A Volatility Spillover Analysis Between Bond and Commodity Markets as an Indicator for Global Liquidity Risk

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Received: 11 August 2018; Accepted: 18 February 2022.

Summary: This study aims to analyze the volatility spillover between bond and commodity markets in terms of global liquidity risk. The data covers the daily closing prices of bond markets in specified countries - Brazil, Russia, India, China, and Turkey - and certain commodities - gold and oil - for the period January 2008 to January 2022. We utilized the DCC-GARCH model to analyze volatility spillover between these markets and the Copula DCC-GACRH model to determine dependence structures between them. Additionally, we applied the 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 (Brazil, China, Russia, and Turkey), and between oil and some of these bond markets (Russia, India and Turkey). Our results indicate a limited diversification benefit for investors and portfolio managers.
Key words: Volatility spillover, Bond markets, DCC-GARCH, Copula DCC-GARCH, Hong causality test
JEL: G10, G15, C32.

A volatility spillover from commodity to bond markets might cause an increase in global liquidity risk. More precisely, increases in commodity prices cause a rise in inflationary pressure (Lutz Kilian and Logan T. Lewis 2011; Cetin Ciner, Constantin Gurdgiev, and Brian Lucey 2013), which leads to an increase in interest rates. Rising interest rates will affect bond prices negatively (Ciner, Gurdgiev, and Lucey 2013). As a result, increasing volatility in bond markets will cause an increase in global liquidity risk. In addition, the existence of volatility spillover from commodity to bond markets will indicate that the economy is open to supply-side shocks. Moreover, it is possible to observe volatility spillovers from the bond to commodity markets causing financial constraints in an economy. Increases in the volatility of bond markets will cause an increase in the borrowing costs of bond issuers. When there is a rise in borrowing costs, financial risks will increase, and financial constraints will occur. Increasing financial restrictions will reduce demand for commodities and their 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. Within this context, the purpose of this paper is to analyze the effects of the volatility spillover between global commodity markets (gold and oil) and the bond

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markets of some selected major emerging economies (Brazil, China, India, Russia, and Turkey), denoted as BRIC-T.

This study consists of three sections. Following the Introduction, Section 1 summarizes related literature. Section 2 consists of the methodology and statistical models. Section 3 discusses the data and empirical findings. Lastly, Section 4 sets out the conclusion and suggests the implications of the study.

1. Literature Review

The literature analyzes various aspects of volatility spillovers among the different financial markets, or among different assets within the same market. As mentioned in the previous section, a plethora of studies examine the relationships of both commodity and bond markets with stock markets in terms of volatility spillovers. However, studies analyzing volatility spillovers between commodity and bond markets are still scarce. In order not to divert from the main topic, here we discuss only studies that include volatility spillover analysis between commodities and bonds.

We can categorize related studies into three parts. The first strand of research focuses on volatility spillover solely between commodity and bond markets. Among these studies, Kang, Ratti, and Yoon (2014) examine oil shocks on U.S. bond market returns and conclude that positive oil market demand shocks affected bond returns negatively for eight months following the shocks. They also find a spillover effect between bond and oil prices that were quite high during the period 2008–2011. Similarly, Tule, Ndako and Onipede (2017) analyze the impact of oil prices on Nigerian sovereign bonds and volatility spillover. Their results show a volatility transmission between them. On the other hand, Agyei-Ampomah, Gounopoulos, and Mazouz (2014) study whether gold - compared to other precious metals, including platinum, palladium, and silver - was a safe haven against sovereign bonds. They find that metals other than gold, especially palladium and copper, were strong safe havens against them. Gormus, Nazlioglu and Soytas (2018) assess the price and volatility transmission relationships between high-yield bond markets and energy markets and find both price and volatility transmission from energy markets to the high-yield bond market. Morrison (2019) explores the impact of oil price shocks on emerging market sovereign bond returns, focusing on 12 emerging markets and tests whether oil-importing and oil-exporting countries' bond markets reacted differently to changes in oil prices. He finds that sovereign governments' bond portfolios are exposed to changes in investor risk perception, rather than oil importing and exporting status. Similarly, Nazlioglu, Gubta and Bouri (2020) examine the return and volatility spillovers between the oil and bond markets of both major oil-exporting and oil-importing countries, using Granger Causality to consider structural breaks. Their results indicate the existence of volatility spillovers from the oil to bond markets of some major oil exporters (Kuwait, Norway, and Russia), and an importer (France). However, the most striking volatility spillovers were from bonds to oil, except for Kuwait and Saudi Arabia. In more recent studies, Zhang et al. (2021) analyze volatility spillovers among gold spots, gold futures, stocks, bonds, and oil by employing multivariate VAR-CCC-GARCH and VAR-DCC-GARCH models for China. In contrast to the findings of previous studies indicating the hedging role of gold, they find that Chinese gold spots and futures could not play such a role, owing to weak correlations with Chinese stocks, Chinese bonds, and international crude oil. In contrast to these studies, Naeem, Adekoya and Oliyide (2021) focus on green bonds instead of conventional ones and study asymmetric connectedness among green bonds and commodities, using the spillover frameworks of Diebold and Yilmaz (2014) and Baruník and Křehlík (2018). Their findings demonstrate strong asymmetric spillovers between green bonds and commodities, including gold and silver, regardless of the period. However, crude oil had a strong connection with green bonds in the long-run.

In other respects, oil price declines may adversely influence oil-dependent economies. This is perceived as an increase in the sovereign credit risk of these economies that may influence their cost of borrowing in international markets. Therefore, there are a number of studies examining volatility spillover between Credit Default Swap (CDS) and commodities. Among these studies, Bouri, Boyrie, and Pavlova (2017) analyze the relationship between sovereign CDS and commodities (including energy, agriculture, precious metals, and industrial metals) in 6 frontiers and 17 emerging markets. Their results indicate strong volatility spillover effects from commodities to CDS for most of the countries. In a more recent study, Bouri, Jalkh, and Rouboud (2019) examine the dependence structure between commodity/energy markets and the sovereign risks of BRIC countries. Their results indicate that the volatility of energy/commodity prices is the common component of systematic risk for both oil-importing and oil-exporting countries. They also show that the level of commodity/energy dependence is important in shaping the volatility of sovereign risks. Lastly, the mid-2014 energy price decline affected the volatility linkages.

The second strand of research incorporates analysis of stock markets and examines the volatility spillover effect among the stock, bond, and commodity markets. Among these studies, Oleg (2011) examines volatility spillover among China's next future commodity contracts, stocks, and 10-year bonds and posits that a negative correlation between 10-year government bonds and future commodity contracts increased with bond volatility. As for stocks, the correlation between stocks and commodities rose during the recession. Mensi et al. (2015) investigate whether Sharia stocks, gold, and T-bills were safe havens for six Gulf countries. Their results show that, save for T-bills, others were a safe haven during the downturn. Narayan, Thuraisamy, and Wagner (2017) investigate the relationship between commodities (gold and oil), stocks, and bonds by including consumer prices and market volatility in the U.S. for the period 1950-2015. They conclude that bonds showed positive Granger causality with regard to stocks but this was reversed from stocks to bonds. Similarly, bonds Granger caused oil negatively, whereas oil Granger caused inflation positively. Also, when positive shocks related to gold occurred, bond prices decreased. Furthermore, they argue that uncertainty in the economy first affected stocks and then bonds, and later led to market volatility. Lastly, they emphasize that market pricing spread from gold to bonds and oil, causing inflation. In another study, Basher and Sadorsky (2016) use the VIX index, as well as stocks, bonds, oil, and gold in their analysis of 23 emerging markets. They compare the models in their study and conclude that asymmetric DCC (ADCC) was the preferred model for hedging stocks by investing in other assets. Among these assets, oil was the best hedging vehicle for stock investments. On the other hand, Chan et al. (2011) analyze the relationship between stocks, bonds, oil, and gold. In contrast to the aforementioned study, they examine the real estate market by implementing the Markov regime-switching model for the U.S. from gold to stocks. They report positive stock returns and low volatility during the expansion period and highlight flight from quality, for example from gold to oil. On the other hand, they find negative stock returns and high volatility during the contraction, and observe contagion effects among oil, stocks, and real estate, as well as detecting quality flights from stocks to bonds. Among the most recent studies, Wang and Li (2021) analyze the asymmetric volatility spillover relationship between the international crude oil market and three major Chinese financial markets, including stocks, bonds, and gold, by using the DCC-MIDAS model with asymmetry effects with the Diebold and Yilmaz spillover index model (Diebold and Yilmaz, 2014). They divide the volatility caused by positive and negative return into good volatility and bad volatility. Their results indicate that the long-term volatility spillover effects were significantly higher than the short-term effects in the crude oil market, and that the good volatility spillover effects were greater than the bad effects. They argue that China's financial markets are dominated by bad volatility spillovers during financial disasters impacted by the crude oil market. In a different study, Dutta, Bouri, and Noor (2021) consider climate bonds, rather than conventional ones, and examine time-varying dynamic correlations and volatility spillovers between these bonds and leading stocks and commodities, including oil and gold, in the light of the COVID-19 outbreak. They employ VAR asymmetric DCC-GARCH (VAR-ADCC-GARCH) models and find that the climate bonds were negatively related with US equities, and positively with gold, but had no relationship with crude oil. They also find a bidirectional volatility linkage between climate bonds and these three markets.

