Domagoj Sajter, PhD
Full Professor
J. J. Strossmayer University of Osijek
Faculty of Economics
E-mail: sajter@efos.hr

TIME-SERIES ANALYSIS OF THE MOST COMMON CRYPTOCURRENCIES*

UDC / UDK: 336.74: 519.246.8
JEL classification / JEL klasifikacija: C32, G15, G23, G29, O33
Preliminary communication / Prethodno priopćenje
Received / Primljeno: March 31, 2019 / 31. ožujka 2019.
Accepted for publishing / Prihvaćeno za tisak: May 27, 2019 / 27. svibnja 2019.

Abstract

This paper aims to gain and improve understanding of the three most common cryptocurrencies (Bitcoin, Ethereum and Ripple) by applying standard econometric tools upon their time-series data. Cryptocurrencies' returns are compared to six major stock indices: two American (S&P500 and Russell 2000), one European (Stoxx 600), one Japanese (Nikkei 225), one Chinese (Hong Kong Hang Seng) and a global index (S&P Global 1200). The findings indicate that observed cryptocurrencies could be regarded as a new asset class, a fully digital, sui-generis financial instruments, as they are not coherently connected to the stock market. However, allocating capital into cryptocurrencies remains in the domain of pure speculation due to their strong volatility.

Keywords: blockchain, cryptocurrencies, time-series, financial markets

1. INTRODUCTION

In a discussion held within the context of the fuming financial crisis in 2009 ex-Chairman of the US Federal Reserve, Paul Volcker, said that the most important financial innovation he has seen in the past 20 years was the automatic teller machine, questioning whether financial innovation contributes anything to economic growth (Murray, 2009). Albeit provoking, the above statement is indicative of the wide-spread belief that crisis-after-crisis financial industry has been lulled into sense of precedence, complacency and irreplaceability, and that there were no distinctive, break-through innovations in finance for decades. That

* The paper was presented at the international meeting SINCERE held in Dubrovnik 25-27 October 2018

is, prior to the proposition of blockchain technology, which – it should be noted – did not emerge from mainstream financial industry.[1]

Starting with the seminal Bitcoin, cryptocurrencies bring disruptive new ideas and technologies to the somewhat ossified industries, trenched in their positions and eager to disqualify newcomers. Bitcoin system integrated known concepts such as public-private cryptography, open-source code and peer-to-peer decentralized design coupled with economic incentives in a novel way. This propelled blockchain as an underlying blueprint for a new class of technology used within finance at first, but subsequently in other fields such as record keeping, supply chain management, securities, "smart contracts", internet-of-things and elsewhere.

This paper examines cryptocurrencies as speculation and/or investment objects. Given that stocks are traditionally most widely accepted higher-volatility assets, cryptocurrencies are weighed against them as they themselves exhibit extremely high volatilities. For these reasons focus of this paper is on the relation between cryptocurrencies and stock market indices.

2. LITERATURE REVIEW

Cryptocurrencies could satisfy a wide range of needs because they offer a broad spectrum of potential interventions into economy (and society in general), dependent on the views and opinions of a person envisioning their possibilities (Figure 1). At the very first and basic level they should be given credit for originating and introducing blockchain technology which spun out into non-financial areas and is becoming ever growing platform (more or less decentralized) for diverse purposes. At the next level many recognize them as a new, fully digital asset class that establishes an additional niche in the universe of possible mediums for financial speculation (short - or medium - term), without necessarily having faith in their viability or even understanding the basics of their design. Moving on; those who trust the durability and sustainability of such an asset employ them as a long-term store of value, as a new investment object and/or as a vehicle to carry value over time. Furthermore, besides being a digital asset, one could also acknowledge cryptocurrencies as mediums of payments and integral parts of new, decentralized payment systems, offering transactions worldwide with the ease of sending an e-mail. Next step is perceiving cryptocurrencies as decentralized application facilitators, with payment systems as a special case deducted from an array of possible decentralized applications run on Turing-complete systems such as Ethereum.[2] Finally, the widest and the strongest impact of cryptocurrencies is expected by those who observe

[1] Even though the true identity of Satoshi Nakamoto, the originator of Bitcoin, is still unknown, given the nature of his character (Popper, 2016) and his propositions it can be safely assumed that he was/is not part of the financial establishment.

[2] For explanation of Turing-completeness see e.g. Narayanan et al. (2016, p. 232).

cryptocurrencies as a "game changer" – a tool for thorough political, legal and societal redesign. It should be emphasized here that the very first block in Bitcoin's blockchain contains encoded headline from the Times of London newspaper involving the chancellor bailing out banks, which is usually interpreted as political statement (Narayanan et al., 2016, p. 57), and that many of the early adopters still have grand expectations.

