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Time-varying volatility spillovers among bitcoin and commodity currencies

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Abstract

The aim of this paper is to examine the volatility spillover between bitcoin, gold and crude oil returns. (VAR) Model and three Multivariate GARCH Models (CCC-GARCH, BEKK-GARCH and DCC-GARCH) estimation techniques are applied using daily data from 1st January 2011 to August 31th, 2018. Further, these estimation results are used to analyze the relationship and the volatility spillovers among bitcoin and these commodity currencies.
The findings reveal that the bidirectional spillover is confirmed between gold return and crude oil return. Low unidirectional spillover; from bitcoin return to gold return and from bitcoin to crude oil. We also notice that the DCC-GARCH model provides a better fit than the CCC-GARCH model and the BEKK-GARCH model. These findings have significant implications for both cryptocurrency these commodity currencies allocations and portfolio management.

JEL Classification Numbers: G10; G11; G58
Keywords: M-GARCH model; VAR model; Gold; Crude oil; Cryptocurrency.

1 Introduction

Being able to model and create accurate forecasts of financial volatility is crucial for risk management purposes, portfolio selections as well as for pricing financial instruments (Hull (2011)). Due to high demand for accurate volatility estimates the interest amongst researches has been tremendous. Volatility is a latent variable and cannot be observed. However, there are some features that are commonly observed in financial data. In this paper, we use vector autoregressive (VAR) Model and three Multivariate GARCH Models to examine volatility spillovers among bitcoin,

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wti and gold; a CCC-GARCH(1,1) model, a dynamic conditional correlation model (DCC-GARCH model), and a the BEKK(1,1) model. The literature covering this model is extensive, and it has been applied to a variety of financial assets. See for example Andersen and Bollerslev (1998), Hansen and Lunde (2005), and Wang and Wu (2012). The extant studies regarding the relationship between bitcoin, gold and wti uncertainty are abundant. Despite the enormous research efforts,this area stills inconclusive. Al-Khazali et al. (2018) analyzethe effects of negative and positive macroeconomic news surprises on gold and Bitcoin, and conclude that the reaction of gold is more pronounced than that of Bitcoin. More accurately, they find that, unlike the digital gold (Bitcoin), precious gold returns and volatility systematically respond to macroeconomic news surprises consistently with its traditional role as a safe-haven. Selmi et al.(2018) noted that the relationship between Bitcoin and oil returns is stronger than the one between gold and oil is rather counterintuitive given because gold is largely known as a hedge and a safe haven to protect against awkward risks and this shiny metal has thus a long history of being a reliable store of wealth. Brière et al. (2015) show the weak correlation of bitcoin with alternative investments (commodities and hedge funds) and traditional assets (stocks, bonds, currencies) and show the diversification capabilities of bitcoin despite its high volatility. Eisl et al. (2015) indicate the inclusion of highly volatile bitcoin into a diversified portfolio is highly profitable and they predicate if some investors lose trust to the entire economy, they might resort to bitcoin. This is one of the reasons why bitcoin has sometimes been called digital gold (Popper (2015)).The value of Bitcoin and its relationship to different financial data (e.g. the Dow Jones, FTSE 100, Nikkei 225 and the WTI oil) was examined by van Wijk (2013). The authors were able to conclude that the Dow Jones, the WTI oil price and the euro-dollar exchange rate have a significant impact on the price of Bitcoin in the short run but only the Dow Jones has a significant impact on the value of Bitcoin in the long run. Also, the researchers concluded that other variables, like the dollar-yen exchange rate and the Nikkei 225, have no statistically significant effect on the formation of Bitcoin price. Luther and Salter (2017) indicate that this cryptocurrency would be seen as an alternative to traditional stores of values, such as gold, and will be considered as a digital gold. Li and Wang (2017) found a significant relationship in the short and long terms between the Bitcoin price and changes in economic fundamentals. Dyhrberg (2015) proves that Bitcoin has comparable hedging capabilities and safe havens like gold, and it would be categorized between gold and American dollar. Baur et al. (2018) criticize the paper of Dyhrberg (2015) and found that Bitcoin has different characteristics to gold.

The present study provides a robust analysis of dynamic linkages among bitcoin, wti and gold that goes beyond a simple analysis of correlation breakdowns. So this paper is organized as follows. Section 2 presents the econometric methodology. Section 3 presents the Data and Preliminary Analyses. Furthermore, section 4 displays and discusses the results and their interpretation, while section 5 provides our conclusions.

