DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
DEPARTMENT OF BUSINESS ADMINISTRATION
BUSINESS ADMINISTRATION DOCTORATE PROGRAM
DOCTORAL DISSERTATION
Doctor of Philosophy (PhD)

A VOLATILITY SPILLOVER ANALYSIS BETWEEN BOND AND COMMODITY MARKETS AS AN INDICATOR FOR GLOBAL LIQUIDITY RISK

Ayşegül KIRKPINAR

Supervisor
Prof. Dr. Pınar EVRİM MANDACI

İZMİR- 2018

DOCTORAL THESIS
APPROVAL PAGE

University	: Dokuz Eylul University
Graduate School	: Graduate School of Social Sciences
Name and Surname	: AYŞEGÜL KIRKPINAR
Title of the Thesis	: A Volatility Spillover Analysis Between Bond and Commodity Markets as an Indicator for Global Liquidity Risk
Defence Date	: 18/05/2018
Supervisor	: Prof.Dr.Pınar EVRİM MANDACI

EXAMINING COMMITTE MEMBERS

Title,Name and Surname	**University**	**Signature**
Prof.Dr.Pınar EVRİM MANDACI	DOKUZ EYLUL UNIVERSITY	....
Prof.Dr.M.Banu DURUKAN SALI	DOKUZ EYLUL UNIVERSITY	....
Prof.Dr.Berna KIRKULAK ULUDAĞ	DOKUZ EYLUL UNIVERSITY	....
Doç.Dr.Dilvin TAŞKIN	YASAR UNIVERSITY	....
Doç.Dr.Sibel KARĞIN	CELAL BAYAR UNIVERSITY	....

Unanimity (X)

Majority of votes ( )

The thesis titled as "**A Volatility Spillover Analysis Between Bond and Commodity Markets as an Indicator for Global Liquidity Risk**" prepared and presented by AYŞEGÜL KIRKPINAR is accepted and approved.

Prof. Dr. Metin ARIKAN
Director

DECLARATION

I hereby declare that this doctoral dissertation titled as "**A Volatility Spillover Analysis between Bond and Commodity Markets as an Indicator for Global Liquidity Risk**" has been written by myself in accordance with the academic rules and ethical conduct. I also declare that all materials benefited in this dissertation consist of the mentioned resources in the reference list. I verify all these with my honour.

Date

…/…/…….

Ayşegül KIRKPINAR

Signature

ABSTRACT

Doctoral Dissertation

Doctor of Philosophy (PhD)

A VOLATILITY SPILLOVER ANALYSIS BETWEEN BOND AND COMMODITY MARKETS AS AN INDICATOR FOR GLOBAL LIQUIDITY RISK

Ayşegül KIRKPINAR

Dokuz Eylül University
Graduate School of Social Sciences
Department of Business Administration
Business Administration Doctorate Program

The aim of this study is to analyze the volatility spillover between bond and commodity markets in terms of global liquidity risk. The data covers daily closing prices of bond markets including Brazil, Russia, India, China, and Turkey (BRIC-T countries) and commodities such as gold and oil for the period from January 2008 to April 2017. We implemented DCC-GARCH model to analyze volatility spillover between these markets and Copula DCC-GACRH to determine dependence structures between them. Additionally, we applied Hong Causality in Variance Test to determine the direction of the causal relationships between these markets.

Our empirical findings indicate the existence of significant volatility spillovers between gold and most of these bond markets including Brazil, Russia and Turkey and between oil and some of these bond markets including Russia and Turkey. Additionally, we observed dependence structures between gold and each of these bond markets as well as between oil and the others. We didn't observe shock dependency between gold and the bond markets. However, we observed shock dependency between oil and the bond markets of Brazil and Turkey. Finally, we determined a unidirectional causality in variance from Brazil bond market to gold and from gold to bond markets of Russia and

Turkey. Additionally, we observed a unidirectional relationship between oil and all of these markets except for India. While the direction of this relationship is from oil to bond markets of Brazil and Turkey, it is opposite for the others. Our results indicate a limited diversification benefit for investors and portfolio managers.

Keywords: Volatility Spillover, Bond Markets, Commodity Markets, DCC-GARCH, Copula DCC-GARCH, Hong Causality Test

ÖZET
Doktora Tezi

KÜRESEL LİKİDİTE RİSKİNİN BİR GÖSTERGESİ OLARAK TAHVİL VE EMTİA PİYASALARI ARASINDAKİ OYNAKLIK YAYILIMININ BİR ANALİZİ

Ayşegül KIRKPINAR

Dokuz Eylül Üniversitesi
Sosyal Bilimler Enstitüsü
İngilizce İşletme Anabilim Dalı
İngilizce İşletme Programı

Bu çalışmanın amacı küresel likidite riski açısından tahvil ve emtia piyasaları arasındaki oynaklık yayılımını analiz etmektir. Çalışma, Brezilya, Rusya, Hindistan, Çin ve Türkiye'yi (BRIC-T ülkeleri) içeren tahvil piyasalarının ve altın ve petrolü içeren emtia piyasalarının günlük kapanış fiyatlarını kapsamakta olup Ocak 2008'den Nisan 2017'ye kadar olan süreyi ele almaktadır. Bu piyasalar arasındaki oynaklık yayılımını analiz etmek için DCC-GARCH modelini ve yine aynı piyasalar arasındaki bağımlılık yapısını ölçmek için Kopula DCC-GARCH modelini kullanmaktayız. Buna ek olarak, bahsedilen piyasalar arasındaki nedensellik ilişkisinin yönünü belirlemek amacıyla Hong Nedensellik Test 'ini uygulamaktayız.

Ampirik bulgular, altın ve Brezilya, Rusya, Türkiye tahvil piyasaları arasında, ayrıca petrol ve Rusya, Türkiye tahvil piyasaları arasında önemli oynaklık yayılımlarının varlığını ortaya koymaktadır. Bununla birlikte, petrol ve tüm tahvil piyasaları arasındaki bağımlılık yapılarının yanı sıra altın ve tüm tahvil piyasaları arasında da bağımlılık yapıları gözlemlenmektedir. Petrol ve Brezilya, Türkiye tahvil piyasaları arasında şok bağımlılığı gözlemlenirken, altın ve tüm tahvil piyasaları arasında şok bağımlılığı gözlemlenmemektedir. Son olarak, Brezilya'dan altına doğru ve altından Rusya ve Türkiye tahvil

piyasalarına doğru tek yönlü varyansta nedensellik bulunmaktadır. Ayrıca, Hindistan hariç bütün piyasalar ile petrol arasında tek yönlü bir ilişki mevcuttur. Bu ilişki petrolden Brezilya ve Türkiye tahvil piyasalarına doğru iken, diğerleri için tam tersi şeklindedir. Sonuçlarımız yatırımcılar ve portföy yöneticileri için sınırlı çeşitlendirmeyi göstermektedir.

Anahtar Kelimeler: Oynaklık Yayılımı, Tahvil Piyasaları, Emtia Piyasaları, DCC-GARCH, Copula DCC-GARCH, Hong Nedensellik Testi

A VOLATILITY SPILLOVER ANALYSIS BETWEEN BOND AND COMMODITY MARKETS AS AN INDICATOR FOR GLOBAL LIQUIDITY RISK

TABLE OF CONTENTS

CHAPTER 2

METHODOLOGY AND EMPIRICAL RESULTS

CHAPTER 3

CONCLUSION

ABBREVIATIONS

ARCH	Autoregressive Conditional Heteroscedasticity
BRIC-T	Brazil Russia India China – Turkey
CAPM	Capital Asset Pricing Model
CCC GARCH	Constant Conditional Correlation Generalized Autoregressive Conditional Heteroscedasticity
DCC GARCH	Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroscedasticity
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
IMF	International Monetary Fund
The UK	United Kingdom
The U.S.	United States

LİST OF TABLES

LİST OF FIGURES

LIST OF APPENDICES

INTRODUCTION

The volatility spillover from commodity to bond markets might cause an increase in global liquidity risk. In more detail, increases in commodity prices will cause a raise in inflation pressure (Kilian and Lewis, 2011; Ciner et al., 2013) which lead an increase in interest rates. Increasing in interest rates will affect bond prices negatively (Ciner et al., 2013). As a result increasing volatility in bond markets will cause an increase in global liquidity risk. The existence of volatility spillover from commodity to bond markets will indicate that the economy is open to supply-side shocks. On the other hand, it is possible to observe a volatility spillover from bond to commodity markets after which we will observe a financial constraint in the economy. The increases in the volatility of bond markets will cause an increase in the borrowing cost of bond issuers such as the firms and governments. When there is an increase in borrowing costs, financial risks increase such as the financial constraints will exits. Increasing financial constraints will reduce demand for commodities and reduces the commodity prices. Therefore, an examination of analysis between these two markets will provide information about supply-side shocks or financial constraints.

Within this context, the purpose of this study is to analyze the effects of the volatility spillover between global commodity markets such as gold and oil and the bond markets of some selected emerging economies including Brazil, China, India, Russia and Turkey, denoted by BRIC-T.

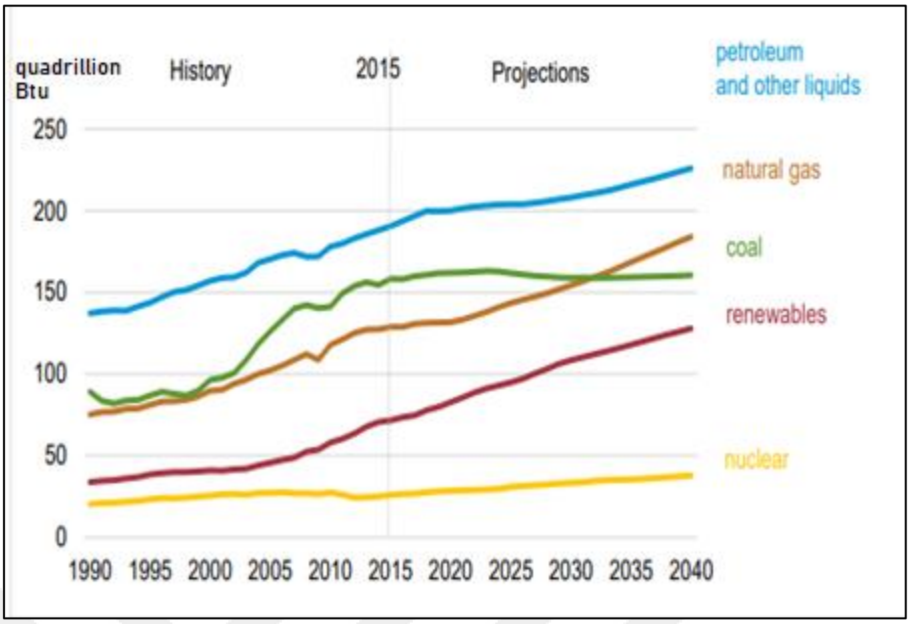
There are many internal and external economic and political factors which affect the prices of commodities such as gold and oil significantly. An increase in the volatility of commodity markets might influence other markets such as bond markets and cause volatility spillover from commodity to bond markets. On the other hand, an increase in the volatility of bond markets might impact the commodity prices such as gold and oil and cause volatility spillover from bond to commodity markets. An increase in the volatility of a financial market indicator is a sign of an increase in the risk of that market. Therefore, if the increase in the volatility of a market spreads or seems to expand to the other markets, it will provide information about the existence of a risk spread between these two markets.

Most of the studies on this issue examine the volatility spillover between commodity and stock markets, or between foreign exchange and stock markets. There are also quite many studies exploring the volatility spillover between stock and bond markets. We discussed all these studies in the literature review part of this study. However, there are just a few studies analyzing the volatility spillover between commodity and bond markets using some common econometric techniques. Moreover, these studies cover mostly bond markets of developed countries. Departing from the existing studies, Copula DCC GARCH method was used to examine the volatility spillover between the commodity markets (such as oil and gold) and the bond markets of some selected developing economies (BRIC-T countries). In addition, this study focused on the economic and financial implications of the volatility spillover between these two markets.

Commodity markets consist of broad categories such as metals, energy, basic metals, grains and agriculture. In this study, only gold and oil were included since they are the most traded commodities globally and viewed as main representatives for commodity markets. They are also the most attractive commodities for investors with their high transaction volumes in global trade. Therefore, it is important to investigate the relationship between these two commodities and other markets.

For many years, oil has been an important source of energy worldwide. It still has the highest share in the world's total energy consumption. Many countries demand oil for consumption or for production purposes. It’s used by many industries as the main input for production which in turn, improves industrialization and induces a growth in economy. Since there is a strong link between the development of the countries and energy, oil has a strategic global importance. Oil is not only preferred by developing countries, but also by developed countries and thus it dominates other resources in world economies. The realized and estimated consumption levels for different types of energy sources including oil are given in Figure 1.

Figure 1: Realized and Estimated Consumption Levels for Energy Sources (1990-2040)



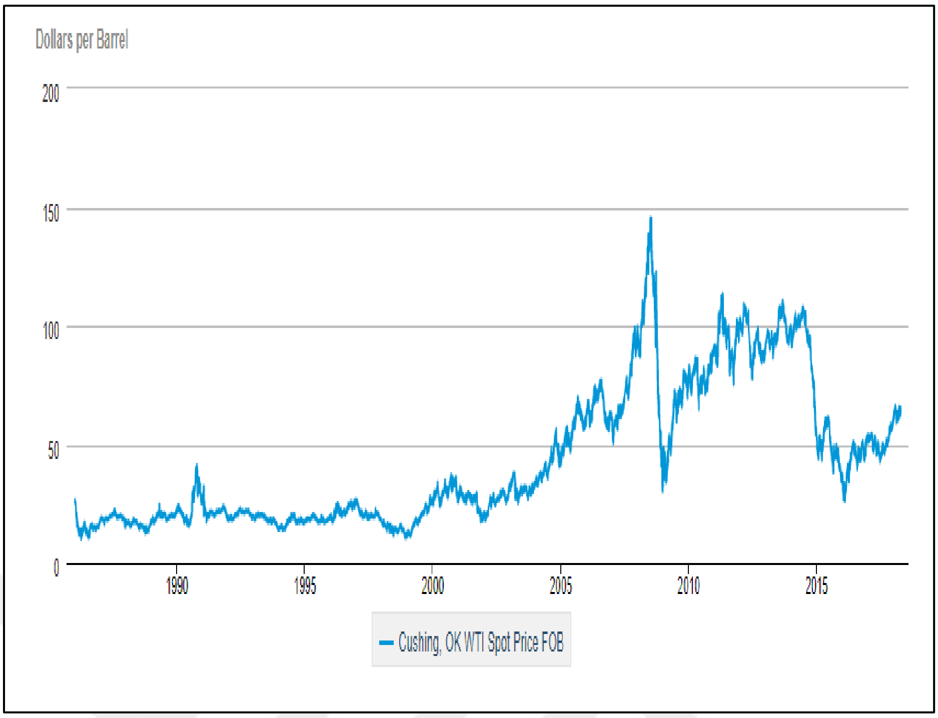
Source: U.S. Energy Information Administration, International Energy Outlook 2017, https://www.eia.gov/outlooks/ieo/world.cfm, (16.04.2018). (Other liquids stand for crude oil. Btu stands for British thermal unit.)

As is apparent in Figure 1, oil is expected to continue its dominance over countries' economies in the future. This figure highlights the importance of oil in the economic development and strategic plans of countries.

When the situation is evaluated in terms of oil prices, these prices have been determined and constantly increasing demand for oil results in an increase in oil prices. The belief that oil reserves will be consumed in the near future has been a major reason for countries to seek other energy sources. All these conditions indicate that oil has a more important and strategic role than other resources.

Countries' economic and political situations can impact on oil prices. For instance, an increase in geopolitical risks in the Middle East causes high volatility in oil prices. Factors such as energy demand, global climate changes, the development level of economies, countries' oil reserves, etc affect oil prices and increased volatility. The changes in crude oil prices over the last two decades are provided in Figure 2 in which it is clear that crude oil prices were at their lowest level in 1998 and highest in 2008.

Figure 2: Average key crude oil spot prices in USD/barrel (1992-2016)

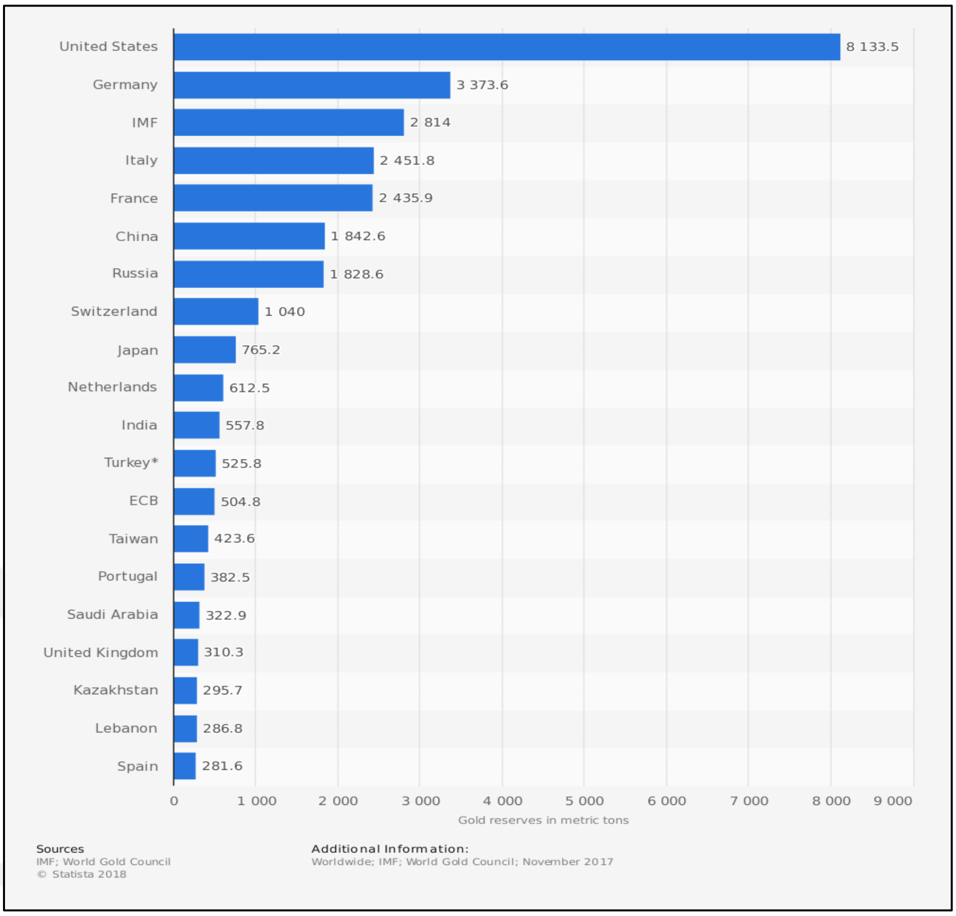


Source: US Energy Information Administration, Petroleum & Other Liquids, https://www.eia.gov/dnav/pet/hist/RWTCD.htm, (16.04.2018).

Significant changes in oil prices have been experienced as a result of recent economic and political developments. As can be seen from Figure 2, sharp declines in oil prices have been realized, especially after the second half of 2014. This situation negatively affects the economies of some developing countries, namely Saudi Arabia, Iran, Russia, and Mexico whose economies are completely based on oil, while it positively affects the economies of countries which import oil.

In today's economies, gold, like oil, is an important mineral resource in commodity markets. Gold has been the subject of many systems from past to present, and used in international commercial activities. It is still a precious metal used in the reserves of countries. Countries consider their gold reserves to be savings which might be needed in case of economic troubles. The gold reserves of various countries are provided in Figure 3. Accordingly, the U.S. has the highest gold reserves with 8133.5 metric tons. Germany, IMF, Italy and France follow the U.S.A.

Figure 3: World Gold Reserves (in metric tons-2017)



Source: Statista, Gold reserves of largest gold holding countries worldwide as of November 2017 (in metric tons), https://www.statista.com/statistics/267998/countries-with-the-largest-gold-reserves/, (16.04.2018).

When gold prices are examined throughout the years, significant changes have been observed. Gold was the basis of the monetary system between 1870 and 1930, and the value of 1 ounce of gold was set at $35 in the Bretton Woods System between 1935 and 1971. However, with the end of the system, there was a steady increase in gold prices up to a value of $70. With the oil crisis that began in 1974, fluctuations in gold prices were paramount. Price jumps during periods of economic crisis are basically due to the rapid increases of gold prices. Gold prices can also rise rapidly in situations such as political crises and wars. Figure 4 depicts the changes in gold prices.

Figure 4: Historical Gold Prices (1974-2018)

Source: Gold Price, http://goldprice.org/spot-gold.html, (16.04.2018).

As illustrated in Figure 4, gold prices changed according to important events. For instance, events such as oil crises and the September 11 attacks caused significant fluctuations in gold prices. In 2000, the fear of rising oil prices and rising inflation rates led people to invest into safe investment tools such as gold. Therefore, during wars and periods of crisis, there are significant increases in gold prices.

This study examined the volatility spillover between the most traded commodity markets including gold and oil and bond markets of BRIC-T countries. There are two important reasons for considering only emerging bond markets. The first reason is that indirect capital flow to emerging markets occurs through bond markets rather than stock markets. Therefore, it is thought that the effect of volatility of commodity prices on the bond markets of developing countries is more important than its impact on stock markets. Secondly, with the "global risk appetite" declining after the 2008 crisis, it was observed that investors pulled out of the stock market and entered low-risky bond market labeled “fly to quality”. For this purpose, we needed to investigate whether there is a volatility spillover between bond and commodity markets.

The analysis of the volatility spillover between commodity and international bond markets is of great importance in setting investment strategies and making investment decisions for individual and institutional investors, international portfolio managers and market regulators. Since a significant volatility spillover between these markets will increase the correlation between them, as a result the diversification benefit will reduce for international investors and portfolio managers. Additionally, since the excess of volatility will increase uncertainty, the use of risk management techniques by investors will gain importance. The excessive volatility spillover in bond markets may cause international investors to pull out of the market, which will also create pressure on the exchange rate. For this reason, market regulators will need to take some measures to reduce the negative effect of commodity prices on the bond markets. In this context, understanding the volatility spillover between these markets will provide information for different purposes such as portfolio management, asset allocation, risk management and financial markets regulation.

In literature, many different statistical methods have been used to examine volatility spillover. Here, we implemented multivariate GARCH (Generalized Autoregressive Conditional Heteroscedasticity) models, especially Dynamic Conditional Correlation GARCH (DCC-GARCH) model. Unlike other research, we also used Copula DCC GARCH model. In addition, we implemented the Hong's Causality Test to determine the causal relationship between commodity and bond markets.

Two main research questions have been determined within the scope of the dissertation. These are;

1. Is there volatility spillover between the selected developing country bond markets and gold market?

2. Is there volatility spillover between the selected developing country bond markets and oil market?

This study contributes to the related literature in many ways.

Firstly, although there are many studies in the literature on volatility spillover between the markets, it has been observed that the majority examine the volatility spillover between different stock markets or among stock markets and others such as bond, commodity and foreign exchange markets. The most important contribution of this study is that it considers the volatility spillover between the bond and commodity markets that is rarely examined in the existing literature. In addition, only a few of studies have evaluated the volatility spillover between the bond markets of the developing countries. Therefore this study differs from the related literature as it considers the bond markets of five selected developing countries. In this context, it is thought that this study will fill an important gap in the literature.

Secondly, the existence of volatility spillover from bond markets to commodity markets indicates that there is more financial constraint in the economy. The reverse direction of this volatility spillover demonstrates that bond markets are open to supply-side shocks. The results on the direction of the relationship will yield information about the existence of supply–side effects or increasing financial risks in these economies.

Thirdly, this study also differs in terms of the methodology used. The volatility in variables such as stock prices, inflation rate, exchange rate, interest rate etc, is estimated with univariate ARCH (Autoregressive Conditional Heteroscedasticity) and GARCH models under a heteroskedastic structure. Multivariate GARCH models are used to measure commonality when there are multiple variables. That is, the multivariate GARCH methods are the techniques used to analyze the volatility spillover among different markets. Furthermore, Copula method, Copula DCC GARCH model in particular, is used in this study. The Copula method creates a more robust model to estimate dependence structure between different asset classes. This is the reason copulas are of great importance to more properly define a correlation structure between assets (Chollete et al., 2011; Patton, 2012). For this purpose, multivariate GARCH methods and Copula method will be used in analyzing the volatility spillover between these markets. Therefore, in terms of its methodology, this study contributes to the literature.

This study consists of three chapters. Following the introduction, Chapter 1 summarizes the theoretical framework including risk and volatility, international diversification, optimal international asset allocation and efficient market hypothesis and the related literature. Chapter 2 consists of the methodology and statistical models which are used for the analysis of volatility spillover and discusses the data and empirical findings. Lastly, Chapter 3 gives the conclusion and makes implications.

CHAPTER 1
THEORETICAL FRAMEWORK AND LITERATURE REVIEW

1.1. THEORETICAL BACKGROUND

This section summarizes the significant theories in finance related to the subject of this dissertation. In this content, we first explain the concepts of risk and volatility, secondly, international diversification, thirdly optimal international asset allocation, and lastly, the efficient market hypothesis.

1.1.1. Risk and Volatility

Risk is a concept that is confronted not only in our decisions about investment areas but also in our daily issues. Since it is a critical factor for returns on investments, the importance of risk management has been greatly emphasized in security investments. In addition, the risk management capacity, the desire to take risks and engaging in forward-looking choices are the main factors which drive the economic system forward (Bernstein, 2006).

Risk is a factor related to individuals' personal and business lives (Fay, 2005). Individuals, businesses, institutions, and investors reach different or unexpected results within the process depending on their identified goals. This possibility that the unexpected results differ from the aims in question is defined as "risk" (Pritchard, 2005).

In finance literature, the concept of "risk" was first discussed in the paper of Harry Markowitz in 1952, in the "Portfolio Selection" (Markowitz, 1952: 77). But he didn't use the term "risk"; he preferred "variance of return":

> *"…the investor does (or should) consider expected return a desirable thing and variance of return an undesirable thing. This rule has many sound points, both as a maxim for, and hypothesis about, investment behavior. We illustrate geometrically relations between beliefs and choice of portfolio according to the expected returns-variance of returns rule."*

In his studies, one in 1952 and the extended version in 1959, Markowitz dealt with individual and total asset investment such as portfolios, portfolio selection, and the fact that the portfolios consisting of several securities were different from owing assets individually. This approach which considers risk and return together has commonly been used as "mean/variance optimization[1]" by professionals and academicians (Bernstein, 2006).

Following Markowitz's Modern Portfolio Theory, the Capital Asset Pricing Model (known thereafter CAPM) was developed by Sharpe (1964) and Lintner (1965). Accordingly, risk was classified as systematic risk (including credit risk, interest rate risk, exchange rate risk, purchasing power risk, market risk, and liquidity risk) and unsystematic risk (such as operational risk, financial risk, managerial risk, and industrial risk). Systematic risk or market risk is uncontrollable; therefore, it cannot be reduced or completely eliminated, whereas unsystematic or unique (firm-specific) risk is controllable, thus, it can be diversified away.

The fluctuation in returns over a certain time period is called "volatility". Volatility is an important concept of finance since it is used as a measurement of risk. Andersen et al. (2006: 780) defined volatility as follows:

> *"…Within economics, it is used slightly more formally to describe, without a specific implied metric, the variability of the random component of a time series. More precisely or narrowly, in financial economics, volatility is often defined as the (instantaneous) standard deviation (or sigma) of the random Weiner-driven component in a continuous- time diffusion model."*

Volatility was identified as the sum of standard deviation of returns by Poon and Granger, 2003. It is calculated as follows:

$$\hat{\sigma}^2 = \frac{1}{N-1}\sum_{t=1}^{N}(R_t - \bar{R})^2$$

where $\hat{\sigma}^2$ is the variance of the returns over the "N" time period, and $\bar{R}$ is

[1] If the best assets have low variance, it means that this combination is an efficient portfolio. The technical name of this approach is "optimization" (Bernstein, 2006).

the mean return.

Furthermore, it is observed that volatility is measured in many different ways and this is why it can be formed in different types. The various types of volatility are historical volatility, Autoregressive Conditional Heteroscedasticity (ARCH) class conditional volatility, options-based (implied) volatility, and stochastic volatility (Poon and Granger, 2005).

Of these, historical volatility, which is also referred to as "realized volatility" (Andersen and Bollerslev, 1998), uses past price movements of the asset, that is, it is generally based on past standard deviations, and contains random walk, autoregressive moving average, whereas ARCH class conditional volatility has more complicated time series. In forecasting financial time series, ARCH class conditional volatility uses some techniques which are based upon high-frequency time dimension. ARCH model, which was developed by Engle (1982), and after Engle's study, the GARCH model generalized by Bollerslev (1986) are the main approaches for forecasting volatility by using high-frequency financial time series. The so-called ARCH family volatility has extensively been implemented by many researchers such as Nelson (1991), Bollerslev, Engle and Nelson (1994), Glosten, Jagannathan, and Runkle (1993), Franses and Dijk (2000), Granger and Hyung (1999), Zumbach (2004), Xu and Malkiel (2003), and Taylor (2008).

On the other hand, options-based or implied volatility deals with the prediction of asset's future volatility in the options market (Figlewski, 1997) and it uses option prices which are determined by the pricing model of Black and Scholes (1973). Implied volatility is also implemented by many practitioners and academics. Bollen and Whaley (2004) examined the impact of net buying pressure on implied volatility by using index and individual stock options. They found that there was a direct relationship between them, and also observed that the net buying pressure affected the stock options. Lee (2004: 470) constructed and proved the "moment formula", which *"shows explicitly how the best constant depends only on the number of finite moments in the underlying distribution"*. Some researchers such as Fleming, 1998, Koopman, Jungbacker, and Hol, 2005, Blair, Poon, and Taylor, 2001, Konstantinidi, Skiadopoulos, and Tzagkaraki, 2008, implemented implied volatility in stock markets and futures markets.

