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Cryptocurrencies and Investment Diversification: Empirical Evidence from Seven Largest Cryptocurrencies

Nguyen Phuc Canh[1], Nguyen Quang Binh[2], Su Dinh Thanh[3]

[1]School of Banking, University of Economics Ho Chi Minh City, Ho Chi Minh City, Vietnam
[2]University of Economics Ho Chi Minh City, Ho Chi Minh City, Vietnam
[3]School of Public Finance, University of Economics Ho Chi Minh City, Ho Chi Minh City, Vietnam
Email: canhnguyen@ueh.edu.vn, binhnq@ueh.edu.vn, dinhthanh@ueh.edu.vn

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Abstract

The study examines the diversification capability of seven cryptocurrencies with the largest market size against risks from economic factors as oil price, gold price, interest rate, USD strength, and S&P500. Using the weekly data of Bitcoin, Litecoin, Ripple, Stellar, Monero, Dash, and Bytecoin in the period Aug/2014-Jun/2018, the study finds that there are structural breaks and ARCH disturbance in each cryptocurrency, suggesting a systematic risk within the cryptocurrency market. However, the causality between cryptocurrencies and economic factors is undirected. Interestingly, our findings show that cryptocurrencies are insignificant correlations with economic factors. The result implies that cryptocurrencies can not be assumed as financial assets to hedge systematic risks from economic factors.

Keywords

Cryptocurrency, Economic Factors, Systematic Risk

1. Introduction

The cryptocurrencies with a decentralized and open-source technology have extensively received attention from finance literature in recent years [1]. The fact is true that some financial institutions, public organizations and governments have recognized Bitcoin and other cryptocurrencies as official financial assets [2]. From the original objective as an alternative payment system independent of any central banks, the popularity of cryptocurrencies has tremendously received much attention from the literature due to their increased capitalization values.

However, because of lacking foundational theories, linkages between cryptocurrencies and economic factors are still open to debate.

Some studies have focused on the volatility of cryptocurrency prices, especially the Bitcoin [3]-[10]. Other studies have emphasized the relationships between Bitcoin price and economic factors. Su, Li, Tao, and Si [11] showed that there have been four explosive bubbles in China and the U.S. market during the periods of the huge surges of Bitcoin prices and the shocks from foreign or domestic markets. Concerning Bitcoin and other assets [12] [13] [14] [15] found that the fundamental price of Bitcoin is close to zero. About the relation between cryptocurrencies, for instance, Bitcoin and Ethereum [16] [17] unveiled clear bubble behaviours during the time after 2013. Gandal, Hamrick, Moore, and Oberman [18] added that the suspicious trading resulted in an unprecedented spike of the USD-BTC exchange rate in late 2013.

Interestingly, as a hedge instrument against market-specific risk and uncertainty, Bitcoin may be a priority choice in portfolio management for financial markets [11] [19] [20] [21]. Some arguments show that the average monthly volatility of Bitcoin returns is higher than for gold or a set of foreign currencies indexed by dollars [22]. The Bitcoin price is more sensitive to changes in economic and market factors in the short-run, but less sensitive to technological factors in the long-run [23]. As in Al-Yahyaee, Mensi, and Yoon [24], the Bitcoin market is easy to be broken in comparison to other currencies markets, while Gajardo *et al.* [2] show that Bitcoin has a greater multifractal spectrum than other assets on its cross-correlation with the WTI, the Gold and the DJIA. Concerning the role of other cryptocurrencies, Ciaian, Rajcaniova, and Kancs [25] revealed that Bitcoin seems to be less affected macro-financial indicators in comparison to the altcoins price formation. On the contrary, Ciaian *et al.* [25] show that relationships among cryptocurrencies are complex, especially in the context of ICOs leading to a huge of cryptocurrencies available [26].

This study contributes to the literature by shedding the light on the capability of seven cryptocurrencies with the largest market capitalization in hedging against the systematic risks in line with economic factors. Specifically, the Granger causality tests between each cryptocurrency with economic factors show that the oil price, and the USD index cause most of the selected cryptocurrencies. While only BTC and LTC are among the cryptocurrencies, which cause the oil price, the USD index, the S&P500 index and the gold price, respectively. In addition, there exist structural breaks and ARCH disturbance in the price of each cryptocurrency, suggesting a systematic risk within cryptocurrency markets. Moreover, the USD index has negative effects on all seven cryptocurrencies, while other economic factors have inconsistent effects on all cryptocurrencies. The results imply that the cryptocurrencies are likely impacted by economic factors other than a hedge for economic factors.

Next section presents the methodology and data. The results and discussions are in Section 3. Some conclusions are remarked in the final section.

2. Methodology and Data

The study surveys all cryptocurrency markets and collects the daily closing price of each cryptocurrency and come up to 20 largest cryptocurrencies. Matching each cryptocurrency together with economic factors to find the longest time span possible, the study narrows down to seven cryptocurrencies in terms of largest market capitalization including Bitcoin, Litecoin, Ripple, Stellar, Monero, Dash, and Bytecoin in the period from 8 Aug 2014-7 June 2018. Economic indicators are proxied by WTI Oil price, Gold price, S&P500 index, LIBOR, and USD index. The weekly data of WTI Oil price, S&P500 index, Gold price, LIBOR (one month), and the bid price of USD index are collected from Thomson Reuter and Fred. All variables are taken by logarithm to reduce heteroskedasticity, except for LIBOR. Definitions, sources, and statistical descriptions of variables are presented in Table 1. The data of cryptocurrencies is collected from Coinmarketcap in Aug/2018. The LIBOR is collected from Federal Reserve Economic Data St. Louis Fed (FRED). All remained economic factors are collected from Thomson Reuter.

In this study, we collect the weekly data of all variables to enlarge the time span of the sample. In which, the weekly close values of all variables are used. Table 1 shows the primary data before taking logarithm. Bitcoin has highest average price then Dash, Monero, and Litecoin in the followings. To examine linkages between cryptocurrencies and world economic indicators, the study conducts Granger causality tests for each of pair variables. To detect the associations of cryptocurrencies with systematic risks, the study uses the GARCH (1, 1) based on the existence of ARCH disturbance. GARCH (1, 1) is formed as followings.

$$Y_t = \beta_0 + \beta_i X_t + \epsilon_t \tag{1}$$

Table 1. Data description (primary data).

Vars.	Definitions	Data	Obs.	Mean	Std. Dev.	Min	Max
OIL	WTI Oil Price	Daily closed price	204	53.713	13.440	29.42	97.65
SP500	SP500 Index	Daily closed index	204	2250.556	262.696	1864.78	2872.87
GOLD	Gold Price	Daily closed price	204	1236.067	71.912	1058.41	1366.4
LIBOR	LIBOR 1 Month	Daily closed interest	204	0.723	0.582	0.152	2.098
USD	USD Index Bid	Daily closed index	204	94.820	4.310	81.424	103.01
BTC	Bitcoin	Daily closed price	204	2480.591	3732.954	208.1	17,706.9
XRP	Ripple	Daily closed price	204	0.181	0.396	0.004	3.05
LTC	Litecoin	Daily closed price	204	34.947	61.386	1.4	299.78
XLM	Stellar	Daily closed price	204	0.056	0.129	0.0014	0.678
XMR	Monero	Daily closed price	204	51.295	93.456	0.256	394.78
DAS	Dash	Daily closed price	204	132.222	238.510	1.28	1179.01
BCN	Bytecoin	Daily closed price	204	0.001	0.002	0.000008	0.014

Note: Time period: 8 Aug 2014-7 June 2018 due to the availability of Cryptocurrency prices from Coinmarketcap [from Aug 2014]. Source: Coinmarketcap, Fred, Thomson Reuters.

$$\epsilon_t \left| \varphi_{t-1} \sim N\left(0, \partial_t^2\right)\right. \quad (2)$$

$$\partial_t^2 = \gamma + \alpha_1 \epsilon_{t-1}^2 + \delta_1 \partial_{t-1}^2 \quad (3)$$

where: Y is each cryptocurrency; X is a set of economic factors including oil price, SP500, gold price, USD index, and LIBOR. β is coefficient. ϵ is conditional error term. ∂^2 is GARCH term. ϵ^2 is ARCH term. To check robustness, the study employs dynamic conditional correlation Multivariate GARCH model (Multivariate Autoregressive Conditionally Heteroskedastic—MGARCH). Due to the existence of ARCH disturbance and structural breaks in variables, MGARCH is more flexible than the conditional correlation MGARCH model, and more parsimonious than the diagonal vech MGARCH model [27] [28] [29]. The estimated results of conditional correlations from DCC MGARCH [30] [31] between each cryptocurrency and economic factors are helpful in detecting the associations between cryptocurrencies and economic factors.

