International Journal of Finance, Insurance and Risk Management
Volume X, Issue 3, 2020

pp. 157-170

Return, Volatility and Shock Spillovers of Bitcoin with Energy Commodities

Submitted 11/06/20, 1st revision 22/07/20, 2nd revision 14/08/20, accepted 30/09/20

Abdelkader Derbali[1], Lamia Jamel[2], Monia Ben Ltaifa[3],
Ahmed K. Elnagar[4]

Abstract:

Purpose: *The purpose of this paper is to examine empirically the spillover impacts between Bitcoin and the major energy commodities.*
Design/methodology/approach: *To do so, we employ an asymmetric multivariate VAR-BEKK-AGARCH model to study spillover effects between Bitcoin and three energy commodities during the period from July 18, 2010 to June 30, 2018.*
Findings: *The empirical findings show return spillovers from energy stock indices to Bitcoin. We find unilateral return and volatility spillovers and bidirectional shock influences and demonstrate portfolio management implications of dynamic conditional correlation. The little correlation of Bitcoin with the stock indices offers portfolio benefits. Our findings imply the importance of Bitcoin in portfolio construction and reflects the importance of diversification of portfolio between energy commodities and the crypto-currencies, mainly Bitcoin.*
Practical Implications: *Bitcoin has qualified a fast development while across a time and several shareholders and investors are demonstrating importance in its possibility as a consolidative component of portfolio variation.*
Originality/value: *The significant extension is the using of a recently established multivariate econometric method, VAR-BEKK-AGARCH, which is utilized to study the degree of incorporation in rapports of instability and return among Bitcoin and energy commodities.*

Keywords: *Bitcoin, energy commodities, spillovers, multivariate GARCH, volatility.*

JEL Classifications: *E52, E63, Q02.*

Paper type: *Research article.*

[1]*Assistant Professor in Finance and Banking at the Community College, Taibah University, Saudi Arabia, e-mail: derbaliabdelkader@outlook.fr;*
[2] *Assistant Professor in Economics at the College of Business Administration, Taibah University, Saudi Arabia, e-mail: lajamel@yahoo.fr;*
[3] *Assistant Professor in Tourism and Hospitality at the Community College, Taibah University, Saudi Arabia, e-mail:aelnagar@taibahu.edu.sa;*
[4] *Assistant Professor in Finance and Banking at the Community College in Abqaiq, King Faisal University, Saudi Arabia, e-mail: monia-mbl@yahoo.fr*

1. Introduction

Since the emergence of Bitcoin in 2009, financial and economic media has come to be drawn by this numerical asset. Preceding surveys view to the influence of regulatory strategy and monetary governance on Bitcoin gains and volatility (Corbet *et al.*, 2017), but additional researches show no considerable impact (Vidal-Tomás and Ibañez, 2018). Moreover, financial and economic captions frequently liken the advantages of gold as a precious commodity and Bitcoin as cryptocurrency asset, demanding that the concluding is too a safe-haven portfolio assumed its pliability to financial instability periods such as the sovereign debt crisis in Europe during the period from 2010 to 2013 and the system banking recession during the period 2012–2013 (Luther and Salter, 2017).

Many studies use standard econometric methodology such as: Granger causality, correlation coefficient, linear regression estimations, and GARCH-based specification and underlines the extremely weak connection among Bitcoin and stock market returns and volatilities (Baur *et al.,* 2018; Brière *et al.,* 2015; Dyhrberg, 2016; Bouri, 2017a, 2017b; Ji *et al.,* 2018). Nevertheless, there is nonetheless a dearth of experimental contrast among the safe-haven assets of Bitcoin, gold, and additional commodities versus world, developing, developed, emerging, and specific financial stock markets.

Additionally, the cryptocurrencies and blockchain have received important consideration from investors, financial institutions, media, and regulatory establishments with a rapidly increasing academic attention from computer science to management, finance, and economic literature (Böhme *et al.,* 2015; Mohamada *et al.,* 2020). Despite the enormous number of cryptocurrencies being released, Bitcoin preserves the lions share with considerable and important market capitalization.

Bitcoin is cryptocurrency build with blockchain technology, which allows decentralized system securely and fairly emit new Bitcoins and confirmation of transactions by solving a crypto puzzle. The necessities in terms of calculating the volatilities of power and energy are huge as Bitcoin transactions augment, additional miners struggle in the Bitcoin network, and the crypto algorithm that confirms blocks and reward miners become additional difficult.

