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Highlight

- We examine the role of trading volume in predicting the returns and volatility in the cryptocurrency market
- We run the CGCD test procedure
- Results show that trading volume carries useful information to predict extreme negative and positive returns of all cryptocurrencies
- However, volume can predict volatility for only three cryptocurrencies (Litecoin, NEM, and Dash), when the volatility is low

Trading volume and the predictability of return and volatility in the cryptocurrency market

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Abstract

We extend our limited understanding on the Granger causality from trading volume to the returns and volatility in the cryptocurrency market via a copula-quantile causality approach. Using daily data of seven leading cryptocurrencies (Bitcoin, Ripple, Ethereum, Litecoin, Nem, Dash, and Stellar), results show that trading volume Granger causes extreme negative and positive returns of all cryptocurrencies under study. However, volume Granger causes return volatility for only three cryptocurrencies (Litecoin, NEM, and Dash) when the volatility is low. However, this latter result only holds when squared returns are used as a proxy of volatility and not when GARCH volatility is employed.

Keywords: trading volume; return; volatility; cryptocurrency; copula-quantile causality.

JEL classification: C22; G15

1. Introduction

Since its inception in 2009 as an open-source digital currency, Bitcoin has brought the attention of economists, policy-makers, and traders. Especially, Bitcoin has dominated the financial press, led by the phenomenal surge in its number of transactions and market value. The latter surpassed $216 billion at end of 2017 after ending the years 2015 and 2016 below $7 billion and $16 billion, respectively. Concurrently, Bitcoin price volatility has sharply increased to extreme levels not seen in any conventional assets. Importantly, Bitcoin has inspired and provoked the release of a large number of cryptocurrencies based on its technology – blockchain (Bouri et al., 2018a). Some of the leading cryptocurrencies, like Ethereum and Litecoin, have surged several thousand percent in price since the beginning of 2017 and have seen a huge increase in trading volume. Interestingly, from the beginning until the end of 2017, the total cryptocurrency market value increased from just $18 billion to more than $600 billion. Furthermore, daily trading volume on some cryptocurrencies, like Ethereum and Ripple, increased exponentially from a couple of thousand coins to hundreds of thousands and even to millions of coins.

A relevant question that arises is whether trading volume can Granger causes price returns and/or volatility of major cryptocurrencies. This is particularly important for at least two reasons. The first is related to the lack of appropriate valuation models to calculate the intrinsic value of most of the cryptocurrencies (Jiang et al., 2017). The second is related to the fact that many market participants in cryptocurrencies generate their trading strategies by relying on technical analysis that, in turn, emphasizes the importance of volume to price and price trends (Balcilar et al., 2017).

While trading volume has been generally shown to Granger cause the returns and volatility of equities in the tails and the centre of the return distribution (see Gebka and Wohar, 2013, for a detailed literature review), it is not clear whether this would also be the case for cryptocurrencies and whether there is some heterogeneity across the different cryptocurrencies, including Bitcoin. To the best of our knowledge, only one paper (Balcilar et al., 2017) has explicitly explored the Granger causality from trading volume to the returns and volatility in the cryptocurrency market. In that interesting paper, Balcilar et al. (2017) apply a causality-in-quantile test and reveal that trading volume can Granger cause Bitcoin returns in normal market environment, but not volatility.

However, the authors (1) disregard copula-based dependency, despite the well-documented power attributed to copula in modelling tail dependence[1], and (2) and focus on Bitcoin only and thus disregard other leading cryptocurrencies, such as Ethereum, Ripple, Litecoin, Nem, Dash, and Stellar, which have substantially increased in value during 2017, gained ground in the cryptocurrency market, and become a hot trading destination for many investors around the globe[2]. Accordingly, the purpose of this study is to examine the causality from trading volume to the returns and volatility of seven leading cryptocurrencies via a copula-based causality in quantiles approach along the lines from Lee and Yang (2014). This makes our paper different from Balcilar et al. (2017) in both the methodology used and the number of cryptocurrencies studied. On the methodological side, the copula-quantile causality approach of

[1] Ning and Wirjanto (2009) apply a copula approach to study the extreme return–volume dependence in East-Asian stock markets.
[2] The total market value of these six cryptocurrencies reached almost 200 billion U.S. dollar at the end of 2017, slightly shy of the 216 billion U.S. dollar that constitutes the value of the Bitcoin market.