2 Econometric methodology

2.1. Vector Autoregressive (VAR) Model

We examine the possibility of spillovers in returns over using a three variables vector autoregressive (VAR) model consisting of returns prices for bitcoin, gold and the wti as follow:

$$y_t = \Pi_0 + \Pi_1 y_{t-1} + \cdots \Pi_l y_{t-l} + \epsilon_t \quad (1)$$

$$\epsilon_t \backslash \Lambda_{t-1} \sim N(0, H_t)$$

where y_t is a three variables vector of returns in the three prices (bitcoin,wti, gold) at time *t;l:* is the lag length; $\Pi_0$is a 3 × 1 vector of intercepts; $\Pi_1$through $\Pi_l$are coefficient matrices, with their elements capturing their own, as well as the cross-market lag effects; and ϵ_t is a 3 × 1 vector of error terms. We assume that elements of $\epsilon_t$are serially uncorrelated, with the conditional variance-covariance matrix represented by the 3 × 3 matrix H_t given the information set Ω_{t-1}.
According to Equation (1), the return in each price is a linear function of its own past, as well as past returns in the other prices. For example, the return on the bitcoin depends on *l* lags of itself, as well as *l* lags of the other two price returns:

$$y_{1,t} = \theta_1 + \sum_{i=1} \phi_{1i} y_{1,t-i} + \sum_{i=1}^{l} \phi_{2i} y_{2,t-i} + \sum_{i=1} \phi_{3i} y_{3,t-i} + \epsilon_{1,t} \quad (2)$$

The possibility of spillover in returns over time can be examined by testing the joint hypotheses that $\phi_{1i} = 0 (i = 1, \ldots, l)$. Similarly, the possibility of spillovers in returns from Market 2 to Market 1 can be examined by testing for the joint hypotheses that $\phi_{2i} = 0 (i = 1, \ldots, l)$.

2.2. Multivariate GARCH Models

2.2.1. MGARCH-BEKK model

The BEKK model of Engle and Kroner (1995) as follow:

$$H_t = C'C + \sum_{i=1}^{k} A_i' \epsilon_{t-i} \epsilon_{t-i}' A_i + \sum_{i=1}^{k} G_i' H_{t-i} G_i \quad (3)$$

where C, $A_i$and $G_i$are $N \times N$ matrices, but C is triangular. This equation guarantees all positive definite diagonal representations. In the analysis that follows, we will set the lag length to one, which results in a parsimonious specification of the BEKK model as:

$$H_t = C'C + A' \epsilon_{t-1} \epsilon_{t-1}' A + G' H_{t-1} G \quad (4)$$

The BEKK model provides a convenient way of decomposing each conditional variance into its ARCH and GARCH components. For example, the ARCH component associated with the conditional variance can be written as:

$$h_{11,t} = c_1 + {\alpha_{11}}^2 {\epsilon^2}_{1,t-1} + {\alpha^2}_{21} {\epsilon^2}_{2,t-1} + {\alpha^2}_{31} {\epsilon^2}_{3,t-1} + 2\alpha_{11}\alpha_{21}\epsilon_{1,t-1}\epsilon_{2,t-1} + 2\alpha_{11}\alpha_{31}\epsilon_{1,t-1}\epsilon_{3,t-1} + 2\alpha_{21}\alpha_{31}\epsilon_{2,t-1}\epsilon_{3,t-1}$$

Here, $\alpha_{11}, \alpha_{21}, \alpha_{31}$, capture the effects of past squared shocks in each market on today' volatility. Similarly, the GARCH conditional variance can be written as:

$$h_{11,t} = \beta_{11}^2 h_{11,t-1} + \beta_{21}^2 h_{22,t-1} + \beta_{31}^2 h_{33,t-1} + 2\beta_{11}\beta_{21}h_{12,t-1} + 2\beta_{11}\beta_{31}h_{13,t-1} + 2\beta_{21}g_{31}h_{23,t-1}$$

Here, $\beta_{11}, \beta_{21}, \beta_{31}$, capture the effects of past volatility in each of the three prices on today's volatility. Although the BEKK model provides a useful framework to analyze cross-market spillovers in volatility, it is not parsimonious and requires the estimation of a large set of parameters Bauwens et al.(2006) .