The DCC GARCH model is given:

$$Y_t = \alpha X_t + \epsilon_t \quad (4)$$

$$\epsilon_t = H_t^{1/2} \gamma_t \quad (5)$$

where: Y is cryptocurrency; X is a set of economic factors; H is the Cholesky factor of the time-varying conditional covariance matrix; γ_t is the vector of normal, independent, and identically distributed innovations.

3. Results and Discussions

3.1. Basic Results

Figure 1 shows that Bitcoin has the highest price with the peak at the end of 2017. All six other cryptocurrencies are the same patterns in this period. The US stock market (S&P500) has a stable trend, while gold price and USD index show a small fluctuation during this time. Oil price steadily decreases from 2014 until 2015 before increasing until 2018. LIBOR shows a steadily increasing trend, especially from 2015 (Figures 1-4).

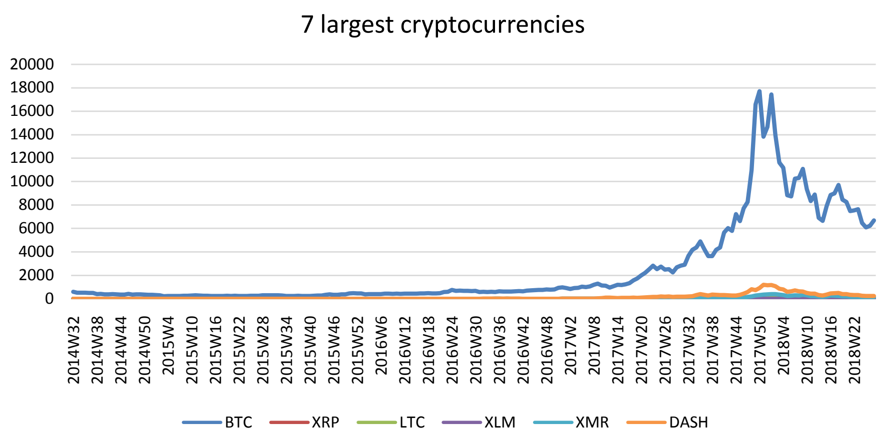


Figure 1. Price of 7 largest cryptocurrencies.

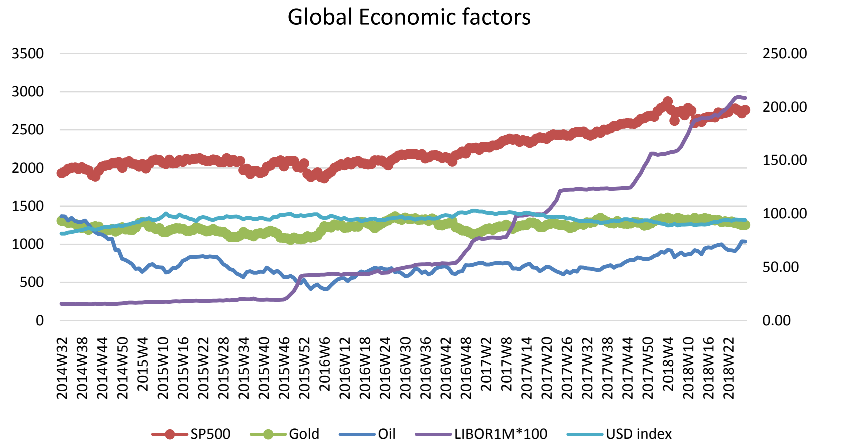
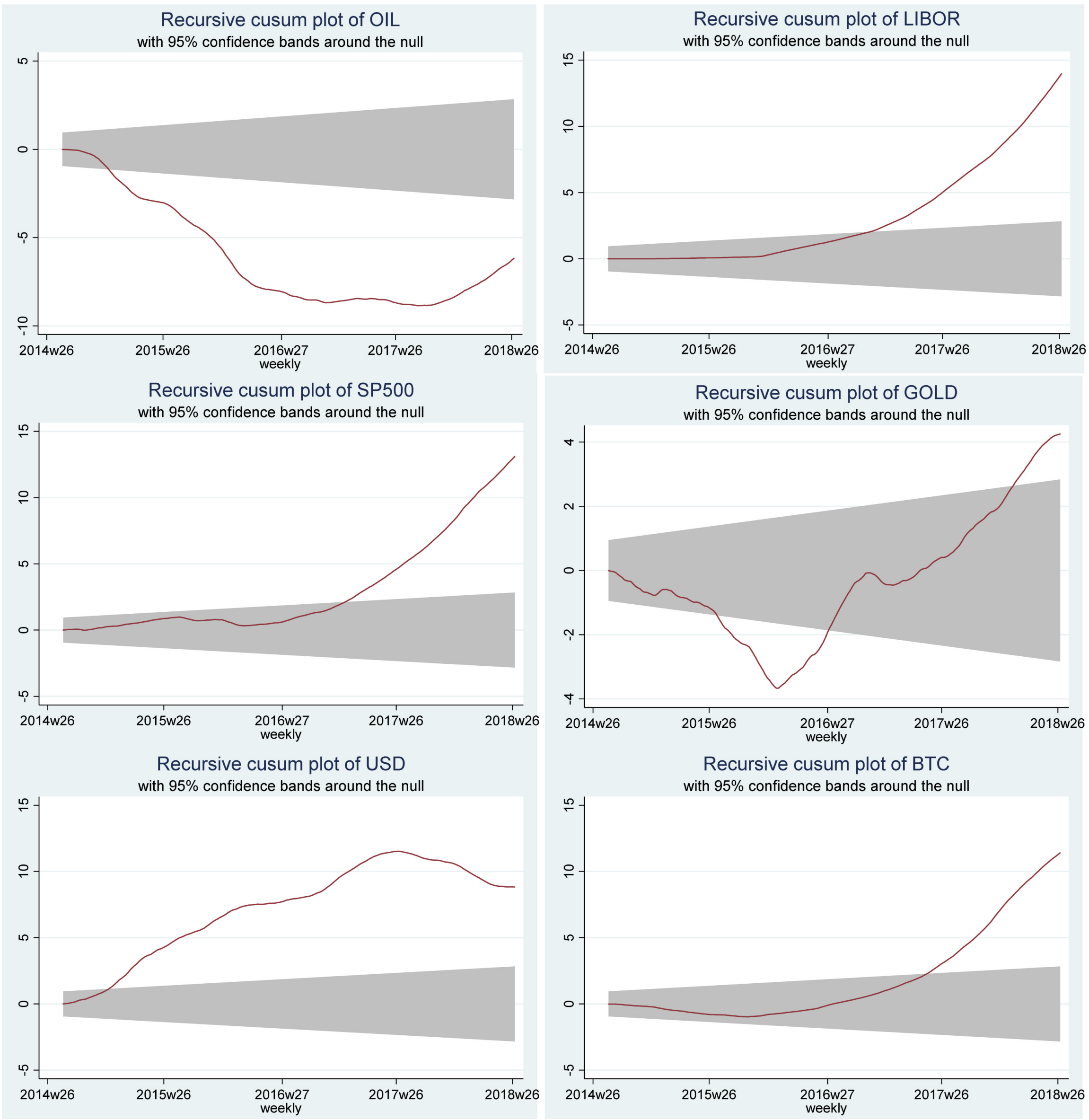


Figure 2. Economic factors in the period Aug/2014-Jun/2018 (SP500 and Gold are left axis; Old, LIBOR (1M) × 100 and USD index are right axis).