Moreover, Christensen and Prabhala (1998) and Pong et al. (2004) compared historical volatility with implied volatility. Christensen and Prabhala (1998) asserted that in forecasting future volatility, implied volatility took informational precedence over historical volatility, whereas unlike the others, Pong et al. (2004) and Canina and Figlewski (1993), determined that implied volatility could be a lower estimate of subsequent historical volatility.

Finally, the stochastic volatility includes second error term. While GARCH models contain error term only in mean equation not in variance equation, stochastic volatility includes second error term in conditional variance equation. Therefore, it is more responsive than the ARCH and GARCH models (Poon and Granger, 2005, and Brooks, 2008). In the ARCH or GARCH type models, volatility is time varying but not stochastic. In stochastic volatility models, parts of the changes in volatility are due to random shocks (Reider, 2009). Thanks to the structure of the model, forecasting the distribution of returns in stochastic volatility is determined implicitly. Meanwhile, stochastic volatility can also be of service to asymmetric effects of return on volatility relation (Shephard and Andersen, 2009). For instance, rather than large up moves in the equity future volatility will be affected more if stock prices have large down moves markets (Reider, 2009).

1.1.2. International Diversification

The benefit of international portfolio diversification is to eliminate the risks of investing in only one country's market. In this manner, the risk or volatility of portfolio diminishes by diversifying in other countries' financial assets. While the financial assets in the same country tend to move together, international assets tend to lower movement when together. The main purpose of this strategy is to reduce risk by diversifying abroad.

The theory of international diversification grounds in the study of Grubel (1968). Grubel (1968) extended the modern portfolio theory of Markowitz (1959) and indicated that investors were likely to reduce risk by holding international rather than individual assets. Later, Levy and Sarnat (1970) demonstrated the fact that co-movements among different national assets were low. On the other hand, Jacquillat and Solnik (1978) asserted that the Multinational American corporations could not reduce risk through international diversification. Therefore, this theory could be relevant for the investors investing into financial assets of different countries, not for the multinational companies operating in different nations (Cohen et al. 1987). On the other hand, Jacquillat and Solnik (1978) claimed that multinational American corporations could not reduce risk by using international diversification.

The correlation coefficient between the financial assets (such as stocks, bonds, commodities, and more complicated financial instruments, such as stock options or currency options) of different countries is an important issue of the international diversification theory. Even though the correlation coefficients between any two of these markets vary in time, they are always far from unity. The low correlation between these markets indicates a successful risk diversification. Makridakis and Wheelwright (1974) and King et al. (1994) found that international correlation was changeable over time. In a similar vein, Longin and Solnik (1995) observed that international correlation and covariance matrices were not stable over the period of 1960-1990, for seven stock markets including Germany, France, England, Canada, United States, Japan, and Switzerland. They stated that market volatility had changed dramatically during that period. These studies used unconditional correlations over periods by comparing conditional correlations with time varying.

Solnik et al. (1996) examined volatility and international market correlation. Although previous studies such as Makridakis and Wheelwright, 1974, King et al., 1994, Longin and Solnik, 1995 stated that international correlations had increased over time, they noted the opposite result. This might be due to the fact that domestic asset prices were significantly influenced by national factors.

Ramchand and Susmel (1998) used conditional time and state varying in order to analyze the relationship between correlation and variance by implementing and switching the ARCH technique. They found that if the U.S. market had a higher state of variance, there were greater correlations among the U.S. and the other markets.

Another issue of the international diversification theory that must be discussed is the portfolio volatility. International diversification usually provides a reduction in the total risk of a portfolio (Solnik et al. 1996). Odier et al. (1995) examined the volatility of both emerging and developed markets and argued that high volatility yielded high returns. Therefore adding the securities of high volatile markets such as the emerging markets might improve the diversification benefits. The study of Longin and Solnik (1995) supports the findings of Odier et al. (1995) and they argued that correlations among international markets were high when the level of market volatility was high. The study of Shawky et al. (1997) also supports the results of Longin and Solnik (1995). They argued that the increase in inter-country correlations was natural when market volatility was high.

There are some studies supporting the argument that small domestic markets are more volatile than larger ones. Empirical studies such as Kenneth and Poterba (1991), Butler and Joaquin (2002), Vermeulen (2013), and Alexander et al. (2016) were implemented in large capital markets since investors, in order to achieve high expected returns, had more benefits in large markets rather than small domestic ones.

And the final feature of the theory of international diversification is currency risk. According to Solnik (1996), currency risk can balance the reduction in security risk through international diversification. Foreign investors shouldn't avoid investments into foreign markets when the currency risk is so large. There are various reasons that prohibit this situation. The first one is that currency risk and market movements are not highly correlated with each other. They are generally low correlated and sometimes negative. Secondly, even if there is a possibility of existence of a currency risk, this risk might be hedged for major currencies by buying or selling currency contracts in derivative markets. Thirdly, the contribution of currency risk should not be measured for individual markets; it should be measured for total portfolio. If this portfolio is composed of just domestic or individual market's shares, the contribution of currency risk in question is insignificant. But if this portfolio has various currencies or foreign assets, the contribution of currency risk is significant and larger for the portfolio. This is because risk is diversified by the portfolio, including several currencies.

Recently, there have been some studies measuring the cost or benefit of international diversification by using the Copula models. Christoffersen et al. (2012) analyzed both developed and developing markets by using dynamic asymmetric copula model. They found that copula correlations were much higher for developed markets than developing markets. Wang et al. (2011) asserted that instead of Japan and the Pacific, the Chinese market was appropriate for international diversification using time-varying copula models. Chollete et al. (2011) evaluated two measurements for diversification, correlations and copulas. In conclusion, these two measurements sent signals regarding risk for countries. Their results indicated that the downside risk for G5 and Latin American countries was higher than that for Asia. Bhatti and Nguyen (2012) investigated the dependence structure of markets including the U.S., Hong Kong, Australia, Japan, Taiwan, and the U.K. by implementing the theory of conditional extreme value and time-varying copula. They recommended that time-varying copula was a suitable method for portfolio management or diversification to provide information across capital markets.

1.1.3. Optimal International Asset Allocation

Asset allocation is an effective method for international diversification to divide portfolio among several asset classes such as bonds, stocks, commodities, and other securities within different markets. It enables a tradeoff between risk and return of the portfolio as an organized strategy of the investment.

Research related to the pricing of securities date back to Markowitz's studies in 1952 and 1959. Subsequently, Sharpe (1964), Lintner (1965) and Mossin (1966) independently developed CAPM in which investors can determine the expected return on their investments depending on the risk-free rate, beta and market risk premium. The formularization of CAPM is derived from mean variance framework Solnik (1974). The CAPM formula is as follows:

$$E(R_{i,t}) = R_f + \beta_i (R_{m,t} - R_f) + \varepsilon_{i,t}$$

where $E(R_{i,t})$ is expected return of asset i at a given time t, R_f is the risk-free rate, β_i represents the sensitivity to the market, $R_{m,t}$ is expected return of market portfolio at a given time t and $\varepsilon_{i,t}$ is the residual term.

In his studies, Solnik (1974, 1977) analyzed whether simple CAPM held true for international markets, in other words, he tested international CAPM. He concluded that different countries' investors could reach high expected returns by combining the risk-free asset and risky portfolio by using the mean-variance function of returns and they would have different optimal portfolios due to exchange risk. He demonstrated that the theory was upheld internationally.

Similarly, Sercu (1980) investigated the international version of the simple CAPM. He stated that if risk free asset was changed by national interest rates, investors would hold unto capital market portfolio, and thus equilibrium was achieved.

On the other hand, Stulz (1981) claimed that the existing models of international asset pricing were used to test the segmentation hypothesis, in other words, asset markets were segmented internationally. Stulz claimed there were no studies rejecting this hypothesis. Thus, Stulz (1981) used different measure of risk in comparison with the earlier models and found that markets were fully integrated rather than segmented. Also, he stated there weren't any barriers for international investment. On the other hand, in their empirical study, Errunza and Losq (1985) indicated doubtful support for the mild segmentation hypothesis in international investments. While Stulz (1981) argued that the benefits of the international asset pricing model were restricted with regard to segmentation, Errunza and Losq (1985) argued that the benefits were partially restricted.

In other respects, Engel et al. (1995) tested a mean-variance efficiency hypothesis differing from previous studies considering the conditional means and covariance of returns as constant; their test enabled that conditional variances would vary over time, and it also enabled predicting conditional variances.

Employing the GARCH model, Santis and Gerard (1997) tested pricing restrictions of CAPM. They evaluated the selected major eight equity markets in the world and concluded that their findings supported pricing restrictions, including price of market risk.

Fernandes (2006) compared equity investments of emerging markets with those of developed markets and observed that emerging markets have contributed to the diversified portfolio of developed markets. Furthermore, he concluded that the risk exposure of emerging markets was the same as that of developed markets. In addition, globalization and liberalization increased integration among these markets.

De Santis (2006) investigated whether international CAPM held or not, and compared the integration within the equity and bond markets. His results indicated that equity markets were more integrated than global bond markets, and he concluded that international CAPM partially held.

Chaieb and Errunza (2007) examined whether or not the deviations of market segmentation and purchasing power parity affected international asset pricing. They demonstrated that international asset pricing would be upheld in mildly segmented market if purchasing power parity was contravened by using the multivariate GARCH model.

1.1.4. Efficient Market Hypothesis

The efficient market hypothesis deals with "available information". This theory states that if the "available information" is fully reflected in prices, we can consider the market to be "efficient" (Fama, 1970: 383).

The studies of market efficiency date back a long time, ranging from Gibson (1889), Bachelier (1900), Mandelbrot (1963), Alexander (1964), to Steiger (1964) (Sewell, 2011). Fama (1965a) first identified an "efficient" market along with the empirical study of the stock prices that followed a random walk. Fama (1965b) dealt with the form of random walk, whereas Samuelson (1965) introduced the concept of fair game to financial economics, and he dealt with the concept of a martingale, which involves the generalized form of random walk.

Roberts (1967) categorized efficiency as weak and strong form (Sewell, 2011). Later, Fama (1970: 383) divided the efficient market hypothesis into three groups, including strong form, semi-strong form, and weak form efficiency. Strong form efficiency means that prices reflect all available public and private information including insider ones. In this case, investors cannot beat the market and they shouldn't be able to consistently obtain above-average profits. Strong form efficiency includes both semi-strong form and weak form efficiency. Semi-strong form is when prices reflect public information such as the announcements of dividend, dividend-yield ratios, book value-market value ratios, economic and political news, and stock splits. Weak form efficiency means that prices reflect historical available price data. For this reason, there is no value to predicting future price changes in weak form efficiency. That is, past price changes aren't related to future price changes. If the weak form efficiency upholds, technical analysis becomes ineffective. If the weak form is in effect, there isn't information in the past series which is useful in predicting future price changes.

The efficient market hypotheses were tested by many researchers for international markets. Chan et al. (1997) investigated the weak form efficiency of international markets including eighteen stock markets as individually or jointly. Their findings asserted that while most of the markets were individually efficient, only a few were jointly effective. In addition, they stated that international diversification could also be effective in these markets since they had no long-run movements. Furthermore, Kan and O'Callaghan (2007) examined the market efficiency in foreign exchange markets including ten Asia Pacific countries, and concluded that market efficiency was valid for some countries pairs. Similarly, Kim and Shamsuddin (2008) investigated whether Asian stock markets were in effect or not. By using new multiple variance ratio tests, they found that the efficiency changed according to the level of development within the countries. While the more developed emerging countries had a pattern of weak form efficiency, less developed emerging countries showed inefficient characteristics. In other respects, Ito and Sugiyama (2009) measured market inefficiency by considering time. They concluded that market efficiency varied depending on the time periods for the U.S.A. While inefficiency characteristics were indicated during the late 1980s, it became more effective after 2000.

We have thus presented the theoretical background of our dissertation by including international diversification, optimal international asset allocation, and efficient market hypothesis. Thereby, in this dissertation, by examining the volatility spillover between the commodity and international bond markets, we can identify whether or not these markets are efficient. This is due to the fact that in an efficient market, there should not be a volatility spillover effect among the markets.

1.2. LITERATURE REVIEW

This section includes the existing literature on the volatility spillover among the commodity markets, between commodity and stock markets, between commodity and foreign exchange markets, between the bond markets, between bond and stock markets, and finally between bond and commodity markets respectively.

1.2.1. The Volatility in Commodity Markets

There are many studies examining the existence of volatility spillover between the commodity markets. Since the commodities such as oil and gold have a vital importance in world trade, the investigation of the volatility spillover among them We have evaluated a few studies investigating the volatility of gold markets (such as Shafiee and Topal, 2010, Uludağ and Lkhamazhapov, 2016, Yurdakul and Sefa, 2015, Todorova, 2017, Omane-Adjepong and Boako, 2017, Kristjanpoller and Minutolo, 2015, and Bentes, 2015) or the volatility spillover between gold and the other commodities (such as Ewing and Malik, 2013, Zhang and Wei, 2010, Narayan et al., 2010, Tiwari and Sahadudheen, 2015, Yaya et al., 2016 and Kumar, 2017). Among these studies, Ewing and Malik (2013) investigated the volatility spillover between gold and oil under structural breakdowns and their results indicated that gold was indirectly affected by oil, and vice versa. Also, both oil and gold volatility were affected by the news. Zhang and Wei (2010) investigated the relationship between gold and oil prices, and found a significant positive relationship between them and argued that oil price had Granger causes on the volatility of gold prices. Narayan et al. (2010) analyzed the long running relationship between oil and gold futures markets and examined whether or not these markets were efficient. They concluded that gold was used by investors in order to hedge against inflation when oil prices went up, and they stated that these markets were inefficient because gold prices could be predicted by using oil prices, and vice versa. Tiwari and Sahadudheen (2015) analyzed the relationship between oil and gold prices and concluded that gold prices were affected by the rise of oil prices. They asserted that gold prices were impacted by both negative and positive shocks in different levels. Poshakwale and Mandal (2016) analyzed the asymmetric return co-movements of gold, oil, bonds, real estate and stocks by using conditional time-varying copula models for the U.S. and determined significant co-movements between each of these asset groups.

Shafiee and Topal (2010) reviewed the global gold market and tried to forecast its prices for the next ten years. They found that its price would stay high anomalously. Uludağ and Lkhamazhapov (2016) investigated the volatility of futures and spot prices of gold in Russia by employing models with structural breaks, and observed a strong long memory in volatility of both of them. Additionally, they found one break related to recent global financial crisis for each series. When they examined the volatility spillover, they documented a strong conditional correlation between each other. Yurdakul and Sefa (2015) determined the factors and their effects on gold prices in the Istanbul Gold Exchange. They found that while the Dow Jones Industrial Index affected the gold prices in the Istanbul Gold Exchange negatively, the London Bullion Market Association's gold prices and Wholesale Price Index influenced it positively. Here are many studies (such as Narayan et al., 2010, Baur and McDermott, 2016, Hood and Malik, 2013 and Smiech and Papiez, 2017) researching whether or not gold is considered to be a safe haven or a hedging instrument against risks. Narayan et al. (2010) and Baur and McDermott (2016) asserted that gold was significantly considered a safe haven. In contrast, researchers such as Hood and Malik (2013) argued that gold was a weak safe haven for the U.S. stock market. Similarly, Smiech and Papiez (2017) asserted that gold was a weak hedge for equity.

On the other hand, the relationship between oil prices and the prices of other commodities especially agricultural commodities was also investigated in many studies (for example, Nazlıoğlu, 2011, Ji and Fan, 2012, Nazlıoğlu et al. 2013, Du et al., 2011, Trabelsi et al., 2017 and Baffes, 2007). Among these studies, Nazlıoğlu (2011) examined the relationship between oil and agricultural commodity prices. According to linear causality analysis, they could not determine any short-run relationship between the agricultural commodity and oil prices. On the other hand, nonlinear causality analysis indicated the existence of nonlinear feedbacks between them and unidirectional nonlinear causality relationships ranging from oil to agricultural commodity prices with the exception of wheat. Nazlıoğlu et al. (2013)

also researched the volatility spillover among them. Unlike the others, they couldn't determine a pre-crisis volatility spillover between agricultural commodity markets and oil, and they stated that there was a volatility spillover from oil to agricultural markets during the post-crisis period. Similarly, Baffes (2007) researched the impact of crude oil on 35 internationally traded primary commodities and found that fertilizer index was the most affected by oil price changes, followed by agriculture and metals. Precious metals also reacted intensely. Du et al. (2011) examined the volatility of oil prices and their effects on agricultural commodity markets. Their results indicated the existence of the volatility spillover among wheat, corn, and crude oil. Ji and Fan (2012) measured if oil prices affected non-energy commodity prices as divided into two groups: pre and post 2008 financial crises, and they concluded that oil prices affected non-energy commodity prices and this effect in the pre 2008 financial crisis was lower than the post 2008 financial crisis. Furthermore, they emphasized that the dollar index used has indicated low impact on commodity markets following the 2008 financial crisis. Trabelsi et al. (2017) examined the volatility between agricultural commodity global markets and oil. They concluded that when compared to downside ones, agricultural commodities were more volatile when upside shocks occurred. The volatility of agricultural commodities was affected more by positive shocks independently than negative shocks. In contrast to other studies, they didn't find that there was evidence regarding price co-movements between oil and agricultural commodities.

Various econometric models were employed in related studies. For instance, Ewing and Malik (2013) ran bivariate and univariate GARCH models incorporating structural breaks by using daily data. In contrast, Nazlıoğlu et al. (2013) implemented impulse response functions and causality in variance tests containing daily data. Du et al. (2011) carried out their analysis by using weekly data and Bayesian Markov Chain Monte Carlo methods. Between 2006 and 2010, Ji and Fan (2012) employed the bivariate EGARCH model with the concept of time-varying correlation with daily data. Between 1994 and 2010, Nazlıoğlu (2011) applied the nonparametric causality method of Diks–Panchenko and Toda-Yamamoto methods with weekly data. Trabelsi et al. (2017) first used GARCH methodology with monthly prices spanning from 1980 to 2014, for measuring volatility and subsequently, they used

Copula models for determining co-movements. Additionally, they measured the risk for those global markets by using Value-at-Risk technique. Zhang and Wei (2010) carried out co-integration and Granger causality tests during the period of 2000-2008 by maintaining daily data. Narayan et al. (2010) employed daily data spanning from 1995 to 2009, by implementing a co-integration test. Uludağ and Lkhamazhapov (2016) applied long memory using daily time series with the models of Corrected Dynamic Conditional Correlation (cDCC) and FIGARCH. Yurdakul and Sefa (2015) implemented Engle-Granger and EGARCH models within the period of 1996- 2012 by using monthly data. Tiwari and Sahadudheen (2015) used GARCH and EGARCH models by incorporating monthly data over a period from 1990 to 2013.

1.2.2. The Relation between Commodity and Stock Markets

In addition to studies examining volatility spillovers in commodity markets, there are many studies in the literature that specifically analyze the relationships between commodity markets and stock markets. Among these studies, Tansuchat et al. (2009), Narayan and Narayan (2010), Malik and Hammoudeh (2007), Arouri et al. (2013), and Malik and Ewing (2009) observed that there was a volatility spillover between stock prices and commodity prices. In addition to these studies, by examining the volatility spillover between stock and commodity markets, Creti et al. (2013) noted that there was a serious volatility spillover between them due to the financial crisis of 2007-2008. By investigating whether there was a spillover effect between stocks and commodity markets, Wang et al. (2013) found that commodity prices led the stock indexes in general, as in others too. Mensi et al. (2013) determined that the S&P 500 had a strong impact on the commodity indices; this was apparent by analyzing the volatility spillover among the energy, food, gold, beverage indices and the S&P 500. Baldi et al. (2016) studied whether shocks in stock markets affected the volatility of commodity prices. They concluded that volatility spread from stock markets to agricultural commodity markets, especially following the 2008 financial crisis.

Some studies examined the volatility of sector indices or the relationship between the commodities and sector indices (Hassan and Malik, 2007, Çağlı et al., 2014, Arouri et al., 2011, and Malik and Ewing, 2009). Among these studies, Hassan and Malik (2007) emphasized that there was volatility transmission among the U.S. sectors. Similarly, Çağlı et al. (2014) researched the impact of oil on sub-sector indices of Turkey. They concluded that oil prices affected sub-sector indices. Arouri et al. (2011) determined the volatility spillover was significant between oil prices and sector stock returns. They concluded that the direction of the volatility was from oil to stock markets. While a uni-directional relationship from oil to the European stock market existed, there was a bi-directional relationship between the oil and the U.S. stock market. Malik and Ewing (2009) observed the evidence of crucial volatility transmission and shocks between oil prices and the various U.S. sector indexes.

In addition, there are some studies examining the relationship between gold and stock prices (such as Mishra et al., 2010, Chkili, 2016, Choudhry et al., 2015, and Raza et al., 2016). For instance, Chkili (2016) examined the dynamic correlations between gold and stock markets for BRICS countries. He emphasized that there were dynamic correlations between them except during periods of great financial crises. Mishra et al. (2010) analyzed the relationship between gold and stock prices. They concluded that stock returns Granger caused domestic gold prices and vice versa for India. Similarly, Choudhry et al. (2015) examined the volatility of stock returns and gold returns incorporating the recent global financial crisis for developed markets covering the U.K., the U.S. and Japan by using multivariate nonlinear methods. Their results suggested that there was a nonlinear feedback effect between these returns during the financial crisis period. On the other hand, there was weak nonlinear feedback during the pre-crisis period. Raza et al. (2016) observed the impact of the volatilities of gold and oil prices on stock returns in emerging markets. They asserted that gold prices had positive effects on BRICS stock prices and negative effects on Thailand, Indonesia, Malaysia, Chile, and Mexico’s stock prices. In addition, they found that the oil prices impacted stock markets globally. Similarly, they claimed that the prices within stock markets of all countries are affected by the volatilities of gold and oil. On the other hand, we observed some studies such as Chkili (2016) and Choudhry et al. (2015) analyzing whether or not gold was used for hedging. Chkili (2016) determined that gold could be a hedging instrument for investors trading in equity markets during major financial crises. On the contrary, Choudhry et al. (2015) argued that gold could not be a safety asset during a period of financial crisis.

Among the studies examining the volatility spillover between the prices of oil and stocks, Gomes and Chaibi (2014) analyzed the relationship between oil prices and stock indices and their volatility spillovers for frontier markets. They found significant bi-directional volatility spillover among oil and some country indices. Demiralay and Gencer (2014) examined volatility transmissions between sector returns and oil prices for some emerging countries. Similar to others, their results indicated that there was volatility transmission and crucial shock between them. In addition, Chang et al. (2013a) investigated volatility spillover between stock and oil returns by using the VARMA-GARCH and VARMA-AGARCH models. They stated that there were low levels of volatility spillover. Malik and Hammoudeh (2007) pointed out significant volatility transmission and shocks among oil prices, in the Gulf and U.S. equity markets. This transmission was from oil prices to Gulf markets with the exception of Saudi Arabia, which had a reverse relationship. Naifar and Dohaiman (2013) analyzed the effect of the volatility of oil prices on Gulf countries' stock returns under regime shifts by implementing several copula models. Their results indicated that the structure of the volatility between stock returns and oil prices volatility was regime dependent.

1.2.3. The Relation between Commodity and Exchange Rates

There are some studies investigating the relationship between commodity prices and other markets such as the foreign exchange markets which are traded in high volume as well as commodities. Different exchange rates can positively or negatively affect the movements of commodities denominated in different currencies. Studies by Nazlıoğlu and Soytaş (2012), Sugimoto, Matsuki, Yoshida (2013), Chang et al. (2013), Coudert et al. (2011), Poshakwale and Mandal (2016), Beckmann et al. (2015), and Reboredo et al. (2014) investigated the relationship between commodity prices and foreign exchange rates. Of these, Nazlıoğlu and Soytaş (2012) investigated the relationship among agricultural commodity, oil prices and the U.S. dollar and observed that changes in both world oil prices and the U.S.

Dollar significantly affected agricultural commodity prices. On the other hand, Sugimoto et al. (2013) studied the volatility spillover between commodities (gold and oil) and the nominal effective exchange rate for African and some developed countries. They argued that there was dispersion from commodity and exchange rate markets towards African markets and crises influenced these markets. Similarly, Chang et al. (2013) analyzed the relationship among oil prices, gold, and the U.S. dollar and concluded that they were independent of each other. Likewise, Beckmann et al. (2015) examined the volatility transmission between gold prices and exchange rates. They stated that exchange rate depreciations initially affected gold prices negatively and then positively in the later days. Coudert et al. (2011) studied the volatility spillover between exchange rates and commodity markets in developing countries. They found that in the developing countries there was volatility spillover from the commodity markets to the exchange rate markets. By using different time periods, Reboredo et al. (2014) characterized the dependency between exchange rates and gold. They concluded that the dependency was positive and stated that gold could be used as a hedging instrument against currency risk in different time periods. Sjaastad (2008) analyzed the relationship between gold and major exchange rates. It is known that major currencies such as the dollar, euro, and yen have caused instability in gold prices; among these the dollar had the strongest impact on gold prices. Dyhrberg (2016) also analyzed the volatility of the U.S. dollar, gold, and bitcoin using the GARCH models. He found that both gold and the dollar could be used for hedging. Bitcoin possessed similar characteristics of the dollar and gold in terms of its usage in risk management and hedging.

1.2.4. The Volatility in Bond Markets

Similar to commodity markets, examining the volatility of bond markets and their relationships with other markets has become attractive for researchers and portfolio managers. While some researchers used bond returns or yields (such as Clare and Lekkos, 2000, Skintzi and Refenes, 2006, Viceira, 2012, Heinen, 2012, Jin, 2015, Fernández-Rodríguez et al., 2015, and Fan et al., 2017), others (such as Delis and Mylonidis, 2011, Diaz et al., 2013, Fontana and Scheicher, 2016, and

Blanco et al., 2005) used CDSs as an indicator of the bond market. Of these, Clare and Lekkos (2000) investigated the relationship between the U.K., the U.S. and German bond markets and concluded that bond yield curves of the countries were affected by international factors such as international interest rates and foreign currencies. In addition, international factors became much more critical during periods of instability. For instance, Skintzi and Refenes (2006) examined the dynamic relationship between the bond markets of twelve European countries. They noticed that volatility spillover existed, ranging from the Eurozone and the U.S. bond market to individual European bond markets. Moreover, Viceira (2012) analyzed time variation in the volatility of bond returns. He concluded that the co-movement of bond returns was changeable during different business cycles. Since the expected return of long term bonds was time varying, time variation was positively connected with movements in the yield spread. On the other hand, Heinen (2012) observed that yield spread could not forecast the volatilities of bond and stock. Then, Jin (2015) investigated the volatility spillover and asymmetry in return between China's exchange T-bond and interbank T-bond markets and determined an asymmetric return spillover. This spillover was due to China's exchange from the T-bond to interbank T-bond market. Moreover, good news in the exchange market led to high interbank returns, whereas bad ones had no effect. In contrast, both bad and good news in interbank markets led to higher exchange returns. Bunda et al. (2009) empirically investigated the co-movement of bond yields in developing markets and tried to find the impact of external and local factors during high market volatility. According to their results, correlations of countries could be more informative during high market volatility. In addition, they indicated that very low spreads and average correlations occurred during the 2008 financial crisis. Fernández-Rodríguez et al. (2015) examined volatility spillovers of eleven EMU sovereign bond markets including central and peripheral countries by dividing them according to pre-and post-groups of the 2008 financial crisis. They found that during the pre-crisis period, rather than peripheral countries, the central countries were enactors of volatility spillover. However, during the crisis period, peripheral countries changed their roles. In other respects, Fan et al. (2017) implemented and compared three models including the jump-diffusion model, the constant volatility model, and the stochastic volatility model to investigate the volatility of Chinese convertible bonds. Their results indicated that stochastic volatility model demonstrated better performance than the others. On the one hand, Maghyereh and Awartani (2016) analyzed the relation between bonds and *sukuk* which refers to Islamic bonds including equities. They determined that *sukuk* was used as a transmission mechanism as well. Their findings also indicated that the volatility transmission from s*ukuk* to the others (bonds and global equities) was very minor and unimportant, whereas the transmission from the others to *sukuk* was high.

On the other side, there are studies considering CDSs as an indicator of bonds. Since bonds and CDSs have the same exposure against the risk and return of debt issued by governments, their prices can be determined by similar risk factors. Among these studies, Delis and Mylonidis (2011) investigated the dynamic relationship between CDSs and government bond spreads and found that CDS prices Granger caused the government bond spreads following the 2007 crisis. Blanco et al. (2005) examined the relationship between CDSs and credit spreads related to bonds, and concluded that the credit spreads were essentially lower than CDS prices and that compared to bond prices, CDS played an important role on price determination. Fontana and Scheicher (2016) examined the relationship between market prices of government bonds in the euro zone and related CDSs. They investigated whether or not sovereign credit risk had different impacts on bond spreads and CDSs. They found that both were positively related to risk premium; however, the relationship between the CDS and credit risk exceeded the bonds. Thus, they supported their hypothesis that crisis impacted the bonds and CDSs differently.

On the other hand, in other studies on the volatility of bond markets, researchers generally examined the impact of macroeconomic news and announcements on bonds. Among these studies, Andritzky et al. (2007) examined how bonds of the developing markets responded to macroeconomic announcements. They stated that global bond spreads reacted to changes and rating movements in U.S. interest rates instead of local announcements, whereas market volatility was affected by all announcements. Moreover, uncertainty was decreased by policy announcements and macroeconomic data, whereas rating movements led to higher volatility. Andersen et al. (2007) characterized the reactions of stocks, bonds and exchange markets of Germany, the U.S. and the U.K. and noticed that the news and announcements generated conditional jumps. Thus, high-frequency exchange rates, bonds, and stocks were found to be associated with news. They concluded that stock markets responded more differently to news items related to the stages of cyclical fluctuations, whereas bond markets responded very strongly to macroeconomic news. Similar to the previous studies, Kim et al. (2004), Christiansen (2000) and Jones et al. (1998) analyzed the relationship between In contrast to others, Jones et al. (1998) showed that the information of the announcement days was reflected in the prices and this situation removed the fluctuations of those days. In addition, Chao (2016) examined whether or not several economic variables could be developed to forecast the volatility of U.S. bond returns. His results indicated that some economic variables such as credit conditions, inflation, and stock return Granger caused the volatility of bond returns, whereas some like employment conditions, productivity, and output growth had a lower impact on bond return volatility. Likewise, Nowak et al. (2011) analyzed the effect of macroeconomic news on bond prices and volatilities. Their results demonstrated that there was an effect of macroeconomic announcements on both bond returns and volatilities, but the impact on volatility was more apparent and durable than bond prices.