The third strand of research investigates the relationship between the bond and the other markets (stock, commodity, and foreign exchange markets). Among them, Lopez (2014) examines implied volatility among commodities, stocks, foreign exchange rates, and government bonds for the U.S. markets, and finds that implied volatility occurred between stocks and government bonds. Diebold and Yilmaz (2012) analyze volatility spillovers across stocks, bonds, foreign exchange rates, and commodity markets for the U.S. and point out both that there was significant volatility in these markets and that the volatility spillover among them was quite limited until the 2007 financial crisis. Tian and Hamori (2016) examine price shocks and volatility shock transmission among those markets for the U.S. and find that price shocks affected all markets instantly, whereas volatility shocks caused volatility spillover to other assets. Moreover, stocks and foreign exchange rates absorbed volatility shocks to a much greater extent, while commodities and bonds absorbed them less. Turhan et al. (2014) analyze the relationship between oil and three other assets (stocks, bonds, and foreign exchange) by using U.S. data. Their findings indicate that following the 2008 crisis, there was a high positive correlation between the dollar and oil, along with high correlations among stocks, oil, and bonds. And lastly, by using U.S. and U.K. data spanning 1990 to 2010, Ciner, Gurdgiev, and Lucey (2013) examine whether five assets (bonds, gold, oil, stocks, and foreign exchange) show evidence of being used to hedge against each other. They found that bonds were regarded as a hedging instrument against stocks, whereas gold had a role as a hedging tool against exchange rates in both countries.

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

Table 1 Econometric Models Used in the Studies

Author	Model	Variables	Market	Data Period	Main Results
Oleg (2011)	GARCH Model	Bond, Stock, commodity	China	2006-2010	The conditional correlation decreases during recession indicating diversification opportunities. And the increases in the negative correlation between bond and commodity futures with the bond volatility indicate that the investors should not tilt more towards commodity futures.
Chan et al. (2011)	Markov Regime Switching Model	Bond, stock, oil, gold, real estate	the U.S.	1987-2008	Evidence of a flight to quality from stock and real estate to bonds during the crisis period
Diebold and Yilmaz (2012)	Their methods based on generalized vector autoregressive framework	Bond, stock, commodity, exchange markets	the U.S.	1999-2010	Evidence of volatility spillovers from stock market to the others during the crisis.
Ciner, Gurdgiev, and Lucey (2013)	GARCH and DCC Models.	Bond, stock, commodity I and gold), exchange markets	the U.S., UK	1990-2010	Bond and gold are safe havens.
Turhan et al. (2014)	DCC-MIDAS Model	Bond, oil, stock, and exchange markets	the U.S.	1983-2013	Flowing Fed's first tapering signals, both the short and long-run correlations between the crude oil and dollar index increased considerably.
Agyei-Ampomah, Gounopoulos, and Mazouz (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	Palladium and copper are more safe havens than gold.
Kang, Ratti, and Yoon (2014)	Structural VAR Model	Bond, oil	the U.S	1982-2011	A positive oil demand shock decreases the U.S. Bond Index returns.
Lopez (2014)	VAR Model	Bond, stock, commodity, exchange markets	the U.S.	2008-2013	Implied volatility is transmitted from the equity market to the Treasury bond market and vice versa.

Table 1 Continued

Mensi et al. (2015)	Vine Copula Models	T-bills, gold and stock	Six Gulf countries: "Saudi Arabia, United Arab Emirates, Bahrain, Kuwait, Oman, and Qatar".	2005-2014	Global investors can benefit from diversification and provide risk reductions during downturn periods by including gold or Dow Jones Islamic World Emerging Market index (DJIWEM) in their portfolios but not the U.S. T-bills.
Tian and Hamori (2016)	Time-Varying Structural VAR Model	Bond, stock, commodity, exchange markets	The U.S.	2006-2015	The volatility shocks in FX and stock markets are absorbed more quickly than those in the bond and commodity markets. Dynamic volatility results indicate that the relationship between the markets depends on current shocks.
Basher and Sadorsky (2016)	Multivariate GARCH, GO-GARCH, DCC, and ADCC Models.	Bond, stock, commodities (oil and gold), 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	In most of the situations, oil is the best asset to hedge emerging stock markets.
Narayan, Thuraisamy, and Wagner (2017)	VAR Model	Bond, gold, oil, stock, consumer prices	the U.S.	1950-2015	Lagged cross-market pricing transmission occurs from gold to bonds to oil and finally to inflation.
Bouri, Boyrie, and Pavlova (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, Colombia, Costa Rica, Hungary, Indonesia, South Korea, Malaysia, Mexico, Panama, Peru, Philippines, Russia, South Africa, Thailand, and Turkey"	2010-2016	Strong volatility spillover effects from commodities to the CDS of most of the countries.

Table 1 Continued

Tule, Ndako, and Onipede (2017)	VARMA-AGARCH Model	Sovereign bonds, oil	Nigeria	2011-2016	A significant cross-market volatility transmission between oil and sovereign bond market by considering structural breaks.
Gormus, Nazlioglu and Soytas (2018)	Fourier Toda-Yamamoto and LM-GARCH methodologies	S&P U.S. Issued High-Yield Bond Index and the futures prices for oil, natural gas, and ethanol	U.S.	2005-2015	Their findings indicate price transmission from the oil and ethanol markets to the high-yield bond market and volatility transmission from all energy markets (including oil, natural gas, and ethanol) to the high-yield bond market.
Morrison (2019)	A structural vector autoregressive (SVAR) model	Oil and emerging market sovereign bond returns	Crude oil market price and JP Morgan Emerging Market Bond Index (EMBI). EMBI Export- Brazil, Colombia, Kazakhstan, Mexico, Russia and Venezuela. EMBI Import- China, Chile, Philippines, Poland, Turkey, and South Africa.	2007-2015	Oil price innovations have a statistically significant influence on emerging market bond total returns.
Nazlioglu, Gubta and Bouri (2020)	The Fourier-Toda and Yamamoto (1995) test and the modified Hafner and Herwartz (2006) test.	Price returns and volatility of the bond and oil markets.	Major oil exporters (Canada, Kuwait, Mexico, Norway, Russia, Saudi Arabia, and Venezuela) and importers (China, France, Germany, India, Japan, the United Kingdom (UK), and the US).	2017-2019, and 1987-2019.	Volatility-based causality from the bond to oil is more prominent.
Bouri, Jalkh and Rouboud (2019)	GARCG-quantile regression approach.	Commodity/ energy markets and sovereign risks.	The Standard and Poor's Goldman Sachs Commodity Index (S&P GSCI) and the S&P GSCI energy sub-index, and CDS spreads of BRIC countries.	2010-2016	The volatility relation between commodity/energy and CDS markets is not the same under different volatility conditions.
Zhang et al. (2021)	VAR-CCC-GARCH and VAR-DCC-GARCH models.	Gold spots, gold futures, stock, bond and oil.	China.	2008-2019.	Chinese gold spots and futures could not play the hedge role due to weak correlations with Chinese stock, Chinese bond, and international crude oil.

Table 1 Continued

Dutta, Bouri and Noor (2021)	VAR-ADCC-GARCH	Climate bonds, U.S. stock, gold and oil	U.S.	2017-2020	Bidirectional volatility linkage between climate bonds and the others.
Naeem, Adekoya and Oliyide (2021)	Diebold and Yilmaz (2014) and Baruník and Křehlík (2018).	Green bonds, gold, silver, crude oil, natural gas, wheat and corn.	International markets	2009-2020	Strong asymmetric spillovers between green bonds and gold and silver regardless of the periods. Strong connection between green bonds and crude oil in the long-run.
Wang and Li (2021)		international crude oil market three major financial markets of China including stock, bond and gold	DCC-MIDAS with the Diebold and Yilmaz (2014)	2003-2019	Asymmetric volatility spillover effects between the crude oil market and different financial markets in China.

Source: Own elaboration.

As can be seen in Table 1, most studies examining the relationship between commodity and bond markets consider developed countries, particularly the U.S. However, in this paper, we take into account the bond markets of major emerging markets, namely the BRIC-T countries, who are also major oil-importing and exporting countries. Moreover, many of the studies use VAR and GARCH, or similar models. However, here we employ the Copula model that has only been used by Mensi et al. (2015) to examine volatility spillovers among Sharia stocks, gold, and Treasury bills. Our paper differs from their study in terms of assets and markets.

2. Methodology

Within the scope of the study, we analyze the volatility spillover between bond and commodity markets by using the DCC-GARCH model and compute dependence structure between markets in accordance with the Copula-based DCC-GARCH model. In addition, we used the Hong Causality in Variance Test to determine the direction of the causal relationships between them.