In other words, we define an electronic coin as a string of electronic signatures. Each owner transfers the coin to the next by signing the hash of the previous transaction, the public key of the next owner, and adding all that to the end of the coin. A recipient can verify the signatures to check the property chain. Thus, Bitcoin is a solution that starts with a timestamp server. A timestamp server works by taking the digital fingerprint of an item block to timestamp and publish it widely, such as in a newspaper or forum on the Internet. The sum yearly energy utilization amounts to 57.69 TWh, shut to the electricity needs of Kuwait (BitcoinEnergyConsumption.com, March

2018). Despite the strong interdependence between energy and Bitcoin, their dynamics and economic and financial relationships have not yet been explored.

With Bitcoin, it is possible to send and receive money, converting it into virtual currency: anywhere in the world, at any time, regardless of public holidays, almost instantly: transactions are very fast from a few seconds to a few hours, without limitation: unlike a bank which establishes daily or monthly ceilings, and independently of the monetary issuance policies of monetary authorities (FED, ECB, 2017).

In principle, the users are the only ones able to order the completion of a transaction. The transaction is irreversible, which constitutes protection for the seller, who cannot be repudiated by the buyer after having shipped the good or service. Merchants cannot charge additional fees without first letting the buyer know.

This paper plugs the gap by investigating in two ways. First, we employ a Vector Autoregression conditional mean process to estimate returns and the asymmetric VAR-BEKKAGARCH (Generalized Autoregressive Conditional Heteroskedasticity process for variances) to study return, volatility, and shock spillovers between Bitcoin and three stock indices of energy commodities as; Crude Oil WTI, Brent Oil and Natural Gas. Second, we investigate empirically portfolio management implications of DCC (dynamic conditional correlations) in a minimum-variance optimal portfolio. The empirical results find that the used model do capture the dynamic structure of the return connections and volatility spillovers and show statistical significance for own past mean and volatility short-and long-run persistence impacts, while there are just a few cross-market impacts for this model.

The restricted literature on Bitcoin occasionally incorporates gold and other commodities (natural gas, crude oil, electricity) inside its experimental investigation, with the objective of examining the connection amongst Bitcoin and gold (Dyhrberg, 2016; Ciaian *et al.,* 2016; Bouri *et al.,* 2017a; Ji *et al.,* 2018).

Our paper expands preceding efforts in cryptocurrencies' and blockchains literature that study the diversification remunerations and inter-dependencies with numerous financial assets (Chebbi and Derbali, 2015; Chebbi and Derbali, 2016a; Chebbi and Derbali, 2016b; Dyhrberg, 2016; Ciaian *et al.,* 2018; Corbet *et al.,* 2018; Symitsi and Chalvatzis, 2018) and investigate Bitcoin returns and volatility (Balcilar *et al.,* 2017; Katsiampa, 2017). This study is directly associated to the strand that examines spillovers in energy commodities (Sadorsky, 2012) and investigates that connect Bitcoin with energy prices and returns, the key constituent for its production and sustainability (Bouri *et al.,* 2017; Hayes, 2017).

The rest of our paper is structured as follows. Section 2 presents data and methodology used in our study. Section 3 discusses and interprets the empirical results. Section 4 provides the most important conclusions and remarks.

2. Data and Methodology

We obtain data used in our study for Energy commodities (Crude Oil WTI, Brent Oil and Natural Gas) and Bitcoin (BTC) from Datastream spanning from July 18, 2010 to June 30, 2018. The sample used in our paper corresponds to a total of 2905 daily observations. The choice of the study period is justified by its coincidence with several crises. Thus, and from 2010, the euro zone experienced a major crisis, that of public debts. To understand this crisis, it is necessary to note that during the 2000s, (too) many countries accumulated public debt. We obviously think primarily of PIIGS (Portugal, Italy, Ireland, Greece, Spain), but it should be noted that other countries such as France are also concerned. However, with the crisis of 2008, the indebtedness of these states becomes unsustainable. This is explained both by the decrease in their tax revenues (due to the contraction in activity) and by plans to stimulate the economy. In addition, other financial and economic crises have appeared throughout this period such as the Spanish real estate bubble (2010), the Venezuelan economic crisis (2012), the Brazilian economic crisis (2014), the Russian ruble crisis of 2014-2015, the stock market crash of 2015 in China, the Turkish lira crisis of 2018 and the Argentine economic crisis of 2018. The daily returns are measured as the first difference of the natural logarithm of daily prices multiplied by 100.

$$R_t = [log(P_t) - log(P_{t-1})] * 100 \quad (1)$$

Table 1 presents the summary statistics of the daily returns of energy commodities and Bitcoin. From this table, we can remark that in average the higher return is for Bitcoin (0.1775) followed, respectively, by Crude Oil WTI (0.0281), Natural Gas (0.0138) and Brent Oil (-0.0109). For the two statistics of skewness (asymmetry) and kurtosis (leptokurtic), we can remark that the two variables utilized in our study are characterized by non-normal distribution. The positive sign of the skewness coefficients indicate that the variable is skewed to the right and it is far from being symmetric for all variables. Also, the Kurtosis coefficients confirm that the leptokurtic for all variables employed in this paper show the existence of a high peak or a fat-tailed in their volatilities.