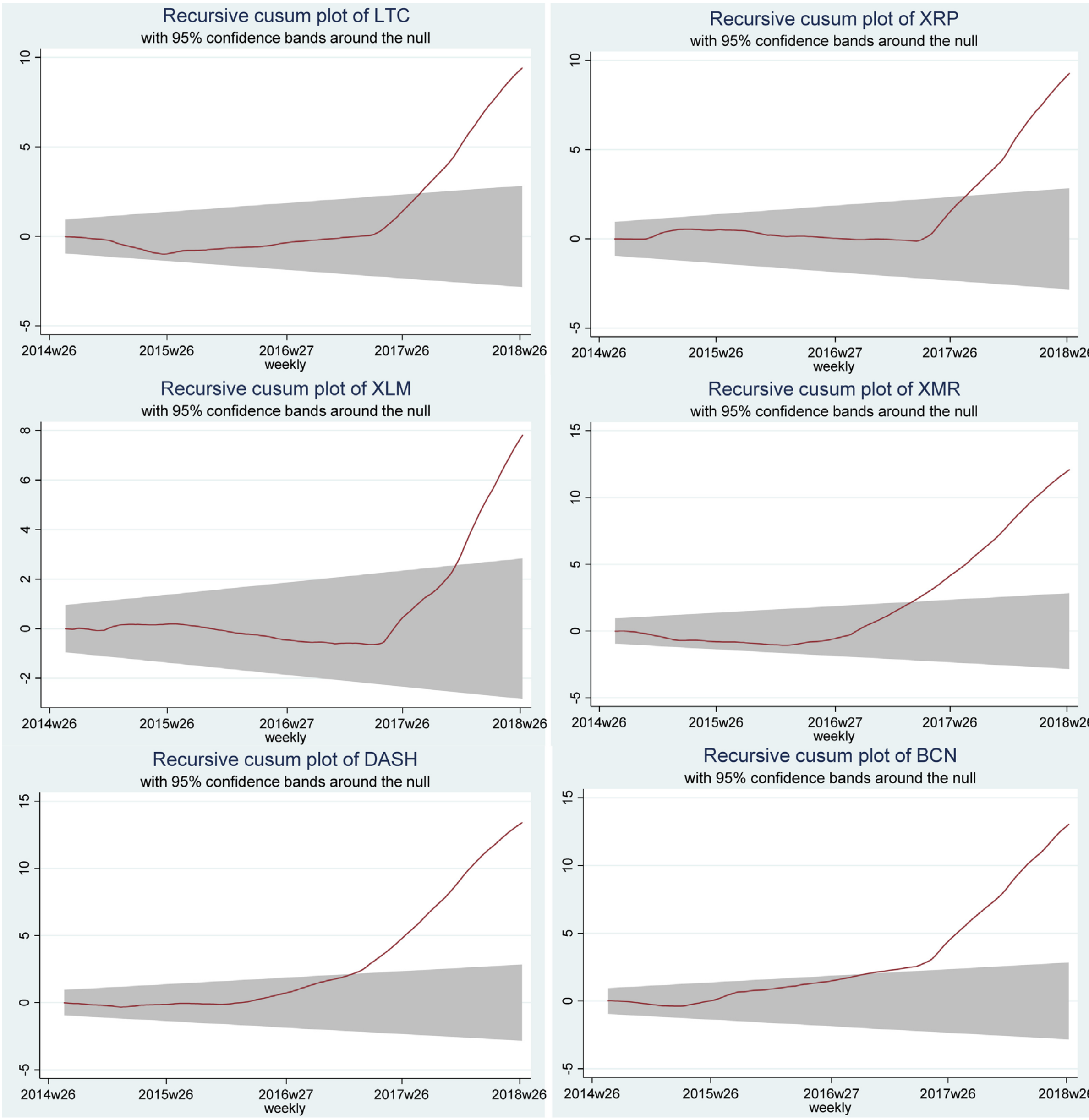
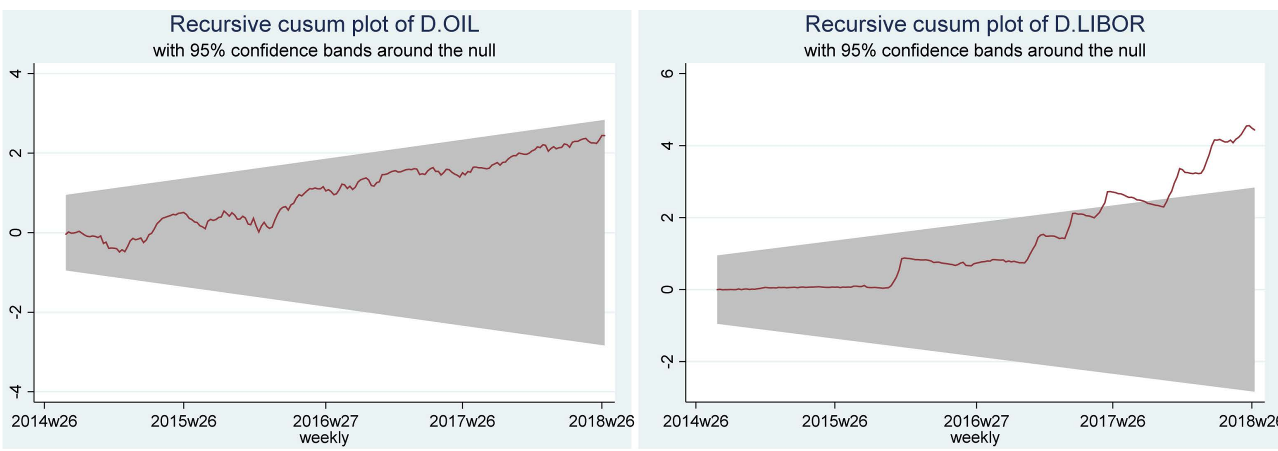
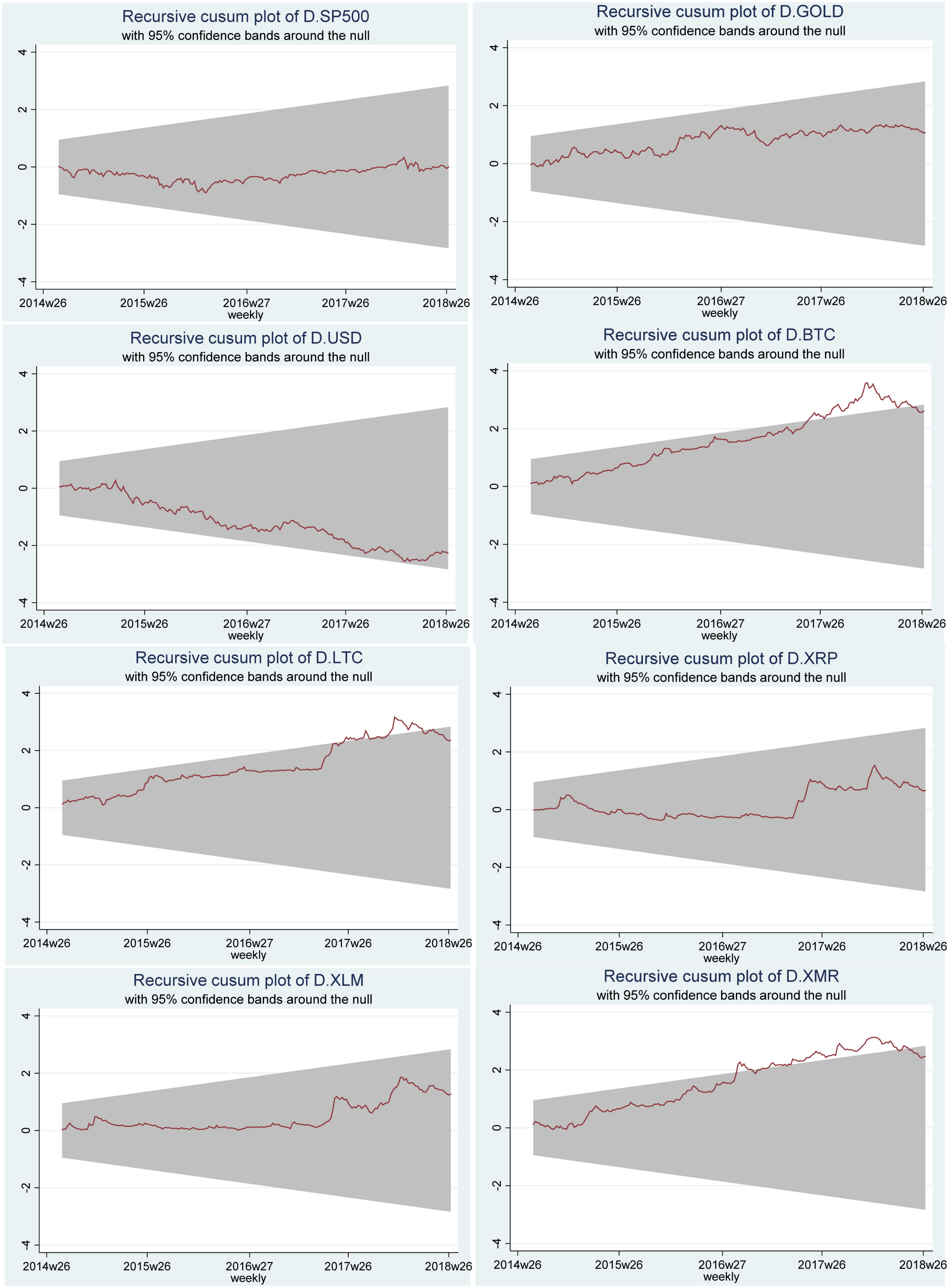


