

# Fed and ECB: which is informative in determining the DCC between bitcoin and energy commodities?

Fed and ECB

77

Abdelkader Derbali

*Department of Administrative and Financial Sciences and Techniques,  
Community College, Taibah University, Medinah, Saudi Arabia*

Lamia Jamel

*Department of Finance and Economics, College of Business Administration,  
Taibah University, Medinah, Saudi Arabia*

Monia Ben Ltaifa

*Department of Human Resource,  
Community College in Abqaiq, King Faisal University, Abqaiq, Saudi Arabia*

Ahmed K. Elnagar

*Department of Administrative and Financial Sciences and Techniques,  
Community College, Taibah University, Medinah, Saudi Arabia, and*

Ali Lamouchi

*Department of Finance and Economics, College of Business Administration in  
Al Rass, Qassim University, Buraidah, Saudi Arabia*

Received 4 July 2020  
Revised 16 July 2020  
Accepted 17 July 2020

## Abstract

**Purpose** – This paper provides an important perspective to the predictive capacity of Fed and European Central Bank (ECB) meeting dates and production announcements for the dynamic conditional correlation (DCC) between Bitcoin and energy commodities returns and volatilities during the period from August 11, 2015 to March 31, 2018.

**Design/methodology/approach** – To assess empirically the unanticipated component of the US and ECB monetary policy, the authors pursue the Kuttner's approach and use the federal funds futures and the ECB funds futures to assess the surprise component. The authors use the approach of DCC as introduced by Engle (2002) during the period from August 11, 2015 to March 31, 2018.

**Findings** – The authors' results suggest strong significant DCCs between Bitcoin and energy commodity markets if monetary policy surprises are incorporated in variance. These results confirmed the financialization of Bitcoin and commodity energy markets. Finally, the DCC between Bitcoin and energy commodity markets appears to respond considerably more in the case of Fed surprises than ECB surprises.

## JEL Classification — E52, E63, O13, Q02

© Abdelkader Derbali, Lamia Jamel, Monia Ben Ltaifa, Ahmed K. Elnagar and Ali Lamouchi. Published in *Journal of Capital Markets Studies*. Published by Emerald Publishing Limited. This article is published under the Creative Commons Attribution (CC BY 4.0) license. Anyone may reproduce, distribute, translate and create derivative works of this article (for both commercial and non-commercial purposes), subject to full attribution to the original publication and authors. The full terms of this license may be seen at <http://creativecommons.org/licenses/by/4.0/legalcode>

The authors would like to thank the Editor in Chief and the anonymous reviewers for their supportive and important suggestions. The authors are grateful to the anonymous referees of the journal for their extremely useful suggestions to improve the quality of the paper.

**Funding:** The author(s) received no financial support for the research, authorship and/or publication of this article.

**Declaration of conflicting interests:** The author(s) declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.



Journal of Capital Markets Studies  
Vol. 4 No. 1, 2020  
pp. 77-102  
Emerald Publishing Limited  
2514-4774  
DOI 10.1108/JCMS-07-2020-0022

**Originality/value** – This study is a crucial topic for policymakers and portfolio risk managers.

**Keywords** DCC, Bitcoin, Energy commodities, Monetary policy surprises

**Paper type** Research paper

## 1. Introduction

The role of a central bank is not naturally and historically dedicated to creditworthiness, although some economists argue that it is not possible to avoid it – see [Goodhart \(1999\)](#). An [IMF report \(2015\)](#) notes the existing challenge to the use of monetary policy for financial stability and the need for appropriate prudential policies. Prudential policies then serve financial stability while monetary policy remains limited to price stability. However, this report also indicates that knowledge about the relationship between monetary policy and financial stability is evolving and that circumstances are changing. In this context, acting with monetary policy on components comprising solvency issues therefore leads to questioning the articulation between monetary policy and the macroprudential policy developed since the early 2000s. Politics has made the choice up to now to implement a macroprudential policy to complement the microprudential tool of central banks or delegated agencies rather than using monetary policy.

Due to growing popularity and significance of Bitcoin, practitioners, investors and researchers have lately begun to evaluate Bitcoin from the viewpoint of finance and economics. Also, [Rogojanu and Badea \(2014\)](#) investigate the benefits and weaknesses of Bitcoin and assess it through additional complementary monetary structures. [Brandvold et al. \(2015\)](#) concentrate on the impacts of Bitcoin trades to price detection. [Ciaian et al. \(2016\)](#) analyze Bitcoin price structure by concentrating on market influences of supply/demand and numerical currencies components. Few surveys have appeared from the viewpoint that Bitcoin represents an alternate to traditional currencies in periods of low confidence, such as through the international financial crisis in 2007, therefore suggesting Bitcoin as numerical gold ([Rogojanu and Badea, 2014](#)). [Baur and Lucey \(2010\)](#) conclude that Bitcoin is a hybrid among important metals and traditional currencies. They furthermore underline its responsibility as a beneficial diversifier and an investment.

The sensitivity of asset prices to monetary policy has proven to be a dominant theme of the past year. Driven by low policy rates and quantitative easing, long-term yields on major bond markets had fallen to unprecedented lows in 2012. Since then, markets have become very sensitive to any signs of a reversal of these exceptional conditions. Concerns over the stance of US monetary policy played a key role - as demonstrated by the episode of bond market turmoil in mid-2013 and other key events of the period under review. However, monetary policy has also had an impact on asset prices and, more generally, on investor behavior. The events of the past year have shown that – by its influence on risk perception and the attitude of market participants in this regard – monetary policy can have a powerful effect on financial conditions, as evidenced by risk premiums and financing conditions. In other words, the effects of the risk-taking channel were widely manifested throughout the period ([Rajan, 2006](#)).

The extraordinary influence exerted by the central banks on the world financial centers was manifested in a very visible way on the main bond markets: the slope of the yield curve was particularly sensitive to all the announcements and changes in policy expectations to come up. While short-term rates remain largely anchored by the low-key rates, medium-term rates react to the forward-looking orientations, and long-term rates were dominated by asset purchases, long-term expectations and the perceived credibility of the central bank. When the Federal Reserve (Fed) – the first major central bank to act – hinted in mid-2013 that it would slow down asset purchases, long-term bonds suffered heavy losses. Even though bond prices fell less than during the massive decommitments of 1994 and 2003, the overall losses in market value were heavier this time because the stock of treasury securities was much higher.

Unconventional monetary policy measures and forward-looking guidelines played a decisive role in the communication of central banks. After Fed expressed to leave federal funds rate low, even after asset programs ended, investors downgraded medium-term expectations for short rates, and the dispersion of opinions has diminished. At the same time, there was a broader consensus among market participants that long-term rates would eventually increase in the medium term.

Bernanke and Kuttner (2005) give proof that monetary policy news takes the lead to reduce stock market returns. Basistha and Kurov (2008) conclude that the response of stock market returns to surprises regarding unexpected fluctuations in US monetary policy varies on the condition of the business phase and on credit market conditions. They find a considerably greater reaction in downturn and in difficult credit market situations. Ehrmann and Fratzscher (2009) conclude that the returns correlated with 50 equity markets internationally clearly react to US monetary policy announcements.

Hayo *et al.* (2012) give persuasive confirmation that US monetary policy greatly influences the returns of 17 emerging equity markets during the period from 1998 to 2009. Hayo *et al.* (2010) show that US target rate adjustments and the Federal Open Market Committee (FOMC) statement have a considerable effect on European and Pacific equity market returns. Wongswan (2009) investigates 15 foreign equity indexes in Asia, Europe and Latin America and concludes that they considerably respond to US monetary policy news at brief time possibilities. A remarkable exclusion is by Bailey (1990), who finds a low suggestion of foreign equity market answers to Federal funds rate announcements.

In recent times, energy commodity futures have appeared as an enormously prevalent asset portfolio for investors and fund managers (Andreasson *et al.*, 2016). The speed in the financialization of energy commodity markets has also significantly increased the numeral of market members and contributors. In addition to remaining employed for hedging and speculative reasons, energy commodity futures can similarly increase away the risk of differentiated stock/bond portfolios, principally during financial and economic recessions. Subsequently, understanding of the elements that explain energy futures markets is possible to make important news for investors and managers.

Among the different energy commodities, crude oil maybe the majority considerable given its vital liability in the globe economy comparative to more energy commodities, principally in requirements of causing crisis (Hamilton, 1983, 2003, 2009, 2013). Additionally, crude oil is essential for transportation, industrial and agricultural segments, whether employed as feedstock in production or as a surface fuel in utilization (Mensi *et al.*, 2014b).

At present, there have been only limited surveys on the influence of shock component in the inventory pronouncement on price change and volatility. Chang *et al.* (2009) employ analysts' predictions from Bloomberg to investigate the responses of intraday crude oil futures returns to unanticipated portfolio fluctuations. They obtain an instantaneous reply of crude oil returns to supply announcements. Besides, they maintained that the response is greater when the assessment was produced by analysts with forecast correctness in the earlier period.

Gay *et al.* (2009) conclude that the unanticipated adjustments in Energy Information Administration (EIA) natural gas inventory accounts have a considerable influence on intraday futures returns directly following a given news. By applying a GARCH (generalized autoregressive conditional heteroskedasticity) models, Hui (2014) tries to measure the influence of the unexpected inventory fluctuations in the EIA statement on daily crude oil returns and volatility. Hui (2014) concludes that inventory shocks have negative influence on returns but recommends that there is no proof of impact on return volatility.

Chiou-Wei *et al.* (2014) investigate the dynamics of US natural gas futures and spot prices across the weekly pronouncements by the EIA statements. Their empirical findings underline an opposite link among the unexpected inventory adjustments and changes in

futures prices. Besides, [Chiou-Wei et al. \(2014\)](#) show no proof of the influence of inventory surprises another than on the date when the EIA report is published.

In recent times, [Ye and Karali \(2016\)](#) utilize intraday data to examine the reply of crude oil returns and volatility to inventory releases by the American Petroleum Institute (API) and EIA during the period from August 2012 to December 2013. They find that inventory shocks in both API and EIA statements apply an instant inverse influence on returns and a positive effect on volatility.

In the same alignment, [Halova et al. \(2014\)](#) conclude at intraday data to examine the effect of the unexpected part in EIA's crude oil inventory statements on both return and volatility. They show that energy returns react further greatly to unexpected variations in inventory levels through the injection period than over the withdrawal period.

Furthermore, crude oil market volatilities are greatly established to spillover to additional commodity markets ([Kang and Yoon, 2013](#); [Kang et al., 2016, 2017](#); [Mensi et al., 2013, 2014a, 2015](#); [Chebbi and Derbali, 2015, 2016a, 2016b](#)), as well as financial markets ([Balcilar and Ozdemir, 2013](#); [Balcilar et al., 2015, 2017](#); [Balli et al., 2017](#); [Bekiros and Uddin, 2017](#); [Bekiros et al., 2017](#); [Berger and Uddin, 2016](#); [Kang et al., 2016](#); [Lahmiri et al., 2017](#); [Mensi et al., 2014a, 2015](#); [Narayan and Gupta, 2015](#)).

