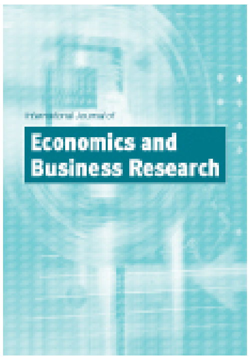

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Asymmetric volatility spillovers between Bitcoin, oil and precious metals

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Abstract: This paper examines the asymmetric spillovers between Bitcoin, oil and four precious metals (silver, gold, platinum and palladium) on daily returns from 18 August 2011 to 2 October 2019. Using a modified version of the Dieblod and Yilmaz (2012, 2014) index and a similar approach to Baruník (2017), our results indicate slight volatility spillovers between the whole systems. Moreover, the results show that gold is the most influential market since it shifts the highest proportion of volatility. Furthermore, we find that oil, Bitcoin and platinum can serve as a hedge and a diversifier as they are neutral in terms of spillovers. Moreover, we find evidence of asymmetric volatility spillovers since good spillovers dominate bad one, which proves the optimistic mood of the whole system. More interestingly, our results shed light on the ability of Bitcoin, the digital gold, to serve as a hedge and diversifier in both good and bad innovations.

Keywords: volatility spillovers; asymmetric volatility; spillovers; Bitcoin; oil; precious metals; good innovations; bad innovations.

JEL codes: C58, D53, F37, G15.

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1 Introduction

The acceleration of international financial integration and liberalisation has increased gradually the volatility spillovers. The volatility spillovers are higher when the interdependence between markets is high. In fact, the volatility spillover effect exists when the volatility of one market is influenced not only by its own early stage but also by the volatility coming from other markets. The volatility spillover effect exists widely in different types of financial markets in different regions. Generally, we introduce the term of asymmetric volatility when the impact of positive and negative shocks is different. The asymmetric volatility spillovers have recently attracted many decision-makers. Many studies (see for example: BenSaïda, 2019; Baruník, 2017; among others) showed that good shocks (news) and bad shocks (news) have different impacts on the dynamic of markets.

The connectedness between markets has increased portfolio risk and reduced the benefits of diversification. So, the fact that asymmetric volatility exists is important to hedging strategies. Bitcoin has recently attracted the attention of investors dealing with financial and commodity markets. Bitcoin (BTC) is an experimental system for the transfer and verification of property based on a peer-to-peer network without any central authority. Bitcoin has become the most popular cryptocurrency market and it is known as blockchain on 2009. Since then, Bitcoin has increasingly gained the attention of practitioners, academicians, regulators and the media. Many studies examined the role of Bitcoin (BTC) in financial markets and found a strong a linkage. For example, Briere et al. (2015) analysed the relationship between Bitcoin and other assets and showed that Bitcoin has a higher return, a higher volatility, and a weak correlation with the other assets. Hence, Bitcoin act as a hedging asset, a safe haven and used for diversification in order to reduce portfolio risk (Dyhrberg, 2016; Bouri, 2017).

Alike Bitcoin, precious metals; such as silver, gold, platinum and palladium, have gained much interest among decision-makers. Many studies showed that precious metals play safe haven roles (Li and Lucey, 2017; Sakemoto, 2018; Mensi et al., 2020).

Similarly, oil has an important role and a significant effect on financial markets and on the whole economy in general. Oil is known as the black gold and is the largest commodity market seen its strong influence on others markets (see for example: Fratzscher et al., 2018; Miller and Rati, 2009; Newell, 2011; Chang and Yu, 2013; Zhu et al., 2011; Lee and Chang, 2015; Wan and Kao, 2015; Arfaoui and Ben Rjeb, 2016; Phan et al., 2015; among others). Also, the oil market is one of the most volatile commodity markets. The oil market has experienced significant instability and violent shocks over the past decade (for example: the dramatic increase in oil prices during the summer of 2008 and the significant price decrease in mid-2014). Therefore, oil is also considered as an important investment instrument for investors. Shocks in oil prices are expected to have an impact on alternative investment instruments and commodity prices due to the linkage between economic growth and financial markets (Yıldırım, 2020).

This study contributes to the existing literature on volatility spillovers in many aspects. First, it examines the volatility spillovers between Bitcoin, oil and precious metals, which are silver, gold, platinum and palladium. Second, it investigates the asymmetric volatility spillovers between Bitcoin, oil and precious metals by distinguishing between spillovers coming from good news and that from bad news.

Finally, our study employs several robustness checks in order to examine the validity of our approach.

The reminder of this study is structured as follows. Section 2 exposes the theoretical background of volatility spillovers. Particularly, we examine, the recent literature related to spillovers measures and the interdependence between the three markets (Bitcoin, oil market and precious metals). Section 3 describes the data and methodology. Section 4, discusses the main results. Section 5 concludes the paper.

2 Literature review

Studying volatility spillover in financial markets is crucial due to its effect and importance for risks managers and investors. Several paper including Wen et al. (2020) and Gulzar et al. (2019) defined the volatility spillover effects as a situation in which the variations in volatility in one market affect the volatility of other markets. Suliman (2011) affirmed that spillovers are likely to occur among interdependent countries within the same geographical region. Since the volatility spillovers can occur between any two markets, it has long been recognised in the literature.

Several studies focus on the role of Bitcoin as a hedging and safe haven asset in financial markets. Wang et al. (2019) found that Bitcoin is a useful hedging asset for stocks, bonds, and SHIBOR, a diversification tool for commodities and FX, and it can be a safe haven for SHIBOR. Dyhrberg (2016) found that Bitcoin can be a hedge against the Financial Times Stock Exchange index and the USD in the short-term. Further, both Bitcoin and gold have proven their role as speculative and safe haven investments. Damianov and Elsayed (2020) find that Bitcoin can be used as a safe haven and can add value to diversified portfolios of global industries. Kliber et al. (2020) found that Bitcoin can act as a hedge, diversifier or safe haven on various stock markets, depending on the economic situation in the countries. Al-Yahyaee et al. (2019) found that Bitcoin and gold provide diversification benefits for oil and S&P GSCI. They reported strong evidence of hedging effectiveness and downside risk reductions, confirming the importance of Bitcoin and gold in oil and S&P GSCI portfolio management. López-Cabarcos et al. (2021) analysed the behaviour of Bitcoin volatility, stock market and investor sentiment across different periods. They found that in periods where stock markets have high volatility, Bitcoin can be used as a safe haven, but when stock markets are stable, Bitcoin becomes attractive to speculative investors.