Figure 3. Cusum test for all variables (in log forms).




Recursive cusum plot of D.SP500
with 95% confidence bands around the null
Recursive cusum plot of D.GOLD
with 95% confidence bands around the null
Recursive cusum plot of D.USD
with 95% confidence bands around the null
Recursive cusum plot of D.BTC
with 95% confidence bands around the null
Recursive cusum plot of D.LTC
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Recursive cusum plot of D.XRP
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Recursive cusum plot of D.XLM
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Recursive cusum plot of D.XMR
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2018w26
weekly

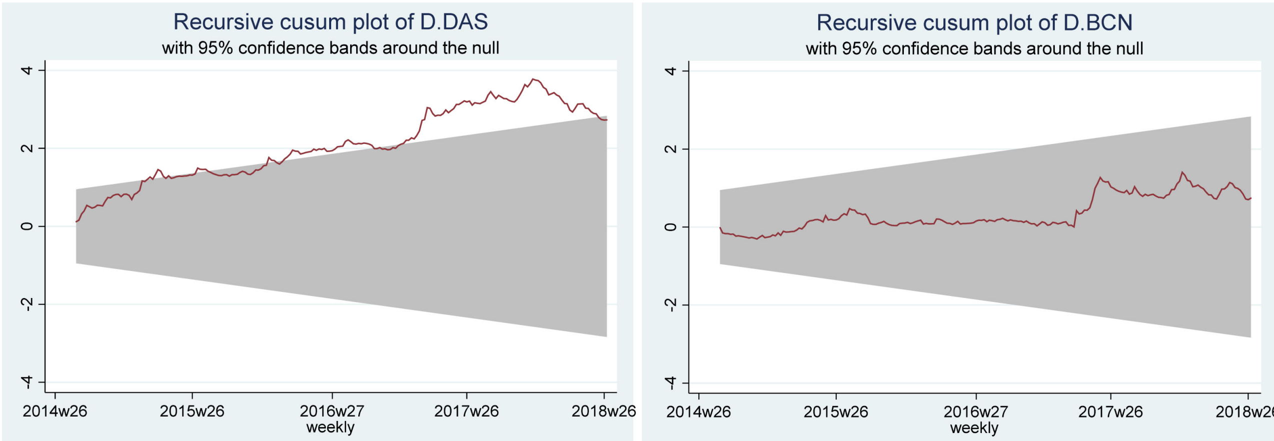

Figure 4. Cusum test for all variables (in 1st difference of log forms).

Tables 2-4 reports the characteristics of variables examined by the Dicky-Fuller unit root test, Johansen Cointegration test, and Granger causality test, respectively.

Results in Table 2 show that all variables (excluding USD index) have stationary at the 1st difference. For testing cointegration, results in Table 3 show that the LIBOR and the USD index have cointegration with all cryptocurrencies. The S&P500 index has cointegration with BTC, XRP, DAS and BCN, while the oil price has cointegration with XMR and DAS. Interestingly, the gold price has no cointegration with all cryptocurrencies. These results suggest that there are strong relationships between the USD index and LIBOR with cryptocurrencies.

The results of Granger causality test for each pair of cryptocurrency and economic indicators are presented in Table 4. The causal relations between these variables are asymmetric. There exists bidirectional causality between the oil price and most of the cryptocurrencies, except for BTC. The USD index causes all cryptocurrencies. However, only BTC, LTC, DAS and BCN, respectively, causes the USD index. The S&P500 index causes BTC, LTC, and DAS, respectively; and only XRP, XLM, and BCN, respectively causes S&P500 index. The goldprice causes BTC, XRP, XMR, and DAS, respectively; and only LTC causes the gold price. In summary, the oil price, and the USD index cause most of the selected cryptocurrencies. Conversely, only BTC and LTC are among the cryptocurrencies, which cause the oil price, the USD index, the S&P500 index and the gold price, respectively.

As in Table 2, all variables are stationary at the 1st difference (excluding USD index. Taking the 1st difference of all variables, we examine the structural breaks and ARCH disturbance for each variable. Results of Table 5 show evidence that there are structural breaks in economic factors (e.g., oil price, LIBOR, USD index). In addition, there is an ARCH disturbance in case of XRP, XLM, XMR and BCN, respectively. We then run GARCH (1, 1) for each cryptocurrency with economic factors and results are reported in Table 6.

The results in Table 6 show that there exist structural breaks and ARCH disturbance in the price of each cryptocurrency, suggesting a systematic risk within

Table 2. Correlation matrix.

	OIL	SP500	GOLD	LIBOR	USD	BTC	XRP	LTC	XLM	XMR	DASH	BCN
OIL	1											
SP500	0.290*** (0.000)	1										
GOLD	0.310*** (0.000)	0.556*** (0.000)	1									
LIBOR	0.221*** (0.0015)	0.946*** (0.000)	0.563*** (0.000)	1								
USD	−0.703*** (0.000)	−0.050 (0.4786)	−0.375*** (0.000)	0.067 (0.000)	1							
BTC	0.280*** (0.0001)	0.944*** (0.000)	0.603*** (0.000)	0.955*** (0.000)	−0.182*** (0.0091)	1						
XRP	0.264*** (0.0001)	0.902*** (0.000)	0.536*** (0.000)	0.899*** (0.000)	−0.243*** (0.0005)	0.915*** (0.000)	1					
LTC	0.311*** (0.000)	0.906*** (0.000)	0.552*** (0.000)	0.929*** (0.000)	−0.291*** (0.000)	0.970*** (0.000)	0.952*** (0.000)	1				
XLM	0.365*** (0.000)	0.883*** (0.000)	0.511*** (0.000)	0.889*** (0.000)	−0.301*** (0.000)	0.894*** (0.000)	0.967*** (0.000)	0.934*** (0.000)	1			
XMR	0.282*** (0.000)	0.943*** (0.000)	0.630*** (0.000)	0.944*** (0.000)	−0.103 (0.1412)	0.970*** (0.000)	0.868*** (0.000)	0.921*** (0.000)	0.836*** (0.000)	1		
DASH	0.197*** (0.005)	0.951*** (0.000)	0.614*** (0.000)	0.949*** (0.000)	−0.089 (0.206)	0.975*** (0.000)	0.911*** (0.000)	0.944*** (0.000)	0.859*** (0.000)	0.974*** (0.000)	1	
BCN	0.176** (0.012)	0.917*** (0.000)	0.529*** (0.000)	0.939*** (0.000)	−0.114 (0.1041)	0.944*** (0.000)	0.939*** (0.000)	0.960*** (0.000)	0.91*** (0.000)	0.923*** (0.000)	0.952*** (0.000)	1

Note: *, **, *** denote significant levels at 10%, 5%, 1% respectively. P-values are in parenthesis. All variables are examined in log forms (exclude LIBOR).