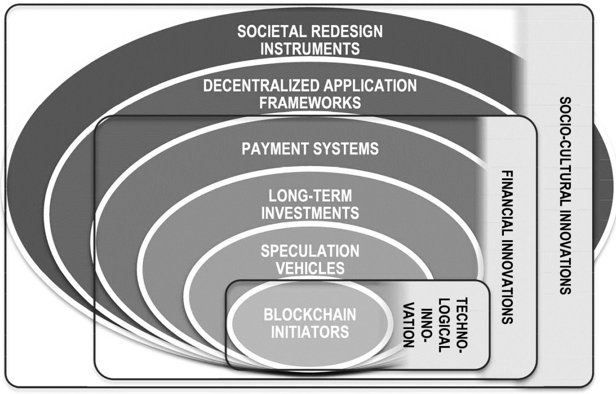


Figure 1 Levels and scopes of cryptocurrencies' potential impact

Source: Author

Cryptocurrencies must be recognised at the very first, narrowest level (it is an undisputable fact), but all of the wider scopes are contingent upon the stance of an observer and open for discussion. Even the second level is discarded by many financial professionals who do not find credibility and intrinsic value in the pitch of cryptocurrencies' advocates. However, their number is shrinking; the most influential news outlets such as Bloomberg.com, CNBC.com, Finance.Yahoo.com, Marketwatch.com, etc. now (as of June 2018) have a permanent section dedicated to cryptocurrencies on their front pages, which is indicative of the acknowledgment of cryptocurrencies and their shift to mainstream economics. Another confirmation of this can be found with the recent inclusion of crypto and blockchain topics into the CFA exam (Patterson and Tan, 2018). This paper aims to further investigate the proposal of a new asset class by assessing them in relation to stock market indices.

Obviously, sceptics could recognise cryptocurrencies as speculation objects, but not as viable, mainstream payment systems. Likewise, some investors believe in their long-term value, but do not trust that society will radically change just because a new technology has been put out. Hence, with each wider scope of impact (Figure 1) the number of enthusiasts decreases.

Following the above context, this paper examines cryptocurrencies at the lower impact intensities – those which are acceptable to a broader audience of observers – with cryptocurrencies regarded as speculation and/or investment objects.

Although cryptocurrencies are relatively new subject there is already a considerable number of papers investigating interrelations between them and traditional financial assets.

In comparison with major world stock indices, bonds, gold, commodities, oil and US dollar on daily and weekly data, Bouri et al. (2017) found that Bitcoin is unsuitable or hedging purposes, but can be employed for diversification of a portfolio. Masiak et al. (2018) applied time series analysis to investigate the market cycles of Bitcoin, Ether and Initial Coin Offerings (ICOs), but did not deal with time-series properties of Bitcoin and Ether in relation to stock market indices. Bitcoin returns were also analysed by Eisl et al. (2015) who showed low correlations with classic financial assets such as stocks, bonds, gold, oil and other currencies, and that including Bitcoin into portfolios increases both the expected returns as well as their risks, even though additional returns seem to outweigh the added risks.

Risk-return trade-off of cryptocurrencies is dissimilar from those of stocks, and the mean and the standard deviation of returns are an order of magnitude higher than those for the traditional asset classes was established by Liu and Tsyvinski (2018).

Corbet et al. (2018) showed that cryptocurrencies are relatively isolated from the traditional financial and economic assets, and could offer diversification benefits, similarly to Guesmi et al. (2018) who also suggest that including cryptos can lower portfolio's risk, and to Glaser et al. (2014) who also propose them as alternative investment vehicles.

Sajter (2018) explored correlations of price movements of the largest cryptocurrencies among themselves, and also regarding two global financial indexes, EUR/USD currency pair, and two commodities: oil (WTI) and gold, but refrained from detailed time-series analysis.

In general, it seems that even though a sizeable number of authors have already begun analysing time-series properties of cryptocurrencies, there are still plenty of gaps left to explore.

3. METHODOLOGY AND DATA

Three cryptocurrencies were analysed: Bitcoin, Ethereum and Ripple. They were chosen for the reason that they had largest market capitalizations within entire crypto-market, with 250,4 billion USD in total (at the time of writing, May 2018); Bitcoin having 39% of entire market cap, while Ether and Ripple had 19% and 7%, respectively.

