indices to changes in oil prices, such as the oil decline of 2014, suggested that first, the correlations were considerably asymmetric, and second, the precision of portfolio restructuring has increased. Such dependence specifications may allow investors to have insights into the TASI market structure in recent years. Hedging strategies for investors aiming to rebalance portfolios may be developed by adding oil as a safe commodity for oil-exporting countries.

The attitude of the TASI stock market to oil price variations was investigated at a sectoral level, using 2012–2015 as the sample period. It was observed that oil prices reached record highs and lows during this period, with the latter occurring in the oil decline of 2014 and the years following. The asymmetric reaction of the stock market to oil prices was captured in the context of sectoral changes. Further, TASI responded rather bravely to the oil price decline, but several sectors needed to reduce their dependence on the oil market. It was suggested that several GCC stock markets, which are closely connected, were and continue to be, severely affected by oil price fluctuations, which often have the greatest repercussions for the TASI market (Khamis et al., 2018). Investing in the Saudi oil sector may allow better portfolio rebalancing and more effective hedging strategies for local and international investors. In the same vein, Wong and El Massah (2018) found that Saudi Arabia, which is considered a major oil exporter and accounts for a large percentage of the global oil reserves, had a particularly significant effect on volatility transmissions in the 2005–2015 sampling period, including when the oil price decline began. They empirically investigated the direction of influence and the response of markets to oil price shocks. Their results revealed that portfolio management at a global scale would provide more information for investors to manage their interests, and the oil price decline served to increase volatility transmissions at the end of the sampling period.

Abid et al. (2019) examined for evidence of contagion spreading from the US to the Saudi stock market through an empirical methodology using a four-factor model. They aimed to study how fluctuating oil and energy prices affect the dependence structure between these two markets, taking into account political, regional, oil and energy price factors. Each factor was found to affect the transmission of volatility between the stock and oil markets of the two countries. Thus, it was necessary to counter the adverse effects of one country's return shocks on the other. The economic diversification plans of the Saudi government to increase its reliance on tourism and other sectors may consolidate the economy in times of oil price declines. Hedging against risk in the TASI market through investing in other commodity sectors may be a viable strategy.

Jawadi and Ftiti (2019) considered the adverse effects of oil price changes on the stock market of Saudi Arabia through a time-dependent analysis. They showed that volatility spillovers due to the crude oil market in Saudi Arabia had a variable impact on the country's economy, depending on the market regime and state. Extreme volatility in crude oil prices was due to slowing economic growth worldwide. This slowdown in oil prices was caused by reduced Chinese demand for oil as well. It was confirmed that the TASI market was reliant upon oil prices, but it was also recognised that the current regime and state of the market affected the threshold effect of the oil sector. These combined could hedge the economy against further oil price collapse, with investors looking to other commodity sectors for safe-haven assets.

Table 3.3 presents a summary of some recent studies on the volatility transmission during the GFC and the oil decline of 2014–2016 between various stock and commodity markets. The table shows the samples examined, the data period, the methodology and the main results for each study. Concluding the present discussion on the volatility transmission effects in developed countries, emerging countries and commodity markets, with a focus on the TASI market, in the GFC and oil decline periods, this section provides an overview of the theoretical and empirical contexts. Therefore, this section supports the analysis with the aim of providing useful insights into the core topics in the recent market literature, especially that on stock and commodity markets. Moreover, it helps to examine the portfolio management issues in these markets, which will be presented in the following section. A variety of topics related to stock and commodity markets were discussed. However, the topic of portfolio management diversification within the stock market of Saudi Arabia, which is a significant way to enrich many theoretical methods mentioned in the next section, will always remain current in the literature.

Table 3.3: Summary of Some Recent Studies on Volatility Transmission between Various Stock and Commodity Markets during the 2008 GFC and 2014–2016 Oil Price Decline

Author(s)	Sample	Data Period	Methodology	Main Findings
Öztek and Öcal (2017)	The indices of S&P 500 and the sectors of precious metals and agriculture of S&P-GSCI.	Weekly data; 4 January 1990 – 20 December 2012	STCC-GARCH and DSTCC-GARCH models	1. During crises, the main source of high correlations seems to be the high market volatility. 2. Commodity markets tend to offer useful diversification resources for investors.
Shahzad et al. (2017)	The indices of DJ, DJIM, 10-yr Treasury bond, crude oil (WTI), Uncert. index and VIX of the US, Japan and UK.	Daily data; 15 July 1996 – 30 June 2016	Spillover index framework and AGDCC-GARCH model	1. Strong evidence of interactions in volatility between the global stock of Islamic markets and the conventional stock markets. 2. Portfolio diversification and a hedging strategy offer benefits, which holds significant implications for investors and policymakers.
Trabelsi (2017)	Crude oil of WTI, TASI and sectors of TASI.	Weekly data; 23 February 2007 – 15 July 2016	Model of ARMA-GARCH and copula-based dependence measures	The sector indices' responses to the fluctuations of oil price are significantly asymmetric.
Tule et al. (2017)	Crude oil of Brent and WTI, Nigerian Sovereign 10-year Bond.	Daily data; 22 March 2011 – 14 April 2016	VARMA-AGARCH model	There is a relationship between oil and sovereign bond markets in terms of cross-market volatility transmission.
Junttila et al. (2018)	COMEX Gold, WTI of crude oil, S&P 500 and S&P 500 Energy IG Price.	Daily data; 11 September 1989 – 13 September 2016.	DCC-GARCH model	1. There are correlations between the US markets and the gold and oil markets. 2. There is correlation between the stock markets and gold market, which is negative in financial crises times.

Table 3.3: Continued

Author(s)	Sample	Data Period	Methodology	Main Findings
Luo and Ji (2018)	Five agricultural commodities (soybeans, corn, cotton, strong gluten wheat and palm) and crude oil of the US	Five-minute high-frequency data; 3 January 2006 – 31 December 2015.	DCC-GARCH and multivariate heteroscedastic autoregressive models	There is market interdependence among these assets.
Abid et al. (2019)	Crude oil, natural gas and equity markets of MENA (Saudi Arabia, United Arab Emirates, Qatar, Oman, Bahrain, Lebanon, Egypt, Jordan, Turkey, Tunisia and Moroccan), Russia and US.	Daily data; 1 January 2004 – 1 November 2018.	A four-factor model	1. The relationship between the US and MENA equity markets indicates a strong contagion. 2. During a market crisis, the oil and gas markets play a significant role in strengthening the dependence between the MENA and US markets.
Bagirov and Mateus (2019)	Nine sector indices of Dow Jones and STOXX Europe 600 index and Brent crude oil.	Weekly data; 3 January 2006 – 29 December 2015.	VAR-GARCH model	1. There is a relationship between the oil and European stock markets. 2. There are volatility spillovers between the stock and oil markets. 3. The global financial crisis (2008–2009) influenced the listed oil and gas firms negatively.
Bouri et al. (2019)	The indices of energy commodities, Brazil, Russia, India and China (BRIC).	Daily data; 4 January 2010 – 31 August 2016	GARCH-quantile regression	1. In Brazil, the sovereign volatility risk has increased after mid-2014. 2. In India, the sovereign volatility risk has decreased after mid-2014.

Table 3.3: Continued

Author(s)	Sample	Data Period	Methodology	Main Findings
Jiang, Jiang et al. (2019)	Five commodity sectors in China (energy, petrochemicals, softs, oils & fats and non-ferrous metals) and oil crude market.	Weekly data; 1 September 2004 – 28 September 2018	DCC-GJR-GARCH model	1. The relationship between the markets of global crude oil and China's commodity sectors in terms of the long-term linkage of return spillover and the time-varying dependence is strong. 2. To effectively reduce risks, diversified portfolios can be used.
W. Xu et al. (2019)	Crude oil (WTI), S&P 500 and SSEC of Shanghai index.	Daily data; 4 January 2007 – 28 April 2016	Realised volatility and semivariance measures; AG-DCC model	The relationship between the oil and stocks markets in terms of volatility shocks is strongly asymmetric.
D. Zhang and Broadstock (2020)	Beverage, fertiliser, food, metal, precious metal, raw materials and crude oil.	Monthly data; January 1982 – June 2017	Connectedness measures and spillover index framework	1. After the GFC, connections have sharply risen. 2. After the GFC, Food has become the most powerful class. 3. Oil prices have no effect.

3.5 Portfolio Diversification Opportunity

Investors who plan to invest in international stocks are expected to consider the volatility in their domestic and global/commodity markets. The selection of optimal weights in effective, globally diversified portfolios follows the mean-variance method; thus, it is built from measuring the mean-variance of the returns on assets. Consistent with this theme, Markowitz (1952, 1959) formulated a modern portfolio theory, known as the principle of diversification, which is frequently employed in finance-related studies. The principle of diversification suggests that investors seek to considerably lower their investment risk without seriously undermining their portfolio returns. One of the earliest analyses in this regard was conducted by Grubel (1968), who proposed that the inclusion of foreign securities allows investors with globally diversified portfolios to realise lower variance in returns owing to non-ideal correlations between various international stock markets.

In addition, some investors have followed the dictum 'do not put all your eggs in one basket' and have chosen to randomly invest in unrelated assets to diversify their portfolios. This strategy is termed a naïve diversification strategy. Normally, investors would invest considerably in local assets without regard to the level of restrictions removed from trading in foreign assets. This inclination to invest in domestic assets as opposed to global ones is called the 'home bias' for financial assets (Coval & Moskowitz, 1999; French & Poterba, 1991; Lewis, 1996). Several authors have focused specifically on developed and emerging countries and their stock market correlations with other markets. For example, Solnik (1974) found that global diversification is preferred for cross-market interrelationships. In addition, Odier and Solnik (1993) suggested that global diversification remains profitable despite increased information integration throughout the world's markets, and this finding is particularly relevant for turbulent periods.

The benefits of portfolio diversification were also explored not only within stock markets but also commodity markets, as in the analysis conducted by Belousova and Dorfleitner (2012). They suggested that investors may benefit from instruments of commodity indices as diverse tools to make investments for obtaining improved portfolio performance. However, this thesis focuses only on the implementation of multivariate GARCH models that were commonly used in asset return analysis because these models can define the volatility of asset returns and allow for time-changing covariances of asset returns. In addition, it constructs an optimal portfolio using the expected conditional covariance matrix of assets. Antoniou et al. (2007), who used the DCC-GARCH model to examine European and American markets, suggested that conditional correlations increased during bear markets and fell in recovery periods. Meric et al. (2008) used the principal components model and Granger causality to analyse the portfolio diversification significance of the sector index co-movement for bull and bear markets in Germany, France, Japan, the US and the UK. They suggested that in a bear market, diversification opportunities are limited because the markets of those countries tend to be more closely correlated, but in a bull market, global diversification may prove fruitful for investors.

The utility of the model of DCC in building the optimal weights for a globally diversified efficient portfolio is somewhat limited. Cha and Jithendranathan (2009) selected the sampling period of January 1996 – December 2004 to develop a portfolio for the S&P 500 index as well as 19 MSCI emerging markets to ascertain the advantages afforded for US investors by global diversification. Their results suggested that the advantages afforded by global diversification in emerging economies were enhanced owing to reduced maximum restricted investments in these economies. Over a decade ago, Gupta and Donleavy (2009) identified the advantages for Australian investors of investing in seven developing economies (Brazil, Chile, Greece, India, South Korea, Malaysia and the Philippines) using February 1988 to December 2005 as the sampling period. They employed an ADCC approach to calculate the optimal weights in an efficient portfolio for these seven countries. Their analysis revealed that Australian investors are afforded greater advantages by investing in emerging markets because globally diversified portfolios result in a greater Sharpe ratio than the Australia-based portfolios.

Jayasuriya and Shambora (2009) investigated the advantages of diversification across market classifications. They considered optimal portfolios for emerging, frontier and developed markets. Their analysis results suggested that the portfolio risk and returns improved on diversifying portfolios to include stocks from six frontier markets. To gauge investors' exposure to domestic risk, Coeurdacier and Guibaud (2011) investigated the hedging behaviour of investors of investing in global stock markets with low dependence on domestic stock markets. They revealed that investors tend to direct their foreign holdings to 183 countries that offer competitive diversification advantages.

Berger et al. (2011) used principal components analysis to study whether investing in frontier market equities would support portfolio diversification, given the integration of international stock markets. Their findings suggested that there was little integration between frontier markets and the global stock markets, which thus present considerable diversification advantages. Daskalaki and Skiadopoulos (2011) suggested that the alleged advantages of diversification may be subject to criticism. Their analysis suggested that the benefits of optimal portfolios are superior even after accounting for transaction costs, given that these portfolios consist of only traditional asset classes for most of the cases they considered.

A VAR-GARCH approach was implemented by Mensi et al. (2013) to examine the dependence between returns and volatility spillover effects between the S&P 500 and the prices of commodities such as beverages, food, gold and energy, for the 2000 to 2011 sampling period. Their analysis results revealed that there were very close relationships between the volatilities of commodity and equity markets. Their additional analysis of adding commodities to a stock-diversified portfolio would enhance the overall risk-adjusted performance of the optimal weights and hedge ratios for the returns of commodity–stock portfolios.

Silvennoinen and Thorp (2013) found that most relationships between commodity futures and stocks were almost negligible in the 1990s. These increased in the early 2000s and reached their peak in the GFC of 2008, because of investors' increased tendency to put their money into strongly integrated commodity and conventional asset markets. Consequently, the advantages afforded because of diversification of commodities against stock markets fell markedly. Büyükşahin and Robe (2014) proved that the increasing financialisation of commodity markets along with the use of many macroeconomic tools could result in more closely integrated commodity and traditional asset markets. Thus, correlations between commodity and conventional assets may eliminate diversification benefits.

The conditional return and volatility based on time-dependent features for the US stock markets and crude oil were investigated by Chkili et al. (2014) through the DCC-FIAPARCH model. Following the 2008 GFC, volatility spillovers between the stock market of the US and the oil market increased. Considering the ideal case of an oil–stock portfolio, Chkili et al. suggested that investors with interests in the American markets should invest in stocks in greater quantities rather than in crude oil assets to mitigate portfolio risk. The implemented model allowed better hedging of the stock portfolio risks for investors than did the DCC-GARCH model.

Gencer and Musoglu (2014) studied the volatility transmission effects between the gold and stock markets in Turkey, using a BEKK-GARCH model to study the interrelationships. Their sampling period was 2006–2013, which was considered a volatile period for the world market and it includes the GFC of 2008. They proved that there was a two-way bidirectional volatility spillover between the Turkish stock market and gold and constructed a hedged portfolio accordingly. They suggested that a gold–stocks portfolio based upon optimal weights and hedge ratios may assist investors in diversifying their stock portfolios by adding gold as a commodity. During a financial crisis, gold is a unique asset to reduce portfolio risk. Their results are valuable for local and foreign investors in managing portfolios.

Kumar (2014) considered the specific case of return and volatility spillovers between the gold and stock sectors in the Indian market and also implemented the approach of optimal weight, hedge ratios and hedging effectiveness using the VAR-ADCC-BVGARCH model. Considerable unidirectional volatility spillovers from gold to the stock market were observed. The estimated time-dependent conditional correlations had negative values and were mostly present during crisis periods in markets, which reflects the portfolio diversification and hedging potential in such periods. Based on the hedging effectiveness and the optimal weights and hedge ratios for the stock market and gold, they concluded that gold in an investor's portfolio is a better diversification strategy than are stock portfolios.

Lee et al. (2014) studied the effects of volatility transmission and dynamic correlations between the stock markets and crude oil for G7 developed economies, with an emphasis on financial crisis periods. They selected 1998–2012 as their sampling period and employed a range of models, including the BEKK, CCC and DCC, to estimate the optimal weights and hedge ratios of a portfolio. They found positive interrelationships between the G7 stock markets and the oil market. Their empirical results suggested that the hedging effectiveness of the DCC model was superior to that of the other considered models, with Japan having the largest optimal portfolio weight and lowest hedge ratio. They suggested that investors need to develop their hedging strategy based on the oil market if investing in stock markets with a low hedge ratio, such as Japan, the US and Germany. When periods of crisis occur, investors tend to turn to the oil market to diversify their portfolios.

B. Lin et al. (2014) studied the effects of oil price variations and volatility spillovers on portfolio management and hedging effectiveness for West African markets, particularly those of Ghana and Nigeria. They adopted multivariate models, such as the VAR-GARCH, VAR-AGARCH and DCC-GARCH, to estimate the optimal weights and hedge ratios for the oil–stock portfolios. For both stock markets, considerable interdependence was observed with the oil market. Comparing all the implemented models, the DCC-GARCH yielded the most effective hedge for the two stock markets. The results for the optimal hedge were in line with those of previous studies, and the inclusion of oil assets was considered integral for a diversified stock portfolio. In the presence of risk associated with oil prices, a deeper comprehension of volatility relationships was necessary for better portfolio management.

Arouri et al. (2015a) investigated the cross-correlations of the Latin American stock markets to estimate optimal portfolio strategies and that of the US for the sampling period 1993–2012, and they used a VAR-GARCH model. They considered the extent of volatility transmission from the viewpoint of US and Latin American investors. Their analysis revealed considerable return and volatility spillovers that must be accounted for in portfolio management strategies involving Latin American assets for effective hedging strategies. The calculated optimal weights and hedge ratios suggested that the addition of Latin American assets could help improve the risk-adjusted returns of globally diversified portfolios. These results reaffirmed the findings of previous studies regarding the presence of cross-market correlations and about effective portfolio management strategies throughout the Latin American region.

Arouri et al. (2015b) studied the effectiveness of hedging and diversification between the Chinese stock market and gold, by implementing a VAR-GARCH model. Specifically, they implemented five variations of the GARCH model (diagonal, scalar and full of BEKK, CCC and DCC). There were considerable return and volatility transmission between the gold and stock markets in China, which were modelled most effectively through the VAR-GARCH model. The portfolio analysis revealed that the addition of gold to a portfolio consisting of Chinese stocks would enhance its risk-adjusted return and allow for hedging against stock risk exposure in the long term. Gold was recognised as a safe-haven asset for stocks in financial crisis periods for the Chinese market.

The link between the stock markets of G7 and the crude oil market was further examined using the transmission of volatility between stock prices and oil for various periods. A new approach, the wavelet based on the MGARCH model, was implemented to account for the multiscale properties of the time series. These analysis results accounted for the multiscale properties of hedge ratios to arrive at conclusions for the optimal portfolio design. Given the considerable volatility transmission effects between the stock markets and oil, the integration of oil assets in a stock portfolio was suggested as an effective hedging strategy for G7 investors. It would allow effective diversification because the stock prices of G7 countries were more volatile than oil prices (Khalfaoui et al., 2015).

The emerging economies were considered in the context of hedging stock prices with oil, gold and other commodities by means of DCC, ADCC and GO-GARCH models. Persistence in volatility transmission was observed between emerging market stock market returns, gold and crude oil. Conditional correlations between these asset classes were studied to obtain dynamic conditional correlations and optimal hedge ratios. Many scenarios under consideration were found to be best hedged using oil as an asset in the emerging markets, even in financial crisis situations. Using the ADCC model, more effective results were obtained for the hedge ratios of stock markets to oil and other commodity markets. Following oil, gold was suggested to be the second most effective asset for hedging against stock markets. The GO-GARCH model yielded different hedge ratio and optimal weight values from the other considered models (Basher & Sadorsky, 2016).

Yaya et al. (2016) focused on the volatility persistence and return spillovers during 1986–2015 between the oil and gold markets and, in particular, on the pre- and post-GFC period. They used the CCC model to investigate the spillover effects and observed that the volatility of the gold market was less than that of the oil market before the GFC, and that volatility transmission was bidirectional. However, after the crisis period, there was one-way volatility spillover from the gold to the oil market, suggesting there was a composition of optimum allocation weights and hedge ratios. They suggested to use gold assets as a hedge against oil prices and in the process, diversify an investor's optimal portfolio.

Majdoub and Sassi (2017) considered the volatility spillovers and hedging effectiveness of China and developing Asian market economies (India, Malaysia, Thailand, Indonesia and South Korea) using MSCI indices and the bivariate VARMA-BEKK-AGARCH model to specifically capture asymmetry. They found significant evidence of two-way volatility spillovers between the economies of China, South Korea and Thailand. A structural break approach was adopted to show a considerable shift before and after the break in the hedge ratio, which holds valuable implications for investors seeking to diversify global portfolios. In particular, they suggested that investors in China need to have more Chinese assets in their portfolios than assets in other Asian stock markets. The portfolio management and hedging effectiveness ratios for this analysis differed from those for previous suggestions.

A. Singh and Singh (2017) studied portfolio hedging strategies for the US and BRIC countries in financial crisis periods, particularly the GFC of 2008. They studied dynamic interactions between the US and BRIC stock markets through the DCC model in a multivariate framework. They used a monthly heat map to capture co-movement between the stock markets and found considerable volatility spillovers, transmitted from the US market to those of BRIC countries. They computed time-dependent optimal weights and hedge ratios accordingly. The effect of the Lehman Brothers collapse was observed most readily for India and Russia, and greater interdependence between the US and Brazil was evident. The optimal hedge ratios comprised the US and Chinese stocks, even during crisis periods and these were suggested as ideal for an US investor.

The portfolio and hedging effectiveness of financial assets in G7 economies was investigated by Izadi and Hassan (2018), who used the DCC approach to study interrelations between equity and commodity returns for the sampling period 2000–2014. Their analysis results suggested that the German index was the most volatile among stock markets and demonstrated spillovers, and the same was the case for the crude oil index among commodities. Negative correlations during periods of the financial crisis were observed between gold–stock pairs. They concluded that hedging portfolios of gold–stock during financial crisis periods may be advantageous. Such hedging effectiveness results suggest that diversification may be beneficial for all commodity and stock portfolios than only for stock portfolios.

Oloko (2018) considered portfolio diversification opportunities between developed and emerging economies for the specific case of the UK and US investors in Nigeria, which attracts the greatest amount of foreign investment in Africa. The potential benefits of portfolio diversification to these investors were studied employing the VAR-BEKK-GARCH model, which employs conditional variance and covariance to obtain approximations for the optimal portfolio weight and hedge ratio. The analysis accounted for a structural break in the model for global portfolio diversification to obtain unbiased results. The analysis found negative spillovers of return from the Nigerian stock market to the US and UK markets. It was concluded that the US and UK investors would gain from investing in Nigerian stocks to diversify their portfolios, although financial risk could be transmitted from the US and UK markets to the Nigerian market.

W. Ahmad et al. (2018) also considered the interdependence and dynamic hedging between sectors in the BRIC countries and global markets, particularly the US and Europe markets. They employed directional spillover and DCC models to capture the interdependence between BRIC commodity markets and BRIC stock markets. Regional and global indices suggested that the latter had a more considerable effect on the BRIC market indices than the former. During the GFC, time-dependent spillover values indicated there were particular turning points. Optimal weight and hedge ratios implied that among the considered countries, China and India provided the best risk management opportunities. The authors recommended that the indices of global and regional be paired with BRIC indices to allow for portfolio diversification opportunities.

Hassan et al. (2019) considered the Islamic stocks in BRIC countries and the crude oil market to uncover conditional correlations and volatility transmission effects between the markets, using the DCC model. Their findings suggested that there were no significant correlations between the oil market and Islamic stocks in the BRIC group, but the correlations between the stock markets of China and India were enhanced during the GFC of 2008. Similarly, volatility transmission between BRIC Islamic stocks and the oil market were not significant either. They concluded that Islamic stocks allowed for greater hedging effectiveness in China and India, and the two markets provided diversification benefits.

Khalfaoui et al. (2019) examined the spillovers of volatility between the countries of oil-importing and oil-exporting and the oil market, as well as portfolio and hedging implications for these countries in the 2010–2016 sampling period. The countries they considered included the US, China, Saudi Arabia and Russia. They used versions of symmetric and asymmetric of DCC and corrected DCC-GARCH models. The GARCH (1,1), GJR-GARCH (1,1), FIGARCH (1,1) and FIEGARCH (1,1) models were used to explore the portfolio and hedging ratios. They found that the oil-importing countries were considerably affected by lags in oil price shocks. Lagged volatility in oil and stock markets affected current market volatilities. The analysis results suggested that there was less dependence between the stock markets of oil-importing and oil-exporting countries and that investors in oil-exporting countries should invest in more oil assets to hedge against risk. Negative shocks were observed to be more dominant than positive shocks.

Jiang, Fu and Ruan (2019) studied the risk transmission between precious metal and stock markets of BRIC for the sampling period 2001–2017, using a DCC-GJR-GARCH model. They explored volatility relationships between the considered markets, finding that these varied considerably during the sample period, particularly during times of crisis. Evidence was provided to suggest that investors should hedge their portfolios through diversification. The optimal weight and hedge ratio were both variables depending on different markets and the hedging effectiveness of precious metals varied considerably from the hedging effectiveness of stock markets after the GFC. Precious metals would serve as a hedge against the risk for India and China, but not Brazil and Russia.

Sarwar et al. (2019) considered the transmission of volatility between the stock markets of Shanghai, Bombay and Nikkei and crude oil returns. For this purpose, they implemented the BEKK-, DCC-, corrected DCC- and GO-GARCH models for the 2000–2016 sampling period. Results were used for analysing optimal portfolio weights and hedge ratios for all these markets. They found evidence of volatility transmission between the stock markets and oil market, other than for China. For example, there was unidirectional volatility spillover from the stock market of India to the oil market. The optimal portfolio weights and hedge ratios suggested that oil assets are valuable for mitigating the associated portfolio risk of stocks, but investors should hold more stocks than oil assets for an optimal portfolio. The cDCC-GARCH model was suggested as the most efficient for minimising risk.

Recently, Ahmed and Huo (2020) investigated the dynamic relationship between China's stock markets, commodity markets and world oil prices from 2 July 2012 to 30 June 2017 and applied a VAR-BEKK-GARCH model. They found that the oil market spillovers have a significantly unidirectional return on the stock market, indicating that the Chinese stock market is strongly dependent on the oil market. The findings demonstrated important unidirectional return to the main commodity indicators in China from the Chinese stock and global markets. Ahmed and Huo found no relationship of returns between gold and stock (oil), which indicates that gold can play the role of safe haven. Their findings also show there is bidirectional volatility of shocks between the oil and stock markets and one-way spillovers of volatility to China's stock market from the oil market. For commodities, there is proof of strong unidirectional spillovers of shock and volatility to commodities from stock/oil. Thus, these commodity markets show no spillover effect on either equity or oil markets, which could contribute to the future diversification of Chinese commodity markets.

Apart from the overall variety of literature that convinces investors who plan to diversify their portfolios in stock/commodity markets, an increasing body of scholarly literature has been dedicated to researching and approximating obstacles and risks associated with investing in the GCC market and specifically the Saudi stock market. Khalifa et al. (2014) investigated portfolio management approaches using models of volatility spillover in regime-switching environments by considering several GCC markets as well as global markets, including the S&P 500 index and the oil market. A multichain Markov-switching model and a VAR model were both implemented to this end, to draw a comparison between the usefulness of the two models. Authors also employed return-based models to approximate optimal hedge ratios and portfolio weights. There was a spillover effect observed from the US stock market to the oil market. Their results revealed that there were considerable time and regime dependence for the optimal portfolio weights and hedge ratios for each pair. These relied on the regimes of the same market as well as of other markets. Portfolio diversification was considered essential for hedging against risk by investing in friendly-regime markets.

Jouini and Harrathi (2014) focused on the GCC stock markets and world oil price in 2005–2011 to identify a portfolio management strategy for investors. Using the BEKK-GARCH model, they documented proof of considerable volatility spillovers between the stock markets of GCC and oil markets. Conditional volatilities displayed extreme fluctuations during the GFC. They recommended that since considerable sensitivity to TASI stock prices was observed, oil as a commodity may be integrated into investors' portfolios to allow better risk-adjusted performance and hedging against fluctuations in financial crisis periods. This relationship was observed to have shifted in recent years, with increased volatility spillovers present.

Interrelationships between stock markets in selected MENA countries and the US stock market during the pre- and post-GFC periods were also explored. Empirical evidence found using multivariate GARCH models suggested that before the GFC, these interrelationships were largely weak and negligible but increased exponentially after the crisis and persisted even during the crisis. The diversification benefits for the US and MENA markets diminished owing to increased spillovers. It was generally concluded that the addition of MENA equities to a US portfolio would considerably improve its performance, but this was limited to the period before the GFC. Following the GFC, the poor performance of the MENA markets has adversely affected risk reduction for portfolios comprising the MENA and US assets (Maghyereh et al., 2015).

To sum up, previous studies were less concerned with exploring the global diversification advantages and efficient risk management strategies with reference to the Saudi stock market. Several studies have revealed that volatility increases during crisis periods as compared with non-crisis periods, which will curtail any benefits of portfolio diversification. It was hypothesised that shifts in economic situations may cause time-dependent changes in correlations, portfolio weights and hedge ratios for stocks and commodities. Table 3.4 presents a summary of some recent selected studies that have investigated the portfolio management implication related to various stock and commodity markets. The table shows the samples examined, the data period, the type of methodology and the main results for each study.

Table 3.4: Summary of Some Recent Studies of Portfolio Management Implications for Various Stocks and Commodities

Author(s)	Sample	Data Period	Methodology	Main Findings
Jouini and Harrathi (2014)	GCC stock and oil markets.	Weekly data; 24 June 2005 – 25 March 2011.	Asymmetric BEKK-GARCH model.	1. In terms of shock and volatility spillover, there is a linkage between the markets of GCC stocks and oil. 2. Policymakers and investors can gain benefits by diversifying their portfolios.
Majdoub and Sassi (2017)	Six Asian emerging countries of Islamic MSCI equities (China, India, Malaysia, Korea, Indonesia and Thailand).	Daily data; 7 February 2011 – 5 February 2016.	VARMA-BEKK-AGARCH model.	1. The relationship between the markets of selected Asian Islamic stocks and China indicates a positive and a negative spillover return. 2. Policymakers and investors can gain benefits from using portfolio management and hedging effectiveness ratios in terms of international portfolio diversification.
W. Ahmad et al. (2018)	Six sectoral indices of global, European, BRIC and US markets.	Weekly data 23 June 2003 – 14 March 2016.	Directional spillover and DCC-MGARCH models.	1. Among BRIC or BRIC and global indices, there is strong heterogeneity. 2. BRIC cannot be considered a homogenous asset class.
Oloko (2018)	US, UK and Nigeria.	Monthly data; January 2004 – June 2015.	VAR-BEKK-GARCH model.	1. Nigerian stocks may yield gains for US and UK investors through equity portfolio diversification. 2. The US or UK investor could mitigate the impact of financial shocks through implementing optimal portfolio weight and optimal hedge ratio results.
Hassan et al. (2019)	Crude oil and BRIC (Brazil, Russia, India and China).	Daily data; 3 June 2002 – 28 March 2017.	Volatility spillover framework and DCC-GARCH model.	1. The relationship between crude oil and Islamic stocks in BRIC in terms of volatility spillovers and correlations are not very high. 2. The better diversification benefits are provided by India and China.

Table 3.4: Continued

Author(s)	Sample	Data Period	Methodology	Main Findings
Jiang, Fu and Ruan (2019)	The indices of BRICS (Brazil, Russia, India, China and South Africa) and precious metals (gold, silver, palladium and platinum).	Daily data; 3 January 2001 – 28 December 2017.	DCC-GJR-GARCH model.	1. There are long-term volatility linkages between precious metals and BRICS. 2. Portfolio diversification mitigates risks and then effectively increases investors' earnings.
Khalfaoui et al. (2019)	US, Russia, China, Saudi Arabia and crude oil.	Daily data; January 2010 – December 2016.	DCC-GARCH, cDCC-GARCH, GJR-GARCH, FIGARCH, FIEGARCH and HYGARCH models.	1. The relationship between the markets of stocks and crude oil in terms of volatility spillover is bidirectional. 2. Investors in oil exporter countries should hold more oil assets in their portfolio to hedge risks.
Sarwar et al. (2019)	Crude oil, China, Japan and India.	Daily data; 1 January 2000 – 27 December 2016.	BEKK-GARCH, DCC-GARCH, cDCC-GARCH and GO-GARCH models.	1. The conditional volatility and shock dependence have a more significant role than volatility spillover. 2. To minimise portfolio risk, oil asset is more useful tool.
Ahmed and Huo, (2020)	CSI300 Index of China, crude oil, gold and silver, copper, aluminium, soybean and wheat.	Daily data; 2 July 2012 – 30 June 2017.	VAR-BEKK-GARCH model.	1. There is evidence of strong dependence of the Chinese stock market on the oil market. 2. Chinese commodity markets have established new diversifications to promote risk and portfolio management.

3.6 The Existing Gap in the Literature

As reviewed in the previous sections, considerable research has been conducted on the effect of volatility transmission for the stock and commodity markets and their effect during crisis/shock periods, and numerous theoretical and empirical conclusions have been drawn. To this end, a variety of econometric models have been implemented, including the ARCH/GARCH class of models that enables the empirical analysis of dynamic interactions between various interlinked markets. Numerous conclusions were evident in this regard: First, there were spillovers between various stock and commodity markets, and second, periods of financial crisis/shock and instability did enhance these spillover effects. Nevertheless, considerable aspects regarding the effects of volatility and information transmission across markets still require further research for improvements and better understanding. In this regard, the present research seeks to provide additional information that exemplifies these relationships through a comparative analysis of the Saudi stock market and its relationship with other markets and trade components, that is, stocks and commodities.

The current literature, as reviewed and leading to the present study's four testing hypotheses, has not adequately dealt with, and has not been suitably integrated with and empirically supported by, modern econometric methodologies, such as multivariate GARCH methods in the case of Saudi Arabia. The improvement of optimal portfolio management in the Saudi stock market, based on global volatility transmission concepts and with updated data, is significant aspect that must be considered by researchers.

The study addresses these gaps and advances the knowledge in the literature on volatility origin in finance in the following ways. It has new integrated conceptual and methodological features that are particularly relevant to the Saudi stock market. Conceptually, first, it recognises the importance of volatility transmission in Saudi Arabia's major partner markets in view of the increasing globalisation and financial integration. Second, it recognises the importance of global volatility transmission of major commodities in view of Saudi Arabia's natural resources. Third, it recognises the importance of the volatility transmission of the GFC in 2008 and oil price collapse in 2014–2016 by comparing the impact of both on the Saudi stock market. Significantly, unlike other previous studies, the integration of all these sources of volatility in the modelling study is the present study's main important and innovative conceptual contribution to the general literature. Methodologically, it uses advanced econometric techniques, namely the CCF and, appropriately, multivariate GARCH models, calculates the associated optimal weight and hedge ratio to assist portfolio management in diversifying portfolios, and especially uses updated daily data for 2007–2018 and later for a more current, practical and credible analysis. The use of these integrated concepts, multivariate econometric models and updated data with expected new improved outcomes for portfolio management has not been performed to date in the Saudi Arabian context. Therefore, the study findings are expected to provide useful portfolio allocation guidance to institutional and individual investors alike and to other stakeholders by providing an efficient portfolio management strategy to hedge/deal with various events, such as the 2008 GFC and 2014–2016 oil price collapse.

3.7 Conclusion

This chapter provided a thorough, critical review of the literature on volatility transmission in financial markets, such as the stock market and the commodity market. It discussed existing empirical studies on the interdependence relationship between the stock and commodity markets and their volatilities, not only with these markets alone but also with a focus on the Saudi stock market. The review of these empirical studies highlighted and explained the dynamics of volatility in the Saudi stock market for internal and external investors.

Studies on volatility transmissions have revealed major effects, not just for the diversification of international portfolios, but also for the predictability of global market returns. Positive and negative market shocks will influence potential returns extremely significantly. This chapter presented a detailed overview of the vast number of papers published on the interdependence between financial and commodity markets. It dealt with the relevant literature that documents this interdependence and its dynamism. Further, the causes and effects of strengthened intermarket interdependence during the GFC and oil decline periods were discussed. Each subsection presented a specific approach and addressed its relative strengths and weakness. A broad and diverse literature using a wide range of methods, covering diverse market locations (North America, Europe and Asia), country classifications, assets (stocks and commodities) and crisis/shock (financial global crisis and the oil decline of 2014–2016) was discussed here. The next chapter discusses the techniques used for evaluating and measuring the relationships between the properties of various time series and markets. To answer the study questions outlined in Section 1.3 of Chapter 1, the next chapter will refer to the unit root and stationarity tests, CCF and MGARCH models and portfolio management.

Chapter 4 Research Methodology

4.1 Introduction

Different econometric models will be explored in the current chapter in relation to the financial market analysis. This chapter explains different GARCH models with a major focus on the advantages of these models that are aligned to the research variables. The main characteristic of the GARCH model is that it only has parameters enabling numerous squared roots. This effect on the conditional variance makes this model more parsimonious compared with the ARCH model. Further, a GARCH model is a better tool in finance studies that analyse data associated with heteroscedasticity or volatility (Ekong & Onye, 2017). This makes the GARCH models a good fit for a study that models time-series data. Nevertheless, these models are not free from limitations. There are a few areas in which the GARCH models can be improved for detecting the characteristics as well as the dynamics of the given time series, as noted by Pilbeam and Langeland (2015).

The GARCH family model is the most appropriate model because its purpose of using the return to analyse the financial assets and it is different from homoscedastic models which are based upon volatility that is constant. The homoscedastic models are not appropriate for asset returns because of changes in volatility during specific periods. On the other hand, the GARCH model is autoregressive and uses past squared observations and variances to analyse the current variance. Returns on financial assets are estimated by the GARCH model by estimation of asset returns and specification of conditional variance. The GARCH model, in this thesis, analyses conditional variance with higher accuracy for a wider range of returns of financial assets.

Moreover, current volatility is better measured by the GARCH process because the model is based upon two things: the conditional variance and conditional mean. The unconditional variance and mean are ignored and treated as constants. On the other hand, conditional variance is taken as a function of the squared root value in the prior period in the GARCH model. Forecast intervals are identified as a measure of volatility by the use of conditional variance. Therefore, for effective implementation of the GARCH model, conditional and unconditional variances are to be separated. It is important to note that conditional variance refers to dependence upon past observations, while unconditional variance refers to constant long-term behaviour. On other side, it is important to note that the CCF model in itself includes one of the family GARCH models which it is EGARCH. This model has a possibility to capture the asymmetric effect during the CCF test. This gives room for the various responses to the lagged error based on the provided signs to emerge. Based on the design of the current research, the EGARCH model will be applied in modelling the stock return as follows given that it is an exponential extension of the GARCH model.

In finance studies, applying proper econometric models is of utmost significance in formulating and testing various hypotheses. This is because these studies involve the quantitative application of statistical as well as mathematical models through the help of different forms of data to test research hypotheses. Hypotheses are tested based on historical information obtained (Bouri, Jain et al., 2017; Maghyereh et al., 2016). Thus, it is important that researchers who conduct and test hypotheses using historical data have a thorough understanding of the benefits of econometric models (Alberg et al., 2008).

In the present study, based on Bansal et al. (2014), volatility is defined as a measure used to underscore the variability in financial asset pricing over a significant period. Volatility, in this case, remains a vital feature in the pricing of financial assets in the practical literature and academically. Following the emergence of the ARCH model designed by Engle and Bollerslev (1986), a vast amount of literature regarding these models has emerged, informing on their application to varied financial markets, such as stocks and commodities. High-frequency data, with precision noted in the volatility models, remain a significant aspect in research studies. Given the challenges resulting from the acquisition and manipulation of high-frequency data, it is essential to note that data at a daily or lower frequency are mainly used in volatility estimation. The basic idea of the GARCH-type of model family is its need to understand the conditional probabilities and densities of the functions while equally describing the density of conditional returns on financial information known in the present day (N. Ahmad et al., 2016).

As aforementioned, this methodology chapter will present different econometric models with reference to the stock and commodity markets. It is divided into three sections—unit root and stationarity tests, presented in Section 4.2; CCF and MGARCH models, explained in Section 4.3; and portfolio management, discussed in Section 4.4. Further, the three major sections are again subdivided into different subsections based on the requirements of every section.

4.2 Unit Root and Stationarity Tests

4.2.1 Introduction

In this research, it is significant to test the stability of the data to be implemented. However, the process of testing data stability is challenging and calls for the utilisation of various techniques to arrive at the required results. Since time-series data will be applied in this research, the unit root process will be used to identify the so-called spurious data series. The unit root test is widely used because it is important to distinguish whether the financial markets in the time series are following a random walk or not (Canarella et al., 2012; Jebb et al., 2015). In most common scenarios, when the hypothesis that a series has a unit root cannot be rejected, the time series is perceived to follow a random walk (Azad et al., 2013). Usually, tests of unit root are applied to determine stationarity in a time series. This is because a time series will tend to have stationarity. Moreover, the unit roots are the main causes of non-stationarity. Nonetheless, unit root tests are largely characterised as possessing fairly low statistical power.

When a time series is found to be not stationary, researchers always find it easier to conduct a study afterwards on the source of the non-stationarity series. A non-stationarity series can be viewed as a stationary indifference, provided that the difference is stationary. To be precise, $Y_t$is not stationary but when the operation Y_t-$Y_{t-1}$is conducted, the difference is found to be stationary, thus justifying the random walk case. Testing for the presence of the unit root in the time series is essential, given that it ensures that the series is not spurious in any way.

In addition, a time series can also be stationary based on the trend of the data in the series. According to Olweny and Kimani (2011), stationarity tests provide an effective platform for researchers to verify whether the series is stationary or not. Two different existing techniques can be relied upon in the verification process. To begin, the unit root tests affirm that a null hypothesis is an undisputed indication that the series adopted is stationary. This assertion is justifiable by the fact that a null hypothesis will always have a unit root. Among the key unit root tests are the augmented Dickey–Fuller (ADF) test and the Phillips–Perron (PP) test. In the same vein, stationarity tests, such as the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test, assert that all series using null hypotheses must be presented as stationary.

4.2.2 Augmented Dickey–Fuller test

Dickey and Fuller (1979) conducted pioneering investigations into the presence of a unit root in time-series data. Notably, the ADF test is in direct alignment with the procedures found in the DF test. It seeks to verify the null hypothesis of the unit root in the time series. Three types of unit root tests will be performed as follows:

$$\Delta Y_t = bY_{t-1} + \sum_{t-1}^{k} \lambda_t \, \Delta Y_{t-1} + \varepsilon_t \tag{4.1}$$

$$\Delta Y_t = \alpha + bY_{t-1} + \sum_{t-1}^{k} \lambda_t \, \Delta Y_{t-1} + \varepsilon_t \tag{4.2}$$

$$\Delta Y_t = \alpha + \beta_t + bY_{t-1} + \sum_{t-1}^{k} \lambda_t \, \Delta Y_{t-1} + \varepsilon_t \tag{4.3}$$

where Δ indicates the first difference of the variable Y, α is an intercept, β_t is a linear trend coefficient, b is the coefficient of lagged dependent variables, k is the lag truncation parameter order of AR process and ε_t is an error term. The primary motivation behind this test is to analyse the null and alternative hypotheses. In the autoregressive model, it determines whether a unit root is present or not. The ADF test involves testing the null hypothesis $H_0: \beta = 0$ and the alternative hypothesis $H_1: \beta < 0$. Based on the provisions of this test, it can be asserted that the null hypothesis of the test is that function Y_t is a random walk with the possibility of having a drift (Kulaksizoglu, 2015). Moreover, there is a pair of possible alternative hypothesis. The first is that Y_t is stationary in the time series with a linear time trend. The second possible alternative hypothesis is that Y_t is stationary but with probably a mean that is not zero but again with no linear time trend in the series. The default possible alternative hypothesis to use is the first one.

4.2.3 Phillips–Perron Test

In 1988, Phillips and Perron developed different tests of unit root that became popular in analysing financial time series. The PP unit root test, as it is commonly referred to, differs from the ADF test discussed in the previous section. This difference is mainly in the way they interact with the serial correlation as well as the heteroscedasticity as far as the errors are concerned (Kipiński et al., 2011). Specifically, the PP unit root test does not recognise the role of serial correlation in the process of test regression. The test regression for the PP unit root test is:

$$\Delta Y_t = \beta' D_t + \pi Y_{t-1} + \mu_t \qquad \textbf{(4.4)}$$

where D_t is a vector of deterministic terms (constant, trend, etc.) and μ_t is used to represent I(0) and can be heteroscedastic in nature.

Further, the PP unit root test is able to correct all serial correlations as well as heteroscedasticity within the errors $\mu_t$of the test regressions. Nonetheless, using alternative stationarity directs that even the null hypothesis is still a unit root, as mentioned before (Chiwira & Muyambiri, 2012). Yet, the nature of the PP unit root of using nonparametric makes it unimportant to include the lags when correcting for high order serial correlation, as observed in the ADF test. In this test, choosing a bandwidth parameter that can create a similar finite problem product as in the ADF test is all that is required. Nevertheless, Vogelsang and Wagner (2013) assert that the test results reject the null hypothesis, and they recommend a unit root when the z-statistic value is found to be higher than the critical value in use.

4.2.4 Kwiatkowski–Phillips–Schmidt–Shin Test

According to Spyridis et al. (2010), the KPSS test is important in investigating the nature of the time-series data since it is used to test the null hypotheses, suggesting that any observable series is perceived to be stationary as far as the deterministic trend is concerned.

However, this test is only appreciated when it is conducted against the unit root alternatives. Unlike other unit root tests that state that the presence of the null hypothesis is a unit root, the KPSS test provides that the presence of the unit root in the time series is an alternative and not a null hypothesis. Thus, this test is built on the foundation that the absence of the unit root is evidence of trend stationarity and not stationarity in general as in other unit root tests (Spyridis et al., 2010). It is important this difference is well understood since it proposes the possibility that the time series will be considered non-stationary and lacking a unit root but will still be referred to as trend stationary. However, the mean of both unit root and trend-stationary processes can change with either positive or negative differences over time. The trend-stationary process is also referred to as mean-reverting because the tend-stationary process has the ability to effectively converge towards the direction of the growing mean whenever there is a shock. Conversely, the unit root process tends to have a permanent effect on the mean, particularly because they do not converge over time. As stated earlier, the KPSS test is employed to test the null hypothesis of the stationarity's existence but against the unit root's alternative. Thus, the KPSS test was built on the following equation:

$$Y_t = \alpha + \delta_t + X_t + V_t \qquad \textbf{(4.5)}$$

$$X_t = X_{t-1} + \mu_t \qquad \textbf{(4.6)}$$

where Y_t is the sum of the deterministic trend, X_t is the random walk, V_t is the stationary error and $\mu_t \sim (0, \sigma_\mu^2)$. V_t is perceived to be stationary in the case of any null hypothesis, whereas Y_t is assumed to be trend stationary in a null hypothesis. Therefore, the KPSS test only requires that σ_μ^2 equals to zero (Spyridis et al., 2010).

$$KPSS_T = \frac{M^{-2} \sum_{i=1}^{M} S_i^2}{\widehat{w_T^2}} \qquad \textbf{(4.7)}$$

where $S_i^2 = \sum_{i=1}^{M} e_i$, i=1,2,…,M and e_i is the regression's residuals of Y on the time trend and intercept and w_T^2 displays the variance estimation of the error term from the model regression.

The details of the calculations of the KPSS test are provided in equation 4.7. However, the default parameter in the lag can calculate the test statistic in an effort that helps determine the short-term and long-term effects. In addition, the p-value is mainly calculated through the interpolation of the test statistic (Valera et al., 2018). In this regard, it is significant to establish that the KPSS test mainly relies on the use of the ordinary least squares (OLS) model to find the equation, an aspect that significantly differs from the other models, since this depends on the level stationarity or rather the trend stationarity. In such a case, a simplified version, therefore, ensures that time trend measures and components are used in testing the level stationarity.

4.3 CCF and MGARCH Models

4.3.1 The Cross-Correlation Function Model

The CCF model, which was designed by Cheung and Ng (1996), is a standard device used by researchers in various finance studies to determine the relationship between a pair of items in a given time series. Most researchers have used the CCF model to understand the volatilities in the time series of financial markets. Using the CCF model involves two stages since a part of the analysis is conducted while performing the tests for the causality in variance. The procedure begins with estimations of the given univariate model for not only the series that allows time variation in the conditional mean but also for the series associated with conditional variance (Giannellis et al., 2010). However, the second stage involves, in this case, deriving the standardised residuals from variance equation (4.9) used in stage one. Further, the CCF is constructed separately for the squared standardised residuals and standardised residuals (Mordret et al., 2010; Nazlioglu et al., 2013). Then, the data from this construction are used in the subsequent steps for testing the causality in the variance.

Importantly, using a univariate model from the GARCH family can help in dealing with the serial correlation as well as heteroscedasticity within the raw data in the time series. H. Xu and Hamori (2012) asserted that a model from the GARCH family is to be incorporated during this testing process in the initial stages of the first step. Based on the design of the current research, the EGARCH model will be applied in modelling the stocks and commodities returns as follows, given that it is an exponential extension of the GARCH model.

$$Y_t = \alpha_0 + \sum_{z=1}^{m} \alpha_z Y_{t-z} + \sum_{s=1}^{n} \varphi_s \zeta_{t-s} + \zeta_t, \;\; \zeta_t/\Omega_{t-1} \tag{4.8}$$

$$log(\sigma_t^2) = \omega_0 + \sum_{d=1}^{q} \omega_d \left|\frac{\zeta_{t-d}}{\sigma_{t-d}}\right| + \gamma \frac{\zeta_{t-d}}{\sigma_{t-d}} + \sum_{b=1}^{p} \beta_b log\,(\sigma_{t-b}^2) \tag{4.9}$$

where $Y_t$stands for the returns, $\zeta_t$refers to the stochastic error that adheres to the generalised error distribution (GED), Ω_{t-1} stands for the information set at time (t-1) and σ_t^2 represents the time-varying conditional variance. To ensure that the conditional variance of ω_d and β_b parameters are always positive and have no constraints to the non-negativity of the variance parameters.

The presence of the two stationary time series X_t and Y_t as well as a set of information stating that $I_{1t} = \{X_{t-j};\, j \geq 0\}\; and\; I_{2t} = \{X_{t-j};\, j \geq 0\}$. Y_t causes X_{t+1} in the variance when:

$$E\{(X_{t+1} - \mu_{x,t+1})^2\, \big| I_{1t}\} \neq E\{(X_{t+1} - \mu_{x,t+1})^2\, \big| I_{2t}\;, \tag{4.10}$$

where $\mu_{x,t+1}$ refers to the mean of X_{t+1} that is conditioned on I_{1t}. The feedback of variance can occur when X_t causes Y_t and Y_t causes X_t only when:

$$E\{\left(X_{t+1} - \mu_{x,t+1}\right)^2\, \big| I_{1t}\} \neq E\{(X_{t+1} - \mu_{x,t+1})^2\, \big| I_{2t} + Y_{t+1} \tag{4.11}$$

Similarly, Y_t can be said to cause X_{t+1}only when:

$$E\{(X_{t+1})^2\, \big| I_{1t}\} \neq E\{(X_{t+1})^2\, \big| I_{2t} \tag{4.12}$$

The CCF approach enables researchers to obtain information on the lag structure within relationships, and in this particular study, the approach will be similar to the CCF approach that can be applied to analysing the causality in variance of two stock markets, A and B. Since the causality in variance can be tested, there will be no normality assumption, given that the test statistics are understood to follow a standard distribution in an asymptotic manner. Let the standard residual for market A be A_t and that for market B be B_t. Therefore, the sample CCF at the n^{th} lag between A_t and B_t will be defined as represented in the following equation:

$$\rho_{AB}(n) = Cov_{AB}(n)/\sqrt{Var_A} \times \sqrt{Var_B} \quad \textbf{(4.13)}$$

where Var_A and Var_B are the variances in the data series for stock market A and stock market B, respectively. Conversely, $Cov_{AB}(n)$ stands for the sample cross-covariance with n^{th} lag. Therefore, this equation can be used to define the test statistic CCF (n) at lag n as follows:

$$CCF(n) = \sqrt{D \times m\rho_{A_tB_t}(n)} \quad \textbf{(4.14)}$$

It can be stated that this equation follows an asymptotically standard normal distribution as the sample size, D, approaches infinity. This equation is used to examine the null hypothesis that indicates non-causality in variance compared with the alternative hypothesis of causality in variance. Further, either the presence or absence of causality at lag n between the return series A and the return series B can be inferred when the hypotheses are tested. This means that the null hypothesis is supported meaning there is no causality and then the alternative hypothesis stating that causality, in fact, exists is supported. While testing for causality using the CCF model, it is preferable to explore numerous issues in detail so that the entire process is effective and succeeds. It was stated earlier that the serial correlation in this process should be addressed with the help of a model from the GARCH family; however, the lags detected optimally should be considered.

