BITCOIN AND STOCK MARKET INDICES: ANALYSIS OF VOLATILITY'S CLUSTERS DURING THE BITCOIN BUBBLE BASED ON THE DYNAMIC CONDITIONAL CORRELATION MODEL

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Abstract. The market of virtual currencies, called cryptocurrency, has grown immensely since 2008 in terms of market capitalisation and the numbers of new currencies. Bitcoin is one of the most famous cryptocurrency with an estimated market capitalisation of nearly $ 69 billion. The fact that Bitcoin prices have fallen about 70% from their peak value and most indices were down double-digit year to date (2018) with a high daily volatility create the appearance that there has to be a correlation.

The purpose of this paper is to investigate the contagion effect between Bitcoin prices and the leading American, European and Asian equity markets using the dynamic conditional correlation (DCC) model proposed by Engle and Sheppard (2001).

Contagion is defined in this context as the statistical break in the computed DCCs as measured by the shifts in their means and medians. Even it is astonishing that the contagion is lower during price bubbles, the main finding indicates the presence of contagion in the different indices among the three continents and proves the presence of structural changes during the Bitcoin bubble. Moreover, the analysis shows that specific market indices are more correlated with the Bitcoin price than others.

Key words: *BitCoin, Financial Contagion, Dynamic Conditional Correlation Model, Volatility*

JEL code: G13, G41, F39

Introduction

The Cryptocurrency markets have recently experienced increased growth leading to some suggesting that they may be seen as a new category of investment assets. For the period from May 2014 to December 2018 the market capitalisation of the oldest and best known, Bitcoin, increased from $ 1.5 billion to $ 68.6 billion, while the price jumped from 103 to 3829 US dollars, with a peak end of 2017 with nearly $ 20.000 per one Bitcoin (Coinmarketcap, 2019). Therefore, it is not surprising that investors, which are attracted by high growth of cryptocurrencies, seek to achieve abnormal returns. These high returns may be a rational response to their high volatility, see Katsiampa (2017). Bitcoin is characterised by anonymity (Bariviera et al., 2017) and tend to be a speculative bubble (Cheah and Fry, 2015). Historical price bubbles, like the Dutch tulip mania in the 1640s or the Dot-Com bubble of the early 2000s, may, in turn, spread contagion and weaken financial stability (Yarovaya et al., 2016, Abreu and Brunnermeier, 2003). Therefore, it is crucial to identify patterns of cryptocurrencies markets and other tradeable asset classes, for instance, stock markets.

The cryptocurrency has become an increasingly important topic widely covered by the media and discussed by governments, businesses and academic communities. Besides the numerous policy papers and reports (European Central Bank, 2012), there were significant attempts by financial scholars to analyse cryptocurrencies as investment assets. Recently, the focus of the research has expanded from the technical aspects and stylised facts of cryptocurrency markets (e.g. Dwyer, 2015) to a variety of issues, such as hedging behaviour of cryptocurrencies (Bouri et al., 2017), speculation (Blau, 2017) or market efficiency (Urquhart, 2016). The majority of these papers, however, focused solely on Bitcoin. Furthermore, there is a lack of research on potential contagion effects between Bitcoin and other markets. To fill this gap, this paper examines the return, and volatility transmission across Bitcoin and three market indices, namely: Dow Jones Industrial Average, STOXX Europe 600 and as well Hang Seng Index. As a robustness check, a dynamic conditional correlation (DCC) model proposed by Engle and Sheppard (2001) should answer the key research are: Is Bitcoin correlated with stocks markets?

This paper is organised as follows. Section 2 provides a brief introduction to the area of financial contagion. Chapter 3 presents our data and descriptive statistics, and Section 4 briefly introduces the methodology. The empirical results are analysed in section 5. Finally, Section 6 concludes the paper.

Financial Contagion

The literature about the contagion effect in financial markets is that extensive to review here shortly. The surveys from Kindleberger (1978) or Kaminskyet al. (2003) are only some of those, which have to be mentioned. In general, the focus of most literatures is the contagion effect across countries. Therefore, the spread of crises from one country to another has been one of the most discussed issues in international finance since the last decades. This is caused by the frequent occurrence of the previous crisis. Financial contagion characterises situations in which local shocks are transmitted to other financial sectors or even countries. One of the most known definition explains a contagion as a “structural change in the mechanism of the proliferation of shocks arising from a particular event or group of events associated with a particular financial crisis”, see Arruda and Pereira (2013). Applied to a financial crisis means this that a specific shock can propagate like a virus, starting in a country and overlapping even to other continents.

The above table gives a short overview of the different researches, which mainly focus on the effect of financial crisis on emerging markets. Filleti et al. (2008) analysed the contagion between the Latin American economies and two emerging markets. Armada et al. (2011) tested the contagion effect between the financial markets of nine developed countries and Azad (2009) for the Asian market. Arruda and Pereira (2013) analysed the contagion effects during the US Subprime crisis. Regarding the technology-bubble, Anderson et al. (2010) studied the proliferation of the technology-bubble. Most of the studies applied variations of Engle and Sheppards’ (2001) DCC model. Koehn and Valls (2017) analysed the contagion effect between American and European indices during the technology-bubble. Corbet et al. (2018) was one of the first study, which analysed a correlation between Bitcoin and gold.