1.2.5. The Relation between Bond and Stock Markets

In literature, there is a plethora of studies analyzing the relationship between stock and bond markets. When stock market volatility increases, and in order to avoid risks, portfolio managers can shift from stocks to bonds. Avoiding risk by shifting from one market to another depends on the relation of the volatility between bonds and stock markets. When the correlation among them is high, it is not worth shifting from one to another. Therefore, to avoid risks, existing relationships are of great importance for investors and portfolio managers. Many studies (such as those by Dean et al., 2010, Goeij and Marquering, 2009, Steeley, 2006, Baele et al., 2007, Baur and Lucey, 2009, Kim et al., 2006, Fang et al., 2006, d'Addona and Kind, 2006, Li and Zou, 2008, Panchenko and Wu, 2009, Yang et al., 2009, Bekaert et al., 2010, Zhou, 2014, and Haesen et al., 2017) have considered the volatility spillover between the stock and bond markets. Among them, Dean et al. (2010) examined the volatility spillover between stock and bond markets for Australia and found that the volatility of the bond market spreads towards the stock market. Likewise, they stated that the volatility relationships of bond and stock markets were intensely asymmetric. Thus, bad news from bond markets led to lower stock returns, while good news from stock markets resulted in lower bond returns. In addition, Goeij and Marquering (2009) investigated the dynamic relationship between bond and stock returns by considering asymmetry in conditional volatility and the level effects and found that there was significant asymmetry in conditional volatility of their interaction and level effects on bond returns. Steeley (2006), like others, analyzed the relation between stock and bond markets of the U.K. and concluded that the correlation between the two markets was not stable and there was strong evidence for negative correlations between bond-stock market shocks. Likewise, Baele et al. (2007) reached a similar result indicating there were negative correlations between bond and stock returns.

Baur and Lucey (2009) analyzed flights effects among eight developed countries. They argued that the flights effect occurred during periods of crises. They analyzed flights effects in two ways: “flight to quality from stocks to bonds” (the first situation) and “flight from quality from bonds to stocks” (the second situation). When the first situation occurred in the crises period, bond returns went up, but stock returns dropped. However, in the second situation, bond returns decreased, but stock returns rose. Similarly, Kim et al. (2006) analyzed the relationship between them for Europe, the U.S. and Japan. Their results indicated that the bond markets shocks were more impressive than those of stock markets. On the other hand, Fang et al. (2006) studied volatility transmission between stock and bond for Japan and the U.S. and found that in domestic markets, there was volatility transmission from stocks to bonds in a unidirectional direction. On the one hand, in international markets there were strong volatility transmissions for stocks, but weak between stocks and bonds. d’Addona and Kind (2006) evaluated the relationship between stock and bond in terms of the asset pricing model. They stated that the volatility of interest rate affected the correlations between bonds and stocks. The changeability of the dividend-yield has reduced this correlation. Similarly, Bekaert et al. (2010) examined the relationship between the stock and bond markets in terms of the asset pricing model. They found a high correlation between bond and stock returns, but the signals of term spread (which was an endogenous variable of their model and was related to expected changes in interest rates) had high risk premiums on both bond and stocks. Li and Zou (2008) analyzed whether or not information and policy shocks affected the relationships between stock markets and T-bonds in China. Their results showed that the correlations between the bond and stock showed more reaction to large shocks of bad news than when compared to good news. When good news affected this correlation, investors shifted their investment from one to other assets, but when the bad news affected it, they tended to transfer from both bonds and stocks in the same direction. Panchenko and Wu (2009) analyzed the relationship between the correlation of the bond and stock markets and the integration of the emerging markets. They determined an inverse relationship. Yang et al. (2009) analyzed the relationship between stocks and bonds by considering the macroeconomic conditions such as inflation and business cycles. They compared the U.S. and the U.K. Their results stated that when compared to the U.K., in order to avoid market risk in the U.S., bonds were more useful for investors than stocks. In addition, they argued that when the interest rates were high and maturity was short, the correlation between the bond and stock markets increased. Additionally, business cycles impacted the correlation between the stock and bond markets of these countries in different ways. For instance, while they observed a higher correlation during the expansion than the recession periods for the U.S. markets, they observed the opposite result for the U.K. Haesen et al. (2017) investigated momentum spillover from stock to bond markets of the U.S. They claimed, momentum spillover is "*the phenomenon that companies that recently outperformed in the equity market tend to subsequently outperform in the corporate bond market.*" Their findings indicated that momentum spillover impacted both the high yield bonds and investment grade bonds.

Some researchers such as Fleming et al., 1998, Bodart and Reding, 1999, Andersen et al., 2007, and Kim and Stock, 2014 included other markets while examining the relationship between stock and bond markets. For instance, Fleming et al. (1998) included money markets and examined the volatility spillover among S&P 500, bonds and Treasury bills. Their findings indicated the existence of volatility spillover and common information has increased these relationships. Andersen et al.

(2007) included foreign exchange markets and examined the volatility spillover for the U.K., Germany and the U.S. by using the effects of macroeconomic news on these markets. They found that macroeconomic news significantly affected bond markets, whereas stock and foreign exchange markets were affected at the same level. Likewise, stock markets reacted to macroeconomic news in a different way during the business cycles. After controlling the news, they observed a volatility spillover among these markets. Bodart and Reding (1999) examined this relationship by considering the international correlations and the impact of exchange rate regime for six European countries. Their findings indicated that the international correlations on stock and bond markets could be based on the exchange rate regime. They found that the relationship between bond and exchange markets was more significant than the relationship between stock and foreign exchange markets. The reason might be the effects of uncertainty of domestic monetary policy on the volatility of bond prices. Additionally, stock prices were affected by overall macroeconomic uncertainties instead of domestic concerns. Kim and Stock (2014) examined the impact of volatility of interest rate and firm's equity on callable and non-callable bond yield spreads. Their results showed a positive but weaker effect of interest rate volatility on callable bond spreads when compared to non-callable ones. They also observed a positive relationship between a firm's equity volatility and bond spreads.

1.2.6. The Relation between Bond and Commodity Markets

Although there are many studies examining the volatility spillover among markets, we only analyzed a few studies considering the volatility spill over between the bond and commodity markets. The main reason for this can be the lack of any analysis based on theoretical approaches. In general, the increase in volatility in the bond market can cause friction in the borrowing market. Therefore, an increase in volatility of the bond markets can lead to an increase in the volatility of commodity markets. In this situation, firms borrow at much higher cost than financial markets. Thus, if there is a spillover from bond markets to commodity markets, it is possible to observe a financial constraint in the economy. In this respect, a financial crisis can be regarded as a leading indicator. Therefore, depending on the spillover between the markets, an analysis between two markets will reveal information about supply side shocks or financial constraint.

Studies involving the relationships between bond and commodity markets analyze the effect of oil shocks on bonds and the volatility spillover between them. Among these studies, Kang et al. (2014) examined the oil shocks on U.S. bond market returns. They concluded that positive oil market demand shocks affected bond returns negatively for eight months following the shocks. They found a spillover effect between bond and oil prices that was quite high during the period of 2008–2011. Similarly, Tule et al. (2017) analyzed the impact of oil prices on Nigerian sovereign bonds and the volatility spillover between them. Their results showed a volatility transmission between them. On the other hand, Agyei-Ampomah et al. (2014) examined whether or not gold- compared to other precious metals including platinum, palladium, and silver- was a safe haven against sovereign bonds. They found that rather than gold, other metals, especially palladium and copper, were strong safe havens against sovereign bonds.

In other respects, Bouri et al. (2017) analyzed the relation between sovereign CDS and commodities (including energy, agriculture, precious metals, and industrial metals) in 6 frontier and 17 emerging markets. Their results indicated strong volatility spillover effects between CDS and commodities for most of the countries. The direction of spillover is from commodities to CDS.

Some other studies (such as Oleg, 2011, Narayan et al., 2016, Basher and Sadorsky, 2016, and Mensi et al., 2015) incorporated stock markets into their analysis and examined the volatility spillover effect among the spot, bond and commodity markets. Of these studies, Oleg (2011) examined the volatility spillover among China's next future commodity contracts, stocks and 10-year bonds and pointed out that the negative correlation between 10-year government bonds and future commodity contracts increased bond volatility. As for stocks, the correlation between stocks and commodities rose during the recession. Mensi et al. (2015) investigated whether or not Sharia stocks, gold, and T-bills were safe havens for six Gulf countries. Their results indicated that with the exception of T-bills, others could be a safe haven during the downturn. Narayan et al. (2016) examined the relationship among commodities (gold and oil), stocks, and bonds by including consumer prices and market volatility in the U.S.A. for the period of 1950-2015. They concluded that bonds Granger caused stocks positively, but stocks Granger caused bonds negatively. Similarly, bonds Granger caused oil negatively whereas oil positively Granger caused inflation. Also, when positive shocks towards gold occurred, then bond prices decreased. Furthermore, they argued that the uncertainty in the economy first affected stocks and then the bonds, and later led to market volatility. Lastly, they emphasized that market pricing spread from gold to bonds, oil and inflation occurred. In other respects, Basher and Sadorsky (2016) used VIX index as well as stocks, bonds, oil, and gold in their analysis for 23 emerging markets. They compared the models in their study and emphasized that asymmetric DCC (ADCC) was the most preferred model for hedging stocks by investing into other assets. Among these assets, oil was the best hedging vehicle for stock investments.

There are a number of studies analyzing the relationships among the bond markets with the other three markets including stock, commodity, and exchange markets which tackle things from a different point of view (for instance Lopez, 2014, Diebold and Yilmaz, 2012, Tian and Hamori, 2016, Ciner et al., 2013, and Turhan et al., 2014). Lopez (2014) examined implied volatility between commodities, stocks, exchange rates, and government bonds for the U.S. markets, and found that implied volatility occurred between stocks and government bonds, and stated that government bonds could not be explained by news announcements on the economic base. Diebold and Yilmaz (2012) analyzed volatility spillovers across stocks, bonds, exchange rates and commodity markets for the U.S. and pointed out that there was significant volatility in these markets and the volatility spillover among them was quite limited until the 2007 financial crisis. Tian and Hamori (2016) examined price shocks and volatility shock transmission among those aforementioned four markets for the U.S. and found that price shocks affected all markets instantly, whereas volatility shocks caused volatility spillover to other assets. Moreover, stocks and exchange rates had absorbed volatility shocks much more; while commodities and bonds absorbed the volatility shocks less. By using the U.S. and U.K. data spanning from 1990 to 2010, Ciner et al. (2013) examined whether or not these four assets such as gold, oil, stock, and exchange rate indicated evidence of a hedge against each other. They found that bonds were regarded as a hedge instrument against the stocks, whereas gold had a role as a hedge tool against exchange rates in both countries. Turhan et al. (2014) analyzed the relationship between oil and three other assets including stocks, bonds, and exchange rates by using the U.S. data. Their findings indicated that following the 2008 crisis, there was a high positive correlation between the dollar and oil, along with high correlations among the stock, oil and bonds.

On the other hand, Chan et al. (2011) analyzed the relationship among stocks, bonds, oil, and gold. Differing from the previous study, instead of the foreign exchange market, they examined the real estate market by implementing Markov regime switching model for the U.S. from gold to stocks. They determined positive stock returns and low volatility during the expansion period, and noticed flight from quality such as from gold to oil. On the other hand, they found negative stock returns and high volatility during the constriction, and observed contagion effects among oil, stocks, and real estate and noticed flight to quality in a direction away from stocks to bonds.

Table 1 summarizes the econometric models, variables, markets and the data period of the related studies.

Table 1: Econometric Models Used in the Studies

Author	Model	Variables	Market	Data Period
Kang et al. (2014)	Structural VAR Model	Bond, oil	the U.S	1982-2011
Narayan et al. (2016)	VAR Model	Bond, gold, oil, stock, consumer prices	the U.S.	1950-2015
Lopez (2014)	VAR Model	Bond, stock, commodity, exchange markets	the U.S.	2008-2013
Tian and Hamori (2016)	Time-Varying Structural VAR Model	Bond, stock, commodity, exchange markets	the U.S.	2006-2015
Tule et al. (2017)	VARMA-AGARCH Model	sovereign bonds, oil	Nigeria	2011-2016
Agyei-Ampomah et al. (2014)	GARCH Model	Bond, precious metals	The U.S., UK, ten Eurozone countries: “Italy, Austria, Portugal, France, Netherlands, Germany, Spain, Greece, Finland, and Belgium”	1993-2012
Bouri et al. (2017)	Lagrange Multiplier (LM) Methodology and GARCH Model	sovereign CDS, commodities: “energy, agriculture, precious metals, industrial metals”	6 frontier markets: “Croatia, Cyprus, El Salvador, Kazakhstan, Venezuela, Vietnam” 17 emerging markets: “Brazil, Chile, China,	2010-2016

			Colombia, Costa Rica, Hungary, Indonesia, South Korea, Malaysia, Mexico, Panama, Peru, Philippines, Russia, South Africa, Thailand, and Turkey”	
Oleg (2011)	GARCH Model	Bond, Stock, commodity	China	2006-2010
Mensi et al. (2015)	Vine Copula Models	T-bills, gold, stock,	six Gulf countries: “Saudi Arabia, United Arab Emirates, Bahrain, Kuwait, Oman, and Qatar”	2005-2014
Basher and Sadorsky (2016)	Multivariate GARCH, GO-GARCH, DCC, and ADCC Models.	Bond, stock, commodities, and VIX	23 emerging markets: “Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Peru, Philippines, Poland, Qatar, Russia, South Africa, Taiwan, Thailand, Turkey, and United Arab Emirates”	2000-2014
Chan et al. (2011)	Markov Regime Switching Model	bond, stock, oil, gold, real estate	the U.S.	1987-2008
Ciner et al. (2013)	GARCH and DCC Models.	Bond, stock, commodity, exchange markets	the U.S., UK	1990-2010.
Turhan et al. (2014)	DCC-MIDAS Model	Bond, oil, stock, and exchange markets	the U.S.	1983-2013
Diebold and Yilmaz (2012)	Their methods based on generalized vector autoregressive framework	Bond, stock, commodity, exchange markets	the U.S.	1999-2010

As can be seen in Table 1, many studies use VAR and GARCH models or similar models. As far as we know, only the study of Mensi et al. (2015) employed another method mainly referred to as the Copula models. In their study, Mensi et al. (2015) examined volatility spillover among T-bills, gold, and stock. Their study did not incorporate bonds. Therefore, this study will be the first examining the volatility spillover between the bonds and commodities by implementing the Copula models. Moreover, while a great majority of studies examine the relationship between commodity and bond markets only for developed countries and especially the U.S. (such as Kang et al., 2014, Narayan et al., 2016, Lopez, 2014, Tian and Hamori, 2016, Chan et al., 2011, Ciner et al., 2013, Turhan et al., 2014, and Diebold and Yilmaz, 2012), only a few investigated this relationship for developing countries (Tule et al., 2017, Bouri et al., 2017, Oleg, 2011, and Basher and Sadorsky, 2016) or

Eurozone countries (Agyei-Ampomah et al., 2014) or Gulf countries (Mensi et al., 2015).

As a result, we can state that in the literature, there are a limited number of studies incorporating the volatility spillover between bond and commodity markets. In addition, the existing studies are mostly for developed markets, specifically the U.S. Since this dissertation focuses on the developing bond markets, it will provide a significant contribution to the international literature. Moreover, examining the volatility spillover for developing countries will be more rational since there is a general argument that the volatility spillover for developing country markets is stronger than that for developed ones. This makes it more attractive for market players. Most of the current literature argues that, while the spillover effect of global variables occurs only after a global financial crisis for the developed countries, these variables significantly affect the volatilities of developing markets both before and after the crisis periods. Since the data period of this dissertation covers the 2008 financial crisis, it will provide information about the volatility spillover among these markets during the crisis period. Thus, this study contributes to the existing literature by empirically analyzing the volatility spillover between the bond markets of the developing countries and commodity markets including oil and gold.

CHAPTER 2
METHODOLOGY

In this section, we briefly explained the methodology, data, and empirical results. Since the aim of the dissertation was to examine the volatility spillover between some selected commodity markets (such as gold and oil) and the bond markets of some selected developing countries (BRIC-T countries, namely Brazil, Russia, India, China and Turkey, we employed multivariate GARCH model, namely DCC GARCH model. Additionally, in order to describe the dependence structure of a d-dimensional random vector to restore the joint distribution (Mensi et al. 2015), we employed Copula model namely Copula DCC GARCH model. Furthermore, we used Hong's Causality test to determine the existence of any causal relationship between these commodity and bond markets. In our analysis we used E Views, QxMetrics, and R programming.

2.1 METHODOLOGY

This section introduces "Constant Conditional Correlation GARCH" (CCC-GARCH) model and "Dynamic Conditional Correlation GARCH" (DCC-GARCH) model which are types of multivariate GARCH models and describes copulas and its models to analyze the volatility spillover between commodity and bond markets.

From the Copula DCC GARCH model point of view, it has become widely popular measure to analyze the dependence structure between assets. This approach depends on the marginal distribution of assets. Because asset classes are not normally distributed, simple correlation coefficients are not sufficient to measure correct relationship between assets. Because of the limitations of correlation-based approach and in order to account for these problematic issues, studies have started to use copula models. In contrast the DCC GARCH model, copula approach creates a more robust model to estimate dependence structure between different asset classes. That's why, copulas are of great importance to define more properly a correlation structure which can be non-linear (Chollete et al., 2011; Patton, 2012). There are some advantages of using copulas in order to estimate dependence structure. Firstly, copulas provide us to describe the dependence structure and the marginal behavior by separating from their joint distribution function. Secondly, copulas allow the degree of the dependence. Linear correlation doesn't give information regarding tail dependence, whereas copulas provide information about asymmetric dependence. Thirdly, in comparison with correlation, copulas don't contain the random variables which show the characteristic of elliptically distributed. Hence, it is suitable for estimating the dependence structure between different financial asset returns. Lastly, correlation is invariant only under linear transformations, whereas copulas are invariant continuous and increasing transformations. When the logarithms of returns of assets or returns of assets are used, copula does not allow changing the dependence structure (Naifar, 2011).

Within the scope of the thesis, we analyze the volatility spillover between bond and commodity markets by using the DCC-GARCH model as a baseline approach and compute dependence structure between markets in accordance with the Copula-based DCC-GARCH model.

2.1.1. Multivariate GARCH Models

Constant Conditional Correlation (CCC) and DCC frameworks depend on the correlations and conditional variances. These models are based on this specification as follows:

$$H_t = D_t P_t D_t$$

where, $D_t = diag(h_{1t}^{\frac{1}{2}}, \dots, h_{Nt}^{\frac{1}{2}})$, P_t is a time-varying correlation matrix. This class of models is divided into two groups as constant correlation matrix (CCC-GARCH) and dynamic correlation matrix (DCC-GARCH).

2.1.1.1. CCC-GARCH Model

CCC-GARCH model was developed by Bollerslev (1990). In this model, conditional correlation matrix has a time invariant property. Thus P_t transforms into P. As $D_t = diag\left(h_{1t}^{\frac{1}{2}}, \dots, h_{Nt}^{\frac{1}{2}}\right)$ and $P = \lfloor p_{ij} \rfloor, p_{ii} = 1, i = 1, \dots, N$, CCC-GARCH model is expressed as follows:

$$H_t = D_t P \, D_t$$

2.1.1.2. DCC-GARCH Model

DCC-GARCH model, which was proposed by Engle (2002), is specified by considering a dynamic matrix process. It is described as follows:

$$H_t = D_t P_t D_t$$

The structure can be extended as follows:

$$Q_t = (1 - \alpha - \beta)S + \alpha \epsilon_{t-1} \epsilon'_{t-1} + \beta Q_{t-1}$$

where, α shows positive and β shows a non-negative scalar parameter under the condition of $\alpha + \beta < 1$. S shows unconditional correlation matrix of standardized residuals ϵ_t.

2.1.2. Copula Models

In this section, the basic features of the copula theory were introduced at first. Then, dependence concepts and families of copulas were introduced.

The milestone of the copula theory, which was first introduced by Sklar (1959), is the Sklar's theorem. A copula is a joint distribution function that connects the marginal distributions. According to the Sklar's theorem, assume that F_{MN} (m, n) is a marginal distribution of two continuous random variables M and N presented in Mensi et al. (2017). The copula function C (u, v) represents the joint distribution functions of these continuous random variables F_M (m) and F_N (n) as follows:

$$C\,(u, v) = F_{MN}\,(m, n)$$

where u = F_M (m) and v = F_N (n). So, a joint distribution function which has uniform marginals is expressed by copula which determines the dependence structure between two random variables.

2.1.2.1. Dependence Concepts

There are many dependence concepts which can be discussed associated with copulas. In general, dependence can be measured using several different concepts. The Pearson linear correlation, the rank correlation and the tail dependence are the most used dependence structures. Whereas the Pearson linear correlation doesn't show the desired characteristics of dependence measures, the tail dependence and the rank correlation which are the copula based dependence measures meet the desired characteristic. In this part, we will explain these three basic dependence concepts briefly.

2.1.2.1.1. Linear Correlation

The Pearson correlation coefficient is the most common dependence measure between two random variables. It is defined as follows:

$$p(X, Y) = \frac{cov(X, Y)}{\sigma_X \sigma_Y}$$

where *cov(X,Y)* is the covariance between X and Y, and $\sigma_{X\,,}\sigma_Y$ are the standard deviations of the random variables X and Y respectively. The linear correlation is a measure of linear dependence (Embrechts et al., 2001). It takes the values between (-1) and (1). When the Pearson linear correlation takes the value (+1), it means that X and Y are perfectly positive dependent. When the Pearson linear correlation takes the value (-1), it means that X and Y are perfectly negative dependent. When the Pearson linear correlation takes the value zero, it means that X and Y are independent from each other.

Pearson correlation is generally appropriate for normal distribution. However, it is unsuitable for measuring dependence for financial time series because financial time series generally show fat-tails and higher moments. That's why, other dependence structures are generally used to determine the dependence structure of financial time series.

2.1.2.1.2. Rank Correlation

Because of the aforementioned limitations of the linear correlation, alternative measures of dependence were developed in later studies (Embrechts et al. (1999); (2001)). Rank correlation coefficient computes the correspondence between rankings of two random variables and assesses its significance. It takes the values between (-1) and (1). When the rank correlation takes the value (+1), it means that the ranks of both the variables are increasing. When the rank correlation takes the value (-1), it means that when the rank of the one variable is increasing, on the other hand, the rank of the other variable is decreasing. There are two accepted correlation measures of non-parametric rank correlations. These are Spearman's rho (Spearman, 1904) and Kendall's tau (Kendall, 1970) rank correlation coefficients. Assume that (X, Y) are a random vector with distribution functions F_1 and F_2. The Spearman's rho linear correlation is between F_1 (X) and F_2 (Y) and defined as;

$$p_s (X, Y) = p\ (F_1 (X), F_2 (Y))$$

Consider that (X_1, Y_1) and (X_2, Y_2) are two random variables from the distribution of (X, Y). Kendall's tau is defined as follows (Embrechts et al., 2001):

$$p_\tau (X, Y) = p\ [(X_1 - X_2)(Y_1 - Y_2) > 0] - p\ [(X_1 - X_2)(Y_1 - Y_2) < 0]$$

Kendall's tau is a dependence measure of the difference between the pairs of (X, Y) in concordance shown as $p[(X_1 - X_2)(Y_1 - Y_2) > 0]$ and in discordance shown as $p[(X_1 - X_2)(Y_1 - Y_2) < 0]$. Concordance pair is if the rank of the second variable is larger than the rank of the first variable. Discordance pair is if the rank is less than or equal to the rank of the first variable (Statistical Research, 2012). That is, Kendall's tau can be shown as:

$$p_\tau (X, Y) = p\,[\text{concordance}] - p\,[\text{discordance}]$$

Spearman's rho and Kendall's tau are important tools in order to measure concordance. Kendall's tau has generally smaller values than Spear-man's rho correlation. It is calculated based on concordance and discordance pairs. On the other hand, Spearman's rho has generally larger values than Kendall's tau. It is calculated based on deviations. But the interpretations of Spearman's rho and Kendall's tau can generally be very similar in most of situations. That's why; it can lead the same inferences.

2.1.2.1.3. Tail Dependence

Tail dependence computes a level of dependence between the variables in the upper-right quadrant and in the lower-left quadrant of the joint distribution function (Nelsen, 2006). Tail dependence is a copula property so it is invariant under monotonically increasing transformation. Tail-dependent distributions are also of great importance for Value at Risk (VaR) estimation as well as asset portfolios. Tail dependence concept has also recently been analyzed in financial area regarding credit or market risk, such as Embrechts et al. (2003).

2.1.2.2. Families of Copulas

Although there are various copulas in literature, within the scope of the thesis, most frequently used copulas are categorized in two groups. These are Elliptical copulas and Archimedean copulas. These copulas show different dependence structures. While Elliptical copulas are also referred implicit copulas, Archimedean copulas are also called explicit copulas.

Elliptical copulas include Gaussian (normal) copula and Student-t copula. Gaussian copula shows the dependence structure of a multivariate normal distribution. Besides, Gaussian copula does not allow for dependence in tails. That is, it has zero tail dependence. Student-t copula represents the dependence structure of multivariate Student-t distributions. Student-t copula has symmetric and higher tail dependence than Gaussian copula. Hence, this makes it useful for financial risk modelling (Singh and Allen, 2017).

Archimedean copulas include Clayton, Gumbel, and Frank copulas which are best known. Clayton and Gumbel copulas show the characteristic of asymmetrical dependence. Clayton copula has lower tail dependence, while Gumbel copula captures upper tail dependence. Frank copula shows the characteristic of symmetrical dependence. It has neither lower nor upper tail dependence. That is, it shows symmetric Archimedean copula with no tail dependence (Mensi et al., 2017).

2.1.2.3. Copula DCC-GARCH Model

In this study, Student-t copula which is the type of the elliptical copulas will be considered. That is, Student-t copula is used to measure the time-varying correlation matrix by means of the DCC model. Copula based DCC GARCH model is based on the DCC model in Engle (2002). It is described as follows (Kim and Jung, 2016; Righi and Ceretta, 2012):

$$r_t \mid I_{t-1} \sim N(0, D_t R_t D_t)$$

$$D_t = \mathrm{diag}(\sigma_{1t}, \sigma_{2t}, \ldots, \sigma_{nt})$$

$$\sigma_{it}^2 = \omega + \sum_{p=1}^{p} \alpha_p \, r_{t-p}^2 + \sum_{q=1}^{Q} \beta_q \, \sigma_{t-q}^2$$

$$F(z_{1t}, z_{2t}, z_{3t}, \ldots, z_{dt}) = C\ F(F_1(z_{1t}), F_2(z_{2t}), F_3(z_{3t}), \ldots, F_d(z_{dt}); R_t)$$

$$\text{“}R_t = diag(Q_t)^{-1/2}\, Q_t\, diag(Qt)^{-1/2}\text{”}$$

$$Q_t = (1-\alpha-\beta)S + \alpha\epsilon_{t-1}\epsilon'_{t-1} + \beta Q_{t-1}$$

Kim and Jung (2016) studied Copula DCC GARCH model in order to forecast volatility of the U.S. stock market data. They compared their results with Kim et al. (2015)'s paper. Their findings showed that Kim and Jung (2016)'s model was more efficient than others. Righi and Ceretta (2012) also analyzed dependence and volatility between German, Hong Kong, U.S., British, and Australian markets by using Copula DCC GARCH model. They stated that estimated copula model runs efficiently for their sample.

In this study, we implemented each conditional correlation by using the function cgarchspec command in the R package called as “rmgarch” applying the Student-t copula.

2.1.3. Hong's Causality Test

There are many studies that examine the causality relations between markets. These are traditional test which is Granger causality and the other one which is causality in variance test. Granger causality test is based on the changes in the mean of two variables, whereas causality in variance test focuses on the estimation of univariate GARCH models of the variables. According to scientific method of studies, causality in variance test has a powerful fit (Okur and Çevik, 2013). Therefore we employ causality in variance test in this study.

Hong's causality test was proposed by Hong in 2001. It is described as follows:

$$Q_1 = \frac{\mathrm{T}\sum_{j=1}^{T-1} k^2(\frac{j}{M})\, \hat{p}^2_{\xi_u \xi_v}(j) - C_{IT}(k)}{\sqrt{2}D_{IT}(k)}$$

where M is a positive integer and k($\cdot\frac{j}{M}$) is a weigh function.

$$C_{IT}(k) = \mathrm{T}\sum_{j=1}^{T-1} k^2(\frac{1-j}{T})\left(\frac{j}{M}\right)$$

$$D_{IT}(k) = \mathrm{T}\sum_{j=1}^{T-1} k^4(\frac{1-j}{T})\{1-(j+1)/T\}\left(\frac{j}{M}\right)$$

$C_{IT}(k)$ and $D_{IT}(k)$ are roughly mean and variance. Hong (2001) summarized its procedure. First, univariate GARCH (p; q) models are estimated and conditional variance estimators are saved. After, the sample cross-correlation function the centered squared standardized residuals are estimated. An integer M is specified, and $C_{IT}(k)$ and $D_{IT}(k)$ are computed. Finally, the test statistic Q_1 is computed. Then, Q_1 is compared with the critical value. If Q_1 is larger than the critical value, then the null hypothesis H_0 is rejected.

2.2. HYPOTHESES OF THE STUDY

The research hypotheses from the research questions are formulated as follows:

H_1: There is volatility spillover between the selected developing countries' bond markets and the gold market.