2.2.2. MGARCH-CCC model

The MGARCH-CCC model of Bollerslev (1990) allows for time-varying conditional variances and covariances, but restricts the conditional correlations to be constant. The conditional variance matrix is defined as:

$$H_t = D_t R D_t = \left(p_{ij}\sqrt{h_{iit}h_{jjt}}\right) \tag{5}$$

Where D_t denotes the 3 × 3 stochastic diagonal matrix with elements$\sigma_{1t}, \sigma_{2t}, \sigma_{3t}$, and R is a 3× 3 time invariant correlation matrix.
A GARCH (1,1) specification of each conditional variance can be defined as:

$$h_{iit} = c_i + a_i\epsilon_{i,t-1}^2 + g_i h_{ii,t-1}$$
$$h_{ijt} = \rho_{ij}\sqrt{h_{iit}h_{jjt}}\ ; i, j = 1, \ldots, 3.$$

The CCC model parameterizes each conditional variance as a linear function of its own past squared shocks and past conditional variance. It also allows for constant conditional correlations between each pair of prices.

2.2.3. MGARCH-DCC model

Tse and Tsui (2002) and Engle (2002) have proposed alternative dynamic conditional correlation (DCC) models, where the conditional correlation is allowed to vary over time. This paper adopts the DCC model of Engle (2002):

$$H_t = D_t R_t D_t \tag{6}$$

where the conditional correlation matrix, R_t, is time varying and is defined as:

$$R_t = diag\left(q_{11,t}^{-1/2} \ldots q_{44,t}^{-1/2}\right) Q_t\, diag\left(q_{11,t}^{-1/2} \ldots q_{44,t}^{-1/2}\right)$$

where the 3 × 3 symmetric positive definite matrix $Q_t = (q_{ijt})$given by:

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

where $Q_t$is the conditional covariance matrix of the error terms, $\bar{Q}$is the unconditional covariance matrix and $\alpha+\beta$ are non-negative scalar parameters with the restriction that
$\alpha+\beta<1. if\ \alpha=\beta=0,$ then $Q_t$is equal to $\bar{Q}$, and the constant conditional correlation model will be enough to estimate the correlation matrix. The value of $\alpha+\beta$ close to one indicates high persistence in the conditional variance.

3 Data and Preliminary Analyses

The empirical work in this study requires daily data on gold price, oil price and the bitcoin price. The closing prices for the bitcoin coindesk index are sourced from coindesk.com. The data of gold price and oil price are drawn from DataStream. The sample covers a period from 01/01/2011 until 31/08/2018, leading to a sample size of 10952 observations. For each exchange rate, the continuously compounded return is computed as:
$R_t = 100 * \ln\left(\frac{P_t}{P_{t-1}}\right)$, where P_t is the price on day t and P_{t-1} is the price on day $t-1$.
We address the missing values by replacing them with values from the prior day when the market was open. Following this adjustment, there are a total of 2801 daily observations.

Table.1: Descriptive Statistics of Returns Series

Statistics	**Bitcoin**	**Wti**	**Gold**
Mean	-0.3594	0.0096	0.0059
Maximum	233.55	11.1257	12.8021
Minimum	-232.11	-11.2892	-7.4825
SD	17.9041	1.7620	0.9037
Skewness	-0.0276	-0.1092	1.5945
Kurtosis	145.0539	8.8841	28.4399
Jarque-Bera	2353412*	4043.498*	76664.99*

Q(40)	696.005*	54972.1*	45132.5*
QS(40)	812.2001*	107959*	122.566*
ARCH(20)	122.8501*	2.8889e+012*	867.44*

Notes: *, ** and *** denote statistical significance at 1%, 5% and 10%, respectively.

Summary statistics for the return series were displayed in Table 1. From this table, the gold price and wti price exhibit similar degrees of volatility, as reflected in their standardeviations. The standard deviations are between 0.9 and 1.8. Bitcoin has the largest standard deviation; gold and wti are about the same volatile series. All return series, except for gold, have small negative skewness. The negative skewness in bitcoin and wti implies that large negative changes in returns occur more often than positive changes. For all return series the kurtosis statistics are positive; indicate that the tails have more observations than in a Gaussian distribution. This is also confirmed by the large Jarque-Bera statistics, which reject the null hypothesis of normal distribution for all series. Finally, the Ljung-Box Q test rejects the null hypothesis of serial independence for each return; the McLeod-Li test rejects the null hypothesis of serial independence in squares of each return series; and the ARCH test rejects the null hypothesis of conditional homoscedasticity.