4.3.2 Multivariate GARCH (MGARCH) Models

4.3.2.1 Introduction

In the finance studies, the MGARCH approach serves to extend the GARCH model's representation of the univariate vectorised conditional-variance matrix (Bauwens et al., 2006; Elder, 2003; Tse & Tsui, 2002; Worthington & Higgs, 2004). The specifications of this new GARCH representation align directly with the traditional ARMA time-series model. Further, the VECH representations are regarded as general in nature and also have many parameters. However, Huang et al. (2010) argued that the empirical applications of the MGARCH models need more restrictions as well as simplifications compared with the univariate GARCH models. In addition, researchers must understand that the diagonal form is the most useful member in the entire family of VECH representation, as confirmed by Laurent et al. (2012). Every variance–covariance term in the diagonal form is designed to adhere to the provisions of GARCH-type equation, which is characterised with the lagged variance–covariance term.

The MGARCH models will be a suitable choice to examine the volatility transmissions in multiple financial markets, which is in line with the justification offered by P. Wang (2009). This examination requires an estimation of the volatility component for the financial market variables; therefore, this thesis will consider the research questions and hypotheses, given the literature gaps and the study's aims and objectives. Four research questions are analysed as follows:

1. Is there volatility transmission between global stock markets and the Saudi stock market?

2. Is there volatility transmission between major commodity markets and the Saudi stock market?

3. How does market volatility transmission of global stock and major commodity markets impact the Saudi Arabian stock market?

4. How did the volatility of global variables influence the Saudi stock market during the collapses of 2008 and 2014–2016?

To address the above research questions, the following list of research hypotheses has been developed and applied to be tested across all markets using different multivariate GARCH models.

H_1: There is volatility transmission between global stock markets and the Saudi stock market.

H_{2a}: There is volatility transmission between oil prices and the Saudi stock market.

H_{2b}: There is volatility transmission between precious metals and the Saudi stock market.

H_3: There is volatility transmission occurring among global stock and major commodity markets during the major financial collapses of 2008 and 2014–2016 for Saudi Arabia's stock market.

Therefore, the following section will discuss various types of multivariate GARCH methods related to the volatility transmission and conditional correlation in the global stock and major commodity markets.

4.3.2.2 Baba, Engle, Kraft and Kroner (BEKK) Model

The individual time series has its volatility pattern, say h, assessed by a simple univariate GARCH model approach. Mostly, it takes the form represented by the following equation:

$$h_t = c_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots \alpha_p \varepsilon_{t-p}^2 + b_1 h_{t-1} + \cdots + b_q h_{t-q} \qquad \textbf{(4.15)}$$

where p and q are used to define the order of the GARCH model used. Nonetheless, this piece of information can be transferred into a multivariate GARCH model that has a variance–covariance matrix relationship, and H_t can be presented as in the following equation:

$$H_t = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix} \qquad \textbf{(4.16)}$$

Following this baseline, the BEKK (1,1) can be represented based on the variance of the H_t term error as follows:

$$H_t = C_0 C_0 + A_{11} \varepsilon_{t-1} \varepsilon_{t-1} A_{11} + B_{11} H_{t-1} B_{11} \qquad \textbf{(4.17)}$$

where A_i and B_i are incorporated in the equation to represent the $n * n$ parameter matrix, and C_0 represents the $n * n$ upper triangular matrix. However, the depiction by Sinha et al. (2012) shows that the bivariate BEKK (1,1) approach can be expanded to the following equation:

$$H_t = C_0 C_0 + \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} + \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \begin{pmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \quad \textbf{(4.18)}$$

From the above equation, there is a set of off-diagonal parameters, b_{21} and b_{12}, that are representatives of B in the matrix. These off-diagonal parameters of the matrix are essential in measuring the dependence of conditional price volatility. In contrast, parameters b_{11} and the b_{22} are significant representatives of the persistence in volatility within their own stock or commodity market. Meanwhile, the a_{12} or the a_{21} parameters stand for the cross-market effects, and both a_{11} and a_{22} represent their own effects in the stock or commodity market. Thus, the important level of every parameter in the matrix is an indicator of the presence of a strong ARCH or GARCH effect. Moreover, this matrix can be used to derive different equations of not only conditional variance but also conditional covariance. This is shown as:

$$h_{11,t} = c_1 + a_{11}^2 \varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 + b_{11}^2 h_{11,t-1} + 2b_{11}b_{21}h_{12,t-1} + b_{21}^2 h_{22,t-1} \quad \textbf{(4.19)}$$

where the volatility of the stock and commodity returns relies on the past conditional variances, and the covariances relate to the precise markets under analysis.

Mohammadi and Tan (2015) asserted on studying the volatility of the Shanghai stock market that the BEKK model can provide researchers a useful framework to analyse cross-market spillovers in any type of volatility scenario comprehensively, including a historic one. However, the BEKK model, as they emphasised, is not parsimonious and needs the estimation of the parameters to be relatively large. However, the CCC and DCC models serve as desirable alternatives since they provide parsimonious specifications (Mohammadi & Tan, 2015).

Numerous finance studies have used the BEKK model to successfully determine the volatility between financial markets. Ağırman et al. (2018) used the VARMA-BEKK-GARCH approach to examine the multivariate relationships of the volatility spillovers in the Turkey and North Africa (ETM) stock markets. They used daily data as well as data for the 2010–2017 period. They found a common trend in the movements of the financial returns in the given framework of the volatility spillovers of some stocks. Further, this model helped the researchers to settle on mid-2014 as the period of increasing volatility within the time series for four different stock markets. This outcome may be the main reason for the researchers' conclusion that stock markets are closely related in those regions.

4.3.2.3 Constant Conditional Correlation (CCC) Model

According to Bollerslev (1990), bivariate GARCH was intended for assumptions on constant conditional correlations. The model is designed with a simplified CCC matrix to result in estimation and consequential estimates, defined by:

$$Y_t = (Y_t|\psi_{t-1}) + \varepsilon_t \quad \textbf{(4.20)}$$

$$H_t = V(\varepsilon_t|\psi_{t-1}) \quad \textbf{(4.21)}$$

where ψ_{t-1} is set of information at time t.

The element in matrix H_t denotes $h_{ij,t}$; $y_{i,t}$ and $y_{j,t}$ are given by equation (4.22), which indicates a conditional correlation between two time series:

$$\rho_{ij,t} = \frac{h_{ij,t}}{\sqrt{h_{ii,t}h_{jj,t}}} \quad \textbf{(4.22)}$$

where $-1 \leq \rho_{ij,t} \leq 1$, the conditional variance is defined as:

$$h_{ii,} = \omega_i \sigma_{i,t}^2 \quad \textbf{(4.23)}$$

where ω_i is a real time-invariant scalar.

H_t is a full conditional variance–covariance matrix, which is presented as:

$$H_t = D_t R D_t \quad \textbf{(4.24)}$$

where D_t denotes an N×N diagonal matrix with elements $\sigma_{1,t}$, $\sigma_{2,t}$, . . ., $\sigma_{N,t}$. R is an N×N time-invariant $\rho_{ij}\sqrt{\omega i \omega j}$.

The likelihood function is defined by:

$$L(\theta) = -\frac{TN}{2} log2\pi - \frac{T}{2} log\,|R| - \sum_{t=1}^{T} log\,|Dt| - \frac{1}{2}\sum_{t=1}^{T} \epsilon_t^1\, R^{-1}\epsilon_t \qquad \textbf{(4.25)}$$

The conditional correlation in the model remains unchanged over time. This results in varying levels of conditional covariance, through individual changes in the respective conditional variance.

4.3.2.4 Dynamic Conditional Correlation (DCC) Model

Most researchers tend to opt for the dynamic conditional correlation (DCC) model, which can be represented as:

$$H_t = D_t R_t D_t = \rho_{ijt}\sqrt{h_{iit}h_{jjt}} \qquad \textbf{(4.26)}$$

where H_t stands for the $n * n$ conditional covariance matrix, R_t represents the $n * n$ conditional correlation matrix and D_t indicates a conditional correlation time-varying matrix. However, Gjika and Horváth (2013) stated that it is important to understand that the baseline representation of the DCC model has been extended by researchers to deal with parameterisation aspects. This thesis aims at filling the gaps in the literature concerning current data sources. Caporin and McAleer (2013) found that understanding the DCC model is linked to the construction of dynamic conditional correlations, which is of great significance to the present research. This is because the representation of the DCC model gives estimated dynamic correlations but only as a by-product of the standardisation process, rather than as a direct result of the equation that governs the multivariate dynamics (Chang et al., 2013; Sadorsky, 2014).

As shown above, the DCC model is widely used and can be represented as a variation of multivariate GARCH. The comparison of the R_t and D_t matrices can be computed as shown in the following equation:

$$D_t = diag(h_{11t}^{\frac{1}{2}}, \dots, h_{nnt}^{\frac{1}{2}}) \qquad \textbf{(4.27)}$$

where $h_{iit}$is incorporated in the equation to represent the univariate GARCH (1,1) process characterised as:

$$R_t = (diagQ_t)^{-1/2} Q_t (diagQ_t) \quad \textbf{(4.28)}$$

where Q_t (4.29) stands for an $n * n$ symmetric definite matrix that is positive in nature satisfying the condition of equation (4.30):

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u_{t-1} + \beta Q_{t-1} \quad \textbf{(4.29)}$$

where $\bar{Q}$ is the unconditional variance matrix of the standardised residuals (u_t), while both α and β are positive scalar parameters that must satisfy the following expression $\alpha + \beta < 1$; therefore, the DCC model is mean-reverting.

$$u_{it} = {}^{\varepsilon_{i,t}}\!\Big/\!\sqrt{h_{i,t}} \quad \textbf{(4.30)}$$

Following the above equations, it is easier to note that the model of DCC-MGARCH is built on the conditional second-order moment of the standardised residuals. The time-varying correlation coefficient ρ_{ijt} for $i \neq j$ is given by:

$$\rho_{ij,t} = \frac{(1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u_{t-1} + \beta Q_{t-1}}{\sqrt{(1 - \alpha - \beta)\bar{Q} + \alpha {u_{t-1}}^2 + \beta Q_{t-1}} + (1 - \alpha - \beta)\bar{Q} + \alpha {u_{t-1}}^2 + \beta Q_{t-1}} \quad \textbf{(4.31)}$$

Although other MGARCH models are derived from the general GARCH model, the DCC model, by contrast, is in most cases stated. Derived models are known to depend on the relationship between the innovations to returns as well as the standardised residuals (Aielli, 2013; Chang et al., 2011; Hafner & Reznikova, 2012). Further, the DCC model representation cannot satisfy the requirement of relating the correlations to the covariances of the dynamic conditions. As Naoui et al. (2010) explained, the DCC model is a recent approach that allows conditional correlation modelling. In this research, the model estimation will involve the two steps highlighted by Saiti et al. (2013) with the initial one focusing on estimating the conditional variance of every market through the univariate GARCH model approach. Moreover, the research will make good use of the standardised regression residuals. The residuals obtained in the first step play a crucial role in modelling the conditional correlations that depict variations over time.

4.4 Portfolio Management

4.4.1 Introduction

Portfolio management is a term that has been widely used in different areas and mainly relates to managing financial assets through various strategies. The aim is to help investors or other interests to maximise the revenue collected but at minimal risk throughout the process. However, Stettina and Hörz (2015) stated that poor portfolio management is directly related to low revenues collected with increased risks. Therefore, investors or portfolio managers should conduct proper portfolio management to increase the chances of collecting large revenues and operating in risk-free business environments. Modern portfolio management theory states that when designing a portfolio, the ratio of every asset has to be chosen and then the selected ratios should be combined carefully in the portfolio to generate maximum revenue at minimum risk (Buttell, 2010; Rasiah, 2012; Vaclavik & Jablonsky, 2012).

Notably, current investors are applying portfolio management concepts, alongside useful models such as those from the GARCH family in making sound decisions. The theoretical frameworks of portfolio management have undergone significant modifications in recent years and are subsequently more effective. For example, the structure of the Markowitz portfolio can be modified by incorporating a GARCH model to calculate the expected return of the two pairs in the financial market. The expected returns can be calculated based on conditional variance using a GARCH-type model. Moreover, the GARCH models can be used in evaluating the anticipated risk of the given portfolio. This means that the volatility of the past period will be significant in determining the risks between a pair of markets, whereby it is measured as the lag of the squared residual obtained through the variance equation in the GARCH term from the forecast of the previous variance. In this section, the focus is on examining both the portfolio weight and hedge ratio comprehensively. Therefore, the fifth and last question to be asked in this thesis is as follows: What is the importance of the research findings in improving optimal portfolio management to reduce risks in Saudi Arabia? To address this question, the following hypothesis will be tested to measure the optimal weight and the hedging ratio strategy, as will be discussed in the following sections.

H_4: There is an optimal weight/hedge ratio that can rebalance the financial portfolio.

4.4.2 Optimal Weight

The portfolio weight of an individual asset is obtained by dividing the value (or units) of that asset by the total value (or total units) of the portfolio. In recent years, numerous approaches have been established to calculate portfolio weights. According to Kumar (2014), calculating the optimal weights of a portfolio is important since it helps individuals to devise appropriate investment strategies. To determine the weight of every stock, two types of data must be obtained: the cash values of all the individual stocks for which weights are to be determined and the value of the portfolio. To obtain the weight of the stock portfolio, the cash values of all stock positions are added after removing the value of all investments, such as stocks and commodities, from the total value of the entire account. Doing so is required to ascertain the weight of the stocks, as shown in the following equation:

$$Portfolio\ weight = \frac{Stock's\ value}{Total\ portfolio\ value} \times 100 \qquad \textbf{(4.32)}$$

The empirical application of the GARCH approach has extended into portfolio management and is conducted within the provisions of the mean-variance portfolio analysis. The mean-variance analysis is built on the assumption that decisions made by investors or portfolio managers in financial markets are dependent on not only the future return but also the conditional variance of the return provided by the given portfolio (Andersen et al., 2007; B. Lin et al., 2014).

Kroner and Ng (1998) stated that investors can avoid forecasting the expected returns when they assume their value is zero. This makes the problem very similar to the process of estimating the risk-minimising portfolio weights from MGARCH models. Thus, the optimal TASI holding in the TASI – global stock market pair (e.g. S&P 500) and TASI – commodity markets pair (e.g. gold) portfolios can be used in defining it as:

$$\omega_{TASIS\&P\ 5\ 00,t} = \frac{h_t^{S\&P\ 5\ 00} - h_t^{TASIS\&P\ 5\ 00}}{h_t^{TASI} - 2h_t^{TASIS\&P\ 5\ 00} + h_t^{S\&P\ 5\ 00}} \quad \textbf{(4.33)}$$

$$\omega_{TASIGold,t} = \frac{h_t^{Gold} - h_t^{TASIGold}}{h_t^{TASI} - 2h_t^{TASIGold} + h_t^{Gold}} \quad \textbf{(4.34)}$$

However, the optimal holdings of the portfolio with TASI and global stocks or major commodities were found to be equivalent to the following equation when a mean-variance utility function was assumed:

$$\omega_{21t}^{*} = \begin{cases} 0 & if \quad \omega_{21,t} < 0 \\ \omega_{21t} & if \quad 0 \leq \omega_{21t} \leq 1 \\ 1 & if \quad \omega_{21t} > 1 \end{cases} \quad \textbf{(4.35)}$$

Kroner and Ng (1998) also indicated that the optimal holdings of the portfolio with TASI and global stocks/major commodities were perceived to be $1 - \omega_{21t}^{*}$.

4.4.3 Hedge Ratio

The hedge ratio is a ratio which compares the extent of stock position with the total equity exposure. It is important to use the minimum variance hedge ratio because this approach aims to minimise the variance of the selected position's value (Kumar, 2014). As commonly known, the optimal hedge ratio is crucial to investors to hedge any given position. The hedge ratio is computed by adding the magnitude of the correlation coefficient between the fluctuations in the actual markets and the expected prices of a stock or commodity. The optimal hedge ratio refers to the quantities of not only the spot instrument but also the hedging instrument.

However, investors can choose optimal one-period holdings at every time t (Kroner & Sultan, 1993). Kroner and Sultan's (1993) equation can be simplified to be in a profitable series that results in a hedge ratio exemplified as (4.36), which demonstrates the risk for the TASI and S&P 500 stocks that hold to a minimum if a long position of \$1 can be the hedge for the short position of $\hat{b}_{12,t}^{*}$ of \$1 in TASI stock market.

$$\hat{b}_{TASIS\&P5\ 00,t}^{*} = \frac{h_t^{\widehat{S\&P\ 5\ 00TASI}}}{\widehat{h_t^{TASI}}} \quad \textbf{(4.36)}$$

The portfolio's optimal hedge ratio is represented by $\hat{b}^{*}_{TASIS\&P5\ 0\alpha t}$. The aim of the optimal hedge ratio is to decrease the variance in a position's value. This thesis seeks to add a practical contribution to the existing literature by estimating the optimal portfolio weight and hedge ratio. The reason is to determine the effects and outcomes of certain dynamics in market conditions (Olson et al., 2014).

4.5 Conclusion

As stated in the introduction section, this methodology chapter entailed examining different econometric models for financial markets. In general, different techniques in regard to the GARCH-type family were discussed in this chapter. The major interest was to determine the effectiveness and efficiencies of different models with reference to the volatility of the stock and commodity markets. Volatility is defined in this chapter as a measure to underscore variability in financial asset pricing over a significant period. Numerous researchers have assessed the theoretical developments of the GARCH family models in an effort to better understand the varying conditional variances.

The GARCH family models described in this chapter are widely applicable in examining the interdependence relationships of financial markets. The CCF model, designed by Cheung and Ng (1996), normally uses a univariate GARCH process to evaluate the causality in variance between variables in two steps. The two steps are as follows: (1) The univariate EGARCH model is estimated to examine the time variation in conditional variance; and (2) the standardised conditional variance (squared residuals) acquired in step one is employed to test the causality in variance. The study uses the MGARCH models because of their effectiveness. A methodological review of CCF and MGARCH (BEKK, CCC and DCC) models was presented. Portfolio management requires the accurate measurement of conditional variance and covariance, which are acquired from the MGARCH models of BEKK and DCC. The estimation of the portfolio weight and hedge ratio is performed using the analyses of Kroner and Sultan (1993) and Kroner and Ng (1998).

Chapter 5 Data and Causality In the Variance Relationship between TASI, Global Stock and Major Commodity Markets

5.1 Introduction

This chapter first describes the data collected and then uses descriptive statistical and simple time-series analysis to describe the behaviour, correlation and causality in variance between Saudi Arabia's TASI, six global stocks and five major commodity markets for the volatility transmission, conditional correlation and portfolio management studies in Chapter 6.

5.2 Data and Data Processing

This thesis looks at the most vital bilateral trade partners of Saudi Arabia in it; it starts with the United States, moves across Europe, then through to Japan, and finally concludes in China (see Figure 2.3). It examines the volatility transmission between Saudi Arabia and international economies, namely the US, Japan, Germany, the UK, China, and the world market index. Not only their trading partners, the UK and US stock markets act as global factors for Saudi Arabia. China and Japan were included due to their extensive trading relations with Saudi Arabia. Additionally, these countries are regarded as rising countries and global leaders. The motives for choosing these countries, their critical position in the global financial system, since they are among the biggest markets of world capitalisation (See for more details subsection 2.3.2.7). In addition to the global stock markets, the consideration of oil prices will help recognize what effect is seen on the stock market in Saudi Arabia (SAMA, 2018). Gold, silver, platinum, and palladium are the major precious metals that serve as qualified financial assets for portfolio diversification. Due to the overall economic fluctuations, stock markets experience unstable periods (Reboredo, 2013; Silvennoinen & Thorp, 2013), these precious metals are seen as place of refuge resources by many investors because their qualities are thought to be more stable than those of different commodities and stock prices. As well, because of their low correlation with equity markets, the hedging ability of precious metals makes them considerably more appealing (Hillier et al., 2006; Sadorsky, 2014). Thus, exploring the dynamics of precious metals prices is of great interest (Chen, 2010; Mutafoglu et al., 2012). As all the major capital markets are now attractive foreign investors, it also means that global investors hold an increasing amount of equity in all markets. A portfolio with multiple foreign equities is particularly well-suited for investors who want to investigate the diverse opportunities of various systems of financial markets.

The data cover a wide date range (2007-2018) for comparison of all financial markets and enables highly accurate modelling for the GARCH-type study performed in this thesis. The sixteen-year data series trend often reveals and suggests the pattern of transmission between covering financial markets.

The empirical studies in this thesis use daily data from *DataStream* (Basher & Sadorsky, 2016; Mensi, Hammoudeh et al., 2015), comprising the closing price of the Saudi main stock market, the stock markets of Saudi Arabia's five major trading partners and the general global index as well as five indexes of major commodity markets. These are as follows: the Standard and Poor's 500 index (S&P 500) of the US; the NIKKEI 225 index of Japan; Germany's Deutscher Aktienindex 30 index (DAX 30); the Financial Times Stock Exchange 100 index (FTSE 100) of the UK; the Shanghai Stock Exchange (SSE) index of China; and the Morgan Stanley Capital International (MSCI) index derived from the global index. For commodity markets, oil prices are based on of West Texas Intermediate (WTI) crude oil. For precious metals, US$/Troy ounce used for gold will be adopted, together with the Zurich silver price in US$/kilogram, the London free market palladium price in US$/Troy ounce and the London free market platinum price in US$/Troy ounce. Returns are based on indices denominated as the local currency for the global stock markets (Jordan et al., 2015; Vivian, 2016).

To perform the initial analysis presented in Sections 5.3–5.6, the data investigation was performed through the EViews software for the estimation of the preliminary analysis, the correlation matrix, the ARCH effect and the unit roots tests, while the CCF model was conducted using Excel. The period from 1 January 2007 to 31 December 2018 is considered to establish dependability. In particular, after excluding weekends and public holidays, the sample consists of 3,131 observations for each market. For proper analysis outcomes in terms of the variables' relationship, the data sample must be split into three subsamples. First, the analysis addresses the relationship between the Saudi stock market and the included variables for the whole period. Second, the analysis examines the GFC period in detail to evaluate its impact. Here, the aim is to understand the effect of an individual market on the Saudi stock market during this phase, based on the links between both. This is followed by including 391 observations for the crisis period, from 1-1-2008 to 30-6-2009. Lastly, the final period when the oil price fell from 1-7-2014 to 29-1-2016 is examined, which amounts to 414 observations, through an analysis similar to that for the GFC period.

The descriptive statistics for the daily nominal return of seven global stock markets and five major commodity markets have been calculated and computed using equation (5.1) for the entire 12-year period as well as the two subperiods. The average mean, median, maximum, minimum and standard deviation (Std Dev) values and observation numbers are reported in the following sections. Further, skewness and kurtosis statistics were calculated. The Jarque–Bera (JB) test (1981) results that show the normality of the return series on all six stock and five commodity markets for all periods are further documented in Tables 5.1–6. To shrink the number, to stabilise the data set and to eliminate heteroscedasticity in the analysis (Mills, 2019), the natural logarithm for the proposed study of the respective daily returns will be calculated, using the following formula:

$$\Delta Y_t = \ln(P_t) - \ln(P_{t-1}) \tag{5.1}$$

where ΔY_t is the return and t represents the time series. $\ln(P_t)$ is the price level for the present day and $\ln(P_{t-1})$ is the price level for the previous day of a stock index. The natural price level logarithm is given by ln.

The time-series estimates and the graphs of the logs of price levels for six global stock indices and five major commodity indices for all periods are provided (see Panel A in Tables 5.1–6 and Figures 5.1–6); from these graphs, the daily movement in various markets is evident. A visual analysis of the data series shows that the indexes of global stock markets (S&P 500, DAX 30, FTSE 100, SSE and MSCI) and major commodity markets (crude oil, gold, silver, palladium and platinum), comparatively broad capital exchanges, pursue identical tracks. The GFC in 2008–2009 led to a great danger and a near catastrophe for all markets, although the size of fall varied from market to market. In fact, the gold market seems to have been largely unaffected by the GFC because it is a safe haven (Baur & McDermott, 2010; Baur & McDermott, 2016; Bildirici & Sonustun, 2018; Ji et al., 2019). Conversely, the other markets suffered substantial declines during this crisis.

The returns for six stock indices and five commodities indices series, measured as the first difference for the normal daily global stocks and major commodity indices' logarithms, are shown in Panel B in Tables 5.1–6 and Figures 5.1–6. Volatility in the global stock markets was higher compared with that of major commodity markets, which was smaller during the 2008 crisis period. Similar to Harvey's (1995) view, the TASI market—because of high level volatility—has changed its price more widely than have its developed partners' markets and the commodity markets. In Chapter 4, the econometric models assume the linearity of the estimated parameters of the relationships of financial markets. Nevertheless, the behaviour of financial markets makes them non-linear because of investors' sentiment of dealing with return and risk (Campbell et al., 1997), in such a way as to consider time variation and hence volatility transmission. In Chapter 3, Section 3.5 discussed the implications of volatility transmission.

In fact, linear models cannot describe some significant frequently noted characteristics in the time series of financial markets, such as leptokurtosis; these features are similar to most financial data (Brooks, 2019). Therefore, the thesis data exhibit these features, which can be clearly observed in Tables 5.1–6 and Figures 5.1–6, and thus encourage us to use MGARCH models to examine the transmission effects of shock and volatility spillover. This chapter and Chapter 6 provide a detailed review of the data that had leptokurtic tails and thus exhibited autoregressive conditional heteroscedasticity. The examined global stock and major commodity markets present ARCH effects, which means that MGARCH models can be used. A comprehensive analysis and discussion concerning the thesis data will be undertaken.

5.3 Preliminary Analysis

Several points were identified in the analysis of descriptive statistics in Tables 5.1–6. The first is that there is a relatively long duration of daily observations, whereas had exceptional economic conditions existed, the findings would not be limited to a single span of time. Second, the average return varied across all 11 markets. With a daily mean return of 56.97% in the stock markets, the S&P 500 performed the best. DAX 30 and MSCI followed, with daily mean returns of 46.95% and 23.88%, respectively. Meanwhile, among the commodity markets, palladium performed the best, with a daily mean return of 136.16%. Gold and silver followed, with daily mean returns of 70.11% and 18.97%, respectively.

Third, daily standard deviation values between 1% and 1.6% were recorded for all the stock markets and between 1.1% to 2.4% for the commodity markets throughout the full period, resulting in the 11 markets experiencing volatility. Among the stock markets, NIKKEI 225 was the most volatile market with a standard deviation of 1.51%, which the GFC period result confirmed. The differences between the maximum and minimum levels confirmed there were volatile returns in these six global stock markets. The largest spread of 0.225 was noted for palladium, which was the most volatile market with a standard deviation of 2.47%—again, confirmed by the GFC period result. Differences between the maximum and minimum levels confirmed there were volatile returns in these five major commodity markets. The largest spread of 1.24 was evident for palladium.

Fourth, in line with portfolio theory, higher risk is linked to greater expected returns (Markowitz, 2016), but the results in Table 5.1, Panel B, do not support this view. In comparison with the theory, the NIKKEI 225 average return was ranked fourth although its risk was the highest. In contrast, the results for palladium in the commodity markets were in line with portfolio theory because it had the highest expected return with the highest risk, as presented in Table 5.2, Panel B. Fifth, returns were negatively skewed in all stock markets as well as the gold, silver and platinum commodity markets over the full period, as shown in Tables 5.1–2, Panel B. There were some extremely negative values in the distribution of returns in these markets. In contrast, over the entire period, the crude oil and palladium returns were positive, suggesting those markets offered risk-averse investors attractive investment opportunities. The results of the kurtosis and JB tests confirmed that returns in these 11 markets were not normal. Both kurtosis values were greater than three. Based on the JB test results, the null hypothesis of normally distributed data was strongly rejected for all 11 markets at 1%.

5.3.1 Full Period (2007–2018)

5.3.1.1 Global Stock Markets

Descriptive statistics on TASI, S&P 500, NIKKEI 225, DAX 30, FTSE 100, SSE and MSCI indices are provided in Table 5.1. Panel B indicates that all stock markets' mean returns were positive, ranging from 56.97% to 7.83%, except for TASI and SSE that had negative returns of −1.35% and −7.51%, respectively. The standard deviation, an indicator of volatility, shows that SSE was the most volatile from Panel B, while NIKKEI was the most volatile from Panel A. Conversely, FTSE 100 was the least volatile with the lowest standard deviation in Panel A, and the MSCI was the least volatile market in Panel B.

Overall, all the time series included in the analysis in Table 5.1 (Panel B) and Figure 5.1 showed the characteristics of a typical time series of financial assets; in particular, the analysis of skewness clearly shows that the values for all sample indices were negative, and in addition, the estimates of kurtosis were high (greater than 3) during the study period. Kurtosis in the study ranged from 7.848 (for SSE) to 14.173 (for TASI). The skewness of the time series ranged from −0.746 (TASI) to −0.01 (DAX 30). The kurtosis estimates suggest that all stock markets' return distributions were fat-tailed, or leptokurtic, while the skewness values indicate that the regular returns had an asymmetric distribution with negative skewness throughout the study period. The JB normality check statistics indicate that regular return levels were not normally distributed. Therefore, the null hypothesis of the normally distributed sequence for all the global stock markets included in the study was rejected. Next, Table 5.1 and Figure 5.1 present descriptive statistics, indicating substantial extreme kurtosis.

Table 5.1: Descriptive Statistics of Global Stock Markets for the Full Period

Panel A: Log Prices

	TASI	S&P 500	NIKKEI 225	DAX 30	FTSE 100	SSE	MSCI
Mean	8.893	7.384	9.534	9.004	8.719	7.997	7.296
Median	8.869	7.330	9.592	8.970	8.744	8.005	7.336
Maximum	9.367	7.983	10.097	9.515	8.972	8.763	7.718
Minimum	8.326	6.517	8.862	8.207	8.164	7.492	6.535
Std. Dev.	0.181	0.325	0.326	0.299	0.151	0.239	0.230
Skewness	0.075	−0.076	−0.135	−0.143	−0.949	0.596	−0.512
Kurtosis	3.058	2.174	1.654	2.106	3.898	3.320	2.899
JB	3.357	92.018	245.940	114.940	574.800	198.856	138.099
Observations	3,131	3,131	3,131	3,131	3,131	3,131	3,131

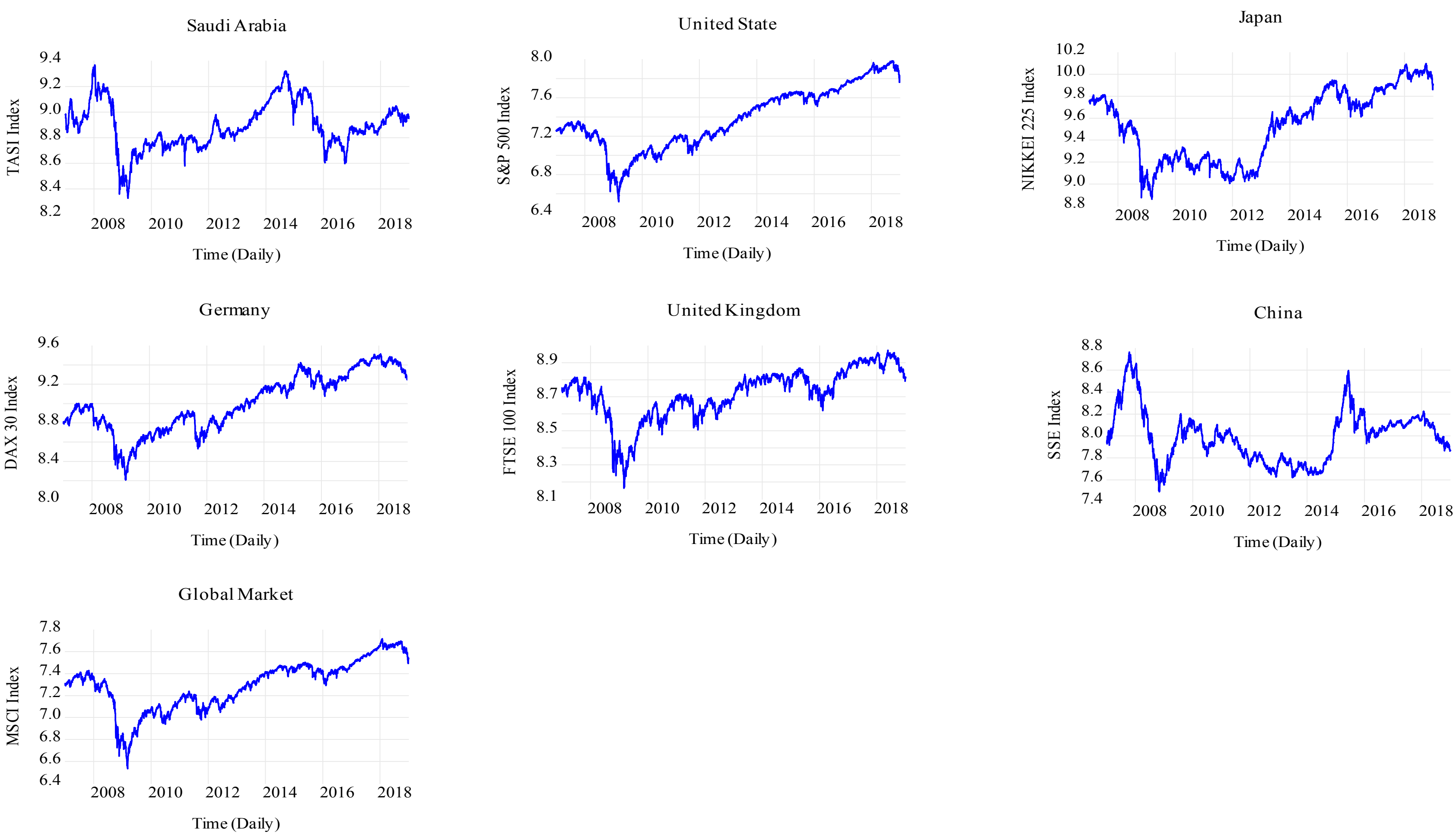
Panel B: Daily Returns

	TASI	S&P 500	NIKKEI 225	DAX 30	FTSE 100	SSE	MSCI
Mean	−4.32E-06	0.00018	4.79E-05	0.00015	2.50E-05	−2.40E-05	7.63E-05
Median	0.000227	0.00031	0	0.000414	2.90E-05	0	0.000577
Maximum	0.091	0.109	0.132	0.108	0.094	0.090	0.091
Minimum	−0.103	−0.095	−0.121	−0.074	−0.093	−0.093	−0.0733
Std. Dev.	0.0134	0.0123	0.015	0.014	0.012	0.016	0.011
Skewness	−0.746	−0.359	−0.536	−0.010	−0.131	−0.642	−0.498
Kurtosis	14.173	14.146	11.666	9.334	11.197	7.848	12.321
JB	16,570.650	16,269.470	9,944.333	5,232.445	8,772.831	3,279.762	11,458.780
Observations	3,130	3,130	3,130	3,130	3,130	3,130	3,130
MR (%) *	−1.35	56.97	14.99	46.95	7.83	−7.51	23.88

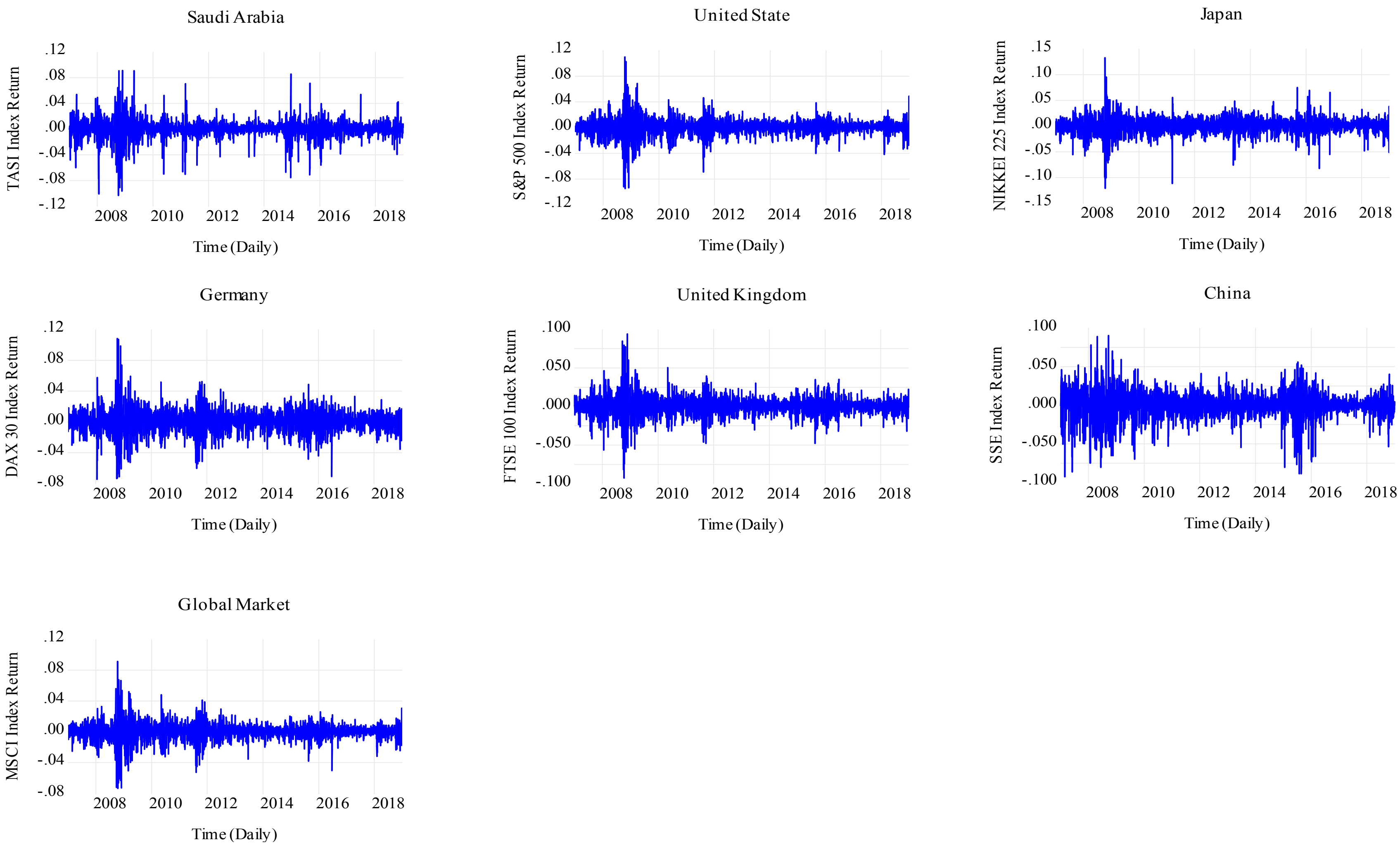
Mean Return (MR) = (Mean * total no. of obs; %)

Figure 5.1: Global Stock Markets for the Full Period

Panel A: Log Prices



Panel B: Daily Returns



5.3.1.2 Major Commodity Markets

Descriptive statistics on crude oil, gold, silver, palladium and platinum are presented in Table 5.2 (Panel B). All major commodity markets showed positive and negative mean returns (%) during the study period, but the palladium index recorded the highest mean return (136.16%) relative to the crude oil index that showed the lowest mean return (−29.83%). In addition, the palladium index also reported a maximum return of 0.633 relative to the crude oil, gold, silver and platinum indices, which showed a maximum return of 0.164, 0.096, 0.137 and 0.097, respectively.

Return volatility in commodity markets, as calculated by the standard deviation, varied between 1.13% and 2.47%. The highest standard deviations were in palladium and crude oil, while gold had the lowest standard deviation in both Panels A and B. It emerges that the risk of the commodity markets is demonstrated by a large standard deviation. Consequently, the risk in the palladium and crude oil markets was higher than in the other markets. Conversely, the return series of gold, silver and platinum were negatively skewed to the left, while those of crude oil and palladium were positively skewed to the right, depending on the predicted skewness statistics. The high-frequency financial return indicates a normal leptokurtic spread in the data since its kurtosis value is assumed to be greater than 3 for all commodity markets returns, and a standard leptokurtic distribution is verified, the return series being higher than the average with a tail thicker than the normal distribution (Bollerslev et al., 1994; Brooks, 2019). Moreover, the JB test results and p-values support these outcomes by rejecting the null hypothesis of normality. Table 5.2 and Figure 5.2 present the descriptive statistics of major commodity markets, indicating substantial extreme kurtosis. Thus, it is reasonable and acceptable to use the MGARCH models to calculate the volatility of returns.

Table 5.2: Descriptive Statistics of Major Commodity Markets for the Full Period

Panel A: Log Prices

	CRUDE OIL	GOLD	SILVER	PALLADIUM	PLATINUM
Mean	4.267	7.077	2.934	6.369	7.146
Median	4.316	7.121	2.848	6.512	7.184
Maximum	4.979	7.548	3.883	7.150	7.730
Minimum	3.265	6.411	2.176	5.124	6.628
Std. Dev.	0.331	0.245	0.319	0.434	0.253
Skewness	−0.394	−0.717	0.726	−0.922	−0.111
Kurtosis	2.249	3.178	2.903	3.190	1.916
JB	154.768	272.300	275.989	448.394	159.815
Observations	3,131	3,131	3,131	3,131	3,131

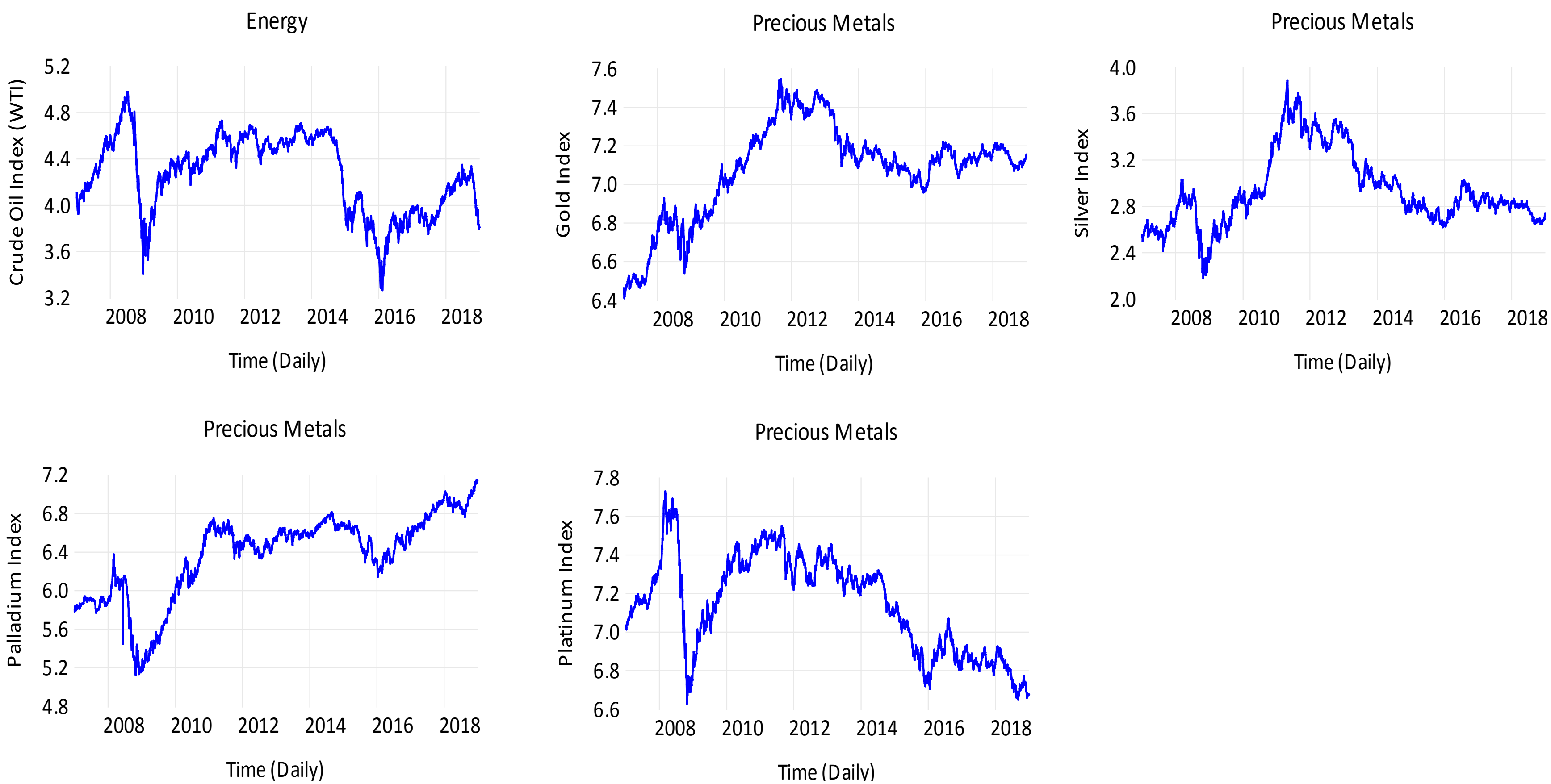
Panel B: Daily Returns

	CRUDE OIL	GOLD	SILVER	PALLADIUM	PLATINUM
Mean	−9.53E-05	0.00022	6.06E-05	0.000435	−0.000109
Median	0	0	0	0	0
Maximum	0.164	0.096	0.137	0.633	0.097
Minimum	−0.128	−0.089	−0.130	−0.610	−0.097
Std. Dev.	0.024	0.011	0.020	0.025	0.014
Skewness	0.076	−0.353	−0.401	0.319	−0.405
Kurtosis	7.880	10.622	8.102	258.562	8.273
JB	3,108.503	7,641.379	3,478.109	8,517,830	3,711.163
Observations	3,130	3,130	3,130	3,130	3,130
MR (%) *	−29.83	70.11	18.97	136.16	−34.12

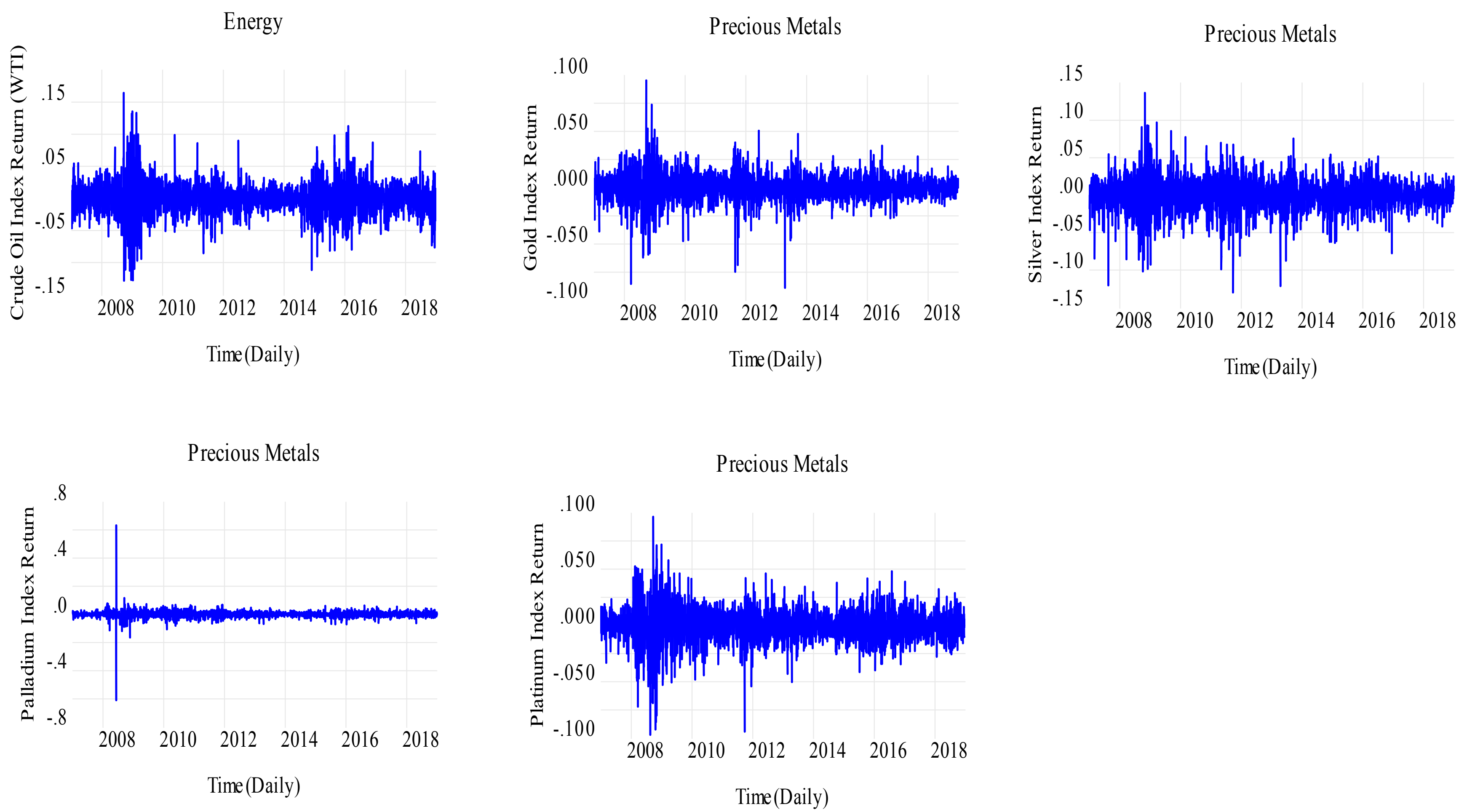
* Mean Return (MR) = (Mean * total no. of obs; %)

Figure 5.2: Major Commodity Markets for the Full Period

Panel A: Log Prices



Panel B: Daily Returns



5.3.2 GFC Period (January 2008 – June 2009)

5.3.2.1 Global Stock Markets

Table 5.3 presents descriptive statistics for the following indices: TASI, S&P 500, NIKKEI 225, DAX 30, FTSE 100, SSE and MSCI. Panel B shows that the mean returns of all global stock markets were negative, ranging from −41.85% to −64.97%. The standard deviation, a measure of uncertainty, reveals that NIKKEI 225 was the most volatile in Panel B and TASI in Panel A. By comparison, DAX 30 was the least volatile with the lowest standard deviation in Panel A, while MSCI was the least volatile in Panel B.