Okorie and Lin (2020) examined the volatility connectedness between crude oil, spot prices and cryptocurrencies by using the VAR-MGARCH-BEKK and MGARCH-DCC modelling techniques. They reported a significant volatility spillovers between both markets and hedging possibilities. Xu et al. (2021) investigated the tail-risk interdependence among 23 cryptocurrencies. A significant risk spillover effect is reported in cryptocurrency markets. Their results showed that Bitcoin is the largest systemic risk receiver and Ethereum is the largest systemic risk emitter. Jin et al. (2019) studied the cross relationship between Bitcoin, gold and crude oil markets. They reported cross-correlations among the three hedging assets and found that Bitcoin is more adequate in pricing fluctuations from gold and crude oil markets. They found, also, that gold dominates crude oil and Bitcoin markets in absorbing new information.

Another strand of empirical literature focused on the volatility spillovers between oil and precious metals markets. Yıldırım (2020) investigated the volatility spillovers between oil price and precious metals such as gold, silver, platinum and palladium using the causality-in-variance test approach proposed by Hong (2001). They found evidence of volatility spillover effect from oil market to the precious metal market. Furthermore, they found evidence in favour of the bidirectional volatility spillover effect between oil and silver return series. Kang et al. (2017) investigated the return and volatility spillover effects among six commodity futures which are gold, silver, West Texas Intermediate crude oil, corn, wheat, and rice. They found a bidirectional return and volatility spillovers across commodity futures markets, and both gold and silver are information transmitters to other commodity futures markets. Liu and Gong (2020) explored the time-varying volatility spillovers between four major crude oil markets (WTI, Brent, Oman, and Tapis). They showed that the volatility spillover between crude oil markets was slowly increasing while that between crude oil markets exhibited obvious cyclical changes.

Using the Diebold and Yilmaz (2009) methodology, Batten (2015) studied the volatility spillovers between the four main precious metal markets, including gold, silver, platinum and palladium. They showed that the market is weakly integrated, that this degree of integration is time varying and that it differs as between returns and volatility. However, Mensi et al. (2017) analysed the time-varying volatility spillovers between precious metal markets (gold, silver, palladium, and platinum) and major stock markets (USA, Japan, Europe and Asia) using the spillover index of Diebold and Yilmaz (2012). They found significant volatility spillovers between precious metal and stock markets. They reported that (except the Japanese market) Stock markets are a source of volatility spillovers and the four precious metal markets are net volatility receivers. Finta et al. (2019) investigated the volatility spillovers among oil and stock markets in the US and Saudi Arabia. They found that the volatility spillover from oil to the stock markets is higher than the other way around. Malik and Hammoudeh (2007) examined the volatility and shock transmission mechanism among US equity, global crude oil market, and equity markets of Saudi Arabia, Kuwait, and Bahrain. They showed that Gulf equity markets receive volatility from the oil market. However, they found a significant volatility spillover from the Saudi market to the oil market.

Mensi et al. (2021) studied the return spillovers between the Chinese equity sectors and the commodity and found evidence of asymmetric return during the global financial crisis, European debt crisis, and COVID-19 outbreak. Fasanya et al. (2021) examined the connection between US EPU and Bitcoin-precious metals spillovers. Using a TVP VAR model. They found that Bitcoin and precious metals with EPU behave in a nonlinear fashion and that the connectedness is higher around the median and higher quantiles.

The asymmetry in volatility spillovers is barely investigated in the literature but in recent years, it has started to attract more attention of many researchers. Several papers argued that bad news (negative shocks) have stronger impact on the volatility than good news (positive shocks). In other words, the bad volatility has a stronger effect than the good volatility. Wang and Wu (2018) examined the asymmetric volatility spillovers between oil and international stock markets. They found that the bad volatility spillovers dominate the good one. Xu et al. (2019) investigated the dynamic asymmetric volatility spillover between oil and stock markets during the period of 2007 to 2016. They showed *t* that bad volatility spillovers dominate good volatility spillovers for most of the sampling period. In addition, Baruník et al. (2015) analysed the asymmetric connectedness on the US stock market. They found that negative spillovers do not strictly dominate positive spillovers. However, Uddin et al. (2020) examined the characteristics of the risk spillover under extreme market scenarios between the US stock market, precious metals (gold, silver and platinum) and oil. They reported an asymmetric volatility spillovers and showed that silver and platinum have the strongest impact on the US stock market in the downside, while oil and platinum do so in the upside periods. Meng et al. (2020) examined the impact of upside and downside global crude oil price fluctuation on China's commodity sectors. They showed that there are upside and downside risk spillover effects from global crude oil to China's commodity sectors. Besides, the degree of the downside spillover effect from crude oil price is higher than that of the upside spillover effect, which is an evidence of an asymmetric spillover effect. Klein et al. (2018) studied the volatility, return, correlation, and portfolio diversification of Bitcoin. They concluded that Bitcoin returns have an asymmetric response to market shocks. They remarked that Bitcoin is no safe haven and offers no hedging possibilities for developed markets.

Rehman (2020) analysed the extreme dependence and risk spillover between Bitcoin and a sample of precious metal such as; gold, silver, copper, wheat, platinum and palladium. They found a spillover effect from Bitcoin to precious metal market. Moreover, they reported asymmetries in upside and downside ΔCoVaR values, suggesting that extreme changes in returns in either of the market has the potential to affect extreme returns in the other market. Mensi et al. (2019) investigated the asymmetric volatility spillovers between Bitcoin and major precious metals markets (gold, silver, palladium and platinum). Using the Diebold and Yilmaz (2014) and Baruník (2017), they found evidence of volatility spillover effects between Bitcoin and precious metals. Moreover, their results support the evidence of an asymmetry in semi-volatility transmission.