On the other hand, six stock indices were selected with the aim of covering global, United States, European, Japanese and Chinese markets. These are:

1. S&P Global 1200 (ticker: SPG1200, hereinafter SPG) – global index with 1200 constituents,
2. Russel 2000 (ticker, hereinafter: RUT) – the Russell 3000 is a capitalization-weighted stock market index that aims to be a benchmark of the entire U.S stock market, while the Russell 2000 is a small-cap stock market index of the bottom 2,000 stocks in the Russell 3000,
3. S&P 500 (ticker: .INX, hereinafter SP500) – Standard&Poor 500, the standard for the large-cap US market,
4. Nikkei 225 (ticker, hereinafter: NI225) – the standard for the large-cap Japan market,
5. Hang Seng (ticker, hereinafter: HSI) – the Hong Kong market index, and
6. Stoxx Europe 600 (ticker: STOXX, hereinafter: STXX) – covering blue-chip European stocks.

Daily data for the first four indices was extracted from Google Finance[3], while Yahoo Finance was the source for the latter two. Cryptocurrency data was obtained from Coinmarketcap.com. The period of observation dates from 28th April 2013 (first available date for Bitcoin at Coinmarketcap) to 14th May 2018.

Interconnectedness of the cryptocurrencies with the stock market will be tested by applying ordinary least squares method. OLS model is defined by the following equation:

$y_i = \alpha_{ij} + \beta_{ij}x_j + \varepsilon$, where
i = 1, 2, 3 for daily, weekly and monthly log-returns of BTC, ETH and RPL,

j = 1, 2,…6 for daily, weekly and monthly log-returns of SP500, NI225, SPG, RUT, HIS and STXX, and

α_{ij} for the constant, β_{ij} for the slope and ε for the residual. The hypothesis is that α's and β's are equal to zero, indicating separate risk-return sphere of the cryptocurrencies in regard to the stock market. Weekly and monthly data was derived by collapsing daily data to their means.

4. RESULTS AND DISCUSSION

Fundamental statistics for the cryptocurrencies and indices are given in Table 1 During the observed period Bitcoin soared from 68 USD to 19.497 USD.

[3] Data was extracted from Google Sheets application from the Google Finance service by using proprietary spreadsheet function (=GOOGLEFINANCE).

At the same time its coefficient of variation (σ/μ) is approx. 15 times larger than S&P500's. Table 1 presents ordinary percentage returns because of somewhat simpler interpretation, but elsewhere in this paper log-returns are used.

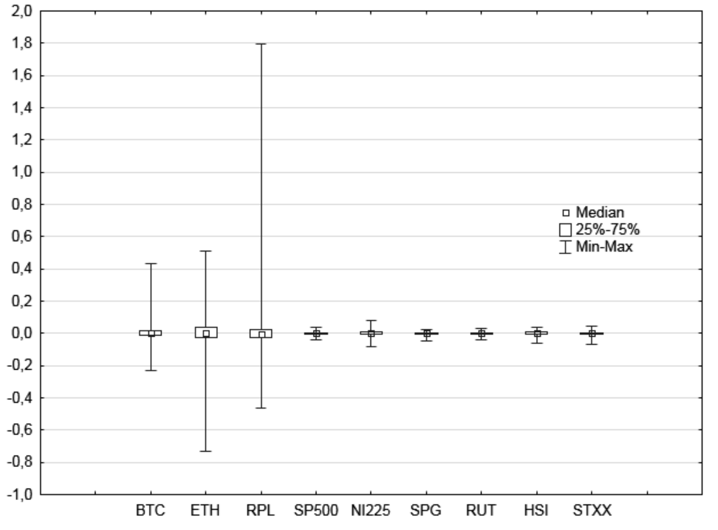
Table 1

Summary statistics of selected assets

Original daily data level								
Assets	**Mean**	**Median**	**Minimum**	**Maximum**	**Std. Dev.**	**Coef. Var.**	**Skew-ness**	**Kurt-osis**
BTC	1.815,96	536,92	68,43	19.497,40	3.277,47	180,48	2,73	7,31
ETH	187,24	12,82	0,43	1.396,42	288,9	154,29	1,76	2,44
RPL	0,13	0,01	0	3,38	0,34	265,73	4,59	27,08
SP500	2.116,65	2.078,56	1.573,09	2.872,87	292,86	13,84	0,49	-0,38
NI225	17.774,59	17.497,72	12.445,38	24.124,15	2.617,01	14,72	0,22	-0,86
SPG	1.942,86	1.903,82	1.560,59	2.518,11	194,19	9,99	0,83	0,18
RUT	1.429,54	1.412,90	1.156,89	1.610,71	101,29	7,09	-0,3	-0,3
HSI	24.142,23	23.333,18	18.319,58	33.154,12	2.960,11	12,26	0,91	0,31
STXX	353,87	347,3	275,66	414,06	29,86	8,44	-0,11	-0,89
Daily percentage returns								
Assets	**Mean**	**Median**	**Minimum**	**Maximum**	**Std. Dev.**	**Coef. Var.**	**Skew-ness**	**Kurt-osis**
BTC	0,33%	0,20%	-23,37%	42,97%	4,51%	1.376,53	0,51	9,83
ETH	0,87%	-0,04%	-72,80%	51,03%	7,79%	891,74	0,23	12,68
RPL	0,62%	-0,27%	-46,00%	179,37%	9,18%	1.479,02	6,1	95,31
SP500	0,05%	0,05%	-4,10%	3,90%	0,79%	1.728,76	-0,51	3,16
NI225	0,05%	0,07%	-7,92%	7,71%	1,38%	2.747,18	-0,29	4,69
SPG	0,03%	0,05%	-5,01%	2,37%	0,68%	2.174,14	-0,83	4,85
RUT	0,07%	0,11%	-3,63%	3,10%	0,88%	1.334,06	-0,33	1,41
HSI	0,03%	0,05%	-5,84%	4,10%	1,06%	3.231,27	-0,33	2,43
STXX	0,02%	0,03%	-7,03%	4,20%	0,97%	4.972,31	-0,56	4,79