Table 1

Empirical researches for financial contagion or volatility spillover effects using multivariate Garch models

Author(s)	Year	Model	Specific topic
Chiang, Jeon and Li	2007	DCC 8 Asian FMs	Financial crisis in Asia in 1997, the effect of credit-rating agencies on the structure of correlation dynamic.
Kuper and Lestano	2007	DCC 6 Asian FMs	Effect of financial crisis on the interdependence of financial and FX markets
Cheung, Fung and Tam	2008	DCC 11 EMEAP and US	Interdependence of financial markets, Contagion risk of in EMEAP region
Cho and Parhizgari	2008	DCC 8 Asian FMs	East Asian financial contagion under DCC–GARCH
Beirne, Caporale, Ghattas, Spagnolo	2009	MGARCH-in-mean 41 FMs: Asia, Latin America, Middle East	Global and Regional volatility spillover
Frank, Gonzalez-Hermosillo und Hesse	2009	DCC, GARCH US: LIBOR, S&P500, ABCP	Transmission of Liquidity Shocks: Evidence from the 2007 Subprime Crisis
Munoz, Marquez and Chulia	2010	TSFA, DCC 19 FMs: North America, Europe, Asia	Asian financial crisis, Dot-com crisis, Global financial crisis
Yiu, Ho and Choi	2010	PCA, ADCC 11 EMEAP and US	Dynamic correlation analysis of financial contagion in Asian markets in global financial turmoil
Naoui, Khemiri and Liouane	2010	DCC 10 FMs: Asia, Latin America and US	Sub-prime crisis 2007
Kenourgios, Samitas and Paltalidis	2011	AG-DCC, copula-DCC BRIC, UK, US	Five recent financial crises
Marcal, Valls, Martin and Nakamura	2011	DCC 9FMs: Argentina, Brazil, South Korea, US, Singapore, Malaysia, Mexico and Japan	Evaluation of contagion or interdependence in the financial crisis of Asia and Latin America, considering the macroeconomc fundamentals
Kazi, Guesmi and Kaabia	2011	DCC 17FMs: OECD countries	Contagion Effect of Financial Crisis on OECD Stock Markets
Celik	2012	DCC GARCH 8 FMs: Japan, Malaysia, Denmark, India, Canada, China, Australia, Brazil	The more contagion effect on emerging markets: The evidence of DCC-GARCH model
Chittedi	2015	DCC GARCH India and US	Financial Crisis and Contagion Effects to Indian Stock Market: DCC–GARCH Analysis
Koehn and Valls	2017	DCC GARCH US and Europe	Speculative bubbles and contagion: Analysis of volatility's clusters during the DotCom bubble based on the dynamic conditional correlation model
Corbet, Meegan, Larkin, Lucey and Yarovaya	2018	DCC GARCH Bitcoin and Gold	Exploring the dynamic relationships between cryptocurrencies and other financial assets

Source: author's construction

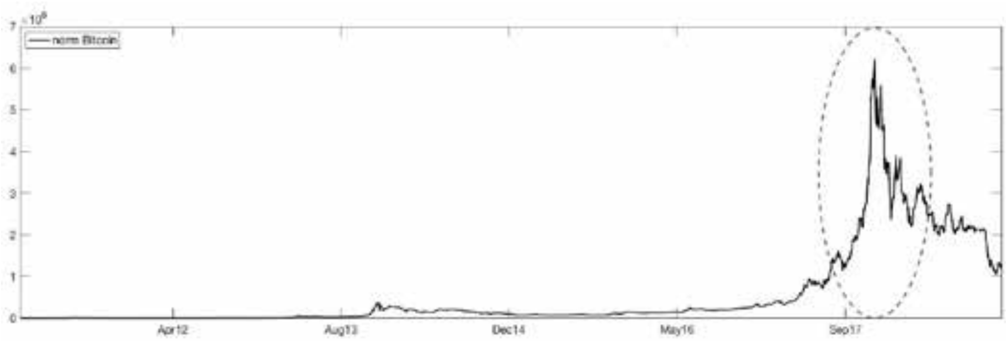
This paper will focus on the contagion within different countries and Bitcoin during the Bitcoin bubble. The presence of a contagion effect can be determined by the increase in conditional correlations of the indices during the period of crisis compared to the previous periods.

A first look at the data

The data on stock market prices consists of the Dow Jones Industrial Average (INDU), STOXX Europe 600 Index (SXXP) and as well Hang Seng Index (HSI). The reason for choosing this group of countries is the idea of having three representatives for American, European and as well as Asian markets. Besides those stock market prices, the daily bitcoin price is also collected. All daily data are collected over the period from January 3, 2011 to December 31, 2018.

