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Energy, precious metals, and GCC stock markets: Is there any risk spillover?

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ABSTRACT

We analyze dynamic return and risk spillovers between commodity futures (energy & precious metals) and the Gulf Cooperation Council (GCC) stock markets. Utilizing dynamic equicorrelation (DECO) models and the spillover index of Diebold and Yilmaz (2012), we show the existence of significant return and risk spillovers between the commodities and the GCC stock markets, particularly during the onset of the 2008–2009 global financial crisis. In addition, silver, platinum, and energy futures markets are net transmitter of returns to stock markets. Precious metals (except silver) and WTI oil are net transmitter of risk to GCC markets. Abdu Dhabi and Dubai are net transmitter of returns and risk to other markets. Moreover, portfolio management analysis shows that the mix of commodities and GCC equities provides diversification opportunities for different crisis periods. Finally, precious metal markets offer superior hedging effectiveness over energy markets for all GCC markets.

1. Introduction

Time-varying correlations across markets and cross-market spillovers are of significant importance to market participants and researchers. The information transmission between financial markets affects asset allocation, hedging, and portfolio management. From a theoretical point of view, investors can diversify their risk and create an optimal portfolio using low correlated equities, and such diversification is invaluable in uncertain and volatile markets. However, such a task is not easy to perform in reality because these correlations vary over time. Worse, in turbulent financial market periods, the correlations between several equity markets intensify due to spillover effects (Longin and Solnik, 1995, 2001; Chiang et al., 2007; Antoniou et al., 2007; Markwat et al., 2009). This problematic structure is sustained for a considerable length of time, thus lowering the benefits of diversification even if a well-diversified equity portfolio is designed (Errunza et al., 1999; Ang and Bekaert, 2002; Capiello et al., 2006; Driessen and Laeven, 2007; You and Daigler, 2010).

Successive global financial downturns since the 1990's only worsened the aforementioned situation and pushed investors and portfolio managers to seek alternative ways to diversify their portfolios and reduce risk. Accordingly, commodities stepped in as eligible financial assets for portfolio diversification. When—for any reason—financial markets experience turbulent times or economic conditions display high uncertainty, many investors view investment commodities (particularly gold) as safe haven assets

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(Abanomey and Mathur, 2001; Baur and Lucey, 2010; Baur and McDermott, 2010; Georgiev, 2001; Gürgün and Ünalmiş, 2014; Hillier et al., 2006; Gorton and Rouwenhorst, 2006; Kat and Oomen, 2007; Chong and Miffre, 2010; Buyuksahin et al., 2010; Belousova and Dorfleitner, 2012).[1] Not surprisingly, commodities are viewed as safe haven assets because their values are considered more stable than those of stocks. They also present hedging opportunities with equity markets because, in theory, their price drivers are usually different from those of equities and are related to their own supply and demand structure in physical commodity markets.[2] Moreover, commodities are useful in protecting against unexpected inflation and other macro risks. Portfolios consisting heavily of equities and traditional bonds are sensitive to losses in value from inflation. In contrast, commodities are real assets, their values reflect prices in areas such as energy, industry, and agriculture, and they provide purchasing power protection against increasing prices.

As the demand for investing in commodities increased considerably in the last decade, so did the interest in commodity related funds both in the spot and derivatives markets, such as exchange-traded funds (ETF) and their derivatives.[3] Investments in these funds have increased dramatically and investment strategies throughout the world have completely changed.

Although commodities seem to present several benefits for investors, in the last decade, the aforementioned dynamics have partially changed in at least two ways. First, given the increasing demand from the emerging markets that are integrated into the global economy and tightened global commodity inventories, the dynamics of supply-demand conditions have abruptly changed, increasing the volatility in commodity prices. Second, given the “financialization” of commodities through commodity-based funds, the commodity markets have started to been driven by the factors non-related to supply and demand. As expectations have become the major price determinant, this financialization of commodities has led to even greater price volatility and intermittently greater informational connections with other risky assets (Tang and Xiong, 2012; Buyuksahin and Robe, 2013; Arezki et al., 2013).

The aforementioned reasoning motivate us to comprehensively analyze the time-varying relationship between commodity and equity markets. In particular, we focus on four precious metals and three energy commodities in the commodity class, and analyze the spillover effects between these commodities and the stock markets in the Gulf Cooperation Council (GCC) region.[4] A large body of literature examines such spillovers between commodity and stock markets, but mostly focuses on developed markets or emerging markets other than GCC members.[5]

During the past fifteen years, GCC economies have attracted increasing attention. These countries hold around 40% of the global oil reserves, with Saudi Arabia, Kuwait, and the UAE holding > 90% of the region's oil reserves. After the wake of the 2003 oil prices, these economies developed into the one of the major sources of global economic growth. Similarly, GCC states hold around 20% of the global natural gas reserves, with Qatar, UAE and Saudi Arabia accounting for > 90% of these reserves. All of these large energy reserves provide member countries with a most important source of comparative advantage and let them become major players in the world energy markets. Moreover, they also have turned into an important part of the global policy debates and imbalances. Because the GCC economies still depend on energy as their main export product and source of revenues, the risk spillovers between commodities and member stock markets has become much more important for GCC economies relative to other countries around the world.

This paper adds to the literature through five major points. First, it analyzes risk spillovers using one of the broadest asset sets in the literature that includes silver, gold, palladium, and platinum as precious metals; crude oil, gasoline, and heating oil as energy commodities; and the equity markets of Saudi Arabia, the UAE (Dubai and Abu Dhabi), Bahrain, Kuwait, Qatar, and Oman. Second, the sample runs from September 2005 through October 2016, which covers several episodes of critical instabilities (especially for energy markets) and downturns, including the global financial crisis (GFC) in 2008–2009 and the sovereign debt crisis in Europe (ESDC) during 2010–2012. Third, this study uses the Dynamic Conditional Correlation (DCC) and the Dynamic Equicorrelation (DECO)-Fractionally Integrated Asymmetric Power ARCH (FIAPARCH) models to assess the time-varying correlations for three blocks (precious metal-stock, energy-stock and precious metal-energy-stock). Compared to the common GARCH modelling, flexibility of the FIAPARCH model is much more extended since it can detect various empirical volatility characteristics, such as asymmetry, long memory, kurtosis, and leverage.[6] Fourth, this study investigates the directional and net return and risk spillovers across precious

[1] Lucey and Li (2015) show that alternative precious metals such as palladium, silver and platinum satisfy safe haven properties even when gold does not.

[2] For example, both precious and base metals have important and diversified use in jewelry, electronic, chemical, automotive, and manufacturing industries. Therefore, a structurally different supply and demand model is expected. Similarly, energy commodities are the number one inputs globally for physical production in almost any sector. Therefore, having different supply-demand structures for these commodities is not surprising.

[3] ETFs are investment funds that try to track a selected benchmark index. They allow investors to invest in an index through ETF shares rather than separately buying the equities included in the index. ETFs were first introduced in 1993, and now represent one of the fastest growing innovations in the financial markets.

[4] The GCC was established in the May of 1981 as a regional entity including six members: Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates (UAE). There were many factors that lead to such a formation including geographical proximity, shared customs, traditions and language, similar economic resources, environments, and political systems. The GCC aims to construct a wide-range integration among its members, with the ultimate goal of being a true union.

[5] To the best of our knowledge, the only study analyzing the risk spillovers between commodities and a GCC member market is that of Mensi et al. (2015). However, the authors consider only the Saudi market from the region, leaving the other five members open for analysis.

[6] Financial time series often display a characteristics called volatility clustering, defined as the large (small) magnitudes of returns being followed by again large (small) magnitudes of returns, therefore it is not realistic to assume that variance remains constant over time. Similarly, positive (optimistic) and negative (pessimistic) shocks to the system are expected to have non-equal impacts on volatility which led to asymmetric volatility

metals, energy commodity futures, and GCC stock markets using the Diebold-Yilmaz spillover index (Diebold and Yilmaz, 2012), a state of the art methodology. Furthermore, we perform a rolling window approach to investigate the dynamic characteristics of the spillover index to observe how the recent major financial crises might have affected the volatility spillover dynamics between the sample markets. The rolling window methodology lets us to analyze the risk spillovers over time without having to use certain cutoff dates to create sub-samples. Even when a major economic, financial or political event occurs in the system, it's full effect might take a long time to be realized. Also, subjectively selected sub-samples limit to capture the dynamics of possible structural breaks. In addition to all above, We further explore the net spillover index and identify the recipient or transmitter of return and volatility shocks between stock and commodity futures markets. Fifth, it provides investors with useful explanations for asset and risk management by determining optimal portfolio weighting plans, hedge ratios and hedging outcomes (effectiveness) for precious metals, energy products and GCC stock portfolios not only for the whole sample period but also pre- and after- Lehman Brothers Collapse and after the recent oil price crisis mid-2014.

The results show a significant dynamic correlation among the considered markets which amplified during the recent GFC in 2008–2009, indicating contagion effects in the sample period. Directed volatility spillover analyses show that, the precious metals have a limited impact on the GCC stock indexes, whereas the energy markets contribute much more to GCC stock markets compared to these metals. The return and risk spillovers among the stock markets are also found to be very high, indicating evidence of increasing integration among GCC countries. The net directed volatility spillover analysis reveals that gold and palladium (silver) were net return (volatility) recipients from the other markets. Energy are net transmitter of returns and receipts of risk (except WTI oil). Abu Dhabi and Dubai stock markets are net transmitter of returns and risk to the commodity futures and the other GCC markets. To contribute to the literature on asset management, we consider synthetic portfolios of commodity futures and GCC stock indices to minimize risk without reducing expected returns. Considering precious metal-stock market pairs, we show that on the average, investors should hold larger proportions of stocks than precious metal assets. Furthermore, stock market investors in the GCC should prefer precious metals over energy assets to hedge their positions during heavily turbulent periods.

The remainder of the paper is structured as the following: Section 2 presents the literature review. Section 3 explains the main methodologies. Section 4 includes the information on the sample data and provides preliminary results. Section 5 reports the empirical findings with a discussion and provide implications for policymakers and risk managers. Finally, Section 6 concludes.

2. Literature review

The literature that examines the risk spillovers between commodity and stock markets is scarce. Creti et al. (2013) test the volatility transmission of price returns between 25 commodities (non-ferrous and precious metals, energy, agriculture, food, livestock, etc.) and stocks using the DCC-GARCH model. The authors show that the correlations between commodity and equity markets were highly volatile at the onset of the 2007–2008 financial crisis. They also find that speculation effect takes place for oil, coffee, and cocoa, whereas the gold still display safe-haven characteristics. Using VARMA-AGARCH and DCC-AGARCH models, Sadorsky (2014) examines the volatility spillovers between emerging stock markets and various other commodities. The author finds a contagion effect between the considered markets and the concept that oil provides the least expensive hedge for emerging equity markets. Olson et al. (2014) show that low US stock market returns lead to dramatic increases in the energy price volatility and reveal the existence of only a slight response from US equity volatility to the shocks to energy prices. The authors also find that the energy index is generally a poor hedging instrument. Mensi et al. (2015) use the DCC-FIAPARCH modelling to explore the time-varying correlations between the Saudi stock market (Tadawul) and major commodities, such as gold, silver, oil, rice, wheat and corn. The authors find long memory characteristics and asymmetric structure in the conditional volatility. They also show that time-varying correlations between the Saudi equity market and sample commodities are insignificant, except for the Tadawul-silver pair. Accordingly, diversification opportunities arise with providing effective hedging, and reductions in the downside risk. Similarly, Öztek and Öcal (2017) use smooth and double smooth transition conditional correlation (STDCC) models to test financialization of commodity markets, especially after the recent financial crisis. Their results show that, during the post sample, portfolio diversification across stock market and commodity index provides superior gains than solely investing in the stock market. In addition, portfolio diversification provides superior improvements in times of calm periods than during highly volatile periods. Ntantamis and Zhou (2015) identify bullish and bearish market periods in commodity prices and share prices of Canadian companies that are mainly involved in mining and marketing the relevant commodities, and investigate the potential presence of linkages between them. The results show limited evidence that the bullish/bearish phases detected for the single stocks are similar to the same phases identified for the commodities.

Zhang (2017) examines the nexus of oil and various global stock markets using the Diebold-Yilmaz spillover index methodology (Diebold and Yilmaz, 2009). The authors reveal that oil shocks make limited contributions to the stock market. More recently, Mensi et al. (2017) combine the variational mode decomposition (VMD) and copula methods to investigate the short- and long-run dependence structures between oil and various north American and European equity markets during bearish and bullish periods. The

(*footnote continued*)
modelling. In contrast, conditional variance is not necessarily a linear function of lagged squared or absolute value of the residuals. Thus, APARCH (Asymmetric Power) models were introduced. Finally, another stylized fact of the financial time series is the long memory of conditional volatility. In order to deal with this problem, fractionally integrated models, such as FIGARCH were developed. To capture all these dynamics in volatility, FIAPARCH model was introduced by Tse (1998).

authors also analyze the asymmetric risk spillovers from oil to equity markets and vice versa. The results show that the investment horizon is a major factor that determines the dependence structure between the assets under consideration. Additionally, the risk spillovers are found to be asymmetric and higher in the long investment horizon compared to the short investment horizon. Kang et al. (2017) has analyzed the time-varying spllovers between oil, precious metal and agricultural futures markets (corn, gold, oil, rice, silver and wheat)using the spillover index of Diebold and Yilmaz and DECO-GARCH model. The authors show dynamic and positive equicorrelations between commodity futures markets. Moreover, a bidirectional return and volatility spillovers across commodity futures markets has been found. Gold and silver (corn, rice, wheat and oil) are net transmitters (receiver) of return and volatility shocks to other commodity futures markets. The hedging strategy analysis (between precious metal and both oil and agricultural commodities) depends on the market statues. Junttila et al. (2018) investigate the linkages between stock and both gold and oil futures markets. The results show negative correlation during financial meltdown periods and that oil and gold offers diversification benefits. Yoon et al. (2019) analyzed the return spillovers from seven stock markets (China, Hong Kong, Japan, Korea, Singapore, and U.S.) to 10-year US Treasury bond, currency (US dollar index), and commodity (WTI crude oil and gold futures) markets using Diebold and Yilmaz approach. The authors show evidence of that the US stock market is the most important contributor of return spillover shock. In addition, the spillover between financial and commodity markets is intensified during the GFC. Xu et al. (2019) examine the asymmetric risk spillovers between stock and oil markets in the case of China and US economies and find that bad volatility spillovers dominate good volatility spillovers, indicating evidence of asymmetry risk spillovers.