Table 3. Dickey Fuller test for stationary for level and first different data.

Coin	**Dickey Fuller test statistic**		
	Level Data	**1st Difference Data**	**Conclusions**
OIL	−2.358	−12.733***	Stationary at 1st Difference
SP500	−0.681	−16.203***	Stationary at 1st Difference
GOLD	−2.378	−12.505***	Stationary at 1st Difference
LIBOR	5.016	−6.549***	Stationary at 1st Difference
USD	−3.330**	-	Stationary at Level
BTC	0.374	−12.819***	Stationary at 1st Difference
LTC	0.020	−12.735***	Stationary at 1st Difference
XRP	−0.207	−9.872***	Stationary at 1st Difference
XLM	0.083	−11.017***	Stationary at 1st Difference
XMR	0.213	−11.652***	Stationary at 1st Difference
DAS	0.055	−12.073***	Stationary at 1st Difference
BCN	−0.308	−12.549***	Stationary at 1st Difference

Note: *, **, *** denote significant levels at 10%, 5%, 1% respectively.

Table 4. Johansen Cointegration test.

Coin	Asset	Test for rank 0	Statistic value	5% critical value	1% critical value	Conclusion
BTC	OIL	Trace test	14.425	15.41	20.04	No cointegration
		Max eigenvalue	14.213	14.07	18.63	Cointegration
XRP	OIL	Trace test	10.578	15.41	20.04	No cointegration
		Max eigenvalue	10.576	14.07	18.63	No cointegration
LTC	OIL	Trace test	11.642	15.41	20.04	No cointegration
		Max eigenvalue	11.490	14.07	18.63	No cointegration
XLM	OIL	Trace test	11.408	15.41	20.04	No cointegration
		Max eigenvalue	11.397	14.07	18.63	No cointegration
XMR	OIL	Trace test	24.129	15.41	20.04	Cointegration
		Max eigenvalue	22.818	14.07	18.63	Cointegration
DAS	OIL	Trace test	19.474	15.41	20.04	Cointegration
		Max eigenvalue	17.786	14.07	18.63	Cointegration
BCN	OIL	Trace test	11.084	15.41	20.04	No cointegration
		Max eigenvalue	10.783	14.07	18.63	No cointegration
BTC	SP500	Trace test	17.362	15.41	20.04	Cointegration
		Max eigenvalue	17.062	14.07	18.63	Cointegration
XRP	SP500	Trace test	9.391	15.41	20.04	No cointegration
		Max eigenvalue	9.390	14.07	18.63	No cointegration
LTC	SP500	Trace test	13.980	15.41	20.04	No cointegration
		Max eigenvalue	13.903	14.07	18.63	No cointegration
XLM	SP500	Trace test	11.009	15.41	20.04	No cointegration
		Max eigenvalue	11.007	14.07	18.63	No cointegration
XMR	SP500	Trace test	17.480	15.41	20.04	No cointegration
		Max eigenvalue	17.333	14.07	18.63	No cointegration
DAS	SP500	Trace test	16.322	15.41	20.04	Cointegration
		Max eigenvalue	16.287	14.07	18.63	Cointegration
BCN	SP500	Trace test	10.352	15.41	20.04	No cointegration
		Max eigenvalue	10.346	14.07	18.63	No cointegration
BTC	GOLD	Trace test	11.508	15.41	20.04	No cointegration
		Max eigenvalue	11.428	14.07	18.63	No cointegration
XRP	GOLD	Trace test	9.396	15.41	20.04	No cointegration
		Max eigenvalue	9.341	14.07	18.63	No cointegration
LTC	GOLD	Trace test	8.802	15.41	20.04	No cointegration
		Max eigenvalue	8.802	14.07	18.63	No cointegration
XLM	GOLD	Trace test	8.133	15.41	20.04	No cointegration
		Max eigenvalue	8.125	14.07	18.63	No cointegration
XMR	GOLD	Trace test	9.876	15.41	20.04	No cointegration
		Max eigenvalue	9.830	14.07	18.63	No cointegration
DAS	GOLD	Trace test	11.571	15.41	20.04	No cointegration

Continued

		Max eigenvalue	11.570	14.07	18.63	No cointegration
BCN	GOLD	Trace test	8.712	15.41	20.04	No cointegration
		Max eigenvalue	8.622	14.07	18.63	No cointegration
BTC	USD	Trace test	20.668	15.41	20.04	Cointegration
		Max eigenvalue	20.525	14.07	18.63	Cointegration
XRP	USD	Trace test	16.059	15.41	20.04	Cointegration
		Max eigenvalue	15.818	14.07	18.63	Cointegration
LTC	USD	Trace test	21.984	15.41	20.04	Cointegration
		Max eigenvalue	21.561	14.07	18.63	Cointegration
XLM	USD	Trace test	15.052	15.41	20.04	Cointegration
		Max eigenvalue	15.050	14.07	18.63	Cointegration
XMR	USD	Trace test	21.245	15.41	20.04	Cointegration
		Max eigenvalue	20.789	14.07	18.63	Cointegration
DAS	USD	Trace test	28.137	15.41	20.04	Cointegration
		Max eigenvalue	26.304	14.07	18.63	Cointegration
BCN	USD	Trace test	19.157	15.41	20.04	Cointegration
		Max eigenvalue	18.106	14.07	18.63	Cointegration
BTC	LIBOR	Trace test	32.398	15.41	20.04	Cointegration
		Max eigenvalue	31.709	14.07	18.63	Cointegration
XRP	LIBOR	Trace test	27.910	15.41	20.04	Cointegration
		Max eigenvalue	25.270	14.07	18.63	Cointegration
LTC	LIBOR	Trace test	27.685	15.41	20.04	Cointegration
		Max eigenvalue	24.040	14.07	18.63	Cointegration
XLM	LIBOR	Trace test	29.167	15.41	20.04	Cointegration
		Max eigenvalue	25.314	14.07	18.63	Cointegration
XMR	LIBOR	Trace test	26.296	15.41	20.04	Cointegration
		Max eigenvalue	25.771	14.07	18.63	Cointegration
DAS	LIBOR	Trace test	25.597	15.41	20.04	Cointegration
		Max eigenvalue	25.592	14.07	18.63	Cointegration
BCN	LIBOR	Trace test	28.396	15.41	20.04	Cointegration
		Max eigenvalue	24.308	14.07	18.63	Cointegration

Note: *, **, *** denote significant levels at 10%, 5%, 1% respectively. All of pair asset are tested to obtain suitable lag-order selection statistics.

Table 5. Granger causality tests for each of pair assets.

