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Article

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

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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

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JCMS 4,1 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 began 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

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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 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

JCMS 4,1 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:

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

where, ω , α and β represent the parameters that want to be estimated.

The conditional correlation matrix R_t of the standardized disturbances ε_t is provided by:

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

where, $\varepsilon_t = D_t^{-1} r_t$ The matrix R_t is assessed as following:

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

Where Q_t is the time-varying covariance matrix of ε_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:

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

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

$$Q_t = \omega + \alpha \varepsilon_{t-1} \varepsilon_{t-1} + \beta Q_{t-1} \tag{5}$$

where $\omega = (1 - \alpha - \beta)\overline{Q}$, with \overline{Q} being the unconditional covariance of the standardized disturbances ε_t . ω , α and β 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:

$$Q_t = \omega + \alpha \varepsilon_{t-1} \varepsilon_{t-1}^{\prime} + \beta Q_{t-1} + \gamma S_t \tag{6}$$

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 oneday 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:

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

Natural gas	0.000167 -0.000157 2.998405 -2.997241 0.499397 0.013953 12.00799 3259.309* 0.000000 964 jateb, Brent Oil, st 11, 2015 until	Fed and ECB
London gas_oil	0.000213 0.000000 2.023857 -2.029023 1.215990 0.014897 2.240287 2.24007000000000000000000000000000000000	83
Heating oil	0.000187 1.28E-05 3.008068 -3.011824 0.484460 -0.003936 12.48761 3615.597* 0.000000 964 amely Crude Oi WT d Natural Gas. The di	
Gasoline RBOB	0.000959 -0.000292 2.989895 -3.004220 0.498457 0.04800 10.11375 2032.653* 0.000000 10.11375 2032.653* 0.000000 964 f energy commodities, n g Oil, London Gas Oil an	
Brent oil	0.000247 0.000452 2.015609 -2.007232 0.450674 0.079595 10.04163 10.04163 10.04163 10.04163 10.04163 10.04163 10.04163 10.04163 an second secon	
Crude oil WTI	0.009484 0.001962 2.012110 -2.008380 0.428115 -0.065129 8.422416 1181.686* 0.00000 964 y statistics of daily ret e Blendstock for Oxyge a at the 1% is denoted h	
Bitcoin	0.003414 0.002461 0.226412 -0.182985 0.040825 -0.133704 7.462392 802.708* 0.000000 964 0.000000 964 ble presents summar teformulated Gasolin tatistical significano	
	Mean Median Maximum Std. Dev Stewness Kurtosis Jarque-Bera Probability Obs Note(s): This tat Gasoline RBOB (R Gasoline RBOB (R	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.

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Natural gas	0.258855 0.196522 1.196166 5.74E-05 0.2174845 1.577967 5.860755 728.777* 5.860755 728.777* 0.000000 964 itermediate),	Fed and ECB
London gas_oil	1.475103 1.471175 2.468987 0.358215 0.33564 -0.148926 3.407241 10.2248* 0.006021 964 det Oil WTI (West Texas In as. The data period is from	85
Heating oil	0.233040 0.159610 1.319846 2.61E-05 0.259116 2.607802 10.15268 3147.595* 0.000000 964 mmodities, namely Cru n Gas Oil and Natural C	
Gasoline RBOB	0.256936 0.237772 0.956800 1.68E-05 0.182356 1.053372 4.293339 245.462* 0.000000 964 or Bitcoin and energy cc ng), Heating Oil, Londor	
Brent oil	0.180787 0.159300 0.760820 0.760820 2.32E-05 0.159270 0.885429 3.441897 133.803* 0.885429 3.441897 133.803* 0.000000 964 0.000000 964 bitional volatilities for sk for Oxygen Blendii is denoted by *	
Crude oil WTI	0.193770 0.159399 0.799828 1.31E-05 0.155414 1.461971 5.515496 597.565* 0.000000 964 964 r statistics of daily cor ed Gasoline Blendstoc significance at the 1%	
Bitcoin	0.001569 0.001017 0.006834 3.36E-05 0.001517 1.116933 3.368603 3.368603 3.368603 2.05.895* 0.000000 964 964 31, 2018. Statistical s 31, 2018. Statistical s	Table 2
	Mean Median Maximum Minimum Std. Dev Skewness Kurtosis Jarque–Bera Probability Obs Dheret Oil, Gasolir Brent Oil, Gasolir Brent Oil, Gasolir Brent Oil, Gasolir	Descriptive statistics for daily conditional volatilities of Bitcoin and energy commodities

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Figure 1.

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





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





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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

Source(s): Elaborated by authors







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





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





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

Source(s): Elaborated by authors

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Figure 10.

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





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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







Figure 14. The conditional volatilities of na

volatilities of natural gas over the period from August 11, 2015 to March 31, 2018



	Fed surprises	ECB surprises	Changes of the target federal funds	Changes of the target ECB funds	Fed and ECB
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	93
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	

Table 3.

Descriptive statistics

monetary policy data

for US and ECB

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

JCMS		DCC between bitcoin and						
4,1		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	
94	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-	61.13896*	74.39849*	77.81108*	54.36380*	63.77566*	70.97769*	
T 11 4	Bera							
Table 4.	Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
Descriptive statistics	Obs	964	964	964	964	964	964	
conditional correlation between Bitcoin and	Note(s): This table presents summary statistics of DCC between Bitcoin and energy commodities, na Crude Oil WTI (West Texas Intermediate), Brent Oil, Gasoline RBOB (Reformulated Gasoline Blendstoc						odities, namely Blendstock for	

with Fed surprises

Crude Oil WTI (West Texas Intermediate), Brent Oil, Gasoline RBOB (Reformulated Gasoline Blendstock for energy commodities 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 *

		Crude oil WTI	DC0 Brent oil	C between bitco Gasoline RBOB	in and Heating oil	London GAS_OIL	Natural gas
	Mean	0.038947	0.02/158	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-	83.14029*	28.63625*	75.36737*	29.16563*	39.95231*	54.59897*
Table 5	Bera						
Table 5.	Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
for dynamic	Obs	964	964	964	964	964	964
conditional correlation	Note(s): This table presents summary statistics of DCC between Bitcoin and energy commodities, name						

Crude Oil WTI (West Texas Intermediate), Brent Oil, Gasoline RBOB (Reformulated Gasoline Blendstock for between bitcoin and Oxygen Blending), Heating Oil, London Gas Oil and Natural Gas in the presence of ECB surprises. The data energy commodities with ECB surprises 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



Source(s): Elaborated by authors



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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

Fed and ECB

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

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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.

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