2.1 DCC-GARCH Model

We used the DCC model to empirically analyze the volatility spillover between bond and commodity markets (Arouri, Jouini, and Nguyen, 2011; Ciner, Gurdgiev, and Lucey, 2013). The DCC-GARCH model, which was first proposed by Robert Engle (2002), is specified by considering a dynamic matrix process. Directly computing the time-varying correlations between bond and commodity markets, as well as coping with a relatively large number of variables in the system, are the most attractive characteristics of the DCC-GARCH model (Walid Mensi, et al. 2014). The DCC-GARCH framework depends on the correlations and conditional variances. This model is based on the following specification:

$$H_t = D_t P_t D_t \tag{1}$$

where, $D_t = diag(h_{bond}^{\frac{1}{2}}, h_{commodity}^{\frac{1}{2}})$, $bond = bond\ yields$ is a time-varying correlation matrix.

$$h_{ii,t} = \omega_{i,0} + k_{ii}\varepsilon_{i,t-1}^2 + l_{ii}h_{ii,t-1},\ i{=}bond,\ commodity \quad (2)$$

where $\omega_{i,0}$, $i=$ *bond, commodity* presents the constant term. k_{ii} and l_{ii} are ARCH and GARCH coefficients, respectively. k_{ii} shows the short-term persistence, whereas l_{ii} represents the long-term persistence. The coefficients of ARCH and GARCH account for the volatility spillovers between countries' bond yields and commodities. The structure can be extended as follows:

$$Q_t = (1 - \alpha - \beta)S + \alpha\epsilon_{t-1}\epsilon_{t-1}' + \beta Q_{t-1} \quad (3)$$

where, Q_t represents time-varying conditional correlation between bond and commodity markets; α shows positive and β shows a non-negative scalar parameter under the condition of $\alpha+\beta<1$. S shows an unconditional correlation matrix of standardized residuals $\epsilon_t = (\epsilon_{bonds}, \epsilon_{commodities})'$.

Before studying the volatility spillovers between bond and commodity markets, we first utilized univariate GARCH models in order to determine the best model for all returns. Then, in the second step, the dynamic conditional correlations between the series were estimated by using the quasi-maximum likelihood (QML) method. The best GARCH model for each of the returns was determined as the GARCH (1,1) model. While choosing this model, Akaike and Swarchz information criteria, the significance of the coefficients, and stationary assumptions were taken into account.

2.2 Copula DCC-GARCH Model

The Copula DCC GARCH model has become widely popular for analyzing dependence structure (Jong M. Kim and Hojin Jung, 2016; Marcelo B. Righi and Paulo S. Ceretta, 2012; Derya Ezgi Kayalar, C. Coşkun Küçüközmen, A. S. Selcuk-Kestel, 2017). It provides to separate the marginal distributions from the dependence structure of a given joint distribution. Copulas allow for the degree of the dependence. Furthermore, copulas do not contain the random variables which show the characteristic of being elliptically distributed. Hence, they are suitable for estimating the dependence structure between different financial asset returns. When the logarithms of returns of assets are used, a copula does not allow for changes in the dependence structure (Naifar, 2011). Therefore, a copula approach creates a more robust model to estimate the dependence structure between different asset classes, which is why it is of great importance in defining accurately a non-linear correlation structure (Chollete, Pena, and Lu, 2011; Patton, 2012). Kim and Jung (2016) examined the Copula DCC-GARCH model in order to forecast the volatility of U.S. stock market data. They compare their results with Kim, Jung, and Qin's study (Kim, Jung, and Qin, 2016). Their findings show that Kim, Jung, and Qin's model was more effective than others (Kim, Jung, and Qin, 2016). Righi and Ceretta (2012) also analyzed dependence and volatility between the German, Hong Kong, U.S., British, and Australian markets by using the Copula DCC-GARCH model. They note that the estimated copula model runs efficiently for their sample. In summary, there are a number of advantages of using the Copula DCC-GARCH model in order to estimate dependence structure. Firstly, it provides for a description of the conditional dependence structure by a copula and for marginal behavior by separating them from their joint distribution function, and at the same time allows for conditional correlation from a DCC-GARCH model. Secondly, the Copula DCC-GARCH model captures the nonlinear dependence ignored by conventional DCC-GARCH specifications. Thirdly, it is not subject to the restrictive requirements of DCC-GARCH models, such as elliptical joint distribution and linear relationship between financial returns (Rania Jammazi, Aviral Kr. Tiwari, Román Ferrer, Pablo Moya, 2015).

The Copula DCC-GARCH model is based on the DCC model in Engle (2002). Dynamic or conditional copulas were then introduced by Patton (2006) to consider time variation in the dependence structure. The Copula DCC-GARCH model is employed in two steps. Firstly, a bivariate DCC-GARCH (1,1) specification estimates and captures the dynamic volatility and linear correlation structure between bond and commodity returns. Secondly, the dependence parameters are estimated by using several time-varying copula functions. In this study, a Student-t copula, which is one of elliptical-type copulas, will be considered. That is, a Student-t copula is used to measure the time-varying correlation matrix using the DCC model between bond and commodity returns. It is described as follows (Kim and Jung, 2016; Righi and Ceretta, 2012):

$$rt \mid It\text{-}1 \sim N\,(0, Dt\,Rt\,Dt) \tag{4}$$

$$Dt = diag(\sigma 1t, \sigma 2t, \ldots, \sigma nt) \tag{5}$$

$$F\,(z_{1t}, z_{2t}, z_{3t}, \ldots, z_{dt}) = C\,F\,(F_1\,(z_{1t}), F_2\,(z_{2t}), F_3\,(z_{3t}), \ldots, F_d\,(z_{dt}); R_t) \tag{6}$$

$$R_t = diag(Q_t)^{-1/2}\, Q_t\, diag(Qt)^{-1/2} \tag{7}$$

$$Q_t = (1-\alpha-\beta)S + \alpha\epsilon_{t-1}\epsilon'_{t-1} + \beta Q_{t-1} \tag{8}$$

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

2.3 Hong's Causality Test

After we implemented the DCC-GARCH and Copula DCC-GARCH models, we employed a causality-in-variance test in order to show causality relationships and the directions between the markets. Hong's causality test was proposed by Yongmiao Hong in 2001. One of the main advantages of this approach is that it can detect the lead and lag structures of causality, as well as at the mean levels. It also has a powerful fit and focuses on the estimation of univariate GARCH models of the variables. It is important to analyze causality-in-variance because volatility incorporates useful data on information flows (Go Tamakoshi and Shigeyuki Hamori, 2014). Therefore, we employ a causality-in-variance test in this study. It is described as follows:

$$Q_1 = \frac{T\sum_{j=1}^{T-1} k^2(\frac{j}{M})\,\hat{\rho}^2_{\xi_u\xi_v}(j) - C_{IT}(k)}{\sqrt{2}D_{IT}(k)} \tag{8}$$

where M is a positive integer and $k\frac{j}{M}$ is a weight function.

$$C_{IT}(k) = T\sum_{j=1}^{T-1} k^2(\frac{1-j}{T})\left(\frac{j}{M}\right) \tag{9}$$

$$D_{IT}(k) = T\sum_{j=1}^{T-1} k^4(\frac{1-j}{T})\{1-(j+1)/T\}\left(\frac{j}{M}\right) \tag{10}$$

$C_{IT}(k)$ and $D_{IT}(k)$ are roughly mean and variance of the bond and commodity returns. Hong (2001) summarized its procedure. First, univariate GARCH (*p; q*) models of the all returns, including bonds and commodities, are estimated and conditional variance estimators are saved. We selected the most appropriate GARCH model, which was the GARCH (1,1) model, for all series. Next, the sample cross-correlation function and centered squared standardized residuals are estimated. An integer M is specified, and 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.

3. Data and Empirical Findings

3.1 Data

We used daily 5-year government bond yields of selected emerging countries as an indicator of the bond market and the daily gold and oil prices as an indicator of commodity markets. 5-year maturity bonds were used as they represent one of the most traded and liquid contracts. Our data period ranged from January 1, 2008 to January 6, 2022 and consisted of 2800 observations. We obtained government bond yields from Global Financial Data, West Texas Intermediate (WTI) oil prices from the official web sites of the U.S. Energy Information Administration, and gold prices from the World Gold Council. 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 in the world economy, as well as the increasing attention of investors in developed economies in these markets. Finally, we also took into consideration their geographical distribution. Although there is a broad range of commodities (for example, metals, energy, basic metals, grains and agriculture), we chose only two of them, namely oil and gold, because they are the most traded and commonly known by investors in the global market.

Figure 1 demonstrates the trajectory dynamics of daily commodity prices, including oil and gold. As illustrated in Panel A of Figure 1, there was a huge decrease in oil prices in 2008, as the financial crisis sent the price of a barrel of crude oil from nearly $150 to $35 in just under six months. Subsequently, prices continued to decline for most of the period. This crisis induced a bear market in oil trading and led to a general drop in asset prices around the world. The decline in prices also gave rise to falling revenues for oil companies. The price of crude oil, which was on an upward trend after the global financial crisis in 2008, rose to $128 per barrel in 2012. Nevertheless, it showed a downward trend after 2012. The decline in prices owing to the surplus supply of oil around the world likely stemmed from the fall in global oil demand on account of the decreasing growth rates of the Asian and European economies, as well OPEC's decisions not to cut oil production. In 2020, due to the COVID-19 pandemic, there was a dramatic drop in worldwide oil demand, since governments closed businesses and imposed travel restrictions. In addition, an unprecedented collapse in oil prices took place in April of that year because Russia and Saudi Arabia could not agree on oil production levels in March (Investopedia, 2021). It caused WTI prices to drop from $18 to about -$37 a barrel, as seen in Panel A in Figure 1.