In this light, our study contributes to Zhang (2017), which also uses the spillover index of Diebold and Yilmaz (2012, 2014). In fact, we analyze the spillovers of different commodity markets (gold, silver, palladium, platinum, copper, crude oil, gasoline, and heating oil) and seven equity markets in the Gulf region. More importantly, we use the results drawn by the Diebold-Yilmaz spillover index to analyze the usefulness of these commodities in terms of hedging effectiveness.

3. Empirical method

3.1. The-multivariate DECO-FIAPARCH model

To estimate long memory and asymmetry in volatility, we consider a univariate AR(1)-FIAPARCH model as follows:

$$r_t = \mu + \varphi_1 r_{t-1}, \text{ with } \varepsilon_t = z_t\sqrt{h_t}, +\varepsilon_t \quad (1)$$

where $|\mu| \in [0, \infty), |\varphi_1| < 1$ and $z_t \sim ST(0, 1, \upsilon)$.[7] h_t is the variance-covariance matrix. The FIAPARCH (1,d,1) model of Tse (1998) can be expressed as:

$$h_t^{\delta/2} = \omega + (1 - \beta L - (1 - \phi L)(1 - L)^d)(|\varepsilon_t| - \lambda\varepsilon_t)^\delta + \beta h_{t-1}^{\delta/2}, \quad (2)$$

where $0 \le d \le 1$, $\omega, \delta > 0$, and $|\lambda| < 1$. $(1 - L)^d$ is the fractional differencing operator. The long memory parameter ($0 \le d \le 1$), indicates the long memory characteristics of volatility. δ δ is the power term of returns and λ > 0 λ > 0representstheasymmetryparameter,measures asymmetry in volatility, where negative shocks have greater impacts on volatility than positive shocks.

To estimate the conditional correlation, we specify t.the conditional variance-covariance matrix H_t as following:

$$H_t = D_t R_t D_t \text{Ht = Dt1/2RtDt1/2}, \quad (3)$$

where R_t denotes the $(n \times n)$ matrix of dynamic conditional correlation, and $D_t = diag(h_{11,\ t}{}^{1/2}, \cdots, h_{NN,\ t}{}^{1/2})$, $h_{ii,\ t}$ represents the conditional variances of each return series. The dynamic conditional correlation matrix R_t (Engle, 2002) decomposes to:

$$R_t = (diag\, Q_t)^{-1/2} Q_t (diag\, Q_t)^{-1/2} \text{Rt = Qt * − 1/2QtQt * − 1/2}, \quad (4)$$

$$Q_t = (1 - \lambda_1 - \lambda_2)\overline{Q} + \lambda_1 u_{t-1}u_{t-1}' + \lambda_2 Q_{t-1} \text{Qt = [qij, t] = 1 − a − bS + aut − 1ut − 1' + bQt − 1}, \quad (5)$$

where Q_t defines the covariance matrix of the standardized residuals $u_t = (u_{i,\ t}, \cdots, u_{k,\ t})$. $\overline{Q} = cov(u_t, u_t') = E(u_t, u_t')$ S = si,j = Eutut'is the $n \times n$ n × n unconditional covariance matrix of u_t, ut,while λ₁a and λ₂b are non-negative scalars, and $\lambda_1 + \lambda_2 < 1$. The basic formulation of DECO is derived from the consistent DCC (cDCC) of Aielli (2013) by the correlation-driving process:

$$Q_t = (1 - \lambda_1 - \lambda_2)\overline{Q} + \lambda_1 (Q_{t-1}^{*1/2} u_{t-1} u_{t-1}' Q_{t-1}^{*1/2}) + \lambda_2 Q_{t-1} \text{Qt = 1 − a − bS * + aQt − 1 * 1/2ut − 1ut − 1'Qt − 1 * 1/2 + bQt − 1}, \quad (6)$$

Engle and Kelly (2012) use the cDCC framework to calculate ρ_t by taking the off-diagonal elements of conditional correlation matrix Q_t .Qt The equicorrelation is specified as (see Mensi et al., 2017):

$$\rho_t^{DECO} \frac{1}{n(n-1)}(A_n' R_t^{cDCC} A_n - n) = \frac{2}{n(n-1)} \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \frac{q_{ij,t}}{\sqrt{q_{ii,t}, q_{jj,t}}} \text{ρtDECO = 1nn − 1Jn'RtcDCCJn} - n = \text{2nn − 1i = 1n − 1j = i + 1nqij, t, qii, tqjj, t}, \quad (7)$$

where $q_{ij,\ t} = \rho_t^{DECO} + a_{DECO}(u_{i,\ t-1}u_{j,\ t-1} - \rho_t^{DECO}) + b_{DECO}(q_{ij,\ t} - \rho_t^{DECO})$qij,t = ρtDECO + αDECOui,t-1uj,t-1-ρtDECO + βDECOqij,t-

[7] The degrees of freedom (ν) measures the degree of leptokurtosis in the return density (Fiorentini et al., 2003).

1-ρtDECO, which is the $(i,j)^{\text{th}}$ element of matrix Q_tQt from the cDCC model. The scalar equicorrelation is used to estimate the conditional correlation matrix:

$$R_t = (1 - \rho_t)I_n + \rho_t A_n \text{Rt} = 1 - \text{ρtIn} + \text{ρtJn} \tag{8}$$

where A_n Jnis the $n \times n$ matrix of ones, and I_nIn is the nn-dimensional identity matrix. This process allows us to estimate the comovement for multiple asset groups using a single correlation coefficient.

3.2. Spillover index framework

In this study, we apply the generalized VAR of Diebold and Yilmaz (2014) to explore the volatility spillover and compare it between different markets (GCC stock and commodity markets). Let us describe market volatilities, X_t by a covariance stationary N-variable VAR (p) process which is expressed as:

$$X_t = \sum_{i=1}^{P} \Psi_i X_{t-1} + \varepsilon_t \tag{9}$$

where X_t is an N × 1 vector of endogenous variables, Ψ_i are N × N autoregressive coefficient matrices, and $\varepsilon_t \sim (0, \Sigma)$ is a vector of error terms with an $i.\ i.\ d.$ process. The moving average representation of the VAR(p) process is given by:

$$X_t = \sum_{i=1}^{\infty} Z_i \varepsilon_{t-1}, \tag{10}$$

where the $N \times N$ matrices Z_i are recursively defined as $Z_i = \Sigma_{k=1}{}^{P} Z_{i-k}$, with Z_0 being the $N \times N$ identity matrix, and $Z_i = 0$ for $i < 0$. To measure the component of the spillover connectedness table across market volatilities, the H-step-ahead forecast error variance decomposition $\Theta_{ij}(H)$ can be written as follows:

$$\Theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' B_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma B_h' e_i)}, \tag{11}$$

where Σ denotes the covariance matrix of errors ε, σ_{jj} is the j^{th} diagonal component of the standard deviation, and e_i is an N × 1 vector, with one as the i^{th} element and zero otherwise. In the connectedness table, each entry of the variance decomposition matrix is normalized by dividing it by the row sum, in the following way:

$$\widetilde{\Theta}_{ij}(H) = \frac{\Theta_{ij}(H)}{\sum_{j=1}^{N} \Theta_{ij}(H)} \tag{12}$$

with $\sum_{j=1}^{N} \widetilde{\Theta}_{ij}(H) = 1$, and $\sum_{i,j=1}^{N} \widetilde{\Theta}_{ij}(H) = N$ by construction. From Eq. (11), we compute two directional connectedness, 'From others' and 'To others'. First, the directional connectedness transmitted from all markets to market i is estimated as:

$$C_{i \leftarrow *}(H) = \frac{\sum_{j=1, j \neq i}^{N} \widetilde{\Theta}_{ij}(H)}{\sum_{ij=1}^{N} \widetilde{\Theta}_{ij}(H)} \times 100 = \frac{\sum_{j=1, j \neq i}^{N} \widetilde{\Theta}_{ij}(H)}{N} \times 100, \tag{13}$$

In a similar fashion, the reverse direction of connectedness received from market i to all markets is computed as:

$$C_{* \leftarrow i}(H) = \frac{\sum_{j=1, j \neq i}^{N} \widetilde{\Theta}_{ji}(H)}{\sum_{ij=1}^{N} \Theta_{ij}(H)} \times 100 = \frac{\sum_{j=1, j \neq i}^{N} \widetilde{\Theta}_{ji}(H)}{N} \times 100, \tag{14}$$

Finally, total connectedness (system-wide connectedness) is computed as:

$$C(H) = \frac{\sum_{i,j=1, i \neq j}^{N} \widetilde{\Theta}_{ij}(H)}{\sum_{i,j=1}^{N} \widetilde{\Theta}_{ij}(H)} \times 100 = \frac{\sum_{i,j=1, i \neq j}^{N} \widetilde{\Theta}_{ij}(H)}{N} \times 100, \tag{15}$$

To build the network topology of connectedness between GCC stock and commodity markets, we follow Diebold and Yilmaz (2014) and interpret our pairwise connectedness table as the adjacency matrix of a weighted directed network. In the pairwise connectedness table, the row sum up the adjacency matrix (node in-degrees) of the directional connectedness 'From others', $C_{i \leftarrow *}(H)$ while the column sums the adjacency matrix (node out-degrees) of the directional connectedness 'To others', $C_{* \leftarrow i}(H)$. Together the 'From others' and 'To others' degrees are the set of edges in the network.

4. Data and preliminary analysis

4.1. Data

This paper considers daily price data for commodity futures and stock indexes. The commodity futures include three energy markets (WTI crude oil, gasoline, and heating oil); and four precious metals (gold, palladium, platinum, and silver). We consider the following GCC stock markets: both the Dubai Financial Market General Index (Dubai-DFM) and the Abu Dhabi General Index (Abu

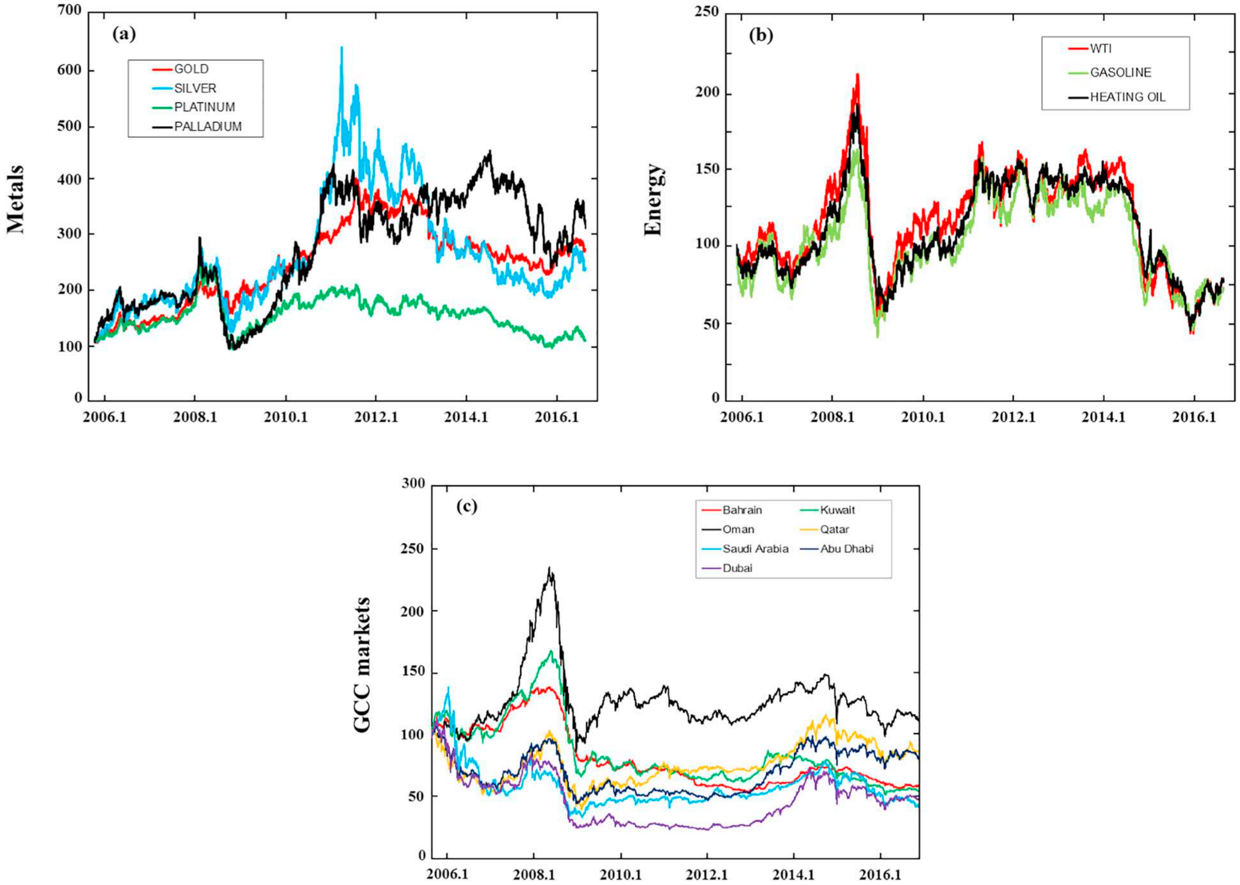

Fig. 1. Price dynamics of the precious metals (a), energy (b), and GCC markets (c).

