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Abstract

This paper examines the return and volatility spillover effects among S&P 500, crude oil and gold by employing the spillover index of Diebold and Yilmaz (2012). Monthly realized volatility and return series covering the period from January 1986 to August 2018 are used to examine the return and volatility spillovers. Our findings indicate a bi-directional return and volatility spillover among these assets. The full sample empirical evidence is consistent with the structure in which oil plays a central role in the information transmission mechanism. The role of oil and gold as a safe haven has changed over time in financial and non-financial economic turbulence time-span. Commodity market financialization has decreased the effectiveness of adding commodities to portfolios after 2002.

Keywords: S&P 500 index; Oil price; Gold Price; Return spillover; Volatility spillover

JEL Codes: C13, C53, C58, G10, G12, G14, Q43

1. Introduction

With the development of various innovative financial instruments, financial markets have made significant progress in terms of volume and magnitude in recent decades. This giant growth in financial markets has also increased the riskiness and has forced investors to seek a safe haven investment. Gold, the most popular of precious metals, has traditionally been the main store of value instrument against inflation and volatile assets. According to the traditional belief, gold has been a safe investment tool for people throughout history and this belief still continues today. For the first time, Baur and Lucey (2010) examined whether gold works as a safe haven asset or not in financial markets and reached the evidence supporting this view during market turmoil by using a regression model for the US, the UK, and Germany. Following this pioneer study, many researchers have investigated this issue such as Anand and Madhogaria (2012), Hood and Malik (2013), Baur and McDermott (2010, 2016) and recently Shakil et al. (2018). Additionally, the gold market can be seen as a good nominee as the representative of precious metal markets.

Crude oil, as one of the leading commodities, has been a vital input to all sectors of the economy such as transportation, telecommunication, agriculture, and other industrial activities, whereas gold has traditionally been the store of value tool. The prices of commodities, especially oil price, faced an unprecedented rise from 2002 to 2008 Global Financial Crisis (GFC). Oil price, which was \$20 in the early 2000s, reached \$45 in 2004 and climbed to \$140 before the 2008 GFC, yielding a return higher than 600% over a period within eight years. It then climbed up to \$110 again in two years after falling to \$50 in the post crisis-period. At the beginning of 2016, the price of oil fell again to \$30, but now it is around \$70. The total transaction volume of crude oil has gradually been increasing since 1985, excluding the 2008-2009 financial crisis period, and the total consumption has reached 98.19 million barrels a day as of 2017. Undeniably, this fluctuation in the price of crude oil, together with high consumption, offers financial investors an opportunity to gain high profits in their portfolio. Various studies have investigated the links between oil market and financial markets, and found that possible increases in crude oil prices may have a significant impact on the global economic situation.

The S&P 500 Index is a kind of market-capitalization-weighted index obtained from 500 largest U.S. publicly traded companies according to their market value. The index is considered to be the best indicator of large-scale US stocks. The total market capitalization of the S&P 500 is nearly \$23.5 trillion, and it forms 80% of the market capitalization of the US stock market. The S&P 500 index is considered to be a general indicator of the US economy. Although the S&P 500 index has had a tendency to increase throughout its history, it has shown a significant decline during the economic downturn. When people believe that economy is going well, they invest more in stocks. In brief, aiming to examine the total and net spillover of these assets, which are expressed in trillions of dollars, enables one to depict the overall financial condition from the early 1990s until today.

Since the financial globalization of commodity markets leads to a rise in integration across the energy, metal and other commodity markets, the investigation of the relationship between these markets by utilizing various kinds of econometrics methods attracts portfolio investors, consumers and producers, policy makers and speculative traders. Numerous investigations have been conducted into the relationship between gold and stock markets (i.e. Mensi et al. (2017a), Miyazaki and Hamori (2013), Chkili (2016), Dar and Maitra (2017)), between oil and stock markets (i.e. Awartani (2013), Ji (2018), Li and Wei (2018), Peng et al. (2018), Shahzad (2018), Wang and Wu (2018), Abdullah et al. (2016) etc.), between oil and gold (Le and Chang (2012), Tiwari and Sahadudheen (2015), Shahbaz et al. (2017) and Kumar (2017)), and among oil, gold and stock markets (i.e. Raza et al. (2016), Mensi et al. (2017b), Lau et al. (2017), Bouri et al. (2017, Tursoy and Faisal (2018)) using various kinds of econometric methods.

Information transmission (both return and volatility) across markets and market assets is more discernible especially during the periods of financial instability. In fact, the rise in inter-market relationships after volatile time periods indicates the presence of contagious effects and appears to be the main factor that reduces the benefits of international portfolio diversification (Mensi et al., 2017a). Recent academic studies further indicate that as the correlation between stock markets increases, an unexpected event in a market causes not only return but also volatility change in other markets (Dedi and Yavas, 2016). Certainly, we can generalize this approach to all

kinds of local and international asset markets interacting with each other and the goods traded in these markets. For this reason, it is plausible to investigate the spillover effects between assets considering both return and risk. Having knowledge about the fundamental process of information transmission among local and international markets and market assets provides leverage for investors to construct outstanding portfolio and hedging strategies. This situation is also valid for policy makers to implement a well-directed economic policy at macro level as well as micro level regarding asset valuation and risk management. If this situation is not understood well, the portfolio investors may face the risk of losing money, and even their whole wealth, and policy makers may fail to predict the consequences of a globally contagious economic crisis, thereby having potential impact on broader economy. Thus, it is necessary even compulsory for whole economic agents to know the direction of return and volatility spillovers between various kinds of assets.

To analyze spillover effects across various kinds of assets in different geographies, various researchers have started to use Diebold and Yilmaz spillover index (DY index) in 2009 and extended the scope of the analysis in 2012. Using this method, Awartani and Maghyreh (2013) found that the oil market transfers information to the Gulf Cooperation Council (GCC) stock indices predominately with regards to both return and volatility spillover for GCC countries. Moreover, Antonakakis and Kizys (2015) attempted to find the dynamic link between returns and volatilities of five commodities and four exchange rates based on weekly data extending from January 1987 to July 2014. Antonakakis et al. (2016) examined the dynamic spillovers between spot and futures market volatilities, volume of futures trading and open interest for the UK and the US from February 2008 to March 2013. Utilizing the DY spillover index, Kang et al. (2017) also evidenced that gold and silver conveys information to other markets, while West Texas Intermediate crude oil, corn, wheat, and rice are the net information receivers during the recent financial crisis period. Using daily data over the period from November 9, 1998 through March 5, 2015, Mensi et al. (2017b) investigated the time-varying equicorrelations and the risk spillovers between the two major commodity markets, crude oil and gold, and both the aggregate Dow Jones Islamic index and its associated ten stock sectors. They evidenced that oil and gold market are the net receivers of risk spillovers with the energy, financial, technology and telecommunications sub-sectors of the DJIM index, whereas the

consumer goods, consumer services, health care, industrials, utilities sub-sectors of DJIM index are the net transmitters. Last but not least, more recent studies such as Restrepo et al. (2018), Wang and Guo (2018), Liow et al. (2018), Antonakakis et al. (2018), Collet and Lelpo (2018), Ahmad et al. (2018), Akkaya et al. (2018), Wang and Wu (2018), Kočenda and Moravcova (2018), Rohit and Dash (2018), and Pavlova et al. (2018) have used the DY spillover index to investigate the intercontinental, inter-country and/or inter-sectoral return and/or volatility spillovers for energy, commodity and financial assets and indices.

Looking through this lens, our study is expected to contribute to the literature by investigating the relationship between the non-financial (i.e. oil and gold) and financial (S&P 500 index) markets considering the return and volatility spillover indices. We identify the following remarkable contribution to the literature. Firstly, investigating the relationship among these three assets enables us to address the US market in a broader perspective with the help of return and risk spillovers in volatile and tranquil periods. Secondly, the issue of whether gold is a safe haven for the investment portfolios or not, which is a topic frequently discussed in the literature, is analyzed in depth with respect to risk view. Thirdly, we also have a chance to evaluate the critical role of oil market for the gold and S&P 500 index especially in non-financial turbulence time-span. Fourthly, we obtain highly appreciated findings for investors following the S&P 500 index regarding the return of gold and crude oil as well as volatility spillover. This also gives valuable information to the US institutions that regulate the US stock market in the middle of the hot debate as to whether commodity market financialization is good or bad for financial markets. Since the analysis period comprises three big economic turmoils in the US (i.e. early 1990 crisis, 2000 Dot-com bubble, and 2008 Global Financial Crisis) and other countries' economic crises (i.e. 1994 Mexico peso crises, 1997 Asian financial crisis and 1998 Russian financial crisis, Chinese stock market crash, Brazilian economic crisis, and Venezuela's economic crisis and recent Turkish currency and debt crisis and so on), we have the opportunity to observe the spillover effect among these important assets in terms of both return and volatility during volatile time spans. All in all, we aim to make a significant contribution to the literature about the issues stated above.