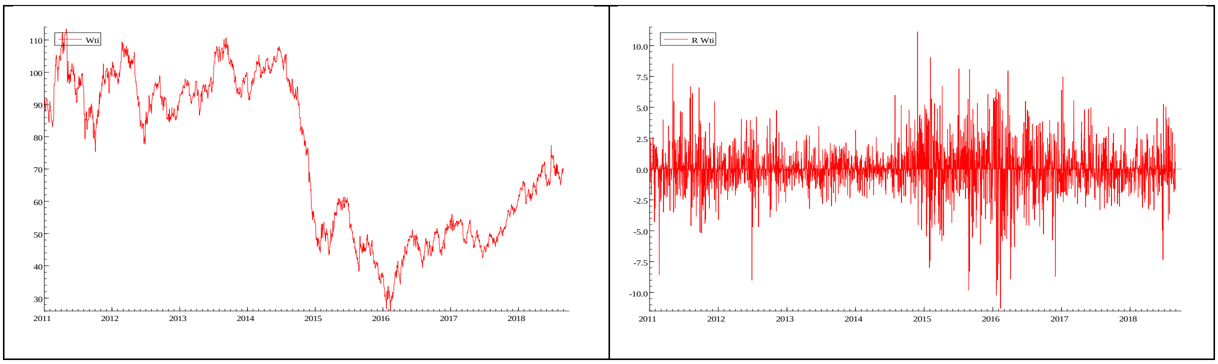

Figure.1. Oil price and oil price return behavior over time.

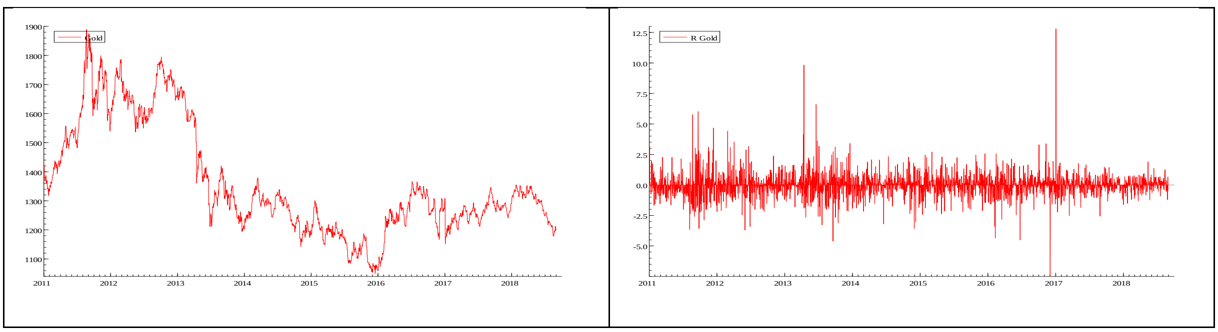

Figure.2. Gold price and Gold price return behavior over time.

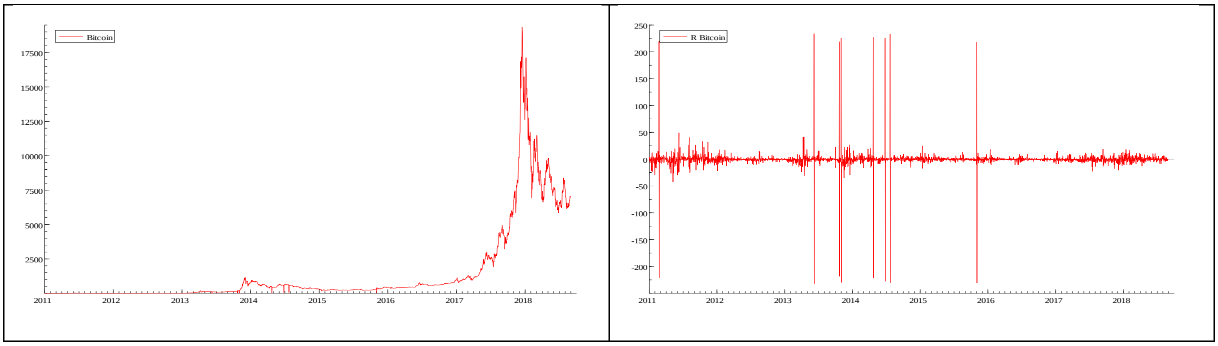

Figure.3. Bitcoin price and Bitcoin price return behavior over time.