Table 2 summarizes the correlation matrix. The unconditional correlation of Bitcoin with Crude Oil WTI and Brent Oil is positive and strongly significant, while the correlation with Natural Gas is negative and significant. However, the correlations between energy commodities are positive and strongly significant. Figure 1 shows the time series of daily prices of energy commodities and Bitcoin. The higher daily prices of all energy commodities are observed in the beginning of the period of study that coincided with the financial and economic crisis. Bitcoin reaches the maximum in daily prices on the last two years during the period of study as; 2017 and 2018.

Figure 2 presents the daily returns of energy commodities and Bitcoin. All indices have significant returns which are accompanied by extreme volatility. This volatility is confirmed by the conditional volatility shown in the Figure 3. However, the main problem with volatility is that it is not directly observable from returns. The unconditional volatility is estimated from the standard deviation of the return series. However, the volatility is not constant over time. Therefore, the conditional volatility is a more appropriate measure of the volatility of a series at time t. From this Figure, we can find that Bitcoin attains his maximum in two periods: 2010 and 2014. The energy commodities reach the maximum in the period from 2011 to 2012.

In our paper, we use the VAR (1)-BEKK-AGARCH (1,1) model of McAleer *et al.* (2009) which considers asymmetries of negative shocks on conditional variance. There are two objectives of this study. First, we use the VAR (1)-BEKK-AGARCH (1,1) model to analyze the return and volatility connections between Bitcoin and stock indices of energy commodities indices. This model cansimultaneously assess returns and volatility cross-effects for the energy commodities markets under consideration. The Multi-GARCH approach additional clarifies the origins, trends, and transmission intensity of the shocks between markets. This model can captures the impacts on the current conditional volatility of own innovations and lagged volatility as well as the cross-market shocks and the volatility transmission of other markets. As concluded by Gallaghar and Twomey (1998), modeling price volatility spillover offers clearer insight into the dynamic price nexus among markets, but inferences about any inter-relationship depend importantly on how we model the cross dynamics in the conditional volatilities of the markets.

Second, this study investigates the importance of not only volatility spillover between bitcoin energy markets, but also the asymmetric impacts of negative and positive shocks of equal magnitude on the conditional variance of modeling one energy market's volatility upon the returns of future prices within and across other energy markets. We do this by using the VAR (1)-BEKK-AGARCH (1.1) model.

For the empirical finding of bitcoin and energy commodities price mean return spillovers, this study assumes that the conditional mean of price returns on bitcoin and energy markets can be described as a Vector Autoregressive (VAR) model. Under the four-variable model. The number of autoregressive terms for the VAR model is chosen by the AIC lag order criterion. Then, the conditional mean and variance are presented as follows:

$$R_t = C + \Phi R_{t-1} + \varepsilon_t | F_{t-1} \sim N(0, H_t) \tag{2}$$

$$\varepsilon_t = z_t \sqrt{H_t}, z_t \sim N(0,1) \tag{3}$$

$$H_t = \psi'\psi + A'\varepsilon_{t-1}\varepsilon_{t-1}^{'}A + B'H_{t-1}B + \Delta^{'}I_{t-1}\varepsilon_{t-1}\varepsilon_{t-1}^{'}\Delta \tag{4}$$

Where, R_t presents a vector of daily returns on energy commodities and Bitcoin (i = 1, 2, 3, 4) at time t; ε_t represents the error term; z_t is an i.i.d. process and H_t is the conditional variance-covariance matrix. The past information obtainable at time t-1 is defined as F_{t-1}. The model parameters of the multivariate GARCH (Generalized Autoregressive Conditional Heteroskedasticity) specification (C, Φ, Ψ, A, B, Δ) are estimated by Quasi-Maximum Likelihood by employing the BFGS algorithm and robust standard errors.