[Miao et al. \(2018\)](#) study the impact of the unexpected part of weekly crude oil inventory in EIA statements on oil futures and options prices. [Miao et al. \(2018\)](#) conclude that prices clearly respond to the inventory shock on news day. Furthermore, they show that futures return considerably reduces with positive surprises and rises with negative surprises. Moreover, as [Shrestha \(2014\)](#) notes, one can predict price detection to appear mostly in the energy futures markets since futures prices respond to new pronouncement faster than spot prices recognized smaller transaction expenses and healthier ease of minor selling associated with energy futures agreements. Furthermore, it is believed that futures market volatilities create spot market volatilities for crude oil ([Baumeister and Kilian, 2014, 2015](#); [Baumeister et al., 2014, 2017](#)). Consequently, defining the issues that drive the energy commodity markets is of main implication for both investors and policymakers, which is our objective for this paper via examination of the significance of surprises from Fed and ECB (European Central Bank) announcements and meeting dates.

This study is extremely directly related to the current literature on the reaction of the energy commodities (Crude Oil WTI (West Texas Intermediate), Gasoline RBOB (Reformulated Gasoline Blendstock for Oxygen Blending), Brent Oil, London Gas Oil, Natural Gas and Heating Oil) returns and volatilities to Fed and ECB events during the period from August 11, 2015 to March 31, 2018. In particular, it is commonly known that transaction movement can be influenced by the new information (Fed and ECB monetary policy events in our paper). Giving this new info is accessible in the financial market, investors respond through portfolio variations of their portfolios further intensively among energy commodities portfolio, which in turn starts to an expansion in trading capacity. As demonstrated by the well-known positive nexus among volatility and trading size ([Andersen, 1996](#); [Karpoff, 1987](#), among others), the growth in trading size might, sequentially, transform into greater volatility. Additional potential justification is presented by [Ross \(1989\)](#), which examines the growth in volatility in asset returns related to the information publication. Therefore, it is crucial to consider the ultimate nexus among monetary policy decisions and volatility of stock market returns, especially, energy commodity returns.

So, we examine in this paper the US and European monetary policy surprises as a potential determinant of the volatility of energy commodity returns is of key significant given a period of quick failure of the European markets and the principal role of US monetary policy movements on financial asset prices. In this study, we examine the time-varying relationships among strategic commodities covering sector of energy (Crude Oil WTI (West Texas Intermediate), Brent Oil, Gasoline RBOB (Reformulated Gasoline Blendstock for Oxygen

Blending), Heating Oil, London Gas Oil and Natural Gas) and Bitcoin, over the period from August 11, 2015 through March 31, 2018. For this purpose, we use the DCC-GARCH approach with incorporating the Fed and ECB monetary policy surprises.

Our empirical results in this paper confirm strong significant dynamic conditional correlations between Bitcoin and energy commodity markets if monetary policy surprises are incorporated in variance. These results proved the financialization of Bitcoin and commodity markets. Also, the results estimated and more specifically those related to the level of the persistence of volatility are sensitive to the presence of monetary policy surprises into the DCC-GARCH (1,1) model. The conditional correlations between Bitcoin and energy commodity markets appear to respond considerably more in the case of Fed surprises than the ECB surprises.

The rest of our paper is organized as follows. [Section 2](#) describes the econometric methodology utilized in this study. [Section 3](#) defines the data employed in this study. [Section 4](#) is devoted to the empirical results of the impact of US and European monetary policy on a sample of energy commodities market. [Section 5](#) concludes. Finally, [Section 6](#) presents policy implications of our paper.

## 2. Econometric methodology

The methodology employed in this study, which tries to measure Bitcoin and energy commodities returns and volatilities responses to monetary policy surprises announced by the Fed and ECB, is based on DCC multivariate model as recommended by [Engle \(2002\)](#).

The DCC model has the elasticity of univariate GARCH models but does not tolerate from the “curse of dimensionality” of multivariate GARCH models. The estimation of GARCH-DCC models involves two stages. We estimate, in the first stage, the conditional mean return and variance of each variable used in this study. In the second stage, we utilize the consistent regression residuals acquired in the first stage to assess conditional correlations between Bitcoin and energy commodities with Fed and ECB surprise monetary policy news.

To attain the reaction of energy commodities returns correlated with Bitcoin to the surprise component, we employ the following model: the GARCH (1,1) model is taken by the following equation:

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \quad (1)$$

where,  $\omega$ ,  $\alpha$  and  $\beta$  represent the parameters that want to be estimated.

The conditional correlation matrix  $R_t$  of the standardized disturbances  $\varepsilon_t$  is provided by:

$$R_t = \begin{bmatrix} 1 & q_{12t} \\ q_{21t} & 1 \end{bmatrix} \quad (2)$$

where,  $\varepsilon_t = D_t^{-1} r_t$

The matrix  $R_t$  is assessed as following:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \quad (3)$$

Where  $Q_t$  is the time-varying covariance matrix of  $\varepsilon_t$  and  $Q_t^{*-1}$  is the inverted diagonal matrix along with the square root of the diagonal components of  $Q_t$ . Remarking that  $Q_t^{*-1}$  is equivalent to:

$$Q_t^{*-1} = \begin{bmatrix} 1/\sqrt{q_{11t}} & 0 \\ 0 & 1/\sqrt{q_{22t}} \end{bmatrix} \quad (4)$$

The DCC-GARCH (1,1) is provided by the following equation:

$$Q_t = \omega + \alpha \varepsilon_{t-1} \varepsilon'_{t-1} + \beta Q_{t-1} \quad (5)$$

where  $\omega = (1 - \alpha - \beta)\bar{Q}$ , with  $\bar{Q}$  being the unconditional covariance of the standardized disturbances  $\varepsilon_t$ .  $\omega$ ,  $\alpha$  and  $\beta$  are the estimated parameters.

In this study, we provide to the literature by including an exogenous variable in the DCC-GARCH (1,1) model, which measures the Fed and ECB monetary policy surprise. Subsequently, the estimated model is given as follows:

$$Q_t = \omega + \alpha \varepsilon_{t-1} \varepsilon'_{t-1} + \beta Q_{t-1} + \gamma S_t \quad (6)$$

where  $S_t$  implies the unexpected Fed and ECB surprise monetary policy announcements at time  $t$ .

Based on [Kuttner \(2001\)](#), we assess the surprise as the scaled version of change in the one-day current-month futures rate at an event date ( $d$  defined as a meeting of the FOMC and ECB). Explicitly, the surprise factor for each target rate change by the FOMC is given by the following formula:

$$S = \frac{D}{D-d} (f_d - f_{d-1}) \quad (7)$$

where  $f_d$  represents the current-month futures rate at the end of the announcement day  $d$ ,  $f_{d-1}$  represents the current-month futures rate at the end of the announcement day ( $d-1$ ) and  $D$  is the number of days in the month.

### 3. Data

The data used in this paper contain daily observations on returns and conditional volatilities of energy commodities and Bitcoin. In line to examine the impact of the policy monetary news, we concentrated on the expected and surprise factors in Federal funds target rate changes and ECB target rate changes. Our data sample covers the period from August 11, 2015 to March 31, 2018.

We notice that all stock price indices of energy commodities and Bitcoin are transmuted into logarithm form. We identify logarithmic return as  $r_t = \ln(p_t/p_{t-1})$ , where  $P_t$  is the price index at time  $t$  and where  $P_{t-1}$  is the price index at time  $t-1$ .

#### 3.1 Bitcoin and energy commodities

[Table 1](#) summarizes main statistical features for the daily returns of energy commodities and Bitcoin. We can show that the lowest possible average of return is 0.000167 for NATURAL GAS but the greatest average is 0.009484 for CRUDE OIL WTI followed by BITCOIN with a value of 0.003414.

For the volatility of the daily return series of energy commodities and Bitcoin, as assessed by the standard deviation, we can show that London GAS OIL exhibits a daily volatility of 1.215990 versus NATURAL GAS with a value of 0.499397. The lowest volatility is for BITCOIN (0.040825).

The coefficients of skewness are negative for BITCOIN, CRUDE OIL WTI and HEATING OIL variables. The negative sign of the statistical skewness means that the distribution of the different variables is asymmetrical left. The existence of the same sign for these variables justifies the existence of a minimum correlation between them. For the case of BRENT OIL, GASOLINE RBOB, London GAS OIL and NATURAL GAS, skewness value is positive indicating a distribution shifted to the right.

We find that the values of the kurtosis are all greater than 0. Then, we discuss about leptokurtic distribution. The notion of leptokurticity is widely employed in the financial

	Bitcoin	Crude oil WTI	Brent oil	Gasoline RBOB	Heating oil	London gas_oil	Natural gas
Mean	0.003414	0.009484	0.000247	0.000959	0.000187	0.000213	0.000167
Median	0.002461	0.001962	0.000452	-0.000292	1.28E-05	0.000000	-0.000157
Maximum	0.226412	2.012110	2.015609	2.989895	3.008068	2.023857	2.998405
Minimum	-0.182985	-2.008380	-2.007232	-3.004220	-3.011824	-2.029023	-2.997241
Std. Dev	0.040825	0.428115	0.450674	0.498457	0.484460	1.215990	0.499397
Skewness	-0.133704	-0.065129	0.079595	0.004800	-0.003936	0.014897	0.013953
Kurtosis	7.462392	8.422416	10.04163	10.11375	12.48761	2.240287	12.00799
Jarque-Bera	802.708*	1181.686*	1992.666*	2032.653*	3615.597*	23.2184*	3259.309*
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000009	0.000000
Obs	964	964	964	964	964	964	964

**Note(s):** This table presents summary statistics of daily returns for Bitcoin and energy commodities, namely Crude Oil WTI (West Texas Intermediate), Brent Oil, Gasoline RBOB (Reformulated Gasoline Blendstock for Oxygen Blending), Heating Oil, London Gas Oil and Natural Gas. The data period is from August 11, 2015 until March 31, 2018. Statistical significance at the 1% is denoted by \*

**Table 1.**  
Descriptive statistics  
for daily returns of  
Bitcoin and energy  
commodities

market literature, specifically with thicker tails than normal extremities, requiring additional frequent abnormal values.

The positive sign of Jarque–Bera statistic implies that we can reject the null hypothesis of normal distribution of the variables utilized in our paper. Furthermore, the high-level value of Jarque–Bera statistic indicates that the series is not normally distributed.

The values of skewness (asymmetry) and kurtosis (flatness) for the different variables used in our paper indicate that the distributions of output are not normally distributed. This is suggested by the test of Jarque–Bera, which rejects the null assumption of normality of the time series of the outputs to a threshold of 1%.

Also, [Table 2](#) summarizes the main statistical features for the conditional volatility of the used series. We can find that on average the high value is for CRUDE OIL WTI (0.009484) followed by BITCOIN (0.003414) and GASOLINE RBOB (0.000959).

The coefficients of skewness are all positive except for the London GAS OIL variable. The positive sign of the statistical skewness means that the distribution of the different variables is asymmetrical right. The existence of the same sign for these variables justifies the existence of a minimum correlation between them. For the case of London GAS OIL, skewness value is negative indicating a distribution shifted to the left.