The objective of this study is to investigate the dynamic volatility spillovers between Bitcoin oil and precious metals using a mixed approach. Specifically, we use the Diebold and Yilmaz (2014) approach while using the E-GARCH model to extract volatility and to capture for the directional spillovers. Then, we employ the approach of Baruník (2017) to explore the asymmetric spillovers. Finally, we employ several robustness checks to test for the plausibility of our results.

3 Data and methodology

3.1 Data

Our data encompasses the daily prices of four precious metals, which are: gold, silver, platinum and palladium, Bitcoins and WTI oil market index for the period that spans from 18 August 2011 to 2 October 2019 containing 2008 observations for each series.

3.2 Methodology

3.2.1 Volatility model

In order to extract the time varying volatility of Bitcoin, oil and precious metals returns we use the EGARCH model, which is a form of the GARCH model introduced by Nelson (1991).

The EGARCH model is written as:

$$\ln\left(h_{i,t}\right) = \omega_i + \varphi_i \ln\left(h_{i,t-1}\right) + \eta_i \left[\frac{\left|\varepsilon_{i,t-1}\right|}{h_{i,t-1}}\right] - E\left(\frac{\left|\varepsilon_{i,t-1}\right|}{h_{i,t-1}}\right) \tag{1}$$

The parameter η_i allows to take into account an asymmetrical effect related to the sign of the innovation Z_t. If $\eta_i > 0$: a positive shock on the conditional variance at the date t will be translated at the date $t + 1$ by an increase in the conditional variance. If $\eta_i < 0$: a positive shock on the conditional variance at the date t will be translated at the date $t + 1$ by a decrease in the conditional variance.

The parameter θ_i allows taking into account an asymmetry related to the amplitude of the innovation Z_t. If $\theta_i = 0$: a positive innovation will have the same effect (in absolute value) on the conditional variance that a negative innovation. If $\theta_i > 0$: a shock of strong amplitude will have a relatively more effect (in absolute value) on the conditional variance than a shock of weak amplitude.

We allow the errors ε_t to follow a standard student's t distribution to account for stylised facts observed on financial markets, such as non-normality and heavy tails.

3.2.2 Volatility spillover measure

To investigate the directional volatility spillovers, we use the spillover index of Diebold and Yilmaz (2012). This spillover measure allows capturing both total and directional volatility spillovers which is invariant to the variable ordering.

We consider a covariance stationary N-variable VAR (p) as follows:

$$X_t = \sum_{i=1}^{p} \phi_i X_{t-1} + \varepsilon_t \tag{2}$$

where

- X_t is an N-dimensional vector of assets volatilities
- ϕ_i is a parameter matrix ε_t is a vector of independently and identically distributed disturbances.

We consider the moving average representation to analyse the variance decomposition, which allows dividing the forecast error variances of each variable into parts attributable to the different system shocks:

$$X_t = \sum_{i=0}^{\infty} \varphi_i \varepsilon_{t-1} \tag{3}$$

where

- φ_i is an $N \times N$ coefficient matrices.

$$\varphi_i = \vartheta_1 \varphi_{i-1} + \ldots + \vartheta_p \varphi_{i-p} \tag{4}$$

With φ_0 an $N \times N$ identity matrix and $\varphi_i = 0$ for $i < 0$.

We consider the KPPS H-step-ahead forecast error variance decompositions, which are invariant to the ordering as following:

$$\theta_{ij}^{g}(H)=\frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_i'\varphi_h\Sigma e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i'\varphi_h\Sigma_h' e_i\right)} \tag{5}$$

where

- Σ is the variance matrix for the error vector ε
- σ_{jj} is the standard deviation of the error term for the j^{th} equation
- e_i is the selection vector, with one as the i^{th} element and zeros otherwise.

The sum of the elements in each row of the variance decomposition table is not equal to one: $\sum_{j=1}^{N}\theta_{ij}^{g}(H)\neq 1.$

We normalise each element of the variance decomposition matrix by the row sum to use the information available in the variance decomposition matrix in the spillover index measure:

$$\tilde{\theta}_{ij}^{g}=\frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}(H)} \tag{6}$$

with

$$\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}(H)=1 \text{ and } \sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H)=N$$

The total volatility spillover index using the volatility contributions from the KPPS variance decomposition is:

$$S^{g}(H)\frac{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}\cdot 100=\frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\tilde{\theta}_{ij}^{g}(H)}{N}\cdot 100 \tag{7}$$

The directional volatility spillovers received by market i from all other markets j:

$$S_{i.}^{g}(H)=\frac{\sum_{\substack{j=1\\ i\neq j}}^{N}\tilde{\theta}_{ij}^{g}(H)}{N}\cdot 100 \tag{8}$$

The directional volatility spillovers transmitted by market i to all other markets j:

$$S_{.i}^{g}(h)=\frac{\sum_{\substack{j=1\\ i\neq j}}^{N}\tilde{\theta}_{ij}^{g}(H)}{N}\cdot 100 \tag{9}$$

Then we obtain the net volatility spillover from market i to all other markets j as the difference between the volatility spillovers transmitted to and those received from all other markets:

$$S_{i}^{g}(H)=S_{.i}^{g}(H)-S_{i.}^{g}(H) \tag{10}$$

3.3 Asymmetric volatility spillovers

To capture the asymmetries in volatility spillovers, we use the spillover asymmetry measure (SAM) proposed by Baruník (2017). The SAM is based on the realised semi-variance framework of Barndorff-Nielsen et al. (2010), which decompose volatility spillovers due to negative and positive returns with a single VAR system. This measure allows decomposing volatility spillovers due to bad or good volatility.

The SAM is defined as the difference between negative and positive spillovers:

$$SAM = S^{+} - S^{-} \tag{11}$$

where

- S^{-} is spillovers from volatility due to negative returns
- S^{+} is spillovers from volatility due to positive returns.

First, we should replace the vector of realised volatility $RV_t = (RV_{1t}, \ldots, RV_{Nt})'$ with the 2N dimensional vector of positive and negative volatility, i.e., $RS_t = (RS_{1t}^{-}, \ldots, RS_{Nt}^{-}, RS_{1t}^{+}, \ldots, RS_{Nt}^{+})'$.