In the non-main diagonal terms of the A and B matrices, α_{ij} and β_{ij} represent the impacts among i-asset and j-asset and the GARCH-type fluctuations among i-asset and j-asset, that is, the risk in the i-asset and j-asset. The matrix which will be estimated are follow:

$$C = \begin{bmatrix} c_{10} & 0 & 0 & 0 \\ c_{20} & 0 & 0 & 0 \\ c_{30} & 0 & 0 & 0 \\ c_{40} & 0 & 0 & 0 \end{bmatrix} \tag{5}$$

$$\Phi = \begin{bmatrix} \phi_{11} & \phi_{12} & \phi_{13} & \phi_{14} \\ \phi_{21} & \phi_{22} & \phi_{23} & \phi_{24} \\ \phi_{31} & \phi_{32} & \phi_{33} & \phi_{34} \\ \phi_{41} & \phi_{42} & \phi_{43} & \phi_{44} \end{bmatrix} \tag{6}$$

$$\Psi = \begin{bmatrix} \psi_{11} & 0 & 0 & 0 \\ \psi_{21} & \psi_{22} & 0 & 0 \\ \psi_{31} & \psi_{32} & \psi_{33} & 0 \\ \psi_{41} & \psi_{42} & \psi_{43} & \psi_{44} \end{bmatrix} \tag{7}$$

$$A = \begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} & \alpha_{14} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} & \alpha_{24} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & \alpha_{34} \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} \end{bmatrix} \tag{8}$$

$$B = \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} \\ \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} \\ \beta_{31} & \beta_{32} & \beta_{33} & \beta_{34} \\ \beta_{41} & \beta_{42} & \beta_{43} & \beta_{44} \end{bmatrix} \tag{9}$$

$$\Delta = \begin{bmatrix} \delta_{11} & \delta_{12} & \delta_{13} & \delta_{14} \\ \delta_{21} & \delta_{22} & \delta_{23} & \delta_{24} \\ \delta_{31} & \delta_{32} & \delta_{33} & \delta_{34} \\ \delta_{41} & \delta_{42} & \delta_{43} & \delta_{44} \end{bmatrix} \tag{10}$$

According to this diagonal description, the conditional variances are functions of their own lagged values and own lagged square return shocks, while the conditional covariances are functions of the lagged covariance and lagged cross-products of the corresponding returns shocks. The estimations of the BEKK models are carried out by the quasi-maximum likelihood (QML), where the conditional distribution of error term is believed to follow a joint Gaussian log-likelihood function of a sample of T observations and K = 4 time series (K = 4 is equal to the number of series used in our study which equal to 4; Bitcoin, Crude Oil WTI, Brent Oil and Natural Gas).

Table 1. *Descriptives Statistics*

	Bitcoin	**Crude Oil WTI**	**Brent Oil**	**Natural Gas**
Mean	0.1775	0.0281	-0.0109	0.0138
Min	-0.3686	-0.0567	-0.0475	-0.0646
Max	0.6402	0.0716	0.0551	0.1162
Std.dev	2827.789	23.62692	26.50799	2.001575
Kurtosis	13.67094	2.128054	1.727342	7.231113
Skewness	3.205986	0.0732757	0.0306165	1.948387

Note: *The sample consists of three Energy commodities (Crude Oil WTI, Brent Oil and Natural Gas) and Bitcoin (BTC) from Datastream during the period from July 18, 2010 to June 30, 2018. This table presents the main statistical features for variables returns.*
Source: *Own elaboration.*

Table 2. *Correlation Matrix*

	Bitcoin	**Crude Oil WTI**	**Brent Oil**	**Natural Gas**
Bitcoin	1.0000			
Crude Oil WTI	0.8098*	1.0000		
Brent Oil	0.7869*	0.9517*	1.0000	
Natural Gas	-0.5775*	0.5011*	0.3621*	1.0000

Note: *The sample consists of three Energy commodities (Crude Oil WTI, Brent Oil and Natural Gas) and Bitcoin (BTC) from Datastream over the period from July 18, 2010 to June 30, 2018. This table presents the correlation matrix for variables returns. (*) denotes significance threshold at 1%.*
Source: *Own elaboration.*

3. Empirical Results

3.1 Return, Volatility and Asymmetric Shock Spillovers

The estimation results are presented in Table 3. We show significant and positive past own return effects on energy commodities (φ_{11}, φ_{22}). Past one-period lagged returns of Bitcoin and energy commodities do not help predict short-term returns. The φ_{41}, φ_{42} and φ_{43} parameters in VAR-mean equation reveal unilateral past return spillovers from energy commodities indices to Bitcoin. In other words, higher returns in Crude oil WTI and Brent Oil predict lower returns in Bitcoin, while there is a positive impact of Natural Gas passed returns on Bitcoin.