To the best of our knowledge, this study is the first to examine the return and volatility spillovers among these prominent assets for the US from the specified perspective. To reach this aim, a well-established econometric methodology, the DY spillover index proposed by Diebold and Yilmaz (2009, 2012) to examine the S&P 500 index, crude oil spot prices, and gold prices over the period from January 1986 to August 2018, was used. This rolling version of the method offers a great advantage to compute the dynamics of return and volatility spillover between variables with respect to not only the total aspect but also the net (pairwise) aspect. The empirical findings can briefly be summarized as follows. We find strong evidence that return and volatility spillover are bi-directional between these assets. Among these three assets, oil plays a major role as an information transmission mechanism in terms of return and risk. For the three assets examined in the study, the characteristics of oil and gold as the store of value instruments have changed over time. Gold is a better diversifier and risk reducer in financial turmoil times, while crude oil fulfills the same duty in the periods of non-financial crisis.

The rest of this paper is organized as follows. Section 2 discusses the econometric methodology used in this study. Section 3 describes the data used and some preliminary analysis. Section 4 reports and discusses the empirical results. Section 5 summarizes and concludes the paper.

2. Methodology

The spillover index developed by Diebold and Yilmaz (2012) paves the way for examining the total and directional spillovers in returns or return volatilities between various assets and asset classes without considering the order of variables. The index depends on forecast error variance decompositions (FEVDs) from vector autoregression models (VARs). Such analyzes can be implemented either between the assets in the same market and/or between different markets. In particular, researchers have been interested in the risk spillovers across various assets after they have witnessed the spread from credit market crunch to other asset classes worldwide during the 2008 GFC. In this analysis, we use the DY index developed by Diebold and Yilmaz (2012) to examine the total and directional spillovers of returns or volatilities among S&P 500 index, crude oil and gold market.

The stationary VAR(p) process can be written as,

$$y_t = c + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \dots + \Phi_p y_{t-p} + u_t \quad (1)$$

where y_t is the $K \times 1$ vector of endogenous variables, Φ_i are $(K \times K)$ coefficient matrices, c is $(K \times 1)$ vector of constants, u_t is zero mean white noise (innovation) $K \times 1$ vector process assumed to be uncorrelated with covariance matrix Σ , and p is the lag order of the VAR model. The generalized forecast-error variance decompositions proposed by Koop et al. (1996) and Pesaran and Shin (1998), hereafter KPPS, can be calculated using the moving average (MA) representation (see Lutkepohl (2005)) as follows;

$$y_t = \mu + (I - \Phi_1 L^1 - \Phi_2 L^2 - \dots - \Phi_p L^p)^{-1} u_t = \sum_{i=0}^{\infty} \Psi_i u_{t-i} \quad (2)$$

where $\Phi(L) = I - \Phi_1 L - \Phi_2 L^2 - \dots - \Phi_p L^p$ is a lag polynomial with $(K \times K)$ coefficient matrices Φ_i , and L is the lag operator. To sum up, we generate the total, directional, and net spillovers from the generalized forecast-error variance decompositions which are obtained using the MA representation in Eq. 2 in this study. H -step ahead generalized forecast-error variance decomposition can be computed as;

$$\theta_{ij}^{\delta}(H) = \frac{r_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Psi_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Psi_h \Sigma \Psi_h' e_i)^2} \quad (3)$$

where r_{jj} is the standard deviation of u_t for the j -th equation, and e_i is the selection vector with one on the i^{th} element, and zero otherwise. Since the row sums of variance decomposition matrix are not unity under the generalized decomposition (i.e. $\sum_{j=1}^K \theta_{ij}^{\delta}(H) \neq 1$), we normalize each entry of the variance decomposition matrix with its row sum as follows:

$$\bar{\theta}_{ij}^{\delta}(H) = \frac{\theta_{ij}^{\delta}(H)}{\sum_{j=1}^K \theta_{ij}^{\delta}(H)} \quad (4)$$

In this way, we achieve $\sum_{j=1}^K \Theta_{ij}^\delta(H) = 1$ and $\sum_{i,j=1}^K \Theta_{ij}^\delta(H) = K$. The total spillover index can be defined by utilizing the volatility contributions from the KPPS variance decomposition as;

$$TS(H) = \frac{\sum_{i,j=1,i \neq j}^K \Theta_{ij}^\delta(H)}{\sum_{i,j=1}^K \Theta_{ij}^\delta(H)} \times 100 = \frac{\sum_{i,j=1,i \neq j}^K \Theta_{ij}^\delta(H)}{K} \times 100 \quad (5)$$

which measures the contribution of spillovers of return or volatility shocks across related assets to the total forecast error variance. In addition to this approach, it is also possible to determine the direction of return and volatility spillover index since the generalized variance decomposition matrix does not depend on the order of variables. Therefore, the directional spillovers received by variable i from all other variables j , $i \neq j$, and the directional spillovers transmitted from variable i to all other variables j , $i \neq j$, can be obtained respectively as:

$$DS_{i \leftarrow j}(H) = \frac{\sum_{j=1,j \neq i}^K \Theta_{ij}^\delta(H)}{\sum_{i,j=1}^K \Theta_{ij}^\delta(H)} \times 100 = \frac{\sum_{j=1,j \neq i}^K \Theta_{ij}^\delta(H)}{K} \times 100 \quad (6)$$

and

$$DS_{i \rightarrow j}(H) = \frac{\sum_{j=1,j \neq i}^K \Theta_{ji}^\delta(H)}{\sum_{i,j=1}^K \Theta_{ji}^\delta(H)} \times 100 = \frac{\sum_{j=1,j \neq i}^K \Theta_{ji}^\delta(H)}{K} \times 100 \quad (7)$$

As for obtaining the net spillover index, we just subtract the expressions obtained in Eq. 6 from Eq. 7,

$$NS_i(H) = DS_{i \rightarrow j}(H) - DS_{i \leftarrow j}(H) \quad (8)$$

and this provides us with clear evidence with regards to how much one asset contributes to the volatility in other assets. Lastly, we calculate the net pairwise spillover in order to obtain the contribution intensity between two assets, which is described as the distinction between the gross volatility shocks transmitted from asset i to asset j and those transmitted from asset j to asset i . This is a highly useful approximation to make meticulous inferences about the spillover based on variable pairs. This statement can be derived as follows,

$$\begin{aligned}
NPS_{ij}(H) &= \left(\frac{\bar{\theta}_{ji}^{\delta}(H)}{\sum_{i,m=1}^K \bar{\theta}_{im}^{\delta}(H)} - \frac{\bar{\theta}_{ij}^{\delta}(H)}{\sum_{j,m=1}^K \bar{\theta}_{jm}^{\delta}(H)} \right) \times 100 \\
&= \left(\frac{\bar{\theta}_{ji}^{\delta}(H) - \bar{\theta}_{ij}^{\delta}(H)}{K} \right) \times 100
\end{aligned} \tag{9}$$

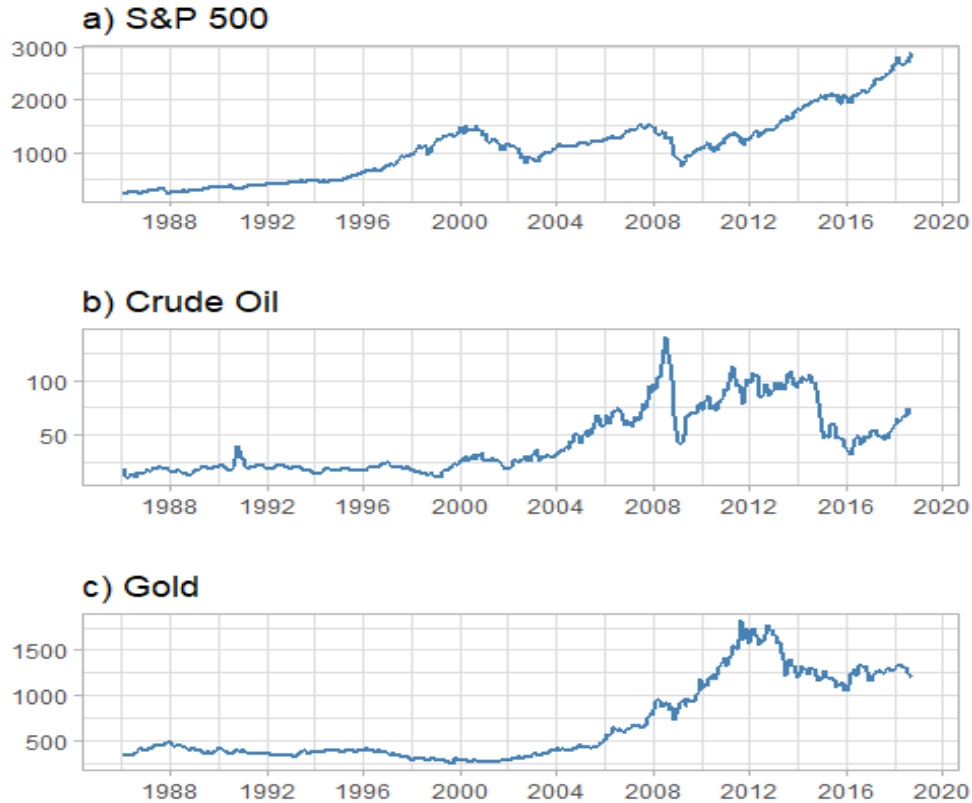
3. Data and preliminary analysis

This paper employs the return and volatility spillovers among three key assets (i.e. S&P 500, crude oil and gold) using the forecast error variance decompositions on 10-step ahead forecast. We use monthly and daily data to calculate the return series and the volatility series, respectively. The monthly data covers the period from January 1986 to August 2018, while the daily data starts from the first day of January 1986 and ends on the last day of August 2018. The gold spot price is given in U.S. dollars per ounce of Troy of bullion. The West Texas Intermediate (WTI) is used for crude oil spot price. The most frequently traded and therefore important benchmark is WTI for the US. Both gold and WTI spot price are expressed in US dollars.