H_2: There is volatility spillover between the selected developing countries' bond markets and the oil market.

2.3. DATA AND DESCRIPTIVE STATISTICS

We used daily 5-year government bond yields of some selected emerging countries as an indicator of bond market and the daily gold and oil prices as an indicator of commodity markets. Our data period ranged from Jan 1, 2008 to April 26, 2017 consisted of 1864 observations. We obtained data from various databases including the Global Financial Data, the official web sites of the U.S. Energy Information Administration and the World Gold Council. We performed our analysis by using E-Views, Ox Metrics, and R package programs.

We selected five bond markets among the emerging economies namely Brazil, Russia, India, China and Turkey (BRIC-T). We made this choice by considering their market size and increasing impact to the world economy. In addition, the increasing attention of investors in developed economies to these markets was also a crucial reason for our selection. And finally, we also took into consideration their geographical distribution.

Although there is a broad category for the commodities such as metals, energy, basic metals, grains and agriculture, we chose only two of them namely oil and gold which were mostly traded and commonly known by the investors in global markets. Table 2 shows our selected data.

Table 2: Data

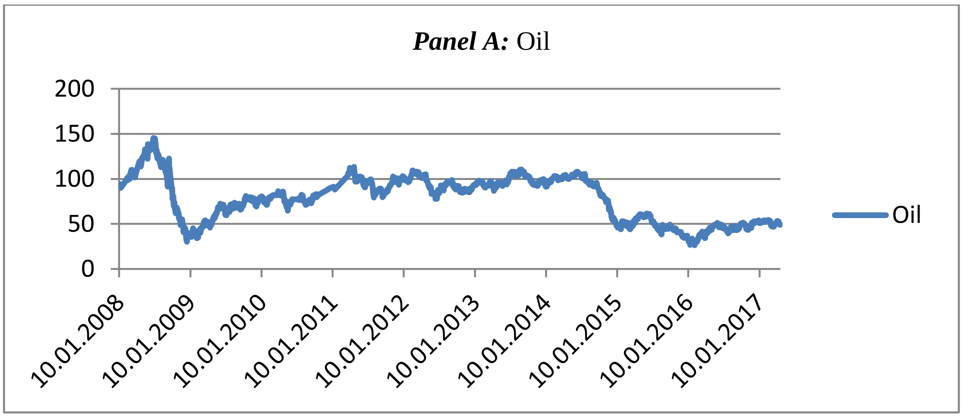
Assets	Period
Brazil 5-year Note Yield	2008 - 2017
China 5-year Government Bond Yield	2008 - 2017
India 5-year Government Bond Yield	2008 - 2017
Russia 5-year Government Bond Yield	2008 - 2017
Turkey 5-year Government Bond Yield	2008 - 2017
Gold Spot Prices	2008 - 2017
Crude Oil Prices	2008 - 2017

We used the following formula to determine the data set of daily log-returns by calculating the return series for all assets using the common log transformation on two daily prices defined as;

$$X_{it} = \log(P_{it}) - \log(P_{it-1})$$

where, X_{it} represents the log return series for each individual commodity and bond indices.

Figure 5: Time Variations of Daily Commodity Prices (2008-2017)



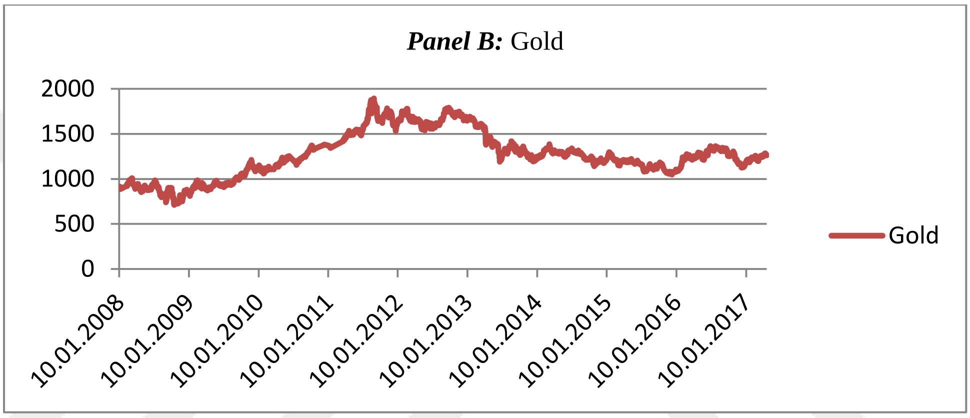


Figure 5 demonstrates the trajectory dynamics of the daily commodity prices including oil and gold. As illustrated in Panel A of Figure 5, there was splendid decrease in oil prices in 2008, subsequently the prices continued decline for most of the period. As for gold in Panel B of Figure 5, it hit peak in September, 2011, subsequently it showed a tendency to rise in the following days. Besides, gold prices had more upward movement than oil prices for the later years.

Figure 6: Time Variations of Daily Bond Yields (2008-2017)

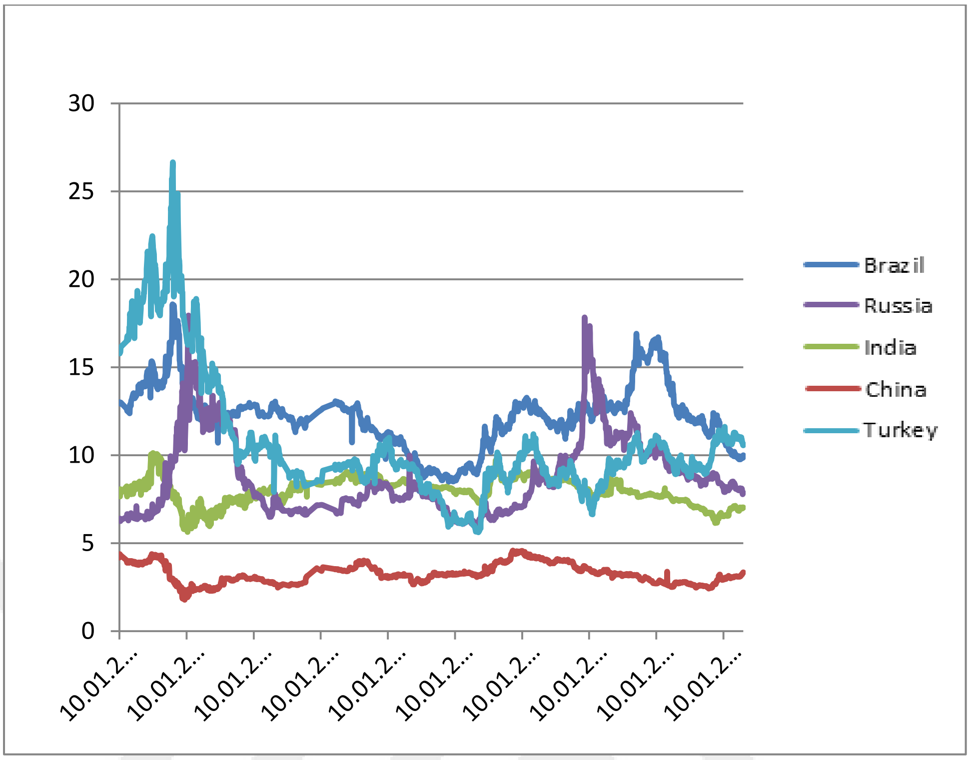


Figure 6 depicts the time variations of daily bond yields for the BRIC-T countries. Figure 6 indicates that in the beginning of the year 2008, it was shown that countries' bond yields had upward movements, which were steeper between the half of 2008 and the half of 2009, and then they started to slump quickly regarding the effect of the global financial turbulence. During those years, Turkey reached to the highest value following by Brazil and Russia.

Figure 7: The Rate of Returns of Bond Markets and Commodities (2008-2017)

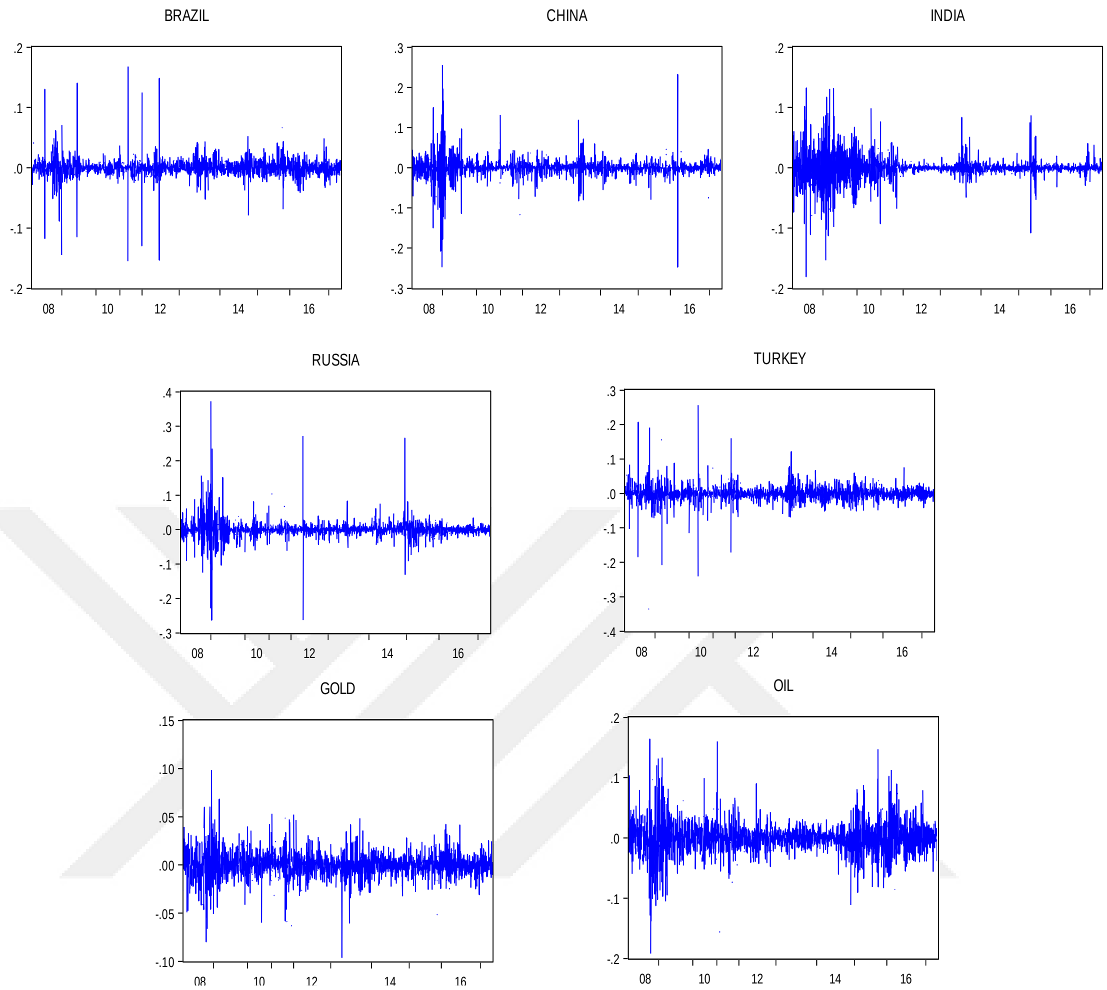


Figure 7 exhibits the volatility clustering for the oil, gold, and five developing bond market return series in the period between 2008 and 2017. Regarding magnitude of the volatility clustering, China, India, Russia, and especially oil looked more volatile than other markets and volatility clusters occurred around 2008-2010 because of the global financial turbulence.

Table 3: Descriptive Statistics of Daily Asset Returns

	Brazil	Russia	India	China	Turkey	Gold	Oil
Mean	-0.000141	0.00012	-0.000068	-0.000121	-0.000217	0.000191	-0.00035
Maximum	0.167126	0.372926	0.132099	0.255806	0.256505	0.098461	0.164137
Minimum	-0.155216	-0.263123	-0.180551	-0.247097	-0.338237	-0.09596	-0.19164
Std. Dev.	0.016132	0.026776	0.020455	0.024699	0.025007	0.013698	0.027947
Skewness	-0.111495	1.855064	-0.211341	-0.289287	-1.021456	-0.1516	0.070545
Kurtosis	37.66532	52.93069	16.2625	35.62527	42.62423	9.143976	8.839088
Jarque-Bera	93284.62***	194593.4***	13667.64***	82650.69***	122201.4***	2937.359***	2648.165***
Sum	-0.263594	0.223302	-0.126643	-0.22458	-0.40496	0.356347	-0.65144
Sum Sq. Dev.	0.484549	1.334955	0.77909	1.135884	1.16436	0.349394	1.454269
Observation	1864	1864	1864	1864	1864	1864	1864

*** denotes the significance level at 1%.

Table 3 provides descriptive statistics of the returns of related the commodities and five developing bond markets between 2008 and 2017. More precisely, the average returns of all assets except gold and Russia are negative indicating the loss. Gold has the highest return that is followed by Russia. Oil has the lowest return followed by Turkey. According to standard deviations of these markets, oil has the highest standard deviation followed by Russia and Turkey respectively. All series other than the oil and Russia are negatively skewed, whereas oil and Russia have positive left-skewed. This might indicate that the negative news affects more than the positive news in tail for oil and Russia. All series exhibit excess kurtosis indicating that the effect of the news in tail aforementioned above increases much. The high skewness and kurtosis give a high Jarque-Bera (J-B)[2] statistic. Based on the J-B test, all the daily returns data series strongly reject the null hypothesis of normality with the significance level of 1%.

[2] the Jarque-Bera test is based on the sample kurtosis and skewness. It is defined as follows:

$$\text{J-B}=\frac{N}{6}\left(S^2+\frac{(K-3)^2}{4}\right)$$

where, N: sample size, K: sample kurtosis, S: sample skewness.

Table 4: Empirical Statistics of the Unit Root Tests of Daily Asset Returns

	Brazil	Russia	India	China	Turkey	Gold	Oil
ADF	-54.24857***	-58.13853***	-35.72382***	-12.62621***	-57.17905***	-43.22288***	-45.76585***
PP	-54.33387***	-59.36309***	-73.17726***	-64.74873***	-57.17905***	-43.22288***	-45.69994***
KPSS	0.095102	0.112091	0.05081	0.104883	0.175572	0.185989	0.074325

Notes: ADF, PP, and KPSS are the test statistics of the Dickey and Fuller (1979), Phillips and Perron (1988), and unit root tests, and Kwiatkowski et al. (1991) stationary test. *** denotes the significance level at 1%.

In order to carry out a variance analysis in high-frequency series, the expected values of these series must be equal to zero. That's why; we employed unit root tests for all series. Table 4 indicates empirical statistics of the unit root tests of daily asset returns. According to unit root and stationary tests, all indices are stationary. Thus, we can make conditional variance analyses.

Table 5: Unconditional Correlation Matrix between Commodities and Bond Yields

	Brazil	Russia	India	China	Turkey	Gold	Oil
Brazil	1						

Russia	0.10286	1					
	0	-----					
India	0.059059	0.052349	1				
	0.0108	0.0238	-----				
China	0.036266	0.029694	-0.042787	1			
	0.1175	0.2	0.0648	-----			
Turkey	0.043213	0.101557	-0.085627	0.073646	1		
	0.0621	0	0.0002	0.0015	-----		
Gold	-0.009838	-0.04961	0.038389	-0.075206	-0.063865	1	
	0.6712	(0.032)**	(0.0972)*	(0.0012)***	(0.0059)***	-----	
Oil	-0.007861	-0.20972	0.050433	0.015334	-0.108238	0.187773	1
	0.7345	(0.0000)***	(0.0296)**	0.5082	(0.0000)***	0	-----

***, **, * denote the significance level at 1%, 5%, 10% respectively.
The values in brackets are p-values.

Table 5 depicts the correlation coefficients among these return series. According to this table, oil is negatively correlated with Russia and Turkey with significance level at 1% and positively correlated with India with significance level at 5%; indicating that the oil prices are related with those markets significantly. The highest negative relationship between oil and the bond markets is observed between oil and Russia correlation. This situation may be indicative of country's dependence on oil. The significant relationship between oil prices and Russia bond market might be the result of the fact that Russia is of great importance for exporting oil to the developing and European countries.

When we look at the correlation coefficients between gold and the selected bond markets, we observe that the gold is negatively correlated with China, Russia and Turkey, whereas positively correlated with India. The correlation between the gold and Brazil bond market is negative however it is not statistically significant. The highest negative correlation is observed between gold and China. One explanation for this could be the fact that China has been less growth rate in recent years than previous years. The private sector and especially industrial enterprises are going to borrow. In other respects, China is the biggest consumer and producer of gold. But debt stock and less growth rate can affect the demand for gold negatively.

2.4. EMPIRICAL FINDINGS

We first estimated constant conditional correlation (CCC) model for gold-BRIC-T and oil-BRIC-T countries. The results of CCC models for all series were provided in Appendix 1. According to the LM test for Constant Correlation of Tse (2000), we rejected the null of constant correlations. Because the CCC models were not appropriate for the series, we estimated dynamic conditional correlation (CCC) model to examine the volatility spillover between markets.

2.4.1. DCC-GARCH Model

We used DCC-GARCH model of Engle (2002) to examine the volatility spillover between commodity and bond markets. DCC-GARCH model also shows whether there is a shock and this shock is continuous or not. Using this model provides a great advantage to detect potential changes in conditional correlations and adjust these correlations for the time-varying volatility in time (Cho and Parhizgari, 2008).

Firstly, we applied DCC-GARCH (1, 1) model to measure the volatility spillover between gold and bond markets of BRIC-T and then between oil and bond markets of BRIC-T countries. Appendix 2 gives the figures of DCC conditional correlations and DCC conditional variances of series. Likewise, Appendix 3 provides DCC-GARCH parameters of series individually. Our results are shown in Table 6 and Table 7 respectively.

Table 6: DCC-GARCH Model for Gold and Bond Markets

	Gold-Brazil	Gold-Russia	Gold-India	Gold-China	Gold-Turkey
Panel A: DCC equation					
γ_{21}	-0.067919 (0.0044)**	-0.088416 (0.0001)***	0.015493 (0.5071)	-0.031843 (0.1537)	-0.088689 (0.0001)***
α	0.008312 (0.5686)	0.0000001 (1.000)	0.010895 (0.613)	0.001554 (0.5075)	0.0000006 (0.9257)
β	0.385402 (0.2196)	0.999990 (0.000)***	0.729871 (0.0003)**	0.277097 (0.7839)	0.323891 (0.8141)
df	3.436687 (0.000)***	3.140097 (0.000)***	3.805253 (0.000)***	3.176689 (0.000)***	3.515757 (0.000)***
Panel B: Diagnostic tests					
Hosking(20) =	[0.7105654]	[0.7689698]	[0.5570425]	[0.0570185]	[0.5740591]
Hosking(50) =	[0.1337046]	[0.6328343]	[0.7267473]	[0.6607938]	[0.5093688]
Li-McLeod(20)	[0.7098085]	[0.7660127]	[0.5557056]	[0.0585050]	[0.5715470]
Li-McLeod(50)	[0.1381722]	[0.6319798]	[0.7228375]	[0.6534096]	[0.5042019]

γ_{21}, α, β, df denote dynamic conditional correlations, the value or vector of autoregressive coefficients, the value or vector of variance coefficients, and degrees of freedom respectively.
The signs of ***, **, * denote the significance level at 1%, 5%, 10% respectively.
The values in ( ) are p-values.
Hosking (1980) and Li-McLeod (1983) are the autocorrelation tests until lag 20 and lag 50.

Table 6 presents the estimation results of the DCC-GARCH models for gold and BRIC-T bond markets. Panel A contains the results from the conditional variance equation estimates; Panel B contains the diagnostic tests. According to DCC equation in Panel A, there are volatility spillovers between gold and the bond markets of Brazil, Russia, and Turkey with a significance level of 5%, 1% and 1% respectively. The signs of these relationships are negative indicating that the increases in the world gold prices impact these markets negatively. These negative relationships are consistent with the studies Oleg, 2011, Ciner et al. 2013, and Turhan et al. 2014 in the literature arguing that commodities such as gold, oil and bond markets have negative relationship for China, the UK and the U.S. data. The volatility spillovers between the gold and these bond markets might not indicate a diversification benefit for the investors holding gold, Brazilian, Russian, and Turkish bonds in the same portfolios.

On the other hand, any previous lagged squared shocks didn't affect the current value of conditional volatility for all of them. But, the volatility spillover between gold and Russia was persistent at 1% significance level. If a volatility spillover was occurred between gold and India, it would have the characteristics of persistence to a shock at 5% significance level.

The diagnostic tests indicate that the model residuals exhibit no remaining ARCH effects and autocorrelation. According to diagnostic tests in Table 6 in Panel B, the results of the Hosking (1980) and McLeod and Li (1983) autocorrelation statistic tests accepted the null hypothesis of no serial correlation in all cases. The results also indicate that the model residuals didn't remain the ARCH effects. In other words, there wasn't any pattern of statistical misspecification.

Table 7 exhibits the estimation results of the DCC-GARCH models for oil and BRIC-T bond markets. Panel A contains the results from the dynamic conditional variance equation estimates; Panel B contains the diagnostic tests. According to Panel A of this table, there was a volatility spillover between oil and the bond markets of Turkey and Russia at a significance level of 5% and 1% respectively. The sign of these relationships were negative for both of these markets indicating that the increases in world oil prices affected both Turkish and Russian bond market negatively. These negative relationships are also consistent with the studies of Ciner et al. 2013 and Turhan et al. 2014. Our results indicate that the investors might not provide benefits by investing into oil and the bond markets of Turkey and Russia in the same portfolios.

Table 7: DCC-GARCH Model for Oil and Bond Markets

	Oil-Brazil	Oil-Russia	Oil-India	Oil-China	Oil-Turkey
Panel A: DCC equation					
γ_{21}	0.006665 (0.7955)	-0.175418 (0.000)***	0.026458 (0.2466)	0.001794 (0.9341)	-0.058672 (0.026)**
α	0.033814 (0.0553)*	0.00000017 (0.9875)	0.0000002 (0.9995)	0.010784 (0.4365)	0.023135 (0.0282)**
β	0.727748 (0.000)***	0.093515 (0.9990)	0.131898 (0.9751)	0.431190 (0.2447)	0.873638 (0.000)***
df	3.962696 (0.000)***	3.568032 (0.000)***	4.371821 (0.000)***	3.682283 (0.000)***	4.099676 (0.000)***
Panel B: Diagnostic tests					
Hosking(20) =	[0.8684467]	[0.0554931]	[0.1110809]	[0.2004961]	[0.0658432]
Hosking(50) =	[0.3269963]	[0.0750689]	[0.1021080]	[0.2882141]	[0.1934457]
Li-McLeod(20)	[0.8667727]	[0.0549198]	[0.1121229]	[0.9986183]	[0.0669546]
Li-McLeod(50)	[0.3340754]	[0.0761535]	[0.1049240]	[1.0000000]	[0.1951530]

γ_{21}, α, β, df denote dynamic conditional correlations, the value or vector of autoregressive coefficients, the value or vector of variance coefficients, and degrees of freedom respectively.
The signs of ***, **, * denote the significance level at 1%, 5%, 10% respectively.
The values in ( ) are p-values.
Hosking (1980) and Li-McLeod (1983) are the autocorrelation tests until lag 20 and lag 50.

Additionally, our results show that any previous lagged squared shocks did not affect the current value of conditional volatility spillover between oil and Turkish bond market with a significance level of 5%. Moreover, the volatility was quite persistent at 1% significance level. Our results indicate that Turkey showed high awareness against the shocks in oil prices however Russia didn't.

On the other hand, we didn't observe a volatility spillover between the oil and the other countries' bond markets including Brazil, China and India. But if a volatility spillover was occurred only the bond market of Brazil, it would have the characteristics of shock transport at 10% and shows persistent to this shock at 1% significance level.

According to diagnostic tests in the Table 7 in Panel B, the results of the

Hosking (1980) and McLeod and Li (1983) autocorrelation statistic tests accepted the null hypothesis of no serial correlation in all cases. The results also indicate that the model residuals didn't remain the ARCH effects. In other words, there wasn't any pattern of statistical misspecification.

Table 8: Kendall's Tau Test Results

	Brazil	Russia	India	China	Turkey	Gold	Oil
Brazil	1						

Russia	0.040943	1					
	0.0085	-----					
India	0.040687	0.03141	1				
	0.0087	0.043	-----				
China	0.013934	-0.02044	-0.02847	1			
	0.3824	0.2006	0.0738	-----			
Turkey	0.087896	0.116609	0.014335	0.011744	1		
	0	0	0.3561	0.4624	-----		
Gold	-0.03812	-0.06739	0.022182	-0.02665	-0.05542	1	
	(0.0139)**	(0.000)***	0.1517	(0.0941)*	(0.0004)***	-----	
Oil	0.00404	-0.12563	0.032314	0.009087	-0.04978	0.095127	1
	0.7944	(0.000)***	(0.0367)**	0.568	(0.0013)**	(0.000)***	-----

***, **, * denote the significance level at 1%, 5%, 10% respectively.
The values in brackets are p-values.

Table 8 depicts the results of Kendall's tau test that is used to find out the dependence between these series. According to this table, oil has negative dependence to Russia and Turkey at 1% significance level and positive dependence to India at 5% significance level. Our results indicate that oil and those bond markets are more integrated. We do not observe a statistically significant dependence between oil and the bond markets of Brazil and China. These findings are similar to those of the findings of unconditional correlation test. Therefore, as a result we can say that oil has dependence to and is correlated with the bond markets of India, Russia, and Turkey.

On the other hand, when we consider the dependence between gold and the related bond markets, our Kendall's tau test results are somewhat different from those of the unconditional correlation test. While gold was negatively correlated with China, Russia and Turkey and positively correlated with India, it was not correlated with Brazil. However according to our dependence tests, it had negative dependence to all of these markets other than India. It had dependence to Russia and Turkey at 1%, to Brazil at 5% and to China at 10% significance level. The lack of dependence between gold and India provides superiority in portfolio diversification. Thus, investors might have more diversification benefit through investing in Indian bond market than the others because of no dependence.

2.4.2. Copula Model

We employed Copula DCC-GARCH model to investigate the determinants of commodity and bond dependence structures. The estimated results of dependence structure using Copula DCC-GARCH model for each pairs of gold and bond markets and oil and bond markets are summarized in the following tables.

Table 9: Gold-Brazil Copula DCC-GARCH Fit

	Estimate	Std. Error	t value	Pr(>|t|)
[Gold].mu	0.00012	0.00019	0.63170	0.52758
[Gold].ar1	0.93664	0.00736	127.19234	0.00000
[Gold].ma1	-0.94679	0.00417	-227.28930	0.00000
[Gold].omega	0.00000	0.00000	0.61735	0.53700
[Gold].alpha1	0.04258	0.01571	2.71031	0.00672
[Gold].beta1	0.95147	0.01469	64.78527	0.00000
[Gold].shape	3.78897	0.47907	7.90899	0.00000
[Brazil].mu	-0.00042	0.00020	-2.12971	0.03320
[Brazil].ar1	-0.23709	0.21094	-1.12398	0.26102
[Brazil].ma1	0.21749	0.21118	1.02987	0.30307
[Brazil].omega	0.00003	0.00001	1.75907	0.07857
[Brazil].alpha1	0.28672	0.10359	2.76770	0.00565
[Brazil].beta1	0.65701	0.12411	5.29369	0.00000
[Brazil].shape	3.05213	0.30449	10.02392	0.00000
[Joint]dcca1	0.00108	0.00230	0.46927	0.63888
[Joint]dccb1	0.99508	0.00743	133.99743	0.00000
[Joint]mshape	10.11827	2.76412	3.66058	0.00025

mu, ar, ma, omega, alpha, beta, shape denote “the mean value, the autoregressive ARMA coefficients, the moving average ARMA coefficients, the constant coefficient of the variance equation, the value or vector of autoregressive coefficients, the value or vector of variance coefficients, and the shape parameter,” respectively.

Table 9 depicts the results of Copula DCC-GARCH test for gold and Brazil. The result for the gold and Brazil from Copula DCC model is parallel to that from the DCC model. According to Copula DCC estimation, there was high dependence structure of current correlation between gold and Brazil at the level 1%, whereas there was no shock dependence in this pair. According to shape parameter, it could be seen that there was an asymmetry in tails for gold and Brazil.

Table 10 shows the results from Copula DCC model for the gold and Russia. Parallel to our findings from DCC-GARCH model, we found a statistically significant dependence structure between gold and Russia. The shock dependence result in Copula DCC-GARCH model is similar to that in DCC-GARCH model in a way that they were both insignificant.

Table 10: Gold-Russia Copula DCC-GARCH Fit

	Estimate	Std. Error	t value	Pr(>|t|)
[Gold].mu	0.00013	0.00022	0.59974	0.54868
[Gold].ar1	0.49284	0.84321	0.58448	0.55890
[Gold].ma1	-0.50665	0.83544	-0.60645	0.54422
[Gold].omega	0.00000	0.00000	0.64024	0.52202
[Gold].alpha1	0.04260	0.01505	2.83117	0.00464
[Gold].beta1	0.95136	0.01429	66.57111	0.00000
[Gold].shape	3.80604	0.45933	8.28609	0.00000
[Russia].mu	-0.00030	0.00019	-1.57109	0.11616
[Russia].ar1	-0.26538	0.41817	-0.63461	0.52568
[Russia].ma1	0.21107	0.42715	0.49414	0.62121
[Russia].omega	0.00003	0.00001	3.61257	0.00030
[Russia].alpha1	0.36510	0.04836	7.55008	0.00000
[Russia].beta1	0.63390	0.05690	11.14073	0.00000
[Russia].shape	2.73028	0.11290	24.18297	0.00000
[Joint]dcca1	0.00313	0.00597	0.52489	0.59966
[Joint]dccb1	0.97033	0.04669	20.78130	0.00000
[Joint]mshape	9.30951	2.10620	4.42005	0.00001

mu, ar, ma, omega, alpha, beta, shape denote “the mean value, the autoregressive ARMA coefficients, the moving average ARMA coefficients, the constant coefficient of the variance equation, the value or vector of autoregressive coefficients, the value or vector of variance coefficients, and the shape parameter,” respectively.