All figures above presents the daily rates of return for the three adjusted prices. Daily returns fluctuate around zero and are characterized by volatility clustering. All returns demonstrate higher volatility. However, the gold and wti appear more volatile. This characteristic cares the use of GARCH family models to investigate prices returns dynamics.

4 Results and Discussion

In the first part we examine the causal relations between the three prices returns using a VAR model, where the lag length of two is chosen by the Akaike information criterion[2].

Table.2: F-statistics for tests of causality in return equations in a three -variable vector autoregressive (VAR) model.

	Dependent Variables		
	Bitcoin	**Wti**	**Gold**
Bitcoin	-	0.6287	0.0718
Wti	2.2306***	-	3.6064**
Gold	2.5246**	3.2790**	-

Notes: *, ** and *** denote statistical significance at 1%, 5% and 10%, respectively.

Table 2 reports the results of F-statistics on tests of causality between the three prices. Line 1 reports the response of bitcoin return to other two prices. For example, the F-value of 0.6287 and 0.0718 suggests that changes in wti and gold returns do not have a significant effect on bitcoin return. Line 2 reports the response of wti return to other two prices; the F-value of 2.2306 and 3.6064 suggests that changes in bitcoin and gold returns have a significant effect on wti

[2] Using the VAR lag order selection criteria, the Akaike information criterion (AIC) chooses two lags

return. All returns are influenced by past returns in Gold, but gold returns are not influenced by the returns in bitcoin; thus, there is evidence of unidirectional spillovers in returns from the gold and bitcoin but there is evidence of bidirectional spillovers in returns from the wti. This finding is consistent with Giudici and Abu-Hashish (2018) which are noted that bitcoin has low correlation between oil and gold. Das et al. (2018) found bilateral causality in mean and variance for gold and crude oil with respect to financial stress, and stocks to be influential to financial stress both in mean and variance. Symitsi et al. (2018) have proved that the low correlation of Bitcoin can also lead to significant reduction of the overall portfolio risk, most apparent in portfolios of commodities.