The SAM is defined as a difference between volatility spillovers due to negative and positive returns.

$$SAM_{2N}^{H} = \sum_{i=1}^{N} S_{2N,i\rightarrow\cdot}^{H} - \sum_{i=N+1}^{2N} S_{2N,i\rightarrow\cdot}^{H} \tag{12}$$

If SAM_{2N}^{H} is null: spillovers coming from RS^{-} and RS^{+} are equal (there is no spillover asymmetry). If SAM_2NH is negative: spillovers coming from RS^{-} are larger than those from RS^{+}. If SAM_{2N}^{H} is positive: spillovers coming fro, RS^{-} are smaller than those from RS^{+}.

We define the hypotheses of symmetric connectedness to test for the presence of potential asymmetries in volatility spillovers as:

$$H_0 : SAM_{2N}^{H} = 0$$
$$H_1 : SAM_{2N}^{H} \neq 0$$

If, we reject the null hypothesis, it means that there are asymmetries in volatility spillover. However, accepting the null hypothesis means that there is a symmetric connectedness.

Our approach is slightly different from the above described analysis. In fact, in order to estimate the spillover we follow the following procedure:

a For a given day, we draw the returns of all markets to keep the connectedness structure between variables.

b Then, we decompose returns into two blocks positive returns and negative returns (r^{+} and r^{-}).

c Estimate the good and bad volatilities using the EGARCH model. The good and bad volatility are computed as follows:

$$\begin{cases} h_{i,t}^{-} = h_{i,t} 1\left[r_{i,t} < 0\right] \\ h_{i,t}^{+} = h_{i,t} 1\left[r_{i,t} > 0\right] \end{cases} \tag{13}$$

where

- $h_{i,t}^{+}$ is volatility estimated from the EGARCH model and coming from positive returns
- $h_{i,t}^{-}$ is volatility estimated from the EGARCH model and coming from negative returns.

d Compute the total spillover as in equation (7) and the asymmetric spillover as in equation (10).

4 Results discussion

In the results discussion, we begin our analysis by the descriptive statistics of the sample. We, then, present the volatilities of WTI and each of the four precious metals and Bitcoin. We, afterwards, proceed with the analysis of volatility spillovers and the implications for portfolio diversification. Finally, we explore the asymmetric connectedness and employ some robustness checks to test the plausibility of our approach.

Table 1 Descriptive statistics of returns

	Bitcoin	*Oil*	*Silver*	*Gold*	*Platinum*	*Palladium*
Mean	0.003304	–0.000225	–0.000413	–9.18E-05	–0.000359	0.000322
Median	0.002578	0.000421	–0.000604	0.000000	–0.000701	0.000916
Maximum	0.484776	0.141761	0.173643	0.048387	0.052263	0.068629
Minimum	–0.663948	–0.111258	–0.155570	–0.095962	–0.050306	–0.097862
Std. dev.	0.060148	0.021558	0.017557	0.010048	0.012214	0.016733
Skewness	–0.914090	0.172355	–0.423434	–0.569601	0.111350	–0.280982
Kurtosis	21.91732	6.616723	17.33515	10.55296	3.892661	5.241584
Jarque Bera test	3,0190.89***	1,103.259***	17,236.03***	4,876.663***	70.74824***	446.3771***

Note: *** indicates statistical significance at 1% level.

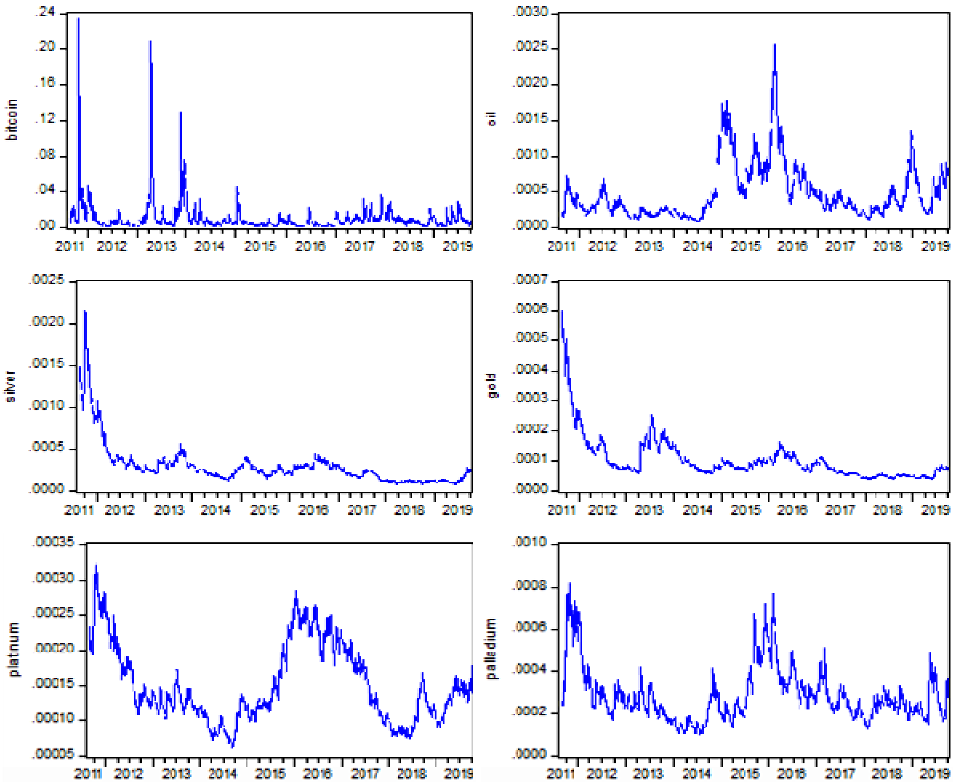
4.1 Descriptive statistics

Table 1 provides descriptive statistics for the log-differenced prices (returns) of Bitcoin, oil and four precious metals. Bitcoin and palladium exhibit positive means, whereas oil, silver, gold and platinum have negative means. All series exhibit high values of Kurtosis and non-null skewness. The Jarque Bera test shows that all the studied series are under the non-normal distribution, which motivates us to use the heteroskedastic volatility model under the student-*t* distribution to take for these stylised facts.