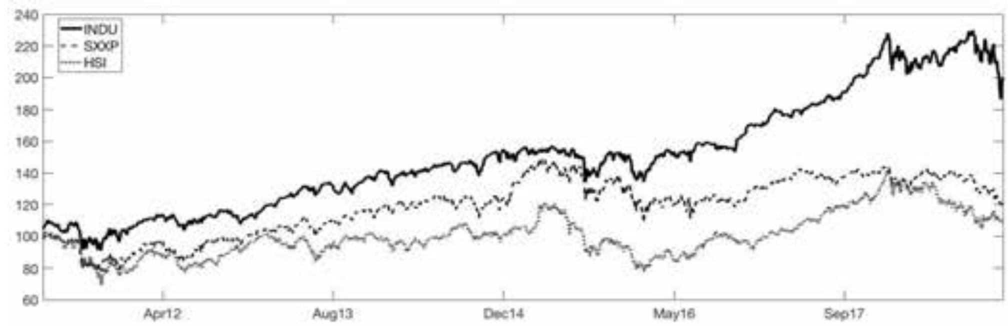
All data are obtained from Bloomberg. Daily data are used in order to retain a high number of observations to adequately capture the rapidity and intensity of the dynamic interactions between markets.

Figure 1 illustrates the normalized Bitcoin prices over a time period between 2011 and 2018. Because of the extreme high normalized price, the market indices have to illustrate separately. Consequently, figure 2 presents the normalised stock market indices with an interesting pattern. Using normalised stock market prices; the figure illustrates better the relative performance of the initial value of each index than plotting all indices naturally. In that specific time frame, Bitcoin nearly 1.500.000x its value, where the best index (INDU) just doubled its value.



Source: author's construction based on data from Bloomberg

Fig. 1. **Normalized Bitcoin Prices**



Source: author's construction based on data from Bloomberg

Fig. 2. **Normalized Stock Market Indices**

Regarding the sample definition, the intention was to select an extensive set of historical data with approximately a 7-year period, which amounted to 2,086 observations for four series. Compounded market returns (i for index, respective Bitcoin) at time t are computed as follows:

$$r_{i,t} = \log(\frac{P_{i,t}}{P_{i,t-1}})$$

where $P_{i,t}$ and $P_{i,t-1}$ are the closing prices for day t and t -1, respectively. Figure 3 indicates those compounded market returns and identifies some clusters. As figure 3 clearly shows, the volatility cluster for Bitcoin is extremely high. Furthermore, in periods of high volatility Bitcoin clusters, it seems that stock indices have a lower volatility. Interestingly, one can identify three Bitcoin volatility clusters. Looking at the stock indices, they do not show the same high volatility cluster during that time. One can argue, combining some of the data from figure 1 and figure 3, that there could be a bitcoin bubble in the timeframe from 2017 to 2018.