Table 5.3 Panel B indicates that the TASI returns registered a negative mean of −0.002. In addition, the maximum and minimum observations for TASI were 0.091 and −0.103, respectively. The mean return performance of S&P 500 was −0.001, and the observations ranged from a high of 0.11 to a low of −0.095. Further, the mean return and maximum and minimum observations of FTSE 100 were −0.001, 0.094 and −0.093, respectively, and the standard deviation was 0.022. The DAX 30 mean return and standard deviation were −0.001 and 0.023, respectively, and its return ranged from 0.108 to −0.074. The mean return of NIKKEI 225 was similar to the mean return of FTSE 100 at −0.001. The maximum return of NIKKEI 225 was 0.132, while the minimum was −0.121, and the standard deviation was 0.026. The mean SSE return was −0.002, the maximum and minimum values were 0.09 and −0.081, respectively, and the standard deviation was 0.025. The mean return of MSCI was −0.001, the standard deviation was 0.02 and the maximum and minimum values were 0.091 and −0.073, respectively.

By contrast, the TASI, S&P 500, NIKKEI 225 and MSCI returns were negatively skewed to the left, while those of DAX 30, FTSE 100 and SSE were positively skewed to the right, based on the expected skewness estimates. Bollerslev et al. (1994), Brooks (2019) and many others have suggested that the high-frequency financial return indicates a natural leptokurtic spread. Since the kurtosis value for all stock market returns is expected to be greater than 3, a normal leptokurtic distribution is verified, with the return sequence on average higher than the regular thick tail. In addition, the JB test results and the p-values endorse rejecting the null normality hypothesis. These early concise stock market statistics indicate significant extreme kurtosis. Therefore, it is reasonable and acceptable to use the MGARCH models to measure the volatility of returns.

Table 5.3: Descriptive Statistics of Global Stock Markets for the GFC Period

Panel A: Log Prices

	TASI	S&P 500	NIKKEI 225	DAX 30	FTSE 100	SSE	MSCI
Mean	8.849	6.978	9.279	8.619	8.496	7.952	7.023
Median	8.890	7.053	9.339	8.667	8.498	7.911	7.075
Maximum	9.367	7.292	9.636	8.996	8.776	8.661	7.371
Minimum	8.326	6.517	8.862	8.207	8.164	7.492	6.535
Std. Dev.	0.310	0.222	0.230	0.202	0.169	0.296	0.249
Skewness	−0.098	−0.151	−0.146	−0.130	−0.020	0.605	−0.114
Kurtosis	1.427	1.409	1.401	1.608	1.492	2.450	1.381
JB	40.923	42.745	43.048	32.686	37.098	28.804	43.526
Observations	391	391	391	391	391	391	391

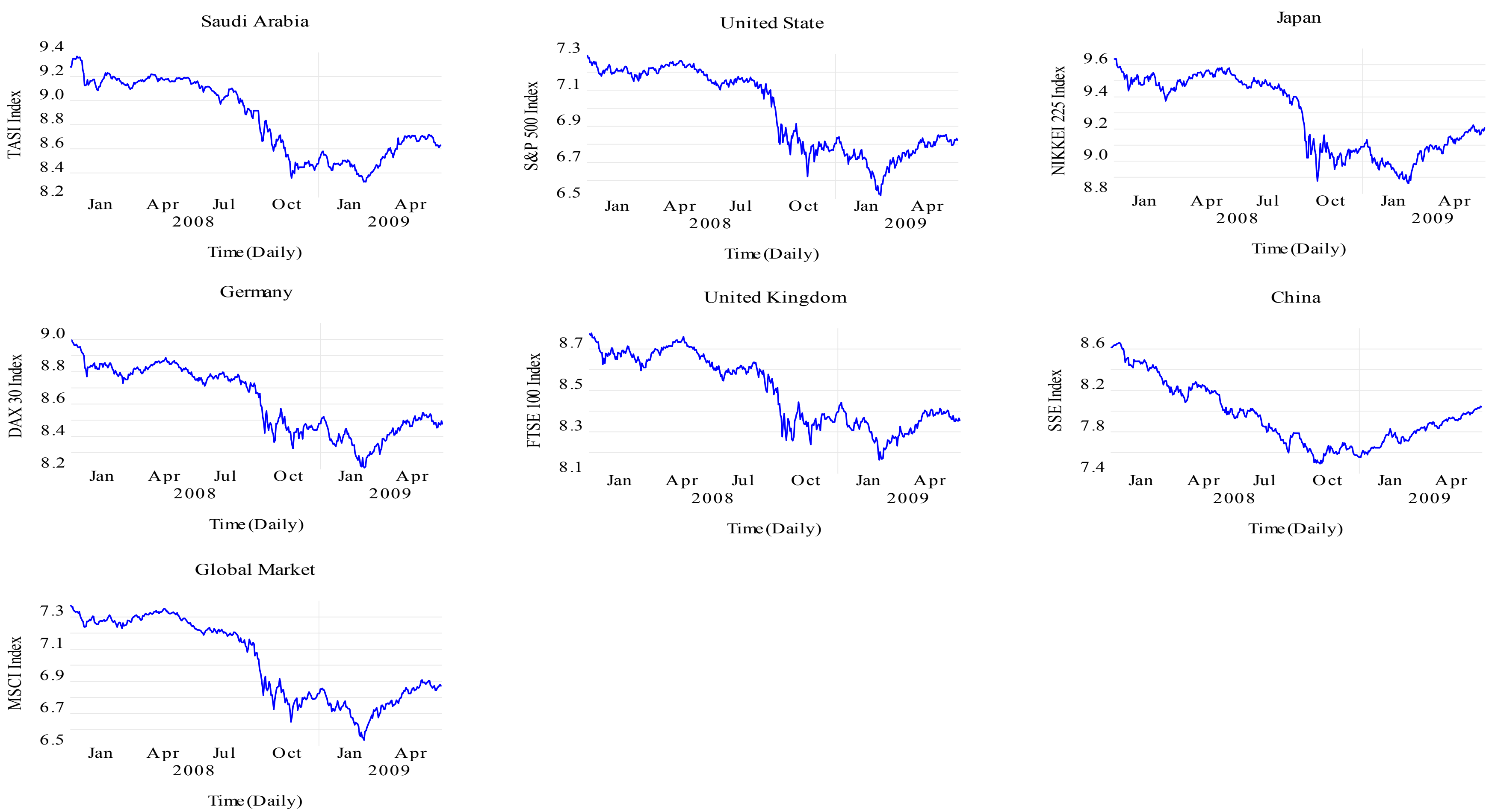
Panel B: Daily Returns

	TASI	S&P 500	NIKKEI 225	DAX 30	FTSE 100	SSE	MSCI
Mean	−0.002	−0.001	−0.001	−0.001	−0.001	−0.002	−0.001
Median	0.000	0.000	0.000	0.000	−0.001	0.000	−0.000
Maximum	0.091	0.110	0.132	0.108	0.094	0.090	0.091
Minimum	−0.103	−0.095	−0.121	−0.074	−0.093	−0.081	−0.073
Std. Dev.	0.024	0.024	0.026	0.023	0.022	0.025	0.020
Skewness	−0.416	−0.034	−0.278	0.403	0.077	0.062	−0.176
Kurtosis	6.779	6.355	7.233	7.221	6.535	4.435	6.373
JB	243.317	182.963	296.130	299.983	203.476	33.730	186.839
Observations	390	390	390	390	390	390	390
MR (%)*	−64.97	−46.84	−42.98	−51.75	−41.85	−57.53	−49.96

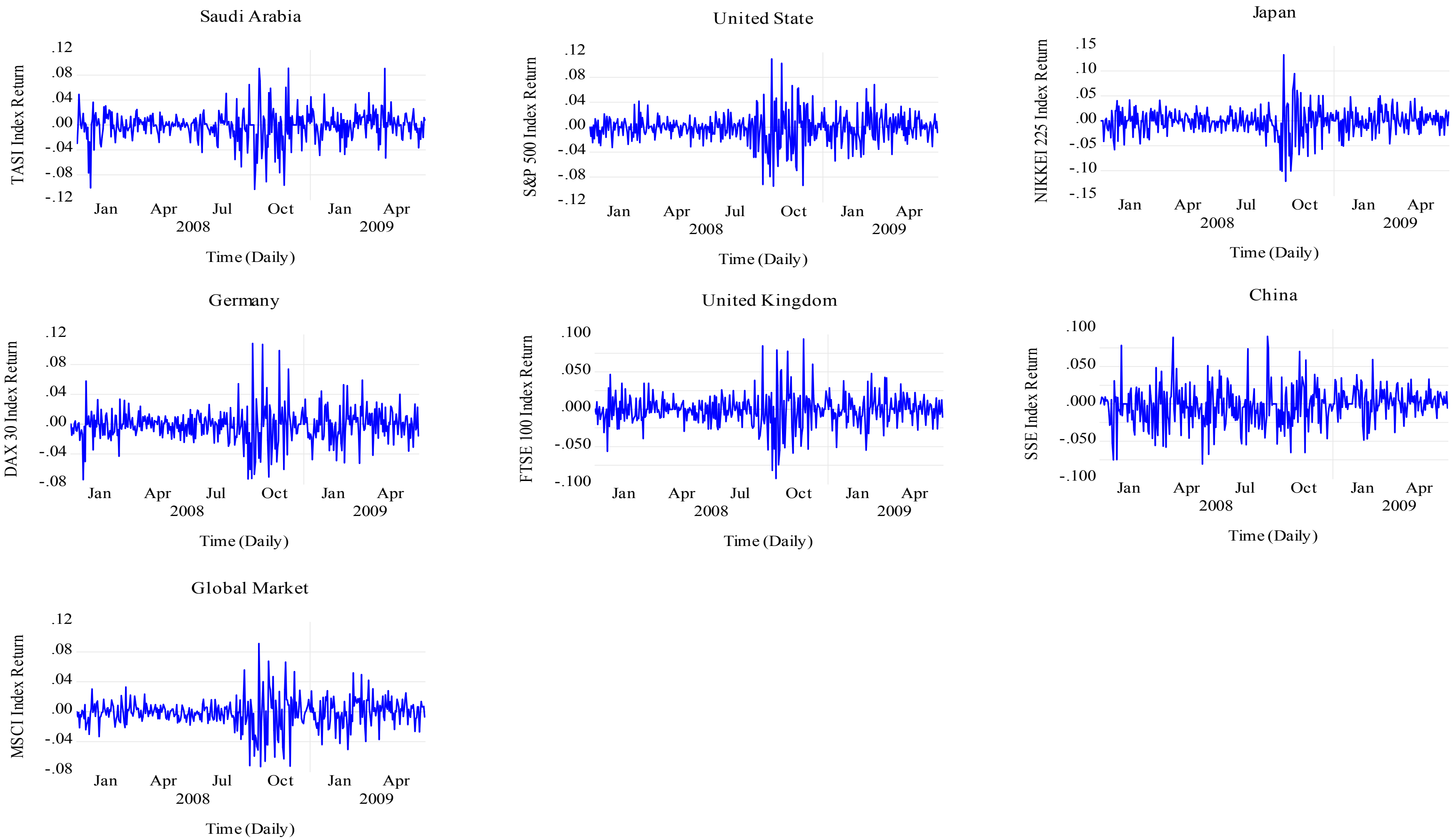
*Mean Return (MR) = (Mean * total no. of obs; %)

Figure 5.3: Global Stock Market for the GFC Period

Panel A: Log Prices



Panel B: Daily Returns



5.3.2.2 Major Commodity Markets

Crude oil, gold, silver, palladium and platinum are listed in Table 5.4 (Panel B). All major commodity markets reported negative average returns except for gold, which recorded a positive average return during the GFC period. Gold registered the highest average returns of 11.78% compared with crude oil, which had the lowest average returns of −37.44%. Volatility return in commodity markets, as measured by the standard deviation, ranged between 1.92% and 5.39%. In both Panels A and B, palladium and crude oil showed the most variations, while gold was the least volatile. Since a significant standard deviation highlights the risk of the commodity market, among the research variables, palladium and crude oil had higher risk than other markets during the GFC period.

The characteristics of the time series of major commodity markets are shown in the analysis in Panel B. Particularly, the skewness analyses showed positive values for crude oil, silver and palladium and negative for gold and platinum. Moreover, there were high kurtosis estimates (greater than 3) for the GFC period, which were shown to be highly positive. The study suggested kurtosis from 4.361 to 92.05, with the lowest in platinum and the largest in palladium. The skewness of the time series varied between −0.327 (platinum) and 0.364 (palladium). The kurtosis estimates indicated that all proportions of commodity market returns are fat or leptokurtic. However, the skewness suggested that the normal returns of commodity markets have an asymmetric distribution. The JB normality test showed that normal return levels are not distributed normally, and hence, the null hypothesis was rejected for all major commodity markets in the study. These early descriptive statistics indicate significant extreme kurtosis.

Table 5.4: Descriptive Statistics of Major Commodity Markets for the GFC Period

Panel A: Log Prices

	CRUDE OIL	GOLD	SILVER	PALLADIUM	PLATINUM
Mean	4.338	6.784	2.645	5.656	7.203
Median	4.489	6.798	2.643	5.501	7.105
Maximum	4.979	6.931	3.030	6.377	7.730
Minimum	3.411	6.540	2.176	5.124	6.628
Std. Dev.	0.434	0.073	0.211	0.369	0.328
Skewness	−0.282	−0.951	−0.282	0.234	0.071
Kurtosis	1.689	3.545	2.023	1.461	1.577
JB	33.163	63.785	20.702	42.139	33.318
Observations	391	391	391	391	391

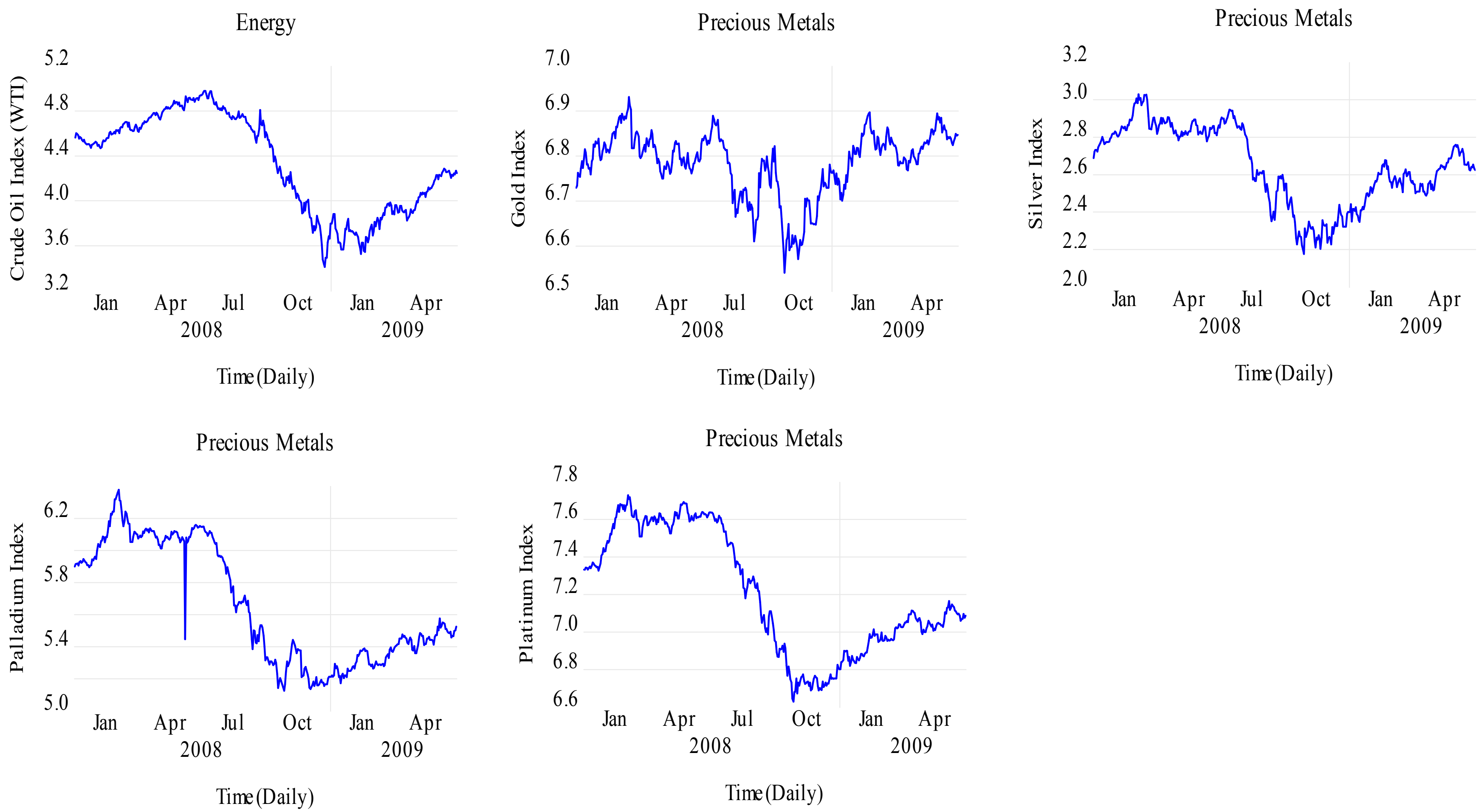
Panel B: Daily Returns

	CRUDE OIL	GOLD	SILVER	PALLADIUM	PLATINUM
Mean	−0.001	0.0003	−0.0002	−0.001	−0.001
Median	0.000	0.000	0.000	0.000	0.000
Maximum	0.164	0.096	0.137	0.633	0.097
Minimum	−0.128	−0.086	−0.102	−0.610	−0.097
Std. Dev.	0.040	0.019	0.030	0.054	0.026
Skewness	0.135	−0.053	0.089	0.364	−0.327
Kurtosis	5.095	6.081	5.171	92.050	4.361
JB	72.474	154.403	77.097	128,870.500	37.038
Observations	390	390	390	390	390
MR (%) *	−31.79	11.78	−6.40	−37.44	−24.57

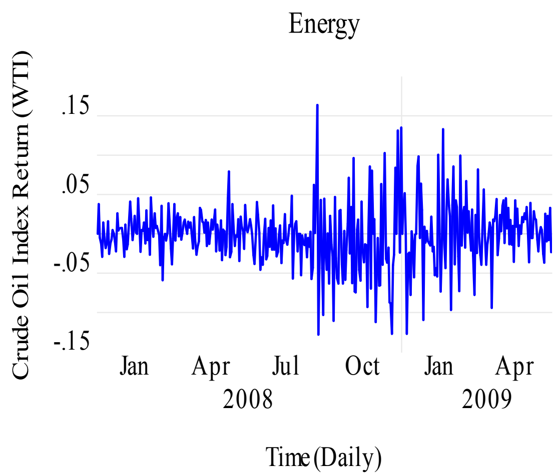
*Mean Return (MR) = (Mean * total no. of obs; %)

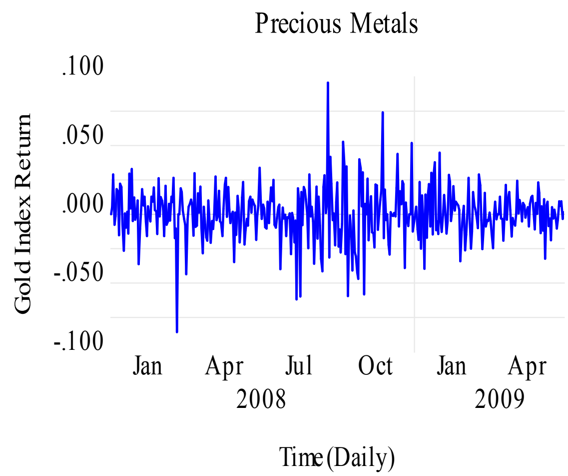
Figure 5.4: Major Commodity Markets for the GFC Period

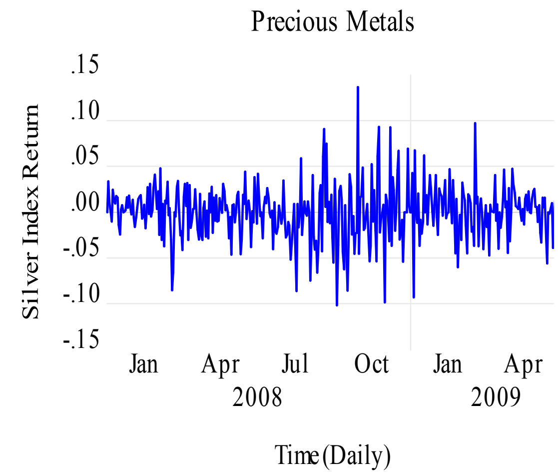
Panel A: Log Prices

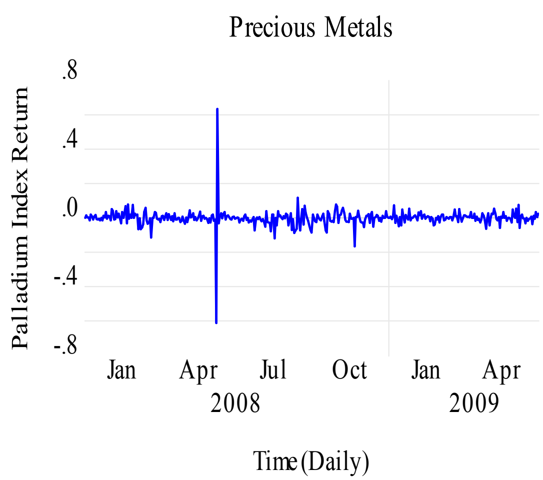


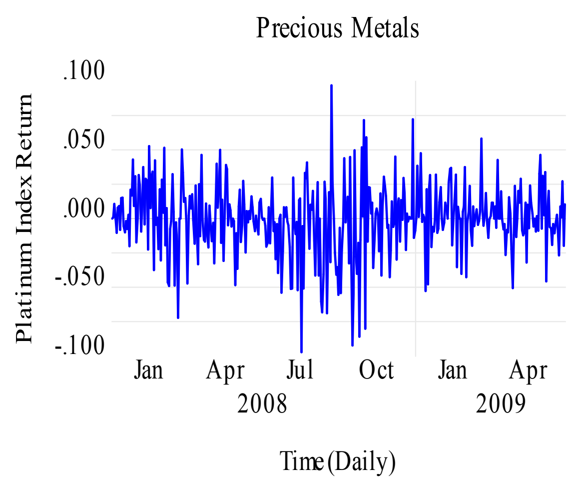
Panel B: Daily Returns











5.3.3 Oil Price Decline Period (July 2014 – January 2016)

5.3.3.1 Global Stock Markets

Table 5.5 presents descriptive statistics for TASI, S&P 500, NIKKEI 225, DAX 30, FTSE 100, SSE and MSCI. Panel B shows that the mean returns of all global stock markets were negative, ranging from −1.06% to −46.88%, except for NIKKEI 225 and SSE. These documented returns of 13.38% and 28.83%, respectively, during the oil decline period. The standard deviation, a measure of uncertainty, reveals that SSE was the most volatile market, in both panels (A and B), because its standard deviation value is the highest. Further, the S&P 500 was the least volatile in Panel A, whereas MSCI was the least volatile in Panel B because their standard deviation value is the lowest.

In Table 5.5, the characteristics of time series are shown, especially skewed analyses which show that the values for all samples were negative except for NIKKEI 225, which was positive. During the oil decline period, high kurtosis estimates larger than 3 showed that kurtosis changed between 3.606 (DAX 30) and 8.98 (TASI). The skewness of the time series ranged between 0.199 and −1.145, the highest in NIKKEI 225 and the lowest in SSE. Kurtosis figures reveal whether the concentrations of stock markets returns are fat tail or leptokurtic. Meanwhile, skewness means that normal returns have an asymmetrical distribution. The normality test of JB indicates that return values are not normally distributed, so the rejection of null hypothesis is confirmed for all global stock markets in the oil decline period. These statistics show significant extreme kurtosis.

Table 5.5: Descriptive Statistics of Global Stock Markets for the Oil Decline Period

Panel A: Log Prices

	TASI	S&P 500	NIKKEI 225	DAX 30	FTSE 100	SSE	MSCI
Mean	9.074	7.617	9.799	9.250	8.790	8.107	7.443
Median	9.122	7.626	9.808	9.240	8.802	8.132	7.449
Maximum	9.319	7.664	9.946	9.423	8.868	8.596	7.502
Minimum	8.605	7.528	9.584	9.056	8.644	7.666	7.308
Std. Dev.	0.161	0.033	0.098	0.087	0.049	0.235	0.038
Skewness	−0.730	−0.667	−0.368	0.036	−0.628	−0.145	−1.087
Kurtosis	2.946	2.535	1.962	1.886	2.565	2.230	4.107
JB	36.820	34.450	27.919	21.483	30.479	11.677	102.717
Observations	414	414	414	414	414	414	414

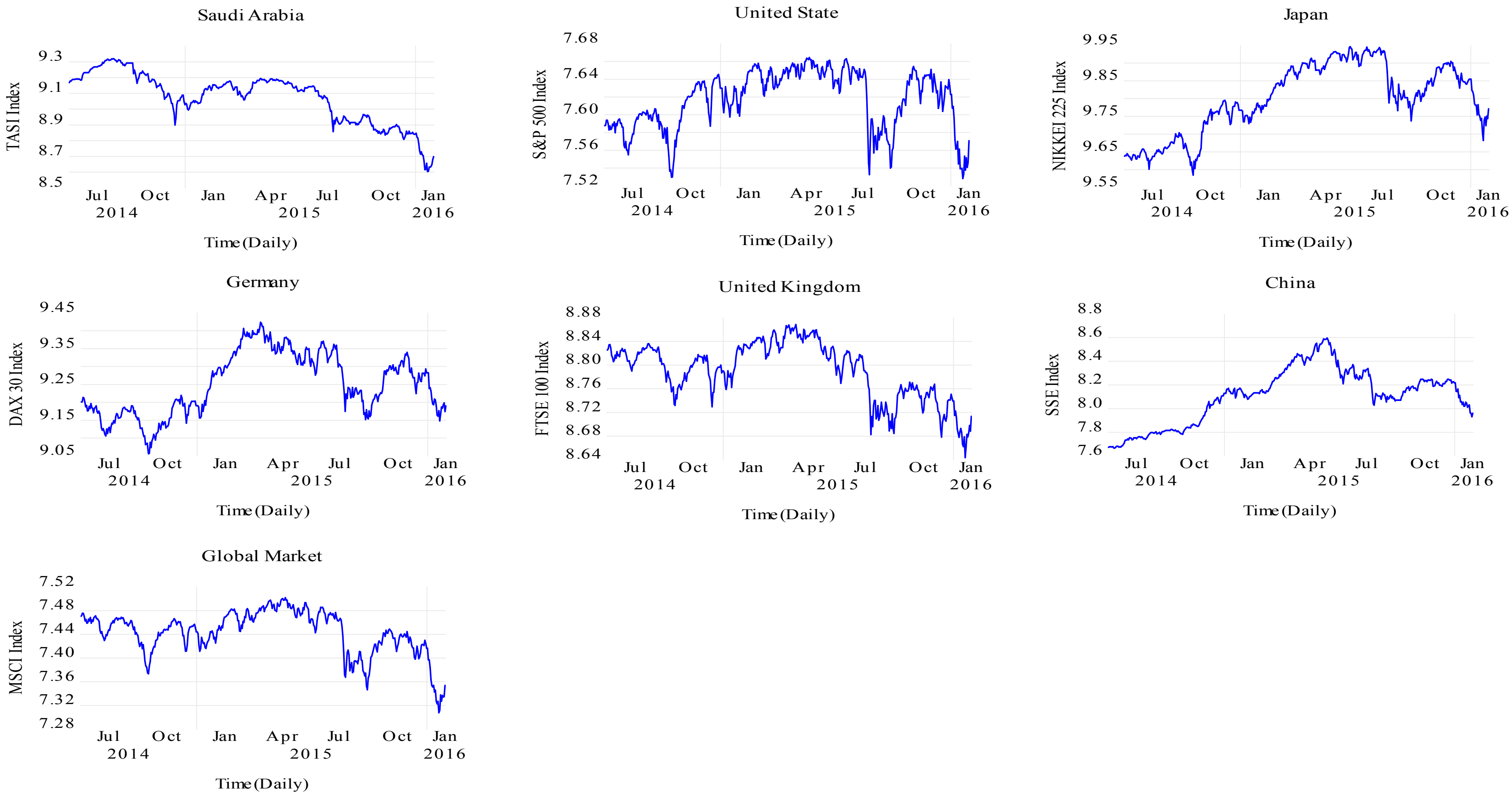
Panel B: Daily Returns

	TASI	S&P 500	NIKKEI 225	DAX 30	FTSE 100	SSE	MSCI
Mean	−0.001	−0.000	0.000	−0.000	−0.000	0.000	−0.000
Median	0.000	0.000	0.000	0.000	0.000	0.002	−0.000
Maximum	0.085	0.038	0.074	0.049	0.035	0.056	0.026
Minimum	−0.075	−0.040	−0.047	−0.048	−0.048	−0.089	−0.038
Std. Dev.	0.016	0.009	0.013	0.014	0.010	0.022	0.008
Skewness	−0.488	−0.222	0.199	−0.167	−0.301	−1.145	−0.409
Kurtosis	8.980	4.799	6.852	3.606	4.969	6.244	5.084
JB	631.803	59.097	258.027	8.243	72.979	271.311	86.289
Observations	413	413	413	413	413	413	413
MR (%) *	−46.88%	−1.69%	13.38%	−1.06%	−11.19%	28.83%	−11.61%

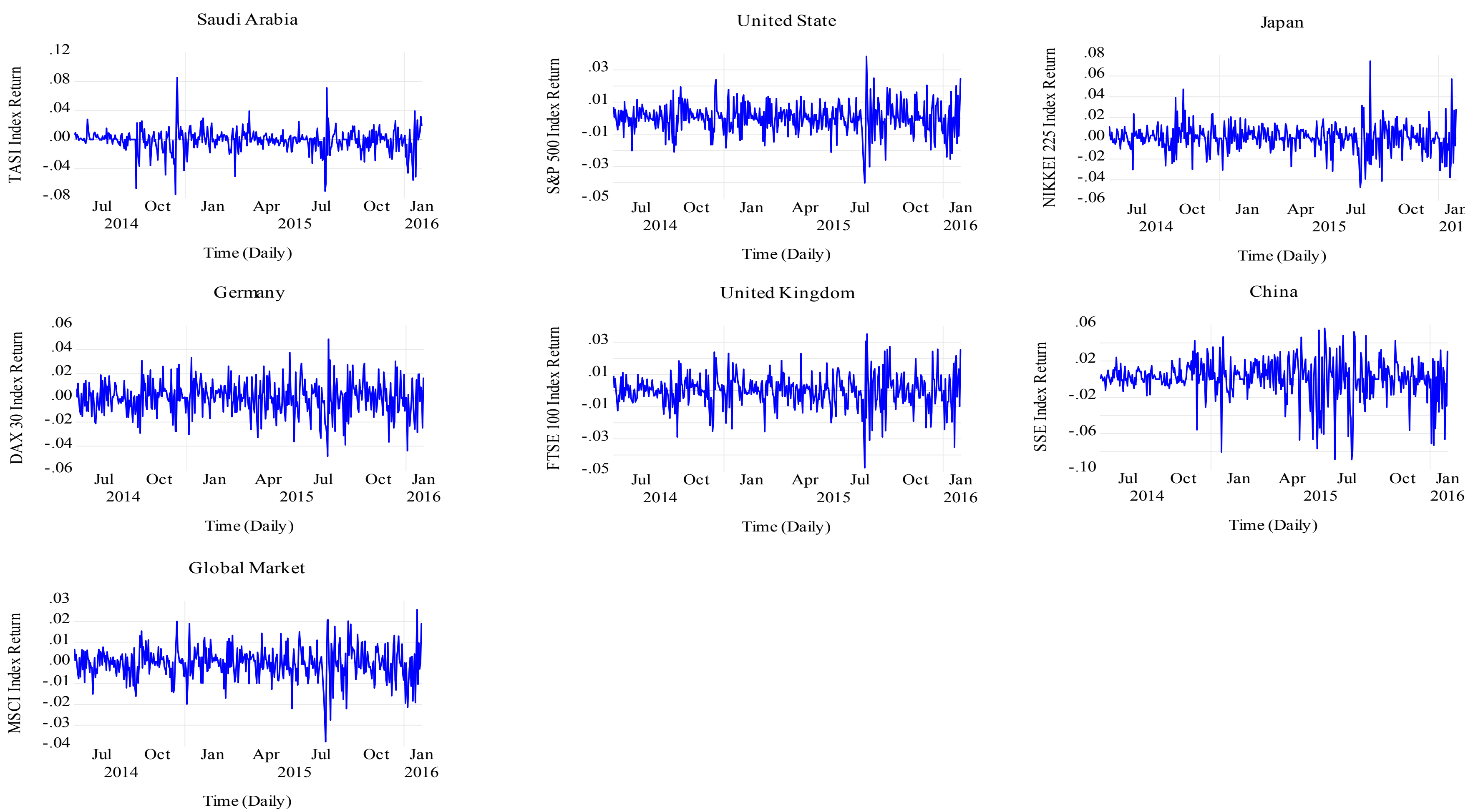
*Mean Return (MR) = (Mean * total no. of obs; %)

Figure 5.5: Global Stock Markets for the Oil Decline Period

Panel A: Log Prices



Panel B: Daily Returns



5.3.3.2 Major Commodity Markets

Table 5.6 mentions crude oil, gold, silver, palladium and platinum. All major commodity markets registered negative average returns varying between −17.51% (gold) and −114.11% (crude oil) over the oil decline period. In addition, the table illustrates that the maximum returns were 0.102, 0.028, 0.054, 0.062 and 0.042, while the minimum returns were −0.111, −0.027, −0.064, −0.07 and −0.041 for crude oil, gold, silver, palladium and platinum, respectively. Volatility return, calculated by standard deviation, varied from 0.808% to 2.811%. The highest volatility with large standard deviation in both Panels A and B was for crude oil, while gold had the lowest volatility with the least standard deviation in these panels. Since the largest standard deviation indicates the most risk, crude oil is considered the higher risk in the sample.

Conversely, based on skew estimates, crude oil, gold, silver and platinum skewed positively to the right, while silver and palladium skewed negatively to the left, in line with the assumption of Bollerslev et al. (1994) and Brooks (2019), which indicated that any high-frequency data of major commodity market returns demonstrate normal leptokurtic spread. In the present research, the kurtosis value of analysis for all major commodity markets returns is assumed to be greater than 3, indicating that a standard leptokurtic distribution is confirmed, with the return series average above the usual thick tail. In addition, the JB test and p-values support the decision of rejecting the null normality hypothesis. These early succinct major commodity markets statistics indicate significant extreme kurtosis. Consequently, it is reasonable and appropriate to use the MGARCH models to calculate the volatility of return.

Table 5.6: Descriptive Statistics of Major Commodity Markets for the Oil Decline Period

Panel A: Log Prices

	CRUDE OIL	GOLD	SILVER	PALLADIUM	PLATINUM
Mean	4.031	7.074	2.791	6.571	7.019
Median	3.952	7.079	2.779	6.644	7.041
Maximum	4.660	7.203	3.068	6.812	7.321
Minimum	3.284	6.957	2.618	6.142	6.706
Std. Dev.	0.328	0.058	0.108	0.164	0.164
Skewness	0.389	0.022	0.675	−0.735	−0.073
Kurtosis	2.284	2.307	2.966	2.410	2.174
JB	19.281	8.328	31.472	43.321	12.139
Observations	414	414	414	414	414

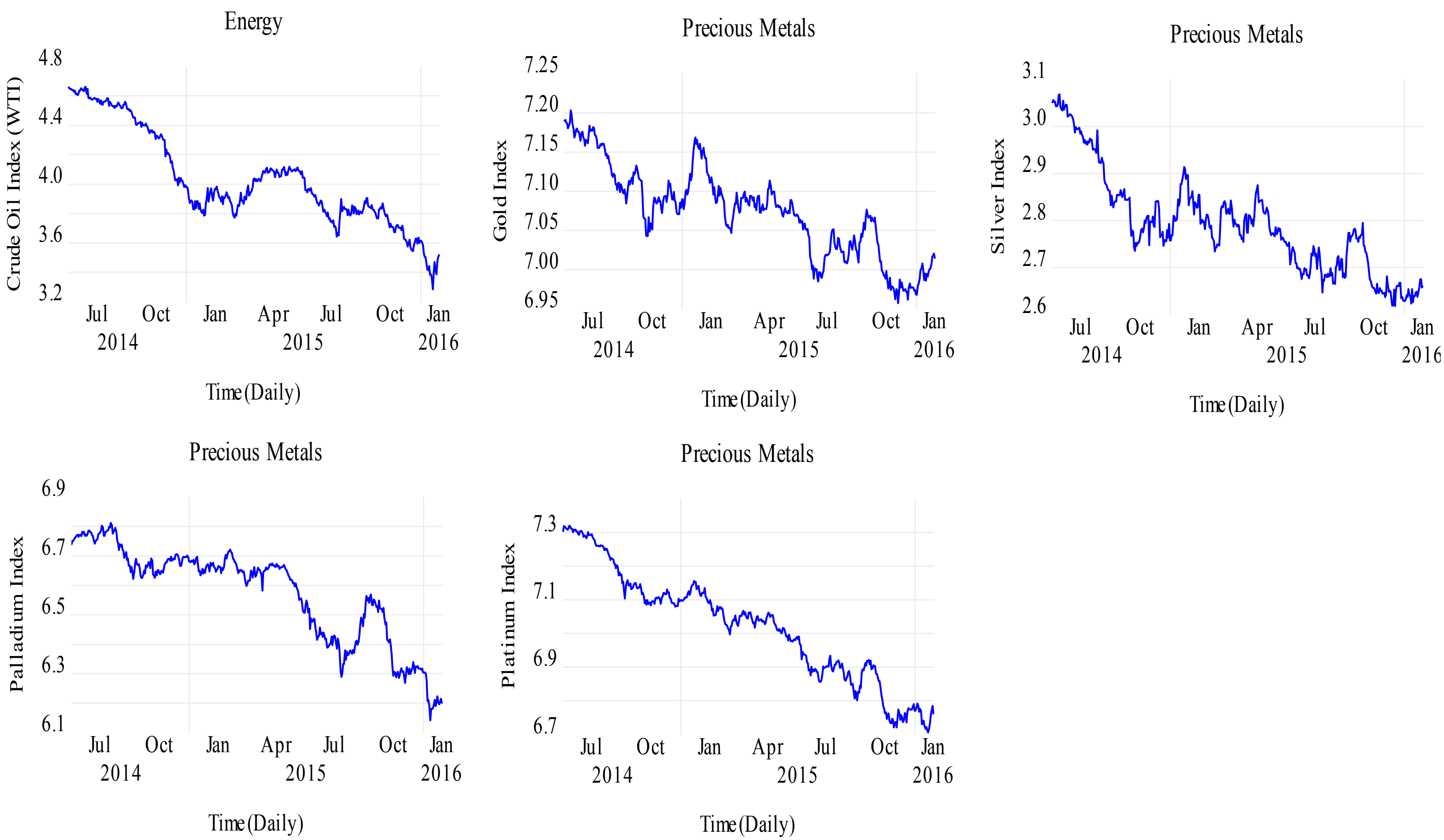
Panel B: Daily Returns

	CRUDE OIL	GOLD	SILVER	PALLADIUM	PLATINUM
Mean	−0.00276	−0.0004	−0.001	−0.0013	−0.0013
Median	−0.003	−0.0006	0.000	0.0000	−0.0008
Maximum	0.102	0.028	0.054	0.062	0.042
Minimum	−0.111	−0.027	−0.064	−0.070	−0.041
Std. Dev.	0.028	0.008	0.016	0.017	0.011
Skewness	0.220	0.222	−0.291	−0.380	0.094
Kurtosis	4.647	3.542	5.481	5.224	3.989
JB	50.005	8.468	111.793	95.094	17.440
Observations	413	413	413	413	413
MR (%) *	−114.11	−17.51	−39.15	−53.90	−54.23

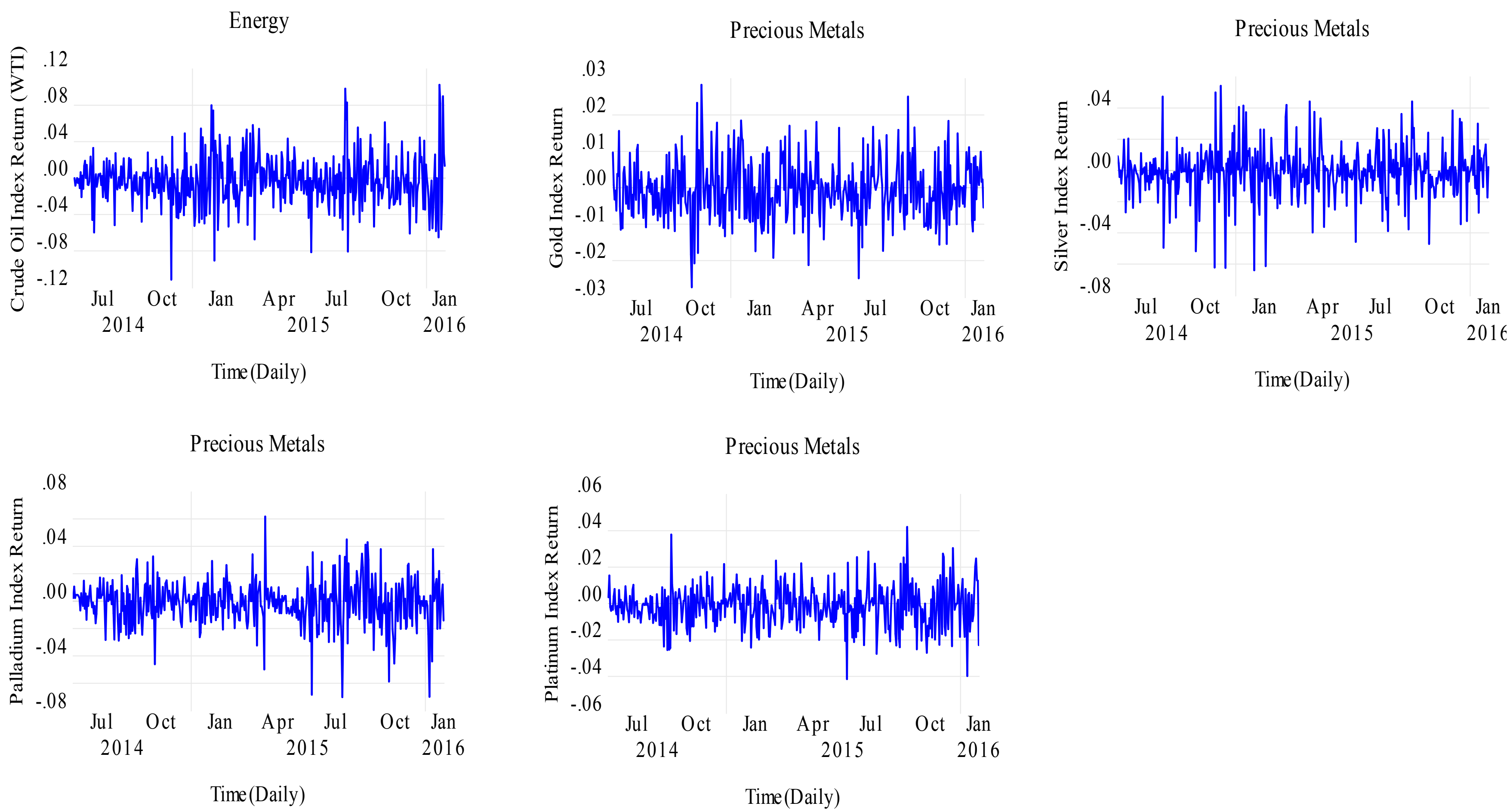
*Mean Return (MR) = (Mean * total no. of obs; %)

Figure 5.6: Major Commodity Markets for the Oil Decline Period

Panel A: Log Prices



Panel B: Daily Returns



5.4 Correlation Matrix for Daily Global Stock and Major Commodity Markets

Correlation coefficients, although non-directional, are a landmark in the analysis of market association. Table 5.7 indicates the correlation matrix between TASI and global stocks/major commodity markets that are included in this study. TASI was positive with all stock and commodity markets during the whole period except for gold and silver. In general, a moderate positive correlation is observed between TASI and the global stock markets of S&P 500, NIKKEI 225, DAX 30 and FTSE 100 of 0.477, 0.521, 0.479 and 0.592, respectively. MSCI showed the highest correlation with TASI (0.608), while SSE showed a weak correlation (0.246). The correlation between the major commodity markets for the TASI was less than that between TASI and the global stock markets. The relationship between TASI and the major commodity markets is low and statistically insignificant because of a negative correlation between gold (−0.087) and silver (−0.064) as well as weak correlation shown by palladium, crude oil and platinum, which are 0.391, 0.367 and 0.156, respectively.

For the GFC period, this table shows positive interrelationships across all global stock and major commodity markets. It is known that all correlations were strong, indicating that all markets were moving in the same direction. Concerning TASI's relationship with various markets, strong and statistically significant associations between TASI/global stock and major commodity markets are found except for gold. Gold was weakly correlated with TASI at 0.209, while the other stock and commodity markets exhibited strong correlations with TASI varying from 0.759 to 0.982. Further, this table demonstrates that in the oil decline period the correlations between TASI and global stock markets were negative or low except for FTSE 100 and MSCI, which were strong. Moreover, the interrelationship between TASI and major commodity markets during the oil decline period was strong. The highest correlations with TASI were for crude oil (0.848) and palladium (0.853), and the lowest for SSE (−0.272) and NIKKEI 225 (−0.308).

In addition, the correlation of linear findings proves that TASI's return series had a negative correlation with gold and silver during the full period, which is in line with the findings of Mensi, Hammoudeh and Kang (2015), and with NIKKEI 225, DAX 30 and SSE during the oil decline period. This finding reveals the effectiveness of mitigating risk by using these assets as hedging tools. In contrast, there were low positive correlations (close to zero) between the Saudi stock market and platinum in the full period and S&P 500 in the oil decline period. Hence, diversification in the short-term can be advantageous. The findings obtained from the estimates of correlations are helpful, but they can be defined as inconclusive, and the relationship between these markets calls for a more detailed examination, which will be performed in the subsequent sections.

Table 5.7: Correlation Coefficients of the Daily Global Stocks and Major Commodities

Market	TASI		
	Full Period	GFC Period	Oil Decline Period
S&P 500	0.477	0.977	0.153
NIKKEI 225	0.521	0.974	-0.308
DAX 30	0.479	0.976	-0.078
FTSE 100	0.592	0.963	0.787
SSE	0.246	0.788	-0.272
MSCI	0.608	0.982	0.681
CRUDE OIL	0.367	0.917	0.848
GOLD	−0.087	0.209	0.732
SILVER	−0.064	0.759	0.740
PALLADIUM	0.391	0.908	0.853
PLATINUM	0.156	0.880	0.838

Note: The table shows Pearson correlation coefficients for the daily returns of 11 markets. The correlation coefficients for the whole period are indicated in the first column, while the values for the two subperiods are exhibited in the second and third columns. The percentage change (increase) over the two subperiods is compared with that for the whole period.

5.5 ARCH Effect

The findings in Table 5.8 are clearly shown the existence of the ARCH effect in the residuals of the estimated model (Engle, 1982). It is relatively straightforward to check the heteroscedasticity of the residuals from a regression. This test is based on OLS regression, in which the OLS residuals from the regression are saved. H_0 is the null hypothesis, which asserts that there is no ARCH effect.

Table 5.8 shows that both the F-statistics and ARCH-LM statistics are statistically significant at 1% for all global stock and major commodity markets, thereby rejecting the null hypothesis of no heteroscedasticity. For global stocks and major commodities returns, the findings of the ARCH-LM test indicate the existence of the ARCH effect, which is also compatible with the graphic representation of the volatility clustering returns. The ARCH effect test results are consistent with those of many other studies that have demonstrated the ARCH effect in different financial markets (Brooks, 2019).

Table 5.8: ARCH Effect for Global Stock and Major Commodity Markets for all Periods

Market	Period	ARCH-LM Test			
		F-statistic		Obs*R-squared	
		Value	Probability	Value	Probability
TASI	Full Period	115.464	0.000	111.423	0.000
	GFC Period	3.979	0.047	3.959	0.047
	Oil Decline Period	51.251	0.000	45.767	0.000
S&P 500	Full Period	119.510	0.000	115.183	0.000
	GFC Period	6.400	0.012	6.328	0.012
	Oil Decline Period	42.992	0.000	39.093	0.000
NIKKEI 225	Full Period	118.358	0.000	114.113	0.000
	GFC Period	3.432	0.065	3.420	0.064
	Oil Decline Period	18.922	0.000	18.174	0.000

Table 5.8: Continued

DAX 30	Full Period	91.261	0.000	88.729	0.000
	GFC Period	4.110	0.043	4.088	0.043
	Oil Decline Period	8.093	0.005	7.975	0.005
FTSE 100	Full Period	197.140	0.000	185.564	0.000
	GFC Period	8.614	0.004	8.470	0.004
	Oil Decline Period	21.883	0.000	20.873	0.000
SSE	Full Period	114.879	0.000	110.877	0.000
	GFC Period	4.560	0.033	4.530	0.033
	Oil Decline Period	13.350	0.000	12.991	0.000
MSCI	Full Period	140.744	0.000	134.767	0.000
	GFC Period	13.346	0.000	12.966	0.000
	Oil Decline Period	8.833	0.003	8.688	0.003
CRUDE OIL	Full Period	194.954	0.000	183.627	0.000
	GFC Period	10.957	0.001	10.709	0.001
	Oil Decline Period	51.551	0.000	46.005	0.000
GOLD	Full Period	48.504	0.000	47.794	0.000
	GFC Period	104.911	0.000	82.873	0.000
	Oil Decline Period	40.287	0.000	36.853	0.000
SILVER	Full Period	149.206	0.000	142.500	0.000
	GFC Period	3.666	0.056	3.650	0.056
	Oil Decline Period	35.787	0.000	33.069	0.000
PALLADIUM	Full Period	907.728	0.000	703.908	0.000
	GFC Period	122.104	0.000	93.185	0.000
	Oil Decline Period	9.846	0.002	9.661	0.002
PLATINUM	Full Period	119.484	0.000	115.158	0.000
	GFC Period	143.480	0.000	105.069	0.000
	Oil Decline Period	6.919	0.009	6.837	0.009

Notes: The ARCH effect is tested with a X^2 of lag (5) distributed Lagrange multiplier (LM) test. For all data, the econometric application of EViews was used.

5.6 Unit Roots Tests

In all global stock and major commodity markets for all periods, the final stage of the preliminary analysis involves checking the stationarity of the daily time series for each market. A test can be conducted to check the unit roots, which cannot ignore their characteristics (Fang & You, 2014), meaning that the existing unit roots in each series' levels and first differences with the expectation of the intercept, both the intercept and trend and without both the intercept and trend will be analysed. The ADF test was conducted using equations (4.1–3), while equation (4.4) was used for the PP test. The most widely used test to check the data stationarity of time series is the unit root test, which is known as a preliminary step. When each lag of the series has a constant mean, variance and auto-covariance, it is defined as stationary (Brooks, 2019).