4.2 Volatility co-movements

From the synchronous returns, we infer the conditional volatilities using equation (1), which are presented in Figure 1.

Figure 1 Volatility of Bitcoin, oil and precious metals (see online version for colours)



The plots show some similarities in volatility patterns which indicate the presence of connectedness across variables. The figures indicate some peaks of the voaltility especially during the terrorist attack that hit the US at the end of 2011, the Brexit vote in mid 2016, among other irregularities that have shaken the world.

4.3 Volatility connectedness between Bitcoin, oil and precious metals

The volatility spillovers between Bitcoin, oil and precious metals calculated as in equation (7) is presented in Table 2.

Table 2 reports the directional and the total volatility spillover between Bitcoin, oil and precious metals markets. The results indicate that the total spillover is fairly low (12.8%), showing a low interdependence among volatilities. From the net spillover, we notice that Bitcoin, oil and platinum are neutral. However, silver and palladium are net receiver of volatility spillover (–3.7% and –1.1% respectively) suggesting that those metals are highly affected by the volatility of the others. Furthermore, gold is the main net volatility transmitters (4%) to all other markets. Therefore, gold is the most influential market since it is the main source of volatility spillover shock from and to other markets which is in line with the work of Elgammal et al. (2021). Our results are crucial for portfolios' managers since it indicates that oil, Bitcoin and platinum can serve as a hedge and a diversifier which is in line with the works of Klein et al. (2018) and Juntilla et al. (2018). The volatility spillovers between Bitcoin, oil and precious metals is depicted in Figure 2.

Table 2 Directional and total volatility spillovers between Bitcoin, oil and precious metals

	Bitcoin	*Oil*	*Silver*	*Gold*	*Platinum*	*Palladium*	*From others*
Bitcoin	98.1	0	0.4	0.4	0.3	0.7	1.9
Oil	0	97.9	0	0.6	1.1	0.4	2.1
Silver	0.1	0.1	80.2	12.7	6.2	0.6	19.8
Gold	1.2	0.5	9.2	74.5	13.9	0.6	25.5
Platinum	0.3	1.1	5.7	14.9	77	1	23
Palladium	*0.9*	*0.3*	*0.7*	*0.9*	*1.6*	*95.6*	*4.4*
To others	2.5	2	16.1	29.5	23.2	3.3	76.6
All	100.6	99.9	96.3	104.1	100.2	98.9	*Total spillovers: 12.8%*
Net	0.6	–0.1	–3.7	4	0.2	–1.1	
Conclusion	*Neutral*	*Neutral*	*Net recipient*	*Net contributor*	*Neutral*	*Net recipient*	

Notes: This table reports the directional volatility spillovers in %. The results are based on generalised variance decompositions of five-day ahead volatility forecast errors with rolling sample analysis. The entry on the i^{th} line and j^{th} column is the spillovers from market to the forecast error variance of market j. The number in ital represents the total volatility spillover index. The column labelled 'from others' presents the directional spillovers received by the market 'i' from all others markets. The row labelled 'to others' presents the directional spillovers transmitted by the market 'i' to all others markets. The row labelled 'net' is the difference between 'to others' and 'from others' spillovers.

Figure 2 Total volatility spillover of Bitcoin, oil and precious metals (gold, silver, platinum and palladium) (see online version for colours)

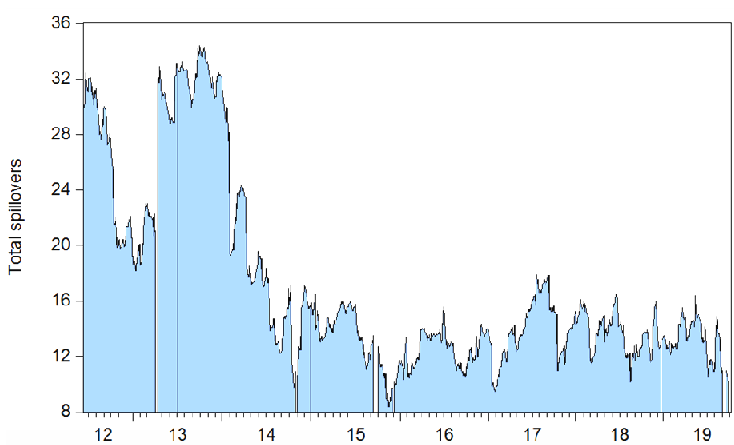


Figure 3 Net directional spillovers (see online version for colours)