Dhabi-ADX) for the UAE, the Tadawul All Share Index (TASI) for Saudi Arabia, the Kuwait Stock Exchange Index (KUW) for Kuwait, the Bahrain Stock Exchange (BSE) for Bahrain, the Qatar Doha Securities Market Index (QAT) for Qatar and the Muscat Securities Market Index (OMN) for Oman's MSM30 index. The study period runs from September 30, 2005 through October 24, 2016, which covers several turbulent periods and crises, including the energy price instabilities, 2008–2009 GFC and the 2010–2012 ESDC. The data for all series are extracted from Bloomberg.

Fig. 1 plots the daily evolution of energy, precious metals, and GCC stock indexes during the sample period. A close view to this figure indicates that all markets decreased between 2008 and2009, corresponding to the GFC period. Further, the energy markets exhibited a second important decline from mid-2014 to 2016, corresponding to recent oil price plunge of oil markets. The GCC stock market trajectories follow the behavior of oil prices in mid-2014 as they exhibit a decline. Generally, gold market experienced an increasing trend during the sample period. The seven GCC stock markets indicate close behavior. Fig. 2. displays the dynamic of return series and shows evidence of volatility clustering (or heteroscedasticity) and that is more pronounced in commodity futures markets. Market participants are thus interested to determine the degree of price volatility as this provide useful information for their decision-making process. This graphical evidence indicates the appropriateness of Generalized Autoregressive Conditional Heteroskedastic (GARCH) model to analyze the relationship between GCC stock and commodity futures markets.

4.2. Preliminary analysis

We calculate continuously compounded daily returns by taking the difference in the logarithmic differences of two consecutive prices. Table 1 provides descriptive statistics on daily returns and statistical test results, as well as unit root tests, unconditional correlation analysis, and ARCH-LM tests.

A closer look at this table shows positive average returns for the four precious metals as well as both Omani, and Dubai market return series, but the returns are negative for energy commodity futures and the rest of the GCC stock markets. Palladium presents the highest average future returns followed by gold, silver and platinum. Looking at the commodity futures, the unconditional volatility (standard deviation) is highest for the energy markets, followed by the silver, and palladium markets. GCC stock markets are less volatile than the commodity markets with the exception of gold. The skewness coefficients are negative except gasoline and WTI crude oil and the kurtosis coefficients are higher than three for all return series. These results indicate that the probability distribution of sample returns represents asymmetry and leptokurtic and rejects the normality distribution confirmed by Jarque-Bera statistics. According to the augmented Dickey and Fuller (ADF) and Phillips and Perron (PP) unit root statistics tests, and the stationarity test of the KPSS test results, all return series are stationary. Furthermore, the Ljung-Box Q(30) and $Q^2(30)$ tests for serial correlation of residuals and square residuals, respectively, as well as the ARCH effect in the return series by applying the ARCH LM(10) tests. The results highlight the presence of both serial correlation and the ARCH effect in all cases.

Table 2 shows that the unconditional correlations are negative or close to zero between gold and stock markets. This result indicates the role of gold as a safe haven asset. The correlation between the energy market and the GCC stock market is weak.

The choice of the appropriate GARCH model is crucial to portfolio management assessment. For this purpose, we investigate the

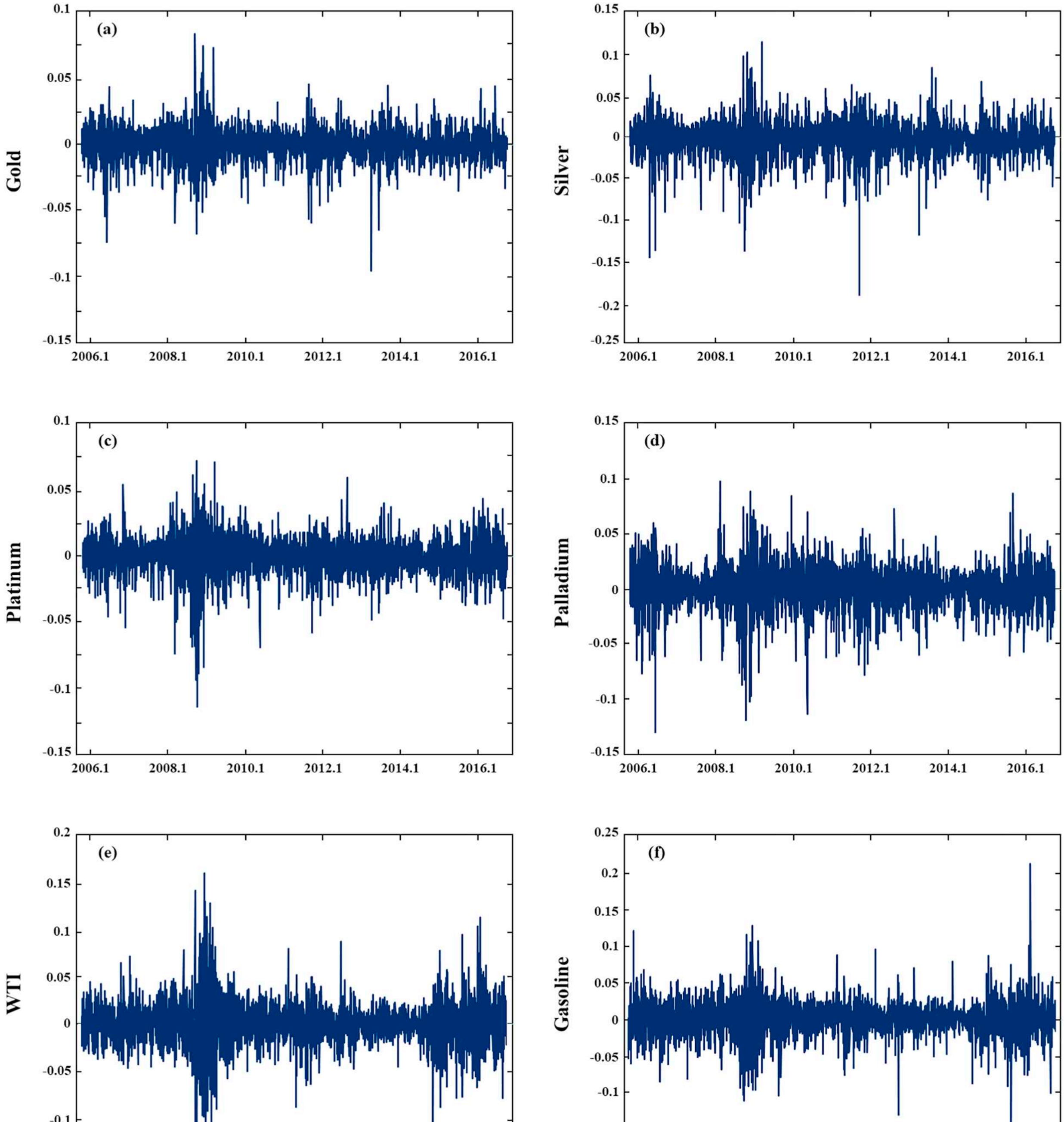

Fig. 2. Dynamics of sample returns.

one-day-ahead forecasting Value at Risk (VaR) performance of various GARCH models, such as the FIAPARCH model for two other competing GARCH models (FIGARCH and FIEGARCH) in this study. Tables 3 and 4 show the back testing results of the GARCH type model and calculate the failure rate and the Kupiec LR test for short and long positions, respectively. With few exceptions, the FIAPARCH model outperforms the volatility forecasts for long and short trading positions in the GCC market compared to the rest of the model.

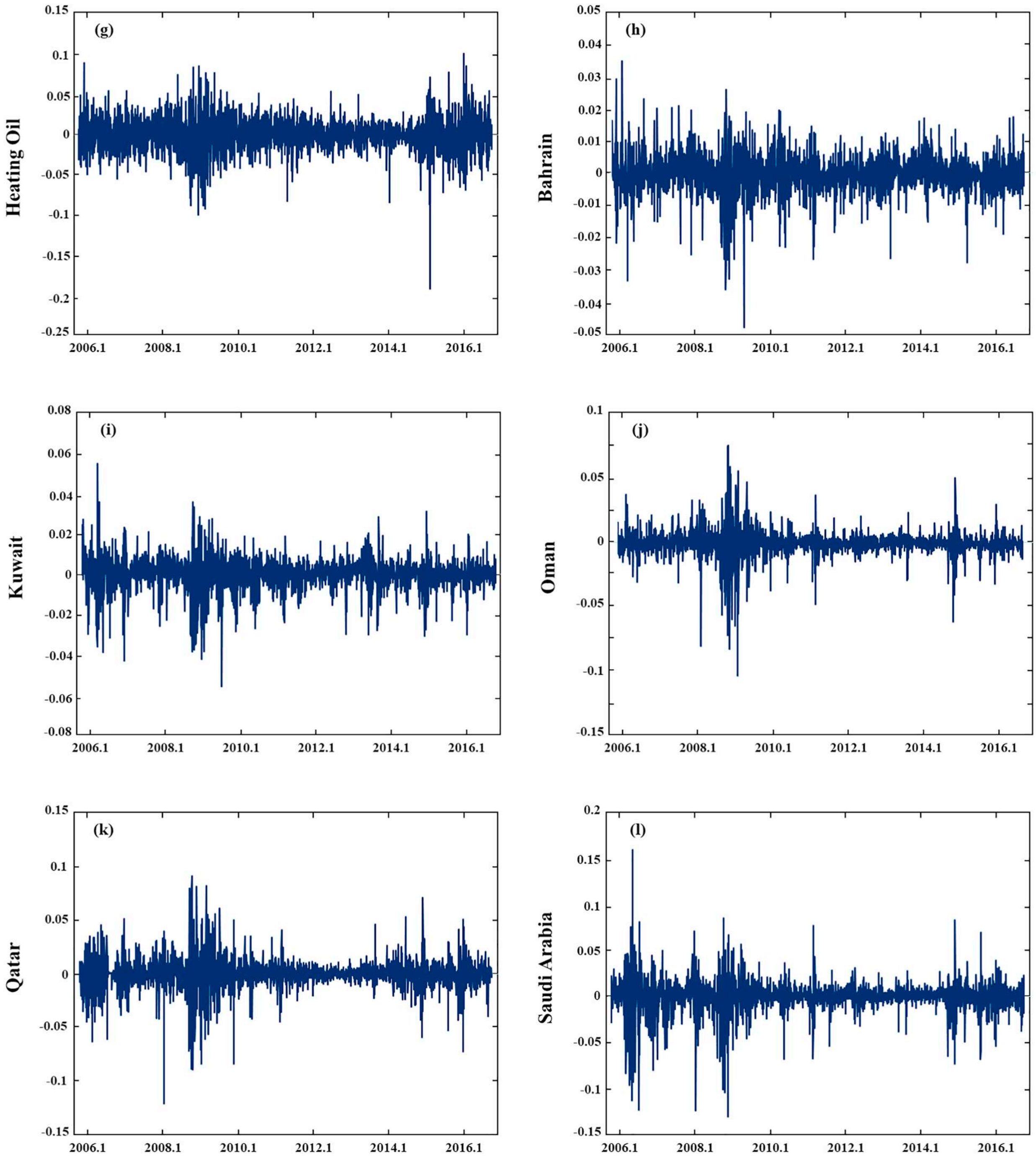

Fig. 2. (*continued*)

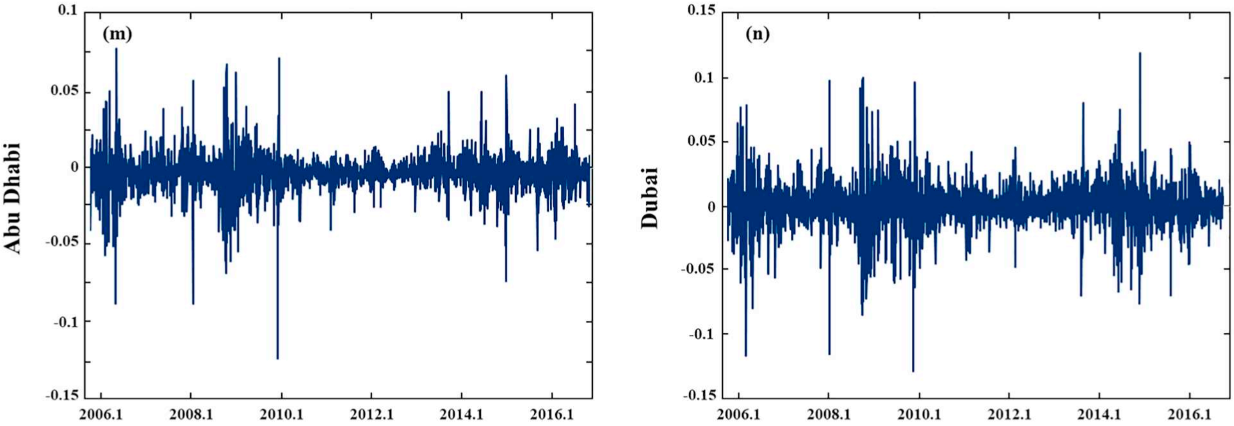

Fig. 2. (*continued*)

5. Empirical results

5.1. Estimates of DECO-FIAPARCH model

In Table 5, we report estimated results of the DECO-FIAPARCH (1,d,1) model between seven commodity futures and seven GCC stock markets.[8] Regarding the mean equation, the autoregressive parameter is statistically significant at the 1% level for all markets (except for gold, silver, gasoline and heating oil). This result shows that the one-period lagged future returns explains the current future returns for the considered markets. Regarding the variance equation, the long memory coefficient (*d*) is statistically significant at 1% level for all markets considered, revealing the presence of long memory behavior in these markets and the appropriateness of fractionally integrated GARCH model. Among all markets, a highest (lowest) parameter is addressed for the Omani (Bahraini) market followed by the Qatari market.