Equation	Excluded	Chi2	df	P-value	Equation	Excluded	Chi2	df	P-Value	Equation	Excluded	Chi2	df	P-Value
BTC	OIL	**2.903***	1	0.088	BTC	SP500	2.170	1	0.141	BTC	GOLD	1.288	2	0.525
OIL	BTC	**5.968****	1	0.015	SP500	BTC	**14.353*****	1	0.000	GOLD	BTC	**6.48****	2	0.039
XRP	OIL	0.383	2	0.826	XRP	SP500	**7.826****	2	0.020	XRP	GOLD	0.101	2	0.951
OIL	XRP	**4.935***	2	0.085	SP500	XRP	3.172	2	0.205	GOLD	XRP	**6.957****	2	0.031

Continued

LTC	OIL	1.012	1	0.315	LTC	SP500	7.115**	2	0.029	LTC	GOLD	5.166*	2	0.076
OIL	LTC	4.948**	1	0.026	SP500	LTC	5.781*	2	0.056	GOLD	LTC	4.065	2	0.131
XLM	OIL	0.371	2	0.831	XLM	SP500	9.238**	2	0.010	XLM	GOLD	0.739	2	0.691
OIL	XLM	7.517**	2	0.023	SP500	XLM	2.377	2	0.305	GOLD	XLM	3.582	2	0.167
XMR	OIL	3.820	2	0.148	XMR	SP500	2.103	2	0.349	XMR	GOLD	1.647	2	0.439
OIL	XMR	8.003**	2	0.018	SP500	XMR	15.51***	2	0.000	GOLD	XMR	6.013**	2	0.049
DAS	OIL	2.764	2	0.251	DAS	SP500	1.949	2	0.377	DAS	GOLD	2.443	2	0.295
OIL	DAS	7.047**	2	0.03	SP500	DAS	11.968***	2	0.003	GOLD	DAS	8.412**	2	0.015
BCN	OIL	0.269	1	0.604	BCN	SP500	9.228**	2	0.010	BCN	GOLD	0.859	2	0.651
OIL	BCN	5.301**	1	0.021	SP500	BCN	4.434	2	0.109	GOLD	BCN	3.860	2	0.145
BTC	USD	6.263**	1	0.012	BTC	LIBOR	1.413	2	0.493					
USD	BTC	3.636*	1	0.057	LIBOR	BTC	10.007***	2	0.007					
XRP	USD	0.431	2	0.806	XRP	LIBOR	8.350**	2	0.015					
USD	XRP	5.462*	2	0.065	LIBOR	XRP	1.482	2	0.477					
LTC	USD	6.677**	1	0.010	LTC	LIBOR	4.019	2	0.134					
USD	LTC	5.389**	1	0.020	LIBOR	LTC	1.286	2	0.526					
XLM	USD	0.335	1	0.563	XLM	LIBOR	9.360*	4	0.053					
USD	XLM	3.905**	1	0.048	LIBOR	XLM	6.397	4	0.171					
XMR	USD	3.947	2	0.139	XMR	LIBOR	1.364	2	0.506					
USD	XMR	4.797*	2	0.091	LIBOR	XMR	2.797	2	0.247					
DAS	USD	17.358***	1	0.000	DAS	LIBOR	0.330	2	0.848					
USD	DAS	4.282**	1	0.039	LIBOR	DAS	1.779	2	0.411					
BCN	USD	3.149*	1	0.076	BCN	LIBOR	25.452***	4	0.000					
USD	BCN	5.196**	1	0.023	LIBOR	BCN	9.481*	4	0.050					

Note: *, **, *** denote significant levels at 10%, 5%, 1% respectively. All of pair asset are tested to obtain suitable lag-order selection statistics.

Table 6. Cumulative sum test and Structural Break test for 1st Difference Data.

Coin	Cumulative sum test for parameter stability					Structural break test			LM test for autoregressive conditional heteroskedasticity [ARCH]		
	Test statistic	1% critical value	5% critical value	10% critical value	Conclusions	Swald test	Estimated break week	Conclusions	Chi2	p-value	Conclusion
D.OIL	0.818	1.1430	0.9479	0.850	No Break	11.660**	2016w3	Break	0.847	0.3573	No ARCH effects
D.LIBOR	1.529***	1.1430	0.9479	0.850	Break	34.769***	2016w46	Break	28.874***	0.0000	ARCH[p] disturbance
D.SP500	0.509	1.1430	0.9479	0.850	No Break	2.061	2016w7	No Break	4.426**	0.0354	ARCH[p] disturbance
D.GOLD	0.667	1.1430	0.9479	0.850	No Break	2.494	2015w49	No Break	0.067	0.7965	No ARCH effects

Continued

D.USD	0.919*	1.1430	0.9479	0.850	Break	12.467***	2015w12	Break	1.508	0.2195	No ARCH effects
D.BTC	1.323***	1.1430	0.9479	0.850	Break	6.608	2015w17	No Break	1.877	0.1707	No ARCH effects
D.LTC	1.170***	1.1430	0.9479	0.850	Break	6.181	2015w17	No Break	0.831	0.3621	No ARCH effects
D.XRP	0.561	1.1430	0.9479	0.850	No Break	4.466	2017w12	No Break	15.396***	0.0001	ARCH[p] disturbance
D.XLM	0.677	1.1430	0.9479	0.850	No Break	5.196	2017w11	No Break	13.810***	0.0002	ARCH[p] disturbance
D.XMR	1.146***	1.1430	0.9479	0.850	Break	6.728	2015w50	No Break	5.156**	0.023	ARCH[p] disturbance
D.DAS	1.387***	1.1430	0.9479	0.850	Break	5.142	2017w49	No Break	0.000	1.0000	No ARCH effects
D.BCN	0.522	1.1430	0.9479	0.850	No Break	2.794	2017w13	No Break	3.026*	0.0819	ARCH[p] disturbance

Note: *, **, *** denote significant levels at 10%, 5%, 1% respectively.

cryptocurrency markets. Concerning economic factors, observations show that the USD index has negative effects on all seven cryptocurrencies, while other economic factors have inconsistent effects on all cryptocurrencies. The implication drawn from these results is that cryptocurrencies are considered as a financial asset to hedge systematic risk from economic factors.

3.2. Check Robustness

The inconsistent results of economic factors in line with the existence of structural breaks and ARCH disturbance among variables leading to an ideal condition for DCC MGARCH model in which the conditional correlation matrix from estimation is robust to analyse the relationship among variables [30] [31]. All results from DCC MGARCH are reported in **Tables 7-13** for each cryptocurrency.

For BTC, as in **Table 7** the oil price, the S&P500 index, and LIBOR have significantly negative correlations with BTC. The results suggest that BTC seems to not be a tool for hedging the risk of USD index and gold price. Our finding is different from the studies [20] [21] that Bitcoin can hedge against USD or any currency.

For XRP, the results of **Table 8** show that XRP has a significant negative correlation with the oil price. Moreover, as in **Table 4**, the oil price causes XRP. These results suggest that the increased oil price reduces the price of XRP.

For other cryptocurrencies, as in **Tables 9-14** DAS has a positive correlation with LIBOR, but negative correlation with USD index. XLM has a positive correlation with SP500 index. Our findings show that the correlations between cryptocurrencies and economic factors are inconsistent, suggesting that cryptocurrencies may be not tools or financial assets to hedge systematic risks, which are caused by economic factors.

Table 7. GARCH (1, 1) for each cryptocurrency.