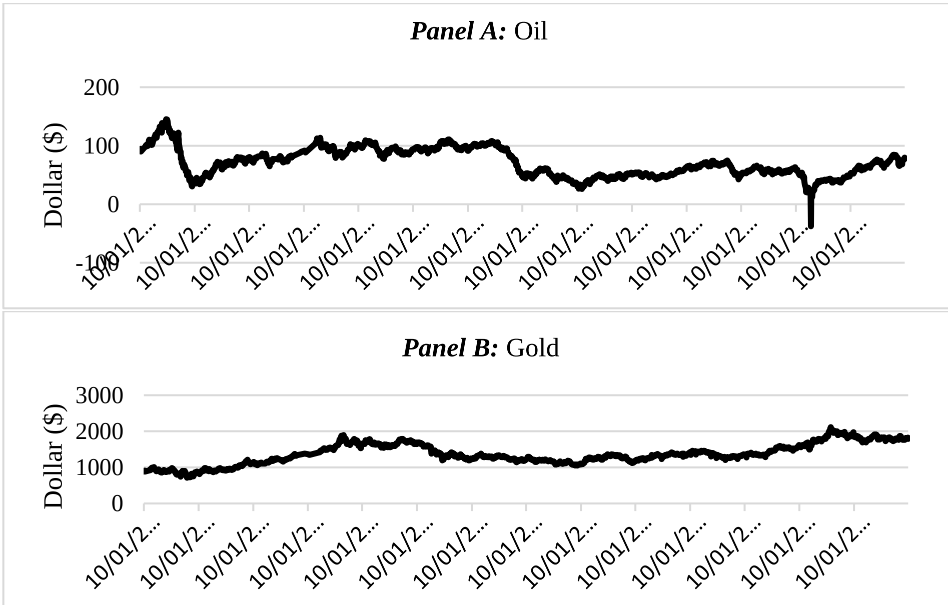

Figure 1 Time Variations of Daily Commodity Prices (2008-2022)

Source: Own elaboration.

As for gold in Panel B of Figure 1, prices hit a peak in September, 2011, and subsequently showed a tendency to stay high in the following period. Political turmoil and economic uncertainties in September, 2011, and tensions in the Middle East, were instrumental in the rise of gold in this period. In general, during periods of economic and political instability, there is an outflow from securities and an increase in demand for gold. As such, gold return has an inverse correlation with the return from securities, which significantly reduces the volatility of a portfolio. Thus, the performance of a portfolio is positively affected by this decrease in volatility. Likewise, in 2020, the global spread of the COVID-19 pandemic and its negative economic effects again led to an increase in gold prices. In short, recent years have seen stronger gold prices than oil prices because of its safe haven nature during crises. Therefore, investors were heavily relying on gold to preserve their capital during the crises.

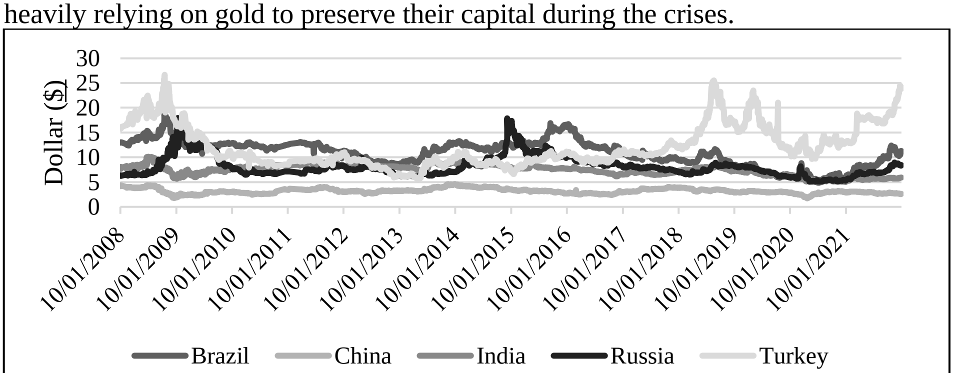

Figure 2 Time Variations of Daily Bond Yields (2008-2022)

Source: Own elaboration.

Figure 2 depicts the time variations of daily bond yields for the BRIC-T countries. It indicates that at the start of 2008, there were increases in countries' bond yields, which were then more pronounced between the middle of 2008 to the middle of 2009. They then slumped quickly as a result of global financial turbulence. During those years, Turkey had the highest yields, followed by Brazil and Russia.

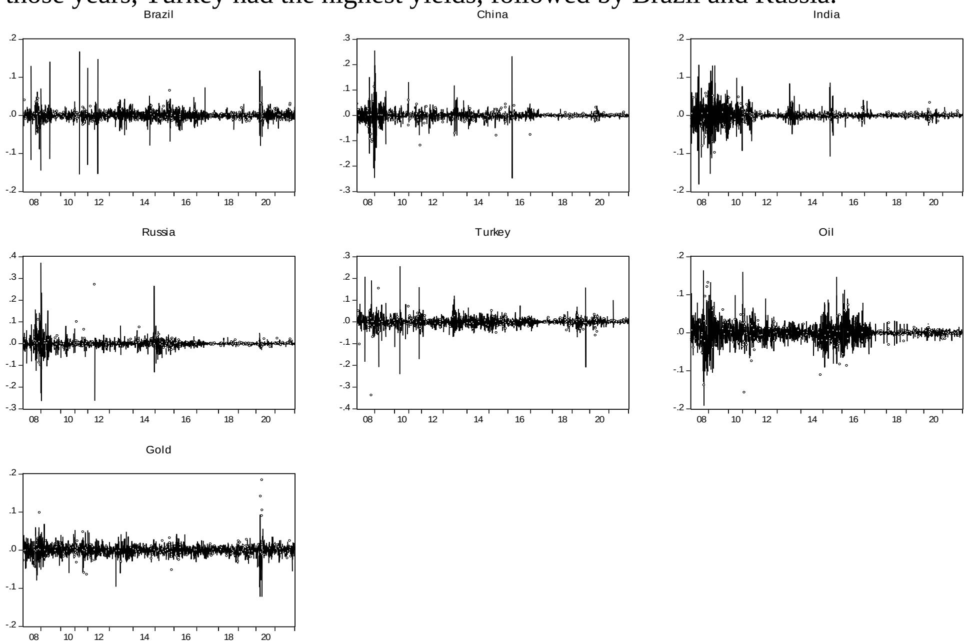

Figure 3 The Rate of Returns of Bond Markets and Commodities (2008-2022)

Source: Own elaboration.

Figure 3 shows the volatility clustering for oil, gold, and the five developing bond market return series in the period between 2008 and 2022. Regarding the magnitude of volatility clustering, China, India, Russia, and especially oil, appear more volatile than other markets and volatility clusters occurred around 2008-2010 because of worldwide economic instability. The reason for the volatility clusterings in 2008-2009 in Figure 3, was the crisis precipitated by the collapse of subprime mortgages in the U.S. in 2008. As a result, Lehman Brothers collapsed and the banking system all over the world went through a credit crunch. This in turn led to a meltdown in financial markets, as the crisis grew and affected the economies of other countries. The BRIC country markets were also affected, resulting in large-scale job losses, as foreign investors left the BRIC stock markets owing to the global recession. As a result, the MSCI BRIC index decreased by 59% in 2008 (MSCI, 2021). Governments took serious and far-reaching measures to prevent the collapse of the financial system. As the decline was particularly deep in Russia and Brazil, the authorities there tried to take precautions by temporarily closing the markets. Moreover, volatility in the bond markets of China, India, and Russia are indicative of the rise in borrowing costs and financial restrictions that may lead to decreasing demand for and prices of commodities.

3.2 Empirical Results

Table 2 provides descriptive statistics of the returns of the related commodities and five developing bond markets between 2008 and 2022. More precisely, the average returns of Russia, Turkey, gold, and oil are positive, whereas the average returns of Brazil, China, and India are negative, indicating loss. Gold has the highest return, 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 except Brazil, China, and oil are negatively skewed, whereas Brazil, China, and oil are positively left-skewed. This may indicate that negative news has a greater effect than positive news for Brazil, China, and oil. All series exhibit excess kurtosis, indicating that the effect of the aforementioned news in tail is significant. The high skewness and kurtosis give a high Jarque-Bera (J-B) statistic. Based on the J-B test, all the daily returns data series strongly reject the null hypothesis of normality, with a significance level of 1%.

Table 2 Descriptive Statistics of Daily Asset Returns

	Brazil	**Russia**	**India**	**China**	**Turkey**	**Gold**	**Oil**
Mean	-0.0000	0.0001	-0.0000	-0.0001	0.0002	0.0002	0.0000
Maximum	0.2686	0.2558	0.1320	0.3729	0.3644	0.0984	0.4231
Minimum	-0.1846	-0.2470	-0.1805	-0.2631	-0.4782	-0.0959	-0.2817
Std. Dev.	0.0192	0.0212	0.0175	0.0229	0.0274	0.0136	0.0310
Skewness	1.4212	-0.2417	-0.2146	2.0462	-1.3889	-0.1702	0.8643
Kurtosis	42.5265	43.4215	20.4167	65.7670	67.6118	9.8943	30.5587
Jarque-Bera	183020.2 ***	190444.6 ***	35373.75 ***	461091.6 ***	487424.1 ***	5553.028 ***	88859.81 ***
Sum	-0.1224	-0.4232	-0.2336	0.3073	0.6273	0.6811	0.1148

Note: *** denotes the significance level at 1%.