Crude Oil WTI and Brent Oil prices have historically been low since the price collapsed in 2014. Its prices increased in 2017 and 2018 because demand was better than expected, along with OPEC (Organization of the Petroleum Exporting Countries) production cuts and tougher penalties, Americans against Iran and Venezuela. This may in some way explain the low impact of Crude oil WTI and Brent Oil on Bitcoin, which is justified by the absence of the strong correlation between oil and bitcoin. Conversely, it is remarkable the application of bitcoin (BTC) on natural gas in mines. This may be a justification for the strong correlation between natural gas and bitcoin. This correlation is defined by the impact of natural gas on bitcoin.

These effects can be explained by the structure of mining procedure, where miners are rewarded with new Bitcoins. Since energy commodities are explanations inputs in Bitcoin creation, they can establish the necessary returns of miners. Energy commodities are better off when there is constancy in the market and there are prospects for expansion and advanced future cash flows. Increase in energy price put parallel pressures on Bitcoin daily price. On the contrary, the period under examination while producers of energy commodities were benefited by government subsidies and fixed-term contracts, energy commodities distributors presented abridged prices when the production was abundant without opportunities for energy storage or change in the production. The limited Bitcoin mining, the advanced energy effectiveness with storage solutions and the smaller and cheaper equipment are anticipated to modify these relations in the future.

As for the estimates of variance-covariance equations, possess conditional ARCH (α_{ii}) and GARCH (β_{ii}) effects are investigative of short and long-run persistence, correspondingly. Our empirical results propose stronger and larger long-run persistence of own volatility than short-term persistence. Crude Oil WTI exhibits the highest long-run persistence, followed by Bitcoin, Brent Oil, and Natural Gas. Short-term volatility spills over from Natural Gas to Bitcoin (α_{43}) that can be giving details by the rising demand of miners for advanced high Natural Gas products. Unilateral long-term spillovers from Bitcoin to Crude Oil WTI and Brent Oil (β_{14}, β_{24}) are investigative of the impact of Bitcoin on energy demand in the long run. We also conclude proof of bilateral negative effect or ‘‘bad news’’ transmissions between Bitcoin and Crude Oil WTI and Natural Gas (δ_{24}, δ_{34}, δ_{42}, δ_{43}).

Even though we do not use in our main investigation DCC (Dynamic Conditional Correlation) or CCC (Constant Conditional Correlation) alternatives of McAleer et al. (2009) due to their inefficiencies in capturing cross market spillovers, we evaluate the VAR(1)-BEKKAGARCH robust against them to augment the fit of our findings. Log Likelihood, AIC, SBC and Hannan–Quinn criteria designate that the model is adequate and sufficient failing to discover residual independence at conventional significance levels for many lags.

Table 3. *VAR (1)-BEKK-AGARCH parameter estimates*

Variable		**Mean**	**Variance**				
		c	**ϕ**	**ψ**	**α**	**β**	**δ**
Bitcoin	(1,0)	0.0006					
	(1,1)		0.0374***	0.2464***	0.2238***	0.2764***	0.1738***
	(1,2)		0.0088***		0.0378	0.0347	-0.0172
	(1,3)		0.0283***		0.0287	0.0091	-0.0264

	(1,4)		0.0004		0.3729	-0.2201***	0.2733
	(2,0)	0.0036					
Crude Oil WTI	(2,1)		-0.0384	−0.0294	-0.0037	0.0388**	-0.0346
	(2,2)		0.0450*	0.1234***	0.0162	0.9029***	0.1283***
	(2,3)		0.0071		0.0285*	-0.0286*	0.7481***
	(2,4)		0.0008		-0.1007	0.0114***	-0.3002***
	(3,0)	0.0364***					
Brent Oil	(3,1)		-0.0492	−0.0153	-0.0830**	-0.0374	0.1829**
	(3,2)		-0.0275	0.2029**	-0.0801	-0.0542*	0.0390
	(3,3)		0.0914	0.1182*	-0.1022*	0.3947***	0.3361***
	(3,4)		0.0009		-0.7301	0.0310	0.6110**
	(4,0)	0.4657***					
Natural Gas	(4,1)		-0.0709***	0.3157**	0.0047	-0.0005	0.0026
	(4,2)		0.0072**	−0.0052	-0.0038	0.0003	-0.0139**
	(4,3)		0.0314***	0.1074	-0.0011**	0.0015	-0.0200*
	(4,4)		0.0001	−0.0000	0.8391***	0.8394***	-0.0181
	Info criteria			Diagnostics of standardized ε_t and ε_{2t}			
Log L			−12154.229	Q(4)		77.985[0.289]	
AIC			14.437	Q(20)		394.203[0.004]	
SBC			14.737	$Q^2$4)		5.104[0.211]	
HQ			14.530	Q^2(20)		15.559[0.591]	