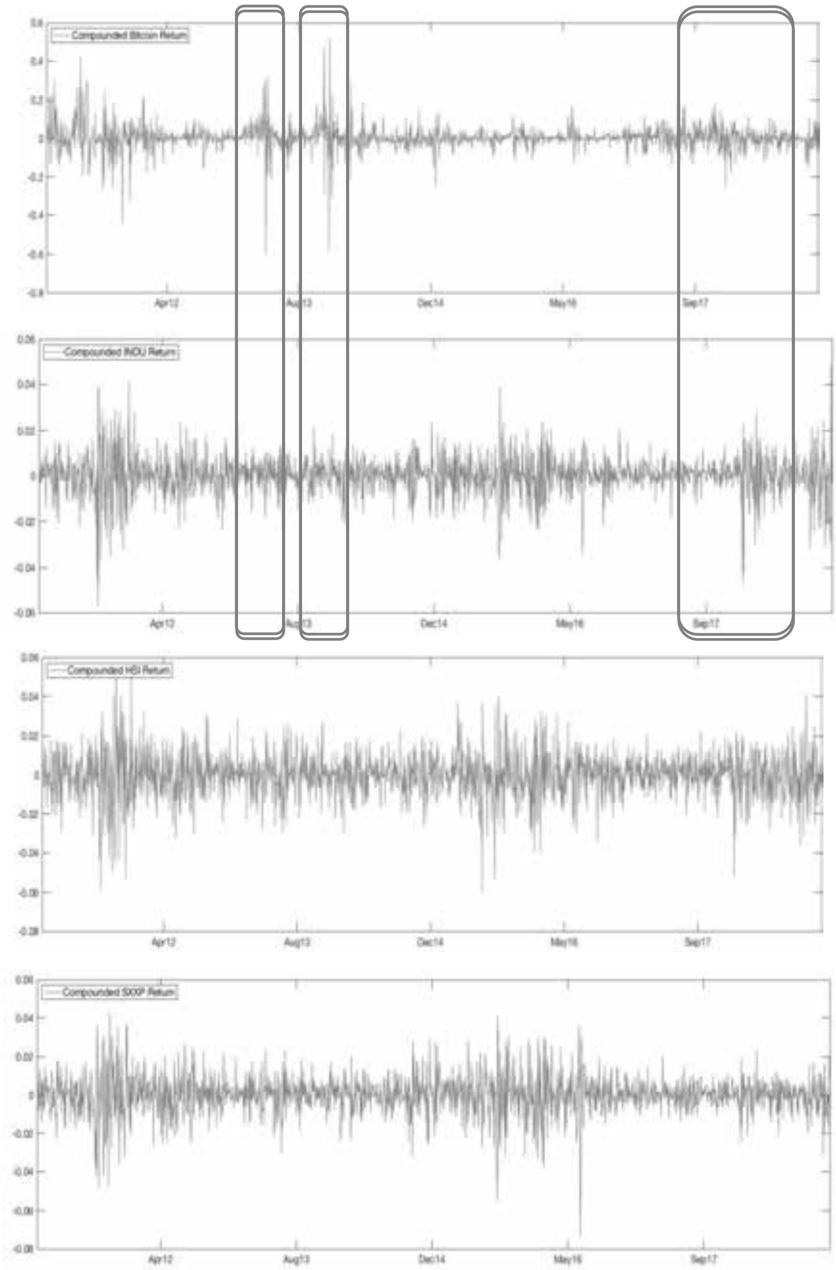


Fig. 3. **Compounded Market Indices as well Bitcoin Returns – Full Sample**

The descriptive statistics of the data are given in the above table, which is divided into two panels A and B. As seen from panel A, the mean value for each return series is close to zero and for each return series the standard deviations are more significant than the mean values and varies from 0.87% to 6.36%. The minimum alters from -5.71% to -60.09% and the maximum ranges from 4.28% to 51.70%. Each compounded market return displays a small negative amount of skewness and a large amount of kurtosis - varies between 5.92 to 19.15 - indicating that there are bigger tails than the normal distribution and therefore, the returns are not normally distributed.

In panel B, unconditional correlation coefficients in stock market index returns as well with Bitcoin returns indicate strong pairwise correlations. The correlations within the different continents and their indices are highly positive over the full sample. Every correlation is bigger than 22.46%. Nevertheless, the correlation between Bitcoin and these three indices are quite low or even negative. The high positive unconditional correlations within the stock indices are the first indicators for a contagion effect. But the low or even negative correlation with Bitcoin disagrees this assumption.

Table 2

Descriptive Statistics of Compounded Stock Market and Bitcoin returns

Panel A: Descriptive statistic							
	Mean	Min.	Max.	Std.dev.	Kurtosis	Skewness	Jarque-Bera
Bitcoin	0,0045	-0,6009	0,5170	0,0636	19,1502	-0,2514	22681,58
INDU	0,0003	-0,0571	0,0486	0,0087	7,6554	-0,5157	1975,25
SXXP	0,0001	-0,0729	0,0428	0,0100	6,9767	-0,4431	1442,04
HSI	0,0000	-0,0602	0,0552	0,0112	5,9291	-0,3302	783,27

Panel B: Summary of unconditional correlation matrix of compounded market returns				
Full sample				
	Bitcoin	INDU	SXXP	HSI
Bitcoin	1,0000	0,0405	0,0272	-0,0359
INDU		1,0000	0,6050	0,1919
SXXP			1,0000	0,4128
HSI				1,0000

The results of the unit root tests for the returns are summarised in table 3. The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are used to explore the existence of unit roots in individual series. The results of unit root tests have rejected the null hypothesis of the unit root for all market returns, indicating that the return series are trend stationary.

Table 3

Unit root test: ADF and PP

Stock market and Bitcoin returns				
	ADF statistics			PP statistics
	None	Constant	Time Trend	
Bitcoin	-43,821	-43,621	-43,909	-44,072
INDU	-46,886	-46,807	-46,855	-46,978
SXXP	-43,564	-43,571	-43,558	-43,561
HSI	-44,714	-44,724	-44,706	-44,704

Figure 4 depicts the plots between every indices and Bitcoin. Visually, one can see a higher relationship between American and European indices than Bitcoin and those indices. It is not a perfect relationship, because not all points are lying exactly on the straight lines. The closer they are to the line (taken all together), the stronger would be the relationship between the variables. These relationships between the series are linearly fitted by straight lines.