We obtained a similar result regarding the Copula DCC-GARCH estimation of gold and India. Our results are provided in Table 11. According to this table, there was a high dependence structure between two markets with significance level of 1%, whereas the result of the DCC model indicated no volatility spillover between them. Additionally, shock dependence between them was found insignificant.

Table 11: Gold-India Copula DCC-GARCH Fit

	Estimate	Std. Error	t value	Pr(>|t|)
[Gold].mu	0.00013	0.00022	0.59979	0.54864
[Gold].ar1	0.49284	0.84318	0.58451	0.55888
[Gold].ma1	-0.50665	0.83538	-0.60650	0.54418
[Gold].omega	0.00000	0.00000	0.63979	0.52231
[Gold].alpha1	0.04260	0.01506	2.82847	0.00468
[Gold].beta1	0.95136	0.01430	66.53913	0.00000
[Gold].shape	3.80604	0.45943	8.28436	0.00000
[India].mu	-0.00035	0.00009	-3.99597	0.00006
[India].ar1	0.20109	0.16624	1.20965	0.22641
[India].ma1	-0.32742	0.16039	-2.04145	0.04121
[India].omega	0.00000	0.00000	0.29305	0.76949
[India].alpha1	0.18358	0.11253	1.63140	0.10281
[India].beta1	0.81543	0.10849	7.51606	0.00000
[India].shape	3.68855	0.26889	13.71789	0.00000
[Joint]dcca1	0.00063	0.00304	0.20813	0.83513
[Joint]dccb1	0.98851	0.02540	38.92005	0.00000
[Joint]mshape	16.30506	6.16862	2.64323	0.00821

mu, ar, ma, omega, alpha, beta, shape denote “the mean value, the autoregressive ARMA coefficients, the moving average ARMA coefficients, the constant coefficient of the variance equation, the value or vector of autoregressive coefficients, the value or vector of variance coefficients, and the shape parameter,” respectively.

Table 12 gives the Copula DCC-GARCH estimates for gold and China. According to Table 12, there was an evidence of a highly dependence structure existing in the correlation between gold and China. However, we did not observe shock dependence in the correlation between them. Although the result of DCC-GARCH model for gold and China indicated no volatility spillover between them, the result of the Copula DCC model demonstrated the existence of dependence structure between them.

Table 12: Gold-China Copula DCC-GARCH Fit

	Estimate	Std. Error	t value	Pr(>|t|)
[Gold].mu	0.00013	0.00022	0.60021	0.54837
[Gold].ar1	0.49284	0.84369	0.58416	0.55912
[Gold].ma1	-0.50665	0.83592	-0.60611	0.54444
[Gold].omega	0.00000	0.00000	0.63959	0.52244
[Gold].alpha1	0.04260	0.01505	2.82989	0.00466
[Gold].beta1	0.95136	0.01429	66.57045	0.00000
[Gold].shape	3.80604	0.46114	8.25357	0.00000
[China].mu	0.00005	0.00013	0.38496	0.70027
[China].ar1	0.04341	0.06880	0.63096	0.52807
[China].ma1	-0.19579	0.06481	-3.02117	0.00252
[China].omega	0.00004	0.00002	2.49087	0.01274
[China].alpha1	0.43393	0.05815	7.46253	0.00000
[China].beta1	0.56507	0.10338	5.46601	0.00000
[China].shape	2.49555	0.06788	36.76443	0.00000
[Joint]dcca1	0.00211	0.00274	0.77115	0.44062
[Joint]dccb1	0.99257	0.00621	159.84604	0.00000
[Joint]mshape	9.43764	2.18409	4.32109	0.00002

mu, ar, ma, omega, alpha, beta, shape denote “the mean value, the autoregressive ARMA coefficients, the moving average ARMA coefficients, the constant coefficient of the variance equation, the value or vector of autoregressive coefficients, the value or vector of variance coefficients, and the shape parameter,” respectively.

Table 13 depicts the results from Copula DCC-GARCH model for Turkey and gold. We observed a significant dependence structure between Turkey and gold at 1% level. This result is also parallel to the result from the DCC-GARCH model indicating a significant volatility spillover between them. On the other side, there was no evidence shock dependence between these series.

Table 13: Gold-Turkey Copula DCC-GARCH Fit

	Estimate	Std. Error	t value	Pr(>|t|)
[Gold].mu	0.00013	0.00022	0.59816	0.54973
[Gold].ar1	0.49284	0.84378	0.58409	0.55916
[Gold].ma1	-0.50665	0.83615	-0.60594	0.54456
[Gold].omega	0.00000	0.00000	0.62744	0.53037
[Gold].alpha1	0.04260	0.01538	2.76995	0.00561
[Gold].beta1	0.95136	0.01464	64.99484	0.00000
[Gold].shape	3.80604	0.46393	8.20384	0.00000
[Turkey].mu	-0.00051	0.00027	-1.85324	0.06385
[Turkey].ar1	-0.18519	0.12378	-1.49613	0.13462
[Turkey].ma1	0.10030	0.12564	0.79833	0.42468
[Turkey].omega	0.00018	0.00005	3.27700	0.00105
[Turkey].alpha1	0.59624	0.14531	4.10330	0.00004
[Turkey].beta1	0.40276	0.09532	4.22535	0.00002
[Turkey].shape	2.58312	0.18056	14.30582	0.00000
[Joint]dcca1	0.00503	0.02681	0.18765	0.85115
[Joint]dccb1	0.98227	0.24428	4.02113	0.00006
[Joint]mshape	9.12671	2.30486	3.95976	0.00008

mu, ar, ma, omega, alpha, beta, shape denote "the mean value, the autoregressive ARMA coefficients, the moving average ARMA coefficients, the constant coefficient of the variance equation, the value or vector of autoregressive coefficients, the value or vector of variance coefficients, and the shape parameter," respectively.

In summary, we can say that the results from Copula DCC-GARCH models for gold and bond markets indicated the existence of dependence structure between them. However none of them had the characteristics of shock dependence. On the other hand the results from DCC-GARCH models indicated the existence of volatility spillover between the gold and the bond markets of only Brazil, Russia, and Turkey.

Table 14 reveals Copula DCC-GARCH model estimation results for oil and Brazil. According to this table, a high dependence structure of current correlation between oil and Brazil occurred with 1% significance level. Additionally we found that oil-Brazil series incorporated shock dependence with the significance level of 10%. This finding is not parallel to our finding using DCC-GARCH model indicating no volatility spillover for the same pair.

Table 14: Oil-Brazil Copula DCC-GARCH Fit

	Estimate	Std. Error	t value	Pr(>|t|)
[Oil].mu	0.00008	0.00050	0.15749	0.87486
[Oil].ar1	-0.62922	0.25222	-2.49472	0.01261
[Oil].ma1	0.59560	0.26291	2.26542	0.02349
[Oil].omega	0.00000	0.00004	0.06256	0.95012
[Oil].alpha1	0.06722	0.27745	0.24228	0.80857
[Oil].beta1	0.93161	0.27009	3.44929	0.00056
[Oil].shape	5.53162	1.95405	2.83085	0.00464
[Brazil].mu	-0.00042	0.00020	-2.13031	0.03315
[Brazil].ar1	-0.23682	0.21088	-1.12300	0.26144
[Brazil].ma1	0.21719	0.21103	1.02923	0.30337
[Brazil].omega	0.00003	0.00001	1.76717	0.07720
[Brazil].alpha1	0.28628	0.10317	2.77492	0.00552
[Brazil].beta1	0.65754	0.12352	5.32323	0.00000
[Brazil].shape	3.05304	0.30181	10.11571	0.00000
[Joint]dcca1	0.02920	0.01671	1.74775	0.08051
[Joint]dccb1	0.74636	0.07457	10.00854	0.00000
[Joint]mshape	18.54858	7.57605	2.44832	0.01435

mu, ar, ma, omega, alpha, beta, shape denote “the mean value, the autoregressive ARMA coefficients, the moving average ARMA coefficients, the constant coefficient of the variance equation, the value or vector of autoregressive coefficients, the value or vector of variance coefficients, and the shape parameter,” respectively.

Table 15 reveals Copula DCC-GARCH model estimation for oil and Russia. Our results indicated a high dependence structure between oil and Russia that was significant at 1% level. This finding is parallel to our findings from the DCC-GARCH model indicating the occurrence of a volatility spillover between them. Furthermore, according to this table, oil-Russia series did not incorporate any shock dependence.

Table 15: Oil -Russia Copula DCC-GARCH Fit

	Estimate	Std. Error	t value	Pr(>|t|)
[Oil].mu	0.00008	0.00051	0.15702	0.87523
[Oil].ar1	-0.62922	0.25230	-2.49393	0.01263
[Oil].ma1	0.59560	0.26294	2.26521	0.02350
[Oil].omega	0.00000	0.00004	0.06243	0.95022
[Oil].alpha1	0.06722	0.27799	0.24181	0.80893
[Oil].beta1	0.93161	0.27063	3.44239	0.00058
[Oil].shape	5.53162	1.95369	2.83137	0.00464
[Russia].mu	-0.00030	0.00019	-1.57078	0.11623
[Russia].ar1	-0.26538	0.41798	-0.63490	0.52549
[Russia].ma1	0.21107	0.42697	0.49435	0.62106
[Russia].omega	0.00003	0.00001	3.60414	0.00031
[Russia].alpha1	0.36510	0.04840	7.54303	0.00000
[Russia].beta1	0.63390	0.05686	11.14932	0.00000
[Russia].shape	2.73028	0.11242	24.28755	0.00000
[Joint]dcca1	0.00377	0.00259	1.45751	0.14498
[Joint]dccb1	0.99240	0.00273	362.96766	0.00000
[Joint]mshape	13.23831	4.24439	3.11902	0.00182

mu, ar, ma, omega, alpha, beta, shape denote "the mean value, the autoregressive ARMA coefficients, the moving average ARMA coefficients, the constant coefficient of the variance equation, the value or vector of autoregressive coefficients, the value or vector of variance coefficients, and the shape parameter," respectively.

The results from the Copula DCC-GARCH model for oil and India is provided in Table 16. Although we did not observe a volatility spillover between them, there was a high dependence structure between them at 1% significance level. On the other hand, there was not shock dependence between these two markets.

Table 16: Oil -India Copula DCC-GARCH Fit

	Estimate	Std. Error	t value	Pr(>|t|)
[Oil].mu	0.00008	0.00050	0.15733	0.87498
[Oil].ar1	-0.62922	0.25240	-2.49294	0.01267
[Oil].ma1	0.59560	0.26308	2.26399	0.02358
[Oil].omega	0.00000	0.00004	0.06247	0.95019
[Oil].alpha1	0.06722	0.27789	0.24189	0.80887
[Oil].beta1	0.93161	0.27050	3.44401	0.00057
[Oil].shape	5.53162	1.95794	2.82523	0.00473
[India].mu	-0.00035	0.00009	-3.99420	0.00007
[India].ar1	0.20109	0.16614	1.21040	0.22612
[India].ma1	-0.32742	0.16033	-2.04223	0.04113
[India].omega	0.00000	0.00000	0.29295	0.76956
[India].alpha1	0.18358	0.11251	1.63163	0.10276
[India].beta1	0.81543	0.10846	7.51843	0.00000
[India].shape	3.68855	0.26776	13.77551	0.00000
[Joint]dcca1	0.00000	0.00732	0.00000	1.00000
[Joint]dccb1	0.95946	0.04643	20.66630	0.00000

mu, ar, ma, omega, alpha, beta, shape denote "the mean value, the autoregressive ARMA coefficients, the moving average ARMA coefficients, the constant coefficient of the variance equation, the value or vector of autoregressive coefficients, the value or vector of variance coefficients, and the shape parameter," respectively.

Table 17 shows Copula DCC-GARCH results for oil and China. Although we found no volatility spillover between these markets according to DCC-GARCH model, Copula DCC-GARCH result pointed out a significant dependence structure between them. On the contrary, there was not a shock dependency in this pair.

Table 17: Oil -China Copula DCC-GARCH Fit

	Estimate	Std. Error	t value	Pr(>|t|)
[Oil].mu	0.00008	0.00050	0.15735	0.87497
[Oil].ar1	-0.62922	0.25254	-2.49160	0.01272
[Oil].ma1	0.59560	0.26322	2.26275	0.02365
[Oil].omega	0.00000	0.00004	0.06242	0.95023
[Oil].alpha1	0.06722	0.27809	0.24172	0.80900
[Oil].beta1	0.93161	0.27070	3.44154	0.00058
[Oil].shape	5.53162	1.95889	2.82385	0.00475
[China].mu	0.00005	0.00013	0.38556	0.69983
[China].ar1	0.04341	0.06883	0.63068	0.52825
[China].ma1	-0.19579	0.06480	-3.02130	0.00252
[China].omega	0.00004	0.00002	2.49116	0.01273
[China].alpha1	0.43393	0.05825	7.44952	0.00000
[China].beta1	0.56507	0.10341	5.46430	0.00000
[China].shape	2.49555	0.06768	36.87223	0.00000
[Joint]dcca1	0.00341	0.00526	0.64844	0.51670
[Joint]dccb1	0.97155	0.01666	58.30419	0.00000
[Joint]mshape	37.48858	25.79422	1.45337	0.14612

mu, ar, ma, omega, alpha, beta, shape denote “the mean value, the autoregressive ARMA coefficients, the moving average ARMA coefficients, the constant coefficient of the variance equation, the value or vector of autoregressive coefficients, the value or vector of variance coefficients, and the shape parameter,” respectively.

Table 18 shows the results from Copula DCC-GARCH model for oil and Turkey. According to this table there was a significant dependent structure between them. This finding is similar to our findings from DCC-GARCH model indicating the existence of volatility spillover between them. Furthermore, there was evidence that oil-Turkey series incorporated shock dependence at a significant level of 5%. As a result, we found a similar pattern between the Copula DCC-GARCH and the DCC-GARCH results for this relation.

Table 18: Oil -Turkey Copula DCC-GARCH Fit

	Estimate	Std. Error	t value	Pr(>|t|)
[Oil].mu	0.00008	0.00050	0.15730	0.87501
[Oil].ar1	-0.62922	0.25239	-2.49301	0.01267
[Oil].ma1	0.59560	0.26310	2.26382	0.02359
[Oil].omega	0.00000	0.00004	0.06244	0.95021
[Oil].alpha1	0.06722	0.27801	0.24178	0.80895
[Oil].beta1	0.93161	0.27062	3.44246	0.00058
[Oil].shape	5.53162	1.95815	2.82492	0.00473
[Turkey].mu	-0.00051	0.00027	-1.86242	0.06254
[Turkey].ar1	-0.18519	0.12353	-1.49914	0.13384
[Turkey].ma1	0.10030	0.12526	0.80074	0.42328
[Turkey].omega	0.00018	0.00005	3.28017	0.00104
[Turkey].alpha1	0.59624	0.14547	4.09881	0.00004
[Turkey].beta1	0.40276	0.09482	4.24768	0.00002
[Turkey].shape	2.58312	0.18057	14.30545	0.00000
[Joint]dcca1	0.02333	0.01103	2.11525	0.03441
[Joint]dccb1	0.86984	0.03758	23.14445	0.00000
[Joint]mshape	21.14284	9.89558	2.13659	0.03263

mu, ar, ma, omega, alpha, beta, shape denote “the mean value, the autoregressive ARMA coefficients, the moving average ARMA coefficients, the constant coefficient of the variance equation, the value or vector of autoregressive coefficients, the value or vector of variance coefficients, and the shape parameter,” respectively.

2.4.3. Hong Causality Test

Before Hong’s Causality test, we first determined standardized residuals derived from GARCH model for all series. And then, we used cross-correlation coefficients for paired series. Finally, we employed Hong’s Causality test to determine the causal relation between commodities and bond markets. Table 19 points out the Hong’s Causality test results between the variances of gold and all related bond market series.

Table 19: Hong's Causality Test Results for Gold and Bond Market Series

	Gold→Brazil		Brazil → Gold	
M	**Q**	**p-value**	**Q**	**p-value**
1	-0.47408	0.68228	1.998182	0.022848
2	-0.47238	0.681674	1.770399	0.03833
3	-0.42316	0.663911	1.473316	0.070333
4	-0.40467	0.657139	1.211	0.112948
5	-0.42945	0.666201	0.983752	0.162619
	Gold→Russia		**Russia → Gold**	
M	**Q**	**p-value**	**Q**	**p-value**
1	0.386238	0.34966	-0.09218	0.536724
2	1.339132	0.090264	-0.23669	0.593551
3	1.887973	0.029515	-0.35296	0.63794
4	2.047787	0.02029	-0.42986	0.66635
5	2.149048	0.015815	-0.4584	0.676668
	Gold→India		**India→Gold**	
M	**Q**	**p-value**	**Q**	**p-value**
1	1.029948	0.151517	-0.53294	0.702962
2	0.985365	0.162222	-0.63278	0.736563
3	0.874812	0.190838	-0.74531	0.771958
4	0.748387	0.227113	-0.63517	0.73734
5	0.615571	0.269089	-0.41007	0.659121
	Gold→China		**China→ Gold**	
M	**Q**	**p-value**	**Q**	**p-value**
1	-0.3613	0.641061	-0.70148	0.758499
2	-0.23226	0.591833	-0.84525	0.801015
3	-0.18953	0.575162	-0.90033	0.816028
4	-0.23165	0.591595	-0.87593	0.809467
5	-0.31154	0.622306	-0.84448	0.800799
	Gold→Turkey		**Turkey→Gold**	
M	**Q**	**p-value**	**Q**	**p-value**
1	0.625924	0.265683	0.039499	0.484246
2	1.320522	0.09333	-0.00266	0.501061
3	1.708611	0.043761	-0.10363	0.541269
4	1.895919	0.028985	-0.22105	0.587472
5	1.98732	0.023443	-0.3369	0.631904

M and Q denote a positive integer and test statistics, respectively.

According to this table there was a unidirectional causality between the variance of gold and Brazil return series. This unidirectional causality was from Brazil to gold. On the other hand, there was not a causality in variance between gold and China and between gold and India. When we look at the direction for causality in variance between gold and Russia, we observed a unidirectional causality from gold to Russia. It might imply that an increase in gold prices affects Russian bond market. Similar to Russia, there was also unidirectional causality between gold and Turkey from gold to Turkish Bond Market indicating that the changes in gold prices affects bond market of Turkey.

Table 20 depicts the Hong's Causality test results between the variances of oil and the related bond market series.

Table 20: Hong's Causality Test Results for Oil and Bond Market Series

	Oil→Brazil		Brazil→Oil	
M	**Q**	**p-value**	**Q**	**p-value**
1	3.682044	0.000116	-0.64084	0.739185
2	3.452338	0.000278	-0.79226	0.785894
3	3.077132	0.001045	-0.93783	0.825834
4	2.716868	0.003295	-1.06714	0.857046
5	2.397066	0.008263	-1.17636	0.880275
	Oil→Russia		**Russia→Oil**	
M	**Q**	**p-value**	**Q**	**p-value**
1	-0.33961	0.632924	22.78958	0.000
2	-0.43184	0.66707	22.52415	0.000
3	-0.50658	0.693775	21.41975	0.000
4	-0.58	0.719041	20.18793	0.000
5	-0.6641	0.746687	19.01749	0.000
	Oil→India		**India→Oil**	
M	**Q**	**p-value**	**Q**	**p-value**
1	-0.17465	0.569322	1.508936	0.065658
2	-0.12969	0.551596	1.466071	0.071314
3	-0.13277	0.552814	1.309442	0.095192
4	-0.14564	0.557898	1.130535	0.129125
5	-0.16215	0.564406	0.973771	0.165085
	Oil→China		**China→Oil**	
M	**Q**	**p-value**	**Q**	**p-value**
1	-0.67434	0.749951	-0.6427	0.739789
2	-0.63686	0.737892	0.490349	0.311943
3	-0.54279	0.706362	1.378509	0.084023
4	-0.40284	0.656468	1.868034	0.030879
5	-0.20415	0.58088	2.100421	0.017846
	Oil→Turkey		**Turkey→Oil**	
M	**Q**	**p-value**	**Q**	**p-value**
1	2.885136	0.001956	-0.69906	0.757742
2	2.821136	0.002393	-0.84885	0.802016
3	2.607789	0.004556	-0.9437	0.827339
4	2.523137	0.005816	-1.00366	0.842229

5	2.523108	0.005816	-1.00254	0.841959

M and Q denote a positive integer and test statistics, respectively.

According to Table 20, there was unidirectional causal relation in variance between Brazil and oil. The causal link run from the oil market to Brazilian bond market indicating that oil affects Brazilian bond market. There was also a unidirectional causal relationship between the oil and China bond market. The causality was from China bond market to oil. We did not observe any causality relationship between oil and India bond market. On the other hand there was causality in variance between oil and Russia. This causality was spanning from Russia to oil as expected since Russia is one of the biggest oil producer in the world. Additionally we found causality in variance between oil and Turkey that was unidirectional running from oil to Turkey as expected since Turkey is a foreign dependent country in oil. A change in oil prices in the world affects the Turkish bond markets.

CHAPTER 3
CONCLUSION

In this chapter, we briefly summarized the importance of this study and its contribution to the existing literature, discussed our findings and made some implications. Finally, we offered some suggestions for further research.

3.1. THE IMPORTANCE AND CONTRIBUTION OF THE STUDY

The aim of this study is to examine the volatility spillover between commodity and bond markets in various countries, in the content of global liquidity risk. Global liquidity risk is the main factor determining the volatility of bond markets. The existence of volatility spillover from commodity to bond markets indicates that when the volatility in commodity prices increases, it will cause increases in inflation pressure and subsequently interest rates as well. As a result of rising interest rates, bond prices decreases. From a macro-economic point of view, we can claim that global liquidity risk will lead to supply-side effects on economies. On the other hand, if there is a spillover from bond to commodity markets, we will observe a financial constraint in the economy. When volatility in bond markets increases, it will cause increases in borrowing costs and financial constraints which in turn, reduce the demand for commodities and negatively affect commodity prices. Therefore, investigating the direction of volatility spillover between these markets is critical since it reveals information about supply side shock or financial constraint in an economy.

In addition, this study is important as it provides information about the integration of these financial markets. The integration between commodity and bond markets in terms of volatility spillover creates low diversification opportunities for investors. On the other hand, the lack of integration of these markets suggests high diversification opportunities for them. Therefore, investors can make investment plans by considering whether or not the markets are integrated. Moreover, policy makers may consider integrations of markets to be an important issue because a crisis or a shock in one market might spillover to others and impact the overall financial performance.

Furthermore, the study is of value because it provides implications concerning global market efficiency to finance researchers. The existence of volatility spillover and causality relationships between these markets indicates the absence of market efficiency. In other words, it demonstrates the fact that according to the "Efficient Market Theory" of Fama (1970), the markets are inefficient in weak form.

This study is also important in terms of its contribution to the existing literature. We realized that the majority of related literature focuses either on the U.S., or partially on various developed countries' bond markets. However, our study considers developing countries' bond markets. We are also aware that the volatility spillovers are mostly evaluated based on stocks markets and other markets such as foreign exchange, commodity and bond markets. However, in most places of the world, instead of stock markets, funds mostly flow through bond markets. Therefore, it is more meaningful to analyze the volatility spillover between bond and commodity markets. Therefore, our findings will provide a significant contribution to the existing literature.

In addition, this study offers a contribution to the existing literature in terms of the methodologies used. We implemented multivariate GARCH (Generalized Autoregressive Conditional Heteroscedasticity) models, namely the Dynamic Conditional Correlation GARCH (DCC-GARCH) model. Departing from the existing studies, we chose to use the Copula DCC GARCH model. Finally, we employed Hong's Causality Test to examine the causal relationship between commodity and bond markets.

3.2. DISCUSSIONS ON FINDINGS

In this study, initially we implemented the DCC GARCH model to determine the volatility spillover between selected commodities such as gold and oil, and the bond markets of BRIC-T countries. Our empirical results indicated the existence of significant volatility spillover among the gold and bond markets of Brazil, Russia, and Turkey. In addition, we observed that the volatility spillover between gold and the Russian bond market was persistent. When we examined the relationship between oil and the selected bond markets, we noted a volatility spillover among the oil and bond markets of Russia and Turkey. We also determined that the volatility spillover between oil and Turkey was persistent.

Our volatility spillover results indicate a negative relationship between these markets. In other words, increases in gold and oil prices will impact bond markets negatively or increases in bond markets will cause decreases in commodity prices such as gold and oil.

The results from the DCC-GARCH model also indicate that the bond markets of Brazil, Russia and Turkey are more integrated to the gold market, and the bond markets of Russia and Turkey are more integrated to the oil market. These findings indicate an increasing correlation between the conditional volatility of commodity and bond markets. Therefore, investing into commodities such as gold and oil will not provide diversification benefits for investors or portfolio managers holding Turkish and Russian bonds in their portfolios. Additionally, investing into gold will not yield diversification advantages for investors holding Brazilian bonds. On the other hand, our findings showed that there was no volatility spillover between the gold and bond markets of China and India or between the oil and bond markets of Brazil, China, and India. As a result, we can claim that investing into gold and oil for investors holding bonds of China and India will provide diversification benefits. Similarly, investing into the oil market will improve diversification advantages for the investors of Brazilian bonds.

Moreover, the results from the Copula DCC GARCH model indicate that the relationships between gold and all related bond markets have a dependence structure, and none have the characteristics of shock dependence. On the other hand, we observed that the relationships between oil and all related bond markets have a dependence structure, and only Brazil and Turkey have the characteristics of shock dependency. However, our Copula DCC GARCH model results displaying high dependency between markets indicate limited diversification benefits for investors and portfolio managers.

Finally, we implemented Hong’s Causality in variance test to determine the causal relationship between commodities and bond markets. Our results from causality tests are consistent with our findings from the DCC-GARCH volatility spillover test results. The results of Hong’s Causality in variance test indicate a unidirectional relationship from Brazil to gold and from gold to the bond markets of Turkey and Russia. It signifies the fact that a change in gold prices affects Russian and Turkish bond market yields. We did not determine a causal relationship in the variance between the gold and bond markets of China and India. On the other hand, we observed a unidirectional relation in the variances of oil and all related bond markets except for those in India. The direction of this relationship is from oil to the bond markets of Brazil and Turkey and from the bond markets of China and Russia to oil. It is apparent that among the BRIC-T countries, Turkish bond market was only affected from the volatilities in both oil and gold prices negatively. Following Turkey, Russian and Brazilian bond markets were affected by gold and oil prices respectively.

As a result, we can claim that the bond markets of Brazil, Russia, and Turkey are vulnerable to supply-side shocks. In these bond markets, increases in the aforementioned commodity prices result in an increase in global liquidity risks. Rising commodity prices lead to increases in inflation and interest rates. As a result, increasing interest rates reduce the bond prices within these countries. Our results indicate that the bond markets of Brazil, Russia and Turkey are more exposed to global liquidity risk. Additionally our findings on the volatility spillover from the bond market of Brazil to gold and from the bond markets of Russia and China to oil indicate financial constraints in those markets. Increasing volatility in the bond market of Brazil and the bond markets of Russia and China are indications of the rises in borrowing costs. Financial constraints in these markets occur and this subsequently reduces both the demand for, and the prices of gold and oil respectively.

Finally, our results can be used not only by domestic but also international investors and portfolio managers. When volatility increases in gold and oil prices, investors should consider the impacts on bond markets or vice versa. In this manner, both investors and portfolio managers can implement risk management techniques and can change and redirect asset allocation strategies in their portfolios. In addition, our results can be implemented by market regulators to prevent bond markets from fluctuations in gold or oil prices. They can create various regulations to reduce the negative impact of volatility spillover among these markets. Furthermore, our results provide information about market efficiency to finance research. We can state that the bond markets of Turkey, Russia and Brazil are not efficient in the weak form since volatility spillovers occur and there is causality in variance relationships between the commodity markets of gold and oil and these bond markets.

3.3. SUGGESTIONS FOR FURTHER RESEARCH

This study can be extended in terms of data, data period and the methodologies used. In this study, we only analyzed the bond markets of BRIC-T countries; it is possible to extend research by including other developing and developed bond markets. Further studies might incorporate other commodities such as metals and different energy sources. Furthermore, the methodology of the analysis can be enriched. This study employed only the Copula DCC-GARCH model. However, there are many various types of copula models. In a later study, Elliptical copulas and Archimedean copulas such as Gaussian, Clayton, Gumbel, and Frank could be used and their results might be compared with the results of this study.

REFERENCES

Agyei-Ampomah, S., Gounopoulos, D., and Mazouz, K. (2014). Does gold offer a better protection against losses in sovereign debt bonds than other metals?. *Journal of Banking & Finance*, 40: 507-521.

Alexander, S. S. (1964). Price movements in speculative markets: Trends or random walks. no. 2, *Industrial Management Review*. 5(2): 25–46.

Alexander, C., Korovilas, D., and Kapraun, J. (2016). Diversification with volatility products. *Journal of International Money and Finance*, 65: 213-235.

Andersen, T. G., and Bollerslev, T. (1998). Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. *International economic review*, 885-905.

Andersen, T.G., Bollerslev, T., Christoffersen, P.F., and Diebold, F.X. (2006), "Volatility and Correlation Forecasting," in G. Elliot, C.W.J. Granger, and Allan Timmermann (eds.), Handbook of Economic Forecasting. Amsterdam: North-Holland, 778-878.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Vega, C. (2007). Real-time price discovery in global stock, bond and foreign exchange markets. *Journal of International Economics*, 73: 251 – 277.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Vega, C. (2007). Real-time price discovery in global stock, bond and foreign exchange markets. *Journal of international Economics*, 73(2): 251-277.

Andritzky, J. R., Bannister, G. J., and Tamirisa, N. T. (2007). The impact of macroeconomic announcements on emerging market bonds. *Emerging Markets Review*, 8: 20 – 37.