Source: Own elaboration.

In order to carry out a variance analysis in high-frequency series, the expected values of these series must be equal to zero. Therefore, we employed unit root tests for all series. Table 3 show the empirical statistics of the ADF, PP, and KPSS tests of daily asset returns, indicating that all indices are stationary at the level of 1%.

Table 3 Empirical Statistics of the Unit Root Tests of Daily Asset Returns

	Brazil	**Russia**	**India**	**China**	**Turkey**	**Gold**	**Oil**
ADF	-54.248***	-58.138***	-35.723***	-12.626***	-57.179***	-43.222***	-45.765***
PP	-54.333***	-59.363***	-73.177***	-64.748***	-57.179***	-43.222***	-45.699***
KPSS	0.095	0.112	0.050	0.104	0.175	0.185	0.074

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

3.2.1 DCC-GARCH Model

We used Engle's DCC-GARCH model to examine the volatility spillover between commodity and bond markets (Engle, 2002). Firstly, we applied the DCC-GARCH (1, 1) model to measure the volatility spillover between the gold and bond markets of BRIC-T countries, and then between oil and their bond markets. Our results are shown in Tables 4 and 5, respectively.

Table 4 DCC-GARCH Model for Gold and Bond Yields (2008-2022)

	Gold-Brazil	**Gold-Russia**	**Gold-India**	**Gold-China**	**Gold-Turkey**
Panel A: DCC equation					
γ_{21}	-0.0507 (0.0155)**	-0.0687 (0.0142)**	-0.0005 (0.9824)	-0.0541 (0.0925)*	-0.0748 (0.0004)***
α	0.0000 (0.9532)	0.0073 (0.2312)	0.0137 (0.4666)	0.0056 (0.2717)	0.0000 (0.9257)
β	0.8224 (0.0035) ***	0.9238 (0.000)***	0.5791 (0.4352)	0.9832 (0.0000)***	0.8148 (0.0108)**
Panel B: Diagnostic tests					
Hosking(20)	[0.0600]	[0.0858]	[0.3684]	[0.0174]	[0.0455]
Hosking(50)	[0.2363]	[0.2311]	[0.2634]	[0.4124]	[0.5072]
Li-McLeod(20)	[0.0599]	[0.0854]	[0.3673]	[0.0173]	[0.0459]
Li-McLeod(50)	[0.2347]	[0.2303]	[0.2650]	[0.4104]	[0.5012]

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

Table 4 presents the estimation results of the DCC-GARCH models for the 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 the DCC equation in Panel A, there are volatility spillovers between gold and the bond markets of Brazil, Russia, China, and Turkey, with a significance level of 5%, 5%, 10% and 1%, respectively. This could be because Russia, Brazil, (Marcelo Bianconi, Joe A. Yoshino, Mariana O. Machado de Sousa, 2013), China, and Turkey are more intensive commodity exporters. Moreover, the volatilities were quite persistent, with a significance level of 1%. These relationships are negative, indicating that the increases in world gold prices impact these markets negatively. Because gold and bonds are safe haven assets, there is a positive relationship between gold and bond prices, whereas there is negative correlation between gold and bond yields, which is the metric used in this study. This is because there is an opportunity cost of holding low-yield gold, so capital flows, and thus volatility spillover, is from gold to bonds if the bond yield is high. However, if bond yields are low, the opposite flows occur. These relationships are consistent with other studies arguing that commodities such as gold, oil, and bond markets have negative relationships according to data for China, the U.K., and the U.S. (Oleg, 2011, Ciner, Gurdgiev, and Lucey 2013, and Turhan et al., 2014). On the other hand, the results show that there was no volatility spillover between gold and the Indian bond market. Any previous lagged squared shocks did not affect the current value of conditional volatility for any of them.

The diagnostic tests indicate that the model residuals exhibit no remaining ARCH effects or autocorrelation. According to the diagnostic tests in Table 4 in Panel B, the results of the Hosking (1980) and McLeod and Li (1983) autocorrelation statistic tests confirm the null hypothesis of no serial correlation in all cases. The results also indicate that the model residuals did not have any remaining ARCH effects. In other words, there was not any pattern of statistical misspecification.

Table 5 DCC-GARCH Model for Oil and Bond Yields (2008-2022)

	Oil-Brazil	Oil-Russia	Oil-India	Oil-China	Oil-Turkey
Panel A: DCC equation					
γ_{21}	-0.0202 (0.4287)	-0.1740 (0.0004)***	0.0401 (0.0523)*	0.0205 (0.3906)	-0.0451 (0.0769)*
α	0.0249 (0.1228)	0.0136 (0.1784)	0.0000 (0.7699)	0.0046 (0.5634)	0.0051 (0.2907)
β	0.7836 (0.6346)	0.7621 (0.9990)	0.8514 (0.9840)	0.9615 (0.4635)	0.9562 (0.000)***
Panel B: Diagnostic tests					
Hosking(20)	[0.8277]	[0.0173]	[0.9957]	[0.8345]	[0.0391]
Hosking(50)	[0.5619]	[0.1088]	[0.9662]	[0.9989]	[0.2905]
Li-McLeod(20)	[0.8251]	[0.0172]	[0.9957]	[0.8337]	[0.0390]
Li-McLeod(50)	[0.5628]	[0.1075]	[0.9657]	[0.9989]	[0.2870]

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

Source: Own elaboration.

Table 5 shows 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 were volatility spillovers between oil and the bond markets of Russia, India, and Turkey at a significance level of 1%, 10%, 10%, respectively, with Russia showing the highest. This result may be attributable to the fact that Russia is among the top oil producers. Moreover, the volatilities were quite persistent at a 1% significance level. These relationships were negative for both of these markets, indicating that increases in world oil prices affected the bond markets of Russia, India, and Turkey negatively. These negative relationships are also consistent with the studies of Ciner, Gurdgiev, and Lucey (2013) who find a weak relationship between oil and bonds; Narayan, Thuraisamy, and Wagner (2017), Turhan et al. (2014), and Nicolau (2011) who find a negative correlation between crude oil prices and bonds; and Dai and Kang (2021) who find that oil returns and bond yields are negatively related. Additionally, our results show that any previous lagged squared shocks did not affect the current value of conditional volatility spillover between oil and all bond markets. Our results indicate that Turkey showed high sensitivity against shocks in oil prices, whereas Russia did not. On the other hand, we did not observe a volatility spillover between oil and other countries' bond markets, including Brazil and China. The diagnostic tests in Table 5 in Panel B showed similar results to the tests reported in Table 4.

In general, our results have important implications for investors and policymakers in both the commodity and bond markets. The volatility spillovers between gold and these bond markets do not indicate a diversification benefit for investors holding gold, Brazilian, Russian, Chinese, and Turkish bonds in the same portfolios. Rather, investors would benefit more from Indian bond yields and gold than from other countries' bond yields. In terms of determining whether BRIC-T can provide diversification opportunities using oil, our results indicate that investors may not get any benefits by investing both in oil and the bond markets of Russia, India, and

Turkey. Furthermore, a negative relationship between oil/gold and bond markets is also to be expected since increases in commodity prices cause inflationary pressure, which leads to an increase in interest rates. Rising interest rates affect bond prices negatively, as argued in the Introduction. As a result, increasing volatility in these bond markets could be a cause of heightened global liquidity risk.

3.2.2 Copula DCC GARCH Model

We employed a Copula DCC-GARCH model to investigate the determinants of commodity and bond dependence structures. The estimated results are summarized in Tables 6 and 7 respectively.

Table 6 Copula DCC-GARCH Fit for Gold and Bond Yields

	Copula DCC GARCH Model for gold-Brazil Bond Yields		
	Estimate	**t value**	**Pr(>|t|)**
[Joint]dcca1	0.0011	0.2918	0.7703
[Joint]dccb1	0.9773	51.9994	0.0000
[Joint]mshape	12.7215	3.8002	0.0001
	Copula DCC GARCH Model for gold-Russia Bond Yields		
	Estimate	**t value**	**Pr(>|t|)**
[Joint]dcca1	0.0010	0.4645	0.6422
[Joint]dccb1	0.9904	62.0475	0.0000
[Joint]mshape	9.3857	5.3916	0.0000
	Copula DCC GARCH Model for gold-India Bond Yields		
	Estimate	**t value**	**Pr(>|t|)**
[Joint]dcca1	0.0016	0.5780	0.5632
[Joint]dccb1	0.9898	31.2820	0.0000
[Joint]mshape	18.0681	2.8177	0.0048
	Copula DCC GARCH Model for gold-China Bond Yields		
	Estimate	**t value**	**Pr(>|t|)**
[Joint]dcca1	0.0004	0.2354	0.8138
[Joint]dccb1	0.9944	266.4463	0.0000
[Joint]mshape	9.3552	4.9674	0.0000
	Copula DCC GARCH Model for gold-Turkey Bond Yields		
	Estimate	**t value**	**Pr(>|t|)**
[Joint]dcca1	0.0043	0.4838	0.6284
[Joint]dccb1	0.9870	15.8525	0.0000
[Joint]mshape	11.4343	3.9036	0.0000

Source: Own elaboration.