Then, we find that the values of the kurtosis are all greater than 0. Then, we talk about leptokurtic distribution.

The positive estimate of Jarque–Bera statistic implies that we can reject the null hypothesis of normal distribution of the variables used in our study. Furthermore, the high value of Jarque–Bera statistic signifies that the series is not normally distributed.

In [Figures 1–7](#), we expose the evolution energy commodities and Bitcoin return series. It can be seen that the used series present some breaks in their return evolutions.

In [Figures 8–14](#), we present the evolution energy commodities and Bitcoin conditional volatilities series. It can be seen that the used variables attain their maximum in the present some breaks in their conditional volatility evolutions mainly in the end of the period of study.

### *3.2 Monetary policy announcements*

[Table 3](#) summarizes the descriptive statistics based on a sample of US and ECB monetary policy actions from August 11, 2015 through March 31, 2018. For instance, the period under consideration spans a total of 42 meetings of the FOMC and 21 meetings of the ECB. The data comprise changes of 25 basis points, 50 basis points or 75 basis points in the Federal funds target rate and in the ECB funds target rate. The average values of the changes of the Target Federal Funds and surprises changes are respectively  $-0.703289$  and  $-1.978831$  (all values are measured in basis points). The average values of the changes of the Target ECB Funds and surprises changes are respectively  $-0.504568$  and  $1.23117$  (all values are measured in basis points). It is curious to notice that the standard deviation of the Fed policy action is greater than those of Fed surprise. However, it is interesting to observe that the standard deviation of the ECB policy evolution is inferior to those of ECB surprise.

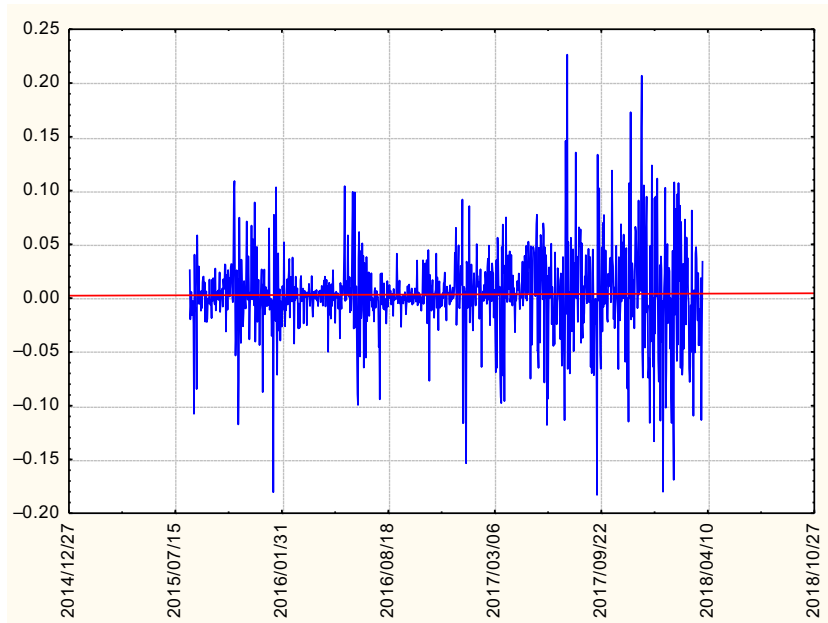
The coefficients of skewness are all negative. The negative sign of the statistical skewness means that the distribution of the different variables is asymmetrical left. The existence of the same sign for these variables justifies the existence of a minimum correlation between them. Then, we find that the values of the kurtosis are all greater than 0. Then, we talk about leptokurtic distribution.

The estimate value of Jarque–Bera statistic implies that we can reject the null hypothesis of normal distribution of the variables used in our study. Furthermore, the high value of Jarque–Bera statistic signifies that the series is not normally distributed.

	Bitcoin	Crude oil WTI	Brent oil	Gasoline RBOB	Heating oil	London gas_oil	Natural gas
Mean	0.001569	0.193770	0.180787	0.256936	0.233040	1.475103	0.258855
Median	0.001017	0.159399	0.159300	0.237772	0.159610	1.471175	0.196522
Maximum	0.006834	0.799828	0.760820	0.956800	1.319846	2.468987	1.196166
Minimum	3.36E-05	1.31E-05	2.32E-05	1.68E-05	2.61E-05	0.358215	5.74E-05
Std. Dev	0.001517	0.155414	0.159270	0.182356	0.259116	0.333564	0.217845
Skewness	1.116933	1.461971	0.885429	1.053372	2.607802	-0.148926	1.577967
Kurtosis	3.368603	5.515496	3.441897	4.293339	10.15268	3.407241	5.860755
Jarque-Bera	205.895*	597.565*	133.803*	245.462*	3147.595*	10.2248*	728.777*
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.006021	0.000000
Obs	964	964	964	964	964	964	964

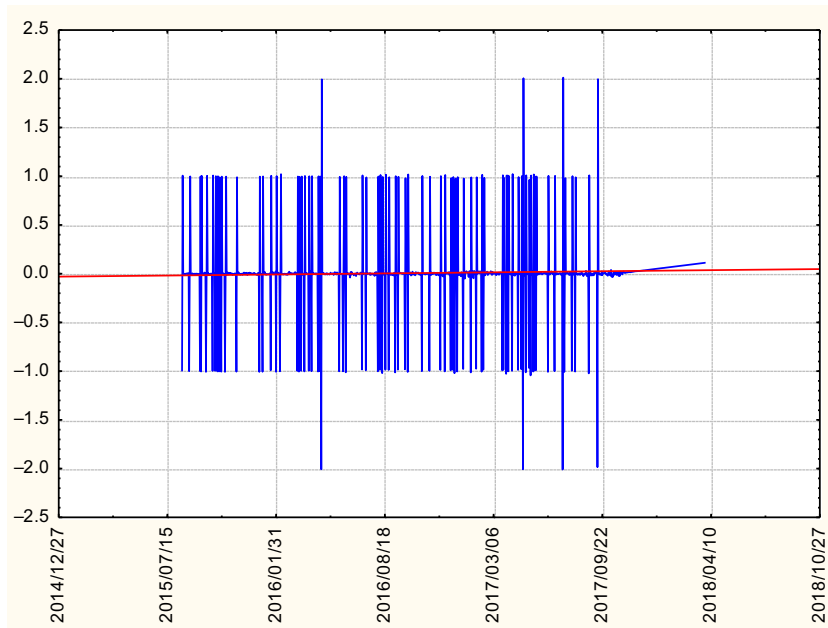
**Note(s):** This table presents summary statistics of daily conditional volatilities for Bitcoin and energy commodities, namely Crude Oil WTI (West Texas Intermediate), Brent Oil, Gasoline RBOB (Reformulated Gasoline Blendstock for Oxygen Blending), Heating Oil, London Gas Oil and Natural Gas. The data period is from August 11, 2015 until March 31, 2018. Statistical significance at the 1% is denoted by \*.

**Table 2.**  
Descriptive statistics  
for daily conditional  
volatilities of Bitcoin  
and energy  
commodities



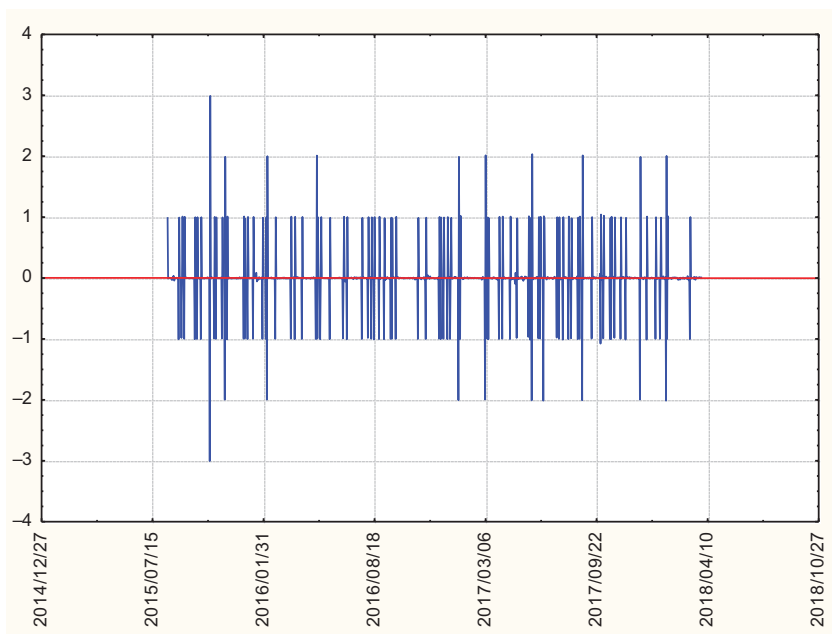
**Figure 1.**  
The returns of Bitcoin  
over the period from  
August 11, 2015 to  
March 31, 2018

Source(s): Elaborated by authors



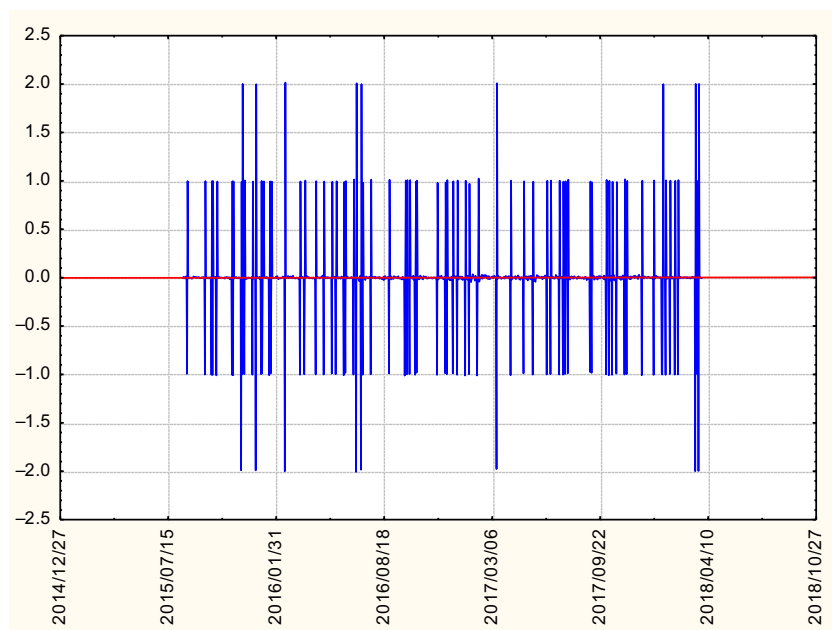
**Figure 2.**  
The returns of crude oil  
WTI over the period  
from August 11, 2015  
to March 31, 2018