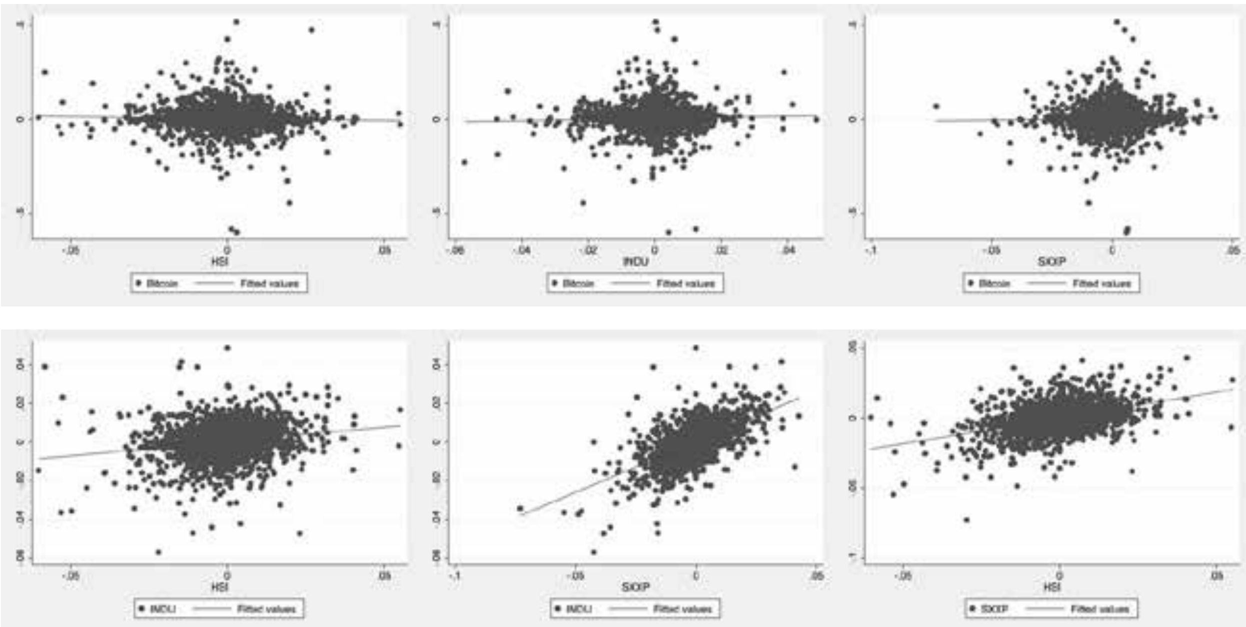


Fig. 4. **Scatter Plot Every Indices and Bitcoin with each other**

Methodology

The econometric method is based on the modelling of multivariate time-varying volatilities. One of widely used models is the Dynamic Conditonal Correlation (DCC) of Engle and Sheppard (2001) as well as Tse and Tsui (2002), which captures the dynamic of time-varying conditional correlations. The main idea of this models is that the covariance matrix, H_t, can be decomposed into conditional standard deviations, D_t, and a correlation matrix, R_t. D_t as well R_t are designed to be time-varying in the DCC GARCH model. The specification of the DCC model can be explained as follows:

$$r_t = \mu + \sum_{s=1}^{p} \phi_s r_{t-s} + \varepsilon_t \;\; for\; t = 1, \dots, T \; and \; \varepsilon_t | \Omega_{t-1} \sim N(0, H_t)$$

where r_t is a 4×1 vector of stock market index returns. The error term, ε_t, from the mean equations of stock market indices can be presented as follows with z is a 4×1 vector of i.i.d errors:

$$\varepsilon_t = \left(\varepsilon_{Bitcoin0,t}, , \varepsilon_{INDU,t}, \varepsilon_{SXXP,t}, \varepsilon_{HSI,t}\right)' = H_t^{\frac{1}{2}} z_t$$

$$with\; z_t \sim N(0, I_4).$$

H_t is the conditional covariance matrix and is given by following equation:

$$H_t = E(\varepsilon_t \varepsilon_t' | \Omega_{t-1})$$

Therefore, equation can be written for the 4 different data sets:

$$\begin{bmatrix} r_{Bitcoin,t} \\ r_{INDU,t} \\ r_{SXXP,t} \\ r_{HSI,t} \end{bmatrix} = \begin{bmatrix} \mu_{Bitcoin,t} \\ \mu_{INDU,t} \\ \mu_{SXXP,t} \\ \mu_{HSI,t} \end{bmatrix} + \sum_{s=1}^{p} \begin{bmatrix} \phi_{11}^s & \phi_{12}^s & \phi_{13}^s & \phi_{14}^s \\ \phi_{21}^s & \phi_{22}^s & \phi_{23}^s & \phi_{24}^s \\ \phi_{31}^s & \phi_{32}^s & \phi_{33}^s & \phi_{34}^s \\ \phi_{41}^s & \phi_{42}^s & \phi_{43}^s & \phi_{44}^s \end{bmatrix} \begin{bmatrix} r_{Bitcoin,t-s} \\ r_{INDU,t-s} \\ r_{SXXP,t-s} \\ r_{HSI,t-s} \end{bmatrix} + \begin{bmatrix} \varepsilon_{Bitcoin,t} \\ \varepsilon_{INDU,t} \\ \varepsilon_{SXXP,t} \\ \varepsilon_{HSI,t} \end{bmatrix}$$

Applying Engle and Sheppard's (2001) dynamic conditional correlation model, the $r_t = \left(r_{Bitcoin,t}, r_{INDU,t}, r_{SXXP,t}, r_{HSI,t}\right)'$ is a 4×1 vector of stock market returns, such that $r_{Bitcoin}$ is the return of Bitcoin, respectively the indices with $r_t | \Omega_{t-1} \sim N(0, H_t)$.