A closer inspection at the estimates of the DECO process (Panel B Table 5) reveals that the a_{DECO} coefficient is positive and statistically significant at the conventional level, underlying the role of shocks between the commodity and the GCC stock markets. Likewise, we can see that volatility throughout the stock and commodity markets continues to increase because the b_{DECO} parameter is also statistically significant and very close to one. The importance of these two parameters will again confirm the choice of our marginal model. More importantly, the dynamic equicorrleations correlations are statistically significant, positive and weak (0.198), implying a sign of potential diversification benefits between stock-commodity portfolios.

The diagnostic tests reported in Panel C support the appropriateness of our model. More precisely, the Ljung-Box test statistics for the squared standardized residuals do reject the null hypothesis of no serial correlation for all markets.

The results of DECO model provides the average correlations along the sample period but cannot show its evolution over the sample period. Thus to have a closer look, we plot the dynamic equicorrelations for the group of energy and precious metal commodity and stock markets. The graphical evidence is reported in Fig. 3 and is consistent with the results in Table 5. Fig. 3 displays a positive and weak time-varying correlation along the sample period. We split the evolution of conditional correlations into three sub-peirods as shown in the chart. A significant increase in correlation is observed before the 2008 GFC (*Sub-period I*) followed by a downside trend (*Sub-period II*) during the two recent crises (GFC and ESDC). The decrease in correlation in 2008 is the result of a historical increase in oil prices during that period, indicating a decoupling effect. We note that the GCC economies are oil-based economies. Between 2013 and 2014, the correlation between commodity and GCC stock markets decreased, supporting a decoupling hypothesis. In the Sub-period III, we how that the conditional correlations ranges between 0.14 and 0.24. We note that along the sample period, the correlations did not exceed 0.35. Thus, the increase/decrease phases in time-varying correlations during the sample period indicate that investors frequently change their portfolio structures.

5.2. Returns and volatility spillover analysis

In this subsection, we explore the directional of both return and volatility spillovers (net receiver and net transmitter of stocks) between stock and commodity markets. The entire return and volatility spillover indexes are divided into the recipient of volatility spillovers ("From others") and the transmitter of volatility spillovers ("To others"). Tables 6-8 and 9-11 present the estimates of the total return and volatility spillover matrices between stock - precious metal pairs, stock-energy pairs and stock-precious metal-energy pairs, respectively.

We show that the total return spillovers between GCC and precious metals is 50.6% and between GCC and energy is 49% and

[8] We have also carried the estimations for spot prices and the results are closely similar for the futures prices. We did not report them in the manuscript but they are available upon request.

Table 1
Descriptive statistics of the daily precious metal, energy, and GCC stock returns.

	Mean(%)	Max.	Min.	Std. dev.	Skewness	Kurtosis	Jarque-Bera	Q(30)	$Q^2(30)$	ADF	PP	KPSS	ARCH-LM(10)
Gold	0.03649	0.0862	−0.0982	0.0128	−0.2962	8.2082	3104.***	63.19***	581.4***	−29.94***	−52.19***	0.3825	16.98***
Silver	0.031402	0.1219	−0.1954	0.0227	−0.8066	9.1393	4553.***	39.95	478.7***	−30.05***	−55.86***	0.2386	14.81***
Palladium	0.04238	0.1001	−0.1338	0.0208	−0.4653	6.4237	1422.***	56.42**	691.0***	−30.00***	−49.06***	0.1533	18.76***
Platinum	0.000002	0.0745	−0.1166	0.0153	−0.6091	7.4899	2445.***	92.59***	1992.***	−29.58***	−48.30***	0.2553	51.23***
WTI	−0.00009	0.1641	−0.1306	0.0245	0.1507	7.4416	2239.***	62.25***	3603.***	−30.63***	54.92***	0.1074	63.05***
Gasoline	−0.01297	0.2165	−0.1616	0.0250	−0.0502	8.1416	2988.***	48.15**	716.0***	−31.15***	−52.96***	0.0783	17.92***
Heating Oil	−0.00001	0.1038	−0.1972	0.0210	−0.3177	7.8622	2717.***	38.66	635.0***	−31.04***	−55.76***	0.1202	18.99***
Bahrain	−0.02186	0.0361	−0.0492	0.0058	−0.6305	9.7888	5534.***	134.9***	557.6***	−28.65***	−48.01***	0.3195	18.73***
Kuwait	−0.02469	0.0562	−0.0578	0.0079	−0.8713	9.2724	4919.***	283.5***	1733.***	−25.53***	−49.02***	0.2094	51.52***
Oman	0.00031	0.0803	−0.1085	0.0105	−1.2631	22.381	44,344.***	304.6***	3395.***	−27.19***	−41.83***	0.1533	98.59***
Qatar	−0.00066	0.0942	−0.1247	0.0145	−0.5663	12.6562	10,973.***	145.3***	2129.***	−28.28***	−45.43***	0.1786	51.41***
Saudi Arabia	−0.03417	0.1643	−0.1347	0.0168	−1.1401	17.482	24,951.***	111.0***	1633.***	−28.26***	−49.31***	0.1659	45.94***
Abu Dhabi	−0.00087	0.0829	−0.0870	0.0121	−0.3092	11.8632	9163.***	98.70***	1299.***	−28.85***	−46.38***	0.3836	50.02***
Dubai	0.03015	0.1220	−0.1216	0.0183	−0.2248	9.2394	4542.***	75.03***	1786. ***	−29.06***	−51.43***	0.5886	64.46***

Notes: *** denotes rejection of the null hypotheses of normality, no autocorrelation, unit root, stationarity, and conditional homoscedasticity at the 1% significance level.

Table 2
Correlations of sample returns among the precious metal, energy, and GCC stock markets.

	Gold	Silver	Palladium	Platinum	WTI	Gasoline	Heating Oil	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	Abu Dhabi	Dubai
Gold	1.0000													
Silver	0.8125	1.0000												
Palladium	0.5093	0.5877	1.0000	0.7048										
Platinum	0.6613	0.6718	0.7048	1.0000										
WTI	0.2623	0.3291	0.3355	0.3233	1.0000									
Gasoline	0.2026	0.2693	0.2989	0.2761	0.7109	1.0000								
Heating Oil	0.2419	0.3089	0.3216	0.3103	0.7893	0.7496	1.0000							
Bahrain	−0.0019	0.0467	0.0491	0.0586	−0.0091	−0.0036	0.0279	1.0000						
Kuwait	−0.0001	0.0569	0.0921	0.1037	0.0696	0.0595	0.0853	0.3367	1.0000					
Oman	0.0069	0.0939	0.1264	0.1348	0.0810	0.0941	0.1194	0.2591	0.3041	1.0000				
Qatar	0.0137	0.0980	0.1092	0.1307	0.1110	0.1010	0.1257	0.2362	0.3494	0.4684	1.0000			
Saudi Arabia	−0.0781	0.0029	0.1076	0.0551	0.0997	0.0742	0.0916	0.1492	0.3101	0.3043	0.3394	1.0000		
Abu Dhabi	−0.0366	0.0559	0.1124	0.1134	0.1030	0.1001	0.1139	0.2394	0.3438	0.4177	0.4964	0.3874	1.0000	
Dubai	−0.0135	0.0744	0.1256	0.1264	0.1058	0.0807	0.1071	0.2390	0.3531	0.4213	0.4730	0.4093	0.7183	1.0000

Table 3
GCC in-sample VaR analysis (short trading positions case).

	Bahrain		Kuwait		Oman		Qatar
Quantile	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT	Failure rate
FIGARCH							
0.9500	0.9465	0.6958[0.404]	0.9623	9.6820[0.001]	0.9540	0.9906[0.319]	0.9569
0.9750	0.9755	0.0404[0.840]	0.9845	12.084[0.000]	0.9777	0.8943[0.344]	0.9748
0.9900	0.9935	4.0297[0.044]	0.9964	15.343[0.000]	0.9935	4.0297[0.044]	0.9878
0.9950	0.9967	2.0060[0.156]	0.9985	9.9135[0.001]	0.9982	7.6427[0.005]	0.9921
0.9975	0.9996	8.0610[0.004]	0.9996	8.0610[0.004]	0.9996	8.0610[0.004]	0.9931
FIEGARCH							
0.9500	0.9537	0.8211[0.240]	0.9691	24.714[0.000]	0.9576	3.6079[0.057]	0.9648
0.9750	0.9870	20.198[0.000]	0.9917	43.129[0.000]	0.9885	26.044[0.000]	0.9781
0.9900	0.9967	17.509[0.000]	0.9992	41.426[0.000]	0.9978	25.468[0.000]	0.9870
0.9950	1.0000	.NaN [0.000]	1.0000	.NaN [0.000]	0.9992	16.148[0.000]	0.9910
0.9975	1.0000	.NaN [0.000]	1.0000	.NaN [0.000]	1.0000	.NaN [0.000]	0.9939
FIAPARCH							
0.9500	0.9450	1.3763[0.240]	0.9587	4.7319[0.029]	0.9547	1.3790[0.240]	0.9497
0.9750	0.9748	0.0018[0.966]	0.9852	14.148[0.000]	0.9763	0.1996[0.655]	0.9727
0.9900	0.9924	1.8649[0.172]	0.9964	15.343[0.000]	0.9931	3.2038[0.073]	0.9906
0.9950	0.9987	0.2820[0.595]	0.9992	16.148[0.000]	0.9982	7.6427[0.005]	0.9960
0.9975	0.9996	8.0610[0.004]	0.9996	8.0610[0.004]	0.9996	8.0610[0.004]	0.9992

	Qatar	Saudi Arabia		Abu Dhabi		Dubai	
Quantile	Kupiec LRT	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT
FIGARCH							
0.9500	2.9472[0.086]	0.9569	2.9472 [0.086]	0.9483	0.1651[0.684]	0.9501	0.0006[0.979]
0.9750	0.0018[0.966]	0.9831	8.5148 [0.003]	0.9752	0.1047[0.746]	0.9766	0.3255[0.568]
0.9900	1.2771[0.258]	0.9953	9.9816 [0.001]	0.9924	1.3419[0.246]	0.9931	3.2038[0.073]
0.9950	3.9914[0.045]	0.9996	20.652 [0.000]	0.9956	0.2820[0.595]	0.9982	7.6427[0.005]
0.9975	14.117[0.000]	1.0000	.NaN [0.000]	0.9989	2.8819[0.089]	0.9996	8.0610[0.004]
FIEGARCH							
0.9500	14.315[0.000]	0.9598	6.0193[0.014]	0.9508	0.0401[0.841]	0.9465	0.6958[0.404]
0.9750	1.1492[0.283]	0.9849	13.092[0.000]	0.9755	0.0404[0.840]	0.9727	0.5769[0.447]
0.9900	2.1996[0.138]	0.9971	19.899[0.000]	0.9906	0.1282[0.720]	0.9928	2.4840[0.115]
0.9950	7.1458[0.007]	1.0000	.NaN [0.000]	0.9949	0.0003[0.985]	0.9967	2.0060[0.156]
0.9975	10.305[0.001]	1.0000	.NaN [0.000]	0.9989	2.8819[0.089]	0.9996	8.0610[0.004]
FIAPARCH							
0.9500	0.0036[0.951]	0.9515	0.1411[0.707]	0.9458	1.0081[0.315]	0.9450	1.3763[0.240]
0.9750	0.5769[0.447]	0.9806	3.9041[0.048]	0.9738	0.1627[0.686]	0.9752	0.0062[0.937]
0.9900	0.1282[0.720]	0.9939	4.9674[0.025]	0.9903	0.0270[0.869]	0.9913	0.5667[0.451]
0.9950	0.6678[0.413]	0.9978	5.7752[0.016]	0.9942	0.2949[0.587]	0.9978	5.7752[0.016]
0.9975	4.9479[0.026]	0.9992	4.9479[0.026]	0.9985	1.4963[0.221]	0.9996	8.0610[0.004]

Notes: This table reports the failure rates and the Kupiec LRT statistics for the in-sample VaR. NaN represents statistics that are not available. The numbers in brackets represent p-values.

Table 4
GCC in-sample VaR analysis (long trading positions case).