Figure 1 illustrates the evolution of monthly data over the sample period. As seen in Fig. 1, while the dynamics of oil and gold price shows a similar pattern, the path followed by S&P 500 index is different from that of this pair. The Panel (a) of Figure 1 shows that the S&P 500 index increased substantially from the beginning of the analysis period to the 2000s and reached a peak before the downward trend up to 2003. Then, it started to rise from approximately 800 at the end of 2002 to almost 1500 until the 2008 GFC, before falling a little bit below the level of 2003 again. As regards the final section of the graph, it is seen that the S&P 500 index has fluctuated around a steadily increasing curve until August 2018. From a general perspective about the S&P 500 series, we can see two business cycle periods, which lasted approximately for 6 years extending from 1997 to 2009. The oil price, which remained stable up to the late 1990s, increased exponentially until mid-2008 and peaked at \$140 in its history as illustrated in Panel (b) of Figure 1. It decreased suddenly from the peak value to \$40 in nearly 6 months, before fluctuating drastically in its upward trend until the mid-2014. Furthermore, from mid-2014 to mid-2016,

crude oil price fell suddenly once more from \$105 to \$33 after starting to rise along a smooth path. The Panel (c) of Figure 1 also depicts the overall picture of gold price, which flattened out over a long period (from 1986 to 2005) before the strong upward trend until a record high of around \$1850 in the late 2011. Then, the price of gold, which fell dramatically until the end of 2015, has continued to fluctuate around \$1200 after that time.

Figure 1. Time-variations of S&P 500, Oil and Gold



We calculate the monthly returns for these three assets by taking the ratio of the two consecutive prices and then multiplying by 100:

$$r_{i,t} = \log(P_{i,t}/P_{i,t-1}) * 100$$

where $r_{i,t}$ denotes the percentage log returns and $P_{i,t}$ is the price level of the considered asset i at time t . On the other hand, in order to calculate S&P 500, crude oil and gold monthly volatility series, we use daily data. This enables us to compute the realized volatility, which was introduced

by Barndorff-Nielsen and Sheppard (2002). There are three steps to calculate the realized volatility: *i-*) The log returns of daily frequency data are calculated: $r_t = \log(P_t) - \log(P_{t-1})$, *ii-*) To calculate the realized variance, we take the sum over the past T squared return: $RVar_t = \sum_{i=1}^T r_t^2$ and *iii-*) Finally, the realized volatility is obtained simply by taking the square root of the realized variance: $RVol_t = \sqrt{RVar_t}$.

Table 1 presents the summary statistics for the return series. The return of S&P 500 has the highest positive mean followed by gold, whereas the return of oil has the lowest mean. With regards to risk evaluation, the standard deviation of oil return is higher than the standard deviation of S&P 500 and gold with approximately the same value. Accordingly, the average returns of the assets are listed from highest to lowest as: S&P 500, oil and gold. Furthermore, all returns have negative skewness, meaning a long left tail, indicating a greater chance of negative return outcomes. From this perspective, if one desired to invest in S&P 500 index among these three assets, he would be likely to face extreme risks. While skewness refers to the asymmetry of the tails, Kurtosis refers to the tails as a whole. As seen in the table, the Kurtosis values of the related returns are greater than 3, which means that the probability of extreme return of all assets is very high. The likelihood of this situation is the highest in the S&P 500 index, followed by crude oil and gold.

Table 1. Statistical properties of the return series

	S&P 500	Oil	Gold
Mean	0.57	-0.13	0.22
Median	1.12	0.74	0.13
Maximum	11.64	30.57	15.23
Minimum	-27.82	-47.87	-20.46
Std. Deviation	4.42	9.73	4.34
Skewness	-1.42	-0.69	-0.23
Kurtosis	8.61	5.62	4.50

Table 2 reports three kinds of unit root test statistics for both the return and volatility series. We evaluate whether these series have unit root or not in a robust manner with the help of the augmented Dickey–Fuller (ADF) test (Dickey and Fuller, 1979), the Phillips–Perron (PP) test (Phillips and Perron, 1988), and the KPSS stationarity test introduced by Kwiatkowski et al. (1992). Panel (a) of Table 2 points to the unit root test results of the return series, while Panel (b)

of Table 2 illustrates the unit root test results of the volatility series. The ADF and PP test results in Panel (a) and Panel (b) of Table 2 indicate that both the return and volatility of S&P 500, oil and gold series reject the null hypothesis of a unit root at 1% level of significance. In other words, the return and volatility series are stationary according to the ADF and PP test statistics. In contrast to the ADF and PP, stationarity is the null hypothesis for the KPSS test as well. The results of the KPSS statistics of return and volatility series are reported at the bottom of Panel (a) and Panel (b). The KPSS statistics does not reject the I(0) hypothesis for all return even at 10% level of significance, except for the gold volatility, which is not rejected at 1% level of significance. Hence, the combined results from ADF, PP and KPSS suggest that both return and volatility series under consideration are stationary.

Table 2. Unit root tests for S&P 500, oil and gold series

	S&P 500	Oil	Gold
<i>Panel A: Various unit-root tests for return series</i>			
ADF	-18.64 ^{***}	-17.68 ^{***}	-21.44 ^{***}
PP	-18.63 ^{***}	-17.77 ^{***}	-21.45 ^{***}
KPSS	0.12	0.05	0.25
<i>Panel B: Various unit-root tests for volatility series</i>			
ADF	-4.62 ^{***}	-6.51 ^{***}	-4.41 ^{***}
PP	-10.15 ^{***}	-10.79 ^{***}	-10.86 ^{***}
KPSS	0.12	0.09	0.69 ^{**}

Notes: *, **, and *** indicates the rejection of the null hypothesis of unit root (ADF and PP tests) and of stationarity (KPSS test) at the 10%, 5%, and 1% level of significance, respectively; the lag length is chosen as 8 by AIC (Akaike Information Criterion) and a constant is included in the test equation for the ADF test; 1%, 5%, and 10% critical values are -3.44, -2.86 and -2.57 and equal according to the ADF and PP tests, respectively; 1%, 5%, and 10% critical values are equal to 0.74, 0.46 and 0.34 according to the KPSS test, respectively.

4. Empirical Results

4.1. Total spillover index

We follow the generalized FEVD framework of Diebold and Yilmaz (2012) to obtain the total, directional, and net (pairwise) spillovers. The optimal lag length is selected as 2 by the Akaike Information Criteria for the VAR models of both the return and volatility series. Table 3 reports the estimation of full sample return and volatility spillover indices and its decompositions as transmitters and receivers among S&P500, oil and gold. We also calculate the net directional

spillover from these transmitters and receivers for each variable. The variable in the row stands for the contributors of spillover to other variables and own-variable, while the variable in the column represents the receiver of spillover from other variables and own-variable. Therefore, the so-called '*to others*' in the column of the table shows the spillover effect from one asset *to other* assets. Similarly, the values in the column called '*from others*' in the row of the table indicate the spillover effect *from other* assets. With the exception of the own-variable spillovers of returns, the sum of the values in the rows and the columns indicates the total spillovers to (received by) and from (transmitted by) each variable. In addition to this, the net spillover effect is calculated to subtract 'to others' from 'from others'. This estimation is important to determine whether an asset is the net transmitter or the net receiver in the market. Lastly, the total spillover effect is calculated by dividing the sum of row named as 'to others' or the sum of column named as 'from others' by the number of variables as illustrated in the lower right corner.