Source(s): Elaborated by authors



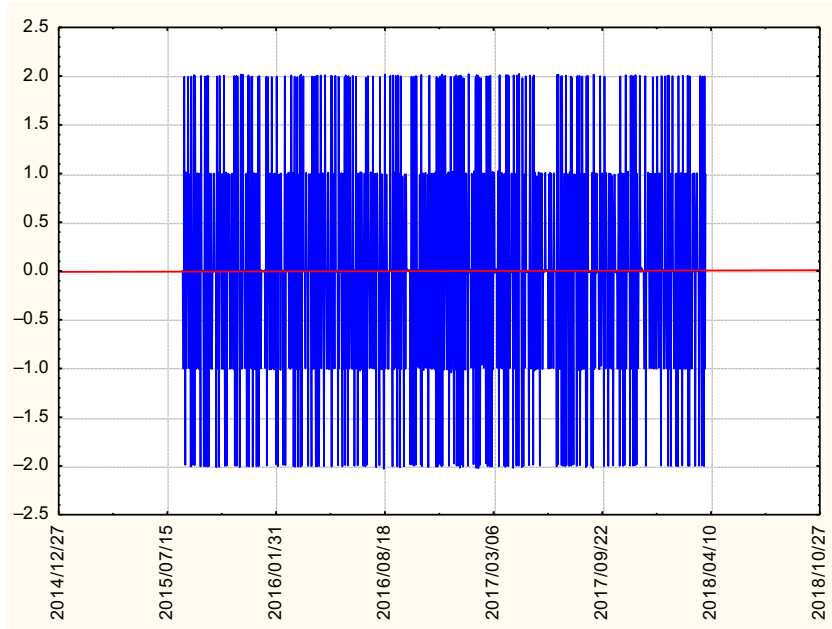
Source(s): Elaborated by authors

**Figure 3.**  
The returns of Brent oil  
over the period from  
August 11, 2015 to  
March 31, 2018



Source(s): Elaborated by authors

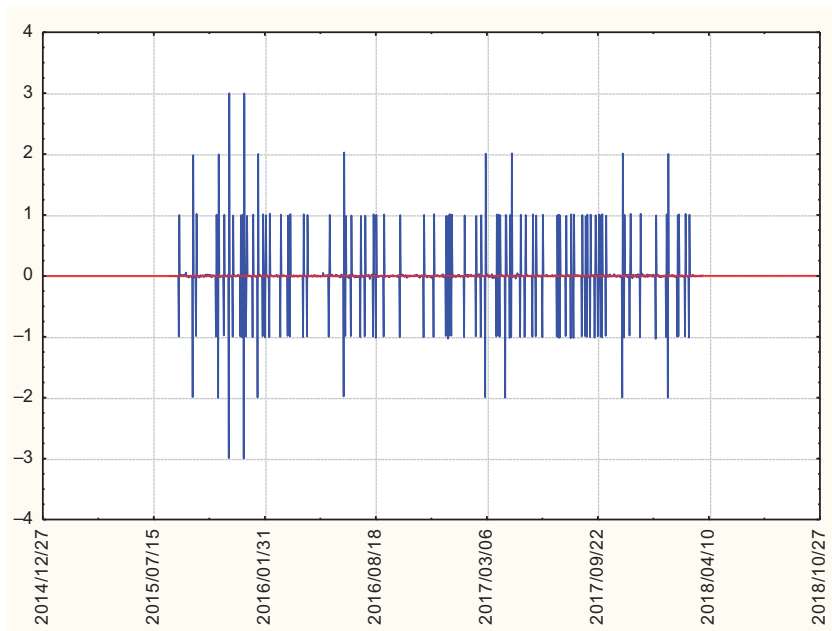
**Figure 4.**  
The returns of gasoline  
RBOB over the period  
from August 11, 2015  
to March 31, 2018



**Figure 5.**  
The returns of heating  
oil over the period from  
August 11, 2015 to  
March 31, 2018

---

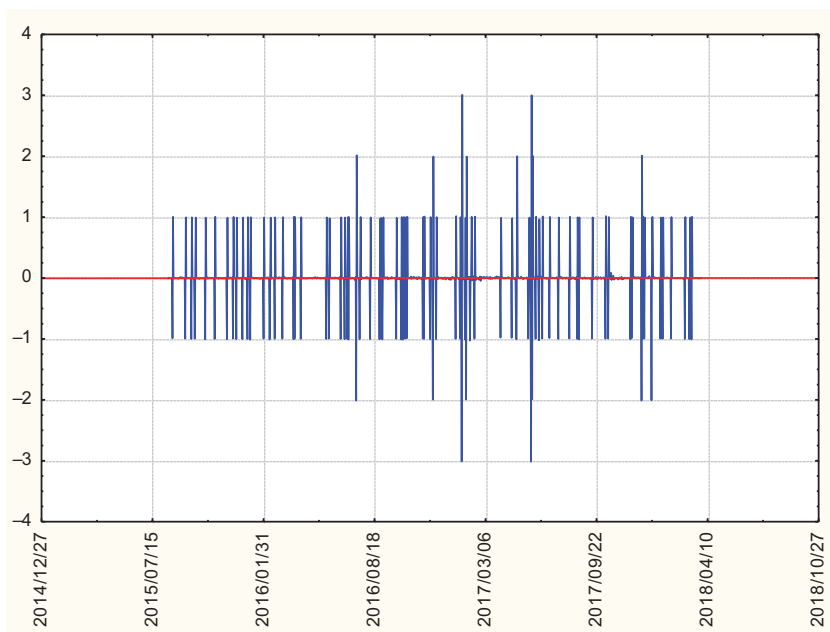
Source(s): Elaborated by authors



**Figure 6.**  
The returns of London  
gas oil over the period  
from August 11, 2015  
to March 31, 2018

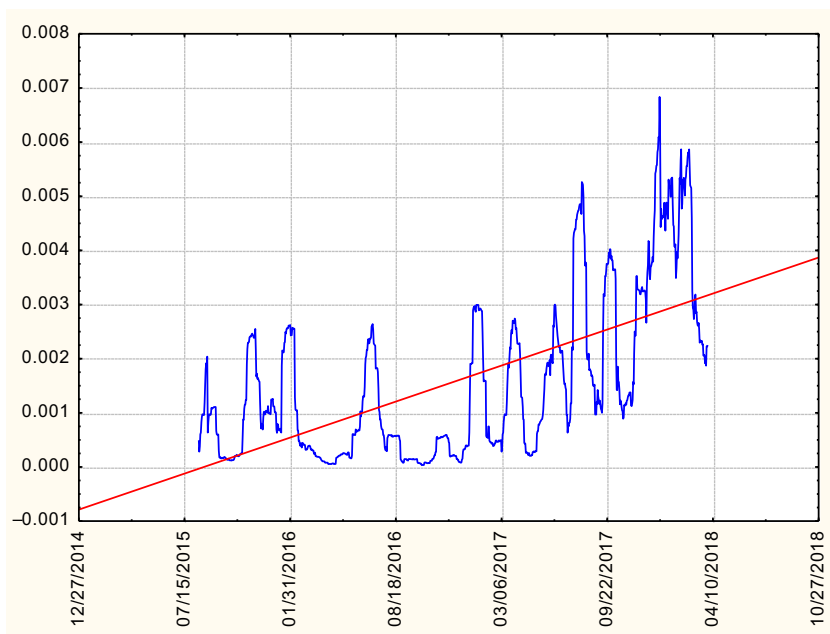
---

Source(s): Elaborated by authors



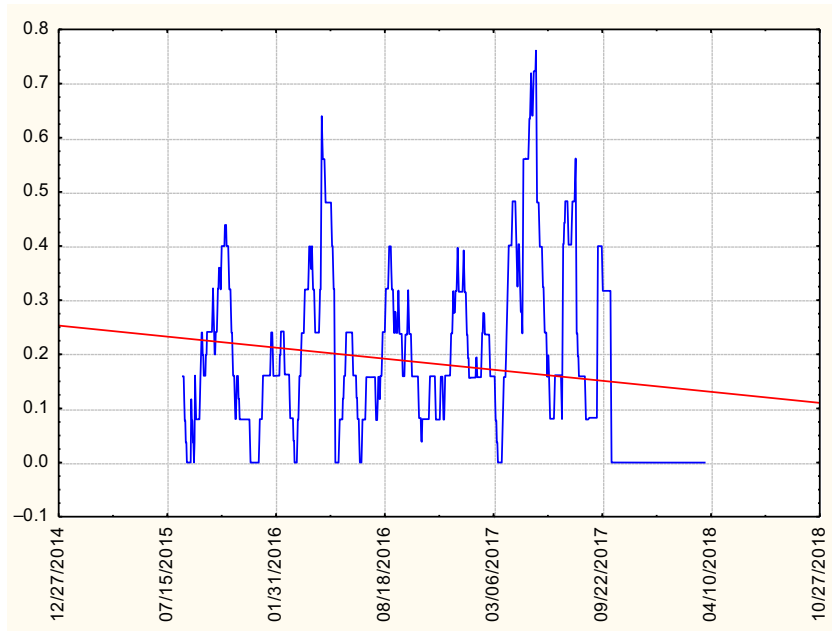
Source(s): Elaborated by authors

**Figure 7.**  
The returns of natural gas over the period from August 11, 2015 to March 31, 2018



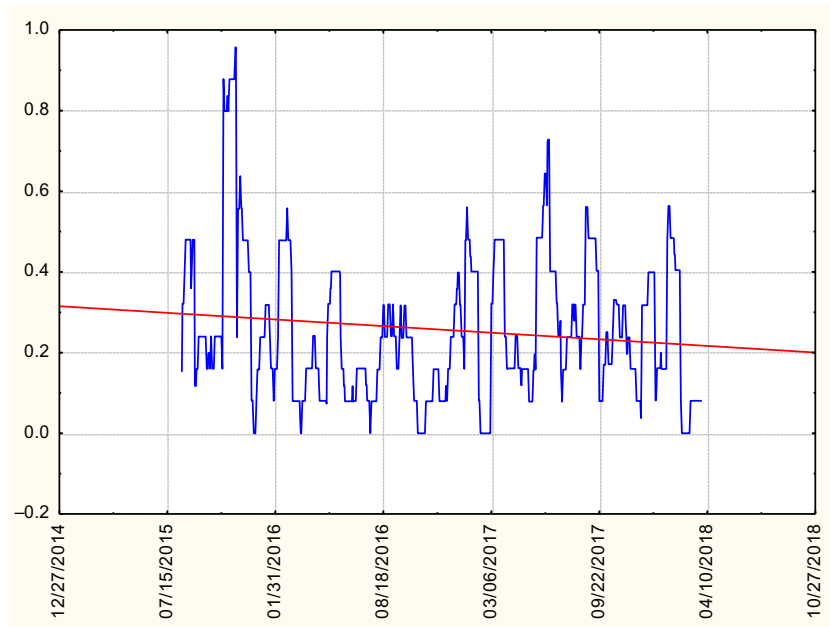
Source(s): Elaborated by authors

**Figure 8.**  
The conditional volatilities of Bitcoin over the period from August 11, 2015 to March 31, 2018



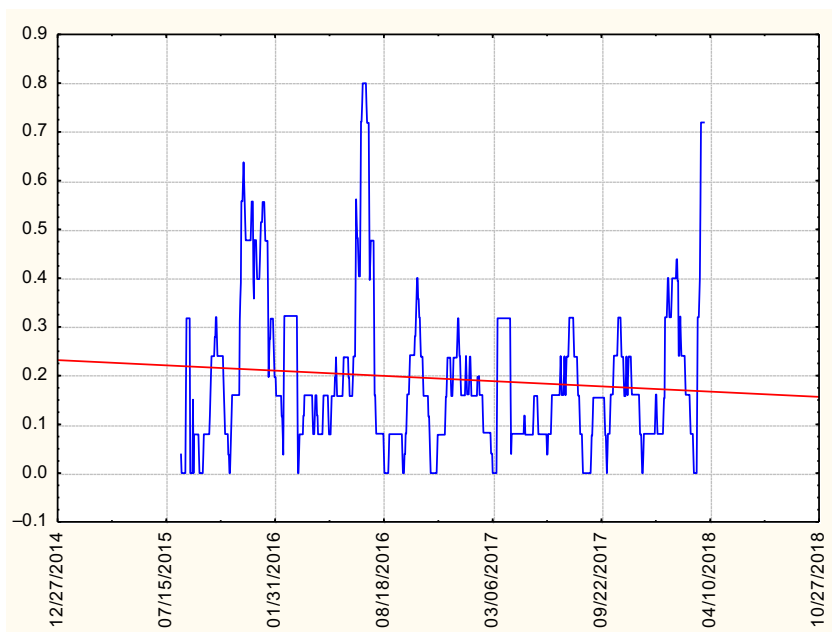
**Figure 9.**  
The conditional volatilities of crude oil WTI over the period from August 11, 2015 to March 31, 2018