	Bahrain		Kuwait		Oman		Qatar
Quantile	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT	Failure rate
FIGARCH							
0.0500	0.0545	1.1852[0.276]	0.0674	16.231[0.000]	0.0577	3.3958[0.065]	0.0488
0.0250	0.0254	0.0266[0.870]	0.0384	17.696[0.000]	0.0312	4.1131[0.042]	0.0308
0.0100	0.0111	0.3448[0.557]	0.0157	8.0304[0.004]	0.0139	4.0019[0.045]	0.0218
0.0050	0.0064	1.0937[0.295]	0.0075	3.1181[0.077]	0.0061	0.6351[0.425]	0.0161
0.0025	0.0028	0.1470[0.701]	0.0039	1.9898[0.158]	0.0035	1.1671[0.280]	0.0125
FIEGARCH							
0.0500	0.0477	0.3043[0.581]	0.0513	0.1025[0.748]	0.0502	0.0036[0.951]	0.0463
0.0250	0.0186	5.0216[0.025]	0.0183	5.6387[0.017]	0.0208	2.1173[0.145]	0.0276
0.0100	0.0039	13.378[0.000]	0.0039	13.378[0.000]	0.0061	4.9674[0.025]	0.0193
0.0050	0.0010	12.690[0.000]	0.0010	12.690[0.000]	0.0032	2.0060[0.156]	0.0150
0.0025	0.0000	.NaN [0.000]	0.0000	.NaN [0.000]	0.0017	0.6167[0.432]	0.0114
FIAPARCH							
0.0500	0.0567	2.5374[0.111]	0.0642	10.969[0.000]	0.0559	2.0321[0.154]	0.0588
0.0250	0.0283	1.2347[0.266]	0.0326	6.1308[0.013]	0.0297	2.4751[0.115]	0.0301
0.0100	0.0114	0.5930[0.441]	0.0129	2.1996[0.138]	0.0111	0.3448[0.557]	0.0136
0.0050	0.0061	0.6351[0.425]	0.0064	1.0937[0.295]	0.0053	0.0805[0.776]	0.0068
0.0025	0.0028	0.1470[0.701]	0.0032	0.5453[0.460]	0.0032	0.5453[0.460]	0.0035

	Qatar	Saudi Arabia		Abu Dhabi		Dubai	
Quantile	Kupiec LRT	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT
FIGARCH							
0.0500	0.0829[0.773]	0.0764	35.578[0.000]	0.0567	2.5374[0.111]	0.0556	1.7998[0.179]
0.0250	3.6673[0.055]	0.0470	44.205[0.000]	0.0287	1.5065[0.219]	0.0287	1.5065[0.219]
0.0100	29.729[0.000]	0.0190	18.118[0.000]	0.0129	2.1996[0.138]	0.0107	0.1619[0.687]
0.0050	43.745[0.000]	0.0100	11.028[0.000]	0.0064	1.0937[0.295]	0.0071	2.3408[0.126]
0.0025	57.225[0.000]	0.0050	5.4963[0.019]	0.0039	1.9898[0.158]	0.0032	0.5453[0.460]
FIEGARCH							
0.0500	0.8211[0.364]	0.0667	14.980[0.000]	0.0509	0.0547[0.814]	0.0531	0.5610[0.453]
0.0250	0.7696[0.380]	0.0290	1.8041[0.179]	0.0240	0.1047[0.746]	0.0254	0.0266[0.870]
0.0100	19.442[0.000]	0.0082	0.9104[0.339]	0.0089	0.3071[0.579]	0.0104	0.0464[0.829]
0.0050	36.850[0.000]	0.0028	2.9990[0.083]	0.0053	0.0805[0.776]	0.0064	1.0937[0.295]
0.0025	47.746[0.000]	0.0007	4.9479[0.026]	0.0032	0.5453[0.460]	0.0035	1.1671[0.280]
FIAPARCH							
0.0500	4.3728[0.036]	0.0667	14.980[0.000]	0.0559	2.0321 [0.154]	0.0513	0.1025[0.748]
0.0250	2.8481[0.091]	0.0308	3.6673[0.055]	0.0279	0.9889 [0.319]	0.0254	0.0266[0.870]
0.0100	3.3473[0.067]	0.0107	0.1619[0.687]	0.0122	1.2771 [0.258]	0.0118	0.9044[0.341]
0.0050	1.6643[0.197]	0.0035	1.2364[0.266]	0.0050	0.0003 [0.985]	0.0068	1.6643[0.197]
0.0025	1.1671[0.280]	0.0007	4.9479[0.026]	0.0028	0.1470 [0.701]	0.0032	0.5453[0.460]

Notes: See notes for Table 3.

Table 5
Estimation of multivariate AR(1)-FIAPARCH(1,d,1)-DECO model.

	Gold	Silver	Palladium	Platinum	WTI	Gasoline	Heating Oil	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	Abu Dhabi	Dubai
Panel A: Estimates of AR(1)-FIAPARCH model														
Const.(μ)	0. 339 (0. 224)	0. 434 (0. 382)	454 (360)	031 (0. 268)	0.008 (337)	−0. 135 (0. 406)	−0. 137 (0. 330)	−0.193** (0.094)	0.026 (0.016)	−0.030 (0.020)	0.321 (0.188)	0.398** (0.288)	0.148 (0.172)	0.046 (0.268)
AR(1)	−0.005 (0.020)	−0.011 (0.023)	0.061*** (0.021)	0.071*** (0.021)	−0.035* (0.021)	−0.003 (0.024)	−0. 011 (0.021)	0.075*** (0.015)	0.146*** (0.025)	0.311*** (0.023)	0.130*** (0.036)	0.107*** (0.031)	0.154*** (0.024)	0.039* (0.021)
Const.(ω)	0.453 (0.404)	0. 628*** (0. 510)	0.192*** (0.256)	0.231*** (0.184)	0.288* (0.148)	0.101*** (0.025)	0.261 (0.178)	0.897*** (0.025)	0.429*** (0.025)	0.182* (0.105)	0.142*** (0.210)	0.720 (0.630)	0.247 (0.160)	0.264 (0.174)
d-Figarch	0.366*** (0.073)	0.380*** (0.078)	0.403*** (0.087)	0.413*** (0.067)	0.435*** (0.058)	0.359*** (0.086)	0.424*** (0.058)	0.254*** (0.045)	0.406*** (0.061)	0.625*** (0.126)	0.545*** (0.088)	0.351*** (0.056)	0.479*** (0.074)	0.423*** (0.052)
Arch	0.326*** (0.097)	0.550*** (0.090)	0.333** (0.095)	0.412*** (0.070)	0.317*** (0.064)	0.317*** (0.025)	0.283*** (0.089)	0.407*** (0.083)	0.251*** (0.072)	0.169*** (0.119)	0.377*** (0.088)	0.022 (0.141)	0.169 (0.112)	0.012 (0.159)
Garch	0.631*** (0.106)	0.770*** (0.056)	0.633*** (0.143)	0.703*** (0.076)	0.653*** (0.079)	0.561** (0.285)	0.618*** (0.097)	0.345*** (0.088)	0.512*** (0.096)	0.555*** (0.161)	0.685*** (0.103)	0.312* (0.162)	0.452*** (0.157)	0.247*** (0.018)
APARCH	0.039 (0.144)	0.024 (0.108)	0.148 (0.129)	−0.007 (0.069)	0.460*** (0.174)	0.183 (0.183)	0.168 (0.121)	0.119 (0.104)	0.429*** (0.092)	0.216*** (0.059)	0.234*** (0.096)	0.840*** (0.226)	0.267*** (0.065)	0.190*** (0.060)
APARCH	1.840*** (0.154)	1.948*** (0.145)	1.739*** (0.262)	1.975*** (0.121)	1.607*** (0.147)	1.466*** (0.108)	1.707*** (0.151)	1.087*** (0.044)	1.349*** (0.060)	1.813*** (0.220)	1.752*** (0.228)	1.307*** (0.166)	1.623*** (0.142)	1.704*** (0.127)
Panel B: Estimates of DCC model														
CORij	0.1982*** (0.0466)													
a_{DECO}	0.0122*** (0.0185)													
b_{DECO}	0.9846*** (0.0300)													
df	6.8534*** (0.1991)													
Panel C: Diagnostic Tests														
Q(30)	34.95 [0.244]	30.61 [0.434]	31.45 [0.393]	46.17 [0.029]	12.97 [0.997]	33.58 [0.297]	30.33 [0.448]	34.40 [0.264]	30.70 [0.430]	31.65 [0.383]	29.01 [0.516]	54.20 [0.004]	44.08 [0.046]	55.65 [0.002]
Q^2(30)	24.58 [0.744]	22.51 [0.834]	23.23 [0.805]	31.49 [0.391]	24.17 [0.764]	25.47 [0.701]	34.57 [0.258]	15.48 [0.986]	18.14 [0.890]	9.774 [0.999]	10.81 [0.999]	32.13 [0.361]	18.75 [0.944]	23.25 [0.804]

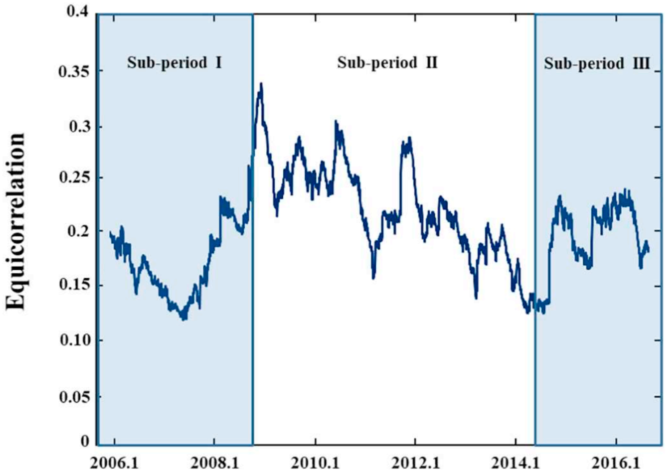

Fig. 3. Dynamic equicorrelation between precious metals, energy, and GCC stock returns.

Table 6
Total return spillovers between GCC stock markets and precious metals.

	Gold	Silver	Palladium	Platinum	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	Abu Dhabi	Dubai	From others
Gold	42.06	27.84	11.09	18.63	0	0	0.01	0.03	0.28	0.04	0.02	57.9
Silver	26.47	40.02	13.91	18.18	0.1	0.14	0.37	0.44	0.01	0.15	0.23	60
Palladium	12.03	15.9	45.84	22.76	0.12	0.37	0.7	0.51	0.46	0.56	0.75	54.2
Platinum	17.86	18.35	20.09	40.54	0.15	0.42	0.69	0.66	0.09	0.54	0.61	59.5
Bahrain	0.01	0.28	0.27	0.37	69.85	8.43	4.53	3.93	3.13	4	5.19	30.1
Kuwait	0.02	0.3	0.6	0.8	5.5	59.07	4.56	6.58	7.1	7.2	8.27	40.9
Oman	0.17	1.08	1.62	1.69	2.8	4.89	51.53	10.65	5.91	9.57	10.09	48.5
Qatar	0.11	0.86	1.08	1.17	2.27	5.92	9.71	48.81	6.56	11.7	11.8	51.2
Saudi Arabia	0.52	0.26	1.2	0.62	1.18	5.44	5.14	6.59	59.83	9.07	10.15	40.2
Abu Dhabi	0.06	0.34	0.76	0.78	1.99	4.65	7.04	9.88	7.13	43.11	24.26	56.9
Dubai	0.1	0.51	0.92	0.81	2.28	5.23	7.27	9.4	7.49	22.99	43.01	57
To others	57.4	65.7	51.5	65.8	16.4	35.5	40	48.7	38.2	65.8	71.4	556.3
All	99.4	105.7	97.4	106.4	86.2	94.6	91.5	97.5	98	108.9	114.4	50.60%
Net	−0.5	5.7	−2.7	6.3	−13.7	−5.4	−8.5	−2.5	−2	8.9	14.4	

Notes: Figures are in %.

between GCC, precious metal and energy pairs is 54.7%. Regarding the total return spillovers between GCC stock markets and precious metals, we show all GCC (except Abu Dhabi and Dubai) are net receiver of return shocks from precious metal markets. Platinum and palladium play significant role in terms of return transmission to Gulf markets compared to gold. In line with the empirical theory (Baur and Lucey, 2010), gold is the most appropriate hedging tool for stock markets. Platinum is the most contributor or return shocks to GCC markets. As for energy markets (Table 7), we find that all energy futures are contributor of return shocks to stock markets where heating oil and WTI oil are the important markets in terms or return spillover to GCC markets. Similar to previous table (Table 6), we find that the GCC markets are net receiver of returns shocks from energy markets. This result is expected because these are rich-oil countries and their government revenues are based principally of oil prices. In addition, the sensitivity to oil price changes are not similar across GCC stock markets. In fact, Saudi Arabia is the largest world oil producer with Russia while Bahrain is small stock markets are has a small portion of oil production. We note also that Qatar is also richest country in the world and the largest exporter of liquefied natural gas. By combing the GCC stock markets with all commodity futures, we show that the same results as previous one. All GCC stock markets are net receiver of return spillovers from the other markets with the exception of both UAE markets (Abu Dhabi and Dubai).

Table 7 reports the results of the total volatility spillovers between GCC stock markets and precious metals and shows that the total volatility spillovers reach 47.3% (whether the market in question is a net receiver or net transmitter of shocks). The directional spillovers transmitted “To others” for precious metals show that gold has a lower impact on the GCC stock indexes. This result is similar to the return spillovers. Platinum and palladium are net transmitters to risk. GCC stock markets except Bahrain, Oman and Saudi Arabia are a net transmitter of risk to the other markets. Kuwait market is the highest transmitter to risk followed by Abu Dhabi Qatar and Dubai. As example, gold and silver contribute to the GCC stock market by 5.62% and 2.87%. Furthermore, the risk spillovers among GCC stock markets are very high, indicating increasing integration among gulf markets. As an example, The Dubai market contributes 23.89%, 11.87%, 6.97%, and 8.2% of the forecasting variance to the Abu Dhabi, Qatari, Kuwait and Saudi

Table 7
Total returns spillovers between GCC stock markets and energy markets.