Note: *The sample consists of three Energy commodities (Crude Oil WTI, Brent Oil and Natural Gas) and Bitcoin (BTC) from Datastream during the period from July 18, 2010 to June 30, 2018. This table presents the VAR (1)-BEKK-AGARCH parameter estimates. ***, **, * denote significance threshold at 1%, 5%, and 10%, respectively. P-values for the squared standardized residual diagnostics are reported in brackets.*
Source: *Own elaboration.*

3.2 Dynamic Correlations and Portfolio Management Implications

The higher variations of conditional correlations recommend that the assumption of constant dependencies is not pragmatic. In addition, the little correlation of Bitcoin with energy markets shows it is possible as an investment opportunity. To demonstrate the implications of our empirical results for a risk-adverse investor who invests in these assets, we estimate optimal weights for the global minimum-variance portfolio which minimizes the risk with no reducing the anticipated returns.

This approach necessitates only the variance-covariance matrix and deals with concerns for the big volatility of Bitcoin exploiting the benefits from its little correlations with other assets. Furthermore, since weights are disentangled from asset returns, our empirical results are not prejudiced by great Bitcoin prices or bubble periods. The global minimum-variance portfolio solves the following problem in every period t:

$$\min \omega_t' H_t \omega_t \quad \text{s.t.} \quad \omega_t' \iota = 1 \text{ and } \quad \omega_t \geq 0 \tag{11}$$

Where, ω_t is a 4×1 vector of portfolio weights and ι is a 4×1 vector of ones. The constraints guarantee that the sum of portfolio weights must be equal to one and short sales are not allowed. The optimal portfolio weights are given by:

$$\omega_t = H_t^{-1}\iota / \iota' H_t^{-1}\iota \tag{12}$$

Table 4 shows the summary statistics of portfolio weights for every asset along with the contribution of every asset in the portfolios crossways the whole sample period (Investment). Bitcoin contributes to 93.92% trading periods maintaining a little average weight of 3.84%. Our empirical results find that the little correlation of Bitcoin with the energy commodities indices trades off the great variance and leads to elevate returns (8.9%) and lesser portfolio risk (79.65%) in comparison to a portfolio that does not comprise Bitcoin. Also, we can classify the energy commodities with their degree of investment. Then, Natural Gas have the best possibility to be taken as an optimal asset with Bitcoin (0.9911) followed by Brent Oil (0.8200) and Crude Oil WTI (0.8111) respectively.

Table 4. *Minimum-variance portfolios*

	Crude Oil WTI	**Brent Oil**	**Natural Gas**	**Bitcoin**
Weights				
Mean	0.1408	0.2461	0.5746	**0.0384**
Std.Dev	0.1390	0.2069	0.2075	0.0369
Max	0.9161	0.8821	1.0000	0.2485
Investment	0.8111	0.8200	0.9911	**0.9392**
Portfolio return	**0.0890**			
Portfolio risk	**0.7965**			

Note: *The sample consists of three Energy commodities (Crude Oil WTI, Brent Oil and Natural Gas) and Bitcoin (BTC) from Datastream during the period from July 18, 2010 to June 30, 2018. This table presents the Minimum-variance portfolios.*
Source: *Own elaboration.*

4. Conclusions

In our paper, we use a VAR-BEKKAGARCH to study return, volatility, and shock spillovers between Bitcoin and three stock indices of energy commodities as: Crude Oil WTI, Brent Oil and Natural Gas. Also, we study empirically portfolio management implications of DCC (dynamic conditional correlations) in a minimum-variance optimal portfolio. We get data for Energy commodities (Crude Oil WTI, Brent Oil and Natural Gas) and Bitcoin (BTC) from Datastream over the period from July 18, 2010 to June 30, 2018.

Our empirical findings show significant and important return spillovers from energy commodities stocks to Bitcoin. Short-run volatility spills over from Natural Gas to Bitcoin, while Bitcoin has long-run volatility impacts on energy indices. We show bidirectional asymmetric shock spillovers between Bitcoin and energy commodities indices.

The continuous speedy development of Bitcoin and the unfettered environment of the market might generate additional weaknesses in the worldwide economic system. Officials and strategy manufacturers must, consequently, scrutinize the Bitcoin marketplace and be informed of the return and volatility spillover impacts between the Bitcoin market and additional asset classes for chosen and individual states. Our paper concentrates on exclusively the spillover impacts among Bitcoin and energy commodities. It could be feasible to simplify the outcomes of the analysis to all other states, because each one has various investing options.

Finally, we find portfolio management implications and benefits from the short dependence of Bitcoin with the energy commodities indices. We conclude that the little correlation of Bitcoin with the energy commodities indices reduces the variance.