Table 6 sets out the results of the Copula DCC-GARCH test for gold and the series of bond markets. The Copula DCC model result for gold and the Brazil bond market parallels the DCC model. According to the Copula DCC estimation, there was a high dependence structure between gold and Brazil of 1%, whereas there was no shock dependence. According to the shape parameter, there was an asymmetry in the tail for gold and Brazil. As for gold and Russia, parallel to our findings from the DCC-GARCH model, we found a statistically significant dependence structure between gold and Russia. The shock dependence result in the Copula DCC-GARCH model was similar to that in the DCC-GARCH model in that they were both insignificant. We obtained a similar result regarding the Copula DCC-GARCH estimation of gold and India. According to the results, there was a high dependence structure of 1% between the two markets, whereas the result of the DCC model indicated no volatility spillover between them. Additionally, the shock dependence between them was found to be insignificant. With regard to China, there was evidence of a high dependence structure existing in the correlation between gold and China, even though the result of the DCC-GARCH model for gold and China indicated no volatility spillover between them. We also did not observe shock dependence in the correlation between them. As for the results from the Copula DCC-GARCH model for Turkey and gold, we observed a significant 1% dependence structure between Turkey and gold. This result is also parallel to the result from the DCC-GARCH model, indicating a significant volatility spillover between them. On the other hand, there was no evidence of shock dependence between these series. In summary, we can say that the results from the Copula DCC-GARCH models for gold and bond markets indicated the existence of dependence structures between them. However, none of them showed characteristics of shock dependence.

Table 7 shows the Copula DCC-GARCH model estimation results for oil and the bond market series. According to the results for the oil-Brazil series, there was a high dependence structure correlation between oil and Brazil of 1% significance. Additionally, we found that the oil-Brazil series indicated shock dependence with a significance level of 10%. This finding is not parallel to the results of our test using the DCC-GARCH model, which indicated no volatility spillover.

Table 7 Copula DCC-GARCH Fit for Oil and Bond Yields

	Copula DCC GARCH Model for oil-Brazil Bond Yields		
	Estimate	**t value**	**Pr(>|t|)**
[Joint]dcca1	0.0263	1.6639	0.0713
[Joint]dccb1	0.7261	12.0569	0.0000
[Joint]mshape	16.5246	2.4341	0.0129
	Copula DCC GARCH Model for oil-Russia Bond Yields		
	Estimate	**t value**	**Pr(>|t|)**
[Joint]dcca1	0.0036	1.4775	0.1329
[Joint]dccb1	0.9932	351.2648	0.0000
[Joint]mshape	15.6285	3.1214	0.0017
	Copula DCC GARCH Model for oil-India Bond Yields		
	Estimate	**t value**	**Pr(>|t|)**
[Joint]dcca1	0.0000	0.0000	0.8364
[Joint]dccb1	0.8367	21.5246	0.0000
	Copula DCC GARCH Model for oil-China Bond Yields		
	Estimate	**t value**	**Pr(>|t|)**
[Joint]dcca1	0.0029	0.5239	0.4650
[Joint]dccb1	0.9316	58.3043	0.0000
[Joint]mshape	42.5127	1.4351	0.1260
	Copula DCC GARCH Model for oil-Turkey Bond Yields		
	Estimate	**t value**	**Pr(>|t|)**
[Joint]dcca1	0.0542	2.3281	0.0337
[Joint]dccb1	0.8696	25.1653	0.0000
[Joint]mshape	21.1593	2.1821	0.0344

Source: Own elaboration.

As for the Copula DCC-GARCH model estimation for oil and Russia in Table 7, our results indicated a high dependence structure between oil and Russia with a significance of 1%. 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, the oil-Russia series did not exhibit any shock dependence. According to the results from the Copula DCC-GARCH model for oil and India, although we did not observe a volatility spillover between them, there was a high dependence structure between them of 1% significance. On the other hand, there was not any shock dependence between these two markets. As for the Copula DCC-GARCH results for oil and China, although we found no volatility spillover between these markets according to the DCC-GARCH model, the Copula DCC-GARCH result indicates a significant dependence structure between them. Nevertheless, there was not a shock dependency between them. The results from the Copula DCC-GARCH model for oil and Turkey showed that there was a significant dependent structure between them. This finding is similar to our findings from the DCC-GARCH model, indicating the existence of volatility spillover between them. Furthermore, there was evidence that the 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 DCC-GARCH results for this series.

3.2.3 Hong Causality Test

Before administering Hong's Causality test, we first determined standardized residuals derived from the GARCH model for all series. Following this, we used cross-correlation coefficients for the paired series. Finally, we employed Hong's Causality test to determine the causal relationship between commodities and bond markets. Table 8 sets out the Hong's Causality test results between the variances of commodity and all related bond markets in the series.

According to Table 8, there were unidirectional causalities in variance between gold and Brazil, gold and China, and gold and Turkey. These unidirectional causalities were from gold to Brazil and Turkey, and from China to gold. This might suggest that an increase in gold prices affects Brazil and Turkey's bond markets. Furthermore, when we look at the direction of causality in variance between gold and Russia, we observed bidirectional causality from gold to Russia.

As for the Hong's Causality test results in respect of the variances between oil and the related bond market series, there were unidirectional causal relationships in the variance between oil and India, and oil and Turkey. The causal link between the oil market and India indicates that a change in oil prices in the world affects Indian bond markets. This same causality also applies to Turkish bond markets and oil, as would be expected since Turkey is dependent on foreign oil. Furthermore, a significant bidirectional volatility linkage is shown between the Russian bond and oil markets. This is likely because Russia is one of the biggest oil producers and consumers in the world. On the other hand, we did not observe any causal relationship between oil and the China and Brazil bond markets.

The Hong's Causality tests support the findings of the DCC-GARCH volatility spillover tests and signify the fact that a change in gold prices affects the bond yields of Brazil, China Russia. The existence of unidirectional relationships (from oil to the bond markets of Brazil, China Russia, and from Russia and Turkey to oil) indicates that our results are inconsistent with the assumption that the interactions between oil and the bonds of oil exporters are stronger than those of oil importers. Therefore, our results support the findings of Morrison (2019) and Nazlioglu, Gubta and Bouri (2020) with regard to differences between oil-importing and oil-exporting countries.

Overall, it is apparent that among the BRIC-T countries, only the Russian bond market was negatively affected by volatilities in oil and gold prices and vice versa. Therefore, information on gold and oil can be used to predict the bond market of Russia.

Table 8 Hong's Causality Test Results for Commodity and Bond Markets Series

	Gold→Brazil		**Brazil → Gold**		**Oil→Brazil**		**Brazil→Oil**	
M	**Q**	**p-value**	**Q**	**p-value**	**Q**	**p-value**	**Q**	**p-value**
1	4.6062	0.0000	-0.5641	0.7136	-0.3135	0.6230	0.2687	0.3940
2	4.3146	0.0000	-0.4799	0.6843	-0.2346	0.5927	0.1012	0.4596
3	4.2757	0.0000	-0.4208	0.6630	-0.2311	0.5913	1.0627	0.3953
4	4.3017	0.0000	-0.3150	0.6236	-0.2833	0.6115	3.0961	0.1439
5	4.2290	0.0000	-0.1711	0.5679	-0.3383	0.6324	5.1186	1.1356
	Gold→Russia		**Russia → Gold**		**Oil→Russia**		**Russia→Oil**	
M	**Q**	**p-value**	**Q**	**p-value**	**Q**	**p-value**	**Q**	**p-value**
1	4.2632	0.0000	-0.7000	0.7580	23.2974	0.0000	2.9033	0.0018
2	3.9908	0.0000	0.0665	0.4734	22.5847	0.0000	3.8173	0.0000
3	3.7357	0.0000	0.7368	0.2306	21.0826	0.0000	4.3186	0.0000
4	3.5163	0.0002	1.1286	0.1295	19.6275	0.0000	4.4309	0.0000
5	3.5714	0.0001	1.4076	0.0796	18.3922	0.0000	4.3543	0.0000
	Gold→India		**India→Gold**		**Oil→India**		**India→Oil**	
M	**Q**	**p-value**	**Q**	**p-value**	**Q**	**p-value**	**Q**	**p-value**
1	-0.3301	0.6293	-0.6359	0.7375	2.7197	0.0032	-0.6451	0.7405
2	-0.4067	0.6579	-0.7882	0.7847	2.5722	0.0050	-0.0017	0.5007
3	0.1807	0.4283	-0.7901	0.7852	2.3054	0.0105	0.4376	0.3308
4	0.8347	0.2019	-0.4433	0.6712	2.0876	0.0184	0.7372	0.2304
5	1.2411	0.1072	0.0174	0.4930	1.9425	0.0260	0.9766	0.1643
	Gold→China		**China→ Gold**		**Oil→China**		**China→Oil**	
M	**Q**	**p-value**	**Q**	**p-value**	**Q**	**p-value**	**Q**	**p-value**
1	-0.7071	0.7602	0.7578	0.2242	-0.6958	0.7567	1.7047	0.4412
2	-0.8408	0.7997	1.1321	0.1287	-0.0703	0.5280	2.9993	0.4353
3	-0.9715	0.8343	1.5169	0.0646	0.5333	0.2969	3.7829	0.5425
4	-1.0854	0.8611	2.1272	0.0166	0.9342	0.1750	4.2362	0.1458
5	-1.1820	0.8814	2.8711	0.0020	1.1642	0.1221	4.5898	0.1213
	Gold→Turkey		**Turkey→Gold**		**Oil→Turkey**		**Turkey→Oil**	
M	**Q**	**p-value**	**Q**	**p-value**	**Q**	**p-value**	**Q**	**p-value**
1	0.6834	0.2471	-0.7065	0.7600	-0.5805	0.7192	-0.6755	0.7503
2	0.7197	0.2358	-0.8359	0.7984	-0.6509	0.7424	0.9427	0.1729
3	0.6506	0.2576	-0.8293	0.7965	-0.4774	0.6834	2.1196	0.0170
4	0.5690	0.2846	-0.8008	0.7884	-0.2757	0.6086	2.7392	0.0030
5	0.4999	0.0855	-0.8128	0.7918	-0.1566	0.5622	3.0633	0.0010