	WTI	Gasoline	Heating Oil	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	Abu Dhabi	Dubai	From others
WTI	45.25	22.86	28.27	0.05	0.33	0.58	0.75	0.64	0.6	0.67	54.7
Gasoline	23.83	47.05	26.45	0.04	0.21	0.55	0.6	0.3	0.56	0.41	52.9
Heating Oil	27.52	24.72	44.07	0.04	0.36	0.76	0.82	0.42	0.63	0.66	55.9
Bahrain	0.45	0.16	0.37	70.23	8.34	4.45	3.84	3.03	3.98	5.16	29.8
Kuwait	1.57	0.74	1.11	5.4	58.71	4.28	6.33	6.78	7.02	8.06	41.3
Oman	2.24	1.76	2.57	2.7	4.59	50.84	10.41	5.67	9.31	9.9	49.2
Qatar	1.61	0.79	1.57	2.2	5.7	9.56	48.61	6.48	11.67	11.81	51.4
Saudi Arabia	1.74	1	1.19	1.1	5.14	4.95	6.5	59.5	8.9	9.99	40.5
Abu Dhabi	1.02	0.93	1.13	1.96	4.52	6.88	9.83	6.99	42.76	24	57.2
Dubai	0.99	0.67	0.93	2.25	5.1	7.2	9.45	7.41	22.94	43.06	56.9
To others	61	53.6	63.6	15.7	34.3	39.2	48.5	37.7	65.6	70.7	489.9
All	106.2	100.7	107.7	86	93	90	97.1	97.2	108.4	113.7	49.00%
Net	6.3	0.7	7.7	−14.1	−7	−10	−2.9	−2.8	8.4	13.8	

Notes: See notes of Table 6.

Table 8
Total return spillovers between GCC stock markets, precious metals and energy markets.

	Gold	Silver	Palladium	Platinum	WTI	Gasoline	Heating Oil	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	Abu Dhabi	Dubai	From others
Gold	39.2	25.94	10.32	17.37	2.78	1.65	2.38	0	0	0.01	0.02	0.28	0.04	0.02	60.8
Silver	23.79	35.96	12.44	16.28	4.03	2.69	3.63	0.09	0.11	0.29	0.37	0	0.12	0.19	64
Palladium	10.51	13.84	40.07	19.85	4.71	3.76	4.41	0.1	0.31	0.56	0.43	0.39	0.45	0.63	59.9
Platinum	15.95	16.32	17.88	36.18	4.19	3.01	3.91	0.12	0.34	0.54	0.54	0.06	0.45	0.51	63.8
WTI	2.71	4.26	4.38	4.17	38.22	19.29	23.91	0.04	0.28	0.49	0.63	0.54	0.5	0.57	61.8
Gasoline	1.76	3.1	3.73	3.24	21	41.48	23.33	0.03	0.19	0.49	0.53	0.26	0.5	0.38	58.5
Heating Oil	2.29	3.73	3.97	3.81	23.76	21.32	38	0.03	0.31	0.64	0.7	0.35	0.54	0.56	62
Bahrain	0.01	0.26	0.25	0.34	0.44	0.15	0.36	69.6	8.26	4.42	3.82	3.02	3.94	5.12	30.4
Kuwait	0.01	0.26	0.56	0.71	1.55	0.72	1.09	5.29	57.69	4.22	6.27	6.7	6.93	7.99	42.3
Oman	0.16	0.96	1.46	1.49	2.17	1.71	2.47	2.61	4.43	48.84	9.94	5.4	8.9	9.45	51.2
Qatar	0.1	0.8	1.02	1.07	1.58	0.78	1.52	2.15	5.59	9.23	47.2	6.25	11.3	11.41	52.8
Saudi Arabia	0.52	0.25	1.13	0.57	1.7	0.97	1.15	1.1	5.05	4.78	6.29	58.06	8.68	9.74	41.9
Abu Dhabi	0.06	0.31	0.7	0.71	1.01	0.92	1.11	1.92	4.46	6.72	9.63	6.86	42.02	23.6	58
Dubai	0.1	0.49	0.87	0.75	0.98	0.67	0.91	2.21	5.04	7	9.19	7.24	22.44	42.12	57.9
To others	58	70.5	58.7	70.3	69.9	57.6	70.2	15.7	34.4	39.4	48.4	37.3	64.8	70.2	765.4
All	97.2	106.5	98.8	106.5	108.1	99.1	108.2	85.3	92.1	88.2	95.6	95.4	106.8	112.3	54.70%
Net	−2.8	6.5	−1.2	6.5	8.1	−0.9	8.2	−14.7	−7.9	−11.8	−4.4	−4.6	6.8	12.3	

Notes: See notes of Table 6.

markets, respectively. Gold is a net recipient of risk from the other markets. The volatility spillover results also confirm the role of precious metal markets as refuge assets during downturn stock market periods, which are in line with the findings of Baur and Lucey (2010), Baur and McDermott (2010), and Bredin et al. (2015).

Regarding the total spillovers results between energy and stock market (Table 10), we show that energy markets contribute a little more than the precious metals markets to the GCC stock markets. The total spillovers are closely similar to those for precious metals. Among energy markets, only the crude oil market is a net transmitter to risk to the GCC markets. Crude oil acts as a predictor for the GCC stock markets. Noting that GCC stock markets are widely influenced by oil price fluctuations. For example, the WTI oil market contributes 0.42% to the Bahraini market, 4.12% to the Kuwaiti market, 4.14% to the Omani market, 3.02% to the Qatari market, 0.08% to the KSA market, 0.478% to the Abu Dhabi market, and 0.37% to Dubai market. The results for the third block (stock-precious metal-energy) reported on Table 11 are similar to the above results for this reason we will not interpret them.

Figs. 3 and 4 plot respectively the time-varying total return and volatility spillover index for the three block (stock-precious metal, stock-energy and stock-precious metal-energy) and shows that both the return and volatility spillovers are affected by structural breaks. More precisely, the returns and volatility spillover is at its maximum during the Lehman Brothers collapse, the oil price plunge, and the U.S. Federal Reserve System's rate hike. We note that the precious metals, energy commodities, and GCC stock market relationships are affected by financial, economic, and geopolitical events. The increases in volatility spillovers lead to decreases in diversification opportunities.

Table 9
Total volatility spillovers between GCC stock markets and precious metals.

	Gold	Silver	Palladium	Platinum	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	Abu Dhabi	Dubai	From others
Gold	56.3	15.68	9.97	15.59	0	0.49	0.03	1.06	0.39	0.49	0	43.7
Silver	25.5	48.58	11.2	11.68	0.01	0.37	0.18	0.43	1.55	0.43	0.07	51.4
Palladium	8.68	6.86	61.05	18.97	0.39	0.32	0.25	0.76	1.18	0.74	0.81	39
Platinum	13.1	6.42	17.69	55.1	0.04	0.84	2.12	3.06	0.28	0.78	0.58	44.9
Bahrain	0.25	0.1	2.54	1.93	66	10.4	2.85	5.02	4.26	2.45	4.19	34
Kuwait	1.54	0.63	2.77	6.39	1.84	62.05	0.82	4.7	4.35	7.95	6.97	38
Oman	1.61	1.03	0.58	6.96	0.7	8.23	49.44	16.67	2.57	6.43	5.78	50.6
Qatar	1.5	0.44	1.3	6.2	0.94	10.04	10.4	40.17	3.79	13.34	11.87	59.8
Saudi Arabia	0.03	0.03	0.8	1.01	0.42	11.89	1.45	7.16	55.13	13.88	8.2	44.9
Abu Dhabi	0.39	0.35	0.47	1.66	1.03	6.88	2.4	13.37	5.38	44.19	23.89	55.8
Dubai	0.3	0.29	0.13	1.45	1.12	8.39	3.79	13.93	4.41	24.65	41.54	58.5
To others	52.9	31.8	47.5	71.9	6.5	57.8	24.3	66.2	28.2	71.1	62.4	520.5
All	109.2	80.4	108.5	127	72.5	119.9	73.7	106.3	83.3	115.3	103.9	47.30%
Net	9.2	−19.6	8.5	27	−27.5	19.8	−26.3	6.4	−16.7	15.3	3.9	

Notes: Figures are in %.

Table 10
Total volatility spillovers between GCC stock markets and energy markets.

	WTI	Gasoline	Heating Oil	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	Abu Dhabi	Dubai	From others
WTI	65.04	15.77	14.14	0.2	1.26	0.73	2.02	0.09	0.48	0.28	35
Gasoline	24.11	52.51	13.79	1.47	2.16	1.2	2.02	0.77	1.23	0.74	47.5
Heating Oil	22.4	12.68	60.47	0.19	0.52	0.77	1.86	0.13	0.68	0.31	39.5
Bahrain	0.42	1.83	0.31	65.2	11.35	3.61	6.12	4.64	2.52	4.01	34.8
Kuwait	4.12	3.7	0.58	2.43	61.65	1.03	5.66	5.11	8.53	7.18	38.4
Oman	4.14	0.8	0.66	1.01	8.12	49.48	18.89	3.21	7.4	6.3	50.5
Qatar	3.02	1.9	1.65	1.28	10.01	11.77	40.58	4.32	13.68	11.81	59.4
Saudi Arabia	0.08	1.17	0.01	0.42	12.13	1.88	7.98	54.62	13.67	8.04	45.4
Abu Dhabi	0.47	1.03	0.12	1.04	6.85	3.01	14.12	5.46	44.04	23.85	56
Dubai	0.37	0.53	0.08	1.09	8.22	4.37	14.55	4.46	24.84	41.5	58.5
To others	59.1	39.4	31.3	9.1	60.6	28.4	73.2	28.2	73	62.5	464.9
All	124.2	91.9	91.8	74.3	122.3	77.8	113.8	82.8	117.1	104	46.50%
Net	24.1	−8.1	−8.2	−25.7	22.2	−22.1	13.8	−17.2	17	4	

Notes: See notes of Table 6.

5.3. Network connectedness analysis

Figs. 5-7 show the network connectedness of the average pairwise direction returns (panel a) and volatility (panel b) spillover indexes for each block based on Tables 6-11. Note that the pairwise spillovers between GCC and commodity futures markets as nodes and edges, respectively, make it a typical complex network. For the first block (precious metal-stock), we identify silver, Abu Dhabi, Dubai and platinum are net transmitters to returns particularly from other markets. If we consider Dubai financial market as an example, it receives and transmits return shocks from and to Abu Dhabi. This results indicates a strong interdependence between those markets. Dubai market also transmits and receives return information form the other GCC stock markets. We note that GCC countries share many economic similarities. Economic reforms adopted by all GCC economies (for example 2030 vision for Saudi Arabia) aim to decrease their dependence to oil revenues and diversify economies (applying taxes, authorize foreign investors to invest in local stock markets, relaxing the restrictions one foreign direct investments (FDI), improving education, encouraging private investment, among others) are the potential determinants factors of the return and volatility spillovers. Gold and silver are integrated as bidirectional return spillovers is observed. Similar results is found among all precious metal markets. Moving to volatility spillover network (panel b), silver, Bahraini, Omani, and Saudi Arabian, markets (green nodes) as net recipients of shocks, whereas the remaining markets (red nodes) are net transmitters to shocks of different magnitudes. These results of plots are in line with the findings in Table 11. As for the second block (energy-stock), we observe a strong return connectedness along energy markets. In addition all the GCC stock markets except Abu Dhabi are net receipt of risk. This results is explained by the increasing integrations among the GCC markets as well as the role of the energy futures market to the GCC markets.

Moving to the volatility connectedness, we show the volatility in Dubai and Abu Dhabi as well as Qatar will be transmitted to other GCC markets. It is worth noting that the source or recipient of net volatility spillovers is sensitive to macro political events. The

Table 11
Total volatility spillovers between GCC stock markets, precious metals and energy markets.

	Gold	Silver	Palladium	Platinum	WTI	Gasoline	Heating Oil	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	Abu Dhabi	Dubai	From others
Gold	55.78	15.61	9.79	15.1	0.68	1.02	0.1	0	0.27	0.02	0.9	0.33	0.38	0	44.2
Silver	25.02	48.29	11.41	11.42	0.73	0.32	0.1	0.02	0.25	0.07	0.39	1.57	0.37	0.05	51.7
Palladium	8.47	6.9	58.65	18.47	0.78	2.39	0.45	0.32	0.26	0.3	0.68	1	0.62	0.71	41.4
Platinum	12.28	6.2	17.77	54.19	2.08	1.22	0.55	0.03	0.35	1.53	2.44	0.25	0.64	0.48	45.8
WTI	1.82	0.55	2.73	5.25	60.44	14.21	13.53	0.01	0.36	0.09	0.67	0.06	0.15	0.1	39.6
Gasoline	0.63	0.3	3.49	2.89	21.76	51.65	13.37	0.93	1.28	0.66	1.09	0.46	0.9	0.6	48.3
Heating Oil	0.17	0.12	0.74	1.64	21.4	12.32	60.64	0.11	0.3	0.45	1.28	0.08	0.52	0.23	39.4
Bahrain	0.2	0.1	2.36	1.72	0.1	1.22	0.2	66.02	9.92	3	4.82	4.01	2.27	4.05	34
Kuwait	0.88	0.39	2.5	5.02	2.36	2.69	0.34	1.84	60.68	0.52	3.87	4.42	7.66	6.83	39.3
Oman	1.02	0.63	0.57	5.93	2.4	0.44	0.43	0.83	6.64	48.92	16.74	2.93	6.61	5.92	51.1
Qatar	1.07	0.33	1.11	5.07	1.41	1.24	1.21	0.92	8.29	9.91	40.08	3.86	13.47	12.04	59.9
Saudi Arabia	0.03	0.02	0.7	0.97	0.08	0.96	0.03	0.39	11.57	1.57	7.25	54.98	13.46	7.99	45
Abu Dhabi	0.29	0.3	0.41	1.46	0.22	0.84	0.07	0.97	6.29	2.29	13.33	5.23	44.39	23.91	55.6
Dubai	0.21	0.23	0.11	1.25	0.18	0.43	0.04	1.11	7.84	3.62	13.96	4.36	24.71	41.97	58
To others	52.1	31.7	53.7	76.2	54.2	39.3	30.4	7.5	53.6	24	67.4	28.6	71.8	62.9	653.3
All	107.9	80	112.3	130.4	114.6	91	91.1	73.5	114.3	72.9	107.5	83.5	116.1	104.9	46.70%
Net	7.9	−20	12.3	30.4	14.6	−9	−9	−26.5	14.3	−27.1	7.5	−16.4	16.2	4.9	

Notes: See notes of Table 6.