The conditional covariance matrix H_t is defined by two components on the CCC model, which are estimated independent of each other: The sample correlations H_t and the diagonal matrix of time varying volatilities D_t. Therefore, the covariance forecast is given by following equations:

$$H_t = D_t R_t D_t$$

where $D_t = diag\left(\sqrt{h_{Bitcoin,t}}, \sqrt{h_{INDU,t}}, \sqrt{h_{SXXP,t}}, \sqrt{h_{HSI,t}}\right)$ is a 4×4 diagonal matrix of time varying standard deviations from the univariate GARCH models, for

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1}$$

$for\;\; i = Bitcoin, INDU,\; SXXP, HSI$ and the time varying conditional correlation matric is defined by:

$$R_t = \{\rho_{i,t}\}$$

Getting the DCC-GARCH model, two steps have to be taken. The first one is to estimate a univariate GARCH model. The second stage is to define the vector of standardized residuals, $\eta_{i,t} = \frac{r_{i,t}}{\sqrt{h_{i,t}}}$ to develop the DCC correlation specification:

$$R_t = diag\left(q_{11}^{-\frac{1}{2}}, \dots, q_{44}^{-\frac{1}{2}}\right) Q_t \; diag\left(q_{11}^{-\frac{1}{2}}, \dots, q_{44}^{-\frac{1}{2}}\right)$$

where $Q_t = (q_{i,j,t})$ is a symmetric - positive defined - matrix. Q_t varies according to a GARCH-type process as follows:

$$Q_t = (1 - \theta_1 - \theta_2)\tilde{Q} + \theta_1 \eta_{t-1} \eta_{t-1}' + \theta_2 Q_{t-1}$$

The variables, θ_1 and θ_2, are positive, $\theta_1 \geq 0 \; and \; \theta_2 \geq 0$ and, therefore, $\theta_1 + \theta_2 < 1$. $\theta_1 \; and \; \theta_2$ define scalar parameters, which capture the effects of previous shocks and previous dynamic conditional correlation on current dynamic conditional correlation. $\tilde{Q}$ explains the 4×4 unconditional variance matrix of all standardized residuals $\eta_{i,t}$ with a correlation estimation like following: $\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}\, q_{j,j,t}}} \leq 1$

Empirical results

Table 4 reports the final prediction error (FPE), Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (SBIC), and the Hannan and Quinn information criterion (HQIC) lag order selection statistics for a series of vector autoregressions of order 1 through a requested maximum lag. The equation for the FPE is given by Luetkepohl (2005), with T as the number of observations and K as the number of equations: $FPE = |\Sigma_u| \left(\frac{T+Kp+1}{T-Kp-1}\right)^K$

AIC, SBIC and HQIC are computed according to their standard definitions, see for those equations Akaike (1974), Schwarz (1978) and Hannan and Quinn (1979):

$$AIC = -2\left(\frac{LL}{T}\right) + \frac{2t_p}{T};\ SBIC = -2\left(\frac{LL}{T}\right) + \frac{\ln(T)}{T}t_p \text{ and } HQIC = -2\left(\frac{LL}{T}\right) + \frac{2\ln(\ln(T))}{T}t_p$$

where LL is the log likelihood and t_p indicates the total amount of parameters in the model. Table 4 is the result as pre-estimation. This pre-estimation version is later used to select the lag order for the MGARCH-model.

Table 4

Obtain Lag-Order Selection Statistics

Sample: 10 -2085 Number of obs: 2075

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
1	23642.4	.	16	.	1.5e-15	-22,7724	22,7565*	-22,7289*
2	23659.5	34	16	0.005	1.5e-15	-22,7735	-22,7417	-22,6866
3	23680.7	42	16	0.000	1.5e-15	-22,7785	-22,7307	-22,6481
4	23701.9	42	16	0.000	1.5e-15*	-22.7835*	-22,7198	-22,6096
5	23716.7	29,707*	16	0.020	1.5e-15	-22,7824	-22,7027	-22,5650

Endogenous: Bitcoin INDU SXXP HSI
Exogenous: _cons

The "*" indicates the optimal lag. Even, the FPE is not an information criterion; the prediction error has to be minimized. Therefore, it is included in the lag selection discussion and is selected by the lag length with the lowest value. Measuring the difference between given model and true model, the AIC has to be as low as possible, shown by Akaike (1973). A similar interpretation provides the SBIC and the HQIC. Luetkepohl (2005) discussed the theoretical advantage of SBIC and HQIC over the AIC and the FPE. In the data series of 3 indices and Bitcoin, the likelihood-ratio (LR) tests selected a model with 5 lags. HQIC and SBIC have chosen a model with only one lag, whereas FPE and AIC have selected a model with four lags. Consequently, a one ARCH term and one GARCH term is used for the conditional variance equation of each indices. In following, table 5 shows the DCC estimation with GARCH(1) and ARCH(1).