Source: Author's calculation

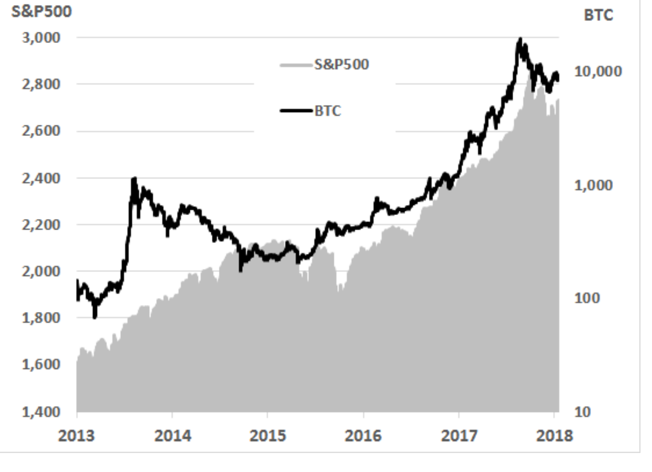
All three cryptocurrencies display considerably wider fluctuations than stock indices (Graph 1). Both Table 1 and Graph 1 show that min-max spreads are 10 to 30 times wider (with volatility measured by standard deviation also approx. 10 times larger) within cryptocurrencies than within indices, which in itself demonstrates the risks plainly.



Graph 1 Box and Whisker plots of daily returns for the selected assets

Source: Author

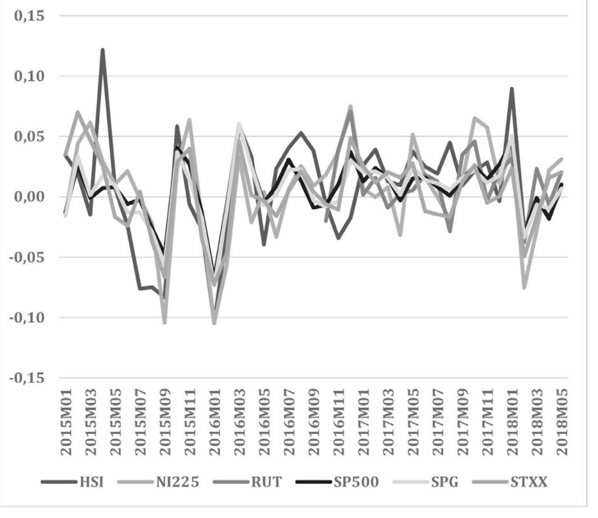
Graph 2 exhibits that the most known and used stock index in the world – S&P500 – and the first cryptocurrency with the largest market impact both enjoyed bull markets during the observed five-year period. However, it should be noted that the vertical scale for the Bitcoin is logarithmic, which indicates greatly broader oscillation.



Graph 2 S&P500 and Bitcoin from 2013 to 2018

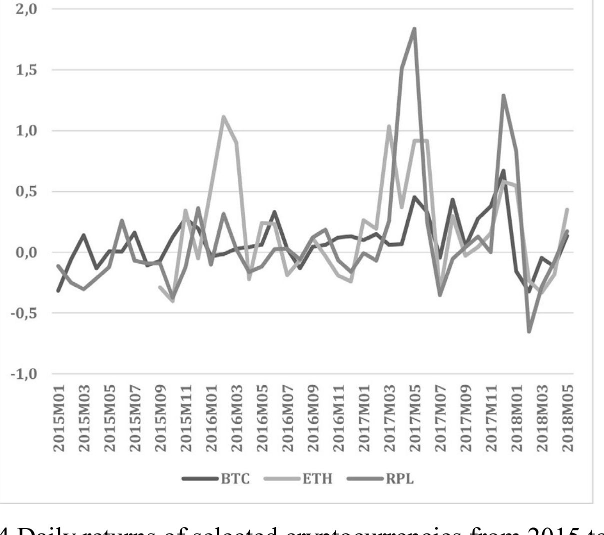
Source: Author

Observable patterns and somewhat homogenous movements can be seen within stock market (Graph 3), while on the other hand during the same period volatility of cryptocurrencies is monitored on the vertical – logarithmic – scale, with more heterogeneous changes (Graph 4).