Arouri, M. E. H., Jouini, J., and Nguyen, D. K. (2011). Volatility spillovers between oil prices and stock sector returns: Implications for portfolio management. *Journal of International Money and Finance*. 30: 1387-1405.

Arouri M. E. H., Lahiani, A., and Nguyen, D. K. (2013). World gold prices and stock returns in China: insights for hedging and diversification strategies. https://hal.archives-ouvertes.fr/hal-00798038

Bachelier, L. (1900). Th´eorie de la sp´eculation, *Annales Scientifiques de l'Ecole Normale Sup´erieure S´er.* 3(17): 21–86.

Baele L, Bekaert, G, and Inghelbrecht, K. (2007). The determinants of stock and bond return comovements. National Bank of Belgium Working Paper. No: 119.

Baele, L., Bekaert, G., and Inghelbrecht, K. (2010). The determinants of stock and bond return comovements. *Review of Financial Studies*, 23(6), 2374-2428.

Baffes, J. (2007). Oil spills on other commodities. *Resources Policy*, 32(3): 126-134.

Baldi, L., Peri, M., and Vandone, D. (2016). Stock markets' bubbles burst and volatility spillovers in agricultural commodity markets. *Research in International Business and Finance*, 38: 277-285.

Baur, D. G., and Lucey, B. M. (2009). Flights and contagion - An empirical analysis of stock–bond correlations. *Journal of Financial Stability*, 5(4): 339-352.

Baur, D. G., and McDermott, T. K. J. (2016). Why is gold a safe haven?, *Journal of Behavioral and Experimental Finance*, 10: 63–71.

Basher, S. A., and 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.

Beckmann, J., Czudaj, R., and Pilbeam, K. (2015). Causality and volatility patterns between gold prices and exchange rates. *The North American Journal of Economics and Finance*, 34: 292-300.

Bekaert, G., Engstrom, E., and Grenadier, S. R. (2010). Stock and bond returns with moody investors. *Journal of Empirical Finance*, 17(5): 867-894.

Bekaert and Harvey. (1997). Emerging Equity Market Volatility. *Journal of Finance Economics.* Vol. 43: 29-77.

Bentes, S. R. (2015). Forecasting volatility in gold returns under the GARCH, IGARCH and FIGARCH frameworks: New evidence. *Physica A: Statistical Mechanics and its Applications*, 438: 355-364.

Bernstein, Peter L. (2006). *Against the Gods: The Remarkable Story of Risk*. John Wiley & Sons Inc.

Black, F., and Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of political economy.* 81(3): 637-654.

Black, F. (1974). International capital market equilibrium with investment barriers. *Journal of Financial Economics,* 1(4): 337-352.

Blair, B. J., Poon, S. H., and Taylor, S. J. (2001). Modelling S&P 100 volatility: The information content of stock returns. *Journal of banking & finance.* 25(9): 1665-1679.

Blanco, R., Brennan, S., and Marsh, I. W. (2005). An empirical analysis of the dynamic relation between investment-grade bonds and credit default swaps. *The Journal of Finance*. 60(5): 2255-2281.

Bodart, V., and Reding, P. (1999). Exchange rate regime, volatility and international correlations on bond and stock markets. *Journal of International Money and Finance*, 18(1): 133-151.

Bollen, N. P., and Whaley, R. E. (2004). Does net buying pressure affect the shape of implied volatility functions?. *The Journal of Finance*, 59(2): 711-753.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of econometrics*, 31(3): 307-327.

Bollerslev, T. (1990), "Modeling the Coherence in Short-Run Nominal Exchange Rates: A Multivariate Generalized ARCH Model," *Review of Economics and Statistics*, 72: 498–505.

Bollerslev, T., Engle, R. F., and Nelson, D. B. (1994). ARCH models. *Handbook of econometrics*, 4: 2959-3038.

Bouri, E., de Boyrie, M. E., and 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.

Brooks, C. (2008). *Introductory econometrics for finance*. Cambridge university press.

Bunda, I, A., Hamann, J. and Lall, S. (2009). Correlations in emerging market bonds: The role of local and global factors. *Emerging Markets Review*. 10: 67–96.

Butler, K. C., and Joaquin, D. C. (2002). Are the gains from international portfolio diversification exaggerated? The influence of downside risk in bear markets. *Journal of International Money and Finance*. 21(7): 981-1011.

Canina, L., and Figlewski, S. (1993). The informational content of implied volatility.

Review of Financial studies. 6(3): 659-681.

Chan, K. F., Treepongkaruna, S., Brooks, R., and Gray, S. (2011). Asset market linkages: Evidence from financial, commodity and real estate assets. *Journal of Banking & Finance.* 35(6): 1415-1426.

Chaieb, I., and Errunza, V. (2007). International asset pricing under segmentation and PPP deviations. *Journal of Financial Economics*. 86(2): 543-578.

Chan, K. C., Gup, B. E., and Pan, M. S. (1997). International stock market efficiency and integration: A study of eighteen nations. *Journal of Business Finance & Accounting*. 24(6): 803-813.

Chan, K. F., Treepongkaruna, S., Brooks, R., and Gray, S. (2011). Asset market linkages: Evidence from financial, commodity and real estate assets. *Journal of Banking & Finance*. 35: 1415–1426.

Chang, C. L., McAleer, M., and Tansuchat, R. (2013a). Conditional correlations and volatility spillovers between crude oil and stock index returns. The North *American Journal of Economics and Finance*. 25: 116-138.

Chang, H. F., Huang, L. C., Chin, M. C. (2013). Interactive relationships between crude oil prices, gold prices, and the NT–US dollar exchange rate—A Taiwan study. *Energy Policy*. 63: 441–448.

Chao, S. W. (2016). Do economic variables improve bond return volatility forecasts?. *International Review of Economics & Finance*. 46: 10-26.

Chkili, W. (2016). Dynamic correlations and hedging effectiveness between gold and stock markets: Evidence for BRICS countries. *Research in International Business and Finance.* 38: 22-34.

Cho, J.H. and Parhizgari, A.M. (2008). East Asian financial contagion under DCC-GARCH. *Int J Bank Finance*. 6(1): 2

Chollete, L., De la Pena, V., and Lu, C. C. (2011). International diversification: A copula approach. *Journal of banking & finance*. 35(2): 403-417.

Chong, J., and Joëlle, M. (2006). Conditional Correlation and Volatility in Commodity Futures and Traditional Asset Market. *Journal of Alternative Investments,* 12, 3: 61-75. Available at SSRN: http://ssrn.com/abstract=822484

Choudhry, T., Hassan, S. S., and Shabi, S. (2015). Relationship between gold and stock markets during the global financial crisis: Evidence from nonlinear causality tests. *International Review of Financial Analysis*. 41: 247-256.

Christensen, B. J., and Prabhala, N. R. (1998). The relation between implied and realized volatility. *Journal of Financial Economics*. 50(2): 125-150.

Christiansen, C. (2000). Macroeconomic announcement effects on the covariance structure of government bond returns. *Journal of Empirical Finance*. 7(5): 479-507.

Christiansen, C. (2007). Volatility-spillover effects in European bond markets. *European Financial Management*. 13(5): 923-948.

Christoffersen, P., Errunza, V., Jacobs, K., and Langlois, H. (2012). Is the potential for international diversification disappearing? A dynamic copula approach. *Review of Financial Studies*. 25(12): 3711-3751.

Ciner, C., Gurdgiev, C., and Lucey, B. M. (2013). Hedges and safe havens: An examination of stocks, bonds, gold, oil and exchange rates. *International Review of Financial Analysis*. 29: 202-211.

Clare, A., and Lekkos, I. (2000). An analysis of the relationship between international bond markets. Bank of England Working Paper No. 123; Cass Business School Research Paper. Available at SSRN: http://ssrn.com/abstract=258021 or http://dx.doi.org/10.2139/ssrn.258021

Cohen, J. B., Zinbarg, E. D., and Zeikel, A. (1987). *Investment analysis and portfolio management.* Burr Ridge: Irwin: 5th edition.

Coudert, V., Couharde, C., and Mignon, V. (2011). Does euro or dollar pegging impact the real exchange rate? The case of oil and commodity currencies. *The World Economy*. 34(9): 1557-1592.

Creti, A., Joëts, M., Mignon, V. (2013). On the links between stock and commodity markets' volatility. *Energy Economics*. 37: 16–28.

Çağlı, E. Ç., Taşkın, F. D., and Mandacı, P. E. (2014). The interactions between oil prices and Borsa Istanbul sector indices. *International Journal of Economic Policy in Emerging Economies*. 7(1): 55-65.

d'Addona, S., and Kind, A. H. (2006). International stock–bond correlations in a simple affine asset pricing model. *Journal of Banking & Finance*. 30(10): 2747-2765.

Dean W. G., Faff, R. W., and Loudon, G. F. (2010). Asymmetry in return and volatility spillover between equity and bond markets in Australia. *Pacific-Basin Finance Journal*. 18: 272–289.

Delis, M. D., and Mylonidis, N. (2011). The chicken or the egg? A note on the dynamic interrelation between government bond spreads and credit default swaps. *Finance Research Letters*. 8: 163–170

Demiralay, S., and Gencer, H. G. (2014). Volatility Transmissions between Oil Prices and Emerging Market Sectors: Implications for Portfolio Management and

Hedging Strategies. *International Journal of Energy Economics and Policy*. 4(3): 442.

De Santis, R. A. (2006). The geography of international portfolio flows, international CAPM and the role of monetary policy frameworks. Europen Central Bank, Working Paper Series No: 678.

Díaz, A., Groba, J., and Serrano, P. (2013). What drives corporate default risk premia? Evidence from the CDS market. *Journal of international money and finance*. 37: 529-563.

Dickey, D. A. and W. A. Fuller (1979). 'Distribution of the estimators for autoregressive time series with a unit root', *Journal of the American Statistical Association*. Vol. 74: 427-431.

Diebold, F. X., and Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*. 28: 57–66.

Du, X., Cindy, L. Y., and Hayes, D. J. (2011). Speculation and volatility spillover in the crude oil and agricultural commodity markets: A Bayesian analysis. *Energy Economics*. 33(3): 497-503.

Dyhrberg, A. H. (2016). Bitcoin, gold and the dollar–A GARCH volatility analysis. *Finance Research Letters*. 16: 85-92.

Embrechts, P., A.J. McNeil and D. Straumann (1999). Correlation: Pitfalls and Alternatives. *Risk.* 69–71.

Embrechts, P., A.J. McNeil and D. Straumann (2001). "Correlation and Dependency in Risk Management: Properties and Pitfalls", in Dempster M., ed., *Value at Risk and Beyond*. Cambridge University Press.

Embrechts, P., Lindskog, F., and McNeil, A. (2003). Modelling Dependence with Copulas and Applications to Risk Management In: Handbook of Heavy Tailed Distributions in Finance, ed. S. Rachev, Elsevier, Chapter 8: 329-384

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the Econometric Society*. 987-1007.

Engle, R. (2002). Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models, *American Statistical Association Journal of Business & Economic Statistics*. Vol. 20: No. 3

Engel, C., Frankel, J. A., Froot, K. A., and Rodrigues, A. P. (1995). Tests of conditional mean-variance efficiency of the U.S. stock market. *Journal of Empirical Finance*. 2(1): 3-18.

Errunza, V., and Losq, E. (1985). International Asset Pricing under Mild Segmentation: Theory and Test, *The Journal of Finance,* Volume 40: Issue 1, 105–124.

Ewing B. T., and Malik, F. (2013). Volatility transmission between gold and oil futures under structural breaks. *International Review of Economics and Finance.* 25: 113–12.

Ewing, B. T., and Malik, F. (2013). Volatility transmission between gold and oil futures under structural breaks. *International Review of Economics & Finance*. 25: 113-121.

Fernández-Rodríguez, F., Gómez-Puig, M., and Sosvilla-Rivero, S. (2015). Volatility spillovers in EMU sovereign bond markets. *International Review of Economics & Finance*. 39: 337-352.

Fama, E. F. (1965a). The behavior of stock-market prices. *The journal of Business*, 38(1): 34-105.

Fama, E. F. (1965b). Random walks in stock market prices. *Financial analysts journal*. 51(1): 75-80.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance*. 25(2): 383-417.

Fan, C., Luo, X., and Wu, Q. (2017). Stochastic volatility vs. jump diffusions: Evidence from the Chinese convertible bond market. *International Review of Economics & Finance*. 49: 1-16.

Fang, V., Lim, Y. C., and Lin, C. T. (2006). Volatility transmissions between stock and bond markets: Evidence from Japan and the U.S. *International journal of information technology*. 12(6): 120-12.

Farzanegan M. R., and Markwardt, G. (2009). The effects of oil price shocks on the Iranian economy. *Energy Economics.* 31: 134–151.

Fay, J. (2005). Security‟s Role in Enterprise Risk Management. *Security Technology & Design.* Vol. 15: No.7, 22.

Fernandes, N. (2006). Market integration and international asset allocation. *Finance Letters.* 4 (1): 4-8.

Figlewski, S. (1997). Forecasting volatility. *Financial markets, institutions & instruments*. 6(1): 1-88.

Fleming, J. (1998). The quality of market volatility forecasts implied by S&P 100 index option prices. *Journal of empirical finance*. 5(4): 317-345.

Fleming, J., Kirby, C., and Ostdiek, B. (1998). Information and volatility linkages in the stock, bond, and money markets. *Journal of financial economics*. 49(1): 111-137.

Fontana, A., and Scheicher, M. (2016). An analysis of euro area sovereign CDS and their relation with government bonds. *Journal of Banking & Finance*. 62: 126-140.

Franses, P. H., and Van Dijk, D. (2000). *Non-linear time series models in empirical finance.* Cambridge University Press.

Gibson, G. (1889). *The Stock Markets of London, Paris and New York: a comparison* New York: G.P. Putnam's Sons.

Glosten, L. R., Jagannathan, R., and Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The journal of finance*. 48(5): 1779-1801.

Goeij P., and Marquering, W. (2009). Stock and bond market interactions with level and asymmetry dynamics: An out-of-sample application. *Journal of Empirical Finance.* 16: 318–329.

Gold Price. (2018). http://goldprice.org/spot-gold.html, (16.04.2018).

Gomes, M., and Chaibi, A. (2014). Volatility Spillovers between Oil Prices and Stock Returns: A Focus on Frontier Markets. *Journal of Applied Business Research*. 30(2): 509.

Granger, C. W., and Hyung, N. (1999). Occasional structural breaks and long memory. *Department of Economics, UCSD. Discussion Paper.* 99-14.

Grieb T. (2013). Does FX Volatility Affect the Distributions of Commodity Futures Returns?. *International Journal of Financial Research*. Vol. 4: No. 4.

Grubel, H. G. (1968). Internationally diversified portfolios: welfare gains and capital flows. *The American Economic Review*. 58(5): 1299-1314.

Haesen, D., Houweling, P., and Van Zundert, J. (2017). Momentum spillover from stocks to corporate bonds. *Journal of Banking & Finance*. 79: 28-41.

Hassan, S. A., and Malik, F. (2007). Multivariate GARCH modeling of sector volatility transmission. *The Quarterly Review of Economics and Finance*. 47: 470–480.

Heinen, A. (2012). A comment on bond risk, bond return volatility, and the term structure of interest rates. *International Journal of Forecasting*. 28(1): 118-120.

Hood, M., and Malik, F. (2013). Is gold the best hedge and a safe haven under changing stock market volatility?. *Review of Financial Economics*. 22(2): 47-52.

Hong, Y. (2001). A test for volatility spillover with application to exchange rates. *Journal of Econometrics*. 103: 183-224.

Hosking, J. R. M. (1980). The multivariate portmanteau statistic. *J. Amer. Statist. Association*. 75: 602-608.

Ito, M., and Sugiyama, S. (2009). Measuring the degree of time varying market inefficiency. *Economics Letters*. 103(1): 62-64.

Jacquillat and Solnik. (1978). Multinationals are poor tools for diversification. *Journal of Portfolio Management.* Vol 4: No. 2, 8–12.

Ji, Q., and Fan, Y. (2012). How does oil price volatility affect non-energy commodity markets?. *Applied Energy*. 89: 273–280.

Jin, X. (2015). Asymmetry in return and volatility spillover between China's interbank and exchange T-bond markets. *International Review of Economics & Finance*. 37: 340-353.

Jones, C. M., Lamont, O., and Lumsdaine, R. L. (1998). Macroeconomic news and bond market volatility. *Journal of Financial Economics*. 47(3): 315-337.

Kan, D., and Andreosso-O'Callaghan, B. (2007). Examination of the efficient market hypodissertation—the case of post-crisis Asia Pacific countries. *Journal of Asian Economics*. 18(2): 294-313.

Kang, W., Ratti, R. A., and Yoon, K. H. (2014). The impact of oil price shocks on US bond market returns. *Energy Economics*. 44: 248-258.

Kendall, M. G. (1970). *Rank Correlation Methods.* 4th edition. London: Griffin

Kenneth R., F., and Poterba, J. M. (1991). Investor diversification and international equity markets. *American Economic Review*. 81(2): 222-226.

Kilian, L., and Lewis, L. (2011). Does the Fed Respond to Oil Price Shocks?. *The Economic Journal*, 121(555): 1047–1072.

Kim, D. H., and Stock, D. (2014). The effect of interest rate volatility and equity volatility on corporate bond yield spreads: A comparison of noncallables and callables. *Journal of Corporate Finance*. 26: 20-35.

Kim, J. M., Jung, H.. (2016). Linear time-varying regression with Copula–DCC–GARCH models for volatility. *Economics Letters*. 145: 262–265.

Kim, J. H., & Shamsuddin, A. (2008). Are Asian stock markets efficient? Evidence from new multiple variance ratio tests. *Journal of Empirical Finance*, 15(3), 518-532.

Kim, S. J., McKenzie, M. D., & Faff, R. W. (2004). Macroeconomic news announcements and the role of expectations: evidence for US bond, stock and foreign exchange markets. *Journal of Multinational Financial Management*, 14(3), 217-232.

Kim, S. J., Moshirian, F., & Wu, E. (2006). Evolution of international stock and bond market integration: Influence of the European Monetary Union. *Journal of Banking & Finance*, 30(5), 1507-1534.

King, Mervyn, Enrique Sentana, Sushil Wadhwani. (1994). Volatility and the links between national stock markets. *Econometrica*, 62, pp. 901-934

Kirkulak-Uludağ, B., & Lkhamazhapov, Z. (2016). The volatility dynamics of spot and futures gold prices: Evidence from Russia. *Research in International Business and Finance*, 38, 474-484.

Konstantinidi, E., Skiadopoulos, G., & Tzagkaraki, E. (2008). Can the evolution of implied volatility be forecasted? Evidence from European and US implied volatility indices. *Journal of Banking & Finance,* 32(11), 2401-2411.

Koopman, S. J., Jungbacker, B., & Hol, E. (2005). Forecasting daily variability of the S&P 100 stock index using historical, realised and implied volatility measurements. *Journal of Empirical Finance,* 12(3), 445-475.

Kristjanpoller, W., & Minutolo, M. C. (2015). Gold price volatility: A forecasting approach using the Artificial Neural Network–GARCH model. *Expert Systems with Applications*, 42(20), 7245-7251.

Kumar, S. (2017). On the nonlinear relation between crude oil and gold. *Resources Policy*, 51, 219-224.

Kwiatkowski, D., P.C.B. Phillips and P. Schmidt (1991). ‘Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?’, Cowles Foundation for Research in Economics at Yale University, Discussion Paper No. 979.

Lee, R. W. (2004). The moment formula for implied volatility at extreme strikes. *Mathematical Finance*, 14(3), 469-480.

Levy, H., and Sarnat, M. (1970). International diversification of investment portfolios. *The American Economic Review*, 60(4), 668-675.

Li, X. M., and Zou, L. P. (2008). How do policy and information shocks impact co-movements of China’s T-bond and stock markets?. *Journal of Banking & Finance*. 32(3): 347-359.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The review of economics and statistics*, 13-37.

Longin, F., and Solnik, B. (1995). Is the correlation in international equity returns constant: 1960–1990?. *Journal of international money and finance*. 14(1): 3-26.

Lopez, R. (2014). Volatility contagion across commodity, equity, foreign exchange and Treasury bond markets. *Applied Economics Letters*, 21(9), 646-650.

Maghyereh, A. I., & Awartani, B. (2016). Dynamic transmissions between Sukuk and bond markets. *Research in International Business and Finance.* 38: 246-261.

Malik, F., and Ewing, B.T. (2009).Volatility transmission between oil prices and equity sector returns. *International Review of Financial Analysis.* 18: 95–100.

Malik, F., & Hammoudeh, S. (2007). Shock and volatility transmission in the oil, US and Gulf equity markets. *International Review of Economics and Finance.* 17: 357–368.

Mandelbrot, B. (1963). The variation of certain speculative prices. *The Journal of Business*. 36(4): 394–419.

Markowitz, H. (1952). Portfolio selection. *The journal of finance*. 7(1): 77-91.

Markowitz, H., and Selection, P. (1959). Efficient diversification of investments. *John Wiley and Sons*. 12: 26-31.

Makridakis, S. G., and Wheelwright, S. C. (1974). An analysis of the interrelationships among the major world stock exchanges. *Journal of Business Finance & Accounting*. 1(2): 195-215.

McLeod, A. 1. and W. K. Li (1983). Diagnostic Checking ARMA Time Series Models Using Squared-residuals Autocorrelations. *Journal of Time Series Analysis*. 4: 269-273.

Mensi, W., Beljid, W., and Boubaker, A. (2013). Shunsuke Managi Correlations and volatility spillovers across commodity and stock markets: Linking energies, food, and gold. *Economic Modelling*. 32: 15–22.

Mensi, W., Hammoudeh, S., Reboredo, J. C., and Nguyen, D. K. (2015). Are Sharia stocks, gold and US Treasury hedges and/or safe havens for the oil-based GCC markets*?. Emerging Markets Review*. 24: 101-121.

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 and Finance*. 75: 258–279.

Mishra, P. K., Das, J. R., and Mishra, S. K. (2010). Gold price volatility and stock market returns in India. *American Journal of Scientific Research*. 9: 47-55.

Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica: Journal of the econometric society*, 768-783.

Naifar, N. (2011). Modelling dependence structure with Archimedean copulas and applications to the iTraxx CDS index. *Journal of Computational and Applied Mathematics.* 235: 2459–2466

Naifar, N., and Al Dohaiman, M. S. (2013). Nonlinear analysis among crude oil prices, stock markets' return and macroeconomic variables. *International Review of Economics & Finance.* 27: 416-431.

Narayan, P. K., Narayan, S., and Zheng, X. (2010). Gold and oil futures markets: Are markets efficient?. *Applied Energy*. 87(10): 3299-3303.

Narayan, P.K., and Narayan, S. (2010). Modelling the impact of oil prices on Vietnam's stock prices. *Applied Energy*. 87: 356-361.

Narayan, P. K., Thuraisamy, K. S., and Wagner, N. F. (2016). How do bond, equity and commodity cycles interact?. *Finance Research Letters.*

Nazlioglu, S. (2011). World oil and agricultural commodity prices: Evidence from nonlinear causality. *Energy policy*. 39(5): 2935-2943.

Nazlioglu, S., Erdem, C., and Soytas, U. (2013). Volatility spillover between oil and agricultural commodity markets. *Energy Economics*. 36: 658–665.

Nazlioglu, S., and Soytas, U. (2012). Oil price, agricultural commodity prices, and the dollar: A panel cointegration and causality analysis. En*ergy Economics.* 34: 1098–1104.

Nelsen, Roger B. (2006). *An Introduction to Copulas.* Portland: Springer.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of the Econometric Society*. 347-370.

Nowak, S., Andritzky, J., Jobst, A., and Tamirisa, N. (2011). Macroeconomic fundamentals, price discovery, and volatility dynamics in emerging bond markets. *Journal of Banking & Finance*. 35(10): 2584-2597.

Odier, P., Solnik, B., and Zucchinetti, S. (1995). Global optimization for swiss pension funds. *Finanzmarkt und Portfolio Management*. 210-231.

Okur, M. and Cevik, E. (2013). Testing Intraday Volatility Spillovers in Turkish Capital Markets: Evidence from Ise. *Economic Research-Ekonomska Istraživanja*. 26(3): 99-116.

Oleg, M. (2011). Volatility Interrelationship between Commodity Futures, Shanghai Stock and 10 Year Bond Indices in China. *International Journal of Economics and Finance*. 3(6): 265.

Omane-Adjepong, M., and Boako, G. (2017). Long-range dependence in returns and volatility of global gold market amid financial crises. *Physica A: Statistical Mechanics and its Applications*. 472: 188–202.

Panchenko, V., & Wu, E. (2009). Time-varying market integration and stock and bond return concordance in emerging markets. *Journal of Banking & Finance*. 33(6): 1014-1021.

Patton, Andrew J. (2012). A review of copula models for economic time series. *Journal of Multivariate Analysis*. 110: 4–18.

Phillips, P. C. B. and P. Perron (1988). ‘Testing for a unit root in time series regressions’, *Biometrika*: Vol. 75: 335-346.

Pierdzioch, C., Rülke, J. C., and Stadtmann, G. (2013). A note on forecasting the prices of gold and silver: Asymmetric loss and forecast rationality. *The Quarterly Review of Economics and Finance*. 53: 294-301.

Piplack, J., and Straetmans, S., (2009). Comovements of different asset classes during market stress. *Working Paper. Tjalling C. Koopmans Research Institute*

Poshakwale, S. S., and Mandal, A. (2016). Determinants of asymmetric return comovements of gold and other financial assets. *International Review of Financial Analysis*. 47: 229-242.

Pong, S., Shackleton, M. B., Taylor, S. J., and Xu, X. (2004). Forecasting currency volatility: A comparison of implied volatilities and AR (FI) MA models. *Journal of Banking & Finance*. 28(10): 2541-2563.

Poon, S.-H., and Granger, C.W.J. (2003). Forecasting volatility in financial markets: a review. *Journal of Economic Literature*. 41: 478–539.

Poon, S. H., and Granger, C. (2005). Practical issues in forecasting volatility. *Financial Analysts Journal. 61 (1):* 45–56.

Pritchard, Carl L. (2005). *Risk Management Concepts and Guidance*, Virginia: ESI International, Third Edition.

Ramchand, L., and Susmel, R. (1998). Volatility and cross correlation across major stock markets. *Journal of Empirical Finance*. 5(4): 397-416.

Raza, N., Shahzad, S. J. H., Tiwari, A. K., and Shahbaz, M. (2016). Asymmetric impact of gold, oil prices and their volatilities on stock prices of emerging markets. *Resources Policy*. 49: 290-301.

Reboredo, J. C., and Rivera-Castro, M. A. (2014). Wavelet-based evidence of the impact of oil prices on stock returns. *International Review of Economics & Finance*. 29: 145-176.

Reider, Rob. (2009). Volatility Forecasting II: Stochastic Volatility Models and Empirical Evidence.

Righi, M. B., and Ceretta P. S. (2012). Global Risk Evolution and Diversification: A Copula-DCC-GARCH Model Approach (Evoluc¸ ˜ao e Diversificacao do Risco Global: Uma Abordagem com Modelo Copula-DCC-GARCH). *Rev. Bras. Financas* (Online), Rio de Janeiro, Vol. 10 (4): 529–550.

Roberts, H. (1967). Statistical versus clinical prediction of the stock market. Unpublished manuscript.

Samuelson, P. A. (1965). Proof that properly anticipated prices fluctuate randomly. *Industrial Management Review*. 6(2): 41–49.

Santis, Giorgio De, and Bruno Gerard. (1997). International asset pricing and portfolio diversification with time-varying risk. *The Journal of Finance*. Volume 52 (5): 1881–1912.

Sercu, P. (1980). A Generalization of the International Asset Pricing Model, *Revue de l'Association Française de Finance*. 1: 91-135.

Sewell, M. (2011). History of the efficient market hypodissertation. Research Note, 11(04), 04. UCL Department of Computer Science.

Shafiee, S., and Topal, E. (2010). An overview of global gold market and gold price forecasting. *Resources Policy*, 35(3): 178-189.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance*. 19(3): 425-442.

Shawky, H. A., Kuenzel, R., and Mikhail, A. D. (1997). International portfolio diversification: a syndissertation and an update. *Journal of international financial markets, Institutions and Money.* 7(4): 303-327.

Shephard and Andersen. (2009). *Stochastic Volatility: Origins and Overview*. Springer.

Singh, Abhay Kumar and David E Allen. (2017). *R in Finance and Economics: A Beginner's Guide*. World Scientific Publishing Co.

Sjaastad, L. A. (2008). The price of gold and the exchange rates: Once again. *Resources Policy*, 33(2), 118-124.

Skintzi, V. D., Refenes, A. N. (2006). Volatility spillovers and dynamic correlation in European bond markets. *Int. Fin. Markets, Inst. and Money*. 16: 23–40

Śmiech, S., and Papież, M. (2017). In search of hedges and safe havens: Revisiting the relations between gold and oil in the rolling regression framework. *Finance Research Letters*. 20: 238-244.

Sklar, A. (1959). Fonctions de répartition à n dimensions et leurs marges. *Publications de l' Institut Statistique de l.universite´ de Paris*. vol. 8: 229-231.

Statista. (2017). Gold reserves of largest gold holding countries worldwide as of November 2017 (in metric tons). https://www.statista.com/statistics/267998/countries-with-the-largest-gold-reserves/, (16.04.2018).

Steeley, J. M. (2006). Volatility transmission between stock and bond markets.

Journal of International Financial Markets, Institutions and Money. 16(1): 71-86.

Solnik, B. (1974). An Equilibrium Model of the International Capital Markets, *Journal of Economic Theory*. 8: 500-524.

Solnik, B. H. (1977). Testing international asset pricing: Some pessimistic views. *The Journal of Finance*. 32(2): 503-512.

Solnik (1996). *International Investments (3rd Edition)*. Addison Wesley Publishing.

Solnik, B., Boucrelle, C., and Le Fur, Y. (1996). International market correlation and volatility. *Financial Analysts Journal*. 17-34.