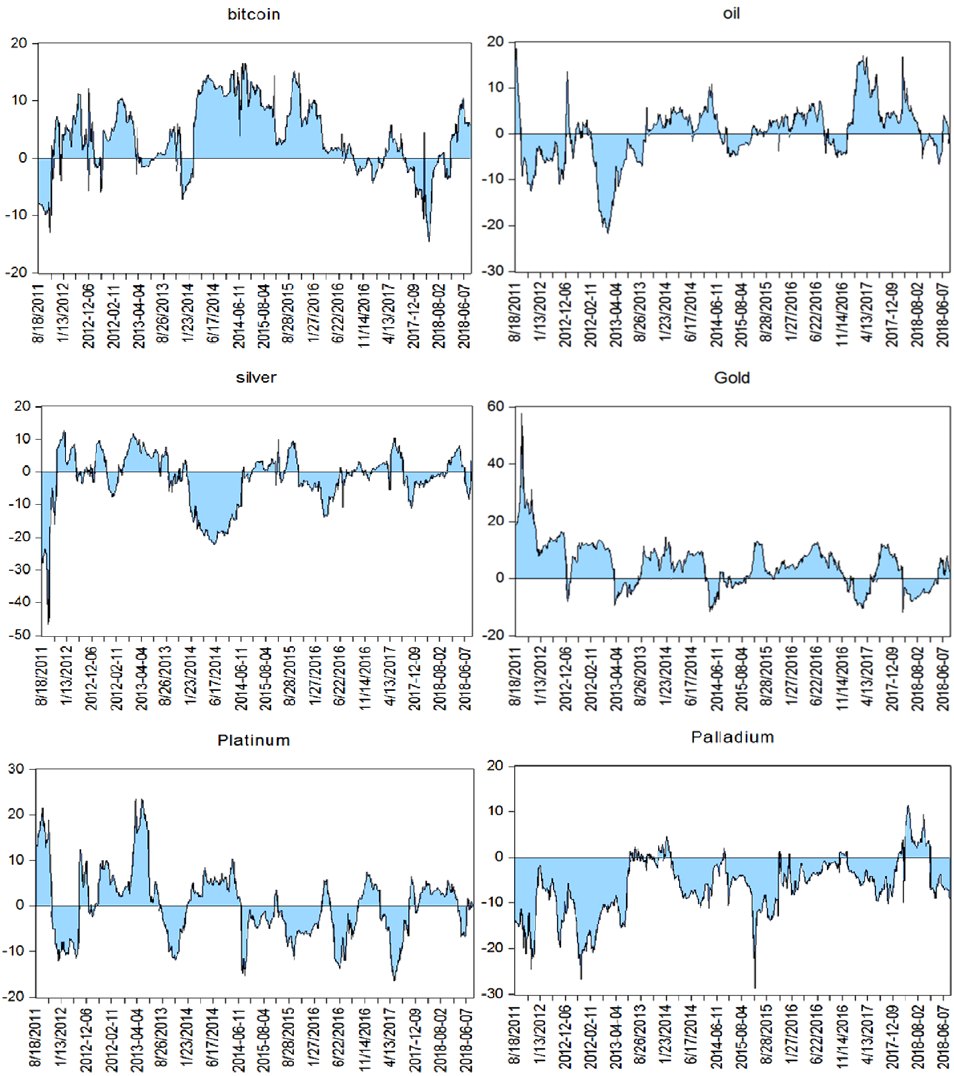


Figure 2 plots the time-varying total volatility spillover index between Bitcoin, oil and precious metals. The graphic illustrates that the volatility spillovers index increases and decreases over time. The first phase of higher volatility spillovers (about 35%) is observed during the mid-2011 until 2014, before they collapse to below 12% ate the end of 2014. This period is related to the uncertainty in the energy market due to the Arab spring that started from Tunisia in 2011, the Lybian political unrest and the turmoil periods in Egypt, Yemen and Syria.

It is important to stress that during the collapse of the oil price in 2014–2015, volatility spillovers reached their lowest level.

The highest peak of spillovers is reached by the third and last quarters of 2013 which corresponds to the drop in oil production of the five major oil companies. Finally, the high levels of total spillover in 2016 and 2017 reflect the fallout of two distinctive events

In line with the work of BenSaïda (2019). The first is the Brexit, whose implications for the global economy were still unclear. The second, and at the same time, is the result of the US presidential election that led to great uncertainty about economic policy in the US. In order better understand the dynamic of spillovers; we present in Figure 3 the net directional spillovers.

A closer inspection of Figure 3 shows that gold is a net transmitter of risk whereas both palladium and silver are net recipients of shocks from other markets. In fact, gold plays an important role in financial markets with flight-to-quality in times of market distress since it is significantly used in central banks' international reserves, and is a store of value. Moreover, Bitcoin, oil and platinum are neutral in terms of spillover contribution. Our results shed light of the capacity of Bitcoin and oil to play an important role in hedging portfolios.

Despite the interesting results presented in Table 2 and Figures 2 and 3, we propose the study of the volatility spillovers based on two scenarios; good volatility and bad volatility having, though, documented that the relationship between our system is time-varying, it is more accurate to examine how these spillovers vary across different regimes.

4.4 *Asymmetries in volatility spillovers*

In this section, we study the asymmetric volatility spillovers between Bitcoin, oil and precious metals. The spillovers due to good and bad volatility are presented in Table 3.

Figure 4 Good and bad volatility spillovers between Bitcoin, oil and precious metals (see online version for colours)

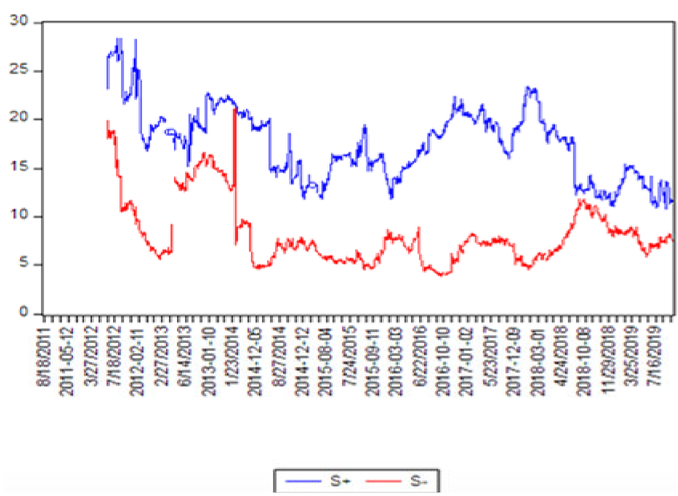


Table 3 show evidence of asymmetric volatility spillovers between Bitcoin, oil and precious metals. In fact, good total volatility index (13.1%) dominates bad volatility (7%) which proves the optimistic mood of the whole system. Moreover, our results indicate that, in good innovations, oil is the highest contributor of good spillovers to other markets by 29.4% followed by gold (25.4%) and silver (21%). However, in bad innovations, gold is the biggest transmitter with a percentage of 13.2% followed by silver with about

10.5%. More interestingly, we find that Bitcoin and platinum are the lowest transmitters (0.4% and 0.8% respectively) and receivers (0.3% and 0.8% respectively) of spillovers in Good innovations showing their weak dependence with the other markets which proves their hedging characteristics during these periods. Moreover, in bad innovations Bitcoin and oil are the lowest transmitters (1.9% and 1.6 respectively) and receivers (1.9% and 1.4 % respectively) of volatility which is of a good importance to portfolios managers. Indeed, Bitcoin, the digital gold, can serve in both scenarios as a hedger and a diversifier.