Also, this correlation leads to elevate returns and lesser portfolio risk in comparison to a portfolio that does not contain Bitcoin. This result implies the importance of Bitcoin in portfolio construction and reflects the importance of diversification of portfolio between energy commodities and the crypto-currencies, mainly Bitcoin.

References:

Balcilar, M., Bouri, E., Gupta, R., Roubaud, D. 2017. Can volume predict Bitcoin returns and volatility? A quantiles-based approach. Economic Modelling, 64(5), 74-81.

Baur, D.G., Dimpfl, T., Kuck, K. 2018. Bitcoin, gold and the US dollar a replication and extension, Finance Research Letters, 25(3), 103-110.

Böhme, R., Christin, N., Edelman, B., Moore, T. 2015. Bitcoin: Economics, Technology, and Governance. Journal of Economic Perspectives, 29(2), 213-238.

Bouri, E., Gupta, R., Tiwari, A.K., Raubaud, D. 2017a. Does Bitcoin Hedge global uncertainty Evidence from wavalet-based quantile-in-quantile regressions, Finance Research Letters, 23(3), 87-95.

Bouri, E., Jalkh, N., Molnár, P., Roubaud, D. 2017b. Bitcoin for Energy Commodities before and after the December 2013 Crash: Diversifier, Hedge or More? Applied Economics, 49(50), 5063-5073.

Bouri, E., Jalkh, N., Molnár, P., Roubaud, D. 2017c. Bitcoin for energy commodities before and after the December 2013 crash: diversifier, hedge or safe haven? Applied Economics, 49(50), 5063-5073.

Briere, M., Oosterlinck, K., Szafar, A. 2015. Virtual currency, tangible return: portfolio diversification with Bitcoins, Journal of Asset Management, 16(6), 365-373.

Chebbi, T., Derbali, A. 2015. The dynamic correlation between energy commodities and Islamic stock market: analysis and forecasting. International Journal of Trade and Global Markets, 8(2), 112-126.

Chebbi, T., Derbali, A. 2016a. A Dynamic Conditional Correlation between Commodities and the Islamic Stock Market. Journal of Energy Markets, 9(1), 65-90.

Chebbi, T., Derbali, A. 2016b. On the role of structural breaks in identifying the dynamic conditional linkages between stock and commodity markets. Journal of Energy Markets, 9(4), 71-81.

Ciaian, P., Rajcaniova, M., Kancs, D. 2016. The economics of bitcoin price formation, Applied Economics, 48(19), 1799-1815.

Ciaian, P., Rajcaniova, M., Kancs, D. 2018. Virtual relationships: Short-and longrun evidence from BitCoin and altcoin markets. Journal of International Financial Markets, Institutions & Money, 52(1), 173-195.

Corbet, S., Meegan, A., Larkin, C., Lucey, B., Yarovaya, L. 2018. Exploring the dynamic relationships between cryptocurrencies and other financial assets. Economic Letters, 165(4), 28-34.

Dyhrberg, A.H. 2016. Bitcoin, gold and the dollar a GARCH volatility analysis. Finance Research Letters, 16(2), 85-92.

Dyhrberg, A.H. 2016. Bitcoin, gold and the dollar: A GARCH volatility analysis. Finance Research Letters, 16(2), 85-92.

Gallaghar, L.A., Twomey, C.E. 1998. Identifying the source of mean and volatility spillovers in Irish equities: A multivariate GARCH analysis. Economic and Social Review, 29(4), 341-356.

Hayes, A.S. 2017. Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin. Telematics Informatics, 34(7), 1308-1321.

Ji, Q., Bouri, E., Gupta, R., Roubaud, D. 2018. Network causality structures among bitcoin and other financial assets: a directed acyclic graph approach. The Quarterly Review of Economics and Finance, 70(3), 203-213.

Katsiampa, P. 2017. Volatility estimation for Bitcoin: A comparison of GARCH models. Economic Letters, 158(9), 3-6.

Luther, W.J., Salter, A.W. 2017. Bitcoin and the bailout. The Quarterly Review of Economics and Finance, 66(3), 50-56.

McAleer, M., Hoti, S., Chan, F. 2009. Structure and asymptotic theory for multivariate asymmetric conditional volatility. Econometric Review, 28(5), 422-440.

Mohamada, S., Abdurrahmanb, A.P., Keong, O.C. 2020. Blockchain Technology: Implications for Accountants, International Journal of Innovation, Creativity and Change, 10(11), 101-117.

Sadorsky, P. 2012. Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. Energy Economics, 34(1), 248-255.