Spearman, C. (1904). The proof and measurement of association between two things. *American Journal of Psychology*. 15: 72-10 1.

Statistical Research, Random Statistics and Data Science. (2012). Kendall Tau. (statistical-research.com)

Steeley, .James M. (2006). Volatility transmission between stock and bond markets. *Int. Fin. Markets, Inst. and Money*, 16, 71–86.

Steiger, W. (1964). *A Test of Nonrandomness in Stock Price Changes,* in P. H. Cootner (ed.), *The random character of stock market prices.* The MIT Press, Cambridge, MA, Chapter XII, 303–312.

Stulz, R. (1981). A model of international asset pricing. *Journal of Financial Economics*. 9(4): 383-406.

Sugimoto, K., Matsuki, T., and Yoshida, Y. (2013). The spillover analysis on the African stock markets in the crises period. June.

Tansuchat, R., McAleer, M., and Chang, C. (2009). Volatility spillovers between crude oil futures returns and oil company stock returns. *In 18th World IMACS/MODSIM Congress*. 13-17.

Taylor, S. J. (2008). *Modelling financial time series*. World Scientific.

Thuraisamy K., Sharma, S.S., and Ahmed, H.A. (2012). The relationship between Asian equity and commodity futures markets. *Financial Econometrics Series.* SWP /07.

Tian, S., and Hamori, S. (2016). Time-varying price shock transmission and volatility spillover in foreign exchange, bond, equity, and commodity markets: Evidence from the United States. *The North American Journal of Economics and Finance*. 38: 163-171.

Tiwari, A. K., and Sahadudheen, I. (2015). Understanding the nexus between oil and gold. *Resources Policy*. 46: 85-91.

Todorova, N. (2017). The asymmetric volatility in the gold market revisited. *Economics Letters*. 150: 138–141.

Trabelsi, J., Jelassi, M. M., and Del Lo, G. (2017). A Volatility Analysis of Agricultural Commodity and Crude Oil Global Markets. *Applied Economics and Finance*. 4(2): 129-140.

Tse, Y. K. (2000). A test for constant correlations in a multivariate GARCH model. Journal of Econometrics. 98 (1): 107-127.

Tule, M. K., Ndako, U. B., & Onipede, S. F. (2017). Oil price shocks and volatility spillovers in the nigerian soverign bonds market. *Review of Financial Economics.*

Turhan, M. I., Sensoy, A., Ozturk, K., and Hacihasanoglu, E. (2014). A view to the long-run dynamic relationship between crude oil and the major asset classes. *International Review of Economics & Finance.* 33: 286-299.

US Energy Information Administration. (2017). Petroleum & Other Liquids. https://www.eia.gov/dnav/pet/hist/RWTCD.htm, (16.04.2018).

U.S. Energy Information Administration. (2017). International Energy Outlook Executive Summary. Washington, DC. https://www.eia.gov/outlooks/ieo/world.cfm, (16.04.2018).

Xu, Y., and Malkiel, B. G. (2003). Investigating the behavior of idiosyncratic volatility. *The Journal of Business.* 76(4): 613-645.

Vermeulen, R. (2013). International diversification during the financial crisis: A blessing for equity investors?. *Journal of International Money and Finance*. 35: 104-123.

Viceira, L. M. (2012). Bond risk, bond return volatility, and the term structure of interest rates. *International Journal of Forecasting*. 28(1): 97-117.

Wang, K., Chen, Y. H., and Huang, S. W. (2011). The dynamic dependence between the Chinese market and other international stock markets: A time-varying copula approach. *International Review of Economics & Finance*. 20(4): 654-664.

Wang Y. M., Lin, C. F., and Li, Y. H. (2013). The Correlation and Hedging Effects between Commodity and Stock Markets. *Journal of Applied Finance & Banking*. vol. 3(5): 269-297.

Yang, J., Zhou, Y., and Wang, Z. (2009). The stock–bond correlation and macroeconomic conditions: One and a half centuries of evidence. *Journal of Banking & Finance*. 33(4): 670-680.

Yaya, O. S., Tumala, M. M., and 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.

Yurdakul, F., and Sefa, M. (2015). An Econometric Analysis of Gold Prices in Turkey. *Procedia Economics and Finance*. 23: 77-85.

Zhang, Y. J., and Wei, Y. M. (2010). The crude oil market and the gold market: Evidence for cointegration, causality and price discovery. *Resources Policy*. 35(3): 168-177.

Zhou, Y. (2014). Modeling the joint dynamics of risk-neutral stock index and bond yield volatilities. *Journal of Banking & Finance*. 38: 216-228.

Zumbach, G. (2004). Volatility processes and volatility forecast with long memory. *Quantitative Finance*. 4(1): 70-86.

Web Sites

Global Financial Data database
(https://www.globalfinancialdata.com/index.html)

US Energy Information Administration
(https://www.eia.gov/)

World Gold Council
(http: /www.gold.org/)

Statistical Research, Random Statistics and Data Science
(https://statistical-research.com/)

APPENDICES

APPENDIX 1

Constant Conditional Correlation (CCC) Model Results of Series

Gold-Brazil				
	Coefficient	**Std.Error**	**t-value**	**t-prob**
γ_{21}	-0.0665	0.0233	-2.8520	0.0044
df	3.4356	0.1093	31.4300	0.0000

Log Likelihood : 11373.178

LM Test for Constant Correlation of Tse (2000),JoE

LMC: 60.2765 [0.0000000]

P-value in brackets.

LMC~X^2(N*(N-1)/2)) under H0: CCC model, with N=#series

Gold-Russia				
	Coefficient	**Std.Error**	**t-value**	**t-prob**
γ_{21}	-0.0884	0.0225	-3.9330	0.0001
df	3.1401	0.0812	38.6900	0.0000

Log Likelihood : 10889.727

LM Test for Constant Correlation of Tse (2000),JoE

LMC: 141.374 [0.0000000]

P-value in brackets.

LMC~X^2(N*(N-1)/2)) under H0: CCC model, with N=#series

Gold-India				
	Coefficient	**Std.Error**	**t-value**	**t-prob**
γ_{21}	0.0152	0.0226	0.6711	0.5022
df	3.8023	0.1479	25.7200	0.0000

Log Likelihood : 11662.158

LM Test for Constant Correlation of Tse (2000),JoE

LMC: 41.6055 [0.0000000]

P-value in brackets.

LMC~X^2(N*(N-1)/2)) under H0: CCC model, with N=#series

Gold-China				
	Coefficient	**Std.Error**	**t-value**	**t-prob**
γ_{21}	-0.0319	0.0223	-1.4350	0.1515
df	3.1765	0.0884	35.9200	0.0000

Log Likelihood : 11009.802
LM Test for Constant Correlation of Tse (2000),JoE
LMC: 122.118[0.0000000]
P-value in brackets.
LMC~X^2(N*(N-1)/2)) under H0: CCC model, with N=#series

Gold-Turkey				
	Coefficient	**Std.Error**	**t-value**	**t-prob**
γ_{21}	-0.0887	0.0227	-3.9030	0.0001
df	3.5158	0.1167	30.1300	0.0000

Log Likelihood : 10559.409
LM Test for Constant Correlation of Tse (2000),JoE
LMC: 51.8802 [0.0000000]
P-value in brackets.
LMC~X^2(N*(N-1)/2)) under H0: CCC model, with N=#series

Oil-Brazil				
	Coefficient	**Std.Error**	**t-value**	**t-prob**
γ_{21}	0.0028	0.0228	0.1232	0.9020
df	3.9584	0.1656	23.9100	0.0000

Log Likelihood : 10156.469
LM Test for Constant Correlation of Tse (2000),JoE
LMC: 94.2122 [0.0000000]
P-value in brackets.
LMC~X^2(N*(N-1)/2)) under H0: CCC model, with N=#series

Oil-Russia				
	Coefficient	**Std.Error**	**t-value**	**t-prob**
γ_{21}	-0.1754	0.0216	-8.1030	0.0000
df	3.1401	0.0812	38.6900	0.0000

Log Likelihood : 9696.809
LM Test for Constant Correlation of Tse (2000),JoE
LMC: 201.788 [0.0000000]
P-value in brackets.
LMC~X²(N*(N-1)/2)) under H0: CCC model, with N=#series

Oil-India				
	Coefficient	**Std.Error**	**t-value**	**t-prob**
γ_{21}	0.0265	0.0228	1.1590	0.2466
df	4.3718	0.2151	20.3200	0.0000

Log Likelihood : 10460.146
LM Test for Constant Correlation of Tse (2000),JoE
LMC: 57.7312 [0.0000000]
P-value in brackets.
LMC~X²(N*(N-1)/2)) under H0: CCC model, with N=#series

Oil-China				
	Coefficient	**Std.Error**	**t-value**	**t-prob**
γ_{21}	0.0006	0.0211	0.0264	0.9789
df	3.6832	0.1404	26.2300	0.0000

Log Likelihood : 9762.967
LM Test for Constant Correlation of Tse (2000),JoE
LMC: 137.262 [0.0000000]
P-value in brackets.
LMC~X²(N*(N-1)/2)) under H0: CCC model, with N=#series

Oil-Turkey				
	Coefficient	**Std.Error**	**t-value**	**t-prob**
γ_{21}	-0.0618	0.0219	-2.8160	0.0049
df	4.0998	0.1775	23.1000	0.0000

Log Likelihood : 9335.363

LM Test for Constant Correlation of Tse (2000),JoE

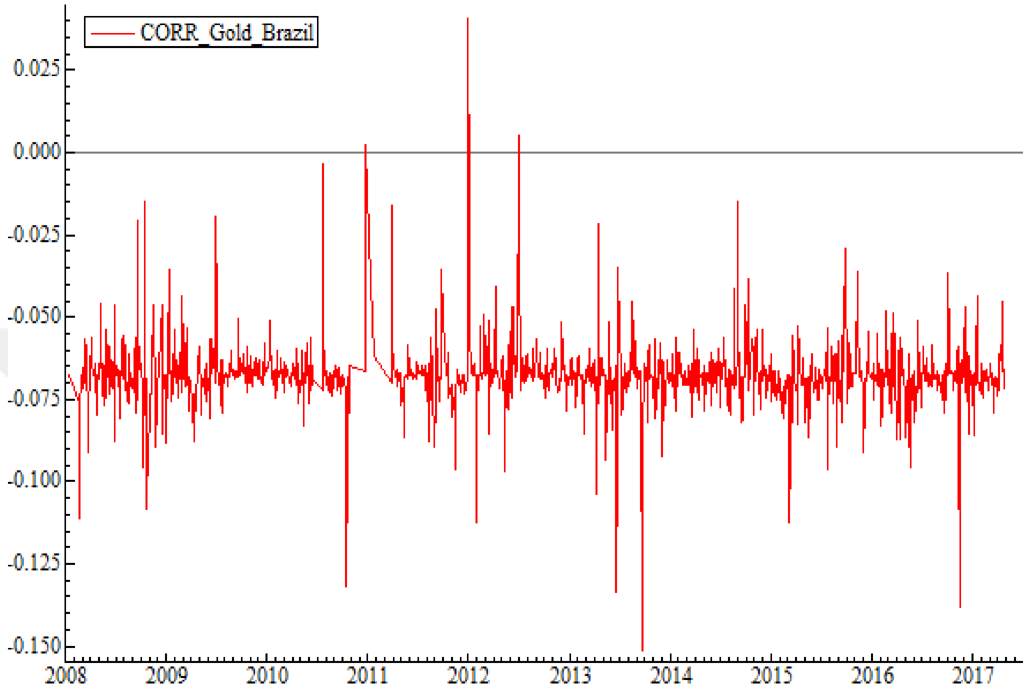
LMC: 63.2048 [0.0000000]

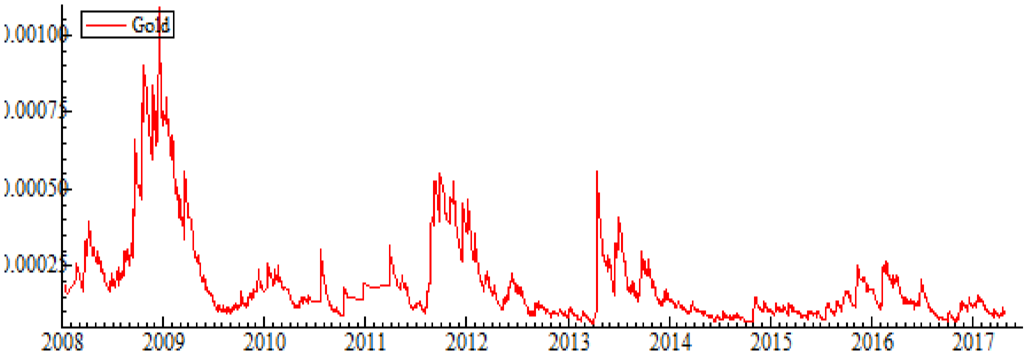
P-value in brackets.

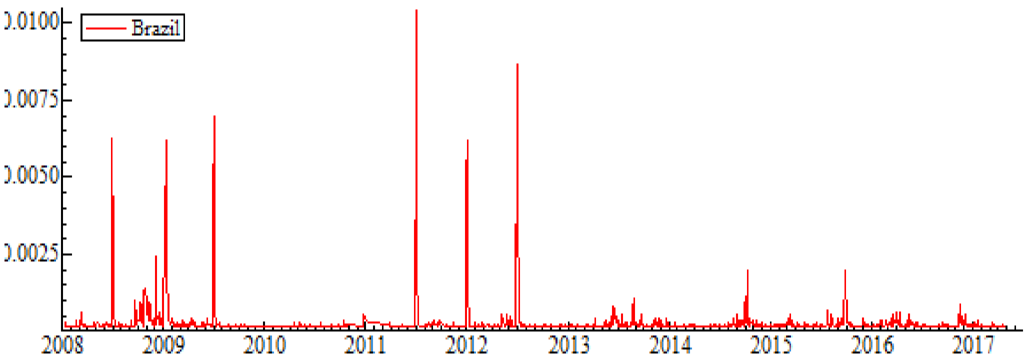
LMC~X^2(N*(N-1)/2)) under H0: CCC model, with N=#series

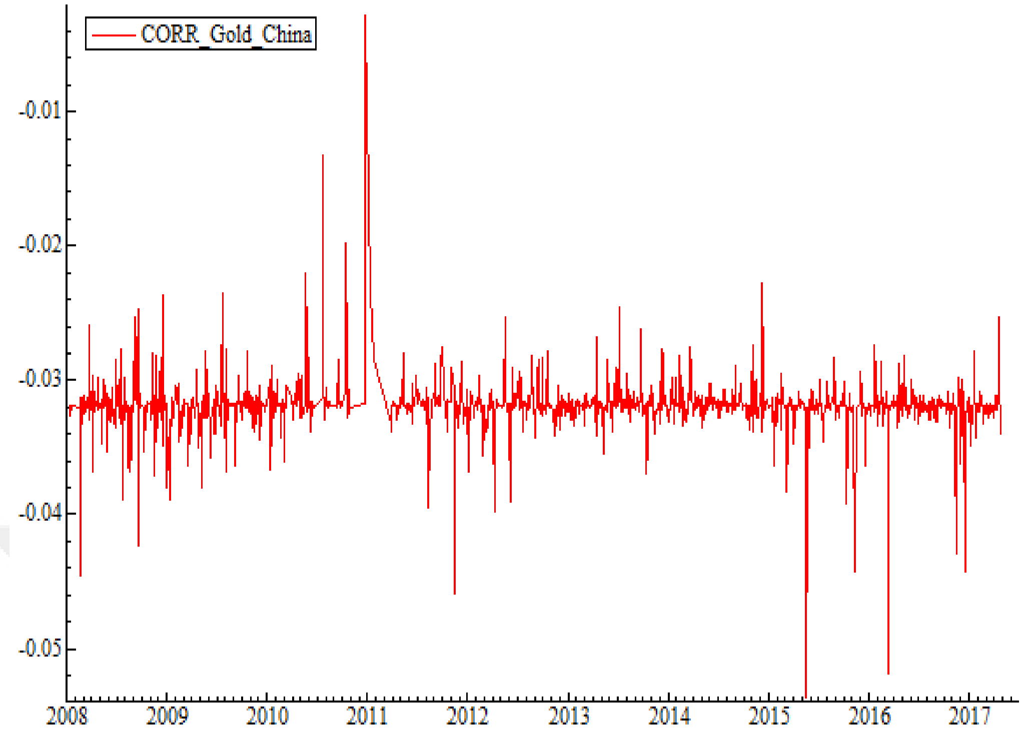
APPENDIX 2

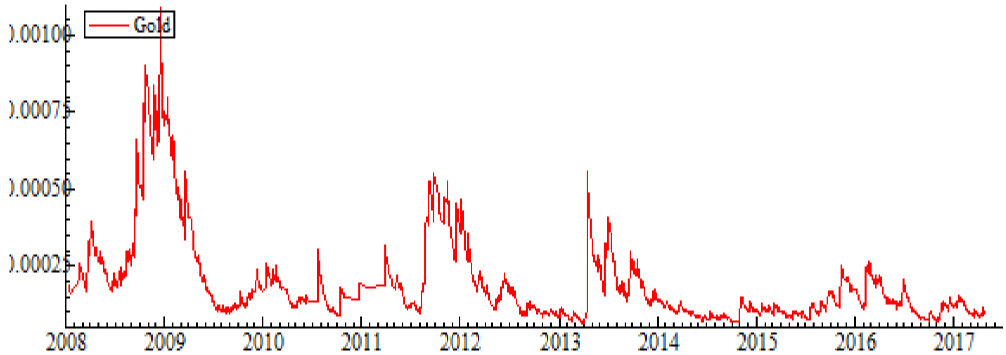
DCC Conditional Correlations and DCC Conditional Variances of Series

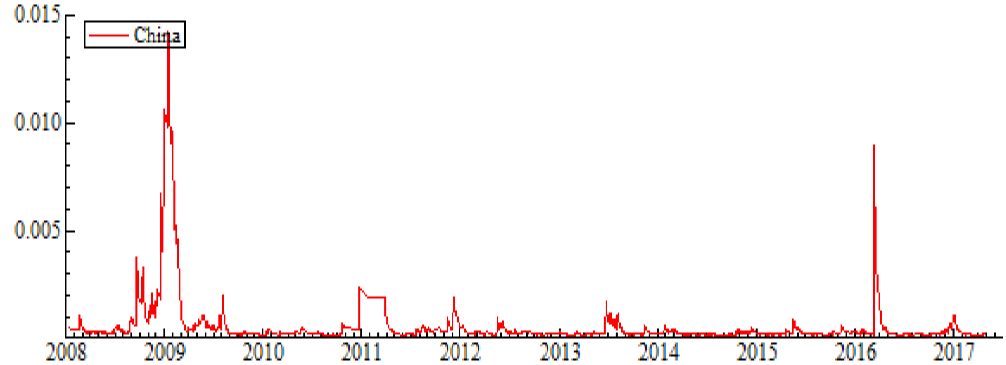


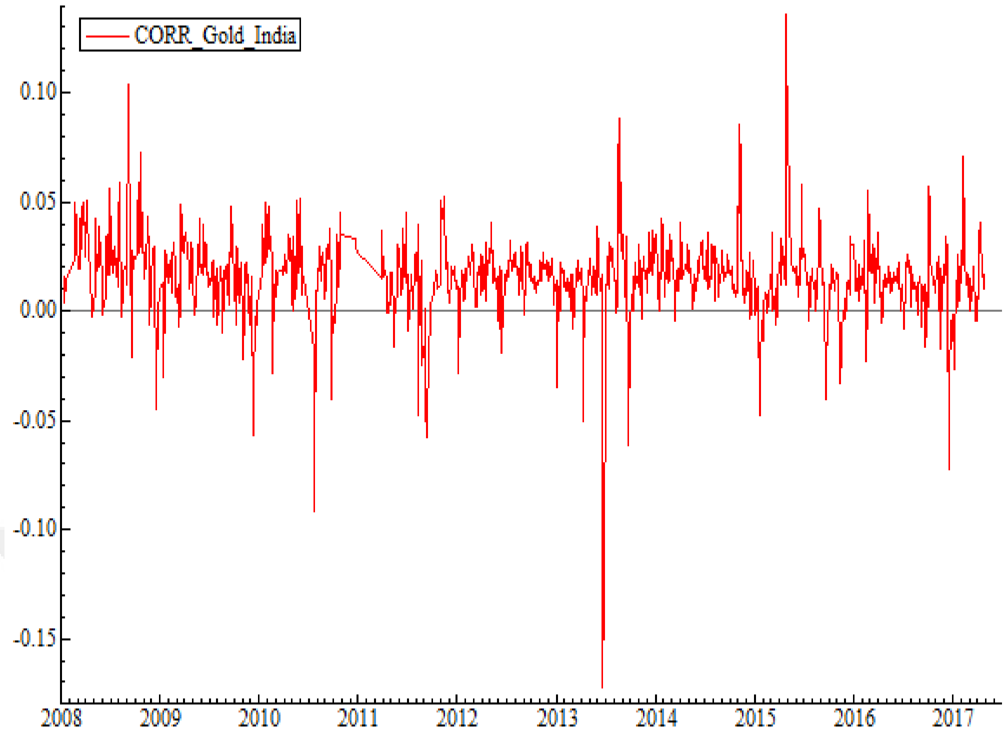


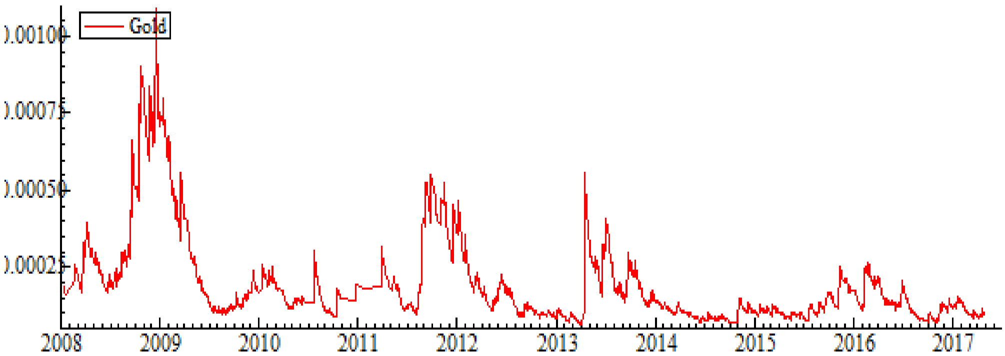


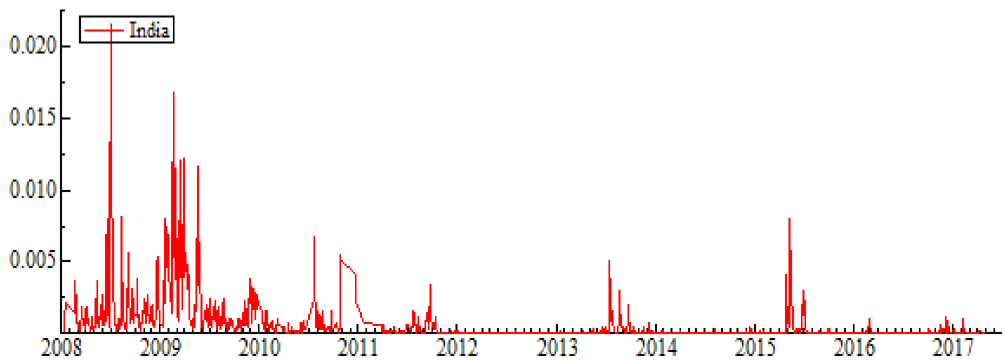

CORR_Gold_China
-0.01
-0.02
-0.03
-0.04
-0.05
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

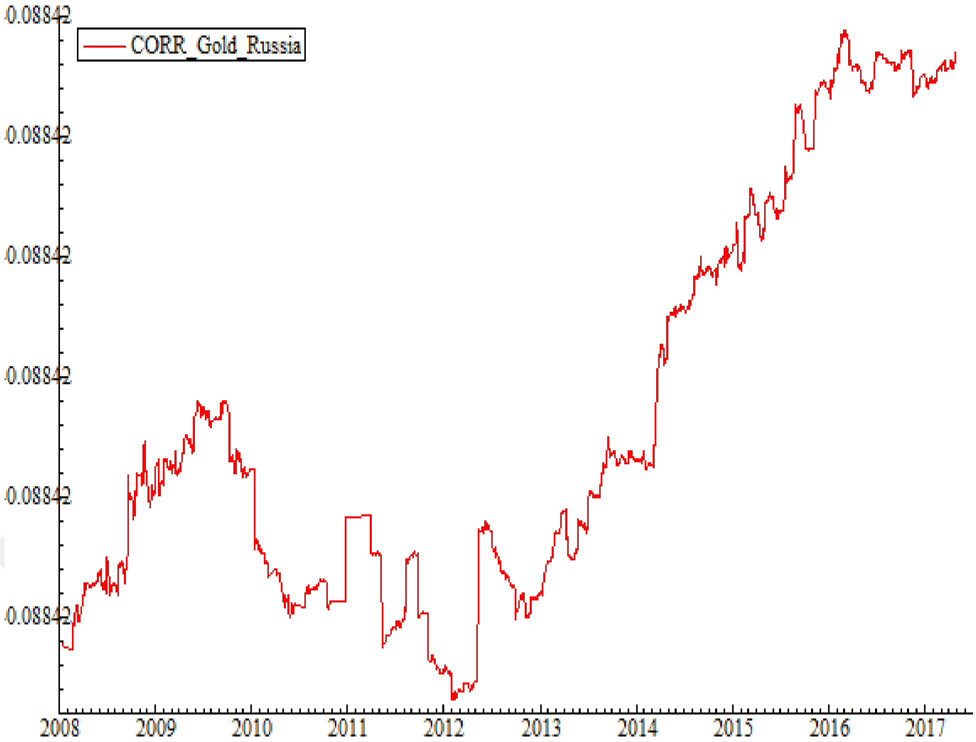

Gold
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

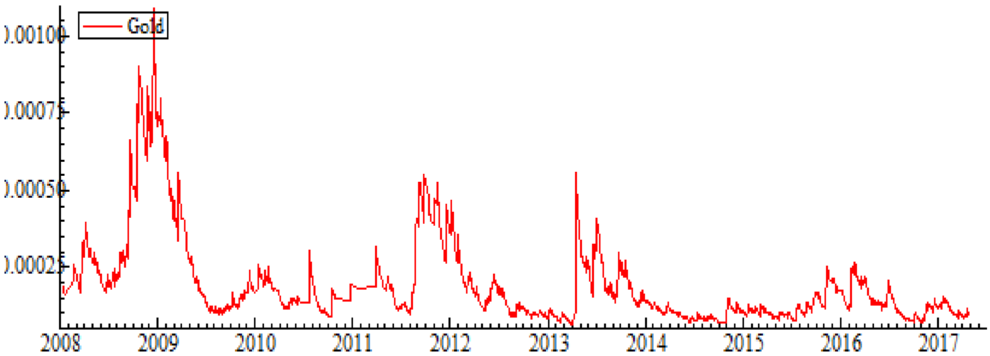

China
0.015
0.010
0.005
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

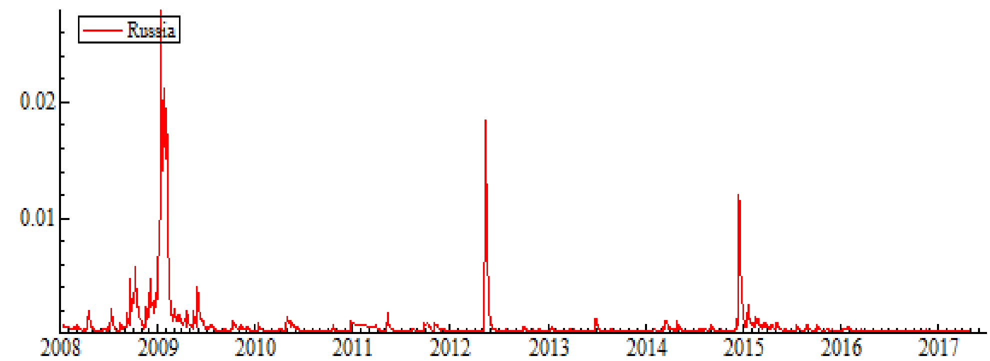

CORR_Gold_India
0.10
0.05
0.00
-0.05
-0.10
-0.15
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

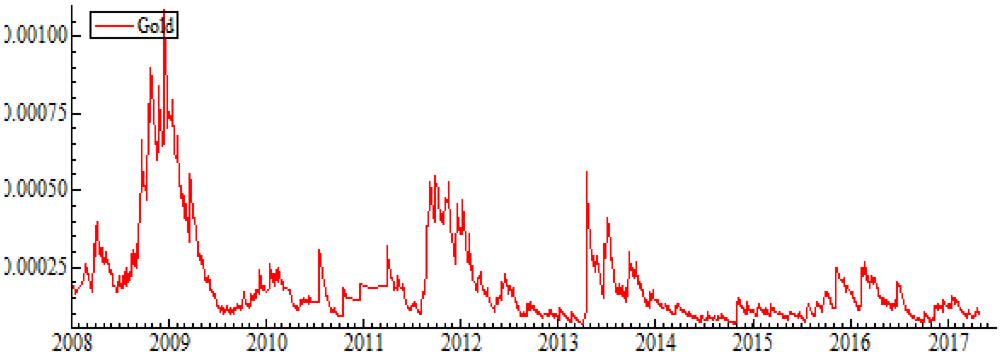

Gold
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

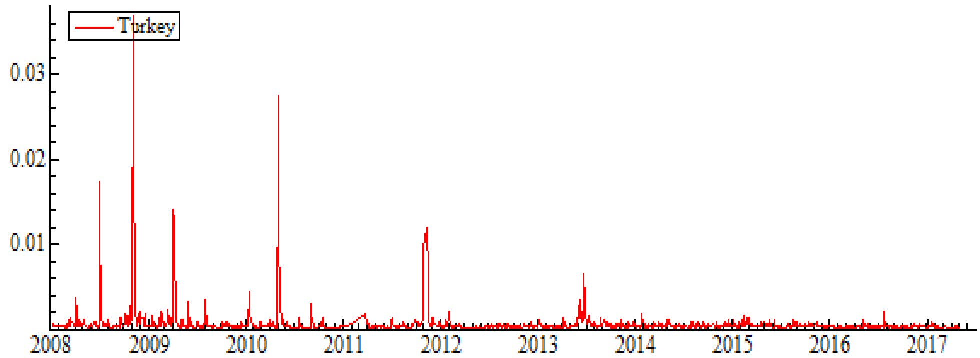

India
0.020
0.015
0.010
0.005
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