Graph 3 Daily returns of selected stock indices from 2015 to 2018

Source: Author



Graph 4 Daily returns of selected cryptocurrencies from 2015 to 2018

Source: Author

Obtained data was examined for the existence of unit roots. As expected, level data was found to be non-stationary, but first differencing in the form of log-returns satisfied the condition of unit root absence. Due to insufficient number of observations only Phillips-Perron test could be used for the stock indices.

Table 2

Unit-root tests on daily percentage returns

	Phillips-Perron		ADF		Elliott -Rothenberg - Stock (***=1%; **=5%)
	adj. t-stat.	prob.	t-stat.	prob.	p-stat.
XBTC	-42.950	0.000	-42.727	0.000	0.169***
XETH	-30.747	0.000	-30.745	0.000	4.741**
XRPL	-40.662	0.000	-26.421	0.000	0.133***
SP500	-32.622	0.000			
NI225	-33.914	0.000			
SPG	-27.937	0.000			
RUT	-18.768	0.000			
HSI	-33.370	0.000			
STXX	-32.054	0.000			

Source: Author's calculation

Correlations of daily log-returns of all the examined assets are presented in Table 3. It comes as no surprise that the global stock market index is correlated with all other indices and – moreover – that most of the indices are mutually correlated. The exceptions are the Hong Kong and Japanese indices which are uncorrelated to American markets.

On the other hand, cryptocurrencies are correlated between themselves but are uncorrelated to the stock markets, with the exception of Ether which is weakly connected to S&P500 and S&P Global.

Table 3

Correlations of daily log-returns

Correlation *Probability*	**HSI**	**NI225**	**RUT**	**SP500**	**SPG**	**STXX**	**XBTC**	**XETH**	**XRPL**
HSI	1.000								

NI225	**0.545**	1.000							
	0.000	-----							
RUT	0.079	0.048	1.000						
	0.197	*0.435*	-----						
SP500	0.061	0.038	**0.800**	1.000					
	0.324	*0.532*	*0.000*	-----					
SPG	**0.340**	**0.314**	**0.716**	**0.886**	1.000				
	0.000	*0.000*	*0.000*	*0.000*	-----				
STXX	**0.352**	**0.306**	**0.433**	**0.443**	**0.620**	1.000			
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	-----			
XBTC	-0.106	-0.018	0.039	0.050	0.011	-0.016	1.000		
	0.084	*0.770*	*0.532*	*0.413*	*0.852*	*0.793*	-----		
XETH	0.060	-0.007	0.077	**0.139**	**0.176**	0.081	**0.445**	1.000	
	0.329	*0.911*	*0.209*	*0.024*	*0.004*	*0.186*	*0.000*	-----	
XRPL	0.041	-0.032	0.002	0.019	0.037	0.069	**0.217**	**0.333**	1.000
	0.509	*0.607*	*0.968*	*0.754*	*0.545*	*0.261*	*0.000*	*0.000*	-----

Source: Author's calculation

As stated in the previous chapter, linear regression models were specified with the cryptocurrencies being the regressands, and indices regressors. Due to the issue of multicollinearity, cryptocurrency – index pairs were tested individually, and Table 4 presents 72 regression specifications with their essential results. Most of the coefficients are statistically insignificant, but even when they are not R^2 is in majority of cases practically zero (since the adjusted R^2 is corrected for the sample size, in many cases it is slightly below zero). This indicates that there is no variance in the returns of cryptocurrencies that is predictable from the selected stock indices. The exception is the relationship of Bitcoin to S&P500 on the monthly basis which has highest coefficient of determination in the analysis, however, still at a lower level.