**Source(s):** Elaborated by authors



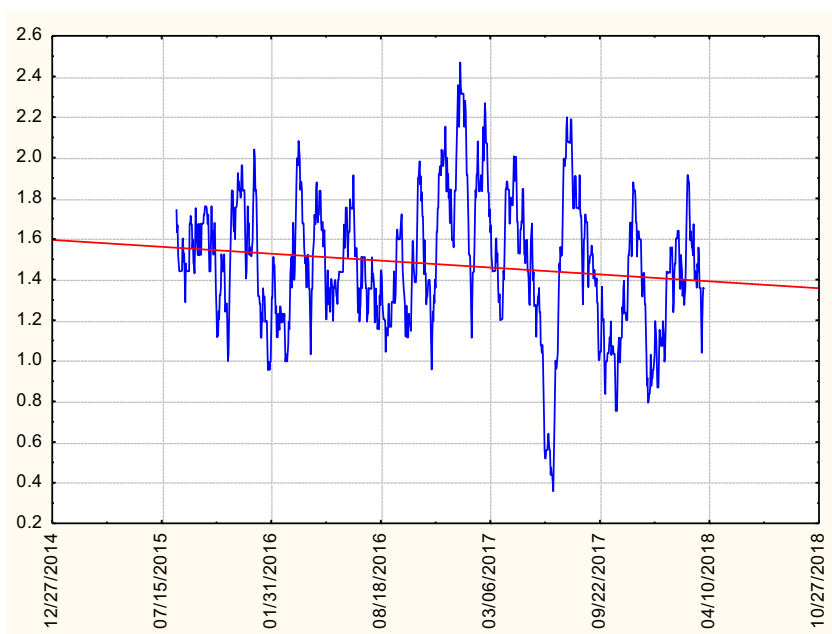
**Figure 10.**  
The conditional volatilities of Brent oil over the period from August 11, 2015 to March 31, 2018

**Source(s):** Elaborated by authors



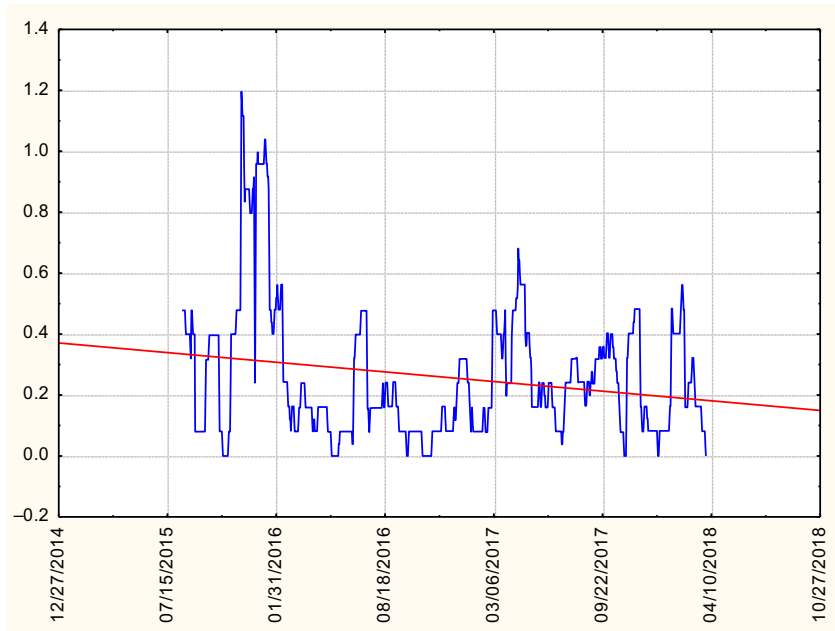
**Figure 11.**  
The conditional volatilities of gasoline RBOB over the period from August 11, 2015 to March 31, 2018

Source(s): Elaborated by authors



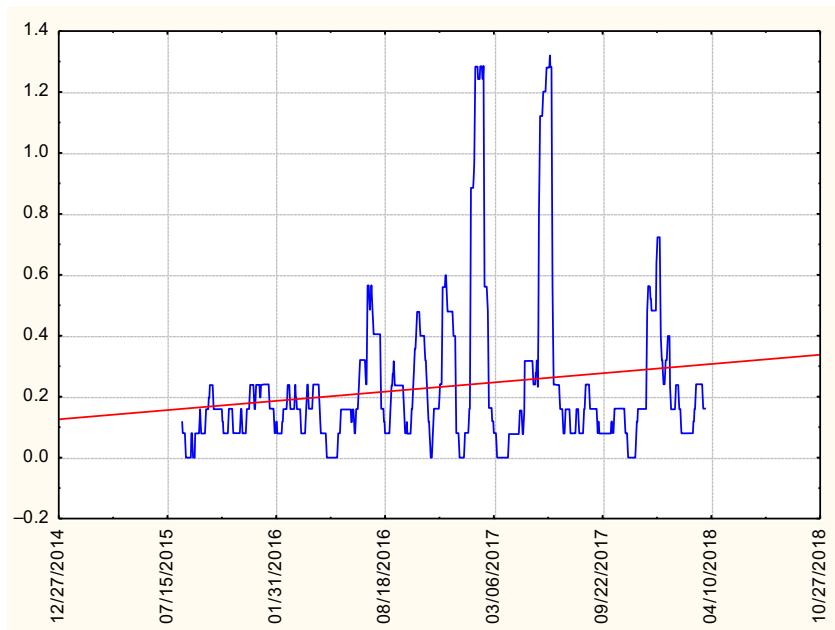
**Figure 12.**  
The conditional volatilities of heating oil over the period from August 11, 2015 to March 31, 2018

Source(s): Elaborated by authors



**Figure 13.**  
The conditional volatilities of London gas oil over the period from August 11, 2015 to March 31, 2018

Source(s): Elaborated by authors



**Figure 14.**  
The conditional volatilities of natural gas over the period from August 11, 2015 to March 31, 2018

Source(s): Elaborated by authors

**Table 3.**  
Descriptive statistics  
for US and ECB  
monetary policy data

	Fed surprises	ECB surprises	Changes of the target federal funds	Changes of the target ECB funds
Mean	-1.978831	1.231170	-0.703289	-0.504568
Median	0.000000	0.154652	0.000000	0.000000
Maximum	26.20568	35.13652	28.00000	18.00000
Minimum	-86.48312	-95.16585	-70.00000	-44.00000
Std. Dev	15.36525	31.55671	28.10057	25.11493
Skewness	-4.720469	-1.416252	-2.022351	-1.00591
Kurtosis	26.32525	6.321631	5.566942	6.18354
Jarque-Bera	922.5516	29.32656	49.85632	55.12839
Probability	0.000000*	0.000000*	0.000000*	0.000000*
Observations	42	21	42	21

**Note(s):** This table presents summary statistics for US and ECB monetary policy announcement surprises. The data period is from August 11, 2015 until March 31, 2018. The monetary announcements surprises are collected from the website of the Fed and from the European Central Bank (ECB). The sample period includes 42 Fed announcements and 21 ECB announcements. We pursue [Kuttner \(2001\)](#) and define the mentioned surprises by applying the one-day change in the current-month futures rate. Statistical significance at the 1% is denoted by \*. Target rate changes and surprises are calculated in basis points. Volatility and returns are measured in percent

#### 4. Empirical findings

In the empirical findings of this study, we examine the effect of the Fed's and ECB monetary policy announcements on the dynamic conditional correlation between Bitcoin and energy commodities returns. The methodology utilized in this study is the DCC model introduced by [Engle \(2002\)](#). The data sample runs in the period from August 11, 2015 until March 31, 2018. The selected energy commodities are Crude Oil WTI (West Texas Intermediate), Brent Oil, Gasoline RBOB (Reformulated Gasoline Blendstock for Oxygen Blending), Heating Oil, London Gas Oil and Natural Gas. Then, we use the approach proposed by [Kuttner \(2001\)](#), which has been popular in the academic literature. More specifically, we employ the changes in the Federal funds futures rates after the FOMC meetings and ECB funds futures rates after the ECB meetings.

[Table 4](#) reports the descriptive statistics for the estimated dynamic conditional correlation between Bitcoin and energy commodities in presence of Fed surprises. From this table, we can find that at maximum the higher dynamic conditional correlation is between Bitcoin and CRUDE OIL WTI (0.974319) and between Bitcoin and NATURAL GAS (0.970986). This result implies the importance of these two commodities in the financial markets. Also, this finding indicates the significance of the dynamic conditional correlation between Bitcoin and energy commodities mainly in the presence of Fed surprises. In this case, we can observe the importance of the responsibility of US monetary policy in financial markets especially, for the energy commodity indices volatilities.

However, [Table 5](#) summarizes the descriptive statistics for the estimated dynamic conditional correlation between Bitcoin and energy commodities in the presence of ECB surprises. From this table, we can show that at maximum the higher dynamic conditional correlation is between Bitcoin and BRENT OIL (0.939158) and between Bitcoin and HEATING OIL (0.935689). This result suggests the importance of these two commodities in the financial markets. Also, this conclusion reveals the significance of the dynamic conditional correlation between Bitcoin and energy commodities mainly in the presence of ECB surprises. Additionally, from [Table 4](#) and [Table 5](#), we can conclude that the Fed surprises are more important than the ECB surprises in operation of financial markets.