As displayed in Panel (a) of Table 3, the total return spillover is 6% among S&P 500, oil and gold, which means that 6% of the return forecast error variance decomposition (FEVD) is obtained from other assets on average. With regards to the bidirectional return spillover across these assets, we can easily see that the crude oil is the largest contributor to the FEVD of the other assets with 8.3%, followed by gold and S&P 500 with 5.57% and 4.12%, respectively. This ranking does not change in terms of receiver with a similar magnitude as well. The S&P 500 index spills 3.38% to oil market and 0.73% to gold market. In addition to this, the oil market contributes 5.22% to gold market and 3.08% to S&P 500. Finally, the return transmissions from gold market to oil and S&P 500 are 4.62% and 0.95%, respectively. Overall, the spillover effect between S&P 500 and gold market is weak, which means that there exists a lower pass-through between them. As for the net directional return spillovers, S&P 500 and oil market are also the net transmitters, with the contribution standing at 0.09% and 0.30%. The gold market, however, contributes to the FEVD of other variables less than it receives from other variables. The findings obtained in the full sample return spillover analysis confirm that gold is a safe haven because return spillover from other markets to gold is small, although there is net return transmission to the gold market the effect is quite small.

As regards the empirical findings of volatility spillover, Panel (b) of Table 3 reports the full sample volatility spillover index for the related three assets as well. The total volatility spillover index is 20.62% and it is more than threefold of return spillover index. Furthermore, with respect to the bi-directional volatility spillover, the S&P 500 index spills 13.02% to oil market and 12.97% to gold market, unlike the findings of return spillover. Moreover, the volatility spillover from oil to other assets has nearly the same intensity (i.e. 6.42% to S&P500 and %4.82 to gold market); however, it is larger than the bi-directional return spillover from oil to other assets. The volatility transmissions from gold market to oil and S&P 500 are 11.07% and 13.57%, respectively. These findings show that unlike the return spillover from gold market to S&P 500, the volatility spillover is much greater. Lastly, the S&P 500 and the gold are the net transmitters of volatility to other markets, whereas the oil market is the net receiver of volatility from other markets. Overall, we can say that the spillover results in Panel (b) of Table 3 are noticeably greater than the results of return spillovers in Panel (a) of Table 3. Also, while the S&P 500 remains as the net transmitter of spillover in both return and volatility analysis, the positions of oil and gold are reversed with regards to receiving or transmitting spillover in the relevant market. In terms of risk spillover, we can conclude that on average gold is a safe haven for portfolio investors during the entire observation period, because the volatility spillover to gold market is relatively small and it is a net volatility transmitter rather than a receiver.

Table 3. The Spillover Table of S&P500, Oil and Gold Return

To (i)	From (j)			From others
	S&P 500	Oil	Gold	
<i>Panel A: Return spillovers</i>				
S&P 500	95.97	3.08	0.95	4.03
Oil	3.38	92.00	4.62	8.00
Gold	0.73	5.22	94.04	5.96
To others	4.12	8.30	5.57	17.99
Directional including own	100.09	100.30	99.61	Spillover index
NET spillovers	0.09	0.30	-0.39	6.00%
<i>Panel B: Volatility spillovers</i>				
S&P 500	80.01	6.42	13.57	19.99
Oil	13.02	75.90	11.07	24.10
Gold	12.97	4.82	82.22	17.78
To others	25.99	11.24	24.64	61.87
Directional including own	106.00	87.14	106.85	Spillover index
NET spillovers	6.00	-12.86	6.85	20.62%

Notes: The underlying variance decompositions are achieved with the VAR model with two and four lags for return spillover and volatility spillover, respectively. They are both dictated by the Akaike Information Criterion and identified using a generalized VAR spillover framework by Diebold and Yilmaz (2012). Spillover indices, derived in Eqns. (3)– (9), are calculated from variance decompositions based on 10-step-ahead forecasts, and the $(i, j)^{\text{th}}$ element of the table displays the estimated contribution to the variance forecast error of asset i resulting from the innovations to asset j .

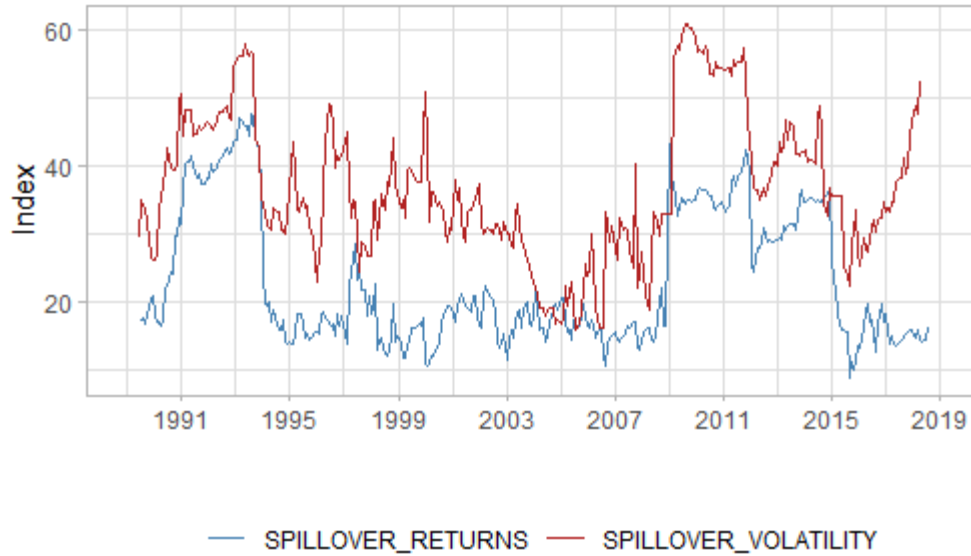
4.2. Rolling-sample spillover analysis

We make an assumption in the previous full sample VAR analysis that the return and volatility spillover coefficients are constant and they do not change over time. Nevertheless, these strong postulates may create erroneous results when the rise-fall cycle and regime shifts in financial markets are considered. For example, one should expect to observe the risk spillovers varying over time especially in the period of regime switching such as economic crises, financial regulations etc. In fact, with the impact of globalization and technological innovations in financial markets, the pass-through effect among assets accelerates in time. To address this issue, we estimate the VAR model using 40-month rolling windows¹, and evaluate the total time varying dynamics of return and volatility spillover indices and its decompositions among S&P 500, oil market and gold market. Figure 2 reports the total return and volatility spillovers of S&P500, crude oil and gold market. The overall picture indicates two similar prominent time intervals in which the total return spillovers are high: 1990-1994 and 2009-2015. These periods correspond to the volatile times of oil price. In the early 1990s, especially the monetary tightening of the developed countries for fear of high inflation and the jumping oil prices due to invasion of Iraq by the US led to the loss of consumer and business confidence. Therefore, as seen in Figure 2, the total return and volatility spillover indices began to rise steeply in the beginning of 1990 and peaked in mid-1993, before the sudden decline in 1994. These kinds of total spillover indices move together in this time interval because the Iraqi invasion of Kuwait in 1990 caused a surge in oil price, which reduced the real sector activities. By the end of 1990, oil price spike deteriorated economic picture and caused slow output growth and deepened recession for most industrial economies. The volatility spillover index remained high in the 1990s, when many financial crises such as 1994 Mexico peso crises, 1997 Asian financial crisis and 1998 Russian financial crisis were experienced. The return and volatility total spillover indices surged

¹ For robustness check, we re-examine the VAR model both in 60-month and 75-month rolling windows (available on request from the authors) while holding the forecast horizon constant at 10 months. We do not observe noticeable differences among these time-varying analyses results.

until the 2008 GFC and then soared up due to the abrupt movements in oil prices. After the large fluctuations in 2012, the total spillover index slumped again in 2015. In parallel with the finding regarding 1990 oil crises, the total return and volatility spillover indices moved together shortly after the start of the 2007-2008 GFC. As seen in Figure 2, the volatility spillover index started to fluctuate after 2005 while the return spillover remained flat until the beginning of 2009. This clear evidence shows that 2008 GFC spilled over from financial sector to real sector in the US economy. Then, the total spillover headed toward its pre-crisis levels, proposing once more some diversification benefits for these assets. As regards the comparison of return and volatility spillover indices, the volatility spillover index is higher than the return spillover index during almost all analysis period. The gap of these spillovers diverges and converges to each other in time. Interestingly, this gap has widened unprecedentedly from 2015 to the present. The rapid upward movement of total volatility spillover index after 2015 can be considered due to the turbulences especially in developing countries such as Chinese stock market crash, Brazilian economic crisis, Venezuela's economic crisis, and recent Turkish currency and debt crisis. It is hard to say that the global financial turmoil ended after 2008 GFC. Also, it is evidenced from Figure 2 that the investors should review their portfolio according to the return spillover findings, while it is not valid for the volatility spillover results after 2015.