Lee and Yang (2014) offers at least two advantages over the causality-in-quantile approach of Balcilar et al. (2017). Notably, it has the advantage of not only uncovering causality relationship in low, middle, and upper quantiles, as in Blacilar et al. (2017), but also in considering different copula functions for testing Granger -causality in distribution and in quantiles.

In particular, the copula-quantile causality approach relies on inverting the conditional copula functions, and thus provides more superior forecasting performance in the tails than in solely quantile-based methods (Lee and Yang, 2014). Furthermore, copula-quantile causality approach avoids the quantile-crossing problem associated with quantile regressions[3]. On the data set level, the use of other leading cryptocurrencies than Bitcoin reflects the declining of Bitcoin dominance in the cryptocurrency market to the detriment of other leading cryptocurrencies. The latter have shown more substantial increase in their market value than Bitcoin (Gandal et al., 2018), making them gain more trading activity, importance, and, thus, attractiveness among market participants in the cryptocurrency market[4].

Empirical analyses indicate that trading volume Granger causes the returns of each of the seven cryptocurrencies under study in bearish (lower quantiles) and bullish (upper quantiles) market phases. Conversely, trading volume doesn't Granger cause volatility, except for Litecoin, Nem, and Dash, when their volatility is very low (in extreme lower quantiles). However, this latter result only holds when squared returns are used as a proxy of volatility and not when GARCH volatility is employed.

2. Data and methodology

2.1 Data

Our dataset includes seven-day week daily price returns of seven large cryptocurrencies (Bitcoin, Ripple, Ethereum, Litecoin, Nem, Dash, and Stellar), their return volatility, and detrended volume[5]. Data were extracted from https://coinmarketcap.com/ (Bouri et al., 2018a; Gandal et al., 2018) and its beginning point is depicted by its availability. The market value of

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[3] Recently, Bouri et al. (2018b) apply a quite similar method while studying the relationship between Bitcoin and global financial stress.
[4] Corbet al. (2018) also noticed that most of published papers dealing with the cryptocurrency empirical finance literature "focused solely on Bitcoin, omitting other cryptocurrencies."
[5] We used detrended volume in line with Balcilar et al. (2017).

those seven cryptocurrencies amounted to 420 billion U.S. dollars at the end of 2017, which represents around 70% of the total cryptocurrency market value.

Accordingly, those large cryptocurrencies are the most liquid, a key element in our choice to include them in this study. Descriptive statistics of the data covering (Table 1) show that trading volume is more volatile than returns for all cryptocurrency markets. The Jarque-Bera test indicates that all data series are non-normally distributed, which justifies our choice of using a copula causality-in-quantiles test[6]. All series are stationary according to the Augmented Dickey-Fuller (ADF) test. Figures 1 to 7 present, respectively, the natural logarithm of closing price and returns, the natural logarithm of volume traded, and the detrended volume for the seven cryptocurrencies.

[Insert Table 1 and Figures 1-7 Here]

2.2 Method

In this section, we present the copula-quantile causality approach that will be used to examine causality from trading volume to price returns/volatility in the cryptocurrency market. The approach follows the Copula-Granger-causality in distribution (CGCD) method of Lee and Yang (2014), through which two tests for CGCD are constructed using copula functions. The parametric test of Lee and Yang (2014) employs six parametric copula functions to uncover the dependence copula density between variables, and the performance matrix of those models are compared with the independent copula density.