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

Source: Own elaboration.

Important conclusions can also be drawn from a macro-economic perspective. Increasing volatility in bond markets can cause increases in global liquidity risk, as discussed in the Introduction. Therefore, the volatility spillovers from gold to the bond markets of Brazil, China, Russia, and Turkey and from oil to India's bond markets, as described in our findings, are potentially specific factors in global liquidity risk. Thus, our findings may be interpreted as evidence that the markets in question are open to supply-side shocks. Moreover, it is possible to observe a volatility spillover from the bond to commodity markets, which could lead to financial constraints in an economy. The volatility spillover from the bond markets of Turkey to oil, for example, suggests such an economic constraint. Furthermore, the existence of bidirectional relationships between the bond market of Russia and gold/oil indicates that Russia can face both supply-side shocks and such financial constraints. Thus, investigating the direction of spillover between these commodities and bond markets is important for policymakers, researchers, investors, and portfolio managers. Policy makers, in particular, should be aware of the volatility spillovers that could occur owing to economic uncertainties and financial instability. They must formulate policies to monitor oil price instability to help investors and portfolio managers investing in these financial assets.

3.3 Empirical Results for Crisis and Recovery Periods

We also divided the data into two periods, covering crisis and recovery periods in accordance with NBER recession dates (NBER, 2021). The crisis period covers the years between January 1, 2008 and June 1, 2009, and the recovery period spans from June 2, 2009 to January 6, 2022.

Table 9 DCC-GARCH Models for Gold and BRIC-T Bond Markets for Crises and Recovery Periods

	Crisis Period					Recovery Period				
	Gold-Brazil	**Gold-Russia**	**Gold-India**	**Gold-China**	**Gold-Turkey**	**Gold-Brazil**	**Gold-Russia**	**Gold-India**	**Gold-China**	**Gold-Turkey**
Panel A: DCC equation										
γ_{21}	-0.065	-0.039	0.152**	-0.101	0.064	-0.052 **	-0.080**	-0.016	-0.049	-0.087***
α	0.055	0.000	0.071	0.000	0.000	0.000	0.009	0.004	0.006	0.000
β	0.51***	0.047	0.399**	0.679	0.97***	0.827**	0.948***	0.620	0.981	0.807***
Panel B: Diagnostic tests										
Hosking(20)	85.225	72.691	58.002	92.411	84.406	97.164	102.158	77.116	66.957	58.714
Hosking(50)	198.125	198.861	222.652	182.681	209.225	211.695	220.396	201.143	167.486	195.589
Li-McLeod(20)	85.106	72.510	58.792	92.590	84.547	97.188	102.176	77.161	67.103	58.946
Li-McLeod(50)	198.345	196.206	215.673	187.157	210.229	211.787	220.401	201.106	167.602	195.868

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

Table 9 presents the estimation results of the DCC-GARCH models for gold and BRIC-T bond markets by reference to these crisis and recovery periods. According to the DCC equation in Panel A, there is volatility spillover between gold and the bond market of India in the crisis period, whereas there are volatility spillovers between gold and the bond markets of Brazil, Russia, and Turkey in the recovery period. On the other hand, any previous lagged squared shocks do not affect the current value of conditional volatility for all of them in the short term. The long-term persistence of shocks to the conditional correlations, as demonstrated by the coefficients of β, indicate that shocks in gold prices have a positive significant effect on the current conditional volatility of all bond markets, save for China and Russia, in the crisis period. Similarly, it appears to have a shock effect on the current conditional volatility of all bond markets, save for India and China, in the recovery period. The volatility spillovers between gold and these bond markets suggest that holding gold and Indian bonds in the same portfolios in the crisis period may not constitute a diversification benefit. This also applies to investors holding gold, Brazilian, Russian, and Turkish bonds in the recovery period.

Gold-bond yield pairs in the recovery period exhibit much more dynamic conditional correlations compared to gold-bond yield pairs in the crisis period. One of the possible explanations could be the increased role of gold after the 2008 crisis. After this crisis, which was both economic and political, although there was a flight from assets, there was also an increase in demand for gold. In this turbulent period, oil prices fell by 62%, while gold appreciated by 4%. In the recovery period, the effects of the global crisis gradually diminished, stock markets recovered, but gold continued to rise and reached its highest ever level in November 2009. This result may be attributable to the fact that the continuous decrease of the dollar during the 2008 crisis impacted demand of gold. The dollar depreciated by about 8% on average against other currencies in the crisis period.

Table 10 DCC-GARCH Models for Oil and BRIC-T Bond Markets for Crises and Recovery Periods

	Crisis Period					**Recovery Period**				
	Oil-Brazil	**Oil-Russia**	**Oil-India**	**Oil-China**	**Oil-Turkey**	**Oil-Brazil**	**Oil-Russia**	**Oil-India**	**Oil-China**	**Oil-Turkey**
Panel A: DCC equation										
γ_{21}	-0.039	-0.125**	0.100	-0.079	-0.006	-0.015	-0.173***	0.036*	0.037	-0.039
α	0.067	0.000***	0.000	0.101	0.077	0.027	0.016	0.000	0.000	0.000
β	0.804***	0.316	0.819***	0.353	0.863	0.744***	0.687***	0.852***	0.850	0.834
Panel B: Diagnostic tests										
Hosking(20)	20.071	83.181	79.923	44.004	95.475	63.784	105.634	98.550	99.188	90.152
Hosking(50)	38.519	193.620	207.093	251.494	210.027	175.226	212.786	211.976	216.030	200.825
Li-McLeod(20)	20.048	83.363	79.935	44.080	94.541	63.939	105.712	98.502	99.157	90.213
Li-McLeod(50)	38.539	195.702	206.077	249.762	209.929	175.508	213.107	212.081	216.071	201.047

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

Table 10 shows the estimation results of the DCC-GARCH models for oil and BRIC-T bond markets during the crisis and recovery periods. As for the DCC equation in Panel A, there is volatility spillover between oil and the bond market of Russia in the crisis period, whereas there are volatility spillovers between oil and the bond markets of Russia and India in the recovery period. In addition, previous lagged squared shocks affect the current value of conditional volatility of Russia in the crisis period in the short term. The long-term persistence of shocks to the conditional correlations, as demonstrated by the coefficients of β, indicate that shocks in oil prices have a positive significant effect on the current conditional volatility of Brazil and India in the crisis period. On the other hand, shock effects have a positive significant effect on the current conditional volatility of Brazil, India and Russia in the recovery period in the long term. That is, Russia has long term shock effects in both periods. These results show that the significant spillover volatility was between oil and Russia in both periods. This indicates that Russia, as one of the countries most involved in oil trading, is always affected in both crisis and recovery periods.