Table 5

Dynamic Conditional Correlation (DCC)

log likelihood 24746,82

		Coef.	OPG Std.Err	z	P>|z|	[95% Conf. Interval]	
ARCH_Bitcoin	arch L1	0,1309	0,0148	8,86	0,000	0,1019	0,1598
	garch L1	0,8760	0,0117	74,90	0,000	0,8531	0,8989
	_cons	0,0000	0,0000	4,74	0,000	0,0000	0,0000
ARCH_INDU	arch L1	0,1521	0,0166	9,19	0,000	0,1197	0,1846
	garch L1	0,7995	0,0199	40,22	0,000	0,7605	0,8384
	_cons	0,0000	0,0000	6,35	0,000	0,0000	0,0000
ARCH_SXXP	arch L1	0,0879	0,0108	8,15	0,000	0,0668	0,1091
	garch L1	0,8861	0,0140	63,15	0,000	0,8586	0,9136
	_cons	0,0000	0,0000	4,50	0,000	0,0000	0,0000
ARCH_HSI	arch L1	0,0468	0,0075	6,28	0,000	0,0322	0,0614
	garch L1	0,9347	0,0110	84,95	0,000	0,9132	0,9563
	_cons	0,0000	0,0000	3,44	0,001	0,0000	0,0000
	corr(Bitcoin,INDU)	0,0155	0,0302	0,51	0,607	-0,0437	0,0748
	corr(Bitcoin,SXXP)	0,0230	0,0301	0,76	0,445	-0,0361	0,0821
	corr(Bitcoin,HSI)	-0,0127	0,0298	-0,43	0,671	-0,0710	0,0457
	corr(INDU,SXXP)	0,6018	0,0191	31,56	0,000	0,5644	0,6392
	corr(INDU,HSI)	0,2003	0,0287	6,98	0,000	0,1441	0,2565
	corr(SXXP, HSI)	0,3930	0,0251	15,68	0,000	0,3439	0,4421
Adjustment	lambda1	0,0079	0,0026	3,02	0,002	0,0028	0,0131
	lambda2	0,9642	0,0116	82,82	0,000	0,9413	0,9870

As table 5 shows, 5 of these 6 estimated conditional quasi-correlations are positive between the volatilities of the 4 different data sets. For instance, the estimated conditional correlation between Bitcoin and INDU is 0.0155. This means that high volatility in the Bitcoin is related to a high volatility in the INDU and vice versa. The only estimated conditional correlation which is negative, is the correlation between HIS and Bitcoin. Finally, table 5 presents the results for the adjustment parameters λ_1 and λ_2. Both estimated values for λ_1 and λ_2 are statistically significant.

Table 6

Wald-Test

1)	[Adjustment]lambda1 - [Adjustment]lambda2 = 0	
2)	[Adjustment]lambda1 = 0	
	chi2(2)	10497.65
	Prob > chi2	0,0E+00

The Bitcoin bubble is timed - as figure 1 shows –between April 2016 to December 2018. An interesting finding can be even seen in table 7. This tables indicate the different conditional correlation matrix and compared them with the null hypothesis that the correlation between different markets (indices respective Bitcoin) is lower during a bubble than sometimes else. The table on the right hand indicates that hypothesis. "Yes" means, that the null hypothesis is right and is not rejected. Meaning that during the Bitcoin-Bubble the correlation between the different data sets were lower than in the time without bubble. "No" indicates that the conditional correlation is higher during the Bitcoin bubble.

Table 7

Dynamic Conditional Correlation- Full-Sample vs Bitcoin

Dynamic Conditional Correlation (DCC): Full Sample

	Bitcoin	INDU	SXXP	HSI
Bitcoin	1	0,0155	0,0230	-0,0127
INDU	0,0155	1	0,6018	0,2003
SXXP	0,0230	0,6018	1	0,3930
HSI	-0,0127	0,2003	0,3930	1

DCC: Full Sample vs Bitcoin Bubble

	Bitcoin	INDU	SXXP	HSI
Bitcoin	1	NO	**YES**	**YES**
INDU	NO	1	**YES**	NO
SXXP	**YES**	**YES**	1	**YES**
HSI	**YES**	NO	**YES**	1

Dynamic Conditional Correlation (DCC): Bitcoin Bubble

	Bitcoin	INDU	SXXP	HSI
Bitcoin	1	0,0365	0,0147	-0,0142
INDU	0,0365	1	0,5481	0,2171
SXXP	0,0147	0,5304	1	0,3886
HSI	-0,0142	0,2171	0,3886	1

Ho: The correlation between different stock markets is lower during a bubble.

Figure 5 visualizes the computed individually DCC plots for pair-wise data sets with the different contagion sources. An interesting outcome is that it seems - even with a general high correlation among some of the data sets - that during the Bitcoin bubble the contagion decreases. This holds for indices, like SXXP and HIS. Nevertheless, the correlation between Bitcoin and INDU is not lower during the Bitcoin bubble in April 2016 to December 2018.