The "forecast performance" based CGCD test of Lee and Yang (2014) is used in this study to test the null hypothesis of X_t does not Granger cause Y_t in distribution: H0: c(u, v) = 1, c(u, v) is the conditional copula density function, with u and v the conditional probability integral transforms of X_t and Y_t. The forecasted conditional variance for $\{X_t\}$ and $\{Y_t\}$, $\hat{h}_{x,t+1}$ and $\hat{h}_{y,t+1}$, are computed by

$$\hat{h}_{x,t+1} = \hat{\beta}_{x0} + \hat{\beta}_{x1} x_t^2 + \hat{\beta}_{x2} \hat{h}_{t,x}$$
$$\hat{h}_{y,t+1} = \hat{\beta}_{y0} + \hat{\beta}_{y1} y_t^2 + \hat{\beta}_{y2} \hat{h}_{t,x} \quad (1)$$

[6] Unreported results show that the relationship between returns and volume are nonlinear in most of the cases, which further justifies the appropriateness of using a quantile-based approach to uncover Granger causality.

The empirical distribution function (EDF) is used to compute the CDF values of $\hat{u}_{t+1}$ and $\hat{v}_{t+1}$ for x_{t+1} and y_{t+1}, while a nonparametric copula function is estimated with EDF values $\{\hat{u}_{t+1}, \hat{v}_{t+1}\}_{t=R}^{T-1}$ using a quartic kernel function:

$$k(u) = \frac{15}{16}(1-u^2)^2 I(|u| \leq 1) \tag{2}$$

In this study, we focus on three distributional regions: the left tail (1% quantile, 5% quantile, and 10% quantile), the central region (40% quantile, median, and 60% quantile), and the right tail (90% quantile, 95% quantile, and 99% quantile). The decision rule regarding refuting the null hypothesis of no copula Granger causality in quantiles is based on the forecast performance on the conditional quantile, $q_\alpha(Y_t|\mathcal{F}_t)$, where α is the left tail probability.

The forecast performance of those quantile forecasting models $q_\alpha(Y_t|\mathcal{F}_t)$ is assessed using the seven (I = 7) copula functions for C(u; v)[7], based on the "check" loss function of Koenker and Bassett (1978)[8]. We also define the corresponding quantile forecast as $q_{\alpha,k}(Y_t|\mathcal{F}_t)$ and its expected check loss as $Q_k(\alpha)$ for each copula function. To evaluate the difference between copula model 1 (i.e., the benchmark model of independent copula) and model k (= 2,…,l), we consider the corresponding check loss-differential as denoted by:

$$D_k = Q_1(\alpha) - Q_k(\alpha) \tag{3}$$

D_k is estimated by:

$$\hat{D}_{k,p} = \hat{Q}_{1,p}(\alpha) - \hat{Q}_{k,p}(\alpha) \tag{4}$$

where $\hat{Q}_{k,p}(\alpha) = \frac{1}{p}\sum_{t=R}^{T-1}[\alpha - I(Y_t - q_\alpha(Y_t|\mathcal{F}_t) < 0)]\big(Y_t - q_\alpha(Y_t|\mathcal{F}_t)\big),\ k = 1, \dots, l.$

The conditional quantile forecasts from using the copula distribution function C_k (k = 2,…) with the largest value $\hat{D}_{k,p}$ will be adopted.

[7] We consider six copulas functions: Gaussian, Frank, Clayton, Clayton Survival, Gumbel, and Gumbel Survival.
[8] For detailed information, please refer to Lee and Yang (2014).

3. Empirical results

Results from applying the copula-quantile causality test to the return-volume relationship are given in Table 2. Based on the p-values for CGCQ test, trading volume strongly Granger-causes price returns of each of the seven cryptocurrencies at the left tail (poor performance) and the right tail (superior performance) of the distribution of the cryptocurrency return conditional on the trading volume. This suggests that causality from volume to returns is pronounced for both high and low quantiles, corresponding to respectively positive and negative returns. This finding indicates trading volume contains somewhat important information about cryptocurrency returns.