[Figures 15–20](#) show the evolution of the dynamic conditional correlation between Bitcoin and energy commodities in the presence of Fed surprises and ECB surprises estimated by

**Table 4.** Descriptive statistics for dynamic conditional correlation between Bitcoin and energy commodities with Fed surprises

	DCC between bitcoin and					
	Crude oil WTI	Brent oil	Gasoline RBOB	Heating oil	London gas_oil	Natural gas
Mean	-0.100685	0.045457	-0.195268	-0.066855	0.058979	-0.087350
Median	-0.158640	0.106953	-0.317919	-0.078081	0.107820	-0.169743
Maximum	0.974319	0.936571	0.938638	0.936129	0.954841	0.970986
Minimum	-0.968756	-0.903448	-0.956786	-0.948544	-0.944242	-0.968992
Std. Dev	0.556703	0.544687	0.523276	0.544002	0.564032	0.561505
Skewness	0.214416	-0.149130	0.503781	0.160189	-0.133205	0.199015
Kurtosis	1.843179	1.672112	2.039778	1.881602	1.768415	1.731673
Jarque-Bera	61.13896*	74.39849*	77.81108*	54.36380*	63.77566*	70.97769*
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Obs	964	964	964	964	964	964

**Note(s):** This table presents summary statistics of DCC between Bitcoin and energy commodities, namely Crude Oil WTI (West Texas Intermediate), Brent Oil, Gasoline RBOB (Reformulated Gasoline Blendstock for Oxygen Blending), Heating Oil, London Gas Oil and Natural Gas in the presence of Fed surprises. The data period is from August 11, 2015 until March 31, 2018. Statistical significance at the 1% is denoted by \*

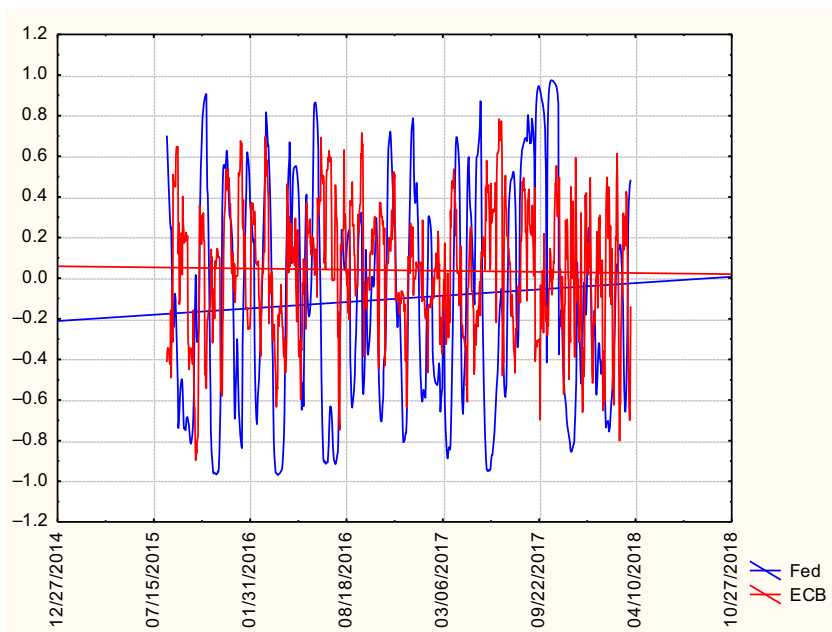
**Table 5.** Descriptive statistics for dynamic conditional correlation between bitcoin and energy commodities with ECB surprises

	DCC between bitcoin and					
	Crude oil WTI	Brent oil	Gasoline RBOB	Heating oil	London GAS_OIL	Natural gas
Mean	0.038947	0.024158	0.043865	0.077832	0.064584	0.009010
Median	0.046171	0.020793	0.025694	0.077423	0.088502	0.027653
Maximum	0.782689	0.939158	0.806293	0.935689	0.851501	0.645694
Minimum	-0.896256	-0.928957	-0.705735	-0.746041	-0.801323	-0.798624
Std. Dev	0.312241	0.325732	0.287408	0.358602	0.323492	0.295952
Skewness	-0.178325	0.104080	0.119512	-0.098820	-0.216749	-0.233398
Kurtosis	2.717530	2.832780	2.638746	2.338116	2.360935	2.392030
Jarque-Bera	83.14029*	28.63625*	75.36737*	29.16563*	39.95231*	54.59897*
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Obs	964	964	964	964	964	964

**Note(s):** This table presents summary statistics of DCC between Bitcoin and energy commodities, namely Crude Oil WTI (West Texas Intermediate), Brent Oil, Gasoline RBOB (Reformulated Gasoline Blendstock for Oxygen Blending), Heating Oil, London Gas Oil and Natural Gas in the presence of ECB surprises. The data period is from August 11, 2015 until March 31, 2018. Statistical significance at the 1% is denoted by \*

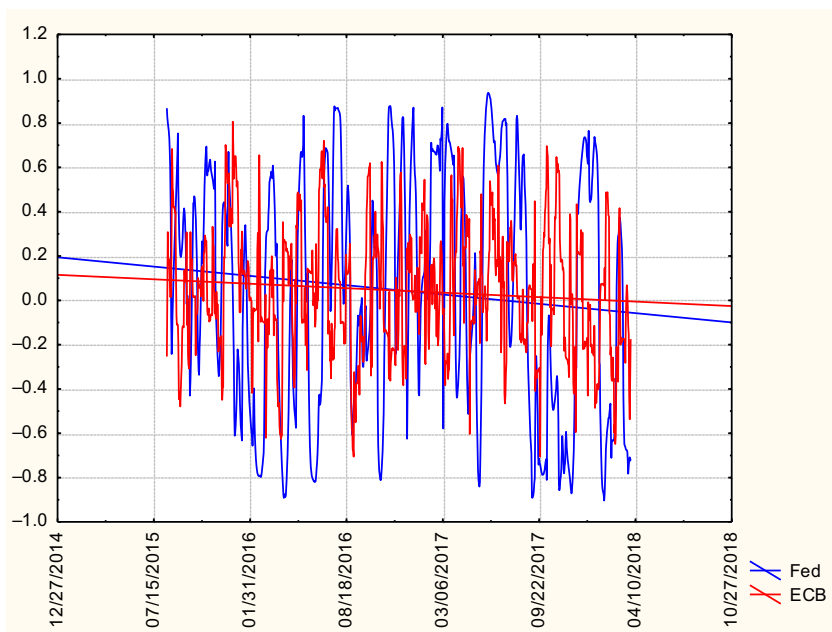
DCC-GARCH (1,1) model. From these figures, we can observe that the correlation between Bitcoin and energy commodities in the presence of Fed surprises is more important and significant than those in the presence of ECB surprises. These findings confirm the conclusions shown in Table 4 and Table 5. Also, we can conclude that the dynamic conditional correlation between Bitcoin and energy commodities in the presence of Fed surprises contains more important peaks (in positive and in negative) than those issued from nexus between Bitcoin and energy commodities in the presence of ECB surprises.

In addition, and looking at the daily period, we can prove that surprise components in Federal funds target rate changes have played a crucial role in the developments of major energy commodities volatilities. This finding is not surprising. One potential justification is that given the essential effect of US economy on the global economy, the news regarding



Source(s): Elaborated by authors

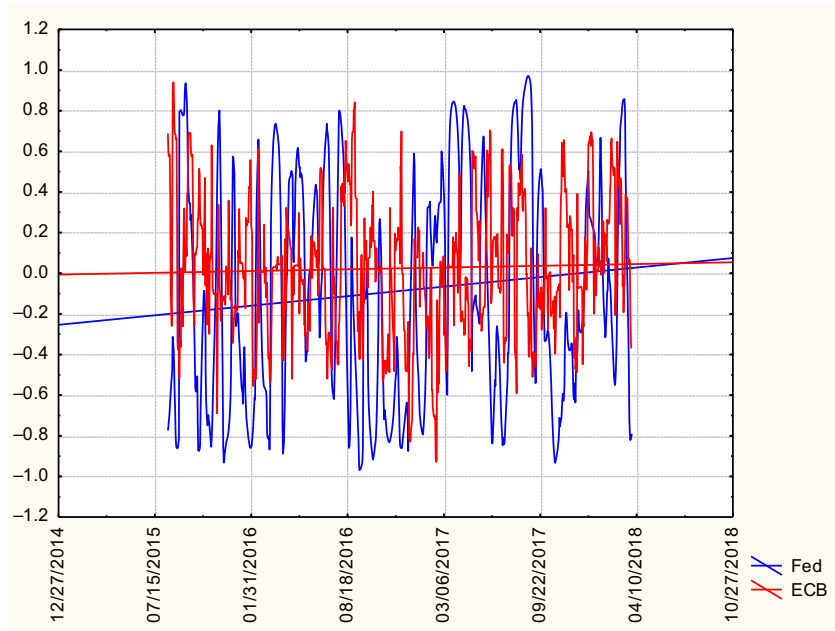
**Figure 15.**  
The DCC between Bitcoin and crude oil WTI in the presence of Fed and ECB surprises over the period from August 11, 2015 to March 31, 2018



Source(s): Elaborated by authors

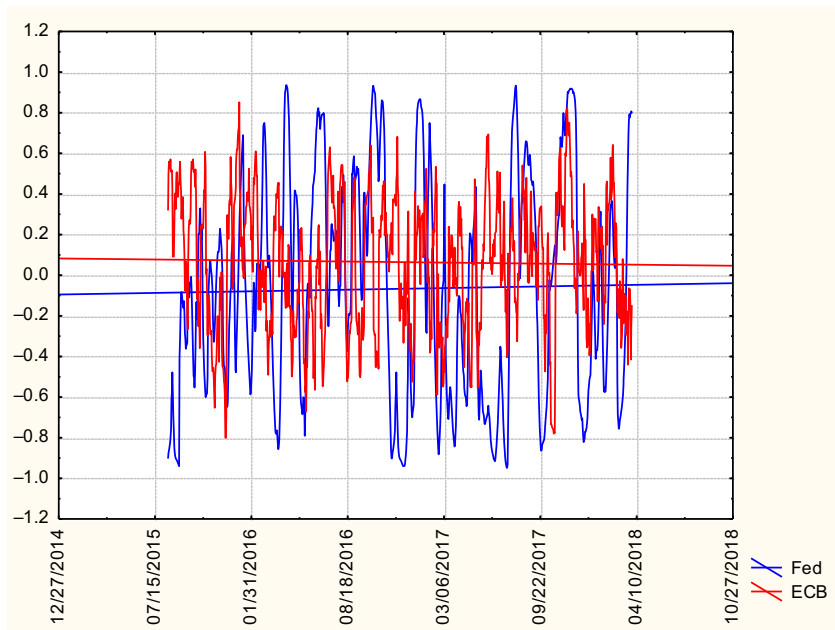
**Figure 16.**  
The DCC between Bitcoin and Brent oil in the presence of Fed and ECB surprises over the period from August 11, 2015 to March 31, 2018

**Figure 17.**  
The DCC between  
Bitcoin and gasoline  
RBOB in the presence  
of Fed and ECB  
surprises over the  
period from August 11,  
2015 to March 31, 2018