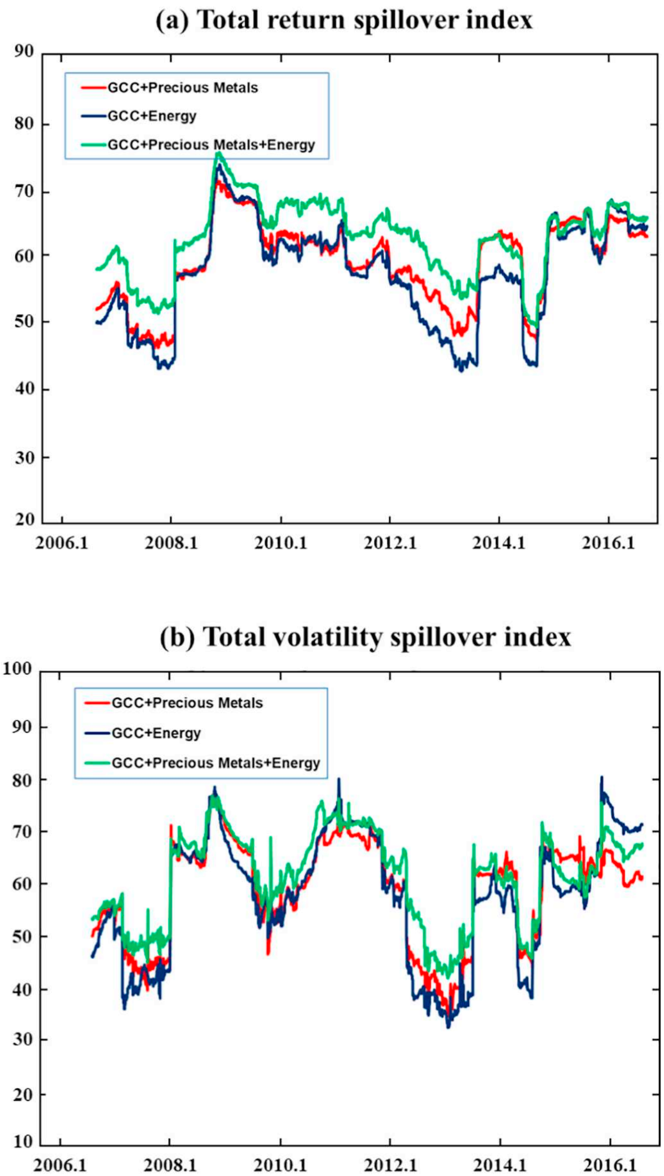

Fig. 4. Dynamics of the total spillover index; (a) returns; (b) volatility.
Notes: Dynamic spillover indexes are calculated from the forecast error variance decompositions on 10-step-ahead forecasts. The total spillover indices are estimated using 200-day rolling windows.

international economic uncertainty (e.g., Chinese economy, US trade wars and oil sanctions on Iran, US shale revolution and the discrepancies among GCC countries) and the geopolitical uncertainty risk deepens the risk spillovers between commodity futures and GCC markets. We note that the Bahraini market receives shocks from the other GCC stock markets, particularly the Abu Dhabi and the Dubai markets. This picture is reasonable because both the Abu Dhabi and the Dubai stock markets have the highest foreign (especially from the United States and Europe) ownership ratio among the sample markets. The initial response from these two markets have a spillover effect on others. Moreover, because the Bahraini market is the smallest market in the Gulf region, bad or good news from the remaining GCC stock markets has the strongest effect on its investors. Gold receives shocks from the GCC stock markets, a possible reflection of the non-synchronous trading in the GCC stock and the yellow metal markets. The gold market was affected by the volatility of the silver and platinum markets. The weak connectedness between precious metal and GCC stock markets justifies the roles of these markets as refuge assets. Crude oil receives shocks from heating oil and gasoline and affects all GCC and metal markets. Fig. 7 reports the contentedness network among the precious metal, energy, and GCC stock markets for returns and volatility. The results show evidence of return spillovers and volatility spillovers between the considered markets and confirms the previous results. Bahrain, Saudi Arabia, Oman, and Gasoline are net transmitter of both return and risk spillovers while Dubai, Abu Dhabi, platinum, WTI are net receipt of return and volatility shocks. The results of the other markets are mixed. All in all, it is evident

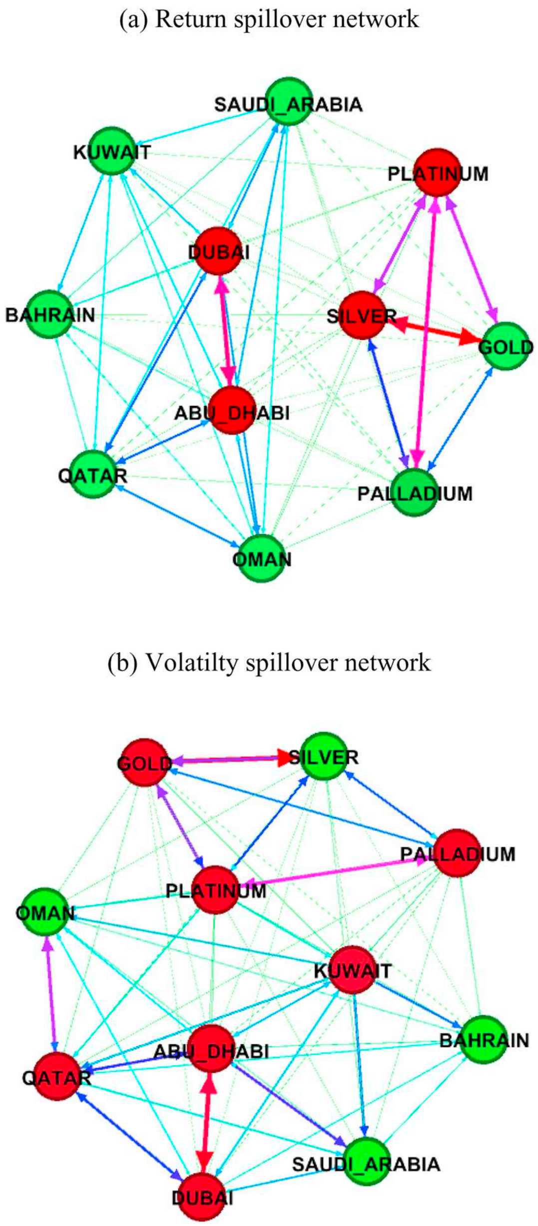

Fig. 5. Connectedness network among the precious metals, and GCC stock markets.
Note: This figure shows returns (a) and volatility (b) connectedness networks within the precious metal and GCC stock markets. A node's green (red) color indicates the most significant transmitter (recipient). The edge colors rank the strength of the pairwise directional spillover from red (strongest) to purple, blue, light blue, and green (weakest). The edge arrow thickness also indicates the strength of the pairwise directional spillover. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

that the direction and magnitude of net volatility spillovers are complex to identify and are sensitive to domestic and international events. These results have important implications for portfolio risk assessments.

5.4. Portfolio risk analysis

These empirical results provide evidence of risk spillovers across the commodity and stock markets. These results have important implications for holding efficiently diversified portfolios and conducting risk management. Practically, portfolio investors require a preliminary and accurate estimation of the temporal covariance matrix to construct an optimal portfolio based on risk management and portfolio allocation decisions. To more efficiently manage the commodity-stock market risk, we apply the estimated results of the DECO-FIAPARCH model in order to help investors to build optimal portfolio. We first calculate the optimal portfolio weights and the

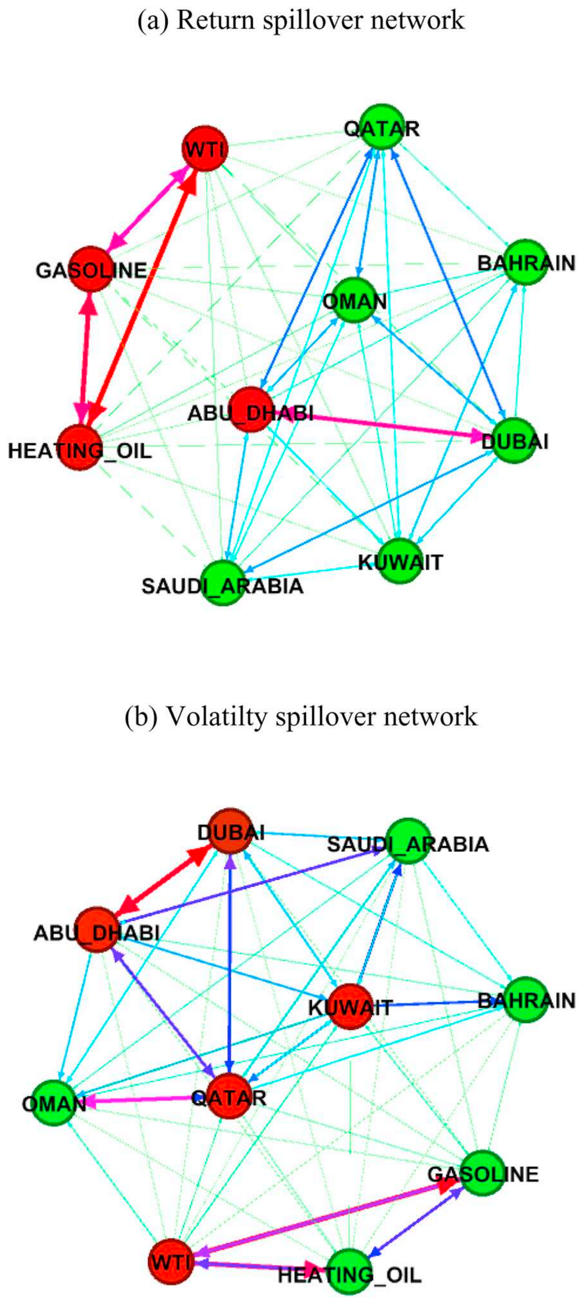

Fig. 6. Connectedness network among the energy and GCC stock markets.
Note: This figure shows returns (a) and volatility (b) connectedness networks within the energy and GCC stock markets. A node's green (red) color indicates the most significant transmitter (recipient). The edge colors rank the strength of the pairwise directional spillover from red (strongest) to purple, blue, light blue, and green (weakest). The edge arrow thickness also indicates the strength of the pairwise directional spillover. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

hedge ratios for designing optimal hedging strategies under different portfolios. More specifically, we use the Kroner and Ng (1998) methodology and compute the optimal weights (w_t) of commodity-stock portfolio by minimizing risk without reducing expected returns. We also follow Kroner and Sultan (1993) methodology to quantify the beta hedge to minimize the risk of this stock-commodity portfolio. Thus, we measure the degree of hedging (β_t) when a long position (buy) of \$ 1 in commodity assets is hedged by short position (selling) in the stock market.