Table 5.9 reports the findings, for the full period as well as both periods of the GFC and oil decline, on the unit root tests of ADF, PP and KPSS that have been applied to enhance the reliability of the findings (Al-Khazali et al., 2006). The results for all series indicated that the null hypothesis[2] of the unit root's existence cannot be rejected. According to the study by ADF and PP, the null hypothesis of unit roots in the series of levels was accepted because the test values are higher than the critical values. Over three periods, both tests of first difference for the examined samples accepted the null hypothesis, indicating they are statistically significant at the 5%level since the absolute values of the t-statistic are less than the critical values. Therefore, the variables in both tests exhibited stationarity at first difference and were non-stationary in levels during the examined sample periods. Moreover, KPSS—the third unit roots test that was performed using equation (4.7)—was used to test the null hypothesis of stationarity around each series level. To supplement and confirm the findings of the ADF and PP tests, the KPSS test was employed. In Table 5.9, the findings of the KPSS test for the full period and two subperiods are provided. Since the values of t-statistic are greater than the critical values, the null hypothesis of stationarity was rejected in levels because they are statistically significant at least at the 5% level. The null hypothesis of stationarity was accepted for the KPSS test, which means all data series exhibit stationarity in their first difference.

[2] The null hypothesis supposes a unit root for ADF and PP and no unit root for KPSS.

Therefore, the KPSS results indeed support the ADF and PP findings because the data series do not exhibit level stationarity; however, all of them are stationary in their first difference form. Figures 5.1–6 (Panel A and B) further support those outcomes, which show data for the full period and both subperiods at its level (Panel A) and first difference (Panel B) form. Stationarity indicates that the time series behaviour data are constant over time. However, in the case of non-stationarity, the influence of a shock will not be consistent over time and may lead to a spurious regression. Strong R^2 and low Durbin Watson (DW) statistics mean that the regression is spurious. Owing to spurious results, OLS regression is inappropriate for analysing long-term relationships between the TASI and global stock and major commodity markets.

Table 5.9: Unit Root Tests of ADF, PP and KPSS for Global Stocks and Major Commodities

Panel A: Intercept (only in the model)

Market	Period	Level			First Difference		
		ADF	**PP**	**KPSS**	**ADF**	**PP**	**KPSS**
TASI	Full Period	−2.308	−2.322	0.620	−50.587	−50.598	0.057
	GFC Period	−1.240	−1.275	2.014	−18.014	−18.039	0.152
	Oil Decline Period	−0.064	0.020	1.832	−17.818	−17.807	0.212
S&P 500	Full Period	−0.439	−0.421	5.926	−43.803	−62.275	0.194
	GFC Period	−1.234	−1.307	2.073	−17.256	−23.439	0.151
	Oil Decline Period	−2.758	−2.813	0.429	−19.774	−19.780	0.083
NIKKEI 225	Full Period	−1.141	−1.028	3.955	−57.839	−58.020	0.291
	GFC Period	−1.429	−1.588	1.881	−13.675	−20.017	0.201
	Oil Decline Period	−1.767	−1.815	1.529	−22.147	−22.128	0.234
DAX 30	Full Period	−1.228	−1.160	5.782	−55.695	−55.787	0.076
	GFC Period	−1.646	−1.757	2.041	−7.517	−20.642	0.149
	Oil Decline Period	−1.598	−1.572	0.880	−21.002	−21.008	0.141
FTSE 100	Full Period	−2.139	−1.921	3.964	−26.995	−58.114	0.064
	GFC Period	−1.453	−1.533	2.075	−9.454	−21.529	0.097
	Oil Decline Period	−1.919	−1.939	1.137	−20.418	−20.419	0.049
SSE	Full Period	−1.884	−1.979	0.732	−55.584	−55.632	0.072
	GFC Period	−2.328	−2.327	1.548	−20.152	−20.151	0.742
	Oil Decline Period	−1.854	−1.779	1.379	−5.029	−18.494	0.497

Table 5.9: Panel A (Continued)

Market	Period	Level			First Difference		
		ADF	**PP**	**KPSS**	**ADF**	**PP**	**KPSS**
MSCI	Full Period	−1.129	−1.115	4.445	−39.851	−49.537	0.137
	GFC Period	−1.254	−1.303	2.050	−11.390	−17.817	0.181
	Oil Decline Period	−2.110	−1.885	0.667	−16.871	−16.792	0.099
CRUDE OIL	Full Period	−1.797	−1.736	1.971	−57.968	−57.977	0.114
	GFC Period	−0.830	−0.972	1.579	−8.664	−20.072	0.220
	Oil Decline Period	−1.139	−1.216	2.026	−22.844	−22.888	0.089
GOLD	Full Period	−2.524	−2.523	2.783	−56.784	−56.787	0.316
	GFC Period	−2.602	−2.628	0.359	−20.186	−20.188	0.048
	Oil Decline Period	−1.929	−1.981	2.031	−19.717	−19.725	0.055
SILVER	Full Period	−1.895	−1.898	1.181	−55.270	−55.266	0.151
	GFC Period	−1.401	−1.406	1.170	−19.319	−19.316	0.118
	Oil Decline Period	−2.250	−2.183	1.965	−22.310	−22.516	0.091
PALLADIUM	Full Period	−1.024	−1.386	4.637	−68.396	−68.547	0.061
	GFC Period	−1.018	−1.107	1.799	−17.591	−27.993	0.165
	Oil Decline Period	−0.052	0.048	2.131	−21.638	−21.638	0.149
PLATINUM	Full Period	−1.082	−1.213	3.431	−54.941	−55.019	0.183
	GFC Period	−0.797	−0.818	1.564	−19.472	−19.480	0.280
	Oil Decline Period	−1.038	−0.903	2.395	−6.760	−20.736	0.031

Table 5.9: Panel B: With intercept and trend in the model (Continued)

Market	Period	Level			First Difference		
		ADF	PP	KPSS	ADF	PP	KPSS
TASI	Full Period	−2.379	−2.392	0.386	−50.581	−50.591	0.048
	GFC Period	−1.309	−1.328	0.283	−18.016	−18.008	0.104
	Oil Decline Period	−2.024	−2.024	0.299	−17.875	−17.848	0.049
S&P 500	Full Period	−2.436	−2.436	0.797	−43.812	−62.314	0.096
	GFC Period	−1.241	−1.531	0.248	−17.262	−23.509	0.108
	Oil Decline Period	−2.675	−2.735	0.347	−19.771	−19.781	0.026
NIKKEI 225	Full Period	−2.445	−2.379	1.133	−57.857	−58.053	0.100
	GFC Period	−0.934	−1.469	0.260	−13.722	−20.052	0.108
	Oil Decline Period	−1.144	−1.271	0.488	−22.210	−22.205	0.046
DAX 30	Full Period	−2.489	−2.389	0.657	−55.687	−55.778	0.072
	GFC Period	−1.778	−1.999	0.233	−9.647	−20.722	0.066
	Oil Decline Period	−1.449	−1.414	0.420	−21.000	−21.006	0.076
FTSE 100	Full Period	−3.185	−2.950	0.408	−26.993	−58.107	0.051
	GFC Period	−1.862	−2.237	0.230	−9.470	−21.528	0.058
	Oil Decline Period	−2.581	−2.572	0.410	−20.398	−20.398	0.031
SSE	Full Period	−1.910	−2.004	0.731	−55.577	−55.625	0.076
	GFC Period	−0.620	−0.584	0.561	−20.516	−20.516	0.038
	Oil Decline Period	−0.593	−0.504	0.526	−5.481	−18.621	0.075
MSCI	Full Period	−2.360	−2.336	0.686	−39.855	−49.536	0.077
	GFC Period	−1.076	−1.068	0.263	−11.410	−17.823	0.131
	Oil Decline Period	−2.505	−2.299	0.328	−16.862	−16.778	0.042

Table 5.9: Panel B (Continued)

Market	Period	Level			First Difference		
		ADF	**PP**	**KPSS**	**ADF**	**PP**	**KPSS**
CRUDE OIL	Full Period	−2.351	−2.294	0.611	−57.971	−57.979	0.051
	GFC Period	−0.876	−1.103	0.287	−8.659	−20.054	0.217
	Oil Decline Period	−1.841	−1.906	0.275	−22.823	−22.866	0.071
GOLD	Full Period	−2.052	−2.030	1.413	−56.814	−56.827	0.064
	GFC Period	−2.599	−2.626	0.352	−20.160	−20.162	0.047
	Oil Decline Period	−2.939	−3.276	0.091	−19.710	−19.711	0.034
SILVER	Full Period	−1.866	−1.866	1.186	−55.275	−55.271	0.054
	GFC Period	−1.661	−1.678	0.357	−19.295	−19.292	0.114
	Oil Decline Period	−3.239	−3.234	0.175	−22.312	−22.516	0.039
PALLADIUM	Full Period	−2.043	−2.106	0.514	−68.387	−68.539	0.060
	GFC Period	−1.285	−1.667	0.337	−17.572	−27.960	0.152
	Oil Decline Period	−2.250	−2.180	0.266	−21.665	−21.663	0.038
PLATINUM	Full Period	−2.368	−2.473	0.921	−54.959	−55.030	0.039
	GFC Period	−1.111	−1.156	0.331	−19.447	−19.455	0.279
	Oil Decline Period	−3.298	−3.161	0.143	−6.756	−20.716	0.029

Table 5.9: Panel C: Without intercept and trend in the model (Continued)

Market	Period	Level			First Difference		
		ADF	PP	KPSS	ADF	PP	KPSS
TASI	Full Period	−0.063	−0.063	====	−50.595	−50.606	====
	GFC Period	−1.391	−1.273	====	−17.960	−18.013	====
	Oil Decline Period	−1.292	−1.294	====	−17.757	−17.768	====
S&P 500	Full Period	0.946	0.960	====	−43.793	−62.254	====
	GFC Period	−1.316	−1.290	====	−17.195	−23.306	====
	Oil Decline Period	−0.102	−0.107	====	−19.798	−19.806	====
NIKKEI 225	Full Period	0.138	0.157	====	−57.847	−58.029	====
	GFC Period	−1.017	−0.979	====	−13.641	−19.970	====
	Oil Decline Period	0.507	0.508	====	−22.161	−22.141	====
DAX 30	Full Period	0.573	0.611	====	−55.698	−55.781	====
	GFC Period	−1.204	−1.310	====	−7.433	−20.555	====
	Oil Decline Period	−0.053	−0.053	====	−21.028	−21.034	====
FTSE 100	Full Period	0.082	0.102	====	−26.999	−58.124	====
	GFC Period	−1.223	−1.221	====	−9.373	−21.394	====
	Oil Decline Period	−0.546	−0.558	====	−20.428	−20.429	====
SSE	Full Period	−0.138	−0.137	====	−55.593	−55.640	====
	GFC Period	−1.251	−1.227	====	−20.106	−20.114	====
	Oil Decline Period	0.440	0.530	====	−5.012	−18.505	====
MSCI	Full Period	0.348	0.358	====	−39.855	−49.544	====
	GFC Period	−1.404	−1.273	====	−11.320	−17.770	====
	Oil Decline Period	−0.610	−0.738	====	−16.874	−16.819	====

Table 5.9: Panel C (Continued)

Market	Period	Level			First Difference		
		ADF	**PP**	**KPSS**	**ADF**	**PP**	**KPSS**
CRUDE OIL	Full Period	−0.363	−0.365	====	−57.976	−57.985	====
	GFC Period	−0.532	−0.490	====	−8.661	−20.088	====
	Oil Decline Period	−2.315	−2.220	====	−22.626	−22.576	====
GOLD	Full Period	1.014	1.039	====	−56.771	−56.776	====
	GFC Period	0.283	0.290	====	−20.208	−20.209	====
	Oil Decline Period	−1.082	−1.047	====	−19.687	−19.699	====
SILVER	Full Period	−0.035	−0.034	====	−55.278	−55.274	====
	GFC Period	−0.219	−0.219	====	−19.343	−19.340	====
	Oil Decline Period	−1.386	−1.455	====	−22.254	−22.431	====
PALLADIUM	Full Period	1.113	1.080	====	−68.381	−68.513	====
	GFC Period	−0.645	−0.581	====	−17.596	−28.014	====
	Oil Decline Period	−1.585	−1.662	====	−21.519	−21.512	====
PLATINUM	Full Period	−0.464	−0.445	====	−54.946	−55.025	====
	GFC Period	−0.510	−0.500	====	−19.486	−19.493	====
	Oil Decline Period	−2.296	−2.367	====	−6.335	−20.472	====

Notes: The table panels (A, B and C) illustrate the ADF, PP and KPSS unit root test findings for the whole period and two subperiods. Panels A, B and C show the results of the unit root test including only the intercept, with both intercept and trend and not including both intercept and trend, respectively. The critical values are −2.56 at the 1% level, −1.94 at the 5% level and −1.61 at the 10% level for the ADF and PP tests. The critical values of KPSS are 0.739 at the 1% level, 0.463 at the 5% level and 0.347 at the 10% level.

5.7 The Cross-Correlation Function Test

Next, the CCF test designed by Cheung and Ng (1996) is used to study the cross-market linkages between the TASI, global stocks and major commodity markets (second moment) to analyse the direction of causality in variance between the bivariate samples. From the univariate conditional variance of the EGARCH model, the test conducted using the CCF model will be based on the squared standardised residuals. The advantage of using the CCF method is that it enables the calculation of sample cross-correlations of the model estimations. These can be performed in two separate stages, which makes it convenient for implementation in practice. The CCF results can provide valuable insights on a multivariate model formulation.

The CCF test, as noted, consists of two separate stages. In the first stage, the univariate time series of the EGARCH model in equation (4.9) that permits time variation in conditional variance is estimated, which provides standardised residuals and squares. In the second stage, the standardised residuals and squares are constructed and then the cross-correlation functions of equation (4.14) are calculated. This serves to test the null hypothesis of no causality in variance up to 10 lag lengths. The results reported in Tables 5.11–16 and 5.18–22 present 11 examples of causality-in-variance relationships of different global stock and major commodity markets. Each table presents the test statistics of two indices of TASI with one of global stocks and major commodities with their lag and lead values. The 'lag' refers to the tests for causality in variance from global stock and major commodity markets to TASI. The 'lead' refers to tests for causality in variance from TASI to global stocks and major commodities.

Table 5.10 indicates there were feedback causalities in variance between global stock markets in different periods with TASI. In addition, all the significant results, which means rejecting the null hypothesis of no causality and accepting the alternative hypothesis of causality between TASI and some global stocks, have a positive relationship. The causality in variance of TASI is found to have caused the causality in variance of the following markets: S&P 500, NIKKEI 225, DAX 30 and MSCI during the full period. Meanwhile, in the GFC period, it differed slightly because it caused causality in variance of the following:

NIKKEI 225, DAX 30, FTSE 100 and SSE. Surprisingly, TASI had no causality in variance to the global stock markets during the oil decline phase. On the contrary, S&P 500, NIKKEI 225 and FTSE 100 showed evidence of causality in variance to TASI in the full period. Moreover, in the GFC period, only DAX 30 and SSE showed causality in variance to TASI. In the same way, S&P 500, FTSE 100 and MSCI reported causality in variance to TASI.

The statistically significant cross-correlation test results in Table 5.11 for TASI and S&P 500 show that the TASI led the S&P 500 in variance up to lag 10 in the full period, while other periods (GFC and oil decline) show no causality in variance. In contrast, S&P 500 influenced TASI in terms of variance through lags 1 to 10 in the full and oil decline periods while interestingly it had no influence in the GFC period. In Table 5.12, the results for one group (TASI and NIKKEI 225) show that the TASI led the NIKKEI 225 in variance up to a lag of 10 for the full and GFC periods, but there was no causality in variance in the oil decline period. Conversely, in the full period, NIKKEI 225 was affected by TASI in terms of variance from lag 1 to 10, whereas in the GFC and oil decline periods it did not exert a significant influence.

The cross-correlation analysis shows evidence of causality in variance in Table 5.13 for the TASI and DAX 30, suggesting that the TASI led the DAX 30 in variance up to 10 lags in both periods (full and GFC); however, the analysis displays proof of no causality in variance in the period of oil decline. Yet, the DAX 30 affected TASI in variance through lags 3 to 10 in the GFC period, while in the full and oil decline periods, DAX 30 did not influence TASI. The variance of TASI in Table 5.14 reveals that the null hypothesis of no causality running from TASI to FTSE 100 up to lag 10 during the GFC can be rejected, while the no causality in variance of the null hypothesis for the full and oil decline periods can be accepted. In contrast, there is only one period in which FTSE 100 showed evidence of causality, namely, the one in which there was causality in variance running from it to TASI through lags 1 to 10 in the full period.

The findings documented in Table 5.15 show an insignificant influence in the cross-correlation for TASI in terms of variance from outgoing and incoming causal linkages with SSE and vice versa in the full and oil decline periods. However, there was a bidirectional causality in variance from SSE to TASI and vice versa in the GFC period for a significant cross-correlation at a certain number of lags/leads. As clarified in Table 5.16, if the cross-correlation analysis reveals significance, the null hypothesis of no causality in variance for TASI cannot be rejected at a certain number of leads for both periods (full and GFC); the exception is the oil decline period. It means there was causality in variance running from TASI to MSCI. Conversely, there is evidence of feedback of causality in variance from MSCI to TASI during the oil decline period and it is statistically significant from 1 to 10 lags.

Overall, Tables 5.11 to 5.16 show causality in variance in the Saudi stock market owing to global volatility risks for three markets in the full period (the S&P 500, NIKKEI 225 and FTSE 100) and in the oil decline period (S&P 500, FTSE 100 and MSCI), and two markets in the GFC period (DAX 30 and SSE). It emerges as being significant and positive. This simply means that international volatility risks are a key determinant for the volatility of the Saudi stock market. Interestingly, since the Saudi stock market volatility influences the volatility variation of some global stock markets, it is worth noting there is an average contemporaneous causality in variance for the direction of TASI ⟶ global stock markets (see Table 5.10). It reveals that the Saudi stock market has positive causality in variance to the international volatility risks of the S&P 500, NIKKEI 225, DAX 30, SSE, MSCI and FTSE 100. Therefore, the cross-correlation findings suggest there are higher volatility shocks expanding from the Saudi Arabian market to global volatility risks, and the findings of Tissaoui and Azibi (2019) are consistent with these results.

The results for the major commodity markets on the sample cross-correlation analysis are provided in Tables 5.17–22. Surprisingly, the null hypothesis of no causality in variance for all major commodity markets was accepted, the exception being crude oil, which was statistically significant for unidirectional causality in variance running from TASI at a certain number of leads in the full period. These findings indicate that the causality in variance of TASI had only one effect on the international volatility risks of the oil market during the full period, which is statistically significant and positive. Meanwhile, in the precious metals' cases, the causality in variance is insignificant for all periods. This result is consistent with that of Tissaoui and Azibi (2019) who also detected a unidirectional causality in variance from TASI to oil market.

Table 5.10: Causality in Variance between TASI and Global Stock Markets

Market	**Global Stock Markets ⟶ TASI**			**TASI ⟶ Global Stock Markets**		
	Full Period	GFC Period	Oil Decline Period	Full Period	GFC Period	Oil Decline Period
S&P 500	+		+	+		
NIKKEI 225	+			+	+	
DAX 30		+		+	+	
FTSE 100	+		+		+	
SSE		+			+	
MSCI			+	+		

Notes: Symbol ⟶ is used to indicate the direction of causality measuring. '+' refers to the causal relationship being significant at least at the 5% level.

Table 5.11: Causality in Variance between TASI and S&P 500

	S&P 500					
	S&P 500 ⟶ TASI			TASI ⟶ S&P 500		
lags	Full Period	GFC Period	Oil Decline Period	Full Period	GFC Period	Oil Decline Period
1	1.48*	−0.59	3.00***	11.47***	0.53	−0.68
2	2.09**	−0.83	4.27***	16.21***	0.75	−0.97
3	2.58***	−1.01	5.26***	19.86***	0.91	−1.20
4	2.99***	−1.16	6.10***	22.98***	1.05	−1.39
5	3.36***	−1.29	6.88***	25.71***	1.18	−1.56
6	3.69***	−1.40	7.59***	28.18***	1.30	−1.71
7	4.00***	−1.50	8.23***	30.44***	1.40	−1.85
8	4.30***	−1.59	8.81***	32.53***	1.36	−1.98
9	4.58***	−1.69	9.37***	34.49***	1.31	−2.10
10	4.84***	−1.77	9.90***	36.34***	1.25	−2.21

Notes: The Q-statistic results are presented in this table for all examined periods between TASI and S&P 500. The symbol ⟶ is used to show the direction of causality measuring. ***, ** and * indicate significance levels for the null hypothesis of no causality in variance at the 1%, 5% and 10% levels, respectively.

Table 5.12: Causality in Variance between TASI and NIKKEI 225

	NIKKEI 225					
	NIKKEI 225 ⟶ TASI			TASI ⟶ NIKKEI 225		
lags	Full Period	GFC Period	Oil Decline Period	Full Period	GFC Period	Oil Decline Period
1	4.61***	−0.56	−0.16	1.48*	4.03***	−0.68
2	6.52***	−0.78	−0.25	2.09**	5.62***	−0.96
3	7.98***	−0.97	−0.31	2.55***	6.83***	−1.18
4	9.21***	−1.12	−0.35	2.96***	7.86***	−1.36
5	10.31***	−1.27	−0.40	3.32***	8.74***	−1.53
6	11.29***	−1.39	−0.44	3.66***	9.57***	−1.67
7	12.22***	−1.51	−0.49	3.97***	10.31***	−1.80
8	13.07***	−1.61	−0.54	4.26***	11.06***	−1.93
9	13.88***	−1.72	−0.59	4.54***	11.74***	−2.04
10	14.64***	−1.83	−0.64	4.80***	12.35***	−2.15

Notes: The Q-statistic results are presented in this table for all examined periods between TASI and NIKKEI 225. The symbol ⟶ is used to show the direction of causality measuring. ***, ** and * indicate significance levels for the null hypothesis of no causality in variance at the 1%, 5% and 10% levels, respectively.

Table 5.13: Causality in Variance between TASI and DAX 30

	DAX 30					
	DAX 30 ⟶ TASI			TASI ⟶ DAX 30		
lags	Full Period	GFC Period	Oil Decline Period	Full Period	GFC Period	Oil Decline Period
1	−0.36	0.80	−0.60	10.89***	18.78***	−0.05
2	−0.50	1.12	−0.87	15.42***	26.62***	−0.08
3	−0.61	1.35*	−1.06	18.88***	32.60***	−0.07
4	−0.71	1.54*	−1.23	21.76***	37.58***	−0.07
5	−0.79	1.72**	−1.39	24.29***	41.92***	−0.08
6	−0.86	1.88**	−1.52	26.57***	45.90***	−0.09
7	−0.92	2.02**	−1.65	28.67***	49.52***	−0.10
8	−0.98	2.13**	−1.76	30.53***	52.80***	−0.10
9	−1.03	2.25**	−1.87	32.28***	55.86***	−0.11
10	−1.08	2.37***	−1.96	33.94***	58.75***	−0.11

Notes: The Q-statistic results are presented in this table for all examined periods between TASI and DAX 30. The symbol ⟶ is used to show the direction of causality measuring. ***, ** and * indicate significance levels for the null hypothesis of no causality in variance at the 1%, 5% and 10% levels, respectively.

Table 5.14: Causality in Variance between TASI and FTSE 100

	FTSE 100					
	FTSE 100 ⟶ TASI			TASI ⟶ FTSE 100		
lags	Full Period	GFC Period	Oil Decline Period	Full Period	GFC Period	Oil Decline Period
1	5.43***	−0.10	0.24	−0.69	4.89***	−0.70
2	7.69***	−0.14	0.36	−0.98	6.93***	−0.99
3	9.44***	−0.18	0.44	−1.20	8.46***	−1.22
4	10.90***	−0.22	0.53	−1.39	9.72***	−1.41
5	12.18***	−0.25	0.59	−1.55	10.80***	−1.57
6	13.33***	−0.29	0.65	−1.70	11.79***	−1.72
7	14.36***	−0.32	0.71	−1.84	12.68***	−1.86
8	15.33***	−0.35	0.75	−1.97	13.39***	−1.99
9	16.23***	−0.37	0.78	−2.09	14.07***	−2.11
10	17.10***	−0.40	0.82	−2.20	14.73***	−2.23

Notes: The Q-statistic results are presented in this table for all examined periods between TASI and FTSE 100. The symbol ⟶ is used to show the direction of causality measuring. *** indicates significance levels for the null hypothesis of no causality in variance at the 1% level.

Table 5.15: Causality in Variance between TASI and SSE

	SSE					
	SSE ⟶ TASI			TASI ⟶ SSE		
lags	Full Period	GFC Period	Oil Decline Period	Full Period	GFC Period	Oil Decline Period
1	−0.68	1.35*	0.11	−0.66	1.39*	−0.58
2	−0.96	1.89**	0.13	−0.93	1.98**	−0.81
3	−1.18	2.29**	0.14	−1.14	2.41***	−1.00
4	−1.36	2.61***	0.14	−1.32	2.75***	−1.16
5	−1.52	2.90***	0.16	−1.47	3.04***	−1.31
6	−1.66	3.15***	0.16	−1.61	3.31***	−1.45
7	−1.79	3.37***	0.17	−1.74	3.54***	−1.58
8	−1.92	3.56***	0.18	−1.87	3.80***	−1.70
9	−2.03	3.75***	0.19	−1.99	4.11***	−1.80
10	−2.14	3.98***	0.20	−2.10	4.37***	−1.91

Notes: The Q-statistic results are presented in this table for all examined periods between TASI and SSE. The symbol ⟶ is used to show the direction of causality measuring. ***, ** and * indicate significance levels for the null hypothesis of no causality in variance at the 1%, 5% and 10% levels, respectively.

Table 5.16: Causality in Variance between TASI and MSCI

	MSCI					
	MSCI ⟶ TASI			TASI ⟶ MSCI		
lags	Full Period	GFC Period	Oil Decline Period	Full Period	GFC Period	Oil Decline Period
1	−0.02	−0.67	3.78***	0.81	1.94**	0.5652
2	−0.03	−0.95	5.48***	1.14	2.68***	0.6014
3	−0.02	−1.16	6.74***	1.40*	3.23***	0.6267
4	−0.02	−1.33	7.78***	1.63**	3.68***	0.6460
5	−0.02	−1.49	8.68***	1.83**	4.06***	0.6609
6	−0.02	−1.63	9.50***	2.00**	4.43***	0.6709
7	−0.02	−1.75	10.23***	2.17**	4.84***	0.6742
8	−0.01	−1.87	10.88***	2.32**	5.27***	0.6771
9	−0.01	−1.98	11.49***	2.45***	5.73***	0.6814
10	0.00	−2.08	12.06***	2.58***	6.16***	0.6913

Notes: The Q-statistic results are presented in this table for all examined periods between TASI and MSCI. The symbol ⟶ is used to show the direction of causality measuring. *** and ** indicate significance levels for the null hypothesis of no causality in variance at the 1% and 5% levels, respectively.

Table 5.17: Causality in Variance between TASI and Major Commodity Markets

Commodity	**Major Commodity Markets ⟶TASI**			**TASI ⟶ Major Commodity Markets**		
	Full Period	GFC Period	Oil Decline Period	Full Period	GFC Period	Oil Decline Period
CRUDE OIL				+		
GOLD						
SILVER						
PALLADIUM						
PLATINUM						

Notes: The symbol ⟶ is used to show the direction of causality measuring. '+' refers to the causal relationship being significant at least at the 5% level.

Table 5.18: Causality in Variance between TASI and Crude Oil

CRUDE OIL						
	CRUDE OIL ⟶ TASI			TASI ⟶ CRUDE OIL		
lags	Full Period	GFC Period	Oil Decline Period	Full Period	GFC Period	Oil Decline Period
1	0.18	−0.53	−0.45	1.97**	−0.65	−0.67
2	0.26	−0.74	−0.65	2.79***	−0.92	−0.95
3	0.30	−0.90	−0.79	3.42***	−1.12	−1.17
4	0.34	−1.04	−0.89	3.96***	−1.29	−1.36
5	0.38	−1.17	−0.99	4.43***	−1.45	−1.52
6	0.41	−1.29	−1.08	4.85***	−1.59	−1.67
7	0.45	−1.40	−1.18	5.24***	−1.72	−1.81
8	0.48	−1.50	−1.27	5.58***	−1.85	−1.93
9	0.51	−1.60	−1.36	5.92***	−1.96	−2.04
10	0.54	−1.70	−1.44	6.25***	−2.08	−2.14

Notes: The Q-statistic results are presented in this table for all examined periods between TASI and Crude Oil. The symbol ⟶ is used to show the direction of causality measuring. *** and ** indicate significance levels for the null hypothesis of no causality in variance at the 1% and 5% levels, respectively.

Table 5.19: Causality in Variance between TASI and Gold

	GOLD					
	GOLD ⟶ TASI			TASI ⟶ GOLD		
lags	Full Period	GFC Period	Oil Decline Period	Full Period	GFC Period	Oil Decline Period
1	−0.61	−0.68	−0.70	−0.70	−0.71	−0.71
2	−0.87	−0.96	−1.00	−1.00	−1.00	−1.00
3	−1.07	−1.18	−1.22	−1.22	−1.22	−1.22
4	−1.23	−1.36	−1.41	−1.41	−1.41	−1.41
5	−1.38	−1.52	−1.58	−1.58	−1.58	−1.58
6	−1.51	−1.67	−1.73	−1.73	−1.73	−1.73
7	−1.63	−1.81	−1.86	−1.86	−1.87	−1.87
8	−1.74	−1.94	−1.99	−1.99	−2.00	−2.00
9	−1.85	−2.05	−2.12	−2.12	−2.12	−2.12
10	−1.95	−2.16	−2.23	−2.23	−2.23	−2.23

Notes: The Q-statistic results are presented in this table for all examined periods between TASI and gold. The symbol ⟶ is used to show the direction of causality measuring.

Table 5.20: Causality in Variance between TASI and Silver

	SILVER					
	SILVER ⟶ TASI			TASI ⟶ SILVER		
lags	Full Period	GFC Period	Oil Decline Period	Full Period	GFC Period	Oil Decline Period
1	−0.49	−0.56	−0.65	−0.61	−0.25	−0.70
2	−0.70	−0.80	−0.93	−0.87	−0.35	−1.00
3	−0.85	−0.98	−1.14	−1.06	−0.42	−1.22
4	−0.98	−1.13	−1.31	−1.22	−0.49	−1.41
5	−1.09	−1.27	−1.46	−1.37	−0.55	−1.57
6	−1.20	−1.39	−1.60	−1.50	−0.60	−1.72
7	−1.29	−1.49	−1.73	−1.62	−0.62	−1.86
8	−1.37	−1.59	−1.85	−1.72	−0.63	−1.99
9	−1.45	−1.68	−1.97	−1.83	−0.65	−2.11
10	−1.53	−1.77	−2.08	−1.92	−0.66	−2.22

Notes: The Q-statistic results are presented in this table for all examined periods between TASI and silver. The symbol ⟶ is used to show the direction of causality measuring.

Table 5.21: Causality in Variance between TASI and Palladium

	PALLADIUM					
	PALLADIUM ⟶ TASI			TASI ⟶ PALLADIUM		
lags	Full Period	GFC Period	Oil Decline Period	Full Period	GFC Period	Oil Decline Period
1	−0.69	−0.57	−0.43	−0.70	−0.70	−0.66
2	−0.98	−0.81	−0.62	−1.00	−1.00	−0.94
3	−1.19	−0.99	−0.77	−1.22	−1.22	−1.15
4	−1.38	−1.14	−0.90	−1.41	−1.41	−1.33
5	−1.54	−1.27	−1.00	−1.58	−1.57	−1.48
6	−1.69	−1.39	−1.10	−1.73	−1.73	−1.62
7	−1.83	−1.50	−1.18	−1.86	−1.86	−1.75
8	−1.95	−1.60	−1.27	−1.99	−1.99	−1.87
9	−2.07	−1.70	−1.35	−2.11	−2.11	−1.98
10	−2.18	−1.79	−1.42	−2.23	−2.23	−2.09

Notes: The Q-statistic results are presented in this table for all examined periods between TASI and palladium. The symbol ⟶ is used to show the direction of causality measuring.

Table 5.22: Causality in Variance between TASI and Platinum

PLATINUM						
	PLATINUM ⟶ TASI			TASI ⟶ PLATINUM		
lags	Full Period	GFC Period	Oil Decline Period	Full Period	GFC Period	Oil Decline Period
1	−0.45	0.17	−0.46	−0.67	−0.56	−0.68
2	−0.64	0.25	−0.65	−0.95	−0.79	−0.95
3	−0.78	0.33	−0.79	−1.17	−0.97	−1.16
4	−0.90	0.40	−0.91	−1.35	−1.12	−1.34
5	−1.01	0.46	−1.01	−1.52	−1.27	−1.50
6	−1.10	0.51	−1.11	−1.66	−1.41	−1.65
7	−1.19	0.53	−1.17	−1.80	−1.53	−1.79
8	−1.27	0.56	−1.23	−1.92	−1.64	−1.92
9	−1.34	0.56	−1.29	−2.04	−1.75	−2.04
10	−1.41	0.58	−1.34	−2.14	−1.86	−2.16

Notes: The Q-statistic results are presented in this table for all examined periods between TASI and platinum. The symbol ⟶ is used to show the direction of causality measuring.

5.8 Conclusion

This chapter summarised the significance of the stock market of Saudi Arabia with reference to six global stock markets, S&P 500, NIKKEI 225, DAX 30, FTSE 100, SSE and MSCI, and five major commodity markets, crude oil, gold, silver, palladium and platinum. The data and their descriptive statistics were provided. As consistent with current work and the literature, the findings suggest that the returns of indexes are not normally distributed. The study of skewness and kurtosis indicated that days of greater market variance are predominant with a smaller market volatility during the periods examined. Evidence was also found of ARCH effects in all periods for all samples. The findings of unit roots tests confirmed that all data in their log differences are stationary. The study of correlations reported that a strong correlation with the strongest connection is between TASI and global stock markets. Meanwhile, the lowest link for TASI was with gold and silver except in the oil decline period.

The CCF based on the EGARCH specification tested the causality-in-variance interactions of the Saudi stock market with global stock and major commodity markets. It was found that the relationships between TASI and global stock markets are of critical importance. No relationship was found between TASI and major commodity markets for all periods except for the full period when unidirectional causality in variance from TASI to crude oil was evident. This means that most of the information concerning the global stock markets is transmitted in TASI and vice versa. In global stock markets, two-way causality in variance between TASI and some global stock markets in different periods was found. More generally, it is the global stock markets (the S&P 500 and NIKKEI 225) that play a crucial role in the transmission mechanism of global volatility.

Chapter 6 TASI's Volatility Transmission, Conditional Correlations and Portfolio Management: Empirical Findings

6.1 Introduction

The literature, from the perspective of the transmission of shock and volatility spillovers, conditional correlations and portfolio management, shows there is less focus on market linkage when referring to Saudi Arabia. Studies in this area tended to analyse relationships between different financial markets using return (variance equation) results. Research on transmission of volatility within MGARCH models has somewhat ignored emerging markets in the MENA region. Studies that have investigated the relationships around Saudi Arabia are still relatively limited. Few analysis—to the best of the researcher's knowledge—has concentrated specifically on the Saudi stock market and used sophisticated econometric methods. Hence, this present chapter aims to use the MGARCH-BEKK model of Engle and Kroner (1995) to, first, examine the transmission of shock and volatility spillovers and, second, to address a gap in current knowledge and contribute to literature on the market linkage between Saudi Arabia's TASI and global stock and major commodity markets. It should also clarify the causal linkages reported in Chapter 5 based on the CCF model estimation. The MGARCH-BEKK model is used to allow the variance to vary over time and to assess whether there are cross-market spillover mechanisms.

The discussion on the nature of the data features in Chapter 5 showed that based on the analysis (descriptive statistics, unit root analysis and ARCH effect), the MGARCH models are most appropriate for investigating the volatility transmission between TASI and global stock and major commodity markets. Accordingly, first, a bivariate GARCH-BEKK model is estimated for all combinations of the sample indices during the full, GFC and oil decline periods. This approach allows the existing transmission of spillover effect of any particular market to be assessed in relation to other markets. This is an important step towards a detailed consideration of some of the world's largest stocks and major commodities in identifying the volatility transmission channels in phases of financial crisis/shock. In addition, investors from the Middle East region can predict volatility by monitoring the biggest markets worldwide, such as S&P 500, NIKKEI 225, DAX 30 and FTSE 100

(Shahzad et al., 2017), which are expected to influence the Saudi stock market volatility. Second, the correlations between TASI and global stock and major commodity markets are examined by estimating MGARCH models: CCC and DCC. The results of correlation models will help to understand the co-movement between TASI and global stock and major commodity markets and take advantage of risk management portfolio aspects. In fact, the theory of traditional asset pricing says that portfolio diversity gains are related to the correlation between the assets in the diversified portfolio (Mensi, Hammoudeh, & Kang, 2015; Sadorsky, 2014). Reducing the average portfolio volatility by combining negative or low positive correlated assets may thus enhance the portfolio outcomes (Benhmad, 2013). This is because shifts in one asset can at least be expected to be set off by shifts in another.

This chapter will examine the conditional correlation between TASI and global stock and major commodity markets for the following periods: full, GFC and oil decline of 2014–2016. The reason for determining the link between TASI and global stocks and major commodities during the financial crisis/shock periods is that global stocks and major commodities emerge as being volatile during these periods (see Figures 6.7 and 6.8). Therefore, to diversify the high-risk portfolio of assets, it should be understood how the two assets can co-move to take advantage of portfolio diversification.

Third, risk management and effective portfolio diversification are important in considering the volatility transmission effect and the conditional correlation between the sample variables. With negligible price transmission impact from a strong connection of stock and commodity markets to TASI, investing in both global stocks and major commodities provides substantial possible incentives for investors or other interests. Before building optimal portfolios based on findings from the BEKK and DCC models, it is necessary to differentiate between some phrases related to portfolios, such as hedge and/or safe haven. In this regard, Baur and Lucey's (2010) description is considered useful to direct the reader through the remainder of this analysis: A diversifier, which allows investors/portfolio managers to have greater diversification in all portfolios would be a different asset that is positively, but not fully, associated with another asset in all portfolios. A hedge is an asset negatively linked or unrelated to a particular asset. A safe haven is an asset that is negatively linked or not associated with another asset during periods of stress market or turbulence.

Therefore, portfolio managers, policymakers or investors must estimate accurately the conditional variance and covariance for using optimal weights and hedging ratios in minimising risk exposures on volatile markets, and volatile price shifts without reducing expected returns. Even so, by investing in both global stocks and major commodities, investors can earn greater diversification profits. Further, portfolio managers or investors can basically modify their portfolio weights to the market situation— whether a bear or bull market (Kang et al., 2017). This chapter examines the TASI and stock and commodity portfolios to reduce risks and to demonstrate the effects of the results of the present research on portfolio management of optimal weights and hedging ratios.

In this context, this research has applied the Kroner and Ng (1998) approach to determine the optimal portfolio weights, and the Kroner and Sultan (1993) approach to determine the hedge ratios by using estimation results from the two MGARCH models, BEKK and DCC. This approach is adopted to construct the optimal portfolio without reducing the expected returns. Two assets in each portfolio constituted the framework of the optimal portfolio weight and hedge ratio. In addition to the CCF results, these steps are the major contribution of this thesis, after examining the potential transmission channels of shock and volatility spillover and the conditional correlation for extracting the optimal weights and hedge ratios for the sample variables in the portfolio. The linkages between the studied markets are explored in more detail.

Data analysis was conducted through the Regression Analysis of Time Series (RATS) software to estimate the MGARCH-BEKK, -CCC and -DCC models for analysing the volatility transmission and conditional correlation between TASI and global stock and major commodity markets. Next, this chapter presents the results of the MGARCH models and establishes the transmission of volatility and shock spillovers (or not), conditional correlations and portfolio management for the full period as well as the subperiods: GFC and oil decline.

6.2 Volatility Transmission Effect

6.2.1 Introduction

The estimated equations are the variance equations (equations 4.14 to 4.19) used in Subsections 6.2.2 and 6.2.3. They are used to examine the interaction relationship between the financial markets in greater depth from the volatility transmission perspective. The evaluated findings from the variance–covariance coefficients for global stocks and major commodities are reported in Tables 6.1–6. For each market and for the cross-market spillovers of shocks and volatility, the diagonals of matrix A and B parameters are divided into their respective coefficients, to assess the interaction between the global stock and major commodity markets in greater depth. The diagonal of matrix A and the diagonal of matrix B represent, respectively, the impact of past market shocks and of market volatility on their own conditional variance (Doan, 2013). Since the ARCH and GARCH effects have been observed in the analysis, the findings of this thesis are in line with that of previous studies, which observed the same effects (Abounoori & Tour, 2019; Ahmed & Huo, 2020; Kang et al., 2013; Shaik & Syed, 2019;).

6.2.2 Volatility Transmission Effect between TASI and Global Stock Markets

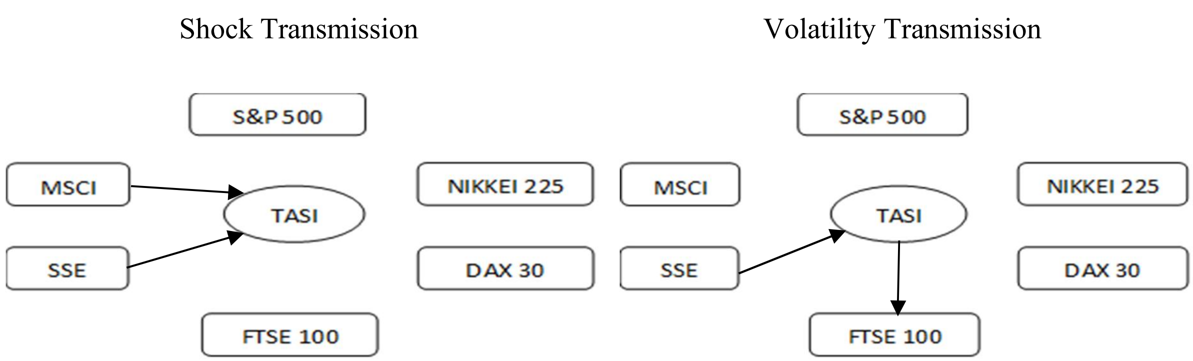
6.2.2.1 Full Period (2007–2018)

As shown in Table 6.1, the A(1,1) coefficient estimates the influence of the past shocks of spillover on the conditional variance of TASI, which is known as the ARCH effect, and the B(1,1) coefficient assesses the impact of the past volatility spillover on own conditional variance, which is known as the GARCH effect. In the same way, A(2,2) and B(2,2) analyse the impact of past shock and capture the volatility spillover of each global stock market on its own conditional variance. Moreover, for all global stock markets throughout the full period, the estimated parameters A(1,1) and B(1,1) are statistically significant at the 1% level.

Next, this thesis examines the transmission of shock and volatility spillovers effect through stock markets. The A and B off-diagonal components catch the cross-market spillover effect of shock and volatility, respectively. Regarding matrix A, the overall effect of cross-market (TASI and other global stock markets) shock spillover for coefficient A(1,2) shows that all coefficients are statistically insignificant during the full period. However, the A(2,1) coefficient, on the other side, tests the effect of cross-market spillover shocks of the global stock markets to TASI over the whole period. It is found that the coefficients of the SSE and MSCI markets are statistically significant at the 10% level (see Figure 6.1). Since this effect of shock spillover determines the short-term effects of innovation from the last period (previous day), it can be recognised that TASI is strongly affected through the result of the preceding period from the SSE and MSCI markets in the full period.

Moving to the off-diagonal parameters of matrix B that capture the spillover effect of volatility, coefficient B(1,2) shows the total cross-market spillover effect of volatility from TASI to global stock markets. For most samples over the entire period, these coefficients are statistically insignificant except that for the FTSE 100, these are statistically significant at the 10% level. Coefficient B(2,1), in the opposite direction, relating to the cross-market spillover impact of volatility from global stock markets to TASI, is significant at the 10% level for SSE for the full period.

Figure 6.1: Dynamic Linkages of TASI with Global Stock Markets for the Full Period, 1 January 2007 – 31 December 2018



Note: The symbols '→' and '←' indicate unidirectional shock or volatility transmission

The findings documented in Table 6.1 and Figure 6.1 show unidirectional spillover shocks from SSE and MSCI to TASI. Further, they demonstrate unidirectional spillover shocks from TASI to FTSE 100 and from SSE to TASI. The findings are largely consistent with the results of Jouini (2015), who provided proof for a weak relationship between the volatility of the Saudi stock market and global stock markets during stable times. The estimated results confirm the weak interaction of TASI with global stock markets. These results are consistent with those of Khalfaoui et al. (2015) and Hassan et al. (2019) in that the results for Saudi Arabia's stock market demonstrate the significance of A(1,1), A(2,2), B(1,1) and B(2,2), which further suggest that the current market volatility corresponds to shock and volatility in its own market. Therefore, the findings in this thesis of the ARCH (past shock) and GARCH (past volatility) coefficients are statistically significant at the 1% level, consistent with previous empirical results. The results not only demonstrate that past shocks and past volatility have a major impact on current volatility, but also indicate that future shocks and the nature of volatility would be heavily influenced by past shocks and past volatility. In addition, the ARCH term coefficients are smaller than the coefficients of GARCH term, which indicates that present volatility reacts more rapidly than lagged shocks to the significant impact of lagged volatility.

Table 6.1: Results of Linkages of TASI with Global Stock Markets for the Full Period

	BEKK-GARCH Model Estimation					
	Global Stock Markets					
	S&P 500	NIKKEI 225	DAX 30	FTSE 100	SSE	MSCI
A(1,1)	0.333***	0.341***	0.327***	0.323***	0.347***	0.340***
	(0.035)	(0.029)	(0.031)	(0.027)	(0.027)	(0.032)
A(1,2)	−0.027	0.006	−0.013	0.034	0.024	−0.006
	(0.038)	(0.052)	(0.083)	(0.024)	(0.019)	(0.033)
A(2,1)	0.067	0.010	0.034	0.015	−0.065*	0.082*
	(0.044)	(0.021)	(0.029)	(0.040)	(0.037)	(0.049)
A(2,2)	0.312***	0.301***	0.246***	0.267***	0.175***	0.271***
	(0.036)	(0.033)	(0.028)	(0.029)	(0.020)	(0.033)
B(1,1)	0.934***	0.934***	0.935***	0.940***	0.930***	0.930***
	(0.015)	(0.010)	(0.011)	(0.010)	(0.010)	(0.014)
B(1,2)	0.011	−0.001	0.003	−0.012*	−0.010	0.002
	(0.016)	(0.022)	(0.038)	(0.007)	(0.008)	(0.015)
B(2,1)	−0.017	−0.0023	−0.006	−0.007	0.013*	−0.014
	(0.011)	(0.007)	(0.011)	(0.009)	(0.008)	(0.011)
B(2,2)	0.942***	0.941***	0.963***	0.958***	0.985***	0.961***
	(0.012)	(0.013)	(0.013)	(0.009)	(0.003)	(0.010)

Notes: Coefficients of multivariate GARCH-BEKK models A and B, respectively, capture the ARCH and GARCH effects. Figures in parentheses indicate standard error values. ***, ** and * indicate the rejection of the null hypothesis at the 1%, 5% and 10% significance levels, respectively.

6.2.2.2 GFC Period (January 2008 – June 2009)

On considering TASI and global stock markets during the GFC period, different assumptions can be drawn from those drawn for the existing major commodity markets for the same period. The related coefficients across some global stocks show that the null hypothesis cannot be rejected. Consequently, the transmission of shock and volatility of global stock markets has risen and spilled over to TASI. Further, in the GFC period, the co-movement was increasing strongly.

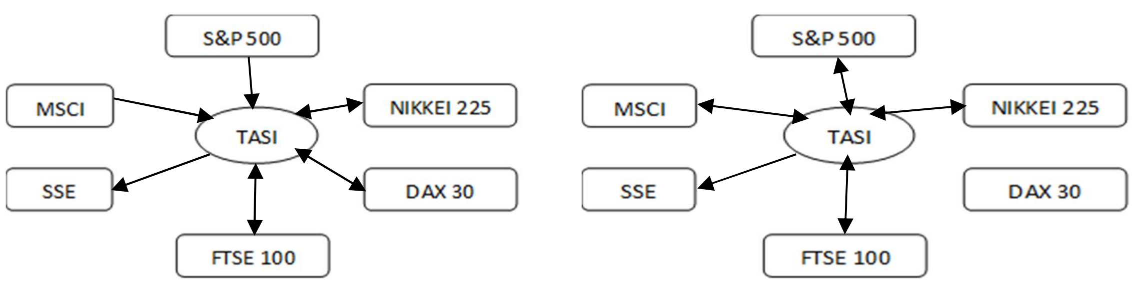
As shown for the GFC period in Table 6.2, the diagonal parameter of A(1,1) is statistically significant at the 5% level for S&P 500, NIKKEI 225, SSE and MSCI; it is not statistically significant for DAX 30 and FTSE 100. For all global stock markets, the diagonal parameter of B(1,1) is statistically significant at the level of 1%. Conversely, the parameter of A(2,2) that captures an ARCH effect is statistically significant at the 5% level for NIKKEI 225, DAX 30, SSE and MSCI. Meanwhile, the B(2,2) parameter that captures a GARCH effect is statistically significant at the 1% level for the global stock market groups.

By examining matrix A, it can be observed that coefficient A(1,2) reflects the overall cross-market effect of TASI shock spillover on global stock markets. These coefficient effects are statistically significant for NIKKEI 225 and FTSE 100 at the 1% level and for DAX 30 and SSE at the 10% level. In contrast, coefficient A(2,1) is statistically significant at the 1% level for S&P 500, NIKKEI 225, FTSE 100 and MSCI and at the 10% level for DAX 30, revealing that cross-market spillover shocks from global stock markets to TASI have a strong ARCH effect. Since the impact of shock spillover is used to examine the short-term effects of change from the last period (previous day), it should be realised that TASI is largely influenced by the effect of the previous period of most global stock markets during the GFC period.

Moving to another aspect of the cross-market spillover effect of volatility, which is captured by the off-diagonal parameters of matrix B, coefficient B(1,2) reveals TASI's overall volatility spillover effect on the global stock markets. For almost all samples throughout the GFC period, their coefficients are statistically significant, except for DAX 30 for which it is statistically insignificant. In the opposite direction, coefficient B(2,1) explores the spillover effect of volatility from global stock markets to TASI. This effect has been mainly heavy for all groups, indicating there is a strong GARCH effect, except for DAX 30 and SSE where the effects were insignificant during the GFC period. These results confirm that although the effects were heterogeneous, the GFC of 2008 affected most markets worldwide. These results correspond with those of the current literature, showing that the crisis was transmitted to other countries and led to increased market interconnections during the crisis (e.g. Mensi, 2019; Rejeb, 2017; G.-J. Wang et al., 2016; Wu, 2020; D. Zhang & Broadstock, 2020).

Figure 6.2: Dynamic Linkages of TASI with Global Stock Markets during the GFC Period, 1 January 2008 – 30 June 2009

Shock Transmission Volatility Transmission



Notes: The symbols '→' and '←' indicate unidirectional shock or volatility transmission, while '↔' indicates bidirectional shock or volatility transmission.