Figure 2 Total Return and Volatility Spillover indices of S&P500, Oil and Gold



Directional return spillovers

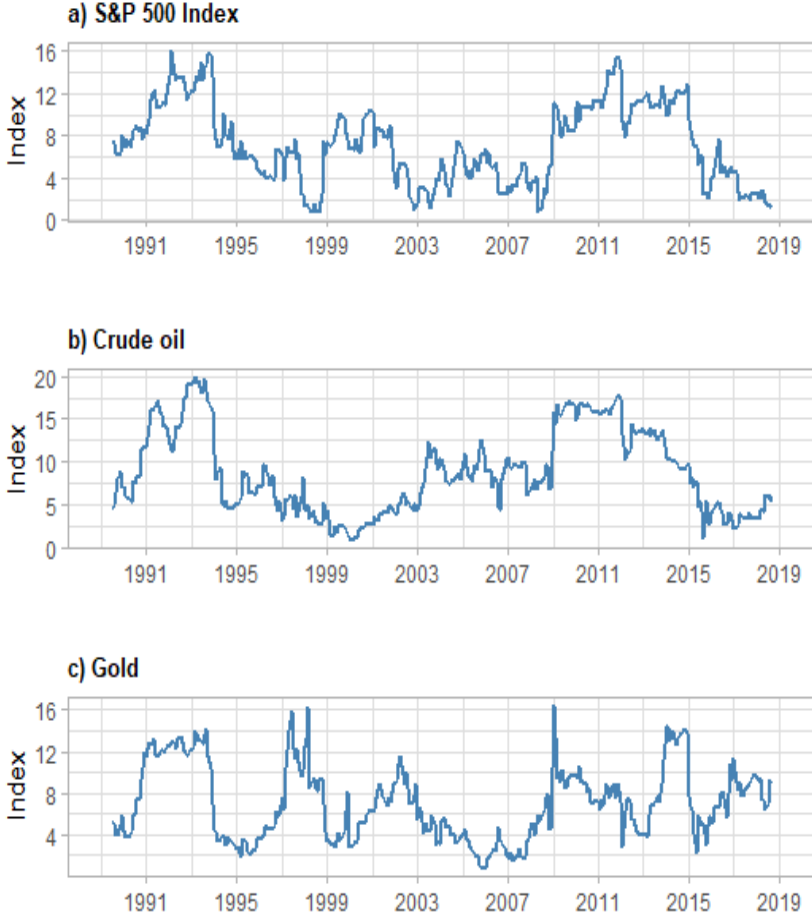
To investigate the dynamic behavior of return spillovers based on each asset, we now obtain return spillover index received by market i from other markets j , termed directionally as ‘from’ and calculated in Eq. 6. In a similar fashion, we also get the directional spillover index transmitted by market i to all other markets j , termed directionally as ‘to’ and calculated in Eq. 7 with the rolling estimation method. We can evaluate these directional return and volatility spillover indices as the decomposition of total spillover index as well. As illustrated in Panel A-a of Figure 3 and Figure 4, the directional spillovers from S&P 500 to other assets and *vice versa* fluctuated around 5% in 1994-2000 and 2015-2018 in parallel with the result of total return spillover index. However, it increased nearly to 16% in volatile times, i.e. 1990-1994 and 2009-2012 and 2012-2015. As regards the directional spillovers from other assets *to* crude oil, we see the same pattern for crude oil in Panel A-b of Figure 3. However, the findings differ with respect to the directional spillovers *from* crude oil to other assets in that they vary greatly from 1994 to 2009 as seen in Panel A-b of Figure 4. Looking at the directional spillovers transmitted *to* others, gold has large fluctuations throughout the entire period as depicted in Panel A-c of Figure 3. The Panel A-c of Figure 4 shows the directional spillovers *from* gold to other assets and the

directional index seems to have stabilized around 6% throughout the entire period except the high volatile times from 1990 to 1994.

The panels on the right in Figure 3 and Figure 4 plot the time-varying directional volatility spillovers *to* and *from* S&P 500, oil and gold. Similar to the directional return spillovers, we observe a significant variation in the rolling estimation of directional volatility spillovers. The volatility spillover from other assets *to* S&P 500 has increased gradually from the beginning of the late 1980s to 2018. Especially in the last few years, the sharp increase of volatility spillover from other assets *to* S&P 500 is noteworthy. That is to say, S&P 500 index investors should pay more attention to the sudden price changes in both oil and gold markets in recent years compared to the past. On the other hand, the volatility spillover *from* S&P 500 to other assets shows a tremendous fluctuation over the analysis period as illustrated in Panel B-a of Figure 4. It actually has a business cycle character with different frequencies. In a similar vein, the volatility spillover from other assets *to* oil market oscillates between 5% and 30% during the entire analysis period. It actually has a business cycle character with extending and shortening frequency. The volatility spillover *from* oil market to other assets is plotted in Panel B-b of Figure 4. After reaching a peak in the U.S. recession of 1990, volatility spillover *from* oil market to other assets continued to go down for a long time, went up again in 2009, and then dropped until 2015. Similar to the volatility spillover from other assets *to* S&P 500, the volatility spillover *from* crude oil to other assets has displayed an extraordinary escalation after mid-2015. The Panel B-c of Figure 3 and Figure 4 depicts the volatility spillovers from other assets *to* gold and vice versa. The volatility spillover from other asset *to* gold have shown similar dynamics with the volatility spillover from crude oil to other markets as mentioned above. The volatility spillover *from* gold to other markets has moved up and down within a wide range during the whole period as well.

Figure 3 Directional Spillovers TO Three Assets

Panel A: RETURN



PANEL B: VOLATILITY

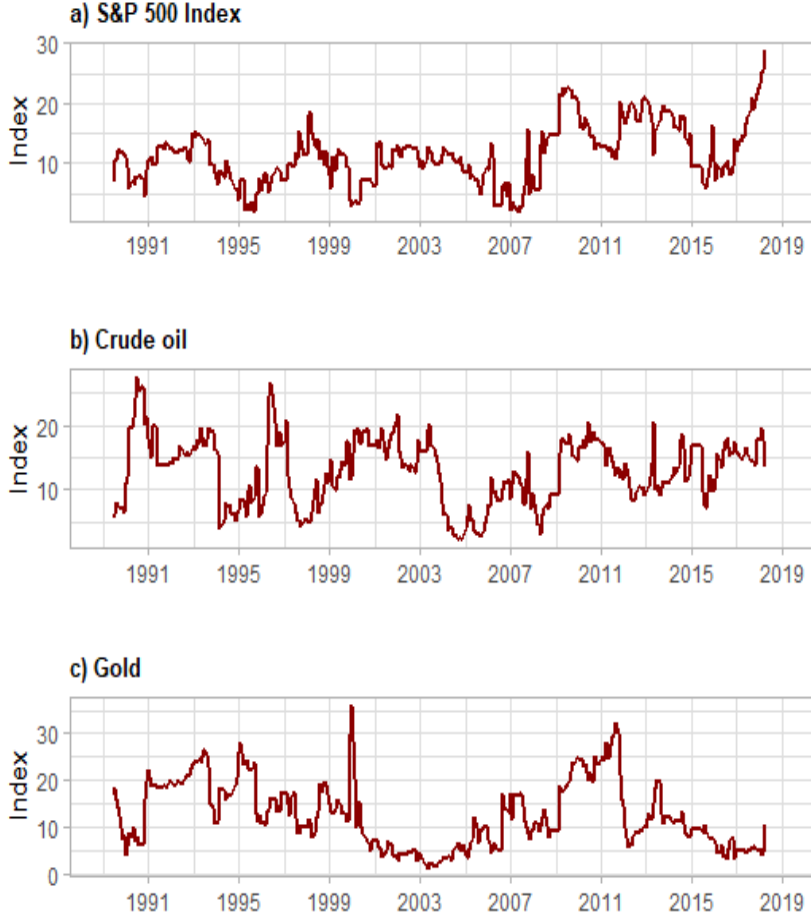
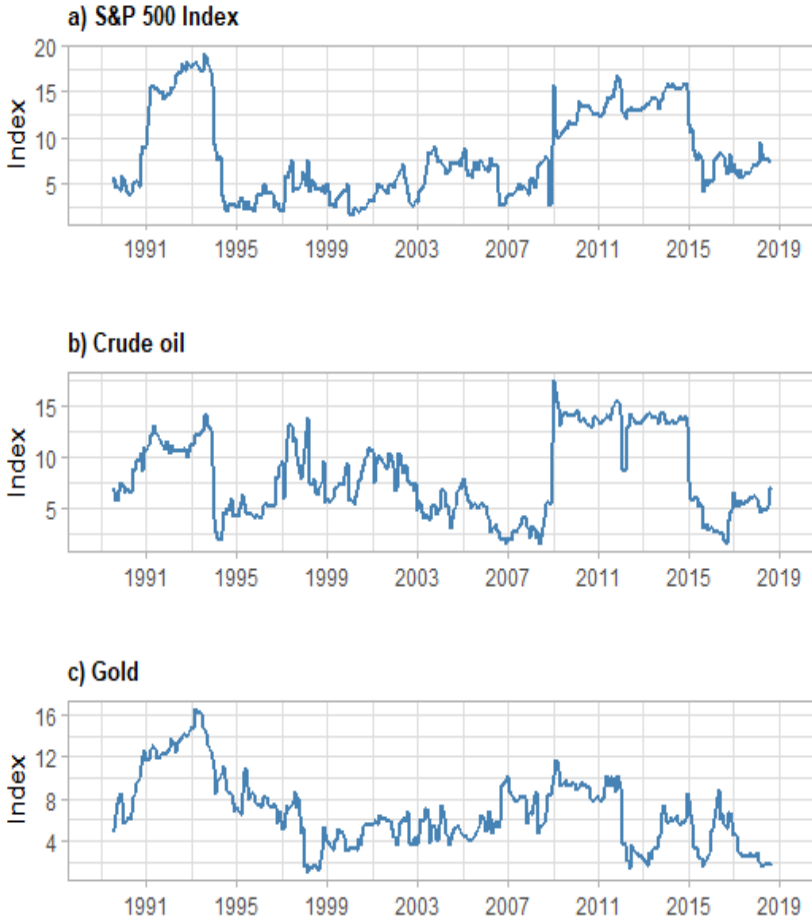
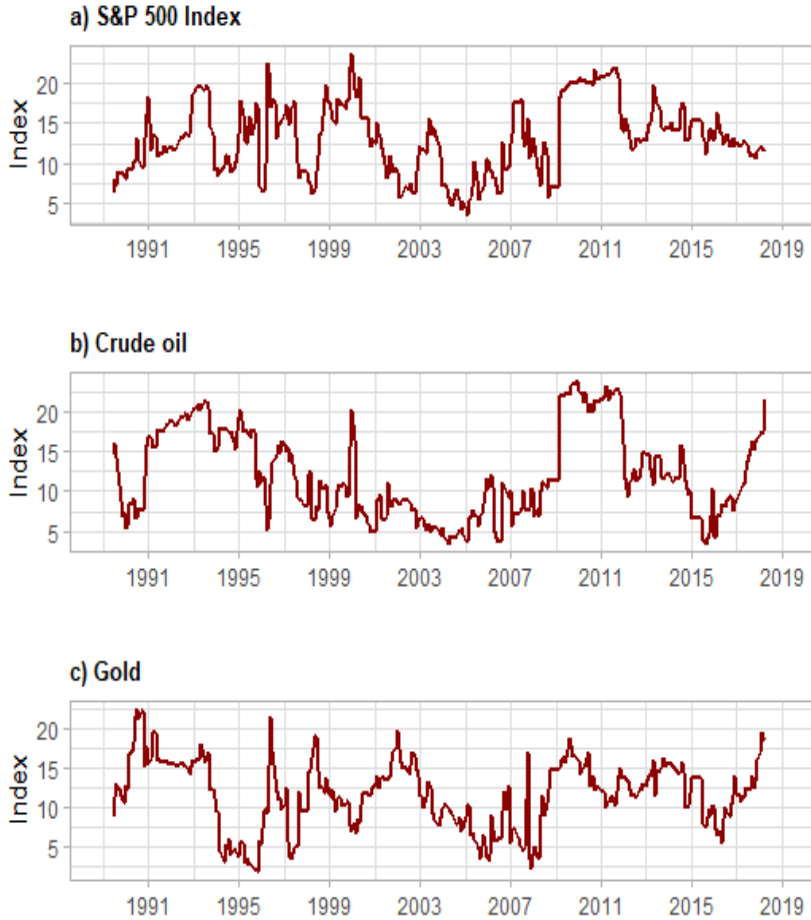