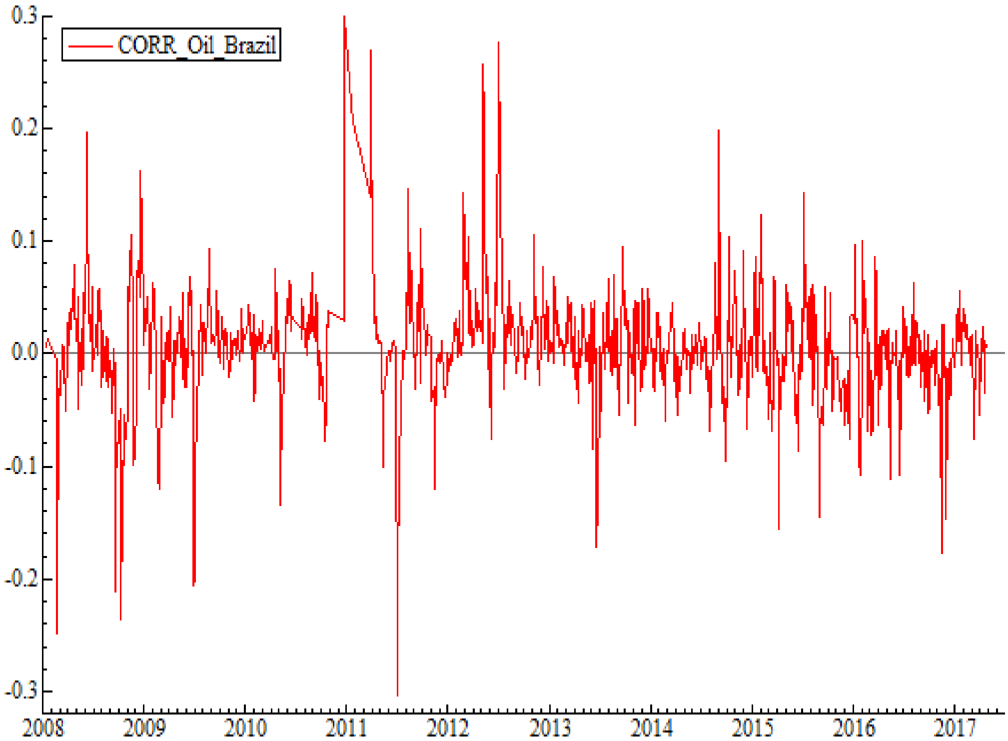

CORR_Gold_Russia
0.08842
0.08842
0.08842
0.08842
0.08842
0.08842
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

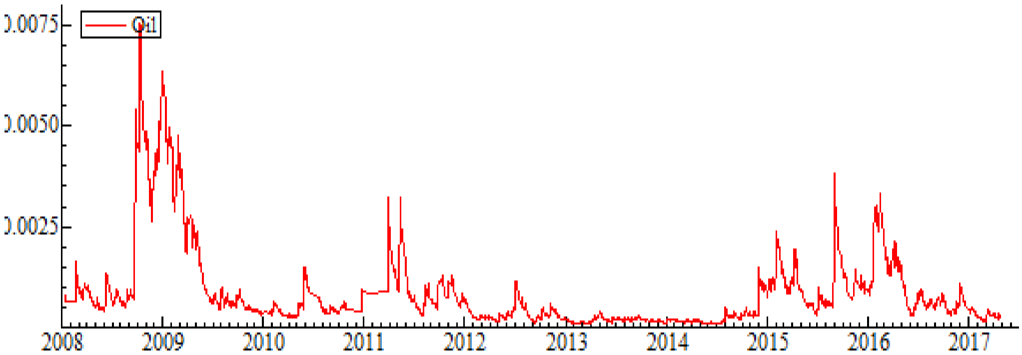

Gold
0.00100
0.00075
0.00050
0.00025
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

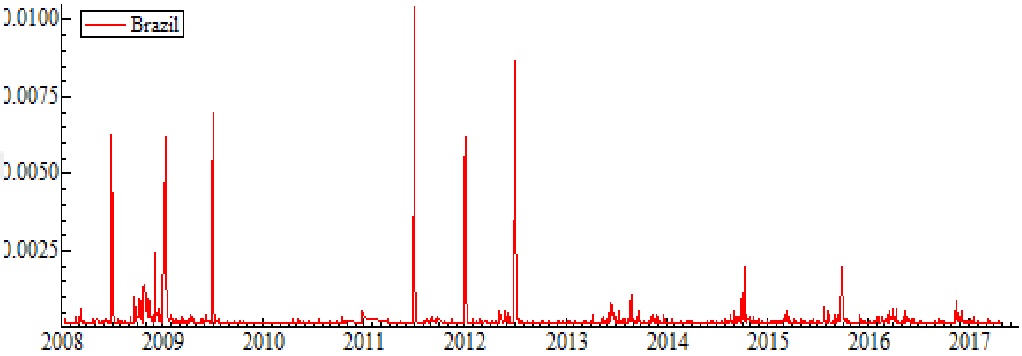

Russia
0.02
0.01
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

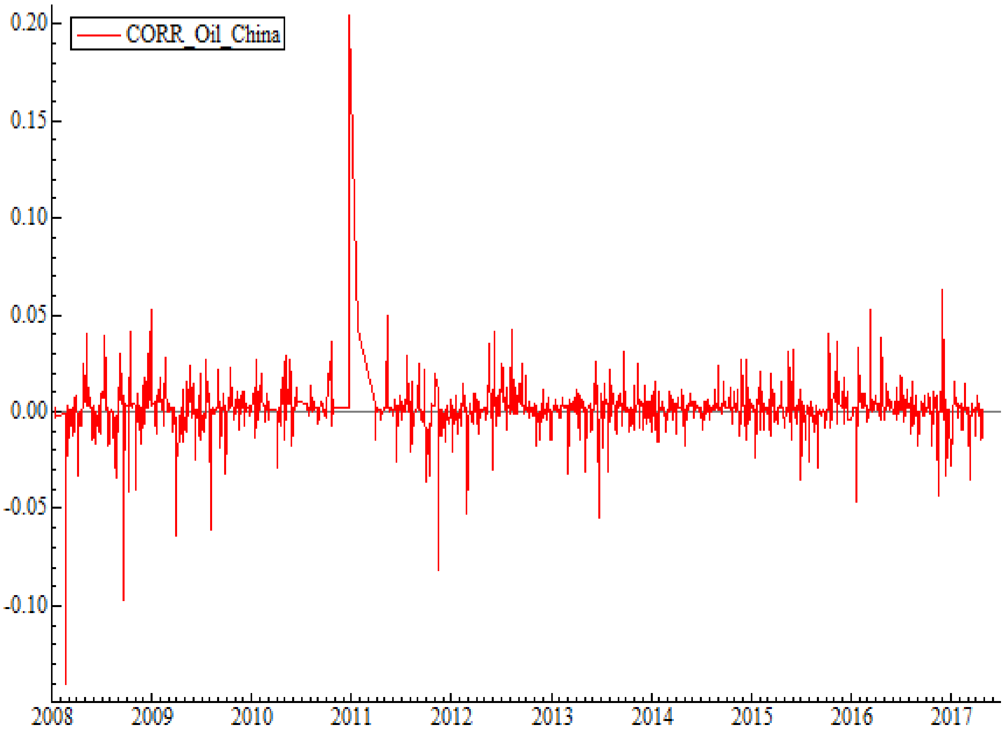

Gold
0.00100
0.00075
0.00050
0.00025
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

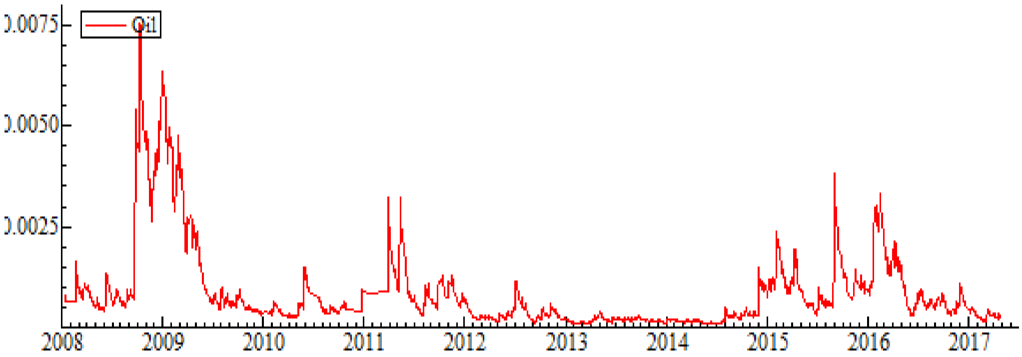

Turkey
0.03
0.02
0.01
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

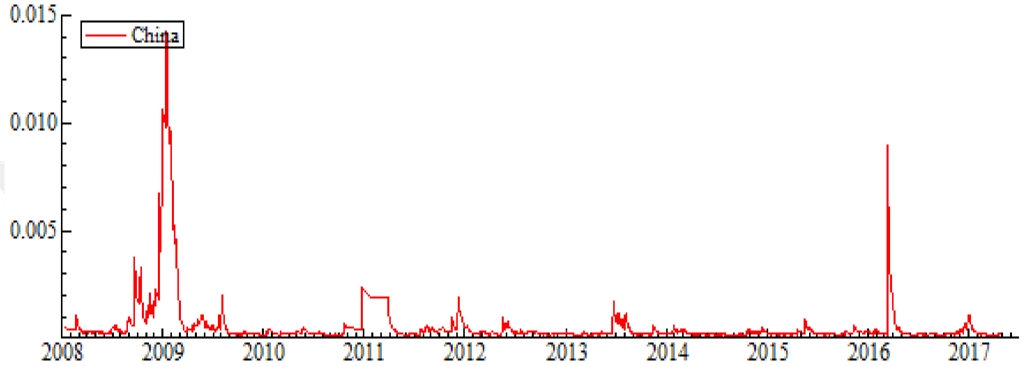

CORR_Oil_Brazil
0.3
0.2
0.1
0.0
-0.1
-0.2
-0.3
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

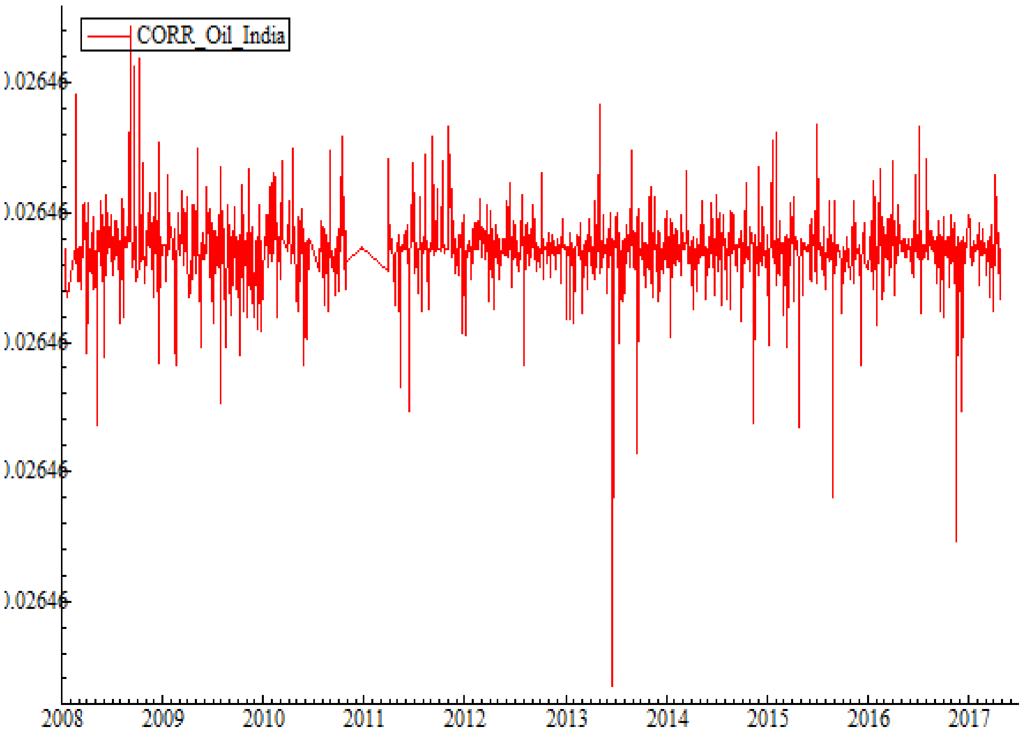

Oil
0.0075
0.0050
0.0025
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

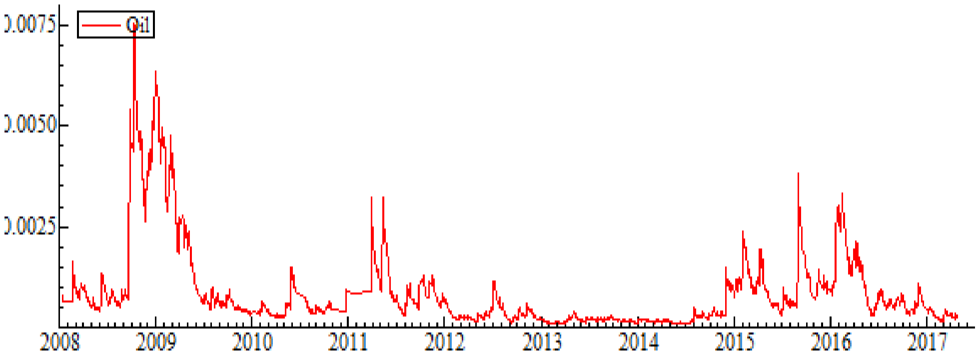

Brazil
0.0100
0.0075
0.0050
0.0025
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

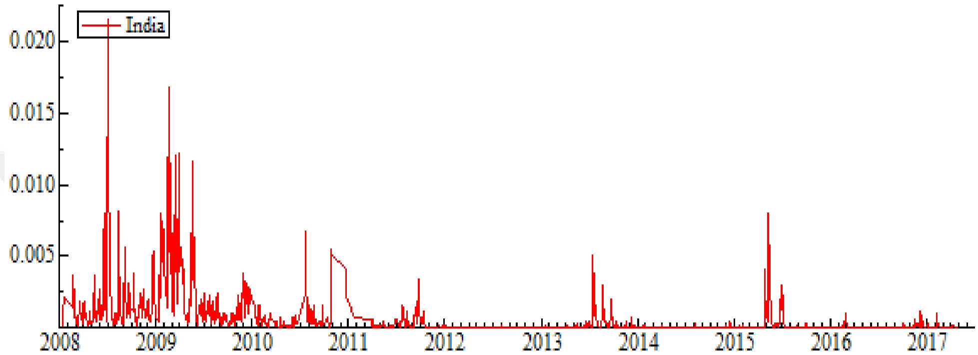

CORR_Oil_China
0.20
0.15
0.10
0.05
0.00
-0.05
-0.10
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

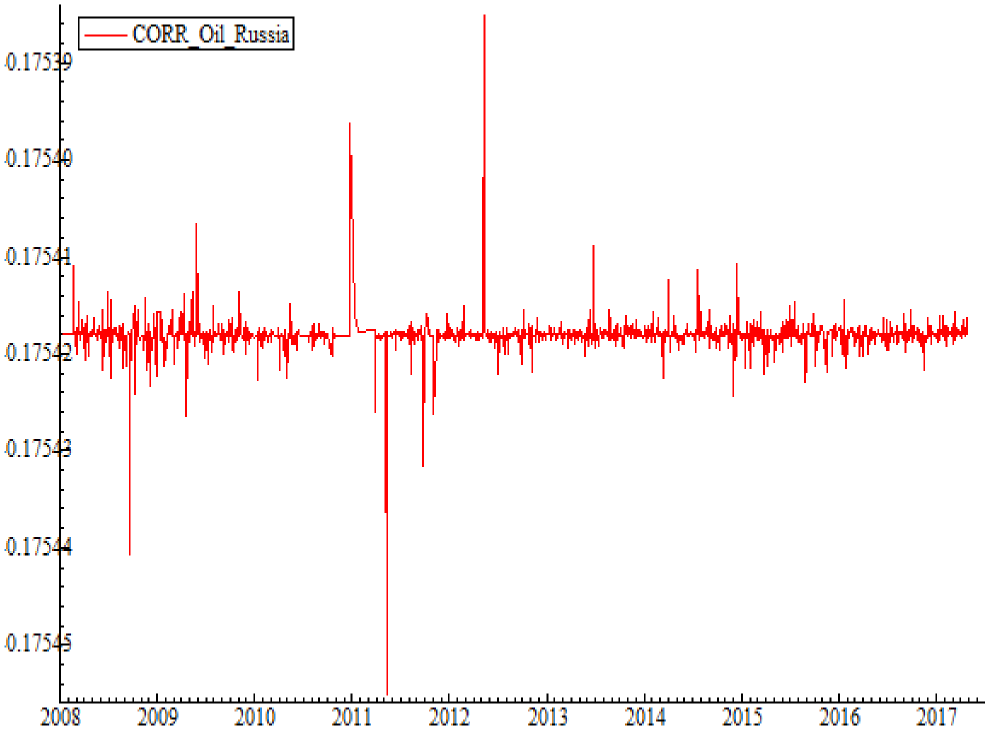

Oil
).0075
).0050
).0025
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

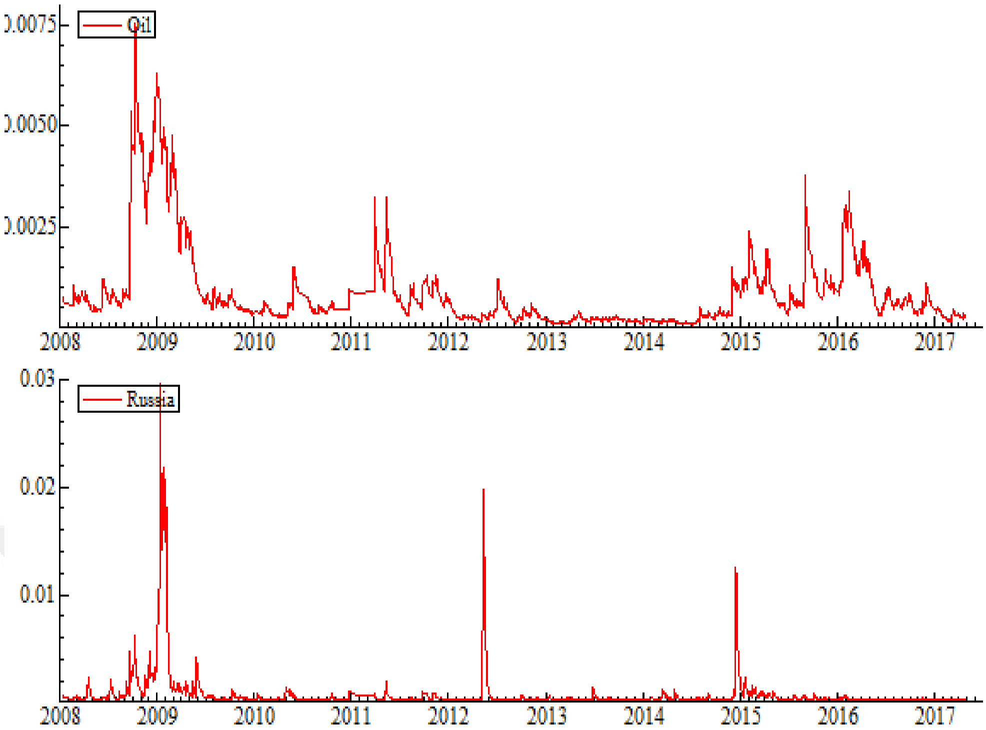

China
0.015
0.010
0.005
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

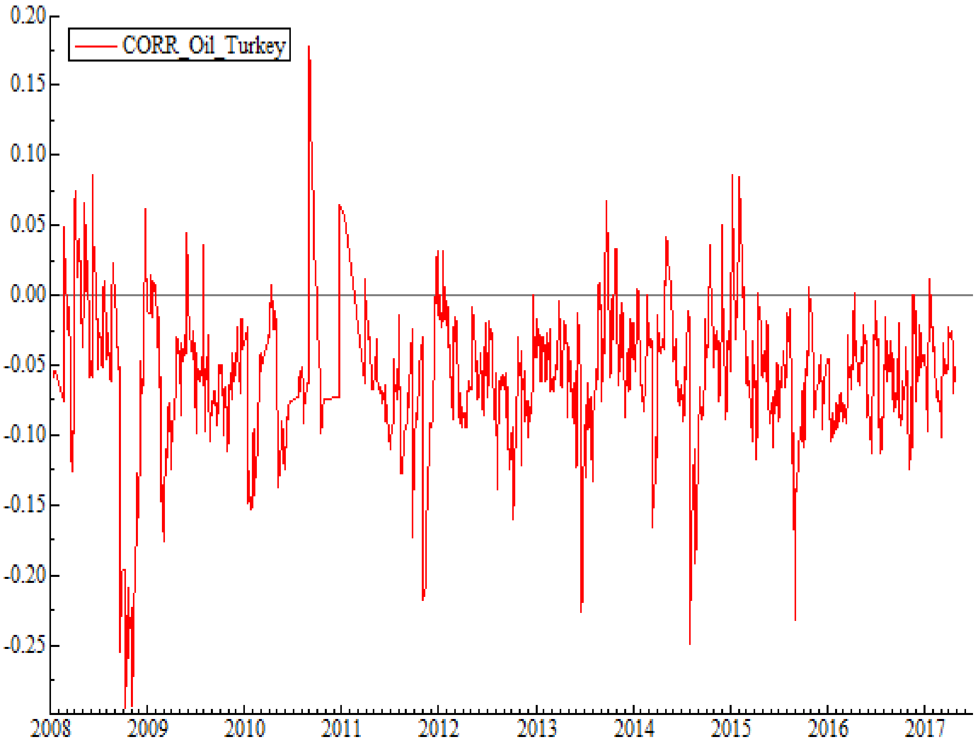

CORR_Oil_India
).02646
).02646
).02646
).02646
).02646
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

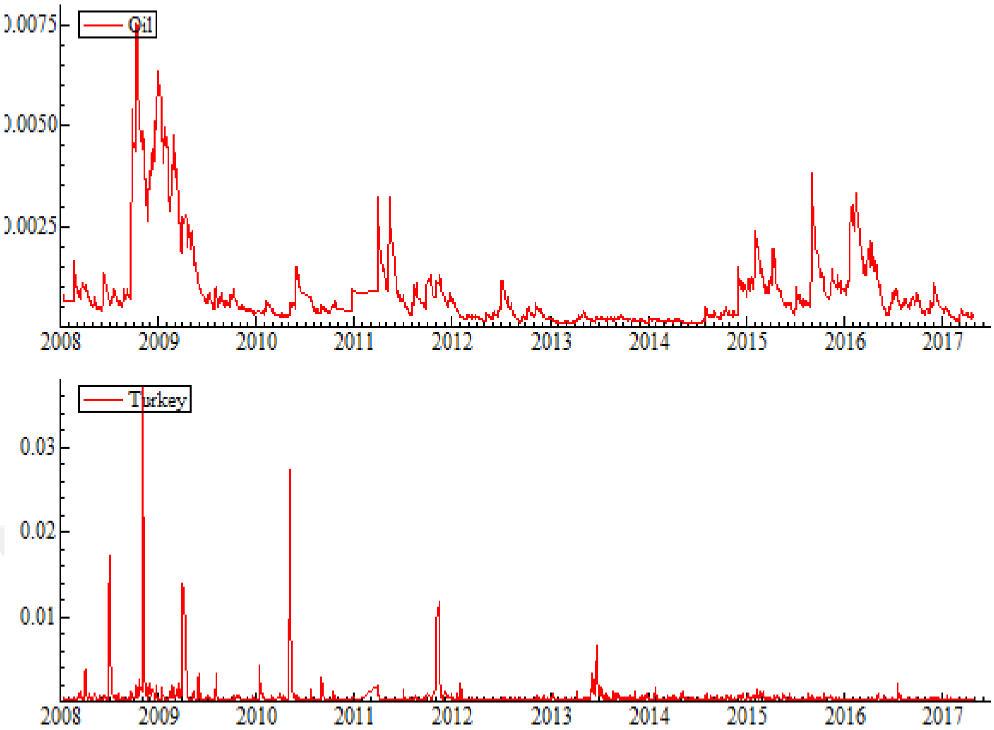

Oil
0.0075
0.0050
0.0025
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017


India
0.020
0.015
0.010
0.005
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017


CORR_Oil_Russia
0.17539
0.17540
0.17541
0.17542
0.17543
0.17544
0.17545
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017


Oil
Russia
0.03
0.02
0.01
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017


CORR_Oil_Turkey
0.20
0.15
0.10
0.05
0.00
-0.05
-0.10
-0.15
-0.20
-0.25
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017



Oil
0.0075
0.0050
0.0025
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
Turkey
0.03
0.02
0.01

APPENDIX 3

DCC GARCH Parameters of Series

Brazil				
	Coefficient	Std.Error	t-value	t-prob
Cst(M)	-0.0005	0.0004	-1.3080	0.1909
Cst(V) x 10^4	0.8779	0.6451	1.3610	0.1738
ARCH(Alpha1)	0.2914	0.1315	2.2160	0.0268
GARCH(Beta1)	0.2914	0.1315	2.2160	0.0268
No. Observations	1863			
No. Parameters	4			
Mean (Y)	-0.0001			
Variance (Y)	0.0003			
Skewness (Y)	-0.1115			
Kurtosis (Y)	37.6653			
Log Likelihood	5305.1140			
Alpha[1]+Beta[1]	0.6626			

China				
	Coefficient	Std.Error	t-value	t-prob
Cst(M)	-0.0001	0.0004	-0.1400	0.8887
Cst(V) x 10^4	0.2617	0.1582	1.6540	0.0982
ARCH(Alpha1)	0.1288	0.0291	4.4280	0.0000
GARCH(Beta1)	0.8150	0.0410	19.8700	0.0000
No. Observations	1863			
No. Parameters	4			
Mean (Y)	-0.0001			
Variance (Y)	0.0006			
Skewness (Y)	-0.2893			
Kurtosis (Y)	35.6253			
Log Likelihood	4873.8560			
Alpha[1]+Beta[1]	0.9438			

India				
	Coefficient	Std.Error	t-value	t-prob
Cst(M)	-0.0007	0.0003	-2.5430	0.0111
Cst(V) x 10^4	0.0429	0.0198	2.1640	0.0306
ARCH(Alpha1)	0.6790	0.3829	1.7730	0.0763
GARCH(Beta1)	0.5734	0.1406	4.0790	0.0000
No. Observations	1863			
No. Parameters	4			
Mean (Y)	-0.0001			
Variance (Y)	0.0004			
Skewness (Y)	-0.2113			
Kurtosis (Y)	16.2625			
Log Likelihood	5736.2310			
Alpha[1]+Beta[1]	1.2525			

Russia				
	Coefficient	Std.Error	t-value	t-prob
Cst(M)	-0.0002	0.0004	-0.6578	0.5107
Cst(V) x 10^4	0.3920	0.2613	1.5000	0.1337
ARCH(Alpha1)	0.1601	0.0561	2.8520	0.0044
GARCH(Beta1)	0.7779	0.0613	12.7000	0.0000
No. Observations	1863			
No. Parameters	6			
Mean (Y)	0.0001			
Variance (Y)	0.0007			
Skewness (Y)	1.8551			
Kurtosis (Y)	52.9307			
Log Likelihood	4721.4010			
Alpha[1]+Beta[1]	0.9380			

Turkey				
	Coefficient	Std.Error	t-value	t-prob
Cst(M)	-0.0012	0.0006	-1.9280	0.0540
Cst(V) x 10^4	1.0853	1.0669	1.0170	0.3092
ARCH(Alpha1)	0.3236	0.2051	1.5780	0.1148
GARCH(Beta1)	0.5441	0.3088	1.7620	0.0782
No. Observations	1863			
No. Parameters	6			
Mean (Y)	-0.0002			
Variance (Y)	0.0006			
Skewness (Y)	-1.0215			
Kurtosis (Y)	42.6242			
Log Likelihood	4550.0650			
Alpha[1]+Beta[1]	0.8677			

Gold				
	Coefficient	Std.Error	t-value	t-prob
Cst(M)	0.0001	0.0003	0.4607	0.6451
Cst(V) x 10^4	0.0289	0.0185	1.5610	0.1187
ARCH(Alpha1)	0.0499	0.0169	2.9500	0.0032
GARCH(Beta1)	0.9340	0.0232	40.2500	0.0000
No. Observations	1863			
No. Parameters	4			
Mean (Y)	0.0002			
Variance (Y)	0.0002			
Skewness (Y)	-0.1516			
Kurtosis (Y)	9.1440			
Log Likelihood	5515.9790			
Alpha[1]+Beta[1]	0.9839			

Oil				
	Coefficient	**Std.Error**	**t-value**	**t-prob**
Cst(M)	0.0000	0.0004	0.1081	0.9140
Cst(V) x 10^4	0.0465	0.0259	1.7970	0.0726
ARCH(Alpha1)	0.0961	0.0271	3.5500	0.0004
GARCH(Beta1)	0.9030	0.0251	36.0400	0.0000
No. Observations	1863			
No. Parameters	6			
Mean (Y)	-0.0004			
Variance (Y)	0.0008			
Skewness (Y)	0.0705			
Kurtosis (Y)	8.8391			
Log Likelihood	4401.4600			
Alpha[1]+Beta[1]	0.9990			