The findings of Table 6.2 and Figure 6.2 show bidirectional spillover shocks between TASI and NIKKEI 225, DAX 30 and FTSE 100. These also indicate unidirectional spillover shocks from S&P 500 and MSCI to TASI and from TASI to SSE. In the GFC period, DAX 30 being the only exception, the findings show bidirectional volatility spillover between TASI and S&P 500, NIKKEI 225, FTSE 100 and MSCI. Coefficient B(1,2) indicates a unidirectional volatility spillover from TASI to SSE. These findings agree with the results of W. Zhang et al. (2019) because S&P 500 and TASI have a bidirectional volatility spillover during the GFC period.

Table 6.2: Results of Linkages of TASI with Global Stock Markets for the GFC Period

	BEKK-GARCH Model Estimations					
	Global Stock Markets					
	S&P 500	NIKKEI 225	DAX 30	FTSE 100	SSE	MSCI
A(1,1)	0.195***	0.224**	0.129	0.122	0.304***	0.220***
	(0.057)	(0.110)	(0.134)	(0.082)	(0.046)	(0.059)
A(1,2)	−0.117	0.302***	−0.189*	−0.180***	0.068*	−0.106
	(0.072)	(0.065)	(0.111)	(0.059)	(0.037)	(0.066)
A(2,1)	0.316***	−0.171***	0.280*	0.445***	−0.049	0.377***
	(0.050)	(0.055)	(0.158)	(0.137)	(0.031)	(0.069)
A(2,2)	0.092	0.112**	0.263***	0.084	0.138***	0.202***
	(0.071)	(0.051)	(0.081)	(0.162)	(0.037)	(0.056)
B(1,1)	0.927***	0.903***	0.920***	0.806***	0.950***	0.923***
	(0.022)	(0.023)	(0.060)	(0.056)	(0.011)	(0.025)
B(1,2)	0.191***	−0.087*	0.009	−0.102**	−0.015**	0.136***
	(0.044)	(0.046)	(0.049)	(0.048)	(0.007)	(0.049)
B(2,1)	−0.140***	0.127***	0.006	0.192***	0.004	−0.165***
	(0.028)	(0.031)	(0.038)	(0.040)	(0.005)	(0.050)
B(2,2)	0.909***	0.954***	0.957***	1.000***	0.988***	0.903***
	(0.024)	(0.028)	(0.029)	(0.018)	(0.005)	(0.034)

Notes: Coefficients of multivariate GARCH-BEKK models A and B, respectively, capture the ARCH and GARCH effects. Figures in parentheses indicate std error values. ***, ** and * indicate rejection of the null hypothesis at the 1%, 5% and 10% significance levels, respectively.

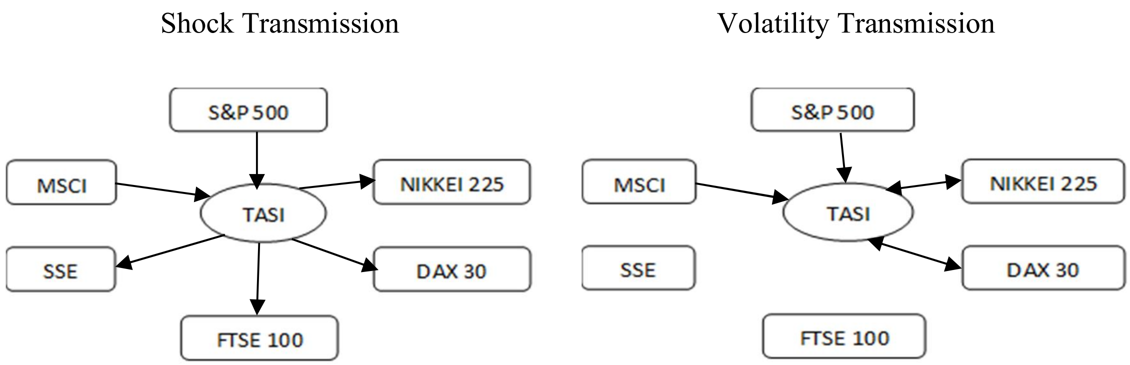
6.2.2.3 Oil Decline Period (July 2014 – January 2016)

As shown for the oil decline period in Table 6.3, all diagonal parameters of A(1,1) and B(1,1) are statistically significant at the 1% level for all global stock markets. These findings show the ARCH and GARCH effects on TASI. Meanwhile, for all global stocks, A(2,2) that captures an ARCH impact and B(2,2) that captures a GARCH effect, are statistically significant at the 5% and 1% levels, respectively.

By illustrating the A matrix, the overall TASI coefficient A(1,2) reveals the effect of shock spillovers to global stock markets. During the oil decline period, the results for NIKKEI 225, DAX 30 and FTSE 100 are statistically significant at the 1% level, while that for SSE is significant at the 10% level, thus indicating a strong ARCH effect of shocks from TASI to some global stock markets. In contrast, the findings of coefficient A(2,1) show the spillover shocks from global stock markets (S&P 500 and MSCI) to TASI and are statistically significant at the 1% level during the oil decline period. Since the impact of shock spillover tests the short-term effects of transition from the last period (previous day), it can be noted that TASI is affected by the spillover shocks effect of the previous day of S&P 500 and MSCI. Conversely, the off-diagonal parameters of matrix B capture the spillover effect of volatility in the oil decline period. Coefficient B(1,2) provides the spillover effect of TASI's volatility on the global stock markets and is statistically insignificant for most global stocks but is statistically significant for NIKKEI 225 and DAX 30 at the 1% level. Coefficient B(2,1) captures the spillover effect of volatility from global stock markets to TASI, and most groups are statistically significant at the 1% level, meaning there is a strong GARCH effect.

Regarding the global stock markets, the results show that Saudi Arabia's stock market was mostly not integrated with global stock markets in the full period, which is in line with the results of Jouini (2015) and Panda et al. (2019). However, the results do reveal that some global stock markets were integrated with TASI during the GFC and oil decline periods. Therefore, investors benefit by diversifying the risk of their portfolios in TASI.

Figure 6.3: Dynamic Linkages of TASI with Global Stock Markets during the Oil Decline Period, 1 July 2014 – 29 January 2016



Note: The symbols '→' and '←' indicate unidirectional shock or volatility transmission, while '↔' indicates bidirectional shock or volatility transmission

The results of Table 6.3 and Figure 6.3 show unidirectional spillover shocks to NIKKEI 225, DAX 30, FTSE 100 and SSE from TASI and from the S&P 500 and MSCI to TASI. Moreover, the findings reveal that there was bidirectional volatility spillover between TASI and both NIKKEI 225 and DAX 30 during the oil decline period. In addition, unidirectional volatility spillovers from the S&P 500 and MSCI affected TASI in this period.

Such outcomes are consistent with the CCF model in Chapter 5 that confirmed the existence of causality in variance arising from the global markets of S&P 500, NIKKEI 225 and FTSE 100 to the Saudi stock market. The key results of this chapter recommend that during the oil decline phase the Saudi stock market was integrated with global stock markets (S&P 500, NIKKEI 225 and FTSE 100), where their volatilities contributed to TASI's volatility. However, the effect of the Saudi stock market on the global stock markets was minimal because of the size of the global stock markets.

Table 6.3: Results of Linkages of TASI with Global Stock Markets for the Oil Decline Period

	BEKK-GARCH Model Estimations					
	Global Stock Markets					
	S&P 500	NIKKEI 225	DAX 30	FTSE 100	SSE	MSCI
A(1,1)	0.350***	0.357***	0.411***	0.393***	0.429***	0.375***
	(0.050)	(0.065)	(0.057)	(0.084)	(0.059)	(0.094)
A(1,2)	−0.055	0.184***	0.235***	0.125***	−0.087*	−0.005
	(0.082)	(0.071)	(0.062)	(0.046)	(0.050)	(0.0520)
A(2,1)	0.502***	0.193	0.045	0.152	−0.012	0.595***
	(0.166)	(0.145)	(0.057)	(0.098)	(0.046)	(0.155)
A(2,2)	0.285**	0.322**	0.163**	0.234**	0.322***	0.252***
	(0.124)	(0.147)	(0.073)	(0.091)	(0.043)	(0.084)
B(1,1)	0.906***	0.837***	0.636***	0.787***	0.830***	0.896***
	(0.025)	(0.033)	(0.113)	(0.222)	(0.051)	(0.033)
B(1,2)	0.051	−0.215***	0.485***	−0.017	0.064	0.035
	(0.057)	(0.049)	(0.123)	(0.060)	(0.039)	(0.025)
B(2,1)	−0.184***	0.220***	0.473***	−0.025	0.016	−0.222***
	(0.054)	(0.073)	(0.153)	(0.174)	(0.012)	(0.065)
B(2,2)	0.883***	0.935***	−0.647***	0.914***	0.949***	0.902***
	(0.104)	(0.038)	(0.165)	(0.078)	(0.012)	(0.038)

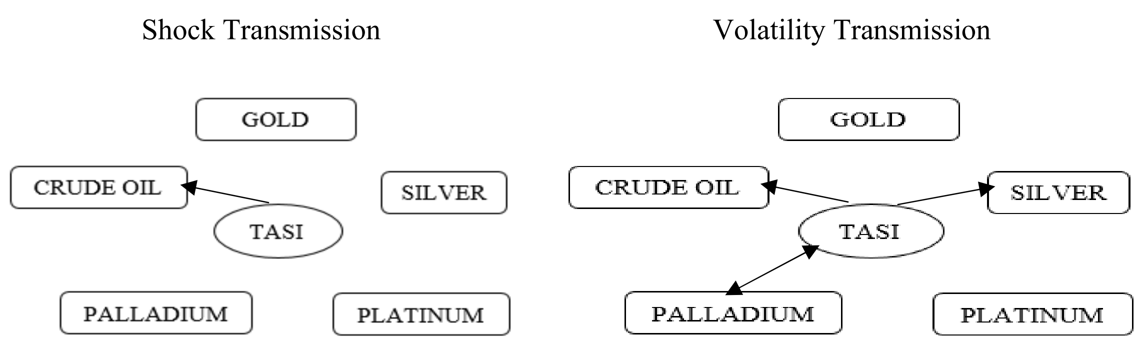
Notes: Coefficients of multivariate GARCH-BEKK models A and B, respectively, capture the ARCH and GARCH effects. Figures in parentheses indicate std error values. ***, ** and * indicate rejection of the null hypothesis at the 1%, 5% and 10% significance levels, respectively.

6.2.3 Volatility Transmission Effect between TASI and Major Commodity Markets

6.2.3.1 Full Period (2007–2018)

For the major commodity markets, first, coefficients A(1,1) and A(2,2) are estimated to examine the shock spillovers to ascertain how they are transmitted. The results are presented in Table 6.4. These coefficients can capture the effects of past shocks of each market on the current volatility. They are statistically significant at the 1% level for all major commodity markets during the full period, which leads to the conclusion that there are ARCH effects. In this way, TASI, crude oil and all the precious metals (gold, silver, palladium and platinum) wield a strong ARCH effect. The conditional variances of the major commodity markets are substantially affected by their own lagged shocks. The results for coefficient A(1,2) show significant transmission of shock spillovers at the 10% level from TASI to crude oil. Thus, past shocks in TASI have significant effects in the short term on the market's volatility to crude oil over the sample period. Conversely, since the coefficients of A(2,1) are statistically insignificant, there is no effect of shock volatility spillover from the major commodities to TASI during the examined period. These findings demonstrate a unidirectional shocks spillover from TASI to crude oil, as shown in Figure 6.4. The findings are consistent with those of Ashfaq et al. (2019) because shock spillover was transmitted from the stock market of Saudi Arabia to crude oil during the full period.

Figure 6.4: Dynamic Linkages of TASI with Major Commodity Markets during the Full Period, 1 January 2007 – 31 December 2018



Note: The symbols '→' and '←' indicate unidirectional shock or volatility transmission, while '↔' indicates bidirectional shock or volatility transmission.

Second, this thesis analyses the volatility spillovers dependent on the coefficients of matrix B, investigate how they are transmitted and then estimate B(1,1) and B(2,2). These coefficients can capture the effects of the past volatility of each market on the present volatility. The values for all major commodity markets during the full period are statistically significant at the 1% level, which means there are GARCH effects. This result confirms that the GARCH effect is strong in TASI, crude oil and all precious metals (gold, silver, palladium and platinum). Further, their own lagged volatility is greatly affected by the conditional variances of these major commodities. Moreover, the volatility spillovers from TASI affect some major commodity markets because the coefficients of B(1,2) are statistically significant for crude oil, palladium and silver at the 1%, 5% and 10% levels, respectively. In the opposite direction, coefficient B(2,1) shows no statistical evidence of volatility spillover effect on TASI from major commodity markets except that it is significant at the 5% level for palladium. The findings noted in Table 6.4 and Figure 6.4 demonstrate a bidirectional volatility spillover between TASI and palladium. There was a unidirectional volatility spillover from TASI to crude oil and silver. With reference to gold, the findings are in line with those of Afsal and Haque (2016) because there was no transmission of shock and volatility spillover from gold to the Saudi stock market or vice versa during the period of full or GFC.

Table 6.4: Results of Linkages of TASI with Major Commodity Markets for the Full Period

	BEKK-GARCH Model Estimations				
	Major Commodity Markets				
	CRUDE OIL	GOLD	SILVER	PALLADIUM	PLATINUM
A(1,1)	0.370***	0.339***	0.353***	0.276***	0.347***
	(0.034)	(0.025)	(0.027)	(0.051)	(0.028)
A(1,2)	−0.069*	−0.000	0.039	−0.349	0.011
	(0.039)	(0.013)	(0.029)	(0.275)	(0.019)
A(2,1)	−0.017	−0.030	0.010	0.020	−0.027
	(0.045)	(0.029)	(0.011)	(0.030)	(0.043)
A(2,2)	0.188***	0.192***	0.141***	0.483**	0.183***
	(0.019)	(0.025)	(0.019)	(0.203)	(0.021)
B(1,1)	0.924***	0.933***	0.930***	0.958***	0.931***
	(0.014)	(0.009)	(0.010)	(0.015)	(0.010)
B(1,2)	0.051***	0.004	−0.022*	0.119**	−0.001
	(0.020)	(0.005)	(0.013)	(0.051)	(0.007)
B(2,1)	0.000	0.003	0.001	−0.016**	0.003
	(0.009)	(0.006)	(0.003)	(0.007)	(0.007)
B(2,2)	0.975***	0.978***	0.989***	0.876***	0.980***
	(0.004)	(0.005)	(0.003)	(0.064)	(0.004)

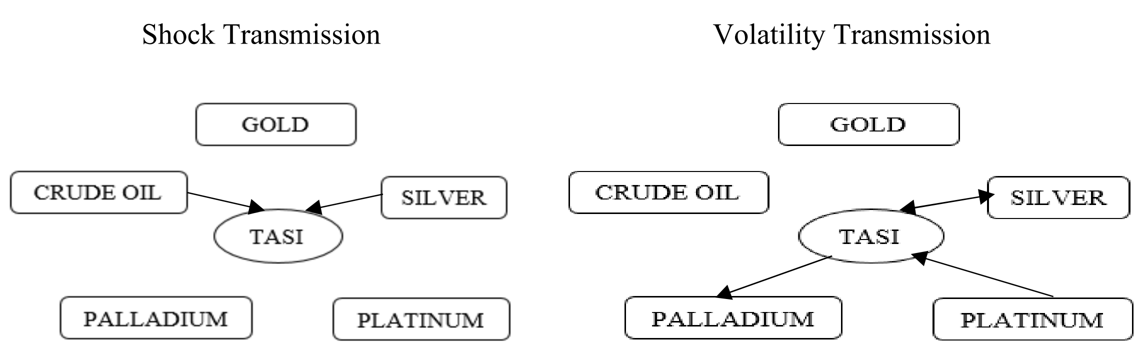
Notes: Coefficients of multivariate GARCH-BEKK models A and B, respectively, capture the ARCH and GARCH effects. Figures in parentheses indicate std error values. ***, ** and * indicate rejection of the null hypothesis at the 1%, 5% and 10% significance levels, respectively.

6.2.3.2 GFC Period (January 2008 – June 2009)

Next, this thesis explores for spillover mechanisms between TASI and other major commodity markets during the GFC period based on the matrix A off-diagonal coefficients. Here, it specifically investigates the transmission of shocks of coefficients A(1,1) and A(2,2). These coefficients can capture the effect of past shocks of each market on present volatility. All coefficients for the major commodity markets are statistically significant, mostly at the 1% level, which means there is a strong ARCH effect. Since all major commodity markets have an ARCH effect, their conditional volatility is influenced by their lagging shocks.

These findings regarding coefficient A(1,2) indicate no shocks spillover between TASI and all major commodity markets during the GFC period. However, during the assessed period, the A(2,1) coefficients of silver and crude oil are statistically significant at the 1% and 5% levels, respectively. This means that past shocks of crude oil and silver have affected TASI volatility for a short period. Further, the tabulated findings demonstrate that TASI was affected by unidirectional shocks spillovers from crude oil and silver during the GFC period.

Figure 6.5: Dynamic Linkages of TASI with Major Commodity Markets during the GFC Period, 1 January 2008 – 30 June 2009



Note: The symbols '→' and '←' indicate unidirectional shock or volatility transmission, while '↔' indicates bidirectional shock or volatility transmission

Then, the volatility spillovers based on matrix B off-diagonal coefficients are assessed. The evaluation and estimation of B(1,1) and B(2,2) coefficients can show the transmission of volatility spillover. The parameters reflect the influence of past market volatility on current volatility. The coefficients for all major commodity markets during the periods of the GFC and oil decline are statistically significant at the 1% level%, indicating that there are GARCH effects. This result also confirms that the impact of GARCH on TASI, crude oil and all precious metals (gold, silver, palladium and platinum) is strong. Further, the conditional variances of major commodities significantly influence their own lagged volatility.

In this thesis, the B(1,2) coefficients for the spillovers of volatility in major commodity markets during the GFC are considered statistically insignificant other than for silver and palladium, which are statistically significant at the1% level. This suggests that GARCH effects exist. Similarly, the B(2,1) coefficients provide no statistical proof of the impact of volatility spillover on TASI from major commodities except that it is statistically significant for silver and platinum at the 1% level. The findings reveal a spillover of bidirectional volatility between TASI and silver. Further, there was a unidirectional volatility spillover from TASI to palladium and from platinum to TASI during the GFC period.

Table 6.5: Results of Linkages of TASI with Major Commodity Markets for the GFC Period

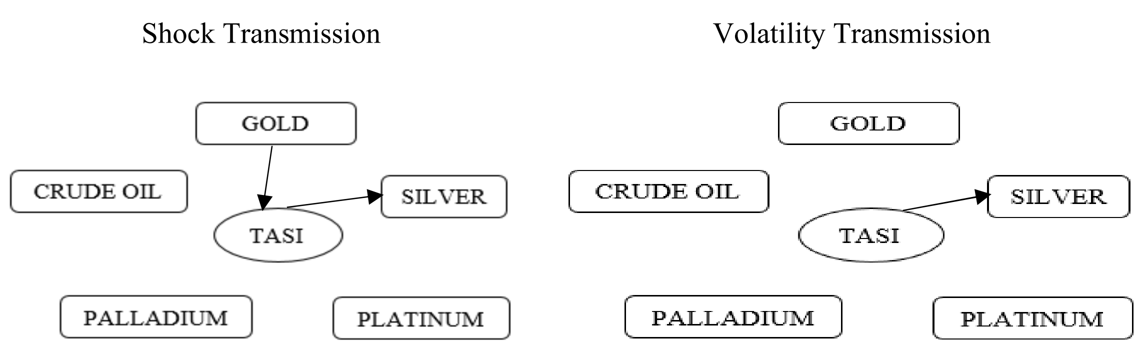
	BEKK-GARCH Model Estimations				
	Major Commodity Markets				
	CRUDE OIL	GOLD	SILVER	PALLADIUM	PLATINUM
A(1,1)	0.206**	0.301***	0.270***	0.315***	0.301***
	(0.101)	(0.040)	(0.085)	(0.042)	(0.050)
A(1,2)	0.112	0.086	−0.108	−0.028	0.066
	(0.147)	(0.060)	(0.085)	(0.109)	(0.063)
A(2,1)	−0.071**	0.064	0.175***	0.001	0.035
	(0.032)	(0.057)	(0.047)	(0.0049)	(0.038)
A(2,2)	0.364***	−0.196***	0.186***	0.322***	0.217***
	(0.059)	(0.047)	(0.067)	(0.082)	(0.036)
B(1,1)	0.960***	0.952***	0.935***	0.947***	0.956***
	(0.019)	(0.014)	(0.023)	(0.013)	(0.014)
B(1,2)	−0.043	0.008	0.071***	0.292***	0.001
	(0.054)	(0.017)	(0.023)	(0.107)	(0.016)
B(2,1)	0.037	−0.036	−0.062***	−0.006	−0.032***
	(0.023)	(0.035)	(0.016)	(0.016)	(0.003)
B(2,2)	0.925***	0.965***	0.964***	0.003	0.950***
	(0.020)	(0.015)	(0.010)	(0.044)	(0.010)

Notes: Coefficients of multivariate GARCH-BEKK models A and B, respectively, capture the ARCH and GARCH effects. Figures in parentheses indicate std error values. ***, ** and * indicate rejection of the null hypothesis at the 1%, 5% and 10% significance levels, respectively.

6.2.3.3 Oil Decline Period (July 2014 – January 2016)

To examine the transmission volatility in the period of oil decline, first, this thesis explores whether there are spillover mechanisms between TASI and all major commodity markets. Then, it analyses the shocks and volatility spillovers, depending on the importance of the off-diagonal coefficients in matrices A and B. First, it explores the spillover shocks of all major commodity markets, relying on conditional variance, finding that the A(1,1) and A(2,2) coefficients are statistically significant for other commodities but insignificant for gold and silver. This result indicates a strong ARCH effect for most commodity groups and implies their own lag of shocks significantly influence the conditional volatility of these markets. The tabulated results for A(1,2) coefficients show no shock transmission from TASI to major commodities, except for silver, for which it is statistically significant at the 10% level. It means previous shocks of TASI influenced the market volatility of silver during the fluctuation period of oil decline. Similarly, there is no impact of commodities shock spillover on TASI since the coefficients of A(2.1) are insignificant other than that for gold, which is statistically significant at the 1% level. It means previous shocks of gold influenced the market volatility of TASI in the oil decline period. These findings show unidirectional spillovers shock from gold to TASI and from TASI to silver.

Figure 6.6: Dynamic Linkages of TASI with Major Commodity Markets during the Oil Decline Period, 1 July 2014 – 29 January 2016



Notes: The symbols '→' and '←' indicate unidirectional shock or volatility transmission.

Next, the spillover volatility is further evaluated based on all conditional variances. Coefficients B(1,1) and B(2,2) of GARCH are statistically significant at the level of 1%

except for gold, which is negligible. Therefore, for most commodities, there is a strong GARCH impact, implying that their own lagged volatility greatly affects their own conditional volatility. Regarding volatility spillovers, this thesis finds that TASI's shifts in some specific major commodities cause volatility spillovers. This is despite coefficient B(1,2) showing no evidence of volatility spillover on major commodity markets except that it is statistically significant at 1% for silver. These results indicate volatility spillovers from TASI to silver. With the opposite effect, coefficients B(2,1) show no statistical proof of the volatility spillover effect from major commodities to TASI. The results indicate a unidirectional volatility spillover from TASI to silver. It is in line with the results of Mensi (2019) because there is no volatility spillover or shock between crude oil and TASI during the oil decline period.

Investors interest in gold as a safe haven increases when stock markets are volatile, which increases the demand to invest in safe assets (e.g. gold) and thus increases asset price volatility. This indicates a transmission between the stock markets and gold, given the increase in stock and commodity volatility during periods of extreme market shocks (Beber et al., 2009; Kiohos & Sariannidis, 2010). This explanation is somewhat consistent with the findings of shock transmission in this thesis. In this regard, Mensi, Hammoudeh et al. (2015) concluded that gold does much better as a safe haven for GCC countries' stock markets.

Table 6.6: Results of Linkages of TASI with Major Commodity Markets for the Oil Decline Period

	BEKK-GARCH Model Estimations				
	Major Commodity Markets				
	CRUDE OIL	GOLD	SILVER	PALLADIUM	PLATINUM
A(1,1)	0.439***	0.401***	0.455***	0.418***	0.375***
	(0.071)	(0.055)	(0.071)	(0.085)	(0.104)
A(1,2)	0.048	0.043	0.122*	0.001	−0.003
	(0.197)	(0.051)	(0.064)	(0.077)	(0.033)
A(2,1)	0.002	−0.619***	0.139	0.177	0.300
	(0.056)	(0.187)	(0.139)	(0.152)	(0.265)
A(2,2)	0.207**	−0.053	0.027	0.353**	0.181*
	(0.092)	(0.368)	(0.065)	(0.158)	(0.101)
B(1,1)	0.832***	0.858***	0.782***	0.854***	0.849***
	(0.075)	(0.035)	(0.092)	(0.065)	(0.082)
B(1,2)	0.071	−0.023	−0.130***	0.028	0.017
	(0.089)	(0.049)	(0.046)	(0.053)	(0.023)
B(2,1)	0.001	0.201	0.018	−0.075	0.039
	(0.016)	(0.239)	(0.031)	(0.057)	(0.079)
B(2,2)	0.952***	0.260	0.983***	0.920***	0.952***
	(0.031)	(0.649)	(0.022)	(0.067)	(0.045)

Notes: Coefficients of multivariate GARCH-BEKK models A and B, respectively, capture the ARCH and GARCH effects. Figures in parentheses indicate std error values. ***, ** and * indicate rejection of the null hypothesis at the 1%, 5% and 10% significance levels, respectively.

6.3 Diagnostic Test of Multivariate GARCH Models

The diagnostic tests for the Q-statistic values of MGARCH (1,1) models shown in Tables 6.7–9 confirm that there is no autocorrelation of the null hypothesis (also known as serial correlation), which means it cannot be rejected. Therefore, for modelling the volatility transmission and conditional correlation between global stock and major commodity markets, there is no evidence of misspecification of the estimated models, which means these are properly stated. Thus, this thesis can proceed to develop optimal portfolio weights and hedge ratios from the estimated chosen models of GARCH-BEKK and -DCC.

Table 6.7: Diagnostics Tests of Standardised Residuals for Global Stock and Major Commodity Markets for the Full Period

Panel A: Global Stock Markets

	BEKK		CCC		DCC	
	$Q(20)r$	$Q(20)r^2$	$Q(20)r$	$Q(20)r^2$	$Q(20)r$	$Q(20)r^2$
TASI	21.823	7.451	22.610	7.816	22.934	8.014
	(0.350)	(0.994)	(0.308)	(0.993)	(0.292)	(0.991)
S&P 500	28.872	27.191	28.506	17.586	28.374	16.118
	(0.090)	(0.129)	(0.097)	(0.614)	(0.100)	(0.709)
NIKKEI 225	13.835	28.977	15.190	14.859	16.391	35.519
	(0.838)	(0.088)	(0.765)	(0.784)	(0.692)	(0.017)
DAX 30	17.235	33.448	15.901	13.626	16.083	13.753
	(0.637)	(0.030)	(0.722)	(0.848)	(0.711)	(0.842)
FTSE 100	11.741	36.182	10.906	19.645	11.357	20.080
	(0.924)	(0.014)	(0.948)	(0.480)	(0.936)	(0.452)
SSE	34.201	42.849	33.494	30.314	33.489	30.156
	(0.024)	(0.002)	(0.029)	(0.064)	(0.029)	(0.067)
MSCI	20.524	30.211	19.471	15.799	19.694	15.884
	(0.425)	(0.066)	(0.491)	(0.729)	(0.477)	(0.723)

Panel B: Major Commodity Markets

CRUDE OIL	11.120	42.523	13.145	18.490	13.615	18.760
	(0.943)	(0.002)	(0.871)	(0.555)	(0.849)	(0.537)
GOLD	16.466	10.901	16.450	13.086	16.463	13.098
	(0.687)	(0.948)	(0.688)	(0.873)	(0.687)	(0.873)
SILVER	20.326	50.025	17.919	23.761	17.912	23.772
	(0.437)	(2.19e-04)	(0.592)	(0.252)	(0.593)	(0.252)
PALLADIUM	10.904	0.314	8.192	6.177	8.185	6.129
	(0.948)	(1.000)	(0.990)	(0.998)	(0.990)	(0.998)
PLATINUM	18.699	18.172	18.477	10.122	18.476	10.136
	(0.541)	(0.576)	(0.555)	(0.965)	(0.556)	(0.965)

Note: The Ljung–Box test statistics show the residuals of standardised Q(20)r and squared standardised Q(20)r^2 up to 20 lags.

Table 6.8: Diagnostics Tests of Standardised Residuals for Global Stock and Major Commodity Markets for the GFC Period

Panel A: Global Stock Markets

	BEKK		CCC		DCC	
	$Q(20)r$	$Q(20)r^2$	$Q(20)r$	$Q(20)r^2$	$Q(20)r$	$Q(20)r^2$
TASI	26.402	15.275	24.152	24.720	24.101	24.779
	(0.152)	(0.760)	(0.235)	(0.212)	(0.237)	(0.210)
S&P 500	17.181	33.069	14.702	28.114	14.760	28.369
	(0.641)	(0.033)	(0.793)	(0.106)	(0.789)	(0.100)
NIKKEI 225	12.135	51.820	13.365	50.468	13.288	51.566
	(0.911)	(1.20e-04)	(0.861)	(1.89e-04)	(0.864)	(1.31e-04)
DAX 30	23.612	26.976	21.661	20.835	21.744	20.439
	(0.259)	(0.135)	(0.359)	(0.406)	(0.354)	(0.430)
FTSE 100	26.939	20.323	23.683	16.918	23.529	17.012
	(0.136)	(0.437)	(0.256)	(0.658)	(0.263)	(0.652)
SSE	28.529	17.014	29.215	17.343	28.680	16.943
	(0.097)	(0.652)	(0.083)	(0.630)	(0.094)	(0.656)
MSCI	22.942	30.974	18.800	35.046	18.588	35.019
	(0.291)	(0.055)	(0.534)	(0.019)	(0.548)	(0.020)

Panel B: Major Commodity Markets

CRUDE OIL	20.141	22.366	17.140	28.800	17.676	25.465
	(0.449)	(0.320)	(0.643)	(0.091)	(0.608)	(0.184)
GOLD	20.827	8.792	23.592	12.731	23.592	12.731
	(0.407)	(0.985)	(0.260)	(0.888)	(0.260)	(0.888)
SILVER	18.832	26.409	22.422	26.827	22.420	26.899
	(0.532)	(0.152)	(0.318)	(0.140)	(0.318)	(0.138)
PALLADIUM	10.377	0.908	7.407	1.813	7.369	1.872
	(0.960)	(1.000)	(0.995)	(1.000)	(0.995)	(1.000)
PLATINUM	19.643	24.823	21.854	21.087	21.901	20.921
	(0.480)	(0.208)	(0.348)	(0.391)	(0.345)	(0.401)

Note: The Ljung–Box test statistics show the residuals of standardised Q(20)r and squared standardised Q(20)r^2 up to 20 lags.

Table 6.9: Diagnostics Tests of Standardised Residuals for Global Stock and Major Commodity Markets for the Oil Price Decline Period

Panel A: Global Stock Markets

	BEKK		**CCC**		**DCC**	
	$Q(20)r$	$Q(20)r^2$	$Q(20)r$	$Q(20)r^2$	$Q(20)r$	$Q(20)r^2$
TASI	11.354	17.507	10.000	19.733	10.161	19.945
	(0.936)	(0.619)	(0.968)	(0.474)	(0.965)	(0.461)
S&P 500	6.707	33.805	7.118	12.531	7.311	12.558
	(0.997)	(0.027)	(0.996)	(0.896)	(0.995)	(0.895)
NIKKEI 225	18.077	26.943	16.867	21.367	16.871	21.335
	(0.582)	(0.136)	(0.661)	(0.375)	(0.661)	(0.377)
DAX 30	15.968	18.103	16.532	24.001	20.491	34.123
	(0.718)	(0.580)	(0.683)	(0.242)	(0.427)	(0.025)
FTSE 100	22.543	20.961	21.514	20.170	24.180	28.800
	(0.311)	(0.399)	(0.367)	(0.447)	(0.234)	(0.091)
SSE	19.142	18.538	19.802	18.768	19.809	18.770
	(0.512)	(0.552)	(0.470)	(0.536)	(0.469)	(0.536)
MSCI	17.304	20.719	16.921	17.696	17.786	47.226
	(0.633)	(0.413)	(0.658)	(0.607)	(0.601)	(5.45e-04)

Panel B: Major Commodity Markets

CRUDE OIL	9.561	20.598	10.893	8.342	10.895	8.336
	(0.975)	(0.421)	(0.948)	(0.989)	(0.948)	(0.989)
GOLD	18.637	33.230	19.434	27.758	19.428	27.745
	(0.545)	(0.031)	(0.493)	(0.115)	(0.494)	(0.115)
SILVER	27.385	27.847	27.162	23.500	27.602	22.731
	(0.124)	(0.113)	(0.130)	(0.264)	(0.119)	(0.302)
PALLADIUM	15.660	11.093	15.707	14.527	15.499	14.704
	(0.737)	(0.943)	(0.734)	(0.802)	(0.747)	(0.793)
PLATINUM	35.916	12.269	28.216	8.987	41.052	22.874
	(0.015)	(0.906)	(0.104)	(0.983)	(0.003)	(0.294)

Note: The Ljung–Box test statistics show the residuals of standardised Q(20)r and squared standardised Q(20)r^2 up to 20 lags.

6.4 Conditional Correlation: TASI and Global Stock and Major Commodity Markets

6.4.1 Introduction

First, the effects of the constant conditional correlation (CCC) were used by applying the CCC-GARCH (1,1) model. The results are presented in Tables 6.10–12 for all periods. According to the structure devised by Bollerslev (1990), the CCC model is assumed to be in an MGARCH setting where the terms of variance–covariance over time are constant. The ideal basis is to approximate the CCC-GARCH model since it ensures a favourable understanding of the covariance matrix and prevents computational difficulty. Second, by following the structure devised by Engle (2002), the dynamic conditional correlation (DCC) is another type of analysis conducted for estimating the parameters of the DCC-GARCH (1,1) model, which are the DCC(A) and DCC(B), corresponding to the dynamic correlation between TASI and the global stock and major commodity markets. The results of the implemented DCC-GARCH (1,1) model are outlined below in Tables 6.10–12 and Figures 6.7–8.

Figures 6.7–8 indicate the dynamic conditional correlation for the link between TASI and global stocks and between TASI and major commodities. The time-varying correlations tend to be volatile over time, suggesting it may be inappropriate to focus on constant conditional correlations for estimating the optimal weights and hedge ratios. In the case of time-varying correlation, the DCC model estimation is used to build the optimal weights and hedge ratios. However, the correlation between the two examined markets varies significantly across the times of crisis/shock (see Figures 6.7–8). These results are similar to those of the empirical studies by Arouri, Jouini and Nguyen (2011) and Kang et al. (2017), which indicated that the correlation between global stocks and major commodities varies across the periods of crisis/shock.

6.4.2 Full Period (2007–2018)

First, Table 6.10 (Panels A and B) reveals the CCC parameters between TASI – global stocks and TASI – major commodities. The CCC-GARCH (1,1) model is a constant co-movement in all global stocks and statistically significant at the level of 1%. The lowest correlation value between TASI and global stocks is for SSE since its coefficient is 0.110, while the highest correlation value is for MSCI because its coefficient is almost 0.227. In the same way, the values for all major commodities are statistically significant at the level of 1%, while that for gold is statistically significant at 10%. The lowest correlation value between TASI and major commodities is for gold since its coefficient is 0.031, while the highest correlation value is for crude oil because its coefficient is almost 0.148. Indeed, the constant conditional correlation between TASI and global stock/major commodity markets is confirmed for the full period.

Second, Table 6.10 (Panel A) also contains the DCC estimation results for TASI and global stocks. The DCC parameters in the full period for global stock markets are statistically significant at least at the level of 10%, which means the conditional correlations vary over time between TASI and those global stocks. The summation of the coefficients of DCC(A) and DCC(B) is close to 1, which means that the position is very persistent with TASI, and it suggests there are high chances of there being time-varying conditional correlation. On the other side of major commodity markets, the results in the same table (Panel B) show the estimation for the DCC model between TASI and major commodity markets for the full period. The coefficients for all samples are statistically significant at the level of 1% for time-varying volatility except for silver, for which it is statistically insignificant, indicating that the sum of the DCC(A) and DCC(B) coefficients is close to 1. So, there is a time-varying conditional correlation or volatility between the examined samples. These results for crude oil and gold are consistent with the results of Mensi et al. (2014), who concluded that the highest time-varying conditional correlations are between stocks and gold and crude oil. Further, the highest average conditional correlation was between TASI and crude oil because Saudi Arabia is considered the largest oil-rich country and the most important OPEC member (Mensi, 2019; Mensi, Hammoudeh, & Kang, 2015; Mohanty et al., 2018;). In the full period, high persistent volatility was observed for all the combinations of TASI with global stocks and major commodities because the high sum of the DCC(A) and DCC(B) coefficients are very close to 1 (see Table 6.10, Panels A and B).

Table 6.10: Results of Linkages of TASI with Global Stocks and Major Commodities for the Full Period

	Estimation of CCC- and DCC-GARCH Models					
	Panel A: **Global Stock Markets**					
	S&P 500	NIKKEI 225	DAX 30	FTSE 100	SSE	MSCI
R(2,1)	0.188***	0.180***	0.212***	0.210***	0.110***	0.228***
	(0.017)	(0.015)	(0.016)	(0.014)	(0.019)	(0.016)
DCC(A)	0.023***	0.021***	0.011*	0.019***	0.008*	0.015***
	(0.003)	(0.000)	(0.005)	(0.003)	(0.004)	(0.004)
DCC(B)	0.000	0.829***	0.979***	0.973***	0.973***	0.975***
	(0.327)	(0.083)	(0.011)	(0.004)	(0.011)	(0.006)

	Panel B: **Major Commodity Markets**				
	CRUDE OIL	GOLD	SILVER	PALLADIUM	PLATINUM
R(2,1)	0.148***	0.032*	0.084***	0.112***	0.109***
	(0.015)	(0.016)	(0.017)	(0.016)	(0.014)
DCC(A)	0.011	0.004	0.046	0.013	0.002
	(0.007)	(0.007)	(0.220)	(0.014)	(0.005)
DCC(B)	0.982***	0.890***	0.389	0.971***	0.846***
	(0.009)	(0.053)	(1.461)	(0.022)	(0.076)

Notes: Coefficients of multivariate GARCH-CCC and DCC models, R(2,1), DCC(A) and DCC(B), indicate, respectively, the constant and dynamic conditional correlations. Figures in parentheses indicate std error values. *, ** and *** indicate rejection of the null hypothesis at the 1%, 5% and 10% levels, respectively.

6.4.3 GFC Period (January 2008 – June 2009)

First, for the GFC period, the CCC parameters between TASI and the global stock and major commodity markets are presented in Table 6.11 (Panels A and B). The CCC-GARCH (1,1) model confirms a CCC in all markets' indexes and statistical significance at the level of 1%. NIKKEI 225 and MSCI have the largest coefficient values of 0.315, while SSE had the lowest correlation with TASI since its coefficient value is 0.141. However, some major commodities in this period, such as gold and silver, had a non-constant correlation with TASI, as indicated by the statistically insignificant coefficient values. Meanwhile, the values for crude oil, platinum and palladium are statistically significant at the level of 1%, 5% and 10%, respectively. Crude oil had the highest correlation with TASI among major commodities because its coefficient value is 0.183, while platinum had the lowest correlation, with a coefficient value of 0.125. Therefore, the CCC between TASI and global stocks and some major commodities is supported.

Second, Table 6.11 (Panel A) summarises the estimations of the DCC model between TASI and global stock markets for the GFC period. All parameters reveal a statistical significance of 1% apart from those for S&P 500, FTSE 100 and MSCI, which are statistically insignificant. They are very close to 1, suggesting there is a time-varying conditional correlation between those significant samples. The same table (Panel B) shows the DCC parameters between TASI and major commodity markets. The estimated coefficients of the correlation equation are all statistically insignificant except that of palladium and platinum, which are statistically significant at the level of 5% and 1%, respectively. This result reveals that conditional correlations are not constant, reflecting the influence of the current co-movement and the existence of time-varying correlations. Nonetheless, the insignificant correlation of gold with TASI implies that gold was irrelevant to TASI during the GFC period (this result was confirmed for the oil decline period also). In addition, the volatility spillover results of Tables 6.5 and 6.6 also confirm the lack of a relationship between TASI and gold for both periods. These results are in line with other researchers' findings (Baur & McDermott, 2010; Creti et al., 2013; Urom et al., 2019), which confirm the important position of gold as a hedging tool during the periods of declining stock markets. In general, this finding demonstrates that despite the periods of market volatility, the GFC and oil decline periods have played a vital role in re-establishing the function of gold as a hedge for the portfolios of the holders of global stocks/major commodities.

Table 6.11: Results of Linkages of TASI with Global Stocks and Major Commodities for the GFC Period

	Estimation of CCC- and DCC-GARCH Models					
	Panel A: **Global Stock Markets**					
	S&P 500	NIKKEI 225	DAX 30	FTSE 100	SSE	MSCI
R(2,1)	0.282***	0.314***	0.297***	0.272***	0.142***	0.316***
	(0.046)	(0.048)	(0.046)	(0.041)	(0.044)	(0.046)
DCC(A)	0.000	0.023*	0.036	0.005	0.0109	0.014
	(0.054)	(0.012)	(0.033)	(0.029)	(0.0132)	(0.030)
DCC(B)	0.189	0.966***	0.819***	0.522	0.8411***	0.614
	(3.983)	(0.015)	(0.094)	(0.354)	(0.083)	(0.507)

	Panel B: **Major Commodity Markets**				
	CRUDE OIL	GOLD	SILVER	PALLADIUM	PLATINUM
R(2,1)	0.183***	0.060	0.062	0.157*	0.125**
	(0.048)	(0.168)	(0.053)	(0.083)	(0.049)
DCC(A)	−0.008	0.037	0.059	0.147**	0.006
	(0.031)	(0.059)	(0.076)	(0.063)	(0.016)
DCC(B)	−0.050	0.499	0.484	0.498**	0.869***
	(2.814)	(0.777)	(0.625)	(0.201)	(0.078)

Notes: Coefficients of multivariate GARCH-CCC and DCC models, R(2,1), DCC(A) and DCC(B), indicate, respectively, the constant and dynamic conditional correlations. Figures in parentheses indicate std error values. *, ** and *** indicate rejection of the null hypothesis at the level of 1%, 5% and 10%, respectively.

6.4.4 Oil Decline Period (July 2014 – January 2016)

First, the parameters of CCC-GARCH (1,1) model represent the results for TASI and the global stock and major commodity markets during the oil decline period in Table 6.12 (Panels A and B). All groups of global stock markets reflect a CCC at a level of 1%. Moreover, the largest correlation in the global stock markets was for FTSE 100 and MSCI because their coefficient values equal 0.294, while the lowest correlation was for the SSE whose coefficient value is 0.135. However, in this period, some major commodities did not show constant correlation with TASI, such as gold and silver, whose coefficient values are statistically insignificant. Those for crude oil, palladium and platinum are statistically significant at least at the level of 5%. Crude oil had the largest correlation with TASI, with a coefficient of about 0.238, whereas that of platinum was the lowest with a coefficient of nearly 0.108. Thus, according to these results, there was CCC between TASI and global stocks and other major commodities.

Second, the coefficients of the DCC parameters between TASI and global stock markets are shown in Table 6.12 (Panel A). In fact, the estimated correlation coefficients are all statistically significant at the 1% level except that for FTSE 100, which is statistically insignificant, indicating the conditional correlation for all global stocks is not constant and influences the current co-movement. For the major commodity markets, the results provided in Panel B for the oil decline period indicate the estimations of DCC parameters between TASI and major commodities. The coefficients for crude oil, silver and platinum are statistically significant at the 1% level, and this is in line with time-varying volatility. Meanwhile, the coefficients for gold and palladium are statistically insignificant.

Table 6.12: Results of Linkages of TASI with Global Stocks and Major Commodities for the Oil Decline Period

	Estimation of CCC- and DCC-GARCH Models					
	Panel A: **Global Stock Markets**					
	S&P 500	NIKKEI 225	DAX 30	FTSE 100	SSE	MSCI
R(2,1)	0.259***	0.221***	0.247***	0.295***	0.135***	0.295***
	(0.046)	(0.040)	(0.056)	(0.055)	(0.050)	(0.045)
DCC(A)	0.025	0.001	0.237***	0.048	0.137***	0.009
	(0.043)	(0.013)	(0.019)	(0.033)	(0.019)	(0.017)
DCC(B)	0.858***	0.453***	0.083	0.000	0.500***	0.963***
	(0.094)	(0.001)	(0.077)	(0.293)	(0.059)	(0.054)

	Panel B: **Major Commodity Markets**				
	CRUDE OIL	GOLD	SILVER	PALLADIUM	PLATINUM
R(2,1)	0.238***	0.035	0.094	0.164***	0.109**
	(0.032)	(0.051)	(0.051)	(0.049)	(0.044)
DCC(A)	0.258***	−0.032	0.078***	0.125	−0.032***
	(0.071)	(0.000)	(0.000)	(0.133)	(0.000)
DCC(B)	0.498**	0.302	0.471***	0.471	0.323***
	(0.208)	(0.002)	(0.000)	(0.485)	(0.009)

Notes: Coefficients of multivariate GARCH-CCC and DCC models, R(2,1), DCC(A) and DCC(B), indicate, respectively, the constant and dynamic conditional correlations. Figures in parentheses indicate std error values. *, ** and *** indicate rejection of the null hypothesis at the level of 1%, 5% and 10%, respectively.

6.5 DCC Model Estimation Graphs

Figures 6.7–8 illustrate the estimated time-varying conditional correlations of TASI with global stock/major commodity markets for the whole sample period extracted from the DCC model. First, it can be observed the conditional correlations for all significant global stocks for the sample period examined are positive. Specifically, NIKKEI 225 and MSCI exhibited greater conditional correlation in periods of high volatility and lesser conditional correlation during periods of low volatility. Most global stock groups had the highest conditional correlations during the full period. Similarly, NIKKEI 225 and MSCI showed conditional correlation during the GFC and oil decline periods. The correlation between TASI and global stock markets varied significantly through much of the crisis/decline phases, which strongly indicates the relationship between them has become very volatile over time. So, in effect, there was no constant correlation. Second, the similarities in all significant major commodities are positive. Crude oil showed a conditional correlation not only during the whole sample period but also throughout the oil decline period, and platinum showed a correlation during the GFC period. Over most crisis/shock periods, the correlation between TASI and major commodities fluctuated partially, which is a strong indicator that the interaction between TASI and major commodity markets was somewhat volatile over time.

Figure 6.7: Dynamic Correlations of Global Stock Markets with TASI from 1 January 2007 to 31 December 2018, estimated based on the DCC-GARCH model

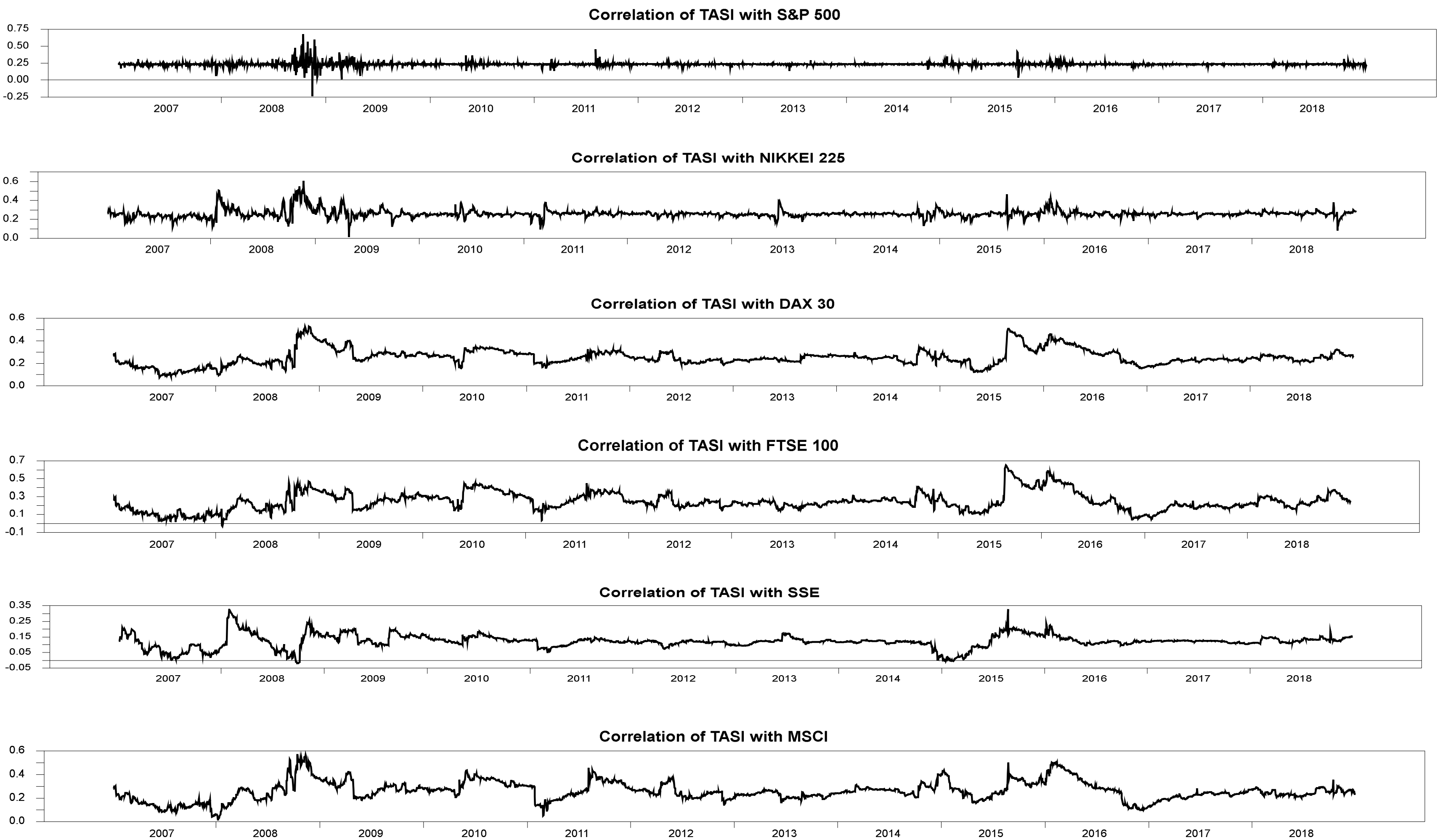
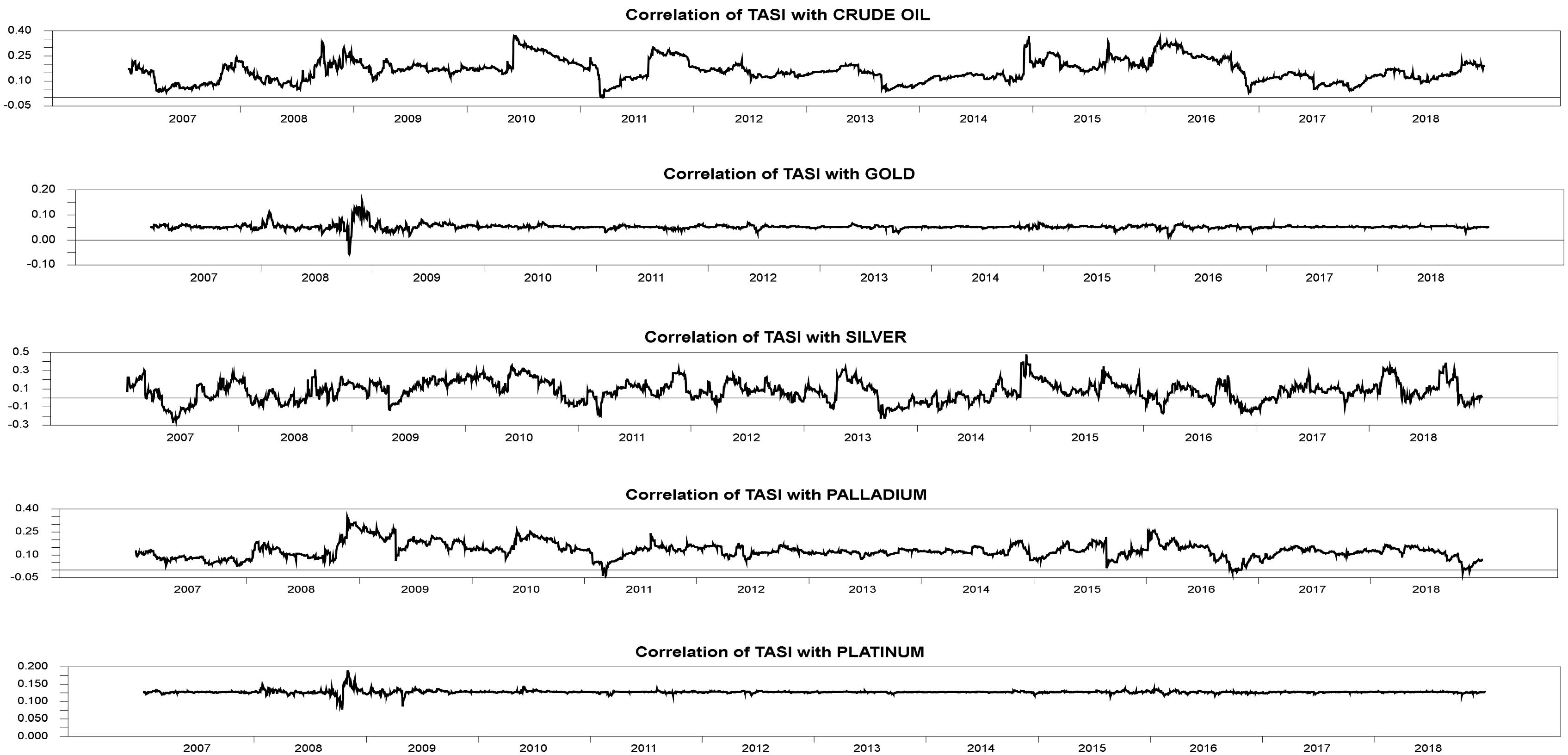


Figure 6.8: Dynamic Correlations for Major Commodity Markets with TASI from 1 January 2007 to 31 December 2018, estimated based on the DCC-GARCH model



6.6 Portfolio Management

6.6.1 Introduction

The identification of the trend of the optimal weights of portfolios of TASI, global stock and major commodity markets, not only in the whole period but also in the GFC and oil decline periods (where the diversification of portfolios is more required), is the primary consideration in this thesis. Over both the GFC and oil decline periods, the weights of TASI, global stocks and major commodities were very volatile, owing to the re-balancing of the portfolio since the correlation of TASI, global stock and major commodity markets was also volatile in crisis/shock times. Further, the optimal weights assigned to global stocks and major commodities in both situations have declined. This fall is probably attributable to two events: first, the GFC; and second, the dramatic decline in oil prices, which began in 2014 because of surplus production, resulting in strong oil price fluctuations.