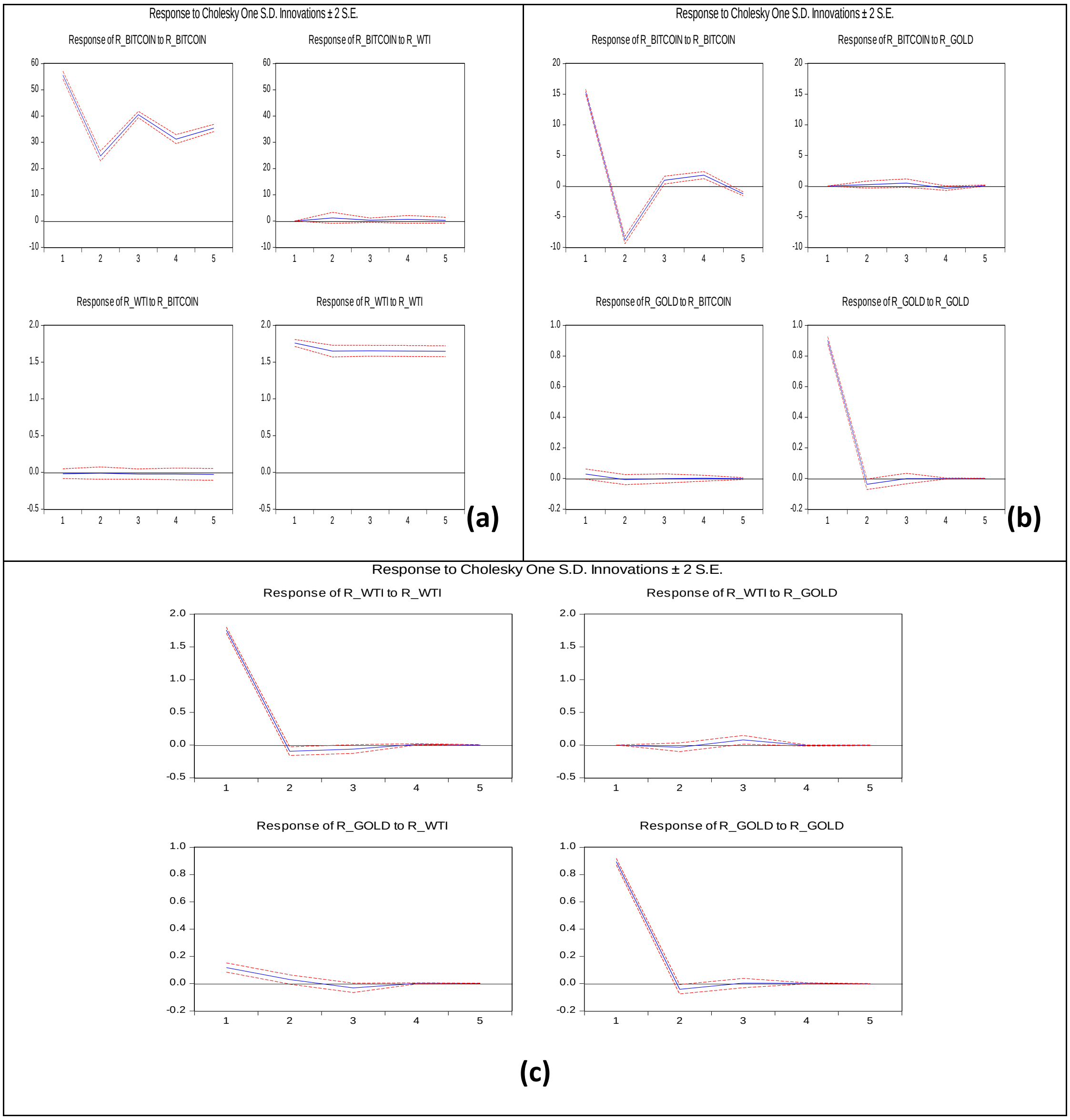

Figure.4. Impulse response functions.

Figure 4 plots the impulse response functions of returns to their own shocks, as well as to shocks in other markets along with their 95% confidence bounds. Three patterns of response are evident: First, the response of returns to their own shocks are positive on the first day, but oscillate and die out after the following days. Second, the responses of gold and bitcoin to shocks in wti are significantly positive following the shock and die out after two days. Three the responses of bitcoin and wti to shocks in old are slightly positive following the shock. Four the responses of gold shocks in bitcoin to are significantly positive following the shock and die out after one day. Finally, the impulse response functions suggest rapid dissemination of price information, which is consistent with an efficient operation of the market.
Next, we examine the patterns of conditional volatility in returns, the possibility of volatility spillovers across markets and the dynamics of conditional correlations in returns across the three prices. We begin with the estimation results for the MGARCH-BEKK model, which are reported in Table 3.

Table.3: Estimation results from the BEKK model.

Dependent Variables			
Panel A. Parameters Estimates			
Parameters	***Bitcoin (. , 1)***	***Wti (. , 2)***	***Gold (. , 3)***
C(i, i)	-0.2872*	-0.0023*	0.1474*
A(1, .)	0.0761***	0.5041**	0.0878*
A(2, .)	0.5041**	-0.0567**	-0.0154*
A(3, .)	0.5604**	-0.0780***	0.2063*
G(1, .)	0.7440*	-0.0002*	1.4634*
G(2, .)	0.6409*	-0.0003*	0.00001
G(3, .)	0.0097	−0.0065*	−0.0021*
Panel B. Diagnostic Tests			
Q(40)	77.123 **	76.141**	56.905
QS(40)	47.971	50.071	73.014 **

Notes: *, ** and *** denote statistical significance at 1%, 5% and 10%, respectively. Q(40) is the Ljung-Box test of serial correlation of up to 40th order in standardized residuals. QS (40) is the McLeod-Li test of serial correlation of up to 40th order in the squares of standardized residuals.