Symitsi, E., Chalvatzis, K.J. 2018. Return, volatility and shock spillovers of Bitcoin with energy and technology companies. Economic Letters, 170(9), 127-130.

Vidal-Tomás, D., Ibañez, A. 2018. Semi-strong efficiency of Bitcoin, Finance Research Letters, 27(3), 259-265.

Figure 1. *Daily prices of Energy commodities (Crude Oil WTI, Brent Oil and Natural Gas) and Bitcoin (BTC) during the period from July 18, 2010 to June 30, 2018*

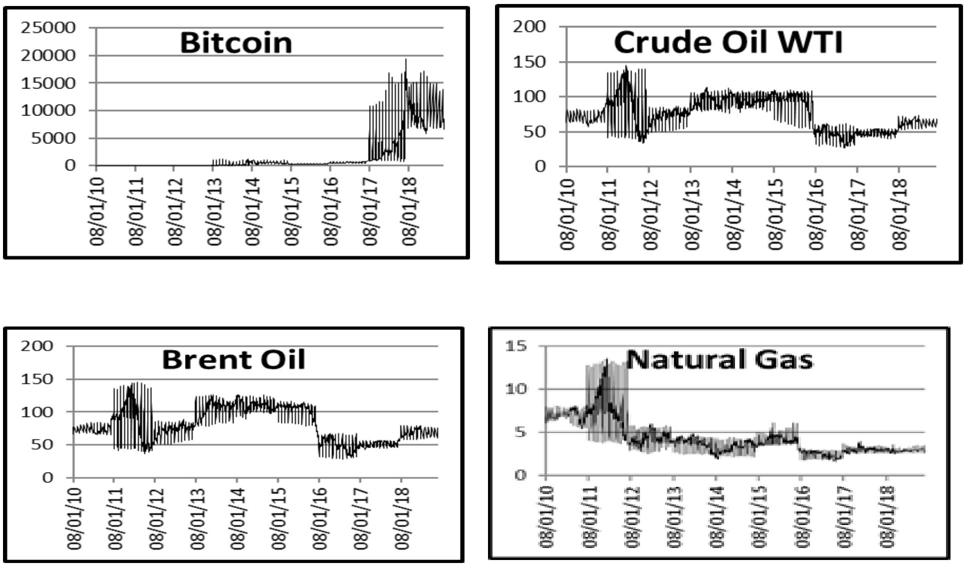

Figure 2. *Daily returns of Energy commodities (Crude Oil WTI, Brent Oil and Natural Gas) and Bitcoin (BTC) during the period from July 18, 2010 to June 30, 2018*

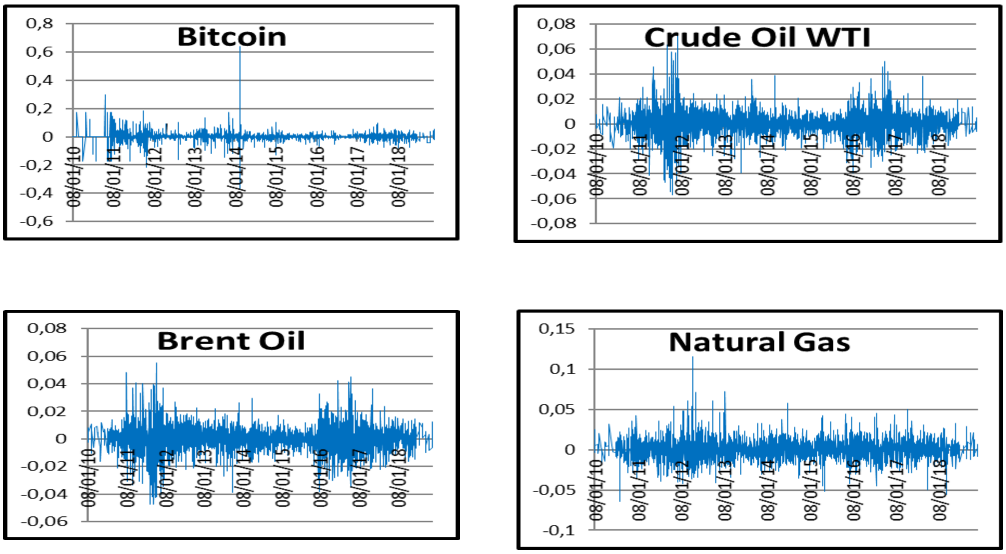

Figure 3. *Conditional volatilities of Energy commodities (Crude Oil WTI, Brent Oil and Natural Gas) and Bitcoin (BTC) during the period from July 18, 2010 to June 30, 2018*