Regarding the specific portfolios of TASI and the global stocks and major commodity portfolios under analysis, this section focuses on building optimal hedge ratios, taking the conditions and covariances obtained from the BEKK and DCC models. Notably, the hedge ratios, in both models for all the periods, vary considerably over time. This does mean investors will actually change their hedging portfolios in response to bear or bull markets (Kang et al., 2017). Furthermore, in all situations, the hedge ratios are small over time (under one).

In addition, the higher hedge ratios in these portfolios of TASI, global stocks and major commodities make the hedging instruments less attractive against crisis/shock of financial market exposures. This is because investors tend to take more short-term positions to reduce the risk of investing in TASI. However, it seems that the major commodity markets perform much better in hedging instruments compared with global stock markets because the hedge ratio values are lower, which indicate a relatively effective hedging approach (Khalfaoui et al., 2019). In particular, the decline in times of uncertainty suggests that owning long TASI – major commodity portfolios reduced the risk of holding a long stock position of the TASI – global stock portfolios.

Figures 6.9–12 reveal the fluctuation of the optimal hedge ratios of portfolios with TASI stocks, global stocks and major commodities over time and also clearly show that the hedge ratios grew considerably during the financial crisis of 2008 and oil decline of 2014–2016. These findings illustrate the relationship between the TASI and global stock and major commodity markets in the context of the GFC and oil decline periods. This correlation clearly shows that in the GFC and oil decline periods, some global stocks and major commodities became an ineffective hedging tool against TASI's risk. In fact, these findings for hedge ratios are in line with those of Kang et al. (2017), which imply that oil is an inefficient hedge instrument in a volatile period, whereas gold and silver may be useful to protect against stock market risk. The trend (see Figures 6.9–12) of the stock–commodity portfolio hedge ratios over time almost perfectly matches that of the aforementioned time-varying correlations (Figures 6.7–8), meaning that the importance of the correlation between assets in the determination of optimal hedge ratios is valid.

6.6.2 Relationship of Weight–Hedge Portfolios Based on the BEKK Model

6.6.2.1 TASI – Global Stock Markets

First, the portfolio optimal weights and hedge ratios of TASI – global stock portfolios derived from the GARCH-BEKK (1,1) model analysis are provided in Table 6.13. On examining the coefficients of the optimal weights of the TASI – global stock portfolios, slight differences are found across markets during the full, GFC and oil decline periods. According to these findings, the weights of most global stocks exceed 45% in the full period apart from MSCI. Thus, the lowest portfolio weight reveals that 55% of the portfolio value was invested in the S&P 500 and 45% in TASI, whereas the highest weight reveals that 36% of the portfolio value was invested in in SSE and the remaining 64% in TASI.

Compared with the whole period, the GFC and oil decline phases show increasing variations in the optimal weights of each global stock portfolio. The findings recommend that to reduce the volatility risk without compromising the anticipated returns, portfolio managers/investors in Saudi Arabia should have more stocks from advanced stock markets in their portfolios. Clearly, the S&P 500, FTSE 100 and MSCI perform much better in crisis/decline periods than other global stock markets. For example, on average, 41% of the combined TASI and FTSE 100 portfolio was invested in TASI, while the remaining 59% of its value was invested in FTSE 100 during the GFC period. Similarly, for the TASI – S&P 500 pair, 25% was invested in TASI, on average, while the remaining value of 75% was invested in the S&P 500 in the oil decline period. For the TASI–MSCI pair, on average, 32% (GFC) and 17% (oil decline) were allocated to TASI, while 68% (GFC) and 83% (oil decline) were allocated to MSCI.

Table 6.13 describes the hedge ratios of different pairs of the TASI and global stock portfolios. Clearly, all hedge ratios are less than one for all groups during the three periods. The average hedging ratios range from +0.09 for the TASI–SSE pair up to +0.27 for the TASI–MSCI pair during the full period. For the TASI – global stock portfolio pairs in the full period, the TASI and S&P 500 pair hedge ratio on average is +0.18, meaning that a long position of $1 in TASI could be hedged with a short hedge position of 18 cents in the S&P 500. The findings on other global markets indicate that $1 in TASI could be hedged by 15, 19, 24, 9 and 27 cents in NIKKEI 225, DAX 30, FTSE 100, SSE and MSCI, respectively.

In contrast to the ratios for the full period, the average hedging ratios during the GFC and oil decline periods indicate that all global stock portfolio pairs increased over +0.30 (GFC) and +0.25 (oil decline) except for SSE in both periods. The average hedging ratios for the GFC period range from +0.16 for the TASI–SSE pair up to +0.42 for TASI–MSCI, and for the oil decline period, these range from +0.08 for TASI–SSE up to +0.63 for TASI–MSCI. The TASI – S&P 500 pair weighted hedge ratios are +0.30 and +0.43, implying that a dollar investment in TASI is hedged by taking a short position on S&P 500 by +0.30 and +0.43 cents in the GFC and oil decline periods, respectively. With reference to other global stock markets, the findings indicate that a $1 investment on TASI could be hedged on NIKKEI 225, DAX 30, FTSE 100, SSE and MSCI, respectively, at 31, 33, 31, 16 and 42 cents in the GFC period and at 25, 29, 38, 8 and 63 cents in the oil decline period. The result for the TASI–SSE pair hedge ratio is in line with the conclusions of Lai and Tseng (2010), Majdoub and Sassi (2017) and W. Ahmad et al. (2018), who claimed that during crises times, the Chinese stock market can serve as a safe haven to diversify portfolios.

Table 6.13: Optimal Weights and Hedge Ratios for TASI and Global Stock Markets Portfolio based on the BEKK model

Portfolio	Full Period		GFC Period		Oil Decline Period	
	ω_t	$\hat{b}_t^*$	ω_t	$\hat{b}_t^*$	ω_t	$\hat{b}_t^*$
TASI, S&P 500	0.45	0.18	0.46	0.30	0.25	0.43
TASI, NIKKEI 225	0.61	0.15	0.49	0.31	0.41	0.25
TASI, DAX 30	0.57	0.19	0.47	0.33	0.47	0.29
TASI, FTSE 100	0.46	0.24	0.41	0.31	0.25	0.38
TASI, SSE	0.64	0.09	0.56	0.16	0.65	0.08
TASI, MSCI	0.38	0.27	0.32	0.42	0.17	0.63

Note: For all periods, the table presents the average values of optimal weights and hedge ratios for portfolios.

Figure 6.9: Time-Varying Hedge Ratios between Global Stock Markets and TASI from 15 January 2007 to 31 December 2018, estimated based on the BEKK-GARCH Model

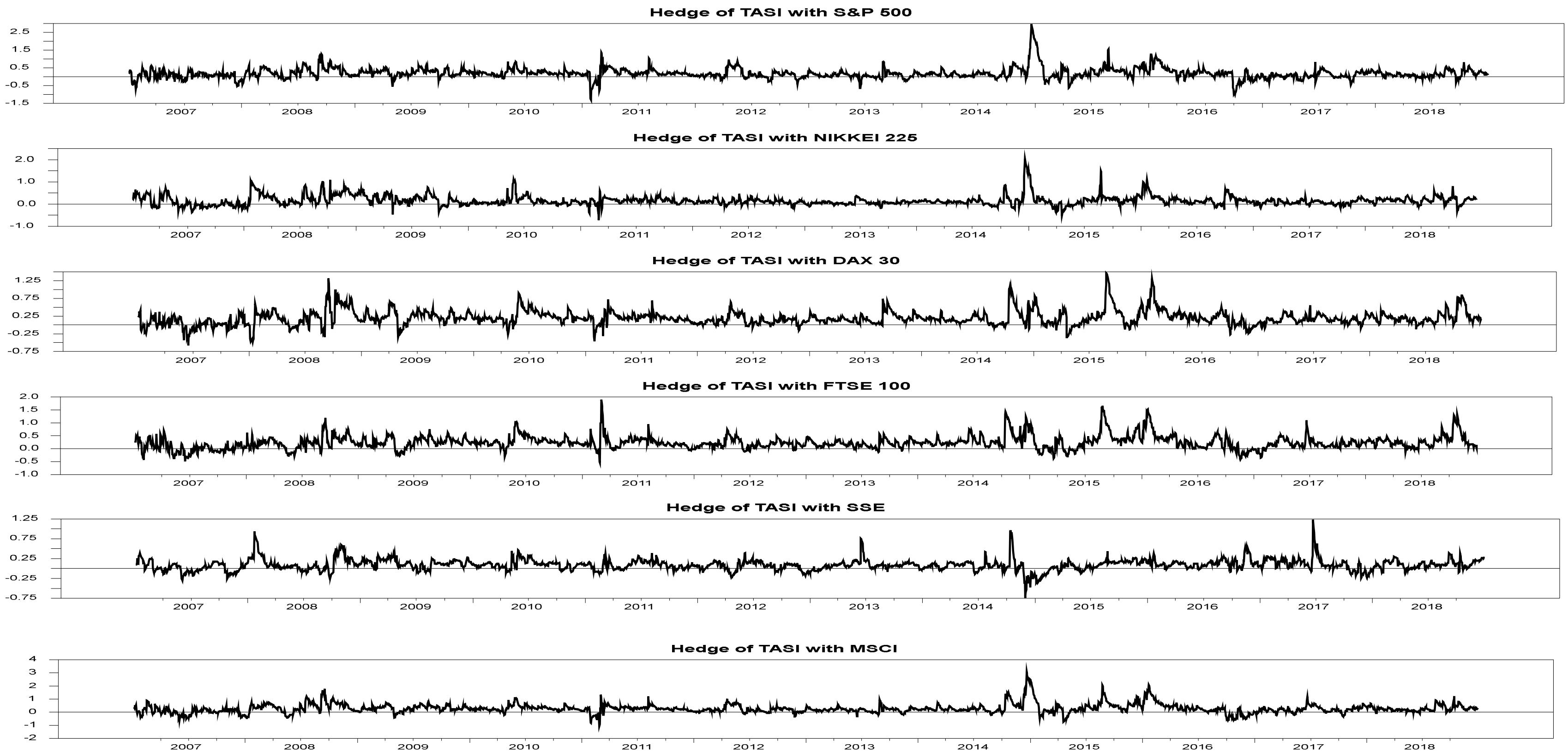
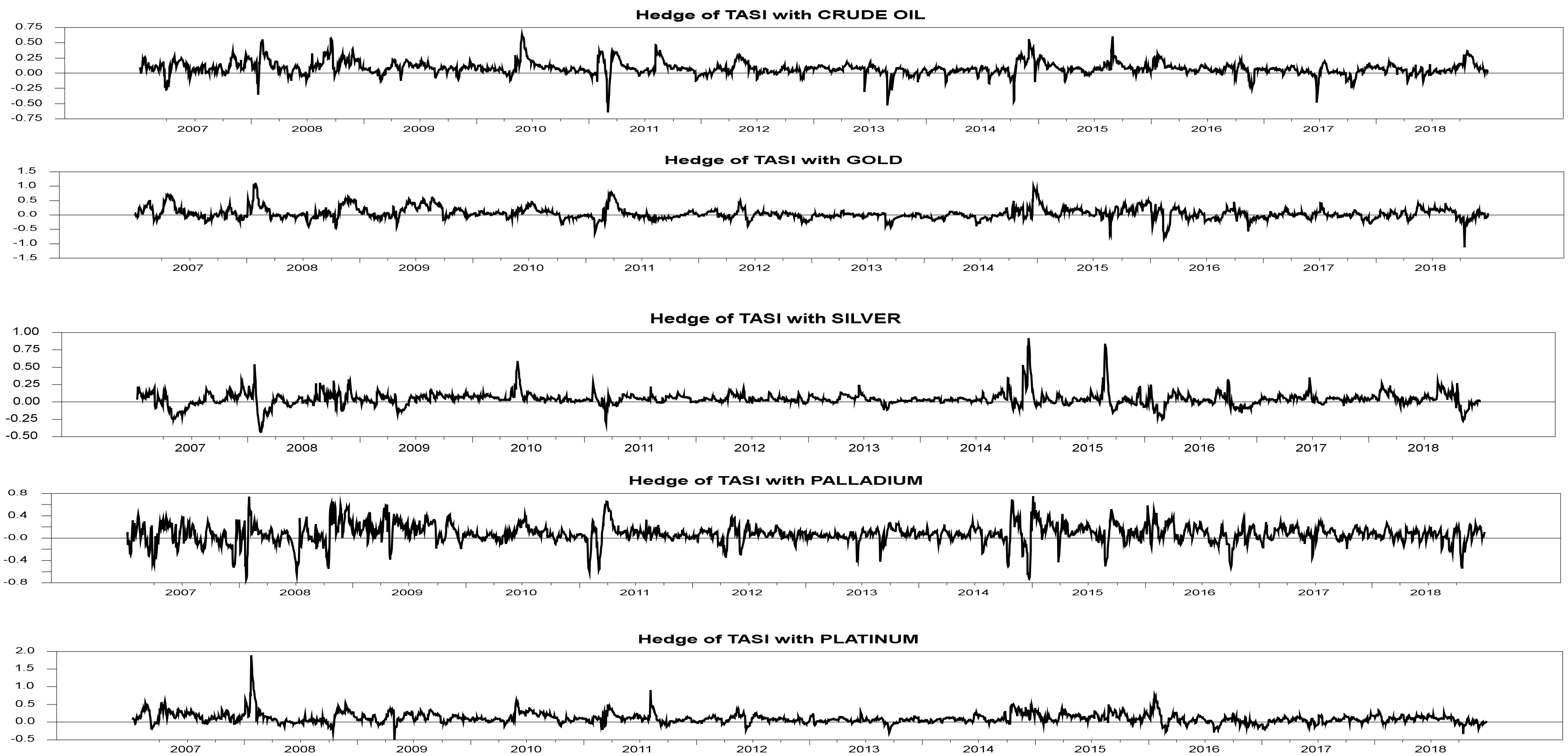


Figure 6.10: Time-Varying Hedge Ratios between Major Commodity Markets and TASI from 15 January 2007 to 31 December 2018, estimated based on the BEKK-GARCH Model



6.6.2.2 TASI – Major Commodity Markets

For the TASI – major commodity portfolios, which also originate from the analysis of GARCH-BEKK (1,1) model, the optimal weights and hedge ratios are provided in Table 6.14. According to the estimates of this thesis, the weights of all major commodities surpass 48% for the entire span. The peak allocation is 81% for crude oil, while the lowest allocation is 48% for gold. It means the portfolio weight invested 81% in TASI and 19% in crude oil and invested 48% in TASI and the remaining in gold.

By contrast, the GFC and oil decline periods gradually reveal differences in each major commodity portfolio's optimal weights. Their results appear to indicate that gold in periods of crisis/oil decline and platinum in periods of oil decline perform better than other major commodity markets. For instance, for the TASI–gold portfolio pair 41% of the portfolio value was invested in TASI and the remaining 59% was invested in gold during the GFC period. Meanwhile, in the oil decline period, for the TASI–gold portfolio pair 28% was invested in TASI and the remaining 72% was invested in gold. For the TASI–platinum pair, 38% was invested in TASI and 62% of the portfolio was invested in platinum in the oil decline period.

As regards the hedge ratio, Table 6.14 explains the various portfolios of TASI and major commodities. Obviously, for all three periods, all hedge ratios are less than one. The average hedging ratio ranges between +0.04 for the TASI–silver pair and +0.11 for TASI–platinum over the full span. The average hedge ratio of the TASI – crude oil pair is +0.08 over the entire span, meaning that a $1 investment in TASI could be hedged in crude oil with a short hedge position of 8 cents. In addition, the results for the other major commodities in the full period indicate that a $1 investment in TASI could be hedged in gold, silver, palladium and platinum with 5, 4, 8 and 11 cents, respectively.

The overall hedging ratios during the GFC and oil decline periods indicate a slight rise compared with the ratios for the whole period, meaning that the hedging performance during crisis periods was weak. This finding is in line with Olson et al.'s (2014) results of increased hedge ratios during extreme market volatility downturns. For the GFC period, the hedging ratio ranges from +0.06 (silver) to +0.14 (platinum), while for the oil decline period, it ranges from +0.06 (gold) to +0.21 (platinum). The weighted hedge ratios of TASI – crude oil are +0.12 and +0.13 in the GFC and oil decline periods, respectively, which means that a $1 investment in TASI could be hedged by taking a short position of +0.12 and +0.13 cents in crude oil. As for other major commodity markets, the results suggest that a $1 investment in TASI could be hedged, respectively, in gold, silver, palladium and platinum with 10, 6, 9 and 14 cents in the GFC period, respectively, and with 6, 9, 13 and 21 cents in the oil decline period, respectively.

The weights of the TASI–gold pair rise both in GFC and oil decline periods, whereas crude oil weights decrease in all periods. The explanation for the fall in stock weights during these times is that stock values are generally correlated with external factors and variables such that in the cycles of economic or financial turmoil, they become less successful (Souček, 2013). Since gold prices appear to respond positively to negative news of financial or economic conditions, investors can optimally add more gold to their portfolios to mitigate risk and maintain anticipated returns during the crisis/shock periods. Further, the best weights for gold declined in most cases in 2014–2016, the clear outcome of the crash of commodity prices in mid-2014 that led to high volatility in commodities.

Overall, the results from the BEKK model estimation for all periods, which are presented in Tables 6.13–14, demonstrate that in most cases, investors or portfolio managers have to maintain more stocks than commodities in their portfolios to decrease risk without diminishing potential returns (which was also confirmed by the DCC model estimation). These results are similar to, and consistent with, those of Arouri et al. (2012), Chkili et al. (2014) and Sarwar et al. (2019), and apart from the finding on gold, are not consistent with those of Mensi, Hammoudeh and Kang (2015) and Al-Yahyaee et al. (2019). They assume that to mitigate the risk of the Saudi stock market's portfolio, investors should include only more commodities during volatile times; however, this thesis concludes that they should combine both.

Table 6.14: Optimal Weights and Hedge Ratios for Major Commodity Markets Portfolios based on the BEKK Model

Portfolio	Full Period		GFC Period		Oil Decline Period	
	ω_t	$\hat{b}_t^*$	ω_t	$\hat{b}_t^*$	ω_t	$\hat{b}_t^*$
TASI, CRUDE OIL	0.81	0.08	0.74	0.12	0.85	0.13
TASI, GOLD	0.48	0.05	0.41	0.10	0.28	0.06
TASI, SILVER	0.74	0.04	0.64	0.06	0.58	0.09
TASI, PALLADIUM	0.80	0.08	0.82	0.09	0.58	0.13
TASI, PLATINUM	0.59	0.11	0.57	0.14	0.38	0.21

Note: For all periods, the table presents the average values of optimal weights and hedge ratios for portfolios.

6.6.3 Relationship of Weight–Hedge for Portfolios Based on the DCC Model

6.6.3.1 TASI – Global Stock Markets

Lastly, the TASI – global stock portfolio weights and hedge ratios resulting from the GARCH-DCC (1,1) model analysis are shown in Table 6.15. With respect to the coefficients of optimal weights of the TASI pairs, there is a small gap in markets with specific reference to the stability period compared with the volatility periods, particularly during the oil decline period. According to the estimates, most TASI – global stock portfolio weights exceed 45% for the whole duration except that of the TASI–MSCI pair, which is 37%. Meanwhile, the TASI–SSE pair has the largest allocation of 63%, and the TASI – S&P 500 pair has the lowest allocation of 45%. This result reveals that 37% of the portfolio value was invested in SSE and 63% in TASI, while 55% was invested in S&P 500 and 45% in TASI.

In contrast, for the GFC and oil decline periods, there are increasing fluctuations in the rising optimal portfolio weight for global stocks. The results indicate that Saudi investors will have the most advanced stock markets in their portfolios to reduce the risk in volatility and to avoid reducing the expected returns. In the GFC period, the average portfolio of optimal weights varies from 32% for TASI–MSCI to 53% for the TASI–SSE portfolio. For example, 52% of the value of the TASI – NIKKEI 225 portfolio was invested in TASI, while the remaining 48% was invested in NIKKEI 225. Further, 47% of the TASI – DAX 30 portfolio was invested in TASI and 53% in DAX 30. Conversely, for the oil decline period, the overall optimal portfolio weights vary from 12% for TASI–MSCI to 58% for the TASI–SSE portfolio. For instance, 24% of the TASI – S&P 500 portfolio value was invested in TASI and 76% was invested in the S&P 500. Moreover, for the TASI – FTSE 100 group, 20% of the portfolio was invested in TASI, while the remainder was invested in FTSE 100.

For hedge ratios, Table 6.15 summarises the statistics for the various pairs of TASI and global stock portfolios. It is obvious that for all global stocks across all three periods, all hedge ratios are less than one. The total hedging ratio for the whole duration varies from +0.10 for TASI–SSE to +0.34 for TASI–MSCI. The TASI – S&P 500 group has a hedge ratio of +0.27 in the full period, and the long $1 invested in TASI could be hedged with a short hedge of 27 cents in the S&P 500 index. The results for the other global markets reveal that a long $1 invested in TASI could be hedged with a short hedge of 22, 24, 27, 10 and 34 cents in NIKKEI 225, DAX 30, FTSE 100, SSE and MSCI, respectively.

The overall hedging levels during the GFC and oil decline phases compared with the whole period show that both pairs increased by more than +0.33 (GFC) and +0.30 (oil decline), with the only exception being the TASI–SSE pair in both periods. The estimated hedging levels for the GFC span vary from +0.17 for TASI–SSE to +0.48 for TASI–MSCI and for the oil decline span from +0.12 for TASI–SSE to +0.72 for TASI–MSCI. The weighted hedge ratios for TASI – S&P 500 pair are +0.33 and +0.51, respectively, which implies that a long $1 invested in TASI is hedged by a +0.33 and +0.51 cents in short position on the S&P 500 for GFC and oil decline periods, respectively. For the other global stock markets, the estimates demonstrate that investors who invest in a long position of $1 in TASI, could hedge it using a short position in the following markets: NIKKEI 225, DAX 30, FTSE 30, SSE and MSCI for 39, 38, 37, 17 and 48 cents, respectively, in the GFC period; and 31, 30, 62, 12 and 72 cents, respectively, in the oil decline period.

Table 6.15: Optimal Weights and Hedge Ratios for Global Stock Market Portfolios based on the DCC Model

Portfolio	Full Period		GFC Period		Oil Decline Period	
	ω_t	$\hat{b}_t^*$	ω_t	$\hat{b}_t^*$	ω_t	$\hat{b}_t^*$
TASI, S&P 500	0.45	0.27	0.46	0.33	0.24	0.51
TASI, NIKKEI 225	0.62	0.22	0.52	0.39	0.41	0.31
TASI, DAX 30	0.57	0.24	0.47	0.38	0.55	0.30
TASI, FTSE 100	0.46	0.27	0.41	0.37	0.20	0.62
TASI, SSE	0.63	0.10	0.53	0.17	0.58	0.12
TASI, MSCI	0.37	0.34	0.32	0.48	0.12	0.72

Note: For all periods, the table presents the average values of optimal weights and hedge ratios for portfolios.

6.6.3.2 TASI – Major Commodity Markets

The optimal weights and hedge ratios of TASI – major commodity portfolios extracted from the GARCH-DCC (1,1) model are listed in Table 6.16, and the weights of all major commodities are estimated to exceed 48% for the entire period. The highest portfolio ratio (82%) is for crude oil, while the lowest ratio (48%) is for gold. This means that by portfolio weight, 82% was invested in TASI and 18% in crude oil as well as 48% in TASI and 52% in gold.

In comparison with the full period, in the periods of the GFC and oil decline, there were increasing variations in the optimal weights of each major commodity portfolio. The findings show that the portfolio weight of gold in the crisis/oil decline period increased and similarly, the portfolio weight of platinum in the oil decline period increased, which means they were stronger and better than other major commodities in the GFC and oil decline periods. For the TASI–gold portfolio pair, for example, 45% was invested in TASI during the GFC period and the remaining 55% was invested in gold. However, in the oil decline period, for the TASI–gold group, 26% was invested in TASI and 74% in gold. Moreover, for the TASI–platinum portfolio, 38% of investment was allocated to TASI, and 62% to platinum in the oil decline period.

Regarding the hedge ratio, different portfolios had different TASI – major commodity pairs, and these are clarified in Table 6.16. All hedge ratios are obviously less than one for all three periods. The total hedging ratio over the entire period varies from +0.05 for TASI–silver to +0.12 for TASI–platinum. More specifically, the hedge ratio of the TASI – crude oil pair across the entire period is +0.09, indicating that a long position of $1 in TASI could be hedged in crude oil with a short hedge position of 9 cents. For the same period, the estimates of other major commodity pairs indicate that a long position of $1 in TASI could be hedged by 6, 5, 7 and 12 cents in gold, silver, palladium and platinum, respectively.

The overall hedging ratios in the GFC period range from +0.05 (silver) to +0.14 (platinum) and in the oil decline period from +0.07 (gold) to +0.19 (platinum). The TASI – crude oil hedge ratios in these two periods are, respectively, +0.11 and +0.14, indicating that a long position of $1 in TASI could hedged with a short hedge position of +0.11 and +0.14 cents of crude oil. The findings for other major commodity markets suggest that investors holding a long position of $1 in TASI could use a short hedge position of 13, 5, 9 and 14 cents in the GFC period and 7, 11, 16 and 19 cents in the oil decline period in gold, silver, palladium and platinum, respectively.

Table 6.16: Optimal Weights and Hedge Ratios for Major Commodity Markets Portfolios based on the DCC Model

Portfolio	Full Period		GFC Period		Oil Decline Period	
	ω_t	$\hat{b}_t^*$	ω_t	$\hat{b}_t^*$	ω_t	$\hat{b}_t^*$
TASI, CRUDE OIL	0.82	0.09	0.74	0.11	0.85	0.14
TASI, GOLD	0.48	0.06	0.45	0.13	0.26	0.07
TASI, SILVER	0.75	0.05	0.66	0.05	0.58	0.11
TASI, PALLADIUM	0.78	0.07	0.81	0.09	0.49	0.16
TASI, PLATINUM	0.60	0.12	0.59	0.14	0.38	0.19

Note: For all periods, the table presents the average values of optimal weights and hedge ratios for portfolios.

Hence, this thesis concludes that gold plays a significant function as a safe haven in severe market situations, which is consistent with the finding of other studies (Baur & McDermott, 2010; Chan et al., 2011; Mensi, Hammoudeh et al., 2015). Even if gold is considered a safe asset, investors are convinced that rising gold price volatility signals that macroeconomic and financial conditions are increasing risks or uncertainties. The cost of covering against cross-market risks will consequently increase as well.

Figure 6.11: Time-Varying Hedge Ratios between Global Stock Markets and TASI from 15 January 2007 to 31 December 2018, estimated based on the DCC-GARCH model

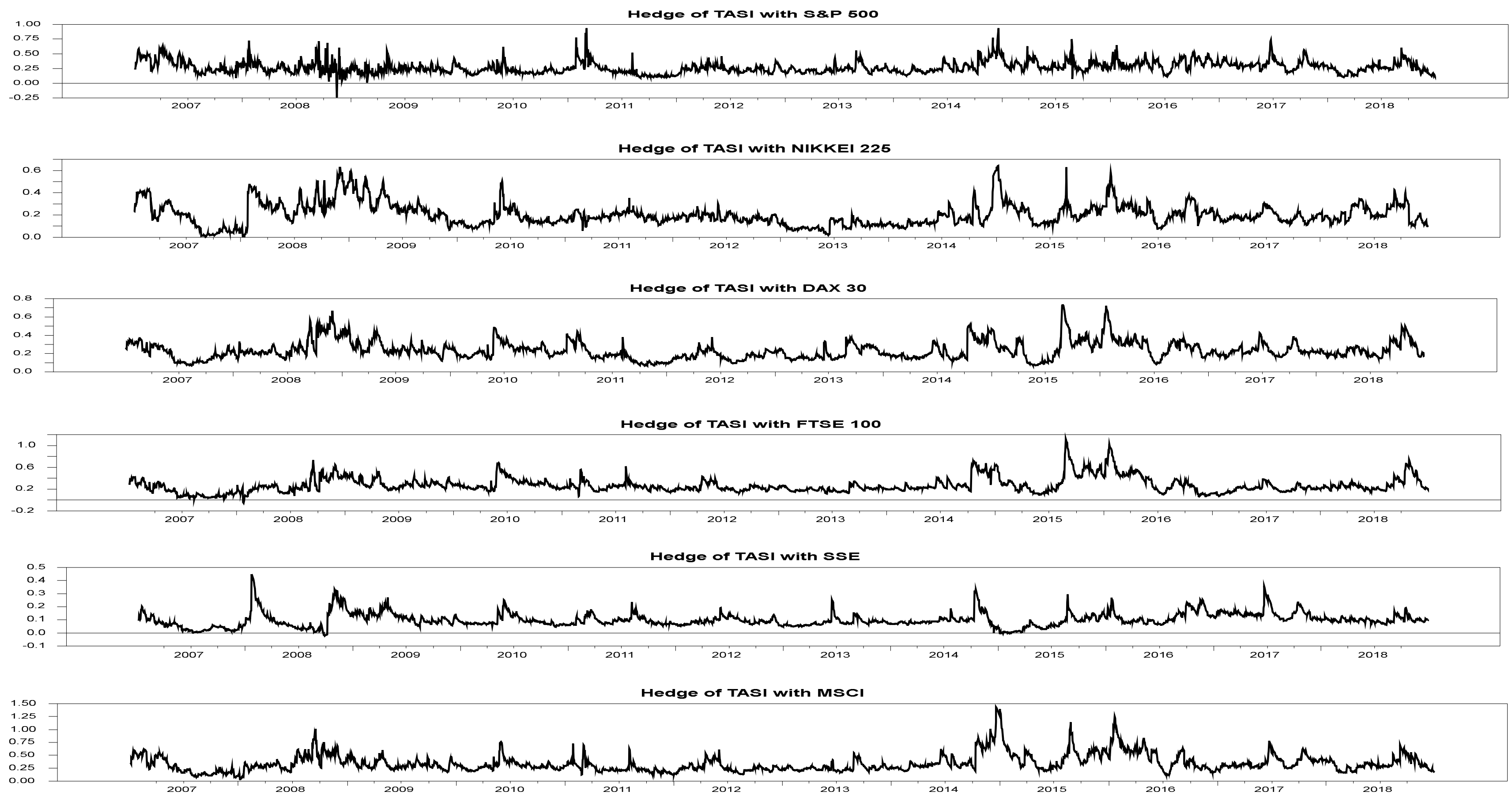
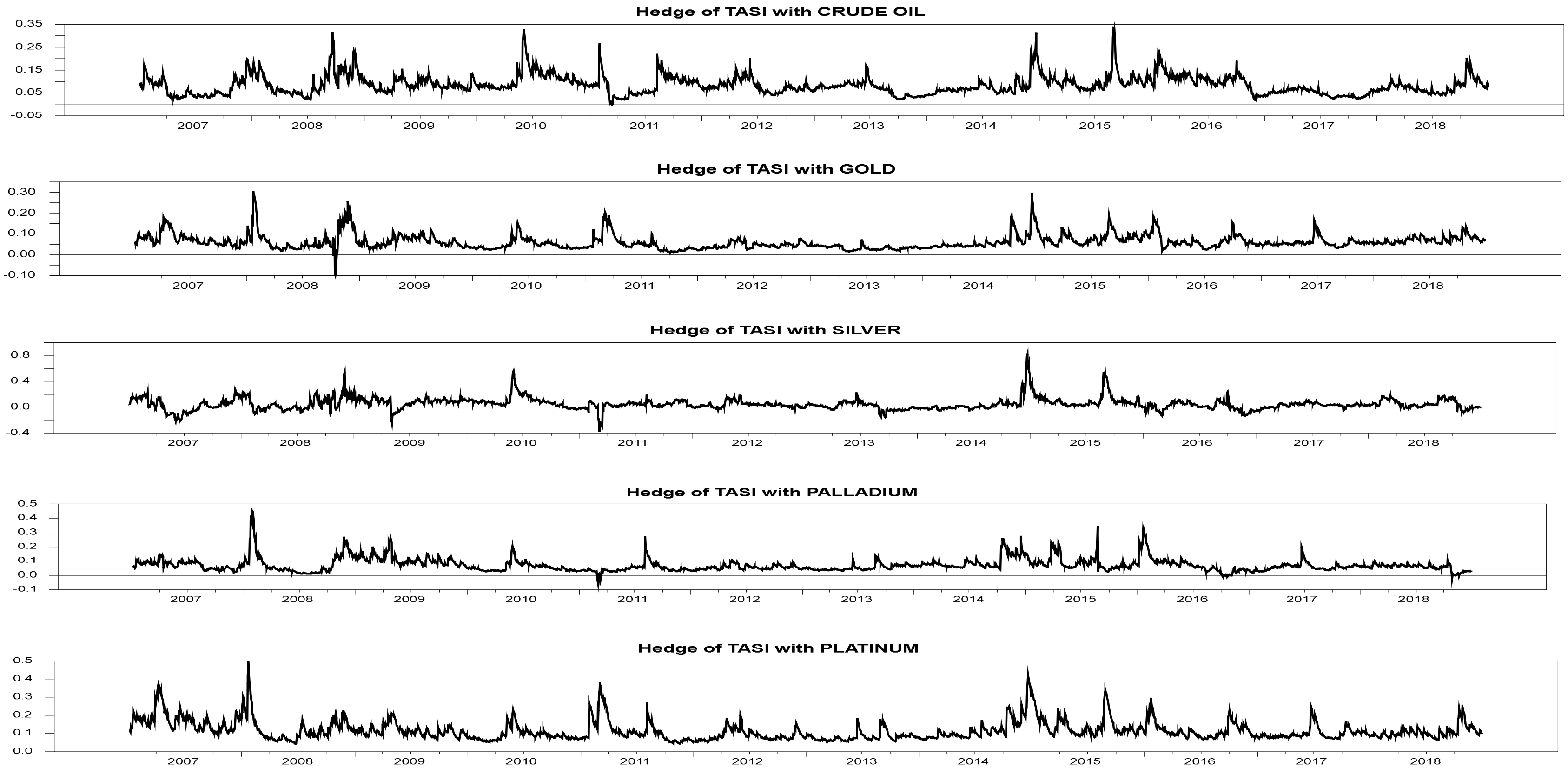


Figure 6.12: Time-Varying Hedge Ratios between Major Commodity Markets and TASI from 15 January 2007 to 31 December 2018, estimated based on the DCC-GARCH model



6.7 Conclusion

This chapter explored the relative importance of the international volatility transmission between six global stock markets, S&P 500, NIKKEI 225, DAX 30, FTSE 100, SSE and MSCI indices, and the Saudi Arabian stock market. Five major commodity markets were also considered: crude oil, gold, silver, palladium and platinum. The study was conducted from three perspectives: (a) volatility transmission, (b) the time-varying behaviour of the constant and dynamic conditional correlations and (c) portfolio management during the full, GFC and oil decline periods during 2007–2018. Various econometric techniques, including MGARCH models—BEKK, CCC and DCC—were employed.

For analysing the transmission of shocks and volatility spillovers between TASI, global stock and major commodity markets, first, it was recognised that there is less evidence on the effect of shocks and volatility spillover in relation to TASI and global stock markets during the whole period by only providing evidence of the following: (a) unidirectional shocks spillovers from SSE and MSCI to TASI at the 10% level of significance; and (b) unidirectional volatility spillovers from TASI to FTSE 100 and from SSE to TASI at the 10% level of significance. However, for the crisis/shock periods (GFC and oil decline), there was strong evidence regarding the effect of TASI and global stock markets on shocks and volatility spillover in the form of bidirectional shock spillover between TASI and NIKKEI 225, DAX 30 and FTSE 100 at the 10% significance level. There was also proof of unidirectional shock spillovers from the S&P 500 and MSCI to TASI and from TASI to SSE at the 1% and 10% significance levels during the GFC period. In addition, for the same period, strong evidence was found of bidirectional volatility spillover between TASI and S&P 500, NIKKEI 225, FTSE 100 and MSCI and of unidirectional volatility spillover from TASI to SSE at least at the 10% significance level. For the oil decline period, there was proof of unidirectional shocks spillovers from TASI to NIKKEI 225, DAX 30, FTSE 100 and SSE and from the S&P 500 and MSCI to TASI as well as bidirectional volatility spillover between TASI and NIKKEI 225 and DAX 30. Apart from these results, unidirectional volatility spillover was evident from S&P 500 and MSCI to TASI during the oil decline period at the 5% significance level.

As a whole, volatility spillovers differed significantly between the three periods and across these periods, clearly, the TASI market responded differently. During the GFC and oil decline periods, some global stock markets reacted differently to TASI's volatility because the findings indicate the coefficients A(1,2) and B(1,2) are both statistically significant, and the volatilities and shocks implications in one market had considerable effect on the other markets. Therefore, during the GFC and oil decline periods, the TASI stock market was more interconnected with global stock markets, and the volatility transmission between these equity markets was substantial.

Second, the findings regarding the major commodity markets demonstrate a unidirectional shock spillover from TASI to crude oil at the 10% level of significance. Further, there was a bidirectional volatility spillover between TASI and palladium as well as a unidirectional volatility spillover from TASI to crude oil and silver during the whole period at least at the 10% level. In addition, during the GFC period TASI was affected by unidirectional shock spillovers from crude oil and silver at the 5% and 1% levels of significance, respectively. Moreover, there were bidirectional volatility spillovers between TASI and silver. Meanwhile, unidirectional volatility spillovers from TASI to palladium and from platinum to TASI occurred during the GFC period at the 1% level of significance. For the oil decline period, the findings revealed unidirectional spillovers from gold to TASI and from TASI to silver at least at the 10% significance level. The findings confirmed a unidirectional volatility spillover from TASI to silver during the oil decline period at the level of 1%. In general, the results indicated there are fewer interactions between the five major commodity markets and TASI.

Further, the results of the CCC model for TASI and the global stock markets for the three periods show highly positive correlations at the 1% significance level. For the pairs of TASI and major commodity markets, the findings showed that all sample groups for all three periods present mostly high positive correlations at mostly the 1% significance level, apart from gold and silver in the GFC and oil decline periods. The estimated coefficients related to the DCC model provided evidence on the dynamic correlations across the TASI, global stock and major commodity markets. These results add up to a value that is less than

1% and is statistically significant, indicating that the dynamic conditional correlations of most TASI, global stocks and major commodity groups are mean-reverting.

For portfolio diversification—which has become increasingly popular with investors investing worldwide in several emerging markets that exhibit volatility in a different way from advanced stock markets—efficient risk management and hedging strategies have to be adopted. The findings regarding portfolios of optimal weights and hedging ratios suggest that by including some global stocks and gold and silver indices into a well-diversified portfolio with TASI, investment risks can be minimised without reducing portfolio performance.

The empirical results showed that for the TASI – global stock pairs, the optimal portfolio weights extracted from both models suggest holding a larger percentage of stocks than commodities, especially in the full period. Conversely, for the major commodity markets, portfolios with the optimal weights from both models recommend holding gold in larger amounts than others. In the case of mitigating risk by using a hedge, the hedge ratios of the BEKK and DCC estimations were generally low, suggesting excellent hedging by choosing gold/silver indices with the Saudi stock market. Consequently, investors can gain better hedging opportunities by investing more in gold and silver to reduce risk to their individual portfolios. The time-varying hedge ratios indicate that portfolio investors/portfolio managers need to change their hedging tools and methods regularly. In general, these findings offer an opportunity for not only foreign investors to increase their investments, but also for local investors in the Saudi stock market to do so. It is critical to adopt this approach if any diversification benefits of a portfolio and enhancing risk-adjusted performance are to be achieved.

Chapter 7 Conclusion, Summary of Findings and Policy Implications

7.1 Introduction

This thesis aimed primarily at undertaking an empirical investigation to determine the transmission channel of shock and volatility spillover effects in the Saudi stock market and various integrated international stock and commodity markets, namely, S&P 500 in the US, NIKKEI 225 in Japan, DAX 30 in Germany, FTSE 100 in the UK, SSE in China and MSCI indices, and crude oil, gold, silver, palladium and platinum. The investigated timespan is 12 years (2007–2018); the period from January 2007 to December 2018 was examined, and it was divided into subperiods to explain the effect of crisis/shock. A comprehensive literature review showed that volatility spillovers and financial crises/shocks are major determinants of the transmission of financial market volatility, and this thesis has examined these concerns in Saudi Arabia's context. To this end, the thesis employed the CCF model to measure the effect from both variables on causality in variance and applied numerous MGARCH models to analyse the transmission channel of shock and volatility spillover effects through the global interconnected financial markets on the Saudi stock market.

First, this study illustrated how the causal relationships of these global stock and major commodity markets interact with the Saudi stock market by applying the CCF model. Second, this study explored the probability of stock volatility transmission and conditional corelation between different markets and, in particular, illustrated how a crisis/shock occurring in each global stock and major commodity market influenced the Saudi stock market volatility. For this purpose, daily data and MGARCH models were used. Lastly, based on the variance and covariance estimations using MGARCH models in Chapter 6, this thesis provided general guidance about implementing these results in portfolio management. Thus, investors, portfolio managers and policymakers would benefit from using the recommendations suggested in this thesis based on the thesis outcomes.

This chapter concludes the thesis by presenting the main findings and the policy implications. Sections 7.2–7.5 describe the major results of this thesis, Section 7.6

discusses the policy implications for portfolio management, Section 7.7 notes the limitations of the thesis and recommends future research directions and Section 7.8 is the conclusion.

7.2 Volatility Origin: Behaviour of Co-movement Relationship of the Saudi Stock Market with Global Stock and Major Commodity Markets

First, the JB normality test served to check whether the 12 indices followed a normal distribution or not. Since the test indicated significance, it was appropriate to reject the null hypothesis; therefore, no normal distribution existed in all indices. The index data were converted into natural logarithms, and the log values were used to evaluate the index data in the normal distribution. The daily logarithm returns were computed, and the summary statistics were generated to analyse the characteristics of the 12 indices.

Second, throughout the full period as well as in all the subperiods investigated, the gold index was considered to represent the highest mean daily returns with low volatility. This result suggested that gold is deemed a safe haven/hedge position with good returns. The three indices that obtained the highest mean daily return during the full period were palladium, gold and S&P 500, while the three least volatile indices for the same period were gold, MSCI and FTSE 100. As in the full period, the three least volatile indices for the GFC were gold, MSCI and FTSE 100. The result was slightly different for the oil decline period, where gold, MSCI and S&P 500 persisted. An interesting observation is that the only index not affected by the GFC of 2008 was gold, while the only indices not influenced by the decline in oil price in 2014–2016 were NIKKEI 225 and SSE. These were the only indices that posted positive daily returns through the GFC and oil price decline.

Third, the presence of co-movements, which is often termed association, indicate the probability of long-term relationships between TASI and the stock and commodity indices. The correlation of TASI during the full period was poor with the SSE and platinum, moderate with S&P 500, NIKKEI 225, DAX 30, FTSE 100, crude oil and palladium, high with MSCI and negative with gold and silver. Additionally, the movement noticed during the GFC was close to one. This finding means that TASI was strongly correlated to each index of the stocks and commodities except for gold. Further, the correlation of TASI during the oil decline period was low with S&P 500, high with FTSE 100, MSCI, crude oil, gold, silver, palladium and platinum and negative with NIKKEI 225, DAX 30 and SSE. This finding indicates that during the oil decline period, TASI was correlated more with commodities than with stocks. In comparison, in the full period, it was correlated more with stocks than commodities.

7.3 Volatility Origin: Causal Relationship of the Saudi Stock Market with Global Stock and Major Commodity Markets

The CCF method, designed by Cheung and Ng (1996), was employed in this thesis to evaluate the causality-in-variance interactions between the examined variables. The two steps were as follows (1) using the univariate EGARCH model to analyse the time variation of conditional variance and (2) applying the standardised conditional variance (squared residuals) acquired in step one to test the causality in variance.

The findings revealed that market indices were constructed with the highest market capitalisation, the S&P 500 and NIKKEI 225, and reflected a positive bidirectional causality-in-variance interaction with TASI during the full period. Moreover, there was positive one-way causality in variance running from TASI to DAX 30 and MSCI, which means that TASI helps to predict the risk in the major stock markets. However, the results revealed there was also positive unidirectional causality in variance running from FTSE 100 to TASI in the full period. In the GFC period, the indices of DAX 30 and SSE exhibited a positive bidirectional causality-in-variance interaction with TASI. These results are in line with those of Vardar et al. (2018) and Z. Liu et al. (2020), who found bilateral causality effects among their samples during the GFC period. Moreover, there was positive unidirectional causality in variance running from TASI to NIKKEI 225 and FTSE 100. However, in the oil decline period there was less causality-in-variance interaction between TASI and global stock markets except for one-way causality from global stock markets (S&P 500, FTSE 100 and MSCI) to TASI. Regarding the commodity markets, it was obvious that the commodity indices had no causality-in-variance interaction except for one-way causality running from TASI to crude oil in the full period. Consistent with the empirical findings documented by Tissaoui and Azibi (2019), this thesis observed there was unidirectional causality-in-variance interaction from TASI to crude oil.

A comparison was made with existing empirical academic studies on the degree of causality in variance with other markets that was observed. The findings of Chapter 5 showed there was a strong and weak interaction between TASI and global stock markets at the same time in the full, GFC and oil decline periods. In contrast, TASI did not have a causal relationship with the commodities market except for crude oil in the full period, a result that is consistent with the findings of the literature reviewed (Ashfaq et al., 2019; Mensi, Hammoudeh, & Kang, 2015; Tissaoui & Azibi, 2019). Studies that examined the relationship between stocks and commodities have concluded there is a partially linked relationship between the two markets, as reviewed in Chapter 3, which showed there is interaction between oil crude and stocks, but in the case of precious metals, the interaction is negative or nil.

Table 7.1: Main Findings for the Causality-in-Variance Relationship between TASI and Global Stocks and Major Commodities

Null Hypothesis	Full Period	GFC Period	Oil Decline Period
Panel A: Global Stock Markets			
TASI does not cause causality in variance in S&P 500	R		
S&P 500 does not cause causality in variance in TASI	R		R
TASI does not cause causality in variance in NIKKEI 225	R	R	
NIKKEI 225 does not cause causality in variance in TASI	R		
TASI does not cause causality in variance in DAX 30	R	R	
DAX 30 does not cause causality in variance in TASI		R	
TASI does not cause causality in variance in FTSE 100		R	
FTSE 100 does not cause causality in variance in TASI	R		R
TASI does not cause causality in variance in SSE		R	
SSE does not cause causality in variance in TASI		R	
TASI does not cause causality in variance in MSCI	R		
MSCI does not cause causality in variance in TASI			R
Panel B: Major Commodity Markets			
TASI does not cause causality in variance in crude oil	R		

Note: R stands for Reject.

7.4 Volatility Origin: Volatility Transmission and Conditional Correlation Relationship between the Saudi Stock Market and the Markets of Global Stocks and Major Commodities

First, it is important to examine the volatility spillover from the perspective of global stocks and major commodities and assess their influence on the Saudi stock market, especially after analysing their causality relationship. The information flow across two financial markets is referred to as spillover or transmission (Ross, 1989; Sarwar et al., 2019). It explains the effect of fluctuations in one market's volatility return on the other market (Bouri, 2015). A variety of explanations was provided in Chapter 3 regarding previous studies that describe the spillover or the transmission of volatility between commodities and the stock markets. To estimate the transmission channel of shock and volatility spillover effects, the MGARCH models were used. In addition, to minimise the volatility risk of global stocks and major commodities, the portfolios of optimal weights and hedging ratios were established. According to the variance matrices of the MGARCH models, investors and portfolio managers can identify the best indices and benefit from using these in their portfolios. Further, an advantage of portfolio diversification in Saudi Arabia is the lower contrast between the returns on the TASI stocks and those in the advanced markets (Harvey, 1995). Thus, investors adding TASI in their portfolios may be willing to reduce their exposure as they receive the same or perhaps better returns (Middleton et al., 2008).