Table 11 Copula DCC-GARCH Models for Gold and BRIC-T Bond Markets for Crises and Recovery Periods

	Crises Period		**Recovery Period**	
	Copula DCC GARCH Model for gold-Brazil Bond Yields		Copula DCC GARCH Model for gold-Brazil Bond Yields	
	Estimate	**Pr(>|t|)**	**Estimate**	**Pr(>|t|)**
[Joint]dcca1	0.000	1.000	0.004	0.200
[Joint]dccb1	0.938	0.000	0.983	0.000
[Joint]mshape	10.849	0.132	9.876	0.000
	Copula DCC GARCH Model for gold-Russia Bond Yields		Copula DCC GARCH Model for gold-Russia Bond Yields	
	Estimate	**Pr(>|t|)**	**Estimate**	**Pr(>|t|)**
[Joint]dcca1	0.000	1.000	0.010	0.326
[Joint]dccb1	0.949	0.000	0.937	0.000
[Joint]mshape	38.475	0.352	8.267	0.000
	Copula DCC GARCH Model for gold-India Bond Yields		Copula DCC GARCH Model for gold-India Bond Yields	
	Estimate	**Pr(>|t|)**	**Estimate**	**Pr(>|t|)**
[Joint]dcca1	0.000	1.000	0.014	0.442
[Joint]dccb1	0.975	0.000	0.654	0.002
[Joint]mshape	49.999	0.126	15.531	0.001
	Copula DCC GARCH Model for gold-China Bond Yields		Copula DCC GARCH Model for gold-China Bond Yields	
	Estimate	**Pr(>|t|)**	**Estimate**	**Pr(>|t|)**
[Joint]dcca1	0.000	1.000	0.002	0.413
[Joint]dccb1	0.793	0.000	0.987	0.000
[Joint]mshape	10.523	0.070	8.699	0.000
	Copula DCC GARCH Model for gold-Turkey Bond Yields		Copula DCC GARCH Model for gold-Turkey Bond Yields	
	Estimate	**Pr(>|t|)**	**Estimate**	**Pr(>|t|)**
[Joint]dcca1	0.000	1.000	0.004	0.628
[Joint]dccb1	0.942	0.000	0.947	0.000
[Joint]mshape	0.010	0.654	9.112	0.000

Table 11 depicts the results of the Copula DCC-GARCH test for the relationship between gold and the bond markets in both crisis and recovery periods. According to the Copula DCC estimations in the crisis period, there were high dependence structures of current correlation between gold and all bond markets, whereas there were no shock dependences. Moreover, it can be seen that there was an asymmetry in the tails for only gold and China in accordance with the shape parameter. As far as the Copula DCC estimations in the recovery period are concerned, we found the same results as for the crisis period, save for the fact that there were asymmetries in the tails for gold and all bond markets.

Table 12 Copula DCC-GARCH Models for Oil and BRIC-T Bond Markets for Crises and Recovery Periods

	Crises Period		**Recovery Period**	
	Copula DCC GARCH Model for oil-Brazil Bond Yields		Copula DCC GARCH Model for oil-Brazil Bond Yields	
	Estimate	**Pr(>|t|)**	**Estimate**	**Pr(>|t|)**
[Joint]dcca1	0.056	0.081	0.032	0.012
[Joint]dccb1	0.760	0.000	0.704	0.000
[Joint]mshape	6.819	0.019	23.532	0.080
	Copula DCC GARCH Model for oil-Russia Bond Yields		Copula DCC GARCH Model for oil-Russia Bond Yields	
	Estimate	**Pr(>|t|)**	**Estimate**	**Pr(>|t|)**
[Joint]dcca1	0.002	0.954	0.004	0.024
[Joint]dccb1	0.981	0.000	0.992	0.000
[Joint]mshape	8.082	0.002	17.081	0.005
	Copula DCC GARCH Model for oil-India Bond Yields		Copula DCC GARCH Model for oil-India Bond Yields	
	Estimate	**Pr(>|t|)**	**Estimate**	**Pr(>|t|)**
[Joint]dcca1	0.035	0.437	0	1.000
[Joint]dccb1	0.278	0.109	0.975	0.000
[Joint]mshape	16.459	0.218	50	0.000
	Copula DCC GARCH Model for oil-China Bond Yields		Copula DCC GARCH Model for oil-China Bond Yields	
	Estimate	**Pr(>|t|)**	**Estimate**	**Pr(>|t|)**
[Joint]dcca1	0.024	0.601	0.001	0.882
[Joint]dccb1	0.611	0.000	0.976	0.000
[Joint]mshape	8.871	0.037	50	0.226
	Copula DCC GARCH Model for oil-Turkey Bond Yields		Copula DCC GARCH Model for oil-Turkey Bond Yields	
	Estimate	**Pr(>|t|)**	**Estimate**	**Pr(>|t|)**
[Joint]dcca1	0.097	0.000	0.007	0.622
[Joint]dccb1	0.833	0.000	0.783	0.071
[Joint]mshape	26.428	0.597	26.5	0.005

Table 12 shows the results of the Copula DCC-GARCH test for the relationship between oil and the bond markets in both crisis and recovery periods. According to the Copula DCC estimations in the crisis period, there were high dependence structures of current correlation between oil and all bond markets, save for India, whereas there were no shock dependences in these markets, except for Brazil and Turkey. Furthermore, there were asymmetries in the tails for all bond markets, save for India and Turkey. As for the Copula DCC estimation in the recovery period, we found high dependence structures of current correlation between oil and all bond markets. In addition, there were shock dependences between oil and the bond markets of Brazil and Russia. Moreover, there were asymmetries in the tails for all bond markets, save China. From a practical point of view, these results represent dependence structures of current correlation between oil/gold and the bond markets. This result is reasonable in light of the fact that gold and oil play a role in the estimation of bond yields thanks to their dependency structures and vice versa.

Overall, we find that gold and oil markets show spillovers with bond yields. These results mirror the studies of Dai and Kang (2021), Narayan, Thuraisamy, and Wagner (2017), Turhan et al., (2014), Ciner, Gurdgiev, and Lucey (2013), Nicolau (2011). Especially after the 2008 crisis, the Federal Reserve's monetary expansion policies and the rise of liquidity increased the demand for fixed assets, such as oil or gold. In addition, the increase in the interconnectedness of global markets, the heightened demand for safe assets, and the ease of capital flow between countries, significantly changed risk perception and correlations between asset classes. This situation is of great importance for investors, market participants, and policy makers.

4. Conclusion

The impacts of fluctuations in commodity prices on stock market returns have been extensively analyzed for both developed and emerging economies. However, there are still gaps that have to be filled in the related literature considering linkages between commodities and bond markets for emerging economies. This paper aims to fill this gap by investigating volatility spillovers between two major commodities, gold and oil, and the bond markets of major emerging economies covering the BRIC-T countries by implementing the DCC GARCH model for the period covering the 2007/2008 global financial crisis and its aftermath. Our volatility spillover results indicate negative relationships between the bond markets of Brazil, Russia, and Turkey and the gold market, as well as between the bond markets of Russia, China, and Turkey and the oil market. These results are consistent with the studies Oleg, 2011, Ciner, Gurdgiev, and Lucey 2013, Turhan et al., 2014, Dai and Kang 2021, and Narayan, Thuraisamy, and Wagner 2017. The increasing correlation between the conditional volatility of oil and bond markets indicates that investing in oil will not provide diversification benefits for investors or portfolio managers holding Chinese, Turkish, and Russian bonds in their portfolios. Similarly, investing in gold will not yield diversification advantages for investors holding Brazilian, Turkish, and Russian bonds. The results of the Copula DCC GARCH test, which displays high dependency between markets, indicates limited diversification benefits for investors and portfolio managers. Finally, the results of Hong’s Causality support the findings of the DCC-GARCH volatility spillover tests and signify the fact that a change in gold prices affects Brazilian, Chinese, and Russian bond market yields. The existence of unidirectional relationships (from oil to the bond markets of Brazil, China Russia, and from Russia and Turkey to oil) indicates that our results are inconsistent with the assumption that the interactions between oil and the bonds of oil exporters are stronger than those of oil importers. Therefore, our findings support those of Morrison (2019) and Nazlioglu, Gubta and Bouri (2020) with regard to the differences between oil-importing and oil-exporting countries. It is apparent from our results that among the BRIC-T countries, the Russian bond market was only affected by volatilities in both oil and gold prices negatively, and vice versa. Therefore, information on gold and oil can be used to predict the bond market of Russia.

As a result, we suggest that the bond markets of Brazil, China, Russia, and Turkey are vulnerable to supply-side shocks because of spillover volatility from gold. The bond market of India is likewise vulnerable to supply-side shocks because of spillover from oil. In these bond markets, increases in commodity prices increase global liquidity risks. Rising commodity prices lead to increases in inflation and interest rates. Increasing interest rates reduce the bond prices in these countries. That is why, our results indicate, the bond markets of Brazil, China, Russia, Turkey (impacted by spillovers from gold) and India (impacted by spillovers from oil) are more exposed to global liquidity risk. In addition, our findings on the volatility spillover from the bond market of Turkey to oil indicates financial constraints in this market. Furthermore, the existence of bidirectional relationships between the bond market of Russia and gold/oil indicates that Russia faces both supply-side shock and financial constraints. Increasing volatility in the bond market of Turkey and Russia are indications of a rise in borrowing costs and financial restrictions that may result in decreasing demand for and prices of these commodities.

Finally, our results show that when volatility increases in gold and oil prices, investors should consider their impacts on bond markets and vice versa. In this regard, both investors and portfolio managers can implement risk management techniques and change asset allocation strategies in their portfolios. In addition, our results can be used by market regulators to prevent bond markets from causing fluctuations in gold or oil prices by implementing regulations to reduce the negative impact of volatility spillovers among these markets. Furthermore, our results provide information for academic research on market efficiency. We can state that the bond markets of Turkey, Russia, and Brazil do appear to be efficient since there is evidence of volatility spillovers and causality relationships between the commodity markets for gold and oil and these countries' bond markets.

It is possible to extend the study in terms of data, data period, and the methodologies used. Further studies may incorporate commodities other than gold and oil. They may also employ different types of copula models, such as Gaussian, Clayton, Gumbel, and Frank.

Statement

This study was produced and extended from a doctoral dissertation.

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