Second, we estimate the hedging effectiveness of a constructed portfolio that can be assessed by comparing realized hedging errors of the hedged (the weighted commodity-stock portfolio (*PF II*)) and non-hedged (or benchmark stock portfolio (*PF I*)) portfolios (Ku et al., 2007). A stronger hedging effectiveness results in a higher hedging HE ratio value, thus implying that the associated

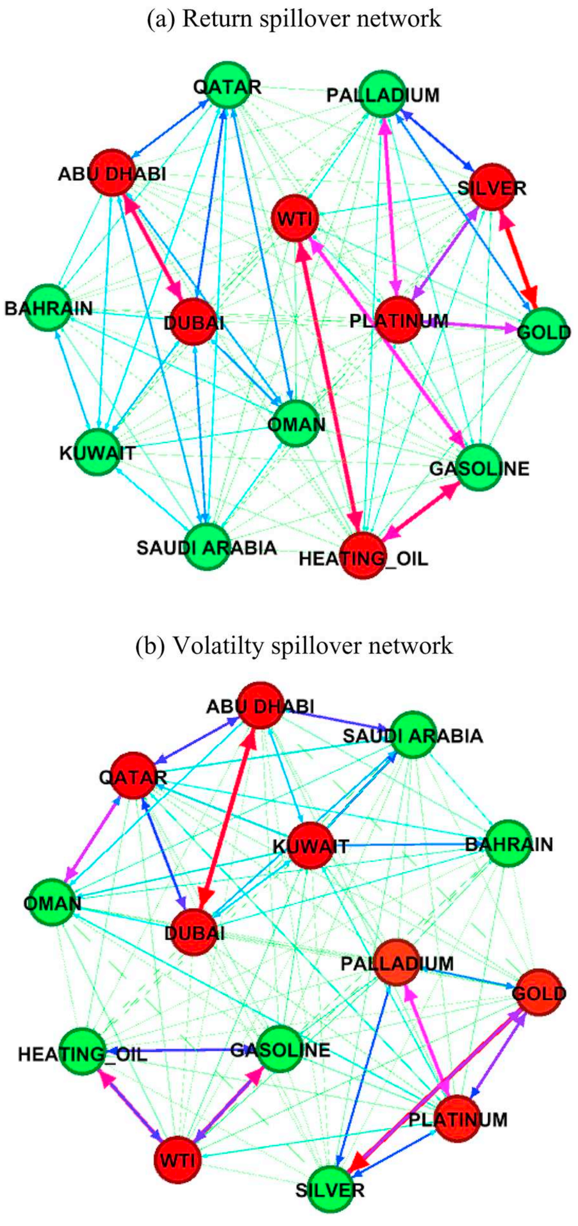

Fig. 7. Connectedness network among the precious metal, energy, and GCC stock markets.
Note: This figure shows returns (a) and volatility (b) connectedness networks within the precious metal, energy and GCC stock markets. A node's green (red) color indicates the most significant transmitter (recipient). The edge colors rank the strength of the pairwise directional spillover from red (strongest) to purple, blue, light blue, and green (weakest). The edge arrow thickness also indicates the strength of the pairwise directional spillover. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

investment policy can be deemed a superior hedging strategy. For a deepen analysis of risk management, we analyze the hedging effectiveness for the whole sample period (*Whole period*), before (*Sub-period I*) and after (*Sub-period II*) collapse of Lehman Brothers as well as after the recent oil price crisis in mid2014 (*Sub-period III*).[9]

Tables 12 and 13 show the results of the optimal portfolio weights, hedge ratios, and hedge effect for precious metals and energy-GCC stock markets, respectively. The results demonstrate that investors, on average, except gold and platinum in the Dubai market, should hold larger weights on stock than precious metals (see Table 10 for the optimal weight). As an example, the optimal weight ranges from 12% for Bahrain to 62% for Dubai. In fact, 12.53% for gold and the rest of the wealth is invested in the Bahraini stock

[9] The results for an optional portfolio weights and hedge ratios for different periods are not reported here but are available upon request.

Table 12
Optimal portfolios' weights, hedge ratios, and hedging effectiveness for the precious metal and GCC stock markets.

Portfolio pairs	Optimal weights	Hedge ratios	*Hedging Effectiveness (HE (%))*			
	w_t	β_t	***Whole period***	***Sub-period I***	***Sub-period II***	***Sub-period III***
Bahrain/ Gold	0.1253	0.0926	79.35	79.60	79.04	80.48
Kuwait/Gold	0.2043	0.1173	87.94	83.21	89.28	85.46
Oman/ Gold	0.2483	0.1382	**96.30**	**97.53**	**95.44**	**95.59**
Qatar/ Gold	0.4351	0.1989	89.73	94.87	74.49	91.40
Saudi Arabia/ Gold	0.5061	0.2321	77.54	85.62	35.45	63.25
Abu Dhabi/ Gold	0.3816	0.1747	57.50	47.09	70.85	40.58
Dubai/ Gold	0.6242	0.2768	75.80	73.69	82.79	64.69
Bahrain/ Silver	0.0253	0.0529	76.85	71.62	77.30	83.18
Kuwait/ Silver	0.0576	0.0672	77.16	73.38	77.81	81.50
Oman/ Silver	0.0927	0.0795	89.56	92.93	**87.87**	86.61
Qatar/ Silver	0.2007	0.1149	92.74	**96.08**	87.09	**92.36**
Saudi Arabia/ Silver	0.2554	0.1331	86.75	88.46	82.31	87.75
Abu Dhabi/ Silver	0.1615	0.1012	85.67	84.60	86.65	85.96
Dubai/ Silver	0.3359	0.1590	88.43	91.83	85.95	87.34
Bahrain/ Palladium	0.0345	0.0571	69.82	64.69	71.96	70.10
Kuwait/ Palladium	0.0754	0.0731	73.91	67.51	74.83	80.48
Oman/ Palladium	0.1093	0.0868	93.26	96.54	**89.64**	**92.76**
Qatar/ Palladium	0.2273	0.1237	95.54	**98.37**	83.97	85.72
Saudi Arabia/ Palladium	0.2840	0.1425	**95.96**	97.84	69.04	60.98
Abu Dhabi/ Palladium	0.1871	0.1096	64.72	74.74	61.27	33.20
Dubai/ Palladium	0.3763	0.1729	76.16	91.04	49.49	4.10
Bahrain/ Platinum	0.0909	0.0789	72.49	76.40	68.69	76.85
Kuwait/ Platinum	0.1571	0.1003	83.60	82.53	83.14	87.35
Oman/ Platinum	0.1945	0.1163	**96.96**	**98.95**	**91.85**	**94.29**
Qatar/ Platinum	0.3620	0.1679	77.59	85.11	43.13	89.27
Saudi Arabia/ Platinum	0.4285	0.1970	58.10	68.33	82.71	66.60
Abu Dhabi/ Platinum	0.3109	0.1493	61.42	19.11	76.82	20.94
Dubai/ Platinum	0.5450	0.2363	75.09	16.58	86.08	46.18

Notes: This table summarizes the results of the optimal weights, hedge ratios and hedging effectiveness. The numbers in bold identify the hedged portfolio with the lowest variance and highest variance reductions. The shaded values indicate the best commodity asset that offers the highest risk reduction for each GCC market.

Table 13
Optimal portfolios' weights, hedge ratios, and hedging effectiveness for the energy and GCC stock markets.

Portfolio pairs	Optimal weights	Hedge ratios	*Hedging Effectiveness (HE (%))*			
	w_t	β_t	***Whole period***	***Sub-period I***	***Sub-period II***	***Sub-period III***
Bahrain/ WTI	0.0335	0.0542	70.67	67.54	73.03	64.79
Kuwait/ WTI	0.0675	0.0681	70.18	69.18	71.93	63.38
Oman/ WTI	0.0866	0.0765	81.65	89.95	75.41	73.86
Qatar/ WTI	0.1929	0.1109	**87.62**	**93.42**	**80.74**	**80.18**
Saudi Arabia/ WTI	0.2448	0.1308	75.78	80.81	68.60	63.79
Abu Dhabi/ WTI	0.1645	0.1006	78.28	77.95	80.71	70.17
Dubai/ WTI	0.3433	0.1599	78.91	83.46	76.52	76.75
Bahrain/ Gasoline	0.0160	0.0488	67.78	49.75	72.95	67.16
Kuwait/ Gasoline	0.0429	0.0617	**99.90**	**99.96**	**99.73**	**91.49**
Oman/ Gasoline	0.0678	0.0714	82.37	84.68	81.07	83.41
Qatar/ Gasoline	0.1559	0.1019	84.65	87.49	82.93	83.75
Saudi Arabia/ Gasoline	0.2072	0.1884	71.22	68.20	74.69	71.69
Abu Dhabi/ Gasoline	0.1250	0.0908	78.47	68.45	83.28	75.18
Dubai/ Gasoline	0.2913	0.1448	79.48	72.90	82.08	78.51
Bahrain/ Heating Oil	0.0374	0.0588	73.58	61.71	77.72	70.28
Kuwait / Heating Oil	0.0781	0.0746	72.11	64.17	75.74	73.70
Oman / Heating Oil	0.1057	0.0858	86.97	**91.02**	84.23	87.15
Qatar / Heating Oil	0.2198	0.1217	**90.98**	94.60	**87.31**	**88.31**
Saudi Arabia / Heating Oil	0.2824	0.1421	81.67	82.30	81.63	79.58
Abu Dhabi/ Heating Oil	0.1858	0.1097	83.74	80.35	85.77	83.08
Dubai/ Heating Oil	0.3832	0.1748	86.73	86.55	86.39	87.72

Notes: See the notes for Table 12.

market. For WTI crude oil, 3.35% of the wealth is invested in the WTI oil and 96.65% in Bahraini stock markets.[10] For the energy case (Table 11), we find that GCC investors prefer precious metals over energy assets to hedge their positions against unfavorable extreme stock price movements. Among all commodity futures, the GCC investors prefer gold futures. This result is in line with Junttila et al. (2018) and Mensi et al. (2015). Regarding the average optimal hedge ratios, the hedge ratios for precious metals are lower than for the energy markets. Among the precious metal markets, the highest (lowest) ratio is for the Dubai stock-gold (Bahraini-silver and Abu Dhabi-silver pairs) portfolio. The hedge ratio value reaches 27.68% for the Dubai stock-gold pair, meaning that a one-dollar long position in gold should be shorted by 27.68 cents of the Dubai stock index. In contrast, the optimal hedge ratios vary slightly across GCC stock markets. Among commodity markets, we conclude that energy assets are the most inexpensive hedge for the GCC stock market, whereas precious metals are an expensive hedge for this stock market. The second column in Tables 10 and 11 exhibits the hedging strategies involving all sample commodity futures and GCC stock markets for different periods.[11] This column shows that commodity futures are able assets for reducing portfolio risk. The hedging effectiveness values for all cases are positive and high for precious metals than for energy markets regardless the period considered. In other words, risk reduction can be realized and hedge portfolios can minimize risk exposure, especially by using metals, during turmoil periods. Among the different sub-periods, gold provides the highest hedging effectiveness after the recent oil price crisis (*Sub-period III*) for both Bahrain and Kuwait while during the pre-Lehman Brothers collapse (*Sub-period I*) for the case of Oman, Qatar and Saudi Arabia and for Abu Dhabi and Dubai after the Lehman Brothers collapse (*Sub-period II*). For the remaining precious metal assets, the results are sensitive to the turmoil periods. For the whole period, gold, platinum and palladium (silver) offer the best variance reduction for the Oman (Qatar) stock market. The WTI oil and heating oil (gasoline) provide the greatest risk reduction in the Qatar (Kuwait) stock market.

We also investigate the commodity that allows for the best hedging effectiveness for each GCC markets. Accordingly, for energy, heating oil provides the best hedging effectiveness for almost all GCC markets regardless the time period. We note that heating oil provides the highest hedging effectiveness for Oman for the first (*Sub-period I*), Qatar for the second and the third sub-periods as well as for the whole sample period. These results are consistent with those of Mensi et al. (2015), who conclude that including commodities (silver, gold, rice, oil, corn, and wheat) to a Saudi stock portfolio reduces the portfolio's risk during a stressful market.

6. Conclusions and policy implications

This paper investigates the dynamic linkages between commodity futures (precious metal and energy) and equity markets in the GCC region during the past decade and attempts to provide suggestions for portfolio risk management. We consider four significant precious metals (silver, gold, palladium, and platinum), and three major energy commodities (crude oil, heating oil, and gasoline) as the commodity classes. We analyze the time-varying conditional correlations and return and risk spillover effects between these commodities and the GCC stock markets using the DECO-FIAPARCH model of Engle and Kelly (2012) and the spillover index developed by Diebold and Yilmaz (2014).

Our empirical results show a statistically significant positive and relatively weak dynamic equicorrelations among the considered markets, which intensified during the recent GFC and the ESDC periods. The increase in correlation in 2008 is found to be related to the historical increase in oil prices at that time, indicating a contagion effect. Between 2013 and 2014, the correlation between commodity and GCC stock markets decreased, supporting the evidence of decoupling hypothesis and diversification opportunities. The increase/decrease phases in the time-varying correlations during the sample period indicate that investors frequently change their portfolio structure according to the different market scenarios. The Diebold and Yılmaz (2014) method shows that, among the precious metals, gold have a weaker impact on the GCC stock indexes. On the other hand, the energy markets contribute much more (in both returns and risk) than the metals markets to the GCC stock markets and, in this process, act as price discovery tools.

The net return spillover results show that gold and palladium are net receiver of return information while silver and platinum are net transmitter to return shocks to GCC markets. Returns shocks in energy markets are net transmitted to precious metals and GCC markets. The net volatility spillover analysis shows that precious metals except silver are net transmitter of risk to GCC markets. In addition, the heating oil (gasoline, and WTI crude oil) are net transmitter (receiver) to (of) risk to (from) GCC markets. Abu Dhabi and Dubail markets are sources of return and volatility spillovers.

In the context of portfolio risk management analysis, the results show that a mix of commodities and GCC equities reduces risk for all GCC markets particularly for turmoil periods. More precisely, precious metal markets offer stronger hedging effectiveness than energy markets for all GCC markets pre- and after Lehman Brothers Collapse and after the recent oil price crisis. Moreover, GCC stock investors should prefer precious metals over energy assets to hedge their positions against unfavorable extreme stock price movements. In contrast, we reveal that energy assets are the least expensive hedge for the GCC stock markets, whereas precious metals are expensive hedges for these markets. Regarding hedging effectiveness, precious metals are much better than energy commodities, meaning that hedged portfolio (through precious metals) can reduce risk significantly. In addition, the network of return and volatility spillovers helps us to identify the transmitter/ recipient of information, as well as information channels across the precious metals, energy and GCC stock markets. This provides policymakers with an opportunity to design a road map of systemic risk to stabilize the GCC stock markets with the commodity futures markets.

Notes: The standard errors are in parentheses. The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

[10] The interpretations are similar for the remaining precious metals markets and for each country. For this reason, we do not develop them.

[11] The shaded color in Tables 12 and 13 indicates the best hedging effectiveness assets for GCC stock markets and the bold value refers to a specific commodity assets that provides the highest hedging effectiveness for the GCC markets.

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