The diagonal parameters, that is, A(1,1) and A(2,2), which are based on the BEKK-GARCH model, measure the previous shock effects on the present volatility (depending on the volatility of one market with lagging innovations) and were statistically significant at the level of 5% for all periods. It indicates that the influence of previous shock effects in stocks or commodities pairs in the new volatility was demonstrated by both stocks and commodities. In addition, the diagonal parameters, B(1,1) and B(2,2) of matrix B, which capture the GARCH effect, measure the previous volatility effects of each individual market. In all periods for all global stocks and major commodities, both parameters were statistically significant at the 5% level, indicating that stocks and commodities had a strong GARCH effect. It means that across the full, GFC and oil decline periods the GARCH effects occurred, and then led the past conditional variance and affected the current conditional volatility significantly. This indicates that there were TASI and global stocks or major commodities pairs persisting for a long time, justifying the volatility in each series. Moreover, their lagged shocks and their own lagging conditional variance greatly affected the conditional variance on each market. In this regard, these findings seem to be consistent with those of Ahmed and Huo (2020). They provide clear evidence about ARCH and GARCH effects and illustrate the suitability of the family of GARCH model in this type of examination. In addition, compared with the GARCH coefficients, the reported ARCH coefficients are low, which reveals that the volatility of the market does not shift quickly and appropriately when there is a shock but moderately and will vary over the time. It also highlights that the previous value of their own volatility is more decisive than their own shocks when their future volatility is predicted.

Then, this thesis investigated the shock and volatility transmission across TASI and global stocks or TASI and major commodities. The A and B matrix comprising off-diagonal components captured the spillover effects of shock and volatility. To emphasise, coefficient A(1,2) reported the overall effect of TASI spillover on any global stocks or major commodities, and for all pairs, excluding the (TASI, crude oil) pair, these were statistically insignificant throughout the full period. Except for NIKKEI 225, DAX 30, FTSE 100 and SSE in both the GFC and oil decline periods and silver in only the oil decline period, the A(1,2) coefficient for the remaining pairs was also insignificant.

Conversely, coefficient A(2,1) measured the effects on TASI from the shock spillover effect of global stocks or major commodities. Throughout the full period, there was no effect except from SSE and MSCI. However, there were effects from all global stocks during the GFC period other than from the SSE index, while for the commodity markets, there were effects only from crude oil and silver. During the oil decline period, the picture is quite different compared with the GFC phase, and most of the global stocks had insignificant effects except for S&P 500 and MSCI. In line with the findings for the global stocks, the effects of commodities other than gold were also insignificant. Owing to the shock impact of A(2,1), which measures the short-term effects of the last day of innovation (previous day), TASI was mainly affected by the previous performance of global stocks and crude oil during the GFC period.

Consequently, the findings confirm the conclusions of several recent studies that reported the market integration has increased because of significant overseas crises and shocks, such as the GFC and oil price decline (Jung & Maderitsch, 2014; Masih & Masih, 2001). In the present study, further transmission of spillover was observed in the GFC and oil decline periods, which strengthens the assumption made by some previous studies that a big exogenous volatility or shock would improve interconnected markets by taking prices to a significantly higher level. Depending on the market analysis, the gains from diversification will vary from the investment in the stock market of Saudi Arabia's trading partners as well as in the major commodities if the Saudi stock market is incorporated into a financial system. It is evident from the research results of this thesis that in the periods of GFC and oil decline, TASI became more volatile, and the long-term benefits of diversifying into equities are changing as well.

The findings from the MGARCH models are consistent with those of other studies and also indicate the major effect of global stock and major commodities in the oil decline period. Investors or financial institutions can be expected to experience numerous benefits or advantages if they consider global negative news to buy/sell global stocks and major commodities. They can lower short-term risks by implementing a hedge policy based on the findings of this thesis. The effect will be a significant change in the price volatility since the behaviour of the TASI is related to that of the global stock markets during a crisis/shock period.

The estimation for the whole period found that the B(1,2) parameter was statistically insignificant for most global stocks except for FTSE 100, and conversely, was statistically significant for most major commodities except for gold and platinum. Another parameter, B(2,1), of measuring the volatility spillover effect from the global stocks and major commodities to TASI was statistically insignificant for global stocks and major commodities excluding the SSE and palladium during the full period. In the GFC period, a statistically strong interconnection was revealed between TASI and some global stocks. Further, there was a bidirectional relationship between them, apart from DAX 30. In contrast, there was a weak interconnectedness between TASI and most major commodities except for silver because there was a bidirectional relationship between them. Similar to the

GFC period, in the oil decline period there were strong global volatility spillover interactions on TASI from most global stocks compared with limited volatility spillover on only NIKKEI 225 and DAX 30 from TASI. This is because there was a unidirectional relationship between those indices and TASI. However, there was no statistically significant relationship of volatility spillover between major commodities and TASI during the oil decline period other than for weak volatility spillover from TASI on silver. The findings documented in Table 7.2 confirmed the interconnectedness of the stock market of Saudi Arabia with other world stock markets, especially during the GFC and oil decline periods for the following: S&P 500, NIKKEI 225 and FTSE 100.

Lastly, the findings on the constants and dynamic conditional correlations between TASI and global stock and major commodity markets show that the relationship between those indices was significant, meaning a strong volatile correlation between TASI and global stocks was observed over the full research period. Meanwhile, interaction between those indices for the GFC and oil decline periods was also found, revealing a strong constant correlation and moderate dynamic correlation (see Tables 7.2 and 7.3). The CCC- and DCC-GARCH models confirmed there was a significant conditional correlation between TASI and global stocks/major commodities in the full period. In contrast, during the GFC period, most stocks and commodities pairs were statistically significant, which means that the conditional correlation was moderate. During the oil decline period, most stocks and commodities pairs exhibited a weak conditional correlation. Therefore, the volatility and conditional correlation during financial crisis/shock periods seems strong in the case of most pairs of global stocks, while in the case of most pairs of commodities, the relationship seems moderate. Therefore, to maintain financial stability and then address the transmission of spillovers from global markets and foreign trading partners, these findings encourage policymakers to create a warning system and investors to develop their portfolio management strategies (Sun et al., 2020).

Table 7.2: Main Findings of Volatility Transmission Interaction between TASI and Global Stock Markets

Period	Market	Parameter	S&P 500	NIKKEI 225	DAX 30	FTSE 100	SSE	MSCI
Full Period	TASI	BEKK						
		A(2,1)					S	S
		B(1,2)				S		
		B(2,1)					S	
		CCC						
		R(2,1)	S	S	S	S	S	S
		DCC						
		DCC(A)	S	S	S	S	S	S
		DCC(B)		S	S	S	S	S
GFC Period	TASI	BEKK						
		A(1,2)		S	S	S	S	
		A(2,1)	S	S	S	S		S
		B(1,2)	S	S		S	S	S
		B(2,1)	S	S		S		S
		CCC						
		R(2,1)	S	S	S	S	S	S
		DCC						
		DCC(A)		S				
		DCC(B)		S	S		S	
Oil Decline Period	TASI	BEKK						
		A(1,2)		S	S	S	S	
		A(2,1)	S					S
		B(1,2)		S	S			
		B(2,1)	S	S	S			S
		CCC						
		R(2,1)	S	S	S	S	S	S
		DCC						
		DCC(A)			S		S	
		DCC(B)	S	S			S	S

Note: S indicates Significant.

Table 7.3: Main Findings of Volatility Transmission Interaction between TASI and Major Commodity Markets

Period	Market	Parameter	CRUDE OIL	GOLD	SILVER	PALLADIUM	PLATINUM
Full Period	TASI	BEKK					
		A(1,2)	S				
		B(1,2)	S		S	S	
		B(2,1)				S	
		CCC					
		R(2,1)	S	S	S	S	S
		DCC					
		DCC(B)	S	S		S	S
GFC Period	TASI	BEKK					
		A(2,1)	S		S		
		B(1,2)			S	S	
		B(2,1)			S		S
		CCC					
		R(2,1)	S			S	S
		DCC					
		DCC(A)				S	
		DCC(B)				S	S
Oil Decline Period	TASI	BEKK					
		A(1,2)			S		
		A(2,1)		S			
		B(1,2)			S		
		CCC					
		R(2,1)	S			S	S
		DCC					
		DCC(A)	S		S		S
		DCC(B)	S		S		S

Note: S indicates Significant.

7.5 Optimal Weight and Hedge Ratio Portfolios based on the Relationship between the Saudi Stock Market and Global Stocks/Major Commodities

According to the variance and covariance tests of the MGARCH models, the estimations of the optimal weight and hedge ratio portfolios during the GFC and oil decline shock periods varied from one period to the other. For both periods, the lowest optimal weight for the portfolio with the TASI–MSCI pair was as follows: 32% and 17% for GFC and oil decline periods, respectively. However, the highest optimal weight (82%) was for the portfolio with the TASI–palladium pair over the GFC period, while that of the TASI – crude oil pair portfolio was the highest (85%) in the oil decline period. Therefore, these results provided evidence in support of the fourth study hypothesis because of the decline in both portfolios in the GFC crisis/shock and oil decline periods. Here, the portfolio with the optimal weight and hedge ratios are useful to minimise the risks that might affect global stocks and major commodities. The findings from the present empirical study are in line with those of other authors, such as Kroner and Sultan (1993), Kroner and Ng (1998) and Sadorsky (2014). It means that investors and portfolio managers must build their asset portfolio using TASI and global stocks/major commodities, to mitigate their portfolios' volatility without curtailing their expected return. This thesis tested the portfolios with optimal weights of the global stocks and major commodities in a portfolio comprising TASI (see Table 7.4; for more details, see Tables 6.13–16). The outcomes can be viewed as motivation to enhance the investment in commodities. These findings are consistent with the belief that investors with portfolios consisting of stocks or commodities can profit from diversification. They are also in line with the findings of Öztek and Öcal (2017), Ahmed and Huo (2020) and D. Zhang and Broadstock (2020), who showed empirically the stronger prospects for commodity markets to be used in diversifying portfolios. When investing in assets or in capital markets, investors are able to mitigate their financial risks.

The findings of this thesis indicate that the best weights for all global stock markets during the GFC and the oil decline periods were under 50%, other than the SSE pair, while those for most major commodity markets were over 50% during the GFC and oil decline periods, apart from gold and platinum. Notably, the portfolio with the lowest hedge ratio is considered the most effective. However, a higher hedging level indicates the riskiest investment on a specific portfolio. It has been stated that the pairs of SSE, crude oil, gold and silver portfolios should be added to the global investment portfolio of TASI, especially during times of crisis and shock. In the context of global risks of crisis and shock, investors, with a goal to protect and maintain their stock portfolios through high risk-adjusted returns, should therefore change their focus from single asset portfolios to multiple asset portfolios.

However, when the integration of global stocks and major commodities with TASI increases during a crisis/shock, the transmission becomes stronger and, subsequently, the spillover influences the correlation and then affects the optimal weight and hedge ratios of the assets so that they, in effect, vary. Therefore, investors/portfolio managers will benefit from two asset classes being diversified. They are advised to update equity allocations across various markets worldwide and/or specific asset groups to improve the diversification of investments and enhance the potential advantages of their strategies. It would, eventually, lead to optimum weight goals. Generally, it can be shown that adding more global stocks or more major commodities should enhance the portfolio's performance as well as make it a well-diversified one; therefore, investors will be able to mitigate the risk exposure for the portfolio without reducing their expected returns. This approach would help investors/portfolio managers to offset the risk of crisis/shock and local economic events. Further, investors/portfolio managers can through their diversified investments and improved hedge strategy enhance and adjust risk efficiency.

Table 7.4: Main Findings for the Optimal TASI Portfolio among Global Stocks and Major Commodities

Optimal TASI Portfolio	**GFC Period**		**Oil Decline Period**	
	Optimal Weight	Hedge Ratio	Optimal Weight	Hedge Ratio
Panel A: Global Stock Markets				
S&P 500	0.46		0.25	
FTSE 100	0.41		0.25	
SEE		0.16		0.08
MSCI	0.32		0.17	
Panel B: Major Commodity Markets				
CRUDE OIL				0.13
GOLD	0.41	0.10	0.28	0.06
SILVER		0.06		0.09
PALLADIUM		0.09		
PLATINUM			0.38	

Note: These portfolio groups consider the best one among the study samples according to both BEKK and DCC estimations.

7.6 Policy Implications

Global events including political instability, major market volatility, oil price movements, economic downturns and natural disasters have affected equity markets. Certainly, equity market volatility will continue to play a significant role in influencing decision-making by policymakers and foreign and domestic investors. Therefore, these players would need to profit from, rather than be afraid of, the consequences of volatility. The Saudi stock market's rising integration with other financial markets means that the benefit of diversification in equities will diminish according to what international investors want. However, the Saudi market's integration with the following indices included in this study—S&P 500, NIKKEI 225, DAX 30, FSTE 100, SSE and MSCI stock markets, namely, crude oil, gold, silver, palladium and platinum indices—is far from complete. Investors and portfolio managers can still use some financial markets to anchor their equity market portfolios. The same concept may also be expanded to Saudi Arabia's domestic investors who want to invest globally.

Given that Saudi Arabia's stock market appears to be linked with its trading partners' stock markets, investors and policymakers both increasingly face a situation domestically and globally in which both crisis and shock can seriously threaten the stock market locally, possibly sacrificing some diversification advantages. The Saudi stock market is a major GCC financial market and is the centre of attraction to players on the world's most influential stock market, including S&P 500, NIKKEI 225, DAX 30 and FTSE 100 (Alotaibi & Mishra, 2015; Ng, 2000; Tissaoui & Azibi, 2019; Tsai, 2014). The benefits to global and local investors of using risk management strategies and information sharing can lead to reduce volatility and then improve efficiency in all equity markets. Since most global stock markets are identified as the most influential players in global information transmission in this analysis, it is recommended that policymakers monitor the movement of global stock markets to avoid any major shocks that may undermine the Saudi stock market's performance and the investment environment it represents.

The effects of the rising predictive capabilities of stocks and commodities will encourage investors to effectively control the Saudi stock market's volatility. The links between TASI and the stock and commodity markets are likely to be further strengthened, and TASI and some global stocks or commodities will be better integrated with significant improvements in their market efficiency. The causal relationship between TASI and some global stocks/crude oil may lead predictably to cross-border channels in the Saudi stock market with substantial foreign investment regulatory barriers.

Currently, because of its geographical position, broader trade, strong economic relationships and financial interactions, not only within the MENA region but also within the OPEC economies, the Saudi stock market is more connected with the international financial system. Consequently, a rapid increase in price volatility will likely occur in such global economies, particularly during times of financial stress, by weakening external markets. Hence, financial stability mechanisms are essential for protecting local markets against a negative overseas spillover. Given Saudi Arabia's growing significance, policymakers are recommended to monitor not only the economic conditions but also the country's financial market carefully and build alert systems for predicting future financial crises. The thesis findings have observed causal, volatility transmission and conditional correlation strengthened between Saudi Arabia's stock market and global stock markets since the GFC and declining oil prices shock. The result was growing interdependence, risking exposure to the financial system and vulnerabilities that are evident worldwide.

In addition, this research has significant policy implications, which would benefit investors/portfolio managers and policymakers. The empirical findings indicate there was increased interconnectedness among the examined samples, as the investors' sentiments shifted because of crisis/shock, and provide important policy recommendations. They also are in line with other studies (Bouri et al., 2019; Jarrett et al., 2019), and thus, investors and portfolio managers have the opportunity to take advantage of allocating and rebalancing their portfolio investments. A properly diversified portfolio should combine stocks and commodities to mitigate risks and increase returns. The success of long-term investment portfolios requires a robust policy for all possible channels to protect investors.

7.6.1 Policy Recommendations for Portfolio Management based on the Causality-in-Variance Analysis

The implications of global causal relationships between the TASI and stock and commodity markets are meaningful to policymakers, and they need to not only protect their domestic markets from economic shocks but also develop policies to effectively manage the global crises/shocks that can devastate a domestic market. Policymakers may need to distinguish between financial action regarding stock market price risks from the perspective of domestic or foreign markets. The increased volatility of stocks not just during periods of financial instability, which has become extremely obvious in the case of Saudi Arabia's stock market during the GFC of 2008–2009 and oil price decline shock in 2014–2016, but even in normal economic circumstances is counterproductive to financial market movement. Thus, mitigating the impact of global volatility/shock on domestic markets is vital (Coeurdacier & Guibaud, 2011).

The presence of a causal relationship between TASI and global stock markets has been confirmed by this study's findings (see Table 7.1); conversely, this study also proved there is no causality-in-variance relationship between TASI and commodity markets for all periods other than a unidirectional causal relationship between TASI and crude oil in the full period. The unidirectional causality in some global stocks or crude oil and TASI pairs may be attributed to the reality that domestic and global demand have affected both markets. When negative shocks occur in any market, investors eliminate their investment in the other market to prevent further potential risk. It means that prices therefore decline in the same market.

Moreover, the presence of a unidirectional relationship from one market to another indicates that informational efficiency exists in the second market. When there is no causal interaction in both directions, all markets are independent. Through diversification of their portfolios through different markets, investors may reduce their risk exposure. When causality interaction occurs in both directions, policymakers can also take more effective action within an appropriate time horizon to mitigate any risk exposure; these results are in line with those of Z. Liu et al. (2020).

The findings in Table 7.1 indicate from the investor's viewpoint that there was no causal interaction between specific stocks or precious metals and TASI over several periods. TASI with these markets should be used as a tool for portfolio diversification to hedge against any risk of crises and shocks. The same may not be said for stocks or commodities that have a causality-in-variance relationship to TASI. Instead of considering popular expectations, investors can cautiously include certain stocks and commodities in their portfolios, although there is no causal connection in either direction. It implies that policymakers could make further efforts to improve the integration between both markets to effectively move in the desired direction and take steps within a fair period during a crisis/shock period. In addition, this thesis's findings suggest that the precious metal commodities are not closely related to the equity market of TASI in the long term and thus have no predictive ability to forecast the stock return of TASI. Investors are recommended to invest in TASI–precious metals pairs together to diversify their asset portfolio.

7.6.2 Policy Recommendations for Portfolio Management based on the Volatility Transmission and Conditional Correlation Analysis

Market outlook expectations are a key strategic component for investors and portfolio managers since they must focus on the transmission of volatility and conditional correlation in decision-making related to their portfolio (Basher & Sadorsky, 2016; Hassan et al., 2019; Lee et al., 2014; Z. Liu et al., 2020). The cross-border volatility and interdependence found in this research between the stock market of Saudi Arabia and international stocks and the major commodities will enable investors and portfolio managers to make better investment decisions. Knowing the effects of the spillover direction and conditional correlation between the TASI and the variables of other financial markets can be a valuable resource in anticipating potential market dynamics. This information could be essential in implementing diversification strategies and managing market volatility. Understanding the effects of interaction between markets in volatility transmission and conditional correlation will enable foreign investment and asset managers to control their portfolios more efficiently (W. Ahmad et al., 2018; A. Singh & Singh, 2017).

This research and its empirical results provide some benefits to investors as these, first, demonstrated the shock and spillover volatility, and second, the conditional correlation of certain global stocks and commodities that are transmitted and move into Saudi Arabia's stock market. Investors are still seeking efficient investments with low risk. For this reason, before making investment choices, it is vitally important to investigate and examine financial market volatility. This thesis observed interaction regarding the transmission of shock and volatility spillover effect and conditional correlation between financial markets (stocks and commodities) and the Saudi stock market.

A possible explanation for the mechanism of positive volatility transmission and conditional correlation from particular global stocks and major commodities to TASI has been modified, so this interpretation to some extent enhances the financialisation of the Saudi stock market and states that investment is transferred in and out of the Saudi markets, which consequently increases market volatility (Büyükşahin & Robe, 2014). The other factor that helps to increase the interaction between global stocks and major commodities and TASI is not only the market fundamentals, but also investors' sentiments. A new type of financial investors views commodities as asset classes, much as stocks and bonds. In the financial markets, shocks, crises and economic weaknesses are transmitted from one market to another. Thus, to hedge risks, investors would then be willing to invest in both markets (stocks and commodities). Evidently, there is a positive relationship between stock markets and some commodity markets after the financial crisis (see Chapter 3, Section 3.4). The explanation is that investors are taking more precautions after a period of volatility and react more carefully in the case of crisis/shock in financial markets. Silvennoinen and Thorp (2013), Bouri, Jain et al. (2017), Öztek and Öcal (2017) and D. Zhang and Broadstock (2020) have drawn similar conclusions.

The general relationship between stocks and commodities is negative (Gorton & Rouwenhorst, 2006; Izadi & Hassan, 2018). Therefore, the negative transmission of volatility, especially from specific commodities to TASI, is attributable to the rise in commodity prices, which subsequently increases the cost of output for these commodities that are used as raw materials. The volatility changes in commodity prices were caused by an increase in commodity demand in the emerging economies. Commodity market volatility wields an effect on markets via the inflation process. For example, Aleisa and Dibooĝlu (2002) highlighted the role of Saudi Arabia in the oil market as affecting the world inflation rate, which, in turn, is transmitted through imports that influence Saudi Arabia's inflation. Further, since investors would benefit from investing in the Saudi stock market to diversify their portfolios, financial risk is possibly transmitted from the commodity markets to the Saudi stock market. These findings are in line with that of Oloko (2018), concluded that UK and US investors would benefit from investing in the Nigerian stock market. In addition, the results of conditional correlation indicate there is a positive correlation between TASI and some commodities during crisis and shock (see Tables 7.2–7.3). Thus, this thesis considers that the expectations of recovering from financial instability are due to the strong economic growth of Saudi Arabia, which may also enhance investor confidence and trigger a positive correlation between the stock market of Saudi Arabia and some major commodities. The country's strong economic growth may limit the consequences of global financial volatility.

The results showed that for the maximum pairs of TASI–commodities, there was no volatility spillover or no conditional correlation at various times. This result may be attributed to the fact that these indices are essentially used as a hedge against price fluctuations so that investors can manage the link between both markets. In contrast to the shock spillover effect, the volatility transmission effect is marginally strong. As explained in Section 7.4, the study revealed that the importance of ARCH and GARCH cross-market coefficients was far lower than that of the ARCH and GARCH coefficients lagging for one period, meaning that past own shocks and volatilities are more significant in predicting present volatility. Moreover, the conditional correlation was strong during the full period while it varied during the crisis and shock periods, indicating the overall correlation is moderate. Hence, the TASI – global stocks and TASI – major commodity indices are not part of the same category; instead, they should be viewed separately and the weighted portfolio efficiency enhanced. It is preferable to add some global stocks and major commodities to the TASI.

Some global stocks and TASI have a risk of spillover and a conditional correlation, which may be caused by large trade volumes in these markets. Therefore, policymakers should take appropriate steps to strengthen investor confidence in Saudi Arabia's stock market to enhance the interaction between TASI and global stocks in general. The volume of trade on the Saudi stock market may be expanded by attracting investors with new products in a bid to increase stock market trading. Policymakers should also reduce transaction costs (see Table 2.1 for more details).

In some cases of the TASI – global stock pairs and the TASI – major commodity pairs, the findings suggest not only weak volatility spillover but also weak conditional correlation, meaning that the information from one market was not transmitted to the other and then both markets are considered inefficient. The reason for this outcome is investors' lower participation in the Saudi stock market, which may be due to lack of information. This thesis considers it a sensible idea to develop an appropriate strategy to enhance the integration between TASI and global stocks and major commodities, which policymakers consider a growing concern (see Table 2.1 for CMA's vision). This study's results will help policymakers to frame policies and strategies that can build investor confidence in the Saudi stock market and thereby increase the integration between TASI and global stocks and major commodities. The interaction link between the prices of TASI and global stock and commodity markets will provide useful information to investors about their possible substitution strategies regarding the best portfolios among the best indices of the study samples. On the basis of this study's estimation, it will also help to provide portfolios of optimal weights and hedge ratios for TASI – global stocks and TASI – major commodities, leading to an increase in investor confidence as well. Investors or other interests can effectively use these optimal weights and hedge ratios to mitigate their portfolio risk.

7.6.3 Policy Recommendations for Selecting a Portfolio based on Variance–Covariance Analysis

The findings in this section have significant practical implications. For instance, portfolio diversification theories suggest that investors need to be aware of the extent of stock market integration or interdependence. If stock markets are less than fully integrated, then potential diversification benefits exist for international investors. This means that the diversification benefits fully depend on the level of stock market interdependence and its determinants. Therefore, understanding the factors that drive stock market correlations is important for investors if they want to take appropriate investment decisions on portfolio diversification into global stocks or major commodities to make the highest risk-adjusted return.

In GCC countries, the crises of GFC and oil price decline forced several management financial institutions to restructure and break their international assets into several securities by raising large stockpiles. While the risk of a GFC is minimised with increasing assets, it is expensive to retain enormous quantities of capital since financial markets tend to allocate funds to extremely volatile and stable assets that produce small returns. Investors/portfolio managers may split their investment portfolio into two categories: stocks and commodities. Some studies, such as that of Sadorsky (2014) and Izadi and Hassan (2018), assumed that investors who diversify their financial portfolios by acquiring stocks only are extremely unlikely to make a profit. Therefore, to gain profits and diversify their investment portfolios, they should include both stocks and commodities through following the specific properties of individual assets for the optimal weights to yield the expected profits. The findings of this thesis on optimal weights and hedge ratios are consistent for both models (BEKK and DCC), which confirms that investors should choose the stock markets of S&P 500, FTSE 100 and MSCI and of the gold commodity market in times of crisis, while in times of shock, they should take the same category plus platinum. Most indices that investors or other interests should consider for hedging their portfolios in the case of a crisis or shock are as follows: SSE of global stock and gold, silver and palladium in a crisis. Meanwhile, during a shock, they should take the same category and replace palladium with crude oil (see Table 7.4).

As discussed earlier, the potential for investment diversification relies mainly on the extent to which stocks and commodities are interdependent. For example, if stocks and commodities are highly interdependent, then the opportunities for portfolio diversification are minimal; if stocks and commodities are less interdependent, then opportunities exist for diversification to thereby obtain higher risk-adjusted returns. If the interdependence degree of global stock and commodity markets is time-varying, then investors must focus on the episodes of lower correlations to diversify. Therefore, investors can diversify their investments in the global markets to gain additional risk-adjusted returns in the short run as well. Investors, including hedgers, portfolio managers and asset allocators, need to understand the concept of hedging through spillover volatility and conditional correlation across various markets. They should adjust their portfolios for improved resistance during times of financial instability, which is consistent with the results of D. Zhang and

Broadstock (2020). In addition, they are mainly motivated to reduce the chances of facing a risk without reducing the predicted return. This motive can be accomplished by using the optimal weights and hedge ratios employed in the present study.

For TASI – global stock pairs, Tables 6.13–15 and Panel A of Table 7.4 show the findings on the optimal weights and hedge ratios. The optimal weights for these pairs range from 32% for TASI–MSCI to 56% for TASI–SSE in the GFC period and from 17% for TASI–MSCI to 65% for TASI–SSE in the oil decline phase. The study findings show that for the TASI–MSCI pair, the optimal weight of TASI holding in the $100 portfolio is 32% (GFC) and 17% (oil decline) with the remainder of 68% (GFC) and 83% (oil decline) in the index of MSCI. Meanwhile, for the TASI–SSE pair, the optimal weight of TASI in the $100 portfolio is 56% (GFC) and 65% (oil decline) with the remainder of 44% (GFC) and 35% (oil decline) in the SSE index. In times of the crisis and shock, the weight of most global equities in the S&P 500, FTSE 100 and MSCI was higher than the weight of TASI in the portfolio. This means that investors must have more global stocks in their portfolio than the stocks in TASI to reduce risk without sacrificing the expected return.

The findings on the hedge ratio show that the TASI – global stock pairs of hedging values vary from 0.16 to 0.42 (GFC) and 0.08 to 0.63 (oil decline) for SSE and MSCI. These findings indicate that the long position of $100 in TASI could be hedged by approximately $16 (GFC) and $8 (oil decline) in SSE and by about $42 (GFC) and $63 (oil decline) in MSCI. The positive hedge ratio of all TASI – global stock pairs means that a long position in TASI and a short position in SSE is the cheapest hedge. Therefore, the highly effective hedging strategy is the one with low hedge ratio values. These findings are consistent with those of Arouri, Lahiani and Nguyen (2011), Lee et al. (2014) and Majdoub and Sassi (2017).

The optimal weight and hedge ratio for the TASI – commodity pairs are shown in Tables 6.14/16 and Panel B of Table 7.4. A TASI portfolio of $100 has the optimal holding weight of 26% (GFC) and 15% (oil decline) of crude oil, and the remaining 74% and 85% are in TASI for the GFC and oil decline periods. The hedge ratio results imply that in the TASI – crude oil case, a $100 long position in TASI can be hedged for $12 (GFC) and $13 (oil decline) in the crude oil index. These findings are consistent with those of Chkili et al.

(2014) and Sarwar et al. (2019), which mean, based on the findings of this thesis, that investors holding the TASI – crude oil pair can have more stocks than crude oil to diminish their risk without lowering their potential return.

The findings of optimal weight and hedge ratios for the TASI – precious metals pairs vary from 41% for TASI–gold to 82% for TASI–palladium in the GFC period and from 28% for TASI–gold to 58% for TASI–silver in the oil decline period. The optimal weight of holding gold in the TASI – precious metal pair is 59% (GFC) and 72% (oil decline) with the remainder of 41% (GFC) and 28% (oil decline) in TASI. In addition, the optimal weight of holding palladium in the TASI – precious metal pair is 18% (GFC) in the portfolio with the remaining 82% in the index of TASI. Meanwhile, for silver, the optimal weight of holding silver in the TASI – precious metal pair is 42% (oil decline) in the portfolio with the rest (58%) in TASI. The thesis findings in this scenario are in line with those of Izadi and Hassan (2018) and Jiang, Fu and Ruan (2019), which mean, based on the findings of this thesis that investors who hold a TASI – precious metals portfolio should add more gold in times of crisis and more gold and platinum in times of shock. However, in the case of other precious metals, investors are advised to include more stocks in their portfolios to improve portfolio performance.

In general, the findings demonstrate that risk reduction and holding balanced portfolios can enhance weighted outcomes and therefore allow more effective protection of global stocks and commodities. Consequently, the findings emphasise the significance of building mixed portfolios of assets for diversification purposes by including commodities, even though the advantages will depend on the presence of portfolio hedging assets. The findings present that the optimal weights and hedge ratios vary across multiple indices during shocks and crises. This research, therefore, shows that TASI innovations offer alternative options to global diversification portfolios. It is apt to conclude that the Saudi stock market provides considerable investment and trading opportunities for investors to achieve higher profits than the returns from investments in traditional stock markets. It is also possible to assume that investing in the TASI is enhanced by developing a portfolio by including S&P 500, FTSE 100, MSCI, gold and platinum indices in the case of optimal weights and SSE, crude oil, gold, silver and palladium indices in the case of hedging ratios. These results are significant for foreign investors who want to obtain increased returns by investing in the Saudi stock market while securing their risk by building the desired portfolio.

7.7 Limitations and Future Research

The empirical studies explained in this thesis are, while comprehensive in coverage and econometric methodology with major policy implications for finance portfolio management and practice, subject to some limitations. This section suggests a variety of possible avenues through which future studies could shed some light on the issues not addressed in this thesis. The major limitation is that the study focused exclusively on the financial market relationship from the Saudi Arabian perspective but not from the perspective of its trading partners or of major commodities because Saudi Arabia has the largest stock market in both the GCC and MENA regions. Further, this research examined relationships between the stock market of Saudi Arabia and specific world financial markets since this study did not describe all global financial markets.

Moreover, the empirical findings are only valid for the in-sample periods considered. Thus, it will be useful to determine the best strategy of hedging for out-of-sample periods, which, in turn, may offer more valuable information for policymakers and portfolio managers on the volatility risk of global stock markets. Further, this study did not concentrate on factors driving market interdependence. This analysis did not consider macroeconomic or microeconomic variables that may, through their economy-wide transmission mechanisms, influence TASI volatility and, as a result, portfolio management. In addition, the thesis covered the volatility transmission and portfolio management by using different econometric models (BEKK, CCC, DCC and CCF), and their findings have focused on significant outcomes for investors and policymakers by providing portfolio weights and hedging ratios (For more details see sections 6.6 and 7.6). The analysis for economic value of volatility transmission may be used in future research studies for further investigation. Finally, this research did not explicitly analyse the recent and devastating COVID-19 pandemic. This event should also be investigated with its effect on the information-sharing mechanisms in global financial markets. It is possible that information flows would have been transmitted through stock returns, price and market size through foreign financial markets, and hence, other time series will have to be used to undertake such research after 2018 and including the COVID-19 pandemic period.

7.8 Conclusion

The main findings of the global transmission and conditional correlation regarding volatility on the Saudi stock exchange have been discussed in this chapter with reference to six world markets. They are S&P 500, NIKKEI 225, DAX 30, FTSE 100, SSE and MSCI indices. Five commodity markets were also considered: crude oil, gold, silver, palladium and platinum. Different econometric methods, such as BEKK, CCC and DCC, were used in this research. These primary outcomes have significant implications for investors and policymakers. The CCF test was focused on the EGARCH criteria to analyse the causality relationships of the Saudi stock market and the global stocks and major commodities. Interactions were found between TASI and the world stock markets, which emerge as significant through the CCF examination. No relationship exists between TASI and commodity markets for all periods other than the full period in which it is apparent that TASI has unidirectional effects on crude oil. In other terms, TASI expresses the majority of the information on the global stock markets and vice versa. In global markets, TASI and some global stocks in various periods demonstrate bidirectional causality. More broadly, the worldwide transmitting mechanism of volatility is controlled by global markets, such as S&P 500 and NIKKEI 225.

First, this thesis found less evidence for the effects on TASI and global markets of shocks and volatility spillovers over the whole period while considering shocks and volatility spillover transmission between TASI and global stock and major commodity markets. In other terms, it is acknowledged that there is strong proof of the influence of TASI and global stock markets since crisis/shock times on shocks and volatility spillover (GFC and oil decline). Over and above the three periods, volatility spillovers significantly vary, and it is evident that TASI reacts differently in these times according to the overall effects of international stock markets. This thesis also showed that some global stocks respond differently during the GFC and oil decline periods to the volatility of TASI; thus, the shock/volatility spillovers effects in one market have major consequences for other markets.

Then, it can be realised that the stock market of Saudi Arabia has become more interconnected with international stock markets throughout the GFC and oil decline periods, in which the transmission of volatility between such financial markets can be proved.

The thesis results for the commodity markets suggest there is shock spillover to crude oil from TASI. These findings reveal volatility spillover from TASI to palladium and from TASI to crude oil and silver over the whole period. The findings during the GFC period also highlight that the TASI has been influenced by crude oil and silver shocks. Additionally, volatility spillovers between TASI and silver are evident. Meanwhile, during times of uncertainty there is a volatility spillover of TASI's influence on palladium and platinum's influence on TASI. These results uncover a spillover shock from gold to TASI and from TASI to silver during the oil decline phase. The volatility from TASI to silver during this phase was reported in the thesis results. In addition, the findings reveal that the five commodity markets were less interactive with TASI.

For the three study periods, the results of the CCC and DCC models implied a strong significant positive correlation for TASI, the global stocks and major commodity markets. Dynamic conditional correlation effects are statistically significant, indicating that the conditional correlations in all stocks; TASI, global stocks and major commodities are mean-reverting. Since global portfolio diversification has become increasingly preferred by international investors in many developing markets worldwide whose volatility is quite different from that of advanced stock markets, effective risk management and hedging policies should be implemented. This thesis recommends that investment risks may be reduced without decreasing portfolio efficiency through implementing the identified samples of optimal portfolio weights and hedge ratio strategies. This goal can be achieved by adding certain global stocks and major commodities within a balanced TASI portfolio. Overall, the thesis results provide not only international investors with the opportunity to boost their portfolios, but also allow domestic investors in the Saudi stock market to use diversification strategies. This approach is necessary to obtain the diversification advantages of a portfolio and improve the risk-adjusted efficiency.

References

Abid, I., Goutte, S., Guesmi, K., & Jamali, I. (2019). Transmission of shocks and contagion from U.S. to MENA equity markets: The role of oil and gas markets. *Energy Policy*, *134*, 110953. https://doi.org/10.1016/j.enpol.2019.110953

Abounoori, E., & Tour, M. (2019). Stock market interactions among Iran, USA, Turkey, and UAE. *Physica A: Statistical Mechanics and its Applications*, *524*, 297–305. https://doi.org/10.1016/j.physa.2019.04.232

Afsal, E. M., & Haque, M. I. (2016). Market interactions in gold and stock markets: Evidences from Saudi Arabia. *International Journal of Economics and Financial Issues, 6*(3), 1025–1034.

Ağırman, E., Bozma, G., & Ahmid, A. B. (2018). The volatility spillovers between Turkey and North Africa (ETM) stock markets: Varma-BEKK GARCH model. *MANAS Journal of Social Studies, 7*(4).

Ahmad, N., Raheem Ahmed, R., Vveinhardt, J., & Streimikiene, D. (2016). Empirical analysis of stock returns and volatility: Evidence from Asian stock markets. *Technological & Economic Development of Economy, 22*(6), 808–829. https://doi.org/i:10.3846/20294913.2016.1213204

Ahmad, W., Mishra, A. V., & Daly, K. (2018). Heterogeneous dependence and dynamic hedging between sectors of BRIC and global markets. *International Review of Financial Analysis, 59*, 117–133. https://doi.org/10.1016/j.irfa.2018.07.005

Ahmed, A. D., & Huo, R. (2020). Volatility transmissions across international oil market, commodity futures and stock markets: Empirical evidence from China. *Energy Economics*. https://doi.org/10.1016/j.eneco.2020.104741

Aielli, G. (2013). Dynamic conditional correlation: On properties and estimation. *Journal of Business & Economic Statistics, 31*(3), 282–299. https://doi.org/10.1080/07350015.2013.771027

Alberg, D., Shalit, H., & Yosef, R. (2008). Estimating stock market volatility using asymmetric GARCH models. *Applied Financial Economics, 18*(15), 1201–1208. https://doi.org/10.1080/09603100701604225

Aleisa, E. A., & Dibooĝlu, S. (2002). Sources of real exchange rate movements in Saudi

Arabia. *Journal of Economics and Finance*, *26*(1), 101–110.

Al-Khazali, O., Darrat, A. F., & Saad, M. (2006). Intra-regional integration of the GCC stock markets: The role of market liberalization. *Applied Financial Economics, 16*(17), 1265–1272. https://doi.org/10.1080/09603100500426630

Alotaibi, A. R., & Mishra, A. V. (2015). Global and regional volatility spillovers to GCC stock markets. *Economic Modelling, 45*, 38–49. https://doi.org/10.1016/j.econmod.2014.10.052

Aloui, C., Hkiri, B., Lau, M. C. K., & Yarovaya, L. (2018). Information transmission across stock indices and stock index futures: International evidence using wavelet framework. *Research in International Business and Finance, 44*, 411–421. https://doi.org/10.1016/j.ribaf.2017.07.112

Alqahtani, A. S. S., Ouyang, H., & Ali, A. (2019). The reaction of stock markets in the Gulf Cooperation Council countries to economic policy uncertainty in the United States. *Economics and Business, 33*(1), 22–34. https://doi.org/10.2478/eb-2019-0002

Al-Yahyaee, K. H., Mensi, W., Sensoy, A., & Kang, S. H. (2019). Energy, precious metals, and GCC stock markets: Is there any risk spillover? *Pacific-Basin Finance Journal, 56*, 45–70. https://doi.org/10.1016/j.pacfin.2019.05.006

Andersen, T. G., Bollerslev, T., Christoffersen, P., & Diebold, F. X. (2007). Practical volatility and correlation modeling for financial market risk management. In *The risks of financial institutions* (pp. 513–548). University of Chicago Press.

Antonakakis, N., & Badinger, H. (2016). Economic growth, volatility, and cross-country spillovers: New evidence for the G7 countries. *Economic Modelling, 52*, 352–365. https://doi.org/10.1016/j.econmod.2015.08.035

Antonakakis, N., Cunado, J., Filis, G., Gabauer, D., & Perez de Gracia, F. (2018). Oil volatility, oil and gas firms and portfolio diversification. *Energy Economics, 70*, 499–515. https://doi.org/10.1016/j.eneco.2018.01.023

Antoniou, A., Pescetto, G. M., & Stevens, I. (2007). Market-wide and sectoral integration: Evidence from the UK, USA and Europe. *Managerial Finance, 33*(3), 173–194. https://doi.org/10.1108/03074350710718266

Arab Monetary Fund. (2017). *Arab capital markets, 4th Quarter Bulletin 2017 Report*.

https://www.amf.org.ae/en/content/arab-capital-markets-4th-quarter-bulletin-2017.

Arouri, M., Jouini, J., & Nguyen, D. (2011). Oil prices and sector stock returns: Implication for portfolio management. *International Journal of Money and Finance, 30*, 1387–1405.

Arouri, M. E. H., Jouini, J., & Nguyen, D. K. (2012). On the impacts of oil price fluctuations on European equity markets: Volatility spillover and hedging effectiveness. *Energy Economics, 34*(2), 611–617. https://doi.org/10.1016/j.eneco.2011.08.009

Arouri, M. E. H., Lahiani, A., & Nguyen, D. K. (2011). Return and volatility transmission between world oil prices and stock markets of the GCC countries. *Economic Modelling, 28*(4), 1815–1825. https://doi.org/10.1016/j.econmod.2011.03.012

Arouri, M. E. H., Lahiani, A., & Nguyen, D. K. (2015a). Cross-market dynamics and optimal portfolio strategies in Latin American equity markets. *European Business Review, 27*(2), 161–181. https://doi.org/10.1108/EBR-04-2013-0069

Arouri, M. E. H., Lahiani, A., & Nguyen, D. K. (2015b). World gold prices and stock returns in China: Insights for hedging and diversification strategies. *Economic Modelling, 44*, 273–282.

Ashfaq, S., Tang, Y., & Maqbool, R. (2019). Volatility spillover impact of world oil prices on leading Asian energy exporting and importing economies' stock returns. *Energy, 188*, 116002. https://doi.org/10.1016/j.energy.2019.116002

Awartani, B., Maghyereh, A. I., & Shiab, M. A. (2013). Directional spillovers from the U.S. and the Saudi market to equities in the Gulf Cooperation Council countries. *Journal of International Financial Markets, Institutions & Money, 27*, 224–242. https://doi.org/10.1016/j.intfin.2013.08.002

Azad, A. S., Ahsan, A., & Fang, V. (2013). An investigation of the deviation from the market efficiency and its Implications for capital market development: The DSE evidence. In Arouri, Mohamed, Boubaker, Sabri and Nguyen, Duc Khuong (ed), *Emerging Markets and the Global Economy: A Handbook*, Academic Press, Oxford, England, pp.143-159.

Azar, S. A., & Chopurian, N. A. (2018). Commodity indexes and the stock markets of the GCC countries. *Arab Economic and Business Journal, 13*(2), 134–142.

https://doi.org/10.1016/j.aebj.2018.08.001

Baele, L. (2005). Volatility spillover effects in European equity markets. *Journal of Financial & Quantitative Analysis, 40*(2), 373–401. https://doi.org/10.1017/S0022109000002350

Bagirov, M., & Mateus, C. (2019). Oil prices, stock markets and firm performance: Evidence from Europe. *International Review of Economics & Finance, 61*, 270–288. https://doi.org/10.1016/j.iref.2019.02.007

Balli, F., Hajhoj, H. R., Basher, S. A., & Ghassan, H. B. (2015). An analysis of returns and volatility spillovers and their determinants in emerging Asian and Middle Eastern countries. *International Review of Economics & Finance, 39*, 311–325. https://doi.org/10.1016/j.iref.2015.04.013

Bampinas, G., & Panagiotidis, T. (2017). Oil and stock markets before and after financial crises: A local Gaussian correlation approach. *Journal of Futures Markets, 37*(12), 1179–1204. https://doi.org/10.1002/fut.21860

Bansal, R., Kiku, D., Shaliastovich, I., & Yaron, A. (2014). Volatility, the macroeconomy, and asset prices. *The Journal of Finance, 69*(6), 2471–2511.

Basher, S. A., & Sadorsky, P. (2006). Oil price risk and emerging stock markets. *Global Finance Journal, 17*(2), 224–251. https://doi.org/10.1016/j.gfj.2006.04.001

Basher, S. A., & Sadorsky, P. (2016). Hedging emerging market stock prices with oil, gold, VIX, and bonds: A comparison between DCC, ADCC and GO-GARCH. *Energy Economics, 54*, 235–247. https://doi.org/10.1016/j.eneco.2015.11.022

Bass, A. (2017). Does oil prices uncertainty affect stock returns in Russia: A bivariate generalized autoregressive conditional heteroskedasticity-in-mean approach. *International Journal of Energy Economics and Policy, 7*(4), 224–230.

Baur, D. G., & Lucey, B. M. (2010). Is Gold a hedge or a safe haven? An Analysis of stocks, bonds and gold. *Financial Review, 45*(2), 217–229. https://doi.org/10.1111/j.1540-6288.2010.00244

Baur, D. G., & McDermott, T. K. (2010). Is gold a safe haven? International evidence. *Journal of Banking & Finance, 34*(8), 1886–1898. https://doi.org/10.1016/j.jbankfin.2009.12.008

Baur, D. G., & McDermott, T. K. J. (2016). Why is gold a safe haven? *Journal of*

Behavioral and Experimental Finance, 10, 63–71. https://doi.org/10.1016/j.jbef.2016.03.002

Bauwens, L., Laurent, S., & Rombouts, J. V. K. (2006). Multivariate GARCH models: A survey. *Journal of Applied Econometrics, 21*(1), 79–109. http://onlinelibrary.wiley.com/journal/10.1002/%28ISSN%291099-1255/issues

Beber, A., Brandt, M. W., & Kavajecz, K. A. (2009). Flight-to-quality or flight-to-liquidity? Evidence from the euro-area bond market. *The Review of Financial Studies, 22*(3), 925–957.

Belousova, J., & Dorfleitner, G. (2012). On the diversification benefits of commodities from the perspective of euro investors. *Journal of Banking & Finance, 36*(9), 2455–2472. https://doi.org/10.1016/j.jbankfin.2012.05.003

Benhmad, F. (2013). Bull or bear markets: A wavelet dynamic correlation perspective. *Economic Modelling, 32*, 576–591. https://doi.org/10.1016/j.econmod.2013.02.031

BenSaïda, A. (2019). Good and bad volatility spillovers: An asymmetric connectedness. *Journal of Financial Markets, 43*, 78–95. https://doi.org/10.1016/j.finmar.2018.12.005

Bera, A. K., & Jarque, C. M. (1981). Efficient tests for normality, homoscedasticity and serial independence of regression residuals: Monte Carlo evidence. Economics letters, 7(4), 313-318.

Berger, D., Pukthuanthong, K., & Jimmy Yang, J. (2011). International diversification with frontier markets. *Journal of Financial Economics, 101*(1), 227–242. https://doi.org/10.1016/j.jfineco.2011.02.009

Bildirici, M. E., & Sonustun, F. O. (2018). The effects of oil and gold prices on oil-exporting countries. *Energy Strategy Reviews, 22*, 290–302. https://doi.org/10.1016/j.esr.2018.10.004

Blake, D. (1990). *Financial market analysis.* McGraw-Hill London.

Bodie, Z., Kane, A., & Marcus, A. J. (2014). *Investments* (10th. ed.). Mc-Graw-Hill Education.

Boldanov, R., Degiannakis, S., & Filis, G. (2016). Time-varying correlation between oil and stock market volatilities: Evidence from oil-importing and oil-exporting countries. *International Review of Financial Analysis, 48*, 209–220.

https://doi.org/10.1016/j.irfa.2016.10.002

Bollerslev, T. (1990). Modelling the coherence in short-run nominal exchange rates: A multivariate generalized ARCH model. *Review of Economics & Statistics, 72*(3), 498. https://doi.org/10.2307/2109358

Bollerslev, T., Engle, R. F., & Nelson, D. B. (1994). ARCH Models. In: Engle, R.F. and McFadden, D., (Eds.), Handbook of Econometrics, (Vol. 4, pp. 2959–3038), North-Holland, Amsterdam.

Booth, G. G., Martikainen, T., & Yiuman, T. (1997). Price and volatility spillovers in Scandinavian stock markets. *Journal of Banking & Finance, 21*(6), 811–823. https://doi.org/10.1016/S0378-4266(97)00006-X

Bouri, E. (2015). Return and volatility linkages between oil prices and the Lebanese stock market in crisis periods. *Energy, 89*, 365–371. https://doi.org/10.1016/j.energy.2015.05.121

Bouri, E., de Boyrie, M. E., & Pavlova, I. (2017). Volatility transmission from commodity markets to sovereign CDS spreads in emerging and frontier countries. *International Review of Financial Analysis, 49*, 155–165. https://doi.org/10.1016/j.irfa.2016.11.001

Bouri, E., Jain, A., Biswal, P. C., & Roubaud, D. (2017). Cointegration and nonlinear causality amongst gold, oil, and the Indian stock market: Evidence from implied volatility indices. *Resources Policy, 52*, 201–206. https://doi.org/10.1016/j.resourpol.2017.03.003

Bouri, E., Jalkh, N., & Roubaud, D. (2019). Commodity volatility shocks and BRIC sovereign risk: A GARCH-quantile approach. *Resources Policy, 61*, 385–392. https://doi.org/10.1016/j.resourpol.2017.12.002

Bouri, E., Kachacha, I., & Roubaud, D. (2020). Oil market conditions and sovereign risk in MENA oil exporters and importers. *Energy Policy, 137*, 111073. https://doi.org/10.1016/j.enpol.2019.111073

Brooks, C. (2019). *Introductory econometrics for finance*: Cambridge University Press.

Buttell, A. E. (2010). Harry M. Markowitz on modern portfolio theory, the efficient frontier, and his life's work. *Journal of Financial Planning, 23*(5), 18.

Büttner, D., & Hayo, B. (2011). Determinants of European stock market integration.

Economic Systems, 35(4), 574–585. https://doi.org/10.1016/j.ecosys.2010.10.004

Büyükşahin, B., & Robe, M. A. (2014). Speculators, commodities and cross-market linkages. *Journal of International Money and Finance, 42*, 38–70. https://doi.org/10.1016/j.jimonfin.2013.08.004

Cai, C. X., Mobarek, A., & Zhang, Q. (2017). International stock market leadership and its determinants. *Journal of Financial Stability, 33*, 150–162. https://doi.org/10.1016/j.jfs.2016.10.002

Cakan, E., Demirer, R., Gupta, R., & Marfatia, H. A. (2019). Oil speculation and herding behavior in emerging stock markets. *Journal of Economics & Finance, 43*(1), 44–56. https://doi.org/10.1007/s12197-018-9427-0

Campbell, J. Y., MacKinlay, A. C., & Lo, A. W. (1997). *The econometrics of financial markets*. Princeton University Press.

Canarella, G., Miller, S., & Pollard, S. (2012). Unit roots and structural change: An application to US house price indices. *Urban Studies, 49*(4), 757–776.