Figure 4 Directional Spillovers FROM Three Assets

Panel A: RETURN



PANEL B: VOLATILITY



Net spillovers and net pairwise spillovers

One may also be interested in determining the net receivers and net contributors to the spillovers between the markets. However the results are limited by the variables in the VAR model, only when all relevant variables included we can determine the sources of the return and volatility spillover completely for each asset. To reach this goal, we calculate the dynamic net volatility spillover index by subtracting directional ‘to’ spillovers from directional ‘from’ spillovers. While the positive green and cyan shaded area presents the source of return spillover to other assets, the negative shaded areas indicated by red and brown specify the recipient of the return from other assets as shown in Figure 5 and Figure 6.

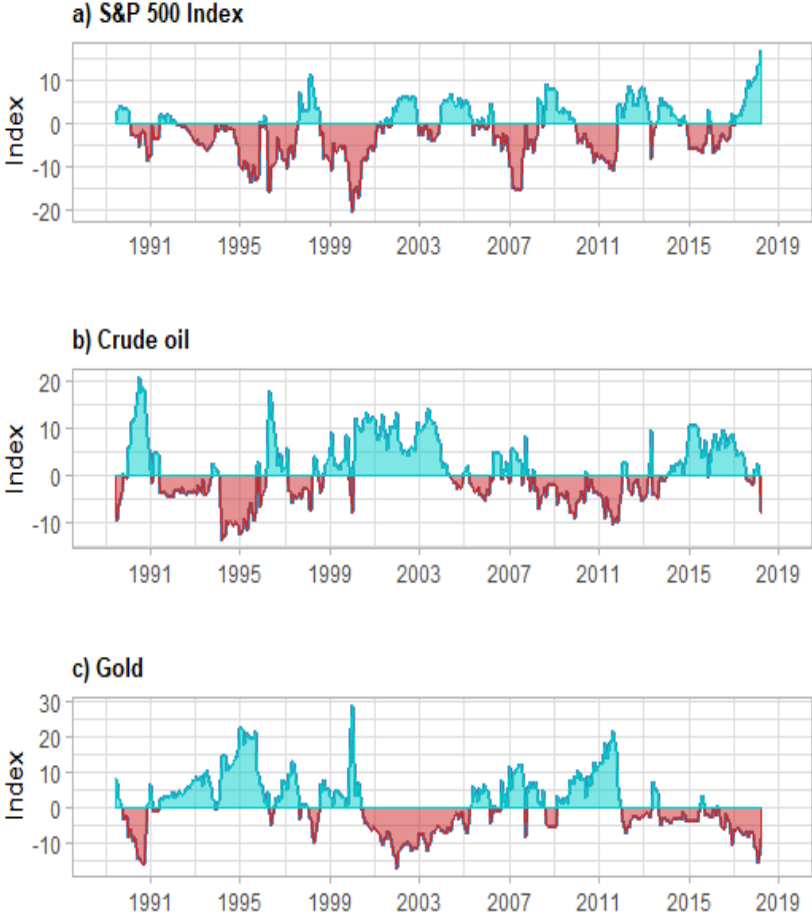
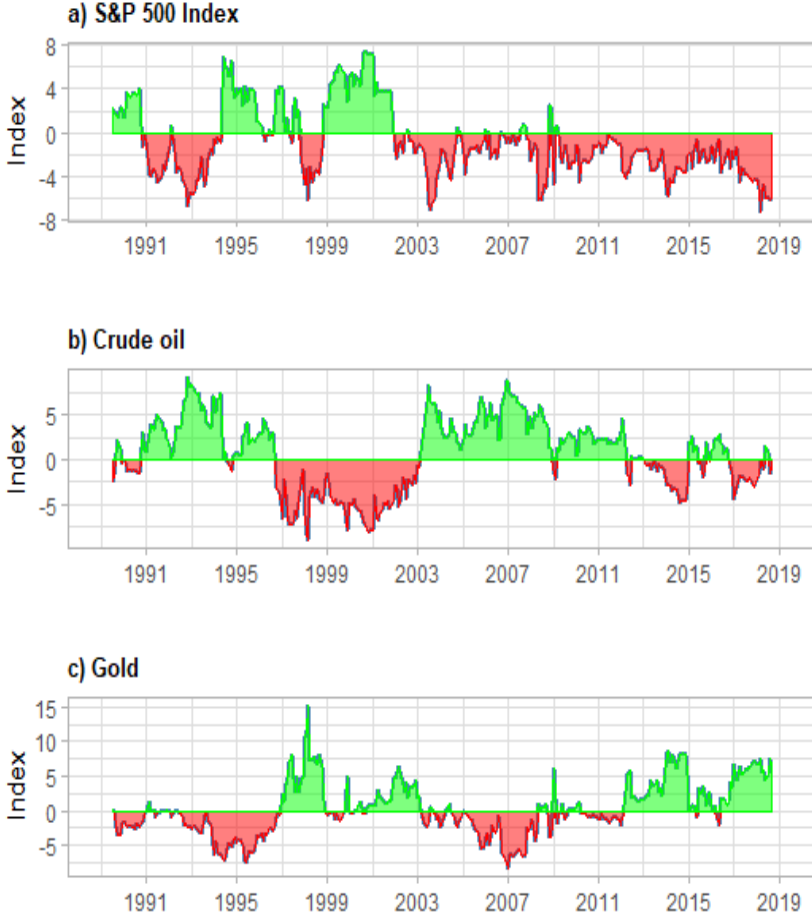
The left-hand panel of Figure 5 depicts the time-varying evolution of the net return spillover indices, whereas the net volatility spillover indices are illustrated in the right panel of Figure 5 for each asset. As shown in the figure, the S&P 500 index is a source of return spillovers for the late 1980s, 1994-1998, 1999-2002 sub-periods, while it is the recipient of risk spillovers from other assets during the 1990-1994, 1998-1999 and 2002-2018 sub-periods. This finding gives us a very interesting clue about the financialization of commodities, indicating clearly that commodity financialization has decreased the effectiveness of adding leading commodity assets to S&P 500 as of 2002. Strikingly, the intensity of being the net receiver of S&P 500 from commodity markets has increased gradually also as of 2002. As regards the relationship between crude oil and gold market, we can easily observe that the mechanisms of these assets work opposite to each other. In other words, gold is the net transmitter of return and volatility spillover during the period while oil is the receiver. For instance, gold is the net contributor of returns in 1997-2003 and 2012-2018 if we disregard a few minor exceptions in the figure. At the beginning of the analysis period, S&P 500 and gold are the net receivers of volatility spillover, while crude oil is the net transmitter. Loosely speaking, S&P 500 and oil market were the net receivers of volatility spillover from 1992 to 2001, whereas gold became the net transmitter of volatility to other assets from 1992 to 1998 with the exception of one year after 1996. From 1998 to 2004, it is evidenced that crude oil turned out to be the net transmitter of volatility, before becoming the net receiver up to 2014 and then again the net transmitter in the market. During almost all these periods, gold acted in opposite direction to crude oil. The volatility shocks in the crude oil market