Table 4

Regression results

Indices	BTC α (p-val.)	BTC β (p-val.)	BTC Adj. R^2	ETH α (p-val.)	ETH β (p-val.)	ETH Adj. R^2	RPL α (p-val.)	RPL β (p-val.)	RPL Adj. R^2
	Daily frequencies								
HSI	0.001 (0.52)	-0.294 (0.06)	0.003	0.006 (0.05)*	-0.063 (0.84)	-0.002	0.006 (0.02)*	-0.346 (0.20)	0.001
NI225	0.000 (0.69)	-0.159 (0.18)	0.001	0.007 (0.04)*	-0.250 (0.30)	0.000	0.006 (0.05)*	-0.139 (0.52)	-0.001
RUT	0.004 (0.20)	0.182 (0.57)	-0.002	0.006 (0.09)	0.551 (0.19)	0.002	0.014 (0.01)**	0.139 (0.82)	-0.003
SP500	0.001 (0.61)	-0.113 (0.56)	-0.001	0.008 (0.01)**	0.249 (0.52)	-0.001	0.006 (0.04)*	0.341 (0.32)	0.000
SPG	0.001 (0.53)	-0.240 (0.27)	0.000	0.008 (0.01)**	-0.184 (0.67)	-0.001	0.007 (0.01)**	0.304 (0.44)	0.000
STXX	0.001 (0.52)	-0.118 (0.47)	0.000	0.006 (0.04)*	-0.337 (0.26)	0.000	0.006 (0.05)*	0.065 (0.82)	-0.001
	Weekly frequencies								
HSI	0.016 (0.01)**	0.219 (0.48)	-0.002	0.043 (0.0)***	0.187 (0.78)	-0.006	0.019 (0.15)	0.423 (0.51)	-0.002
NI225	0.016 (0.01)**	0.419 (0.12)	0.005	0.043 (0.0)***	0.207 (0.74)	-0.006	0.018 (0.16)	0.514 (0.39)	-0.001
RUT	0.031 (0.01)**	0.265 (0.70)	-0.010	0.044 (0.02)*	1.166 (0.28)	0.002	0.052 (0.07)	0.079 (0.96)	-0.012
SP500	0.014 (0.02)*	1.012 (0.03)**	0.014	0.041 (0.0)***	0.973 (0.33)	0.000	0.018 (0.16)	0.498 (0.61)	-0.003
SPG	0.015 (0.01)**	0.619 (0.18)	0.003	0.042 (0.0)***	0.809 (0.41)	-0.002	0.019 (0.15)	0.367 (0.70)	-0.003
STXX	0.017 (0.01)**	0.208 (0.56)	-0.003	0.044 (0.0)***	0.248 (0.75)	-0.006	0.020 (0.12)	-0.183 (0.80)	-0.004
	Monthly frequencies								
HSI	0.066 (0.05)*	0.622 (0.43)	-0.006	0.182 (0.03)*	1.220 (0.53)	-0.019	0.081 (0.21)	1.351 (0.40)	-0.005
NI225	0.057 (0.08)	1.506 (0.04)*	0.056	0.190 (0.02)*	0.484 (0.78)	-0.030	0.068 (0.29)	2.427 (0.12)	0.027
RUT	0.122 (0.05)*	1.173 (0.58)	-0.037	0.230 (0.04)*	-2.199 (0.57)	-0.036	0.219 (0.19)	1.634 (0.78)	-0.051
SP500	0.039 (0.24)	3.474 (0.01)**	0.084	0.173 (0.04)*	2.298 (0.45)	-0.013	0.063 (0.35)	3.137 (0.26)	0.005
SPG	0.052 (0.11)	2.918 (0.03)*	0.061	0.173 (0.03)*	2.774 (0.34)	-0.002	0.073 (0.27)	2.754 (0.31)	0.001
STXX	0.064 (0.05)*	1.183 (0.28)	0.003	0.191 (0.02)*	1.383 (0.60)	-0.023	0.086 (0.19)	0.612 (0.78)	-0.017
All calculations were made with log-return transformation									

Source: Author's calculation

Another specification of the OLS model was tested; this time with lagged variables (Table 5). Since the financial markets in the present information age are extremely dynamic, it was assumed that no rational market participant would wait for a week (or even a month) in order to react to new information. Therefore, only one-day lagged variables were tested, and as expected, there were no significant results.