Caporin, M., & McAleer, M. (2013). Ten things you should know about the dynamic conditional correlation representation. *Econometrics, 1*(1), 115–126. https://doi.org/10.3390/econometrics1010115

Cardona, L., Gutiérrez, M., & Agudelo, D. A. (2017). Volatility transmission between US and Latin American stock markets: Testing the decoupling hypothesis. *Research in International Business and Finance, 39*, 115–127. https://doi.org/10.1016/j.ribaf.2016.07.008

Cha, H. J., & Jithendranathan, T. (2009). Time-varying correlations and optimal allocation in emerging market equities for the US investors. *International Journal of Finance & Economics, 14*(2), 172–187.

Chambet, A., & Gibson, R. (2008). Financial integration, economic instability and trade structure in emerging markets. *Journal of International Money & Finance, 27*(4), 654–675. https://doi.org/10.1016/j.jimonfin.2008.02.007

Chan, K. F., Treepongkaruna, S., Brooks, R., & Gray, S. (2011). Asset market linkages: Evidence from financial, commodity and real estate assets. *Journal of Banking & Finance, 35*(6), 1415–1426. https://doi.org/10.1016/j.jbankfin.2010.10.022

Chang, C.-L., McAleer, M., & Tansuchat, R. (2011). Crude oil hedging strategies using dynamic multivariate GARCH. *Energy Economics, 33*(5), 912–923. https://doi.org/10.1016/j.eneco.2011.01.009

Chang, C.-L., McAleer, M., & Tansuchat, R. (2013). Conditional correlations and volatility spillovers between crude oil and stock index returns. *North American Journal of Economics and Finance, 25*, 116–138. https://doi.org/10.1016/j.najef.2012.06.002

Chen, N.-F., Roll, R., & Ross, S. A. (1986). Economic forces and the stock market. *Journal of Business*, 383–403.

Chen, M.-H. (2010). Understanding world metals prices—Returns, volatility and diversification. *Resources Policy, 35*(3), 127-140.

Chen, Y., & Qu, F. (2019). Leverage effect and dynamics correlation between international crude oil and China's precious metals. *Physica A: Statistical Mechanics and its Applications*, *534*, 122319. https://doi.org/10.1016/j.physa.2019.122319

Cheung, Y. W., & Ng, L. K. (1996). A causality-in-variance test and its application to financial market prices. *Journal of Econometrics, 72*(1–2), 33–48. https://doi.org/10.1016/0304-4076(94)01714-X

Chiwira, O., & Muyambiri, B. (2012). A test of weak form efficiency for the Botswana stock exchange (2004–2008). *British Journal of Economics, Management & Trade, 2*(2), 83-91.

Chkili, W., Aloui, C., & Nguyen, D. K. (2014). Instabilities in the relationships and hedging strategies between crude oil and US stock markets: Do long memory and asymmetry matter? *Journal of International Financial Markets, Institutions and Money, 33*, 354–366. https://doi.org/10.1016/j.intfin.2014.09.003

Ciner, C. (2001). Energy shocks and financial markets: nonlinear linkages. *Studies in Nonlinear Dynamics & Econometrics, 5*(3).

Capital Market Authority. (2008). *Annual report*. http://www.cma.org.sa

Capital Market Authority. (2009). *Annual report*. http://www.cma.org.sa

Capital Market Authority. (2010). *Annual report*. http://www.cma.org.sa

Capital Market Authority. (2017). *Annual report*. http://www.cma.org.sa

Coeurdacier, N., & Guibaud, S. (2011). International portfolio diversification is better than you think. *Journal of International Money and Finance, 30*(2), 289–308. https://doi.org/10.1016/j.jimonfin.2010.10.003

Coval, J. D., & Moskowitz, T. J. (1999). Home bias at home: Local equity preference in domestic portfolios. *Journal of Finance*, *54*(6), 2045–2073. https://doi.org/10.1111/0022-1082.00181

Creti, A., Joëts, M., & Mignon, V. (2013). On the links between stock and commodity markets' volatility. *Energy Economics, 37*, 16–28. https://doi.org/10.1016/j.eneco.2013.01.005

Cunado, J., & Perez de Gracia, F. (2005). Oil prices, economic activity and inflation: Evidence for some Asian countries. *Quarterly Review of Economics and Finance, 45*(1), 65–83. https://doi.org/10.1016/j.qref.2004.02.003

Daskalaki, C., & Skiadopoulos, G. (2011). Should investors include commodities in their portfolios after all? New evidence. *Journal of Banking & Finance*, *35*(10), 2606–2626. https://doi.org/10.1016/j.jbankfin.2011.02.022

Degiannakis, S., & Filis, G. (2017). Forecasting oil price realized volatility using information channels from other asset classes. *Journal of International Money and Finance, 76*, 28–49. https://doi.org/10.1016/j.jimonfin.2017.05.006

Diaz, E. M., Molero, J. C., & Perez de Gracia, F. (2016). Oil price volatility and stock returns in the G7 economies. *Energy Economics, 54*, 417–430. https://doi.org/10.1016/j.eneco.2016.01.002

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association, 74*(366), 427. https://doi.org/10.2307/2286348

Dimitriou, D., Kenourgios, D., & Simos, T. (2013). Global financial crisis and emerging stock market contagion: A multivariate FIAPARCH–DCC approach. *International Review of Financial Analysis, 30*, 46–56. https://doi.org/10.1016/j.irfa.2013.05.008

Doan, T. (2013). RATS handbook for ARCH/GARCH and volatility models. *Estima WINRATS*.

Dungey, M., & Gajurel, D. (2014). Equity market contagion during the global financial crisis: Evidence from the world's eight largest economies. *Economic Systems, 38*(2), 161–177. https://doi.org/10.1016/j.ecosys.2013.10.003

Dutta, A., Bouri, E., & Roubaud, D. (2019). Nonlinear relationships amongst the implied volatilities of crude oil and precious metals. *Resources Policy, 61*, 473–478.

https://doi.org/10.1016/j.resourpol.2018.04.009

Ekong, C. N., & Onye, K. U. (2017). Application of GARCH models to estimate and predict financial volatility of daily stock returns in Nigeria. *International Journal of Managerial Studies and Research*, 5(8), 18–34. https://doi.org/10.20431/2349-0349.0508003

Elder, J. (2003). An impulse-response function for a vector autoregression with multivariate GARCH-in-mean. *Economics Letters, 79*(1), 21–26. https://doi.org/10.1016/S0165-1765(02)00283-5

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics, 20*(3), 339–350. https://doi.org/10.1198/073500102288618487

Engle, R. F. (1982). autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica, 50*(4), 987–1007. https://doi.org/10.2307/1912773

Engle, R. F., & Bollerslev, T. (1986). Modelling the persistence of conditional variances. *Econometric Reviews, 5*(1), 1–50.

Engle, R. F., Ito, T., & Lin, W.-L. (1990). Meteor showers or heat waves? Heteroskedastic Intra-daily volatility in the foreign exchange market. *Econometrica, 58*(3), 525–542. https://doi.org/10.2307/2938189

Engle, R. F., & Kroner, K. F. (1995). Multivariate simultaneous generalized ARCH. *Econometric Theory, 11*(1), 122–150. https://doi.org/10.1017/S0266466600009063

Eun, C. S., & Shim, S. (1989). International transmission of stock market movements. *The Journal of Financial and Quantitative Analysis, 24*(2), 241–256. https://doi.org/10.2307/2330774

Ewing, B. T., & Malik, F. (2016). Volatility spillovers between oil prices and the stock market under structural breaks. *Global Finance Journal, 29*, 12–23. https://doi.org/10.1016/j.gfj.2015.04.008

Fabozzi, F. J., & Modigliani, F. (2009). *Capital markets: Institutions and instruments* (4th ed.). Prentice Hall.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work.

Journal of Finance, 25(2), 383–417. https://doi.org/10.2307/2325486

Fang, C.-R., & You, S.-Y. (2014). The impact of oil price shocks on the large emerging countries' stock prices: Evidence from China, India and Russia. *International Review of Economics & Finance, 29*, 330–338. https://doi.org/10.1016/j.iref.2013.06.005

Finta, M. A., Frijns, B., & Tourani-Rad, A. (2019). Volatility spillovers among oil and stock markets in the US and Saudi Arabia. *Applied Economics, 51*(4), 329–345. https://doi.org/10.1080/00036846.2018.1494811

French, K. R., & Poterba, J. M. (1991). Investor Diversification and International Equity Markets. *The American Economic Review, 81*(2), 222-226. Retrieved December 21, 2020, from http://www.jstor.org/stable/2006858

Gallo, G. M., & Otranto, E. (2008). Volatility spillovers, interdependence and comovements: A Markov switching approach. *Computational Statistics & Data Analysis, 52*(6), 3011–3026. https://doi.org/10.1016/j.csda.2007.09.016

Gencer, H. G., & Musoglu, Z. (2014). Volatility transmission and spillovers among gold, bonds and stocks: An empirical evidence from Turkey. *International Journal of Economics and Financial Issues, 4*(4), 705–713.

Giannellis, N., Kanas, A., & Papadopoulos, A. P. (2010). Asymmetric volatility spillovers between stock market and real activity: Evidence from the UK and the US. *Panoeconomicus, 57*(4), 429–445. https://doi.org/10.2298/PAN1004429G

Gjika, D., & Horváth, R. (2013). Stock market comovements in Central Europe: Evidence from the asymmetric DCC model. *Economic Modelling, 33*, 55–64. https://doi.org/10.1016/j.econmod.2013.03.015

Glick, R., & Rose, A. K. (1999). Contagion and trade. Why are currency crises regional? *Journal of International Money & Finance, 18*(4), 603. https://doi.org/10.1016/S0261-5606(99)00023-6

Gorton, G., & Rouwenhorst, K. G. (2006). Facts and fantasies about commodity futures. *Financial Analysts Journal, 62*(2), 47–68.

Grigoli, F., Herman, A., & Swiston, A. (2019). A crude shock: Explaining the short-run impact of the 2014–16 oil price decline across exporters. *Energy Economics, 78*, 481–493. https://doi.org/10.1016/j.eneco.2018.11.025

Grubel, H. G. (1968). Internationally diversified portfolios: Welfare gains and capital flows. *The American Economic Review, 58*(5), 1299–1314.

Güloğlu, B., Kaya, P., & Aydemir, R. (2016). Volatility transmission among Latin American stock markets under structural breaks. *Physica A: Statistical Mechanics and its Applications, 462*, 330–340. https://doi.org/10.1016/j.physa.2016.06.093

Gupta, R., & Donleavy, G. D. (2009). Benefits of diversifying investments into emerging markets with time-varying correlations: An Australian perspective. *Journal of Multinational Financial Management, 19*(2), 160–177. https://doi.org/10.1016/j.mulfin.2008.10.001

Hafner, C. M., & Reznikova, O. (2012). On the estimation of dynamic conditional correlation models. *Computational Statistics & Data Analysis, 56*(11), 3533–3545.

Hamao, Y., Masulis, R. W., & Ng, V. (1990). Correlations in price changes and volatility across international stock markets. *Review of Financial Studies, 3*(2), 281–307.

Hamdi, B., Aloui, M., Alqahtani, F., & Tiwari, A. (2019). Relationship between the oil price volatility and sectoral stock markets in oil-exporting economies: Evidence from wavelet nonlinear denoised based quantile and Granger-causality analysis. *Energy Economics, 80*, 536–552. https://doi.org/10.1016/j.eneco.2018.12.021

Hamilton, J. D. (1983). Oil and the macroeconomy since World War II. *Journal of Political Economy, 91*(2), 228–248. https://doi.org/10.1086/261140

Hammoudeh, S., Nguyen, D. K., Reboredo, J. C., & Wen, X. (2014). Dependence of stock and commodity futures markets in China: Implications for portfolio investment. *Emerging Markets Review, 21*, 183–200. https://doi.org/10.1016/j.ememar.2014.09.002

Harvey, C. R. (1995). Predictable Risk and Returns in Emerging Markets. *The Review of Financial Studies, 8*(3), 773-816. Retrieved December 21, 2020, from http://www.jstor.org/stable/2962239

Hassan, K., Hoque, A., & Gasbarro, D. (2019). Separating BRIC using Islamic stocks and crude oil: Dynamic conditional correlation and volatility spillover analysis. *Energy Economics, 80*, 950–969. https://doi.org/10.1016/j.eneco.2019.02.016

Hemche, O., Jawadi, F., Maliki, S. B., & Cheffou, A. I. (2016). On the study of contagion in the context of the subprime crisis: A dynamic conditional correlation–

multivariate GARCH approach. *Economic Modelling, 52*, 292–299. https://doi.org/10.1016/j.econmod.2014.09.004

Hillier, D., Draper, P., & Faff, R. (2006). Do Precious Metals Shine? An Investment Perspective. *Financial Analysts Journal, 62*(2), 98-106.

Hu, J. W.-S., Chen, M.-Y., Fok, R. C. W., & Huang, B.-N. (1997). Causality in volatility and volatility spillover effects between US, Japan and four equity markets in the South China Growth Triangular. *Journal of International Financial Markets, Institutions and Money, 7*(4), 351–367. https://doi.org/10.1016/S1042-4431(97)00027-9

Huang, Y., Su, W., & Li, X. (2010) Comparison of BEKK GARCH and DCC GARCH models: An empirical study. In: L. Cao, J. Zhong, & Y. Feng (Eds) *Advanced data mining and applications*. *ADMA 2010. Lecture Notes in Computer Science* (Vol. 6441, Pages 99–110). Springer. https://doi.org/10.1007/978-3-642-17313-4_10

Husain, S., Tiwari, A. K., Sohag, K., & Shahbaz, M. (2019). Connectedness among crude oil prices, stock index and metal prices: An application of network approach in the USA. *Resources Policy, 62*, 57–65. https://doi.org/10.1016/j.resourpol.2019.03.011

Investment Jadwa. (2016, April). The Saudi stock exchange (Tadawul) in 2016. http://www.jadwa.com/en/researchsection/research/capital-market

Izadi, S., & Hassan, M. K. (2018). Portfolio and hedging effectiveness of financial assets of the G7 countries. *Eurasian Economic Review, 8*(2), 183–213. https://doi.org/10.1007/s40822-017-0090-0

Jammazi, R., & Nguyen, D. K. (2015). Responses of international stock markets to oil price surges: A regime-switching perspective. *Applied Economics, 47*(41), 4408–4422. https://doi.org/10.1080/00036846.2015.1030566

Jarrett, U., Mohaddes, K., & Mohtadi, H. (2019). Oil price volatility, financial institutions and economic growth. *Energy Policy, 126*, 131–144. https://doi.org/10.1016/j.enpol.2018.10.068

Jawadi, F., & Ftiti, Z. (2019). Oil price collapse and challenges to economic transformation of Saudi Arabia: A time-series analysis. *Energy Economics, 80*, 12–19. https://doi.org/10.1016/j.eneco.2018.12.003

Jayasuriya, S. A., & Shambora, W. (2009). Oops, we should have diversified! *Applied*

Financial Economics, 19(22), 1779–1785.

Jebb, A. T., Tay, L., Wang, W., & Huang, Q. (2015). Time series analysis for psychological research: Examining and forecasting change. *Frontiers in Psychology, 6*. 727 https://doi.org/10.3389/fpsyg.2015.

Ji, Q., Bouri, E., Roubaud, D., & Kristoufek, L. (2019). Information interdependence among energy, cryptocurrency and major commodity markets. *Energy Economics, 81*, 1042–1055. https://doi.org/10.1016/j.eneco.2019.06.005

Ji, Q., & Fan, Y. (2012). How does oil price volatility affect non-energy commodity markets? *Applied Energy, 89*(1), 273–280. https://doi.org/10.1016/j.apenergy.2011.07.038

Ji, Q., Liu, B.-Y., Cunado, J., & Gupta, R. (2020). Risk spillover between the US and the remaining G7 stock markets using time-varying copulas with Markov switching: Evidence from over a century of data. *North American Journal of Economics & Finance*, *51*, N.PAG. https://doi.org/10.1016/j.najef.2018.09.004

Jiang, Y., Fu, Y., & Ruan, W. (2019). Risk spillovers and portfolio management between precious metal and BRICS stock markets. *Physica A: Statistical Mechanics and its Applications, 534*, 120993. https://doi.org/10.1016/j.physa.2019.04.229

Jiang, Y., Jiang, C., Nie, H., & Mo, B. (2019). The time-varying linkages between global oil market and China's commodity sectors: Evidence from DCC-GJR-GARCH analyses. *Energy, 166*, 577–586. https://doi.org/10.1016/j.energy.2018.10.116

Jones, C. M., & Kaul, G. (1996). Oil and the stock markets. *Journal of Finance, 51*(2), 463–491. https://doi.org/10.1111/j.1540-6261.1996.tb02691.x

Jordan, S. J., Vivian, A., & Wohar, M. E. (2015). Location, location, location: Currency effects and return predictability? *Applied Economics, 47*(18), 1883–1898. https://doi.org/10.1080/00036846.2014.1000537

Jouini, J. (2015). New empirical evidence from assessing financial market integration, with application to Saudi Arabia. *Economic Modelling, 49*, 198–211. https://doi.org/10.1016/j.econmod.2015.04.010

Jouini, J., & Harrathi, N. (2014). Revisiting the shock and volatility transmissions among GCC stock and oil markets: A further investigation. *Economic Modelling, 38*, 486–494. https://doi.org/10.1016/j.econmod.2014.02.001

Joyo, A. S., & Lefen, L. (2019). Stock market integration of Pakistan with its trading partners: A multivariate DCC-GARCH model approach. *Sustainability (Switzerland), 11*(2). https://doi.org/10.3390/su11020303

Jung, R. C., & Maderitsch, R. (2014). Structural breaks in volatility spillovers between international financial markets: Contagion or mere interdependence? *Journal of Banking & Finance, 47*, 331–342. https://doi.org/10.1016/j.jbankfin.2013.12.023

Junttila, J., Pesonen, J., & Raatikainen, J. (2018). Commodity market based hedging against stock market risk in times of financial crisis: The case of crude oil and gold. *Journal of International Financial Markets, Institutions and Money, 56*, 255–280. https://doi.org/10.1016/j.intfin.2018.01.002

Kalyanaraman, L. (2014). Stock market volatility in Saudi Arabia: An application of univariate GARCH model. *Asian Social Science, 10*(10), 142.

Kang, S. H., Cheong, C., & Yoon, S.-M. (2013). Intraday volatility spillovers between spot and futures indices: Evidence from the Korean stock market. *Physica A: Statistical Mechanics and its Applications, 392*(8), 1795–1802. https://doi.org/10.1016/j.physa.2013.01.017

Kang, S. H., McIver, R., & Yoon, S.-M. (2017). Dynamic spillover effects among crude oil, precious metal, and agricultural commodity futures markets. *Energy Economics, 62*, 19–32. https://doi.org/10.1016/j.eneco.2016.12.011

Karolyi, G. A. (1995). A multivariate GARCH model of international transmissions of stock returns and volatility: The case of the United States and Canada. *Journal of Business & Economic Statistics, 13*(1), 11–25. https://doi.org/10.2307/1392517

Karunanayake, I., Valadkhani, A., & O'Brien, M. (2010). Financial crises and international stock market volatility transmission. *Australian Economic Papers, 49*(3), 209–221. https://doi.org/10.1111/j.1467-8454.2010.00397.x

Khalfaoui, R., Boutahar, M., & Boubaker, H. (2015). Analyzing volatility spillovers and hedging between oil and stock markets: Evidence from wavelet analysis. *Energy Economics, 49*, 540–549. https://doi.org/10.1016/j.eneco.2015.03.023

Khalfaoui, R., Sarwar, S., & Tiwari, A. K. (2019). Analysing volatility spillover between the oil market and the stock market in oil-importing and oil-exporting countries: Implications on portfolio management. *Resources Policy, 62*, 22–32.

https://doi.org/10.1016/j.resourpol.2019.03.004

Khalifa, A. A. A., Hammoudeh, S., & Otranto, E. (2014). Extracting portfolio management strategies from volatility transmission models in regime-changing environments: Evidence from GCC and global markets. *Economic Modelling, 41*, 365–374. https://doi.org/10.1016/j.econmod.2014.05.027

Khamis, R., Anasweh, M., & Hamdan, A. (2018). Oil prices and stock market returns in oil exporting countries: Evidence from Saudi Arabia. *International Journal of Energy Economics and Policy, 8*(3), 301–306.

King, M. A., & Wadhwani, S. (1990). Transmission of volatility between stock markets. *Review of Financial Studies, 3*(1), 5–33. https://doi.org/10.1093/rfs/3.1.5

Kiohos, A., & Sariannidis, N. (2010). Determinants of the asymmetric gold market. *Investment Management and Financial Innovations*, *7*(4), 26–33.

Kipiński, L., König, R., Sielużycki, C., & Kordecki, W. (2011). Application of modern tests for stationarity to single-trial MEG data: Transferring powerful statistical tools from econometrics to neuroscience. *Biological Cybernetics, 105*(3–4), 183–195. https://doi.org/10.1007/s00422-011-0456-4

Kling, J. L. (1985). Oil price shocks and stock market behavior. *The Journal of Portfolio Management, 12*(1), 34–39.

Koutmos, G., & Booth, G. G. (1995). Asymmetric volatility transmission in international stock markets. *Journal of International Money and Finance, 14*(6), 747–762. https://doi.org/10.1016/0261-5606(95)00031-3

Kristoufek, L., & Vosvrda, M. (2016). Gold, currencies and market efficiency. *Physica A: Statistical Mechanics and its Applications, 449*, 27–34. https://doi.org/10.1016/j.physa.2015.12.075

Kroner, K. F., & Ng, V. K. (1998). Modeling asymmetric comovements of asset returns. *Review of Financial Studies, 11*(4), 817.

Kroner, K. F., & Sultan, J. (1993). Time-varying distributions and dynamic hedging with foreign currency futures. *Journal of Financial & Quantitative Analysis, 28*(4), 535–551.

Kulaksizoglu, T. (2015). Lag order and critical values of the augmented Dickey-Fuller test: A replication. *Journal of Applied Econometrics, 30*(6), 1010–1010.

https://doi.org/10.1002/jae.2458

Kumar, D. (2014). Return and volatility transmission between gold and stock sectors: Application of portfolio management and hedging effectiveness. *IIMB Management Review, 26*(1), 5–16. https://doi.org/10.1016/j.iimb.2013.12.002

Kumar, D. (2015). Risk spillover between the GIPSI economies and Egypt, Saudi Arabia, and Turkey. *Emerging Markets Finance & Trade, 51*(6), 1193–1208. https://doi.org/10.1080/1540496X.2015.1080520

Kundu, S., & Sarkar, N. (2016). Return and volatility interdependences in up and down markets across developed and emerging countries. *Research in International Business and Finance, 36*, 297–311. https://doi.org/10.1016/j.ribaf.2015.09.023

Lai, Y., & Tseng, J.-C. (2010). The role of Chinese stock market in global stock markets: A safe haven or a hedge? *International Review of Economics & Finance, 19*(2), 211–218. https://doi.org/10.1016/j.iref.2009.10.004

Lau, M. C. K., Vigne, S. A., Wang, S., & Yarovaya, L. (2017). Return spillovers between white precious metal ETFs: The role of oil, gold, and global equity. *International Review of Financial Analysis, 52*, 316–332. https://doi.org/10.1016/j.irfa.2017.04.001

Laurent, S., Rombouts, J. V. K., & Violante, F. (2012). On the forecasting accuracy of multivariate GARCH models. *Journal of Applied Econometrics, 27*(6), 934–955. https://doi.org/10.1002/jae.1248

Lee, Y. H., Wu, C. Y., & Huang, Y. L. (2014). Dynamic correlations and volatility spillovers between crude oil and stock index returns: The implications for optimal portfolio construction. *International Journal of Energy Economics and Policy, 4*(3), 327–336.

Lewis, K. K. (1996). What can explain the apparent lack of international consumption risk sharing? *Journal of Political Economy, 104*(2), 267–297.

Li, H. (2020). Volatility spillovers across European stock markets under the uncertainty of Brexit. *Economic Modelling*, *84*, 1–12. https://doi.org/10.1016/j.econmod.2019.03.001

Lin, B., Wesseh, P. K., & Appiah, M. O. (2014). Oil price fluctuation, volatility spillover and the Ghanaian equity market: Implication for portfolio management and hedging effectiveness. *Energy Economics, 42*, 172–182. https://doi.org/10.1016/j.eneco.2013.12.017

Lin, W. L., Engle, R. F., & Ito, T. (1994). Do bulls and bears move across borders? International transmission of stock returns and volatility. *Review of Financial Studies, 7*(3), 507-538.

Liu, Y. A., & Pan, M.-S. (1997). Mean and volatility spillover effects in the US and Pacific-Basin stock markets. *Multinational Finance Journal, 1*(1), 47–62.

Liu, Z., Tseng, H.-K., Wu, J. S., & Ding, Z. (2020). Implied volatility relationships between crude oil and the US stock markets: Dynamic correlation and spillover effects. *Resources Policy, 66*, 101637.

Lucey, B. M., & Li, S. (2015). What precious metals act as safe havens, and when? Some US evidence. *Applied Economics Letters, 22*(1), 35–45. https://doi.org/10.1080/13504851.2014.920471

Luo, J., & Ji, Q. (2018). High-frequency volatility connectedness between the US crude oil market and China's agricultural commodity markets. *Energy Economics, 76*, 424–438. https://doi.org/10.1016/j.eneco.2018.10.031

Maghyereh, A. I., Awartani, B., & Bouri, E. (2016). The directional volatility connectedness between crude oil and equity markets: New evidence from implied volatility indexes. *Energy Economics, 57*, 78–93. https://doi.org/10.1016/j.eneco.2016.04.010

Maghyereh, A. I., Awartani, B., & Hilu, K. A. (2015). Dynamic transmissions between the U.S. and equity markets in the MENA countries: New evidence from pre- and post-global financial crisis. *Quarterly Review of Economics & Finance, 56*, 123–138. https://doi.org/10.1016/j.qref.2014.08.005

Majdoub, J., & Sassi, S. B. (2017). Volatility spillover and hedging effectiveness among China and emerging Asian Islamic equity indexes. *Emerging Markets Review, 31*, 16–31.

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance, 7*(1), 77–91. https://doi.org/10.1111/j.1540-6261.1952.tb01525.x

Markowitz, H. (1959). *Portfolio selection: Efficient diversification of investments*. Yale University Press.

Markowitz, H. M. (2016). *Risk-return analysis, volume 2: The theory and practice of rational investing*. McGraw-Hill Education.

Masih, R., & Masih, A. M. M. (2001). Long and short term dynamic causal transmission amongst international stock markets. *Journal of International Money & Finance*, *20*(4), 563–587. https://doi.org/10.1016/S0261-5606(01)00012-2

Mei-Se, C., Shu-Jung, C. L., & Chien-Chiang, L. (2018). Time-varying co-movement of the prices of three metals and oil: Evidence from recursive cointegration. *Resources Policy, 57*, 186–195. https://doi.org/10.1016/j.resourpol.2018.03.003

Mensi, W. (2019). Global financial crisis and co-movements between oil prices and sector stock markets in Saudi Arabia: A VaR based wavelet. *Borsa Istanbul Review, 19*(1), 24–38. https://doi.org/10.1016/j.bir.2017.11.005

Mensi, W., Al-Yahyaee, K. H., & Hoon Kang, S. (2017). Time-varying volatility spillovers between stock and precious metal markets with portfolio implications. *Resources Policy, 53*, 88–102. https://doi.org/10.1016/j.resourpol.2017.06.001

Mensi, W., Beljid, M., Boubaker, A., & Managi, S. (2013). Correlations and volatility spillovers across commodity and stock markets: Linking energies, food, and gold. *Economic Modelling, 32*, 15–22. https://doi.org/10.1016/j.econmod.2013.01.023

Mensi, W., Hammoudeh, S., Al-Jarrah, I. M. W., Sensoy, A., & Kang, S. H. (2017). Dynamic risk spillovers between gold, oil prices and conventional, sustainability and Islamic equity aggregates and sectors with portfolio implications. *Energy Economics, 67*, 454–475. https://doi.org/10.1016/j.eneco.2017.08.031

Mensi, W., Hammoudeh, S., & Kang, S. H. (2015). Precious metals, cereal, oil and stock market linkages and portfolio risk management: Evidence from Saudi Arabia. *Economic Modelling, 51*, 340–358. https://doi.org/10.1016/j.econmod.2015.08.005

Mensi, W., Hammoudeh, S., Nguyen, D. K., & Yoon, S.-M. (2014). Dynamic spillovers among major energy and cereal commodity prices. *Energy Economics, 43*, 225–243. https://doi.org/10.1016/j.eneco.2014.03.004

Mensi, W., Hammoudeh, S., Reboredo, J. C., & Nguyen, D. K. (2015). Are Sharia stocks, gold and U.S. Treasury hedges and/or safe havens for the oil-based GCC markets? *Emerging Markets Review, 24*, 101–121. https://doi.org/10.1016/j.ememar.2015.05.007

Mensi, W., Hammoudeh, S., Shahzad, S. J. H., & Shahbaz, M. (2017). Modeling systemic risk and dependence structure between oil and stock markets using a variational mode decomposition-based copula method. *Journal of Banking & Finance, 75*, 258–279. https://doi.org/10.1016/j.jbankfin.2016.11.017

Mensi, W., Hkiri, B., Al-Yahyaee, K. H., & Kang, S. H. (2018). Analyzing time–frequency co-movements across gold and oil prices with BRICS stock markets: A VaR based on wavelet approach. *International Review of Economics & Finance, 54*, 74–102. https://doi.org/10.1016/j.iref.2017.07.032

Meric, I., Ratner, M., & Meric, G. (2008). Co-movements of sector index returns in the world's major stock markets in bull and bear markets: Portfolio diversification implications. *International Review of Financial Analysis, 17*(1), 156–177. https://doi.org/10.1016/j.irfa.2005.12.001

Middleton, C. A. J., Fifield, S. G. M., & Power, D. M. (2008). An investigation of the benefits of portfolio investment in Central and Eastern European stock markets. *Research in International Business and Finance, 22*(2), 162–174. https://doi.org/10.1016/j.ribaf.2007.04.001

Mills, T. C. (2019). *Applied time series analysis: A practical guide to modeling and forecasting.* Academic Press.

Mohammadi, H., & Tan, Y. (2015). Return and volatility spillovers across equity markets in Mainland China, Hong Kong and the United States. *Econometrics, 3*(2), 215–232.

Mohanty, S. K., Onochie, J., & Alshehri, A. F. (2018). Asymmetric effects of oil shocks on stock market returns in Saudi Arabia: Evidence from industry level analysis. *Review of Quantitative Finance and Accounting, 51*(3), 595. https://doi.org/10.1007/s11156-017-0682-5

Mollah, S., Quoreshi, A. M. M. S., & Zafirov, G. (2016). Equity market contagion during global financial and Eurozone crises: Evidence from a dynamic correlation analysis. *Journal of International Financial Markets, Institutions and Money, 41*, 151–167. https://doi.org/10.1016/j.intfin.2015.12.010

Morana, C. (2008). International stock markets comovements: The role of economic and financial integration. *Empirical Economics, 35*(2), 333–359.

Mordret, A., Jolly, A. D., Duputel, Z., & Fournier, N. (2010). Monitoring of phreatic eruptions using interferometry on retrieved cross-correlation function from ambient seismic noise: Results from Mt. Ruapehu, New Zealand. *Journal of Volcanology and Geothermal Research, 191*(1), 46–59. https://doi.org/10.1016/j.jvolgeores.2010.01.010

Mutafoglu, T. H., Tokat, E., & Tokat, H. A. (2012). Forecasting precious metal price movements using trader positions. *Resources Policy, 37*(3), 273-280.

Naoui, K., Liouane, N., & Brahim, S. (2010). A dynamic conditional correlation analysis of financial contagion: The case of the subprime credit crisis. *International Journal of Economics and Finance, 2*(3), 85–96.

Nazlioglu, S., Erdem, C., & Soytas, U. (2013). Volatility spillover between oil and agricultural commodity markets. *Energy Economics, 36*, 658–665. https://doi.org/10.1016/j.eneco.2012.11.009

Ng, A. (2000). Volatility spillover effects from Japan and the US to the Pacific-Basin. *Journal of International Money & Finance, 19*(2), 207.

Nguyen, C. C., & Bhatti, M. I. (2012). Copula model dependency between oil prices and stock markets: Evidence from China and Vietnam. *Journal of International Financial Markets, Institutions and Money, 22*(4), 758–773. https://doi.org/10.1016/j.intfin.2012.03.004

Nobi, A., & Lee, J. W. (2017). Financial states of world financial and commodities markets around sovereign debt crisis. *Journal of the Korean Physical Society, 71*(10), 733–739. https://doi.org/10.3938/jkps.71.733

Odier, P., & Solnik, B. (1993). Lessons for international asset allocation. *Financial Analysts Journal, 49*(2), 27–27. https://doi.org/10.2469/faj.v49.n2.63

Oloko, T. F. (2018). Portfolio diversification between developed and developing stock markets: The case of US and UK investors in Nigeria. *Research in International Business and Finance, 45*, 219–232. https://doi.org/10.1016/j.ribaf.2017.07.153

Olson, E., J. Vivian, A., & Wohar, M. E. (2014). The relationship between energy and equity markets: Evidence from volatility impulse response functions. *Energy Economics, 43*, 297–305. https://doi.org/10.1016/j.eneco.2014.01.009

Olweny, T. O., & Kimani, D. (2011). Stock market performance and economic growth Empirical evidence from Kenya using causality test approach. *Advances in*

Management and Applied Economics, 1(3), 177.

Öztek, M. F., & Öcal, N. (2017). Financial crises and the nature of correlation between commodity and stock markets. *International Review of Economics & Finance, 48*, 56–68. https://doi.org/10.1016/j.iref.2016.11.008

Paas, T., & Kuusk, A. (2012). Contagion of financial crises: What does the empirical evidence show? *Baltic Journal of Management, 7*(1), 25–48.

Panda, A. K., Nanda, S., & Paital, R. R. (2019). An empirical analysis of stock market interdependence and volatility spillover in the stock markets of Africa and Middle East region. *African Journal of Economic and Management Studies, 10*(3), 314–335. https://doi.org/10.1108/AJEMS-10-2018-0293

Paramati, S. R., Roca, E., & Gupta, R. (2016). Economic integration and stock market dynamic linkages: Evidence in the context of Australia and Asia. *Applied Economics, 48*(44), 4210–4226. https://doi.org/10.1080/00036846.2016.1153794

Pescetto, G. M. (1993). Capital markets (book). *Economic Journal, 103*(416), 289–289.

Pilbeam, K., & Langeland, K. (2015). Forecasting exchange rate volatility: GARCH models versus implied volatility forecasts. *International Economics & Economic Policy, 12*(1), 127–142. https://doi.org/10.1007/s10368-014-0289-4

Prasad, N., Grant, A., & Kim, S.-J. (2018). Time varying volatility indices and their determinants: Evidence from developed and emerging stock markets. *International Review of Financial Analysis, 60*, 115–126.

Pretorius, E. (2002). Economic determinants of emerging stock market interdependence. *Emerging Markets Review, 3*(1), 84. https://doi.org/10.1016/S1566-0141(01)00032-2

Rasiah, D. (2012). Post-modern portfolio theory supports diversification in an investment portfolio to measure investment's performance. *Journal of Finance and Investment Analysis, 1*(1), 69–91.

Raza, N., Jawad Hussain Shahzad, S., Tiwari, A. K., & Shahbaz, M. (2016). Asymmetric impact of gold, oil prices and their volatilities on stock prices of emerging markets. *Resources Policy, 49*, 290–301. https://doi.org/10.1016/j.resourpol.2016.06.011

Reboredo, J. C. (2013). Is gold a hedge or safe haven against oil price movements? *Resources Policy, 38*(2), 130-137.

Rejeb, A. B. (2017). On the volatility spillover between Islamic and conventional stock markets: A quantile regression analysis. *Research in International Business and Finance, 42*, 794–815.

Rejeb, A. B., & Boughrara, A. (2015). Financial integration in emerging market economies: Effects on volatility transmission and contagion. *Borsa Istanbul Review, 15*(3), 161–179.

Ripley, D. M. (1973). Systematic elements in the linkage of national stock market indices. *Review of Economics & Statistics, 55*(3), 356. https://doi.org/10.2307/1927959

Ross, S. A. (1989). Information and volatility: The no-arbitrage martingale approach to timing and resolution irrelevancy. *Journal of Finance, 44*(1), 1–17. https://doi.org/10.1111/j.1540-6261.1989.tb02401.x

Sadorsky, P. (1999). Oil price shocks and stock market activity. *Energy Economics, 21*(5), 449–469. https://doi.org/10.1016/S0140-9883(99)00020-1

Sadorsky, P. (2014). Modeling volatility and correlations between emerging market stock prices and the prices of copper, oil and wheat. *Energy Economics, 43*, 72–81. https://doi.org/10.1016/j.eneco.2014.02.014

Saiti, B., Bacha, O. I., & Masih, A. M. M. (2013). Estimation of dynamic conditional correlations of Shariah-compliant stock indices through the application of multivariate GARCH approach. *Australian Journal of Basic and Applied Sciences, 7*(7), 259–267.

Salisu, A. A., & Oloko, T. F. (2015). Modeling oil price–US stock nexus: A Varma–BEKK–AGARCH approach. *Energy Economics, 50*, 1–12. https://doi.org/10.1016/j.eneco.2015.03.031

Saudi Arabian Monetary Agency. (2007). *Annual report* (no. 43). http://www.sama.gov.sa

Saudi Arabian Monetary Agency. (2008). *Annual report* (no. 44). http://www.sama.gov.sa

Saudi Arabian Monetary Agency. (2009). *Annual report* (no. 45). http://www.sama.gov.sa

Saudi Arabian Monetary Agency. (2011). *Annual report* (no. 47). http://www.sama.gov.sa

Saudi Arabian Monetary Agency. (2017a). *Annual report* (no. 53). http://www.sama.gov.sa

Saudi Arabian Monetary Agency. (2017b). *Annual statistics*. http://www.sama.gov.sa

Saudi Arabian Monetary Agency. (2018). *Annual report* (no. 54). http://www.sama.gov.sa

Saudi Arabian Monetary Agency. (2019). *Annual report* (no. 55). http://www.sama.gov.sa

Saudi Arabian Monetary Agency. (2020). *Annual report* (no. 56). http://www.sama.gov.sa

Samarakoon, L. P. (2011). Stock market interdependence, contagion, and the U.S. financial crisis: The case of emerging and frontier markets. *Journal of International Financial Markets, Institutions & Money, 21*(5), 724–742. https://doi.org/10.1016/j.intfin.2011.05.001

Samontaray D.P., & Alanuzi A.A. (2015) The Impact of Gold Price Changes on Saudi Stock Market. In: Chatterjee S., Singh N., Goyal D., Gupta N. (eds) Managing in Recovering Markets. Springer Proceedings in Business and Economics. Springer, New Delhi. https://doi.org/10.1007/978-81-322-1979-8_37

Sarwar, S., Khalfaoui, R., Waheed, R., & Dastgerdi, H. G. (2019). Volatility spillovers and hedging: Evidence from Asian oil-importing countries. *Resources Policy, 61*, 479–488. https://doi.org/10.1016/j.resourpol.2018.04.010

Savva, C. S., Osborn, D. R., & Gill, L. (2009). Spillovers and correlations between US and major European stock markets: The role of the euro. *Applied Financial Economics, 19*(19), 1595–1604. https://doi.org/10.1080/09603100802599563

Shahzad, S. J. H., Ferrer, R., Ballester, L., & Umar, Z. (2017). Risk transmission between Islamic and conventional stock markets: A return and volatility spillover analysis. *International Review of Financial Analysis, 52*, 9–26. https://doi.org/10.1016/j.irfa.2017.04.005

Shaik, A. R., & Syed, A. M. (2019). Intraday return volatility in Saudi stock market: An evidence from Tadawul All Share Index. *Management Science Letters, 9*(7), 1131–1140. https://doi.org/10.5267/j.msl.2019.3.012

Silvennoinen, A., & Thorp, S. (2013). Financialization, crisis and commodity correlation dynamics. *Journal of International Financial Markets, Institutions & Money, 24*, 42–65. https://doi.org/10.1016/j.intfin.2012.11.007

Singh, A., & Singh, M. (2017). A revisit to stock market contagion and portfolio hedging strategies: BRIC equity markets and financial crisis. *International Journal of Law & Management, 59*(5), 618–635. https://doi.org/10.1108/IJLMA-03-2016-0026

Singh, P., Kumar, B., & Pandey, A. (2010). Price and volatility spillovers across North American, European and Asian stock markets. *International Review of Financial Analysis, 19*(1), 55–64. https://doi.org/10.1016/j.irfa.2009.11.001

Sinha, K., Gurung. B., Paul, R., K., Kumar, A., Panwar, S., Alam, W., Ray, M. & Rathod, S. (2017). Volatility Spillover using Multivariate GARCH Model: An Application in Futures and Spot Market Price of Black Pepper. *Journal of the Indian Society of Agricultural Statistics,* 71(1), 21–28.

Solnik, B. H. (1974). An equilibrium model of the international capital market. *Journal of Economic Theory, 8*(4), 500–524. https://doi.org/10.1016/0022-0531(74)90024-6

Souček, M. (2013). Crude oil, equity and gold futures open interest co-movements. *Energy Economics, 40*, 306–315. https://doi.org/10.1016/j.eneco.2013.07.010

Spyridis, T., Sevic, Z., & Theriou, N. (2010). The long-run relationship between stock indices and economic factors in the ASE: An empirical study between 1989 and 2006. *International Journal of Business, 15*(4), 425.

Stettina, C. J., & Hörz, J. (2015). Agile portfolio management: An empirical perspective on the practice in use. *International Journal of Project Management, 33*(1), 140–152. https://doi.org/10.1016/j.ijproman.2014.03.008

Sun, X., Wang, J., Yao, Y., Li, J., & Li, J. (2020). Spillovers among sovereign CDS, stock and commodity markets: A correlation network perspective. *International Review of Financial Analysis, 68*, 101271. https://doi.org/10.1016/j.irfa.2018.10.008

Susmel, R., & Engle, R. F. (1994). Hourly volatility spillovers between international equity markets. *Journal of International Money and Finance, 13*(1), 3–25. https://doi.org/10.1016/0261-5606(94)90021-3

Syriopoulos, T., Makram, B., & Boubaker, A. (2015). Stock market volatility spillovers and portfolio hedging: BRICS and the financial crisis. *International Review of Financial Analysis, 39*, 7–18. https://doi.org/10.1016/j.irfa.2015.01.015

Tadawul. (2007). *Annual statistical report 2007*. https://www.tadawul.com.sa

Tadawul. (2009). *Annual statistical report 2009*. https://www.tadawul.com.sa

Tadawul. (2018). *Annual report 2018*. https://www.tadawul.com.sa

Tang, K., & Xiong, W. (2012). Index investment and the financialization of commodities. *Financial Analysts Journal, 68*(6), 54–74.

Tanizaki, H., & Hamori, S. (2009). Volatility transmission between Japan, UK and USA in daily stock returns. *Empirical Economics, 36*(1), 27–54. https://doi.org/10.1007/s00181-007-0182-x

Tavares, J. (2009). Economic integration and the comovement of stock returns. *Economics Letters, 103*(2), 65–67. https://doi.org/10.1016/j.econlet.2009.01.016

Theodossiou, P., & Lee, U. (1993). Mean and volatility spillovers across major national stock markets: Further empirical evidence. *Journal of Financial Research, 16*(4), 337. https://doi.org/10.1111/j.1475-6803.1993.tb00152.x

Thorbecke, W. (2019). Oil prices and the U.S. economy: Evidence from the stock market. *Journal of Macroeconomics, 61*, 103137. https://doi.org/10.1016/j.jmacro.2019.103137

Tissaoui, K., & Azibi, J. (2019). International implied volatility risk indexes and Saudi stock return-volatility predictabilities. *The North American Journal of Economics and Finance, 47*, 65–84. https://doi.org/10.1016/j.najef.2018.11.016

Trabelsi, N. (2017). Asymmetric tail dependence between oil price shocks and sectors of Saudi Arabia System. *The Journal of Economic Asymmetries, 16*, 26–41. https://doi.org/10.1016/j.jeca.2017.05.001

Tsai, I. C. (2014). Spillover of fear: Evidence from the stock markets of five developed countries. *International Review of Financial Analysis, 33*, 281–288. https://doi.org/10.1016/j.irfa.2014.03.007

Tse, Y. K., & Tsui, A. K. C. (2002). A multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations. *Journal of Business & Economic Statistics, 20*(3), 351–362. https://doi.org/10.1198/073500102288618496

Tule, M. K., Ndako, U. B., & Onipede, S. F. (2017). Oil price shocks and volatility spillovers in the Nigerian sovereign bond market. *Review of Financial Economics, 35*, 57–65. https://doi.org/10.1016/j.rfe.2017.03.003

Uludag, B. K., & Khurshid, M. (2019). Volatility spillover from the Chinese stock market to E7 and G7 stock markets. *Journal of Economic Studies*, *46*(1), 90–105. https://doi.org/10.1108/JES-01-2017-0014

Urom, C., Anochiwa, L., Yuni, D., & Idume, G. (2019). Asymmetric linkages among precious metals, global equity and bond yields: The role of volatility and business cycle factors. *The Journal of Economic Asymmetries, 20*, e00120. https://doi.org/10.1016/j.jeca.2019.e00120

Vaclavik, M., & Jablonsky, J. (2012). Revisions of modern portfolio theory optimization model. *Central European Journal of Operations Research, 20*(3), 473–483. https://doi.org/10.1007/s10100-011-0227-2

Valera, H. G. A., Holmes, M. J., & Hassan, G. M. (2018). Is inflation targeting credible in Asia? A panel GARCH approach. *Empirical Economics, 54*(2), 523–546. https://doi.org/10.1007/s00181-016-1212-3

Vardar, G., Coşkun, Y., & Yelkenci, T. (2018). Shock transmission and volatility spillover in stock and commodity markets: evidence from advanced and emerging markets. *Eurasian Economic Review, 8*(2), 231–288. https://doi.org/10.1007/s40822-018-0095-3

Vivian, A. (2016). Stock index return predictability in frontier markets: Is it there? In P. Andrikopoulos, G. N. Gregoriou, & V. Kallinterakis (Eds.), *Handbook of frontier markets* (pp. 193–216). Academic Press.

Vo, X. V., & Ellis, C. (2018). International financial integration: Stock return linkages and volatility transmission between Vietnam and advanced countries. *Emerging Markets Review, 36*, 19–27. https://doi.org/10.1016/j.ememar.2018.03.007

Vogelsang, T. J., & Wagner, M. (2013). A fixed-*b* perspective on the Phillips–Perron unit root tests. *Econometric Theory, 29*(3), 609–628. https://doi.org/10.1017/S0266466612000485

Wälti, S. (2011). Stock market synchronization and monetary integration. *Journal of International Money & Finance*, 30(1), 96–110. https://doi.org/10.1016/j.jimonfin.2010.07.004

Wang, G.-J., Xie, C., Jiang, Z.-Q., & Stanley, H. E. (2016). Extreme risk spillover effects in world gold markets and the global financial crisis. *International Review of Economics & Finance, 46*, 55–77. https://doi.org/10.1016/j.iref.2016.08.004

Wang, P. (2009). *Financial Econometrics* (2nd edition.): Routledge.

Wang, X., & Wang, Y. (2019). Volatility spillovers between crude oil and Chinese sectoral equity markets: Evidence from a frequency dynamics perspective. *Energy Economics, 80*, 995–1009. https://doi.org/10.1016/j.eneco.2019.02.019

Wong, V. S. H., & El Massah, S. (2018). Recent evidence on the oil price shocks on Gulf Cooperation Council stock markets. *International Journal of the Economics of Business, 25*(2), 297–312. https://doi.org/10.1080/13571516.2017.1379216

Worthington, A., & Higgs, H. (2004). Transmission of equity returns and volatility in Asian developed and emerging markets: A multivariate GARCH analysis. *International Journal of Finance & Economics, 9*(1), 71–80. https://doi.org/10.1002/ijfe.222

Wu, F. (2020). Stock market integration in East and Southeast Asia: The role of global factors. *International Review of Financial Analysis, 67*, 101416. https://doi.org/10.1016/j.irfa.2019.101416

Xiao, L., & Dhesi, G. (2010). Volatility spillover and time-varying conditional correlation between the European and US stock markets. *Global Economy and Finance Journal, 3*(2), 148–164.

Xu, H., & Hamori, S. (2012). Dynamic linkages of stock prices between the BRICs and the United States: Effects of the 2008–09 financial crisis. *Journal of Asian Economics, 23*(4), 344–352. https://doi.org/10.1016/j.asieco.2012.04.002

Xu, W., Ma, F., Chen, W., & Zhang, B. (2019). Asymmetric volatility spillovers between oil and stock markets: Evidence from China and the United States. *Energy Economics, 80*, 310–320. https://doi.org/10.1016/j.eneco.2019.01.014

Yarovaya, L., Brzeszczyński, J., & Lau, C. K. M. (2016). Intra- and inter-regional return and volatility spillovers across emerging and developed markets: Evidence from stock indices and stock index futures. *International Review of Financial Analysis, 43*, 96–114. https://doi.org/10.1016/j.irfa.2015.09.004

Yavas, B. F., & Dedi, L. (2016). An investigation of return and volatility linkages among equity markets: A study of selected European and emerging countries. *Research in International Business and Finance, 37*, 583–596. https://doi.org/10.1016/j.ribaf.2016.01.025

Yaya, O. S., Tumala, M. M., & Udomboso, C. G. (2016). Volatility persistence and returns spillovers between oil and gold prices: Analysis before and after the global financial crisis. *Resources Policy, 49*, 273–281. https://doi.org/10.1016/j.resourpol.2016.06.008

Yıldırım, D. Ç., Erdoğan, S., & Çevik, E. İ. (2018). Regime-dependent effect of crude oil price on BRICS stock markets. *Emerging Markets Finance & Trade, 54*(8), 1706–1719. https://doi.org/10.1080/1540496X.2018.1427062

Yiu, M. S., Alex Ho, W.-Y., & Choi, D. F. (2010). Dynamic correlation analysis of financial contagion in Asian markets in global financial turmoil. *Applied Financial Economics, 20*(4), 345–354. https://doi.org/10.1080/09603100903494946

Yu, J.-S., & Hassan, M. K. (2008). Global and regional integration of the Middle East and North African (MENA) stock markets. *The Quarterly Review of Economics and Finance, 48*(3), 482–504. https://doi.org/10.1016/j.qref.2006.06.003

Zhang, C., Shi, X., & Yu, D. (2018). The effect of global oil price shocks on China's precious metals market: A comparative analysis of gold and platinum. *Journal of Cleaner Production, 186*, 652–661. https://doi.org/10.1016/j.jclepro.2018.03.154

Zhang, D., & Broadstock, D. C. (2020). Global financial crisis and rising connectedness in the international commodity markets. *International Review of Financial Analysis, 68*, 101239. https://doi.org/10.1016/j.irfa.2018.08.003

Zhang, W., Zhuang, X., & Wu, D. (2019). Spatial connectedness of volatility spillovers in G20 stock markets: Based on block models analysis. *Finance Research Letters*. https://doi.org/10.1016/j.frl.2019.08.022

Zheng, T., & Zuo, H. (2013). Reexamining the time-varying volatility spillover effects: A Markov switching causality approach. *North American Journal of Economics & Finance, 26*, 643–662. https://doi.org/10.1016/j.najef.2013.05.001