Variables	BTC	XRP	LTC	XLM	XMR	DAS	BCN
OIL	0.013	−0.467***	0.307	−0.0004	−0.313	0.043	0.130
	[0.146]	[0.149]	[0.229]	[0.209]	[0.325]	[0.197]	[0.339]
SP500	0.092	1.560***	−0.773	0.934	−0.110	0.330	−0.647
	[0.426]	[0.483]	[0.505]	[0.945]	[0.844]	[0.551]	[0.822]
GOLD	−0.347	0.670	−0.093	0.353	−0.280	−0.225	0.603
	0.405	[0.481]	[0.629]	[0.765]	[0.806]	[0.689]	[0.872]
USD	−0.555	−1.285**	−1.497	−0.338	−1.619	−2.596**	1.119
	[0.893]	[0.653]	[1.041]	[1.775]	[1.488]	[1.062]	[1.314]
LIBOR	−0.048	4.342***	0.105	0.323	1.177*	1.454**	−3.292***
	[0.447]	[0.380]	[0.462]	[0.635]	[0.601]	[0.645]	[0.704]
cons	0.009	−0.025**	0.001	0.0002	0.008	0.002	0.036*
	[0.013]	[0.01]	[0.012]	[0.014]	[0.020]	[0.016]	[0.021]
ARMA							
AR(1)	0.969***	−0.308	−0.844***	−0.911***	0.511	0.483	0.457
	[0.161]	[0.286]	[0.131]	[0.094]	[0.618]	[0.380]	[0.314]
MA(1)	−0.860***	0.554**	0.861***	1.064***	−0.355	−0.283	−0.229
	[0.188]	[0.241]	[0.131]	[0.106]	[0.674]	[0.416]	[0.299]
MA(3)	−0.090	−0.115**	−0.096**	−0.192***	−0.034	0.009	0.069
	[0.080]	[0.048]	[0.046]	[0.048]	[0.109]	[0.095]	[0.097]
ARCH							
L1.ARCH	0.157**	1.139***	0.699***	0.347***	0.213**	0.236**	0.650***
	[0.07]	[0.186]	[0.145]	[0.083]	[0.100]	[0.115]	[0.204]
L1.GARCH	0.788***	0.212***	0.055	0.614***	0.202	0.533***	0.303**
	[0.084]	[0.072]	[0.065]	[0.074]	[0.304]	[0.200]	[0.124]
cons GARCH	0.001*	0.004**	0.011***	0.004***	0.019**	0.005*	0.014***
	[0.0003]	[0.002]	[0.001]	[0.002]	[0.009]	[0.003]	[0.005]
N	203	203	203	203	203	203	203
Log likelihood	192.008	81.109	107.206	54.210	66.557	112.707	18.956
Chi2	266.4***	284.88***	122.06***	128.88***	16.38**	34.89***	39.91***
				Test L1.ARCH = 0; L1.GARCH = 0			
Chi2[2]	531.07***	70.35***	31.17***	189.11***	6.39**	41.47***	43.89***

Note: *, **, *** denote significant levels at 10%, 5%, 1% respectively. Standard errors are in bracket.

Table 8. Dynamic conditional correlation MGARCH model of Bitcoin.

Variables	BTC	OIL	SP500	GOLD	USD	LIBOR
Cons	0.009 [0.006]	0.0002 [0.003]	0.002** [0.001]	0.0001 [0.001]	0.0006 [0.0007]	0.003*** [0.0007]

Continued

L1.ARCH	0.168** [0.071]	0.084* [0.051]	0.227*** [0.072]	0.060 [0.048]	0.07* [0.0403]	0.957*** [0.180]
L1.GARCH	0.776*** [0.071]	0.786*** [0.123]	0.712*** [0.072]	−0.798*** [0.227]	0.881*** [0.087]	−0.005 [0009]
Cons ARCH	0.001** [0.0003]	0.0003 [0.0002]	0.00002* [0.00001]	0.006*** [0.0001]	0.000005 [0.000007]	0.00006*** [0.000008]
N	203					
Log likelihood	2905.324					
	Test b[Adjustment:lambda1] = b[Adjustment:lambda2] = 0					
Chi2	5.52*					
Lambda1	0.0402 [0.025]					
Lambda2	0.330 [0.278]					

Correlations	BTC	OIL	SP500	GOLD	USD
OIL	0.002 [0.074]				
SP500	0.050 [0.074]	0.212*** [0.073]			
GOLD	−0.015 [0.075]	0.039 [0.075]	−0.189*** [0.072]		
USD	−0.048 [0.075]	−0.115 [0.074]	0.139* [0.075]	0.556*** [0.052]	
LIBOR	0.076 [0.075]	0.01 [0.076]	−0.019 [0.075]	−0.117 [0.074]	−0.014 [0.075]

Note: *, ** and *** denote the significance level at 10%, 5% and 1%. Standard errors are in bracket.

Table 9. Dynamic conditional correlation MGARCH model of Ripple.

Variables	XRP	OIL	SP500	GOLD	USD	LIBOR
Cons	−0.006 [0.012]	0.001 [0.003]	0.002** [0.001]	−0.00005 [0.001]	0.001 [0.001]	0.003*** [0.001]
L1.ARCH	0.484*** [0.146]	0.086* [0.052]	0.216*** [0.070]	0.064 [0.056]	0.069* [0.039]	0.956*** [0.180]
L1.GARCH	−0.010 [0.068]	0.792*** [0.124]	0.721*** [0.072]	−0.770** [0.299]	0.879*** [0.087]	−0.005 [0.009]
Cons ARCH	0.024*** [0.003]	0.0002 [0.0002]	0.00002* [0.00001]	0.001*** [0.0001]	0.00006 [0.00007]	0.00006*** [0.000008]
N	203					
Log likelihood	2776.066					
	Test b[Adjustment:lambda1] = b[Adjustment:lambda2] = 0					
Chi2	3.07					
Lambda1	0.033 [0.023]					

Continued

Lambda2	0.264 [0.361]					
Correlations	**XRP**	**OIL**	**SP500**	**GOLD**	**USD**	
OIL	−0.133* [0.072]					
SP500	0.042 [0.073]	0.221*** [0.071]				
GOLD	0.038 [0.074]	0.041 [0.075]	−0.195*** [0.071]			
USD	−0.076 [0.074]	−0.108 [0.074]	0.143* [0.074]	−0.560*** [0.052]		
LIBOR	0.054 [0.075]	0.006 [0.075]	−0.014 [0.075]	−0.115 [0.073]	−0.015 [0.074]	

Note: *, ** and *** denote the significance level at 10%, 5% and 1%. Standard errors are in bracket.

Table 10. Dynamic conditional correlation MGARCH model of Litecoin.

Variables	**LTC**	**OIL**	**SP500**	**GOLD**	**USD**	**LIBOR**
Cons	−0.003 [0.010]	0.0002 [0.003]	0.002** [0.001]	0.0001 [0.001]	0.001 [0.001]	0.003*** [0.001]
L1.ARCH	0.457*** [0.170]	0.085* [0.051]	0.237*** [0.074]	0.063 [0.049]	0.074* [0.040]	0.950*** [0.179]
L1.GARCH	0.181 [0.168]	0.788*** [0.122]	0.707*** [0.072]	−0.792*** [0.238]	0.876*** [0.084]	−0.005 [0.009]
Cons ARCH	0.011*** [0.003]	0.0003 [0.0002]	0.00002* [0.00001]	0.001*** [0.0001]	0.00001 [0.00001]	0.00006*** [0.00001]
N	203					
Log likelihood	2820.564					
	Test b[Adjustment:lambda1] = b[Adjustment:lambda2] = 0					
Chi2	6.41**					
Lambda1	0.05* [0.026]					
Lambda2	0.295 [0.274]					
Correlations	**LTC**	**OIL**	**SP500**	**GOLD**	**USD**	
OIL	−0.002 [0.076]					
SP500	0.014 [0.076]	0.215*** [0.073]				

Continued

GOLD	0.024	0.040	−0.195***		
	[0.075]	[0.076]	[0.072]		
USD	−0.091	−0.113	0.148**	−0.566***	
	[0.075]	[0.075]	[0.075]	[0.052]	
LIBOR	0.045	0.011	−0.021	−0.111	−0.018
	[0.076]	[0.076]	[0.076]	[0.074]	[0.075]

Note: *, ** and *** denote the significance level at 10%, 5% and 1%. Standard errors are in bracket.

Table 11. Dynamic conditional correlation MGARCH model of Stellar.