Table 5

Regression results with lagged independent variables

Indices, one-day lag	**Daily frequencies**								
	BTC			**ETH**			**RPL**		
	α (p-val.)	β (p-val.)	Adj. R^2	α (p-val.)	β (p-val.)	Adj. R^2	α (p-val.)	β (p-val.)	Adj. R^2
HSI(-1)	0.001 (0.36)	-0.170 (0.26)	0.000	0.002 (0.64)	0.132 (0.72)	-0.002	0.004 (0.14)	0.045 (0.86)	-0.001
NI225(-1)	0.001 (0.50)	0.061 (0.58)	-0.001	0.005 (0.22)	0.035 (0.91)	-0.002	0.004 (0.18)	-0.171 (0.40)	0.000
RUT(-1)	0.004 (0.19)	-0.347 (0.29)	0.000	0.003 (0.35)	-0.021 (0.96)	-0.003	0.008 (0.12)	0.281 (0.63)	-0.002
SP500(-1)	0.001 (0.52)	-0.075 (0.69)	-0.001	0.004 (0.30)	-0.021 (0.96)	-0.002	0.003 (0.23)	-0.352 (0.27)	0.000
SPG(-1)	0.001 (0.49)	-0.110 (0.61)	-0.001	0.004 (0.34)	0.116 (0.83)	-0.002	0.004 (0.16)	-0.343 (0.35)	0.000
STXX(-1)	0.001 (0.39)	0.039 (0.81)	-0.001	0.002 (0.55)	0.687 (0.07)	0.004	0.004 (0.10)	-0.175 (0.52)	-0.001
All calculations were made with log-return transformation									

Source: Author's calculation

Correlations (Table 3) showed that cryptocurrencies co-move in their own designated space, apart from stock markets. With the Bitcoin being the primary and the seminal cryptocurrency, it was interesting to observe how Ether (Table 6) and Ripple (Table 7) react to other two coins' returns lagged and non-lagged, as well as for the proposed auto-regression. It was found that approx. 13% of the variation in the return of Ether can be explained by the Ether's previous-day-return together with Bitcoin and Ripple (Graph 5).

Table 6

Autoregression of Ether and its interconnectedness with Bitcoin and Ripple (daily log-returns)

Independent Variables	Coeff.	Prob.
Const.	0.004	0.04*
ETH(-1)	0.081	0.00**
BTC	0.538	0.00**
BTC(-1)	-0.028	0.62
RPL	0.099	0.00**
RPL(-1)	-0.032	0.25
Adj. R^2		0.129
F-stat. (p-val.)		30.864 (0.00)

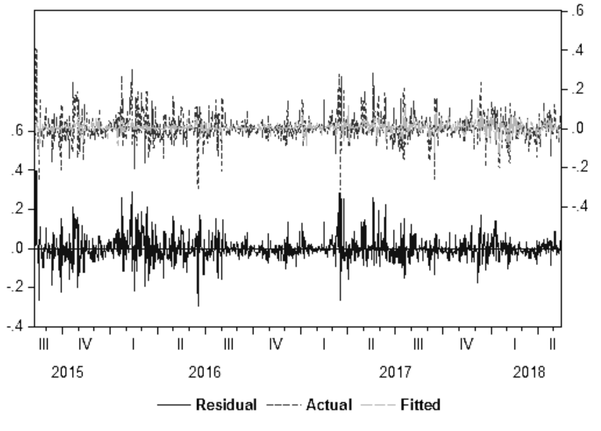
Source: Author's calculation

Table 7

Autoregression of Ripple and its interconnectedness with Bitcoin and Ether (daily log-returns)

Independent Variables	Coeff.	Prob.
C	0.002	0.39
RPL(-1)	-0.001	0.97
BTC	0.422	0.00**
BTC(-1)	-0.082	0.19
ETH	0.129	0.00**
ETH(-1)	0.050	0.11
Adj. R^2		0.077
F-stat. (p-val.)		17.896 (0.00)

Source: Author's calculation



Graph 5 Autoregression of Ether and its interconnectedness with Bitcoin and Ripple (daily log-returns), R^2=0.13

Source: Author

Overall results further emphasize the novelty of cryptocurrencies as the new asset class which brought a new ground available for investment diversification purposes.

5. CONCLUSION

A bubble of epic proportions was evident with the prices of cryptocurrencies at the turn of the year 2017 to 2018. From the 6,767 USD for one Bitcoin on the November 1st, 2017 the price rocketed to 19,497 on December 16th, only to rebound back to 6,844 on April 1st, 2018. If anything, this *hype* provided a platform for a swift consensus about the scope of risks when investing in cryptocurrencies. Furthermore, this was another factor attracting academic community to this innovative and disruptive field. However, regardless of their tremendous volatility, cryptocurrencies remain a controversial subject due to the scope of societal interventions they propose, as they are often incorporated in worldviews which span from mildly anti-establishment-oriented to downright revolutionary and/or anarchistic.

The aim of this paper was to further establish cryptocurrencies as a new asset class, a fully digital, sui-generis financial instruments. Interconnectedness of three most important cryptocurrencies with six major stock market indices was closely examined. Altogether 74 specifications of the OLS were performed, and it can be noted that variation of cryptocurrencies' return does not respond to variations in stock market indices' yield, regardless of the data frequency. Within the crypto-market Ether has an auto-regression component (one-day lag) and is related to Bitcoin, while Ripple is weakly related to Bitcoin and Ether.