Panel A of the table reports the estimates of BEKK parameters. Here, A(. , *i*) and G(. , *i*) are the corresponding ARCH and GARCH parameters associated with price *i*. The squared ARCH parameters $[A(. , i)]^2$ capture the responses of volatility in market i to squared standardized innovations in each of the three prices. For example, the estimated ARCH response for bitcoin ($i = 1$) to its own innovations, $[A(1, 1)]^2$, is 0.061, to innovations in wti is $[A(2, 1)]^2 = (0.5041)^2$, to innovations in gold is $[A(3, 1)]^2 = (0.025)^2$. Thus, the volatility of bitcoin responds significantly to past squared shocks in its own market and also for the other two markets. All diagonal elements A(1, 1), A(2, 2) and A(3, 3) are statistically significant, suggesting that each conditional variance depends on its own squared lagged innovations. The results also show that own spillovers are always much larger than the cross-market spillovers.

Panel B of the table reports two diagnostic tests for each price. The Q(40) is the Ljung-Box test of the serial independence of 40th order. We fail to reject the null hypothesis for the gold, but reject it for the bitcoin and wti. Similarly, QS(40) is the McLeod-Li test of serial independence in the squares of standardized residuals. We fail to reject the null hypothesis for all but the gold. These results provide some indications of misspecification in the VAR-BEKK model. Next, we examine the performance of the MGARCH-CCC model of Bollerslev (1990). This model estimates the own ARCH and GARCH effect, as well as the correlations between each of the two markets. The results are reported in Table 4.

Table.4: Estimation results from the CCC model.

Dependent Variables			
A. Estimates of CCC Model Parameters			
	Bitcoin	***Wti***	***Gold***
c	0.0015*	0.0028*	0.0024*
a	0.0706*	0.0645*	0.0813*
g	0.847*	0.9128**	0.9061**
B. Estimates of Constant Conditional correlation Parameters			
Bitcoin	1		
Wti	0.0113***	1	
Gold	0.0308**	0.1306*	1
C. Model Diagnostics			

Q(40)	70.4771*	49.6189	43.2788
QS(40)	38.6004	29.4513	47.3481

Notes: *, ** and *** denote statistical significance at 1%, 5% and 10%, respectively.

Panel A reports the parameter estimates for the conditional variance models for each of the three prices. Here, *c* is the estimated constant term for each conditional variance, and *a* and *g* represent the estimated own ARCH and GARCH parameters, respectively. All of the estimated parameters are significantly different from zero, suggesting the existence of own ARCH and GARCH effects. Panel B of the table reports the corresponding conditional correlations between the pairs of three prices. Again, all estimated conditional correlations are positive and significantly different from zero. Two patterns of correlation emerge: (1) a high correlations of 0.1306 among gold and wti; The high conditional correlation reflects the presence of interconnectivity and close proximity between them. (2) low correlations of 0.0113 and 0.0308 among the bitcoin and other prices respectively; The low conditional correlations reflect the absence of strong direct interconnections between their markets.Finally, Panel C reports the diagnostics for the CCC model. First, we fail to reject the null hypothesis of serial independence in the wti and gold, but reject the null for the bitcoin as reflected in the values of Ljung-Box Q(40) statistics. Second, the McLeod-Li test statistic fails to reject the null hypothesis of no serial correlation in the squares of standardized residuals for all three markets. Thus, while evidence of model misspecification persists, the CCC model is a better fit than the BEKK alternative.

Table.5: Estimation results from the VAR (2)-DCC GARCH model.

Dependent Variables			
A. Estimates of the VAR(2) Parameters			
	Bitcoin	*Wti*	*Gold*
Bitcoin t−1	−0.1031*	−0.0149**	−0.0401*
Bitcoin t−1	−0.1013**	−0.03012*	0.0211**
Wti t−1	0.0895*	−0.0121**	0.0297*
Wti t−1	0.0845*	0.0291*	−0.0181*
Goldt−1	−0.0095***	−0.1201*	0.010*
Goldt−1	−0.0372*	−0.0312***	−0.0298*
B. Estimates of the DCC-GARCH parameters			

c	0.0017*	0.0018*	0.0014*
a	0.0891**	0.0704*	0.0592*
g	0.9008**	0.8127*	0.9789**
α	0.014		
β	0.980		
C. Model Diagnostics			
Q(40)	47.8951	51.7825	42.5517
QS(40)	42.9132	28.4127	41.9031