during the Gulf War (2 August 1990 – 28 February 1991) and 2003 Iraq War increased and spilled over mostly to the gold market rather than the stock market. Furthermore, the same situation was experienced in the post-2014 period when wars and regional risks increased in the Middle East, which seriously affected oil supply. On the other hand, the volatility shocks in the gold market spilled over mainly to oil market in the periods of financial turbulence. Impressively, we evidence that the crude oil market and the gold market work opposite to each other regarding both return and volatility spillover in analysis period. This means that, gold offers better diversification benefits and risk reductions than oil in financially turbulent times, while crude oil fulfills this task in non-financial crises such as war. Lastly, the net volatility spillover of S&P 500 index has shown a business cycle character with 1-year frequency. All in all, we find strong evidence to support the time varying dynamics regarding the net return and volatility spillover for S&P 500, oil and gold in contrast to the full sample assumption of constant spillover over the sample period.

Figure 5 Net Spillovers of Three Assets

Panel A: RETURN

PANEL B: VOLATILITY



Note: Green and cyan indicate sources of spillover while red and brown indicate receivers of spillover.

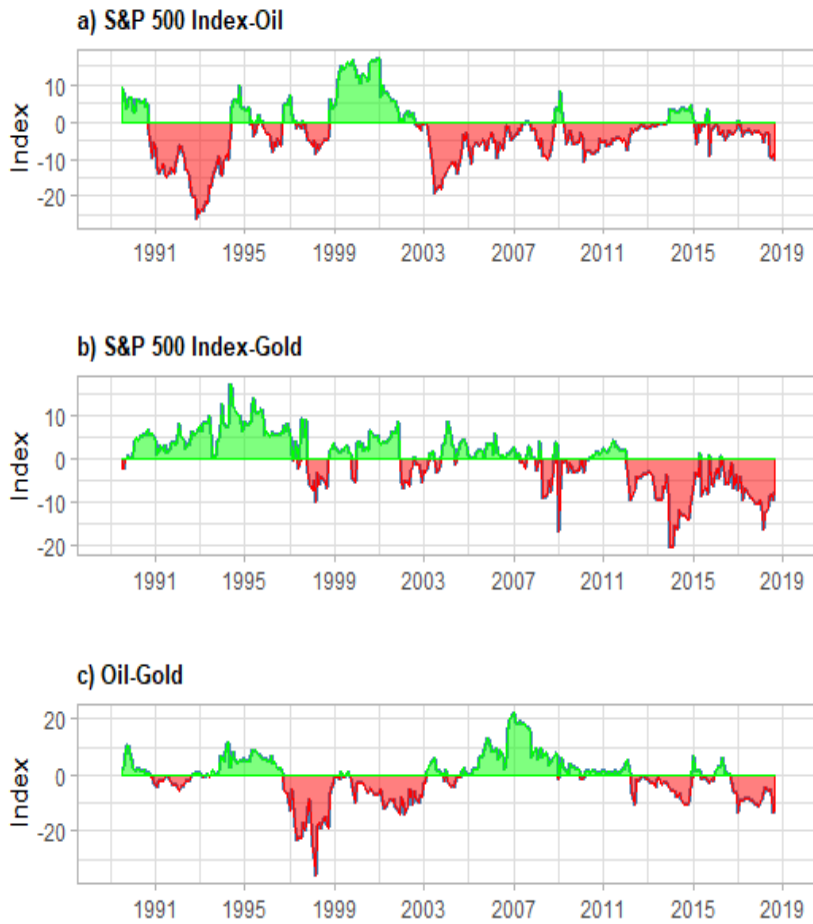
Figure 6 presents the net time-varying pairwise index to determine the net transmitter and recipient of return and volatility spillovers between two assets. As we have three variables in the VAR model, we get three different combinations as illustrated in the figure. As explained above, we also show the return and volatility pairwise spillovers in the left and right panels respectively. The return spillovers from S&P 500 to oil remained positive throughout several parts of the analysis period except for some sub-periods: the late 1980s, 1999-2002 and some minor sub-periods. When we compare Panel A-a of Figure 5 and Panel A-a of Figure 6, the time-varying spillovers among S&P 500 and other markets and the time-varying spillovers between S&P 500 and oil are similar to each other. Hence, we can conclude that crude oil plays a more dominant role than gold in S&P 500 index with the exception of 1994-1998 sub-periods. Until 2012, we detect a positive net return spillover effect from S&P 500 to gold except for some short-term period (as illustrated with the small area shaded by red) in Panel A-b of Figure 6, and then things changed dramatically after 2012 and risk spillover effect flows from gold market to S&P 500. Furthermore, looking at Panel A-c of Figure 6, one can see two major episodes of net pairwise spillover effects between oil and gold market. The net return spillover from crude oil to gold market is positive from the beginning of the analysis period to 1997, and 2003-2012, while the net spillover is reversed in other time periods with some exception periods. One of the remarkable points here is that S&P 500 received the return spillover from oil rather than gold between 2003 and 2012, but gold took crude oil's place as return spillover transmitter to S&P 500 after 2012.

As for the net pairwise volatility spillover findings illustrated in Panel B of Figure 6, the S&P 500 index loosely received the risk spillover from both the oil and gold markets between the late 1980s and early 2000s. Furthermore, regarding the rest of time, it is seen that the S&P 500 index is the net contributor to the gold market for the 2001-2005, 2008-2010, 2012-2018 sub-periods and to the oil market for the 2004-2006, 2008-2010, 2012-2013 and 2017-2018 sub-periods. As for the risk spillover between the gold and oil markets, it is evidenced that the volatility spillovers from the oil to gold market take a positive value for the 1990-1991, 2000-2004 and 2014-2018 sub-periods with variable amplitude. Similar to the net return spillover results illustrated above, we also find strong evidence to support the time-varying dynamics of net pairwise volatility spillover among asset pairs. Interestingly, after volatile time periods like the early 1990s, early

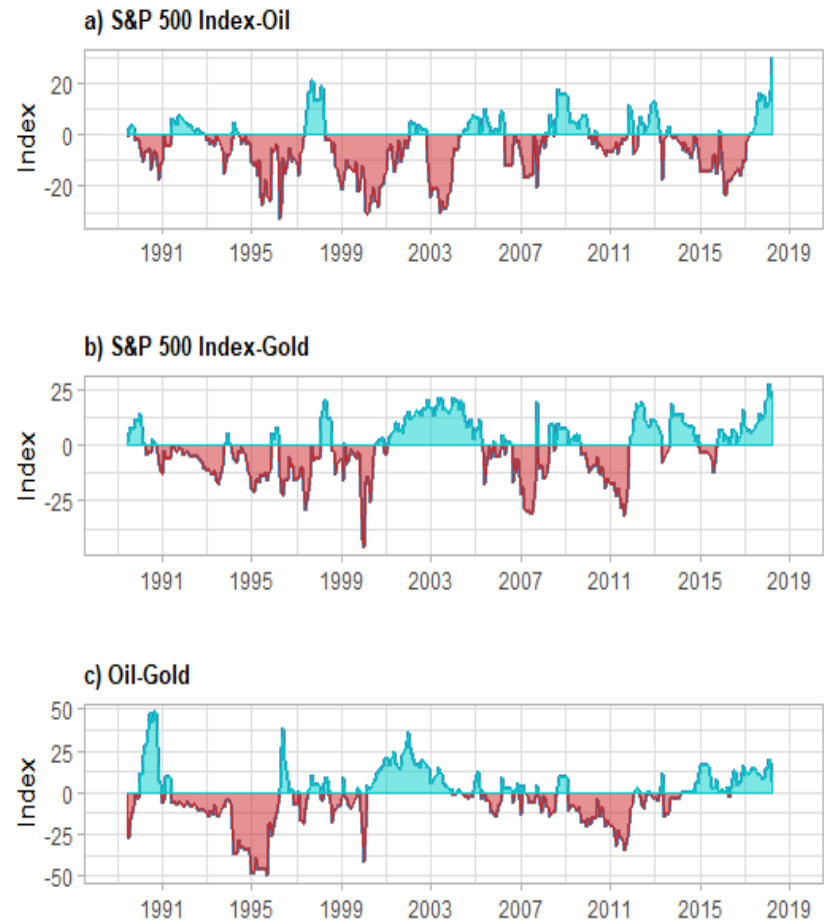
2000s and 2008 GFC, the S&P 500 index became the net volatility spillover recipient from both the oil and gold markets. In addition to these findings, the volatility spillover from both S&P 500 and oil to gold, which is considered to be the store of value, shows similar dynamics over the analysis period. Gold is not the recipient of volatility spillover from other assets during the financially unstable periods.