The above results are partially in line with evidence of significant causality from trading volume to stock return, which is generally concentrated in the tails (Gebka and Wohar, 2013). For the case of Bitcoin, our results differ from Balcilar et al. (2017), suggesting that the adopted copula-based causality in distribution approach has managed to uncover different results.

[Insert Table 2 Here]

Moving to the causality from trading volume to price volatility, two proxies for price volatility are used as in Balcilar et al. (2017): (1) GARCH-based estimate of volatility resulting from the estimation of a GARCH (1,1) model and (2) squared returns. Results from Table 3 show no evidence of causality in any quantile when the first proxy of volatility is considered. As argued by Balcilar et al. (2017), this finding supports the mixture of distribution hypothesis developed by Clark (1973), which assumes that the volume-volatility relation depends on the rate of information flow into the market. This suggests that all participants in the cryptocurrency market receive new information simultaneously, which makes it impossible for past volume data to Granger cause volatility.

One possible explanation could be related to the easy dissemination of information across crypto-traders, given that Bitcoin and most of other cryptocurrencies involve an open source, software-based online payment system (Balcilar et al., 2017). However, using squared returns, trading volume Granger-causes price volatility of Litecoin, NEM, and Dash at the left tail distributional region (Table 4), i.e., during extreme low volatility conditions.

[Insert Tables 3 and 4 Here]

4. Conclusions

This study provided significant evidence of Granger causality from trading volume to the returns of seven large cryptocurrencies at both left and right tails. This suggests that during extreme market conditions, there is interest in searching out relevant information, such as trading volume, on behalf of market participants. The homogeneity and symmetric features in the causality from trading volume to returns in the seven cryptocurrencies are not present when considering price volatility (squared returns). For the latter, the causality is found to differ across upper and lower quantiles in three cases only. Future research could consider the time-varying effect of the causality while considering specific events.

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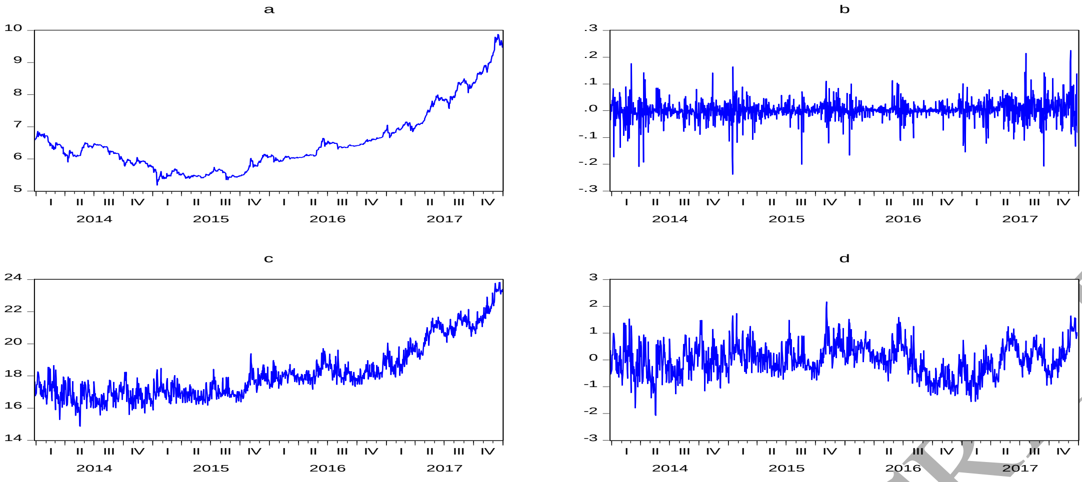

Figure 1: Bitcoin: a) Natural logarithm of closing price of Bitcoin. b). Bitcoin returns. c). Natural logarithm of volume traded. D). Detrended volume.