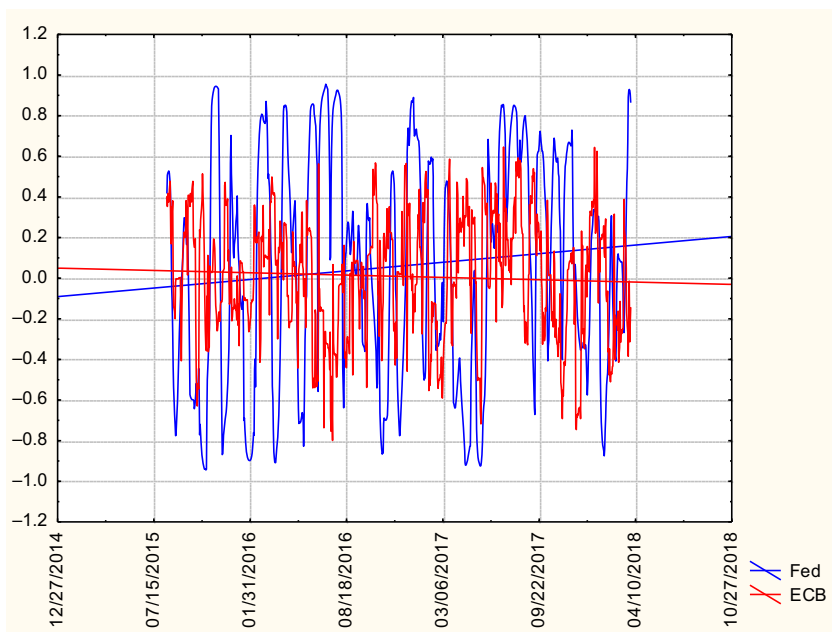


**Source(s):** Elaborated by authors

**Figure 18.**  
The DCC between  
Bitcoin and heating oil  
in the presence of Fed  
and ECB surprises over  
the period from August 11,  
2015 to March  
31, 2018

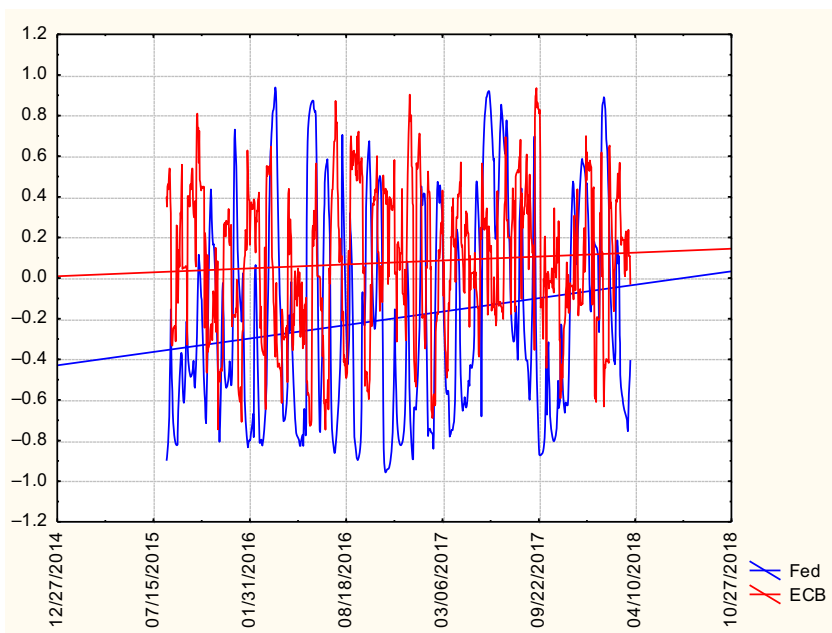


**Source(s):** Elaborated by authors



Source(s): Elaborated by authors

**Figure 19.**  
The DCC between Bitcoin and London GAS OIL in the presence of Fed and ECB surprises over the period from August 11, 2015 to March 31, 2018



Source(s): Elaborated by authors

**Figure 20.**  
The DCC between Bitcoin and natural gas in the presence of Fed and ECB surprises over the period from August 11, 2015 to March 31, 2018

adjustments in US monetary policy may significantly influence foreign economic fundamentals and thus the volatility of energy markets.

Then, the lowest impact of ECB monetary policy is justified by the importance of the US strategies and the US investors to dominate the international financial markets and the global economy. More specifically, in all cases, the Fed monetary policy surprises have a significant impact on major energy commodities volatilities than the European monetary policy surprises.

Table 6 reports the estimation results of dynamic conditional correlation GARCH (1,1) between Bitcoin and energy commodities in the presence of Fed surprises and ECB surprises. Some interesting evidences appear from this estimation. First, we can observe that Fed surprises and ECB surprises affect the dynamic conditional correlation between Bitcoin and energy commodities similarly. This negative sign indicates that US and European monetary policies and shocks drop the mean level of volatility. According to the impact of US and European monetary policies on the correlation between Bitcoin and selected energy commodities in this study, the results reported in Table 4 reveal that 1% raise in the surprise of FOMC monetary policy reasons a decline of roughly 0.0534862% in the correlation between Bitcoin and London GAS OIL returns, and respectively, 0.0180978, 0.0154627, 0.0115703, 0.0097802 and 0.0056482 for the correlations associated with the returns of NATURAL GAS, CRUDE OIL WTI, GASOLINE RBOB, HEATING OIL and BRENT OIL.

Additionally, we can find that 1% raise in the surprise of ECB monetary policy reasons a decline of roughly 0.0802546% in the correlation between Bitcoin and HEATING OIL returns, and respectively, 0.0637925, 0.0488792, 0.0376008, 0.0196583 and 0.0188527 for the correlations associated with the returns of London GAS OIL, BRENT OIL, NATURAL GAS, CRUDE OIL WTI and GASOLINE RBOB. In this case, we can observe the important difference between FOMC monetary policy and European monetary policy and their impact on the correlation between Bitcoin and energy commodities returns.

In addition, there is a corroboration that the sum of the volatility coefficients ( $\alpha+\beta$ ) is very close to unity, for the case of all correlation between Bitcoin and energy commodities indices as exposed demonstrating the higher persistence of volatility between the US and ECB monetary policies and commodity markets indices. There is one probable clarification, which finds that such persistence goes along with the financialization of stock market indices, Bitcoin and energy commodities (Creti *et al.*, 2013; Chebbi and Derbali, 2015, 2016a). Our empirical findings emphasize the importance of using GARCH-DCC (1,1) in modeling the time-varying dynamic conditional correlations.

## 5. Conclusion

The links between Bitcoin and energy commodity markets have been examined by many researchers using various econometric methodologies. Several significant advancements have also been addressed in order to enrich the estimated findings. Among these improvements, we can notice the presence of monetary policy surprises in the volatility models. These monetary policy surprises in volatility could be caused by country-specific economic and financial events, regional and global economic and financial events (e.g. 2007–2008 financial crisis, European sovereign-debt crisis, 2011 Arab Spring, FOMC monetary policy, ECB monetary policy).

In this paper, we explore the time-varying relationships among strategic commodities covering sector of energy (Crude Oil WTI (West Texas Intermediate), Brent Oil, Gasoline RBOB (Reformulated Gasoline Blendstock for Oxygen Blending), Heating Oil, London Gas Oil and Natural Gas) and Bitcoin, over the period from August 11, 2015 through March 31, 2018.

For this purpose, we use the DCC-GARCH approach with incorporating the Fed and ECB monetary policy surprises. The empirical results in this paper suggest strong significant dynamic conditional correlations between Bitcoin and energy commodity markets if monetary policy surprises are incorporated in variance. These results proved the

Parameters	$\omega_i$	$\alpha_i$	$\beta_i$	Fed surprises	ECB surprises
Crude oil wti	0.0429856 (2.33)**	0.1150879 (7.88)*	0.8733594 (51.75)*	-0.0154627 (-4.09)*	-0.0196583 (-4.57)*
Brent oil	0.0628791 (2.41)**	0.1435628 (7.09)*	0.8500179 (48.49)*	-0.0056482 (-4.51)*	-0.0488792 (-4.96)*
Gasoline RBOB	0.0583357 (2.51)**	0.1055647 (7.37)*	0.8722564 (47.01)*	-0.0115703 (-4.37)*	-0.0188527 (-4.79)*
Heating oil	0.0495135 (2.23)**	0.1395173 (7.19)*	0.8600179 (40.15)*	-0.0097802 (-4.82)*	-0.0802546 (-4.31)*
London gas oil	0.0585297 (2.38)**	0.1369820 (7.28)*	0.9066973 (42.60)*	-0.0534862 (-5.66)*	-0.0637925 (-4.39)*
Natural gas	0.0687532 (2.53)**	0.0822564 (7.46)*	0.9255558 (87.61)*	-0.0180978 (-4.17)*	-0.0376008 (-4.10)*
	0.052486 (1.89)***	0.052257 (7.57)*	0.8596632 (79.90)*		
	0.0591375 (1.94)***	0.1385279 (7.53)*	0.8702980 (61.73)*		
	0.0856734 (3.22)*	0.1255687 (7.95)*	0.8916693 (70.99)*		
	0.0500684 (3.94)*	0.1069837 (7.35)*	0.8506201 (39.36)*		
	0.0480679 (2.27)**	0.1385698 (7.75)*	0.8590758 (59.16)*		
	0.0730705 (2.36)**	0.1373491 (7.07)*			

**Note(s):** This table summarizes estimated coefficients from DCC-GARCH model. To empirically test this model, we employ daily volatility series of returns for Bitcoin and energy commodities, namely Crude Oil WTI (West Texas Intermediate), Brent Oil, Gasoline RBOB (Reformulated Gasoline Blendstock for Oxygen Blending), Heating Oil, London Gas Oil and Natural Gas from August 11, 2015 through March 31, 2018. Statistical significance at the 1, 5 and 10% levels is denoted by \*, \*\* and \*\*\*, respectively. Values in parentheses represent the *t*-Student

**Table 6.** Estimation results of dynamic conditional correlation GARCH (1,1) between Bitcoin and energy commodities

financialization of Bitcoin and commodity markets. Also, the results estimated and more specifically those related to the level of the persistence of volatility are sensitive to the presence of monetary policy surprises into the DCC-GARCH (1,1) model. The conditional correlations between Bitcoin and energy commodity markets appear to respond considerably more in the case of Fed surprises than the ECB surprises. Finally, we assume that behavior of every commodity regarding Bitcoin fluctuations indicates the suggestion that commodities cannot be viewed as a homogeneous asset class.

## 6. Policy implications

Our paper is a crucial topic for policymakers and portfolio risk managers. From a policymaking viewpoint, having precise estimates of the volatility spillovers throughout markets is an important step in formulating successful monetary policy decisions. From the perspective of portfolio risk managers, our empirical findings are reliable with the idea of cross-market hedging.