Figure 6 Net Pairwise Spillovers of Related Assets

Panel A: RETURN



PANEL B: VOLATILITY



Note: See note to Figure 5.

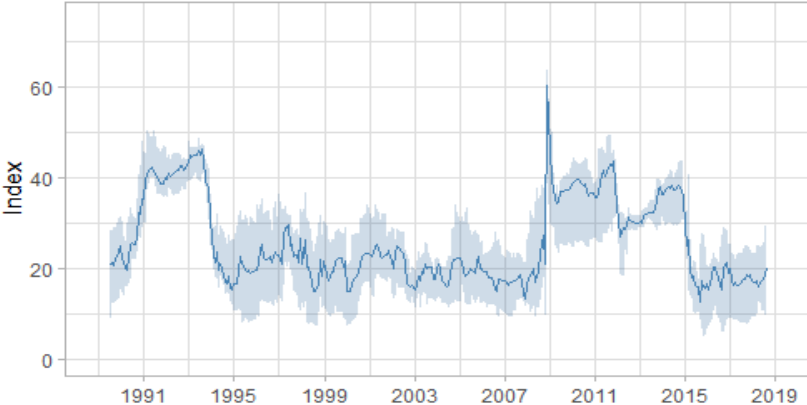
Robustness tests

We employ three different robustness tests to evaluate the sensitivity of our time-varying return spillover results. The first one uses alternative rolling windows as 60 months and 75 months, and we do not detect an important distinction among these time-varying analysis results. Secondly, we estimate the time-varying spillover index for VAR orders varying from 1 to 4 and plot the minimum, maximum and median values of the related estimations which are obtained in Figure 7. Finally, we allow the forecast horizon H to range from 2 to 10 months at 40 months rolling window VAR analysis. As seen in Figure 7, the dynamic total spillover plot is not sensitive to the choice of the order and the forecast horizon of the VAR model.

Figure 7 Sensitivity Analysis

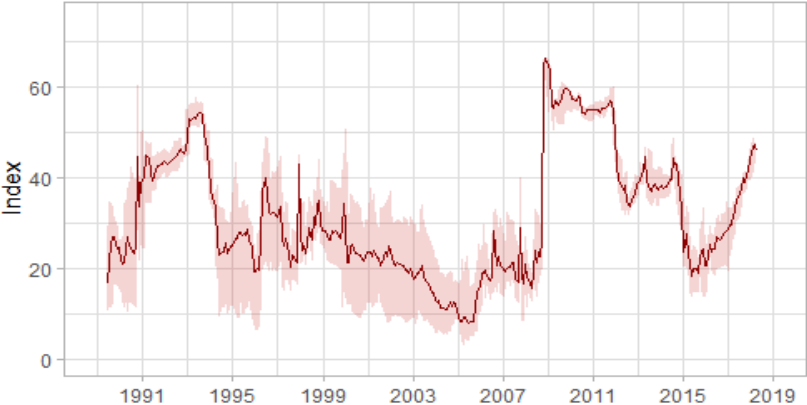
PANEL A: RETURN

A-1) Total return spillovers to VAR lag structure

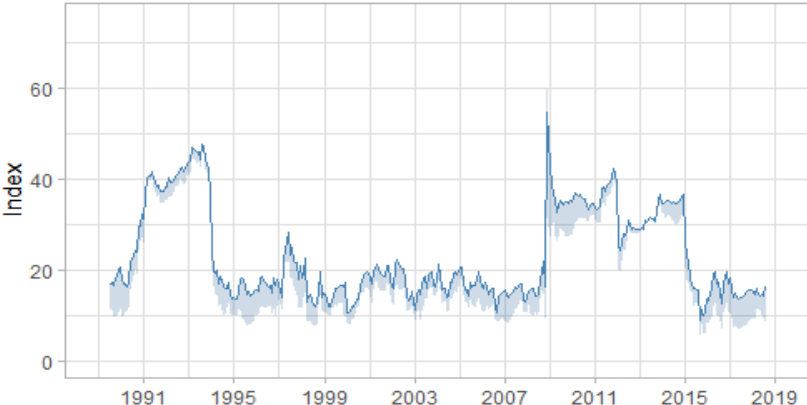


PANEL B: VOLATILITY

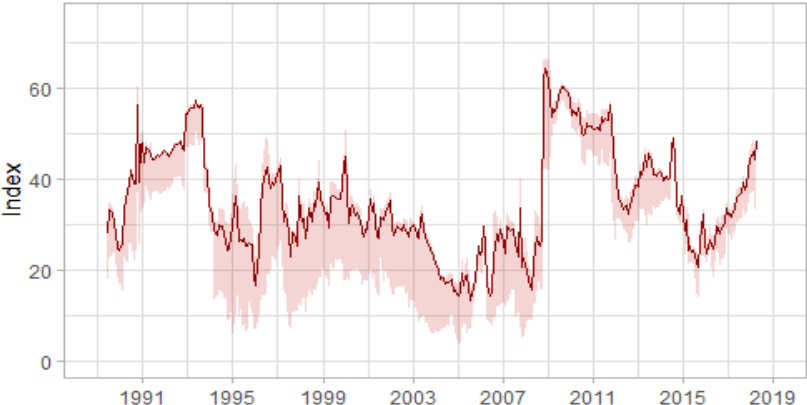
B-1) Total volatility spillovers to VAR lag structure



A-2) Total return spillovers to forecast horizon



B-2) Total volatility spillovers to forecast horizon



Conclusion

Having knowledge of transmission mechanisms between the returns and volatilities of financial and non-financial markets may be useful for portfolio managers, policy makers and speculative traders to develop exploitable trading strategies. It may also be beneficial to allocate assets in financial portfolio especially after financial integration. In this study, we investigate the dynamic links between the returns and the volatilities of S&P 500 index, crude oil and gold market utilizing the spillover index developed and extended by Diebold and Yilmaz (2009, 2012) based on the forecast error variance decomposition analysis. We estimate both the return and volatility spillover transmission among the related assets over the period from January 1986 to August 2018. The full sample VAR analysis shows that S&P 500 index and crude oil are the net transmitters, whereas gold is the net receiver of returns spillovers. On the other hand, the role of the S&P 500 remains unchanged, but gold becomes the net transmitter, while crude oil is the net receiver with respect to volatility spillover outcomes. As a result of the volatility (risk) spillover analysis, we see gold as a safe haven asset. The S&P 500 index and crude oil are the net transmitters, whereas gold is the net receiver of returns spillovers. Interestingly, the opposite positions of gold and crude oil as the transmitter and receiver are also valid in time varying return and volatility estimation during almost the entire period. Oil is the largest contributor (receiver) of return (volatility) spillovers among these three assets. Therefore, the analysis is performed both as return and volatility spillover, which makes it possible to have a more comprehensive view of the financial situation. According to the return spillover results, there is a stronger bilateral relationship between oil and gold, while we see this stronger link between S&P 500 and gold market with respect to volatility spillovers.

In general perspective, the total spillover has remained very high during the 1990-1994 and 2009-2015 sub-periods despite the noteworthy fluctuations in other periods. From 1994 to 2000s, the total volatility spillovers remain high unlike return spillover effects due to the financial crises that occurred in other countries. While crude oil is the net volatility transmitter in times of non-financial crises, such as war, the gold takes crude oil's place in the period of financial turmoil. Gold has partially fulfilled its duty as an instrument of value store in the financial economic crisis such as 1994 Mexico peso crises, 1997 Asian financial crisis, 1998 Russian

financial crisis, 2000 technology crisis, and 2008 GFC and aftermath. Nevertheless, it has completely lost its store of value capability during the non-financial crises period such as war. Also, the rolling return spillover estimation shows that the financialization of commodity started to mitigate the efficiency of adding oil and gold to S&P 500 basket as of 2002. Last but not least, our empirical findings are endorsed by some robustness tests in which VAR lag length, forecast horizon, and rolling time span are altered within the predetermined range.

There are several methods of modeling nonlinear relations among economic and financial variables in economics. The prominent models of parametric nonlinear VAR models are the vector threshold autoregressive, the vector smooth transition autoregressive, and the vector Markov-switching autoregressive model. In the future, it will be interesting to extend this work using these nonlinear models with different interrelated assets in local or international markets.

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