Table 3 Directional asymmetric volatility spillovers

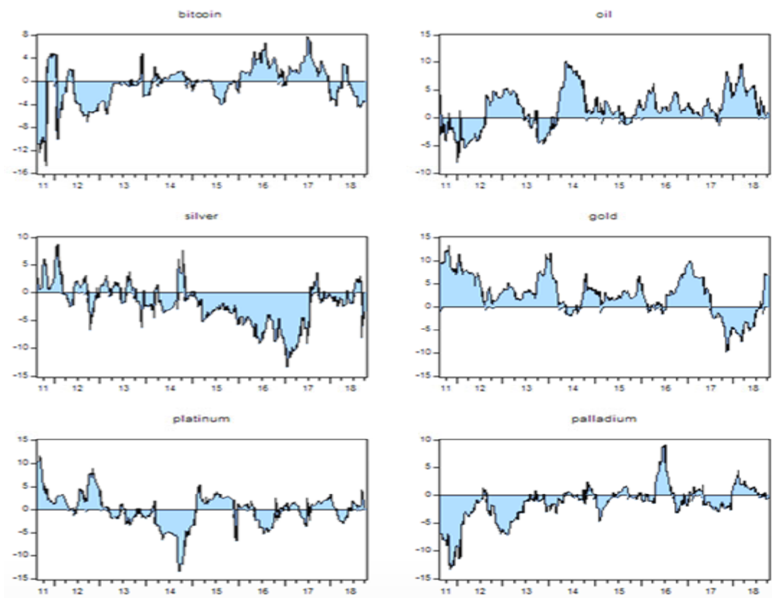
		Bitcoin	*Oil*	*Silver*	*Gold*	*Platinum*	*Palladium*	*Contribution from others*
Good	Bitcoin	99.7	0.1	0.0	0.1	0.0	0.1	0.3
	Oil	0.2	73.2	10.9	15.6	0.0	0.1	26.8
	Silver	0.1	12.2	77.5	9.1	0.6	0.5	22.5
	Gold	0.1	16.6	8.6	74.3	0.0	0.3	25.7
	Platinum	0.0	0.2	0.4	0.1	99.2	0.1	0.8
	Palladium	0.0	0.5	1.0	0.5	0.2	97.8	2.2
	Contribution to others	0.4	29.7	21.0	25.4	0.8	1.2	*Total index: 13.1%*
	Contribution including own	100.1	102.9	98.4	99.7	100.0	99.0	
	Net spillover	0.1	2.9	–1.5	–0.3	0	–1	
Bad	Bitcoin	98.1	0.0	0.1	1.5	0.1	0.1	1.9
	Oil	0.0	98.6	1.1	0.0	0.0	0.1	1.4
	Silver	0.1	1.0	89.8	8.4	0.5	0.3	10.2
	Gold	1.5	0.3	7.8	86.9	0.9	2.6	13.1
	Platinum	0.1	0.3	1.2	1.0	92.8	4.6	7.2
	Palladium	0.1	0.0	0.3	2.3	3.7	93.6	6.4
	Contribution to others	1.9	1.6	10.5	13.2	5.3	7.8	*Total index: 6.7%*
	Contribution including own	100.0	100.2	100.3	100.1	98.1	101.4	
	Net spillover	0	0.2	0.3	0.1	–1.9	1.4	

Notes: This table reports the good and bad volatility directional spillovers in %. The results are based on generalised variance decompositions of five-day ahead volatility forecast errors with rolling sample analysis. The entry on the i^{th} line and j^{th} column is the spillovers from market to the forecast error variance of market j. Numbers in bold represent the total volatility spillover indices.

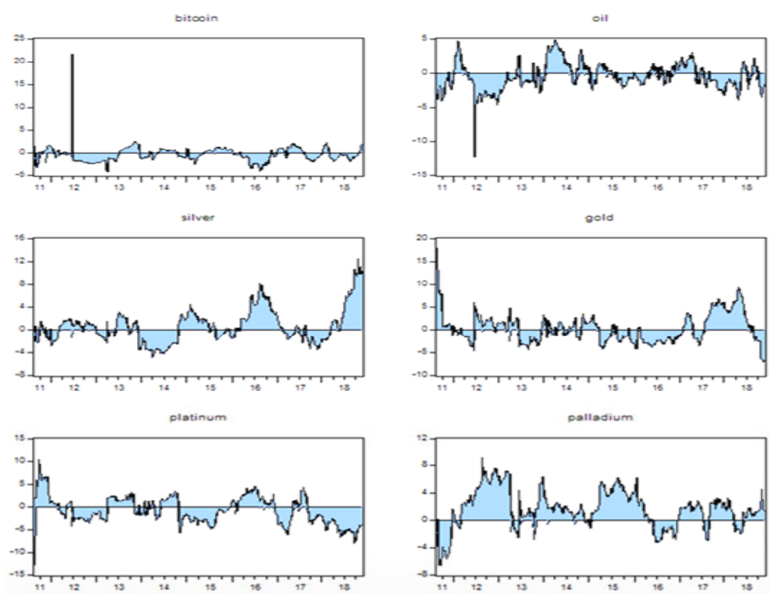
The good and bad volatility spillovers calculated are presented in Figure 4.

Figure 4 illustrates the good and bad volatility spillovers between Bitcoin, oil and precious metals (silver, gold, platinum and palladium). The decomposition of volatility into bad and good volatility can be considered as upward and downward risk (Feunou et al., 2013). Figure 4 shows clearly that positive spillovers dominate bad spillovers, which proves the optimistic mood of the system and the domination of informed traders in those markets. In fact, according to Avramov et al. (2006), a positive return is followed by selling activity that is dominated by informed traders who tend to reduce volatility.

Figure 5 Net positive and negative spillovers (see online version for colours)



Positive spillovers



Negative spillovers

The volatility records a substantial contribution of spillovers due to positive returns in 2012 which corresponds to the political turbulence in Tunisia, Egypt, Libya, Yemen, and Bahrain which drove oil prices to $95 per barrel in the beginning of 2011 and even to $103 per barrel by 24 February 2011 when oil production was shortened by the political disruption in Libya.