## References

- Andersen, T.G. (1996), "Return flow and trading volume: an information flow interpretation of stochastic volatility", *Journal of Finance*, Vol. 51 No. 1, pp. 169-204.
- Andreasson, P., Bekiros, S., Nguyen, D.K. and Uddin, G.S. (2016), "Impact of speculation and economic uncertainty on commodity markets", *International Review of Financial Analysis*, Vol. 43, pp. 115-127.
- Bailey, W. (1990), "U.S. Money supply announcements and pacific rim stock markets: evidence and implications", *Journal of International Money and Finance*, Vol. 9 No. 3, pp. 344-356.
- Balcilar, M. and Ozdemir, Z.A. (2013), "The causal nexus between oil prices and equity market in the US: a regime switching model", *Energy Economics*, Vol. 39, pp. 271-282.
- Balcilar, M., Gupta, R. and Miller, S.M. (2015), "Regime switching model of US crude oil and stock market prices: 1859 to 2013", *Energy Economics*, Vol. 49, pp. 317-327.
- Balcilar, M., Gupta, R. and Wohar, M.E. (2017), "Common cycles and common trends in the stock and oil markets: evidence from more than 150 years of data", *Energy Economics*, Vol. 61, pp. 72-86.
- Balli, F., Uddin, G.S., Mudassar, H. and Yoon, S.-M. (2017), "Cross-country determinants of economic policy uncertainty spillovers", *Economics Letters*, Vol. 156, pp. 179-183.
- Basistha, A. and Kurov, A. (2008), "Macroeconomic cycles and the stock market's reaction to monetary policy", *Journal of Banking and Finance*, Vol. 32 No. 3, pp. 2606-2616.
- Baur, D.G. and Lucey, B.M. (2010), "Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold", *Financing Reviews*, Vol. 45, pp. 217-229.
- Baumeister, C. and Kilian, L. (2014), "What central bankers need to know about forecasting oil prices.prices?", *International Economic Review*, Vol. 55 No. 3, pp. 869-889.
- Baumeister, C. and Kilian, L. (2015), "Forecasting the real price of oil in a changing world: a forecast combination approach", *Journal of Business and Economic Statistics*, Vol. 33 No. 3, pp. 338-351.
- Baumeister, C., Kilian, L. and Lee, T.K. (2014), "Are there gains from pooling real-time oil price forecasts?", *Energy Economics*, Vol. 46, pp. S33-S43.
- Baumeister, C., Kilian, L. and Lee, T.K. (2017), "Inside the crystal ball: new approaches to predicting the gasoline price at the pump", *Journal of Applied Econometrics*, Vol. 32 No. 2, pp. 275-295.
- Bekiros, S. and Uddin, G.S. (2017), "Extreme dependence under uncertainty: an application to stock, currency and oil markets", *International Review of Finance*, Vol. 17 No. 1, pp. 155-162.
- Bekiros, S., Nguyen, D.K., Junior, L.S. and Uddin, G.S. (2017), "Information diffusion, cluster formation and entropy-based network dynamics in equity and commodity markets", *European Journal of Operational Research*, Vol. 256 No. 3, pp. 945-961.
- Berger, T. and Uddin, G.S. (2016), "On the dynamic dependence between equity markets, commodity futures and economic uncertainty indexes", *Energy Economics*, Vol. 56, pp. 374-383.

- Bernanke, B.S. and Kuttner, K.N. (2005), "What explains the stock market's reaction to federal reserve policy?", *Journal of Finance*, Vol. 60 No. 3, pp. 1221-1257.
- Brandvold, M., Molnár, P., Vagstad, K. and Valstad, O.C.A. (2015), "Price discovery on bitcoin exchanges", *Journal International Financing Mark Institute Money*, Vol. 36, pp. 18-35.
- Chang, C., Daouk, H. and Wang, A. (2009), "Do investors learn about analyst accuracy? A study of the oil futures market", *Journal of Futures Markets*, Vol. 29 No. 5, pp. 414-429.
- Chebbi, T. and Derbali, A. (2015), "The dynamic correlation between energy commodities and Islamic stock market: analysis and forecasting", *International Journal of Trade and Global Markets*, Vol. 8 No. 2, pp. 112-126.
- Chebbi, T. and Derbali, A. (2016a), "A dynamic conditional correlation between commodities and the islamic stock market", *Journal of Energy Markets*, Vol. 9 No. 1, pp. 65-90.
- Chebbi, T. and Derbali, A. (2016b), "On the role of structural breaks in identifying the dynamic conditional linkages between stock and commodity markets", *Journal of Energy Markets*, Vol. 9 No. 4, pp. 71-81.
- Chiou-Wei, S.Z., Linn, S.C. and Zhu, Z. (2014), "The response of U.S. natural gas futures and spot prices to storage change surprises: fundamental information and the effect of escalating physical gas production", *Journal of International Money and Finance*, Vol. 42, pp. 156-173.
- Ciaian, P., Rajcaniova, M. and Kancs, D.A. (2016), "The economics of bitcoin price formation", *Applications Economics*, Vol. 48 No. 19, pp. 1799-1815.
- Creti, A., Joëts, M. and Mignon, V. (2013), "On the links between stock and commodity markets' volatility", *Energy Economics*, Vol. 37, pp. 16-28.
- Ehrmann, M. and Fratzscher, M. (2009), "Global financial transmission of monetary policy shocks", *Oxford Bulletin of Economics and Statistics*, Vol. 71 No. 6, pp. 739-759.
- Engle, R. (2002), "Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models", *Journal of Business and Economic Statistics*, Vol. 20 No. 3, pp. 339-350.
- Gay, G.D., Simkins, B.J. and Turac, M. (2009), "Analyst forecasts and price discovery in futures markets: the case of natural gas storage", *Journal of Futures Markets*, Vol. 29, pp. 451-477.
- Goodhart, C.A.E. (1999), "Myths about the lender of last resort", *International Finance*, Vol. 2 No. 3, pp. 339-360.
- Halova, M.W., Kurov, A. and Kucher, O. (2014), "Noisy inventory announcements and energy prices", *Journal of Futures Markets*, Vol. 34, pp. 911-933.
- Hamilton, J.D. (1983), "Oil and the macroeconomy since world war II", *Journal of Political Economy*, Vol. 91 No. 2, pp. 228-248.
- Hamilton, J.D. (2003), "What is an oil shock?", *Journal of Econometrics*, Vol. 113, pp. 363-398.
- Hamilton, J.D. (2009), "Causes and consequences of the oil shock of 2007-08", *Brookings Papers on Economic Activity*, Vol. 40 No. 1, pp. 215-283.
- Hamilton, J.D. (2013), "Historical oil shocks", in Parker, R.E. and Whaples, R. (Eds), *Routledge Handbook of Major Events in Economic History*, Routledge Taylor and Francis Group, New York, NY, pp. 239-265.
- Hayo, B., Kutan, A.M. and Neuenkirch, M. (2010), "The impact of U.S. Central bank communication on European and pacific equity markets", *Economics Letters*, Vol. 108 No. 2, pp. 172-174.
- Hayo, B., Kutan, A.M. and Neuenkirch, M. (2012), "Federal reserve communications and emerging equity markets", *Southern Economic Journal*, Vol. 78 No. 3, pp. 1041-1056.
- Hui, B.U. (2014), "Effect of inventory announcements on crude oil price volatility", *Energy Economics*, Vol. 46, pp. 485-494.
- International Monetary Fund (2015), "Monetary policy and financial stability", *IMF Staff Report* August, p. 28.

- Kang, S.H. and Yoon, S.-M. (2013), "Modeling and forecasting the volatility of petroleum futures prices", *Energy Economics*, Vol. 36, pp. 354-362.
- Kang, S.H., McIver, R. and Yoon, S.-M. (2016), "Modeling time-varying correlations in volatility between BRICS and commodity markets", *Emerging Markets Finance and Trade*, Vol. 52 No. 7, pp. 1698-1723.
- Kang, S.H., McIver, R. and Yoon, S.-M. (2017), "Dynamic spillover effects among crude oil, precious metal, and agricultural commodity futures markets", *Energy Economics*, Vol. 62, pp. 19-32.
- Karpoff, J. (1987), "The relation between price changes and trading volume: a survey", *Journal of Financial and Quantitative Analysis*, Vol. 22 No. 1, pp. 109-123.
- Kuttner, K.N. (2001), "Monetary policy surprises and interest rates: evidence from the fed funds futures market", *Journal of Monetary Economics*, Vol. 47 No. 3, pp. 523-544.
- Lahmiri, S., Uddin, G.S. and Bekiros, S. (2017), "Nonlinear dynamics of equity, currency and commodity markets in the aftermath of the global financial crisis", *Chaos, Solitons and Fractals*, Vol. 103, pp. 342-346.
- Mensi, W., Beljid, M., Boubaker, A. and Managi, S. (2013), "Correlations and volatility spillovers across commodity and stock markets: linking energies, food, and gold", *Economic Modelling*, Vol. 32, pp. 15-22.
- Mensi, W., Hammoudeh, S. and Yoon, S.-M. (2014a), "How do OPEC news and structural breaks impact returns and volatility in crude Oil markets? Further evidence from a long memory process", *Energy Economics*, Vol. 42, pp. 343-354.
- Mensi, W., Hammoudeh, S. and Yoon, S.-M. (2014b), "Dynamic spillovers among major energy and cereal commodity prices", *Energy Economics*, Vol. 43, pp. 225-243.
- Mensi, W., Hammoudeh, S. and Kang, S.H. (2015), "Precious metals, cereal, oil and stock market linkages and portfolio risk management: evidence from Saudi Arabia", *Economic Modelling*, Vol. 51, pp. 340-358.
- Miao, H., Ramchander, S., Wang, T. and Yang, J. (2018), "The impact of crude oil inventory announcements on prices: evidence from derivatives markets", *Journal of Futures Markets*, Vol. 38 No. 1, pp. 38-65.
- Narayan, P.K. and Gupta, R. (2015), "Has oil price predicted stock returns for over a century?", *Energy Economics*, Vol. 48, pp. 18-23.
- Rajan, R. (2006), "Has financial development made the world riskier?", *European Financial Management*, Vol. 12 No. 4, pp. 499-533.
- Rogojanu, A. and Badea, L. (2014), "The issue of competing currencies. Case study-bitcoin", *Theoretical Applications Economics*, Vol. 21 No. 1, pp. 103-114.
- Ross, S. (1989), "Information and volatility: the no-arbitrage martingale approach to timing and resolution irrelevancy", *Journal of Finance*, Vol. 44 No. 1, pp. 1-17.
- Shrestha, K. (2014), "Price discovery in energy markets", *Energy Economics*, Vol. 45, pp. 229-233.
- Wongswan, J. (2009), "The response of global equity indexes to U.S. monetary policy announcements", *Journal of International Money and Finance*, Vol. 28 No. 2, pp. 344-365.
- Ye, S. and Karali, B. (2016), "The informational content of inventory announcements: intraday evidence from crude oil futures market", *Energy Economics*, Vol. 59, pp. 349-364.

#### Corresponding author

Abdelkader Derbali can be contacted at: [derbaliabdelkader@outlook.fr](mailto:derbaliabdelkader@outlook.fr)

For instructions on how to order reprints of this article, please visit our website:

[www.emeraldgroupublishing.com/licensing/reprints.htm](http://www.emeraldgroupublishing.com/licensing/reprints.htm)

Or contact us for further details: [permissions@emeraldinsight.com](mailto:permissions@emeraldinsight.com)