Variables	XLM	OIL	SP500	GOLD	USD	LIBOR
Cons	0.002	0.0003	0.002**	0.0001	0.001	0.003***
	[0.011]	[0.003]	[0.001]	[0.001]	[0.001]	[0.001]
L1.ARCH	0.412***	0.086*	0.219***	0.062	0.073*	0.953***
	[0.139]	[0.052]	[0.069]	[0.049]	[0.040]	[0.180]
L1.GARCH	0.566***	0.788***	0.726***	−0.794***	0.872***	−0.006
	[0.115]	[0.123]	[0.071]	[0.237]	[0.087]	[0.008]
Cons ARCH	0.005**	0.000	0.00002*	0.001***	0.000006	0.00006***
	[0.002]	[0.000]	[0.00001]	[0.0001]	[0.000007]	[0.000008]
N	203					
Log likelihood	2769.843					
	Test b[Adjustment:lambda1] = b[Adjustment:lambda2] = 0					
Chi2	4.53					
Lambda1	0.046*					
	[0.025]					
Lambda2	0.228					
	[0.309]					
Correlations	**XLM**	**OIL**	**SP500**	**GOLD**	**USD**	
OIL	−0.049					
	[0.075]					
SP500	0.136*	0.212***				
	[0.073]	[0.073]				
GOLD	0.000	0.039	−0.194***			
	[0.075]	[0.075]	[0.071]			
USD	−0.039	−0.114	0.145	−0.564***		
	[0.075]	[0.074]	[0.074]	[0.052]		
LIBOR	−0.065	0.009	−0.018	−0.115	−0.018	
	[0.076]	[0.075]	[0.075]	[0.074]	[0.074]	

Note: *, ** and *** denote the significance level at 10%, 5% and 1%. Standard errors are in bracket.

Table 12. Dynamic conditional correlation MGARCH model of Monero.

Variables	XMR	OIL	SP500	GOLD	USD	LIBOR
Cons	0.012	0.00004	0.002**	0.0001	0.001	0.003***
	[0.013]	[0.003]	[0.001]	[0.001]	[0.001]	[0.001]
L1.ARCH	0.164*	0.086*	0.228***	0.061	0.071*	0.95***
	[0.09]	[0.051]	[0.072]	[0.049]	[0.04]	[0.178]
L1.GARCH	0.109	0.784***	0.711***	−0.792***	0.881***	−0.005
	[0.205]	[0.123]	[0.072]	[0.243]	[0.086]	[0.009]
Cons ARCH	0.024***	0.0003	0.00002*	0.001***	0.00001	0.00006***
	[0.007]	[0.0002]	[0.00001]	[0.0001]	[0.00001]	[0.00001]
N	203					
Log likelihood	2777.998					
	Test b[Adjustment:lambda1] = b[Adjustment:lambda2] = 0					
Chi2	6.11**					
Lambda1	0.054**					
	[0.027]					
Lambda2	0.257					
	[0.273]					

Correlations	XMR	OIL	SP500	GOLD	USD
OIL	−0.084				
	[0.076]				
SP500	−0.020	0.203***			
	[0.076]	[0.074]			
GOLD	0.048	0.042	−0.192***		
	[0.075]	[0.076]	[0.072]		
USD	−0.080	−0.109	0.150**	−0.56***	
	[0.075]	[0.075]	[0.075]	[0.053]	
LIBOR	0.064	0.008	−0.024	−0.114	−0.014
	[0.076]	[0.076]	[0.076]	[0.074]	[0.075]

Note: *, ** and *** denote the significance level at 10%, 5% and 1%. Standard errors are in bracket.

Table 13. Dynamic conditional correlation MGARCH model of DASH.

Variables	DAS	OIL	SP500	GOLD	USD	LIBOR
Cons	0.008	0.0002	0.002**	0.0001	0.0007	0.002***
	[0.011]	[0.003]	[0.001]	[0.001]	[0.001]	[0.001]
L1.ARCH	0.200**	0.088*	0.239***	0.061	0.065*	0.929***
	[0.091]	[0.052]	[0.074]	[0.05]	[0.038]	[0.174]
L1.GARCH	0.551***	0.782***	0.71***	−0.793***	0.897***	−0.005
	[0.154]	[0.123]	[0.071]	[0.24]	[0.076]	[0.009]

Continued

Cons ARCH	0.006**	0.0003	0.00002*	0.001***	0.000004	0.0001***
	[0.003]	[0.0002]	[0.00001]	[0.0001]	[0.00001]	[0.00001]
N	203					
Log likelihood	2824.785					
	Test b[Adjustment:lambda1] = b[Adjustment:lambda2] = 0					
Chi2	8.44**					
Lambda1	0.041					
	[0.025]					
Lambda2	0.44					
	[0.327]					

Correlations	DAS	OIL	SP500	GOLD	USD
OIL	0.007				
	[0.077]				
SP500	0.070	0.211***			
	[0.076]	[0.074]			
GOLD	0.072	0.039	−0.194***		
	[0.077]	[0.076]	[0.073]		
USD	−0.195***	−0.112	0.146*	−0.555***	
	[0.074]	[0.075]	[0.076]	[0.054]	
LIBOR	0.175**	0.004	−0.029	−0.125*	−0.008
	[0.076]	[0.076]	[0.076]	[0.074]	[0.076]

Note: *, ** and *** denote the significance level at 10%, 5% and 1%. Standard errors are in bracket.

Table 14. Dynamic conditional correlation MGARCH model of Bytecoin.

Variables	BCN	OIL	SP500	GOLD	USD	LIBOR
Cons	0.029**	0.0001	0.002**	−0.0001	0.001	0.003***
	[0.014]	[0.003]	[0.001]	[0.001]	[0.001]	[0.001]
L1.ARCH	0.308*	0.083*	0.221***	0.069	0.07*	0.928***
	[0.159]	[0.05]	[0.07]	[0.052]	[0.041]	[0.176]
L1.GARCH	0.566***	0.789***	0.72***	−0.769***	0.88***	−0.012***
	[0.146]	[0.122]	[0.071]	[0.264]	[0.088]	[0.004]
Cons ARCH	0.011**	0.0003	0.00002*	0.001***	0.00001	0.0001***
	[0.005]	[0.0002]	[0.00001]	[0.0001]	[0.00001]	[0.00001]
N	203					
Log likelihood	2731.926					
	Test b[Adjustment:lambda1] = b[Adjustment:lambda2] = 0					
Chi2	5.83*					
Lambda1	0.035					

Continued

Correlations	BCN	OIL	SP500	GOLD	USD
	[0.025]				
Lambda2	0.395				
	[0.277]				
Correlations	**BCN**	**OIL**	**SP500**	**GOLD**	**USD**
OIL	0.065				
	[0.074]				
SP500	0.105	0.215***			
	[0.075]	[0.073]			
GOLD	0.099	0.033	−0.196***		
	[0.073]	[0.076]	[0.072]		
USD	−0.007	−0.108	0.141*	−0.559***	
	[0.074]	[0.074]	[0.075]	[0.053]	
LIBOR	−0.114	0.001	−0.026	−0.117	−0.017
	[0.09]	[0.075]	[0.075]	[0.074]	[0.074]

Note: *, ** and *** denote the significance levels at 10%, 5% and 1%. Standard errors are in bracket.

4. Conclusions

With the assumption as financial assets, the question on the capability of cryptocurrencies in hedging to systematic risk is quite worthy to investigate. Selecting seven cryptocurrencies with largest capitalization level, the study investigates correlations between the selected cryptocurrencies and economic factors that are proxied by oil price, gold price, interest rate, USD strength, and S&P500. Some main findings are noticeable.

First, there are strong correlations between cryptocurrencies. Moreover, there are also structural breaks and ARCH disturbance in each cryptocurrency. We suggest a systematic risk within the cryptocurrency market. *Second*, the Granger causality tests show that the relationship between cryptocurrencies and economic factors are undirected. *Third*, GARCH (1, 1) tests provide evidence that cryptocurrencies are insignificant correlations with economic factors with the implication that cryptocurrencies are not assumed as financial assets to hedge systematic risks. The results are robust by DCC MGARCH tests. The results are significant for financial investors on the perspective of the diversification. That is, the financial investor must be more careful in using cryptocurrencies as financial assets, especially in diversifying their portfolio since they have low capability in diversification within cryptocurrency market and also with economic risks.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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