Considering that with the advent of globalization and the development of information technology all financial assets became more correlated, this implies that cryptocurrencies can be a useful new playground for those seeking high returns (as always, accompanied with high risks) together with new diversification options. Having this in mind, policy makers need to closely observe new investment vehicles but also refrain from hindering new possibilities for diversification.

Further research could expand these findings with cointegration analysis between cryptocurrency market and traditional financial markets, and also expanded with post-crypto-crash data.

REFERENCES

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., Hagfors, L. I., 2017. On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? Finance Research Letters 20, 192–198. https://doi.org/10.1016/j.frl.2016.09.025

Corbet, S., Meegan, A., Larkin, C., Lucey, B., Yarovaya, L., 2018. Exploring the dynamic relationships between cryptocurrencies and other financial assets. Economics Letters 165, 28–34. https://doi.org/10.1016/j.econlet.2018.01.004

Eisl, A., Gasser, S., Weinmayer, K., 2015. Caveat Emptor: Does Bitcoin Improve Portfolio Diversification? (SSRN Scholarly Paper No. ID 2408997). Social Science Research Network, Rochester, NY.

Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M.C., Siering, M., 2014. Bitcoin - Asset or Currency? Revealing Users' Hidden Intentions (SSRN Scholarly Paper No. ID 2425247). Social Science Research Network, Rochester, NY.

Guesmi, K., Saadi, S., Abid, I., Ftiti, Z., 2018. Portfolio diversification with virtual currency: Evidence from bitcoin. International Review of Financial Analysis. https://doi.org/10.1016/j.irfa.2018.03.004

Liu, Y., Tsyvinski, A., 2018. Risks and Returns of Cryptocurrency (Working Paper No. 24877). National Bureau of Economic Research. https://doi.org/10.3386/w24877

Masiak, C., Block, J. H., Masiak, T., Neuenkirch, M., Pielen, K. N., 2018. The Market Cycles of ICOs, Bitcoin, and Ether (Research Papers in Economics No. 2018– 04). University of Trier, Department of Economics.

Murray, A., 2009. Paul Volcker: Think More Boldly [WWW Document]. Wall Street Journal. URL https://www.wsj.com/articles/SB10001424052748704825504574586330960597134 (accessed 2.22.18).

Narayanan, A., Bonneau, J., Felten, E., Miller, A., Goldfeder, S., 2016. Bitcoin and Cryptocurrency Technologies: A Comprehensive Introduction. Princeton University Press.

Patterson, M., Tan, A., 2018. 'This Is Not a Passing Fad': CFA Exam Adds Crypto, Blockchain Topics [WWW Document]. Bloomberg.com. URL https://www.bloomberg.com/news/articles/2018-07-16/cfa-exam-adds-crypto-blockchain-topics-as-wall-street-dives-in (accessed 7.17.18).

Popper, N., 2016. Digital Gold: Bitcoin and the Inside Story of the Misfits and Millionaires Trying to Reinvent Money, Reprint edition. ed. Harper Paperbacks, New York.

Sajter, D., 2018. Financijska analiza kriptovaluta u odnosu na standardne financijske instrumente, in: Financije - teorija i suvremena pitanja. Ekonomski fakultet u Osijeku, Osijek, pp. 277–301.

Dr. sc. Domagoj Sajter
Redoviti profesor
Sveučilište J. J. Strossmayera u Osijeku
Ekonomski fakultet
E-mail: sajter@efos.hr

TIME-SERIES ANALIZA NAJČEŠĆIH KRIPTOVALUTA

Sažetak

Cilj ovoga rada je omogućiti što bolje razumijevanje triju najčešćih kriptovaluta (Bitcoin, Ethereum i Ripple) primjenom standardnih ekonometrijskih alata prema njihovim time-series podatcima. Povrat ulaganja u kriptovalute uspoređuje se sa šest glavnih indeksa dionica: dva američka (S&P500 i Russel 2000), jednim europskim (Stoxx 600), jednim japanskim (Nikkei 225), jednim kineskim (Hong Kong Hang Seng) i globalnim indeksom (S&P Global 1200). Rezultati pokazuju da se istražene kriptovalute mogu smatrati novom klasom imovine, potpuno digitaliziranim, sui-generis financijskim instrumentima, jer nisu jasno povezane s tržištem dionica. Međutim, raspoređivanje kapitala u kriptovalute ostaje u domeni čiste spekulacije zbog njihove izrazite nestalnosti.

Ključne riječi: lanac blokova, kriptovalute, time-series, financijska tržišta.

JEL klasifikacija: C32, G15, G23, G29, O33.