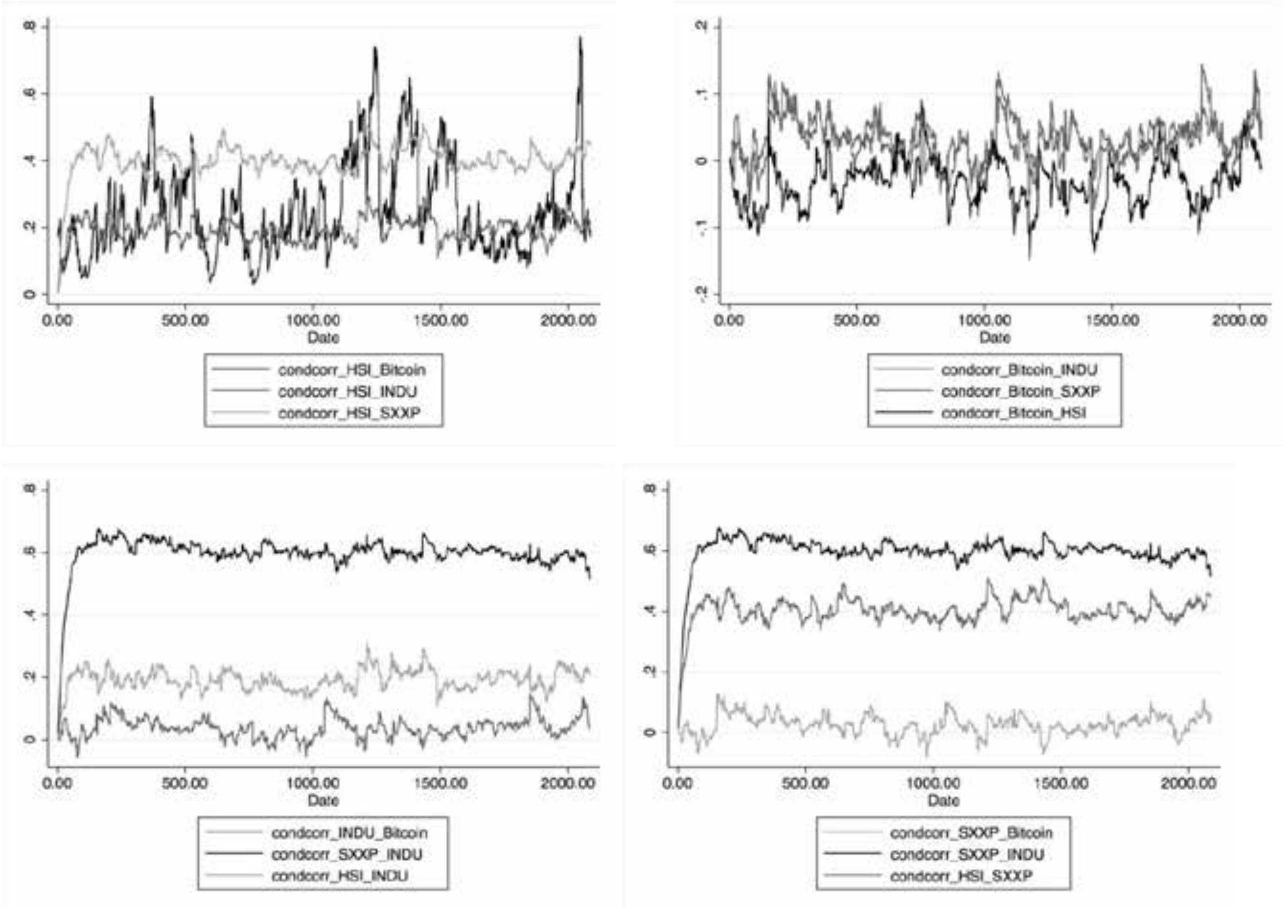


Fig. 5. **Estimated Dynamic Correlation Coefficients**

Conclusions

Given the main objective of this paper to analyse the phenomenon of financial contagion between stock market returns of different continents and the cryptocurrency. The DCC-GARCH by Engle and Sheppard (2001) is used as a multivariate conditional correlation volatility model. Throughout this work, this methodology is applied to daily returns of SXXP (Europe), INDU (United States), HSI (Asia) and Bitcoin for the period from 2011 to 2018 and confronted with other models most widespread in the literature on the subject.

First, we found that Bitcoin is relatively isolated from market-driven external shocks and one of the key findings is those specific market indices are more correlated with the Bitcoin price than others. INDU as well SXXP are positively correlated to the Bitcoin price, whereas HSI is negatively correlated to Bitcoin.

Contagion is defined as the statistical break in the computed DCCs as measured by the shifts in their means and medians. The result does not reject the hypothesis of higher contagion between American and Asian stock markets during the Bitcoin Bubble. Nevertheless, the result does reject the hypothesis of higher contagion in American and European stock markets during that time. Therefore, the contagion test does not show clearly that multivariate estimates are significant for all returns in those models. It demonstrates that there are some changes in the structure of dependence between American, Asian, European markets and Bitcoin. This can be caused by different facts, like micro- and macroeconomic factors or even investors behaviour. Without any doubt, those impacts can distort the efficient allocation of investment portfolios and should take into consideration regarding a potential diversification analysis.

Our research has indicated that cryptocurrencies are relatively isolated from market shocks and are decoupled from popular financial market indices. This brings the question if Bitcoin could play a role in an investor portfolio with excess volatility and high returns on the one hand, and with low stock market correlations on the other hand. Further research is needed to observe the behaviour of cryptocurrencies. Furthermore, our work has to be repeated with a longer timeframe of cryptocurrencies or even other financial asset classes, like gold or currencies.

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