A much smaller peak in 2015 that coincides with the Greek debt crisis that threatens the European Union. The last peak of positive spillovers is reached in 2018 with the economic growth of the global economy.

4.5 Robustness checks

In this section, we employ some robustness checks as in Narayan et al. (2014) and BenSaïda (2019) by modifying the lags, the horizon and the order of our variables. The lags of the VAR model vary from 1 to 12. In addition, the forecasting horizon vary from 2 to 12 days.

Table 4 reports the total good and bad volatility spillovers in percentage for different horizon, different lags and various orders of variables.

Our results show that the spillover measures are almost invariant to the VAR model, the lags retained and the forecasting horizon. In other words, we found that the spillover effects are robust as they hold across the different lag orders of the VAR model, as well as over different horizons. So, our approach is robust and shows that positive spillovers dominate a negative spillover which proves the general optimistic mood of the system.

Table 4 Robustness of total asymmetric spillovers

	Horizon	*Lag*	*Good*	*Bad*
Generalised	2	1	12.90%	6.50%
		4	14.50%	5%
		9	14.30%	4.70%
		12	14.40%	4.80%
	5	1	*13.10%*	*6.70%*
		4	15.20%	6%
		9	15.20%	6.20%
		12	15.30%	6.30%
	12	1	13.40%	6.80%
		4	16%	6.20%
		9	17.30%	7.60%
		12	17.30%	8.20%

Notes: *, **, ***, indicate respectively order 1, order 2 and order 3 of variables.
Order 1: silver-gold-platinum-palladium-oil-Bitcoin.
Order 2: oil-silver-gold-platinum-palladium-Bitcoin,
Order 3: Bitcoin-oil-silver-gold-platinum-palladium. Numbers in ital correspond to the reference spillover indices as reported in Table 9.

Table 4 Robustness of total asymmetric spillovers (continued)

	Horizon	*Lag*	*Good*	*Bad*
Cholesky	2	1	7.20%*	4.00%*
			7.20%**	4.10%**
			7.20%***	4.00%***
		4	7.80%*	2.90%*
			7.80%**	2.90%**
			7.80%***	3.00%***
		9	8.60%*	2.90%*
			7.70%**	2.80%**
			7.70%***	2.90%***
		12	9.00%*	3.00%*
			7.70%**	2.80%**
			7.70%***	3.00%***
	5	1	7.30%*	4.30%*
			7.30%**	4.40%**
			7.30%***	4.30%***
		4	8.50%*	3.80%*
			8.50%**	3.80%**
			8.50%***	4.10%***
		9	9.30%*	4.40%*
			8.50%**	4.30%**
			8.50%***	4.60%***
		12	10.20%*	4.50%*
			8.60%**	4.30%**
			8.50%***	4.70%***
	12	1	7.70%*	4.40%*
			7.70%**	4.40%**
			7.70%***	4.40%***
		4	9.10%*	4.10%*
			9.10%**	4.10%**
			9.10%***	4.40%***
		9	11.20%*	5.80%*
			10.60%**	5.70%**
			10.60%***	6.00%***
		12	12.80%*	6.30%*
			10.6%**	6.20%**
			10.80%***	6.60%***

Notes: *, **, ***, indicate respectively order 1, order 2 and order 3 of variables.
Order 1: silver-gold-platinum-palladium-oil-Bitcoin.
Order 2: oil-silver-gold-platinum-palladium-Bitcoin,
Order 3: Bitcoin-oil-silver-gold-platinum-palladium. Numbers in ital correspond to the reference spillover indices as reported in Table 9.

5 Conclusions

The asymmetric volatility spillovers are a recent fact that attracts the attention of many portfolio managers, investors, traders, scholars and market practitioners. Several previous studies (Baruník, 2017; Weiju et al., 2019; BenSaïda, 2019) showed that the volatility of an asset depends on the sign of the shock. So good and bad news have different impact on the volatility.

This paper investigates the asymmetric volatility spillovers between Bitcoin, oil and precious metals, which are silver, gold, platinum and palladium.

First, we found evidence of small volatility spillovers between Bitcoin, oil and precious metals (silver, gold, platinum and palladium). More preciously, 12.8% of the volatility forecast error variance in all our six markets (Bitcoin, oil, silver, gold, platinum and palladium) comes from spillovers. Second, gold is the main net volatility transmitters to all other markets. Therefore, gold is the most influential market since it is the main source of volatility spillover shock from and to other markets. However, Bitcoin, oil and platinum are neutral. Our results are crucial for portfolios' managers since it indicates that oil, Bitcoin and platinum can serve as a hedge and a diversifier which is in line with the works of Klein et al. (2018) and Juntilla et al. (2018).

Our results show evidence of asymmetric volatility spillovers since good and bad news have different impact on volatility. In fact, good volatility spillovers dominate bad ones which prove the optimistic mood of the whole system.

Moreover, we find that oil is the highest transmitter in good innovations. However, gold is the biggest contributor among all variables in bad innovations. In addition, the Brexit and the US election in 2016 were the most potent contributors of negative spillovers. While, good volatility spillovers chiefly due to global economic growth.

More interestingly, we find that Bitcoin and platinum are the lowest transmitters and receivers of spillovers in Good innovations showing their weak dependence with the other markets which proves their hedging characteristics during these periods. Moreover, in bad innovations Bitcoin and oil are the lowest transmitters and receivers of volatility which is of a good importance to portfolios managers. Indeed, Bitcoin, the digital gold, can serve in both scenarios as a hedger and a diversifier.

Our findings can help market participants (investors, traders, market practitioners, portfolio managers, etc.) in terms of hedging and diversification by providing new evidence on spillovers and cross relationship between several assets. Therefore, investors should modify their portfolio structures and choose an alternative investment by considering the identified asymmetries in volatility spillovers, especially the role of Bitcoin to serve as a hedge.

Finally, our results have proven to be robust across Models, the data frequency, forecast horizons.

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