We report the results of estimating the complete VAR(2)-DCC model in Table 5. Panel A of the Table reports the estimated parameters for the VAR(2) model. As reflected in the first all returns prices are influenced by their own past returns, as well as past returns in the other returns prices. Panel B reports the ARCH, GARCH and conditional correlation parameter estimates for the DCC model. Note that all of the estimated parameters are statistically significant, suggesting the existence of the own ARCH and GARCH effects. Furthermore, the estimated α and β parameters associated with the dynamic conditional correlation are statistically significant, supporting the time-varying nature of the conditional correlation. Finally, Panel C of the table provides model diagnostics. First, there is no evidence of serial correlation in the standardized residuals for all returns prices, as reflected in the small values of their Ljung-Box Q statistics. Second, there is no evidence of serial correlation in the squares of standardized residuals as reflected by the small values of the McLeod-Li statistics. Thus, the DCC model also provides a better fit than the BEKK model.

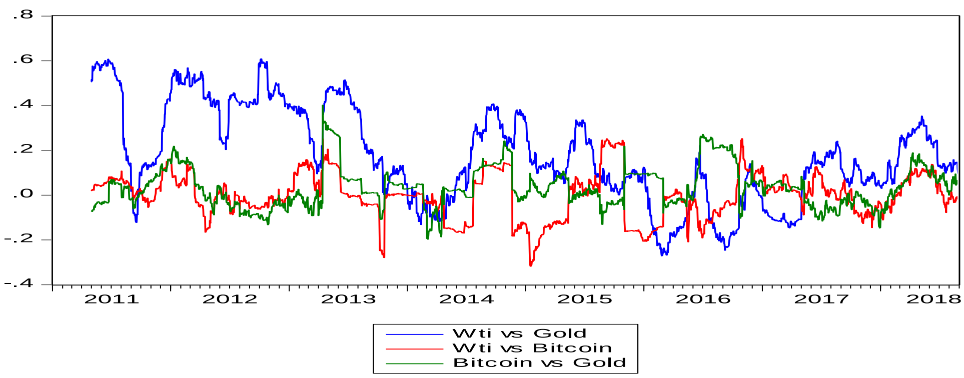

Figure.5. Rolling correlation at 4 months

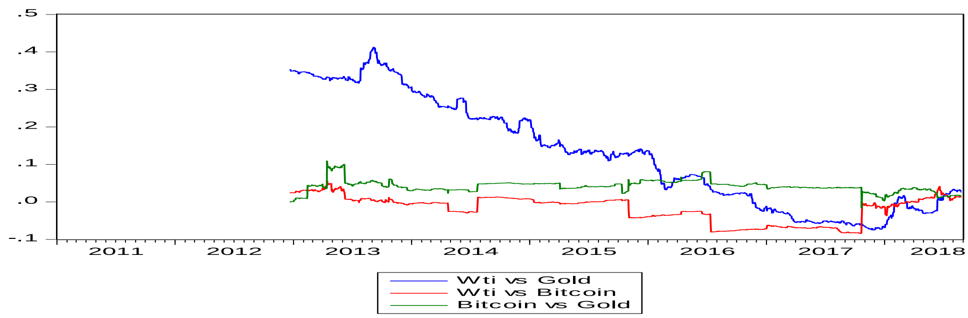

Figure.6. Rolling correlation at 24 months

In Figure 5 and figure 6, we plot the rolling correlations between each pair of prices with time spans of four months and two years and four years, respectively. Interestingly, we find more fluctuations of the rolling correlations in downward directions between each pair, particularly after 2012, regardless of the selected time spans. Moreover, we mainly detect sharp decreases in the correlations between each pair since 2017.

5 Conclusion

This study examined the dynamic relationships between the gold bitcoin and wti using daily data from 1 January 2011 to 31 August 2018.The primary purpose of the investigation was to explore the possibility of spillovers in returns and in conditional volatility across these three markets. For to do we examine models from different categories. We use three different volatility models; a CCC-GARCH(1,1), a dynamic conditional correlation model (DCC-GARCH model), and a bivariate-BEKK(1,1). The results of this investigation may have important implications regarding international investment, portfolio diversification and risk management. The results of our investigation reveal the following: (1) bilateral causality between gold and wti; (2) unidirectional spillovers in returns from bitcoin the other two prices; (3) Thus, the DCC model also provides a better fit than the CCC model and the BEKK model. The rolling correlation suggests a modest increase in conditional correlation between each pair since 2017.

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