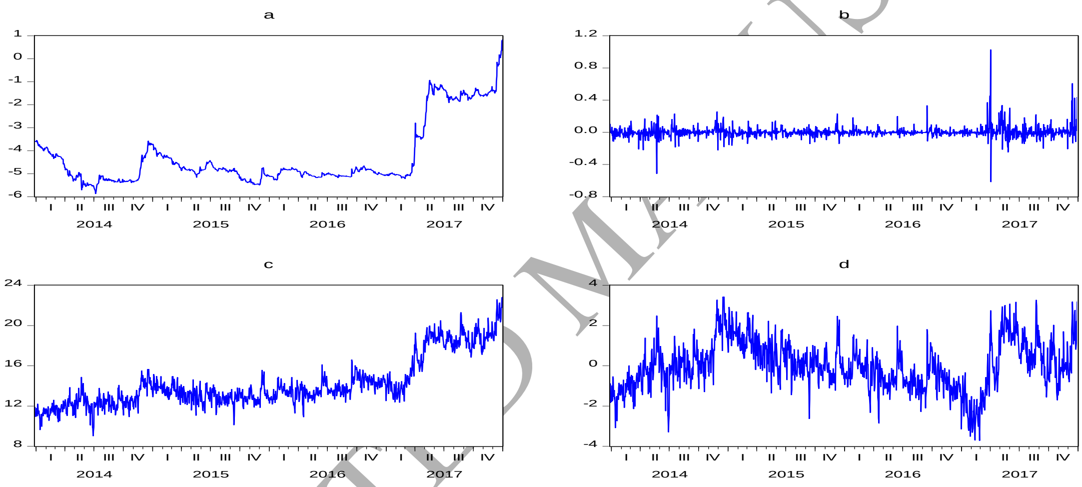

Figure 2: Ripple: a) Natural logarithm of closing price of Ripple. b). Ripple returns. c). Natural logarithm of volume traded. D). Detrended volume.

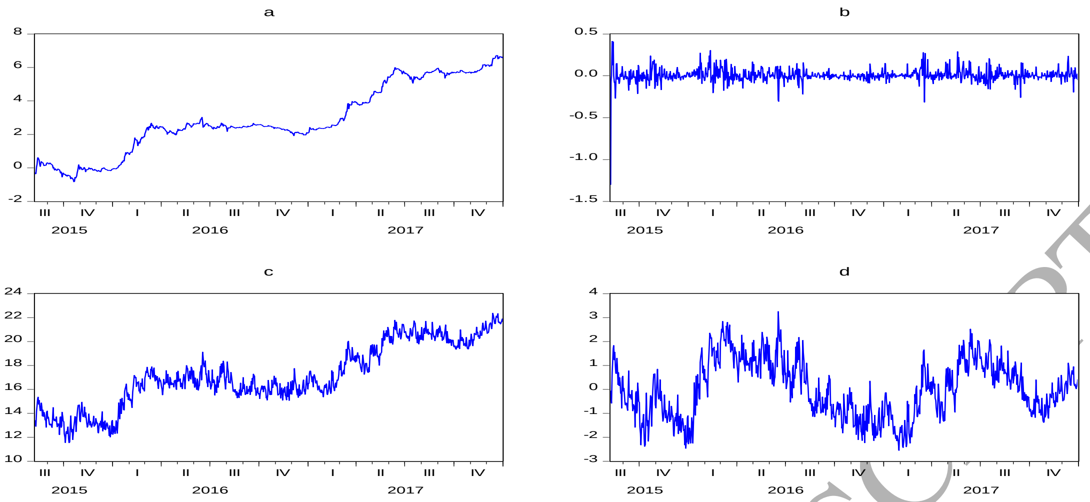

Figure 3: Ethereum: a) Natural logarithm of closing price of Ethereum. b). Ethereum returns. c). Natural logarithm of volume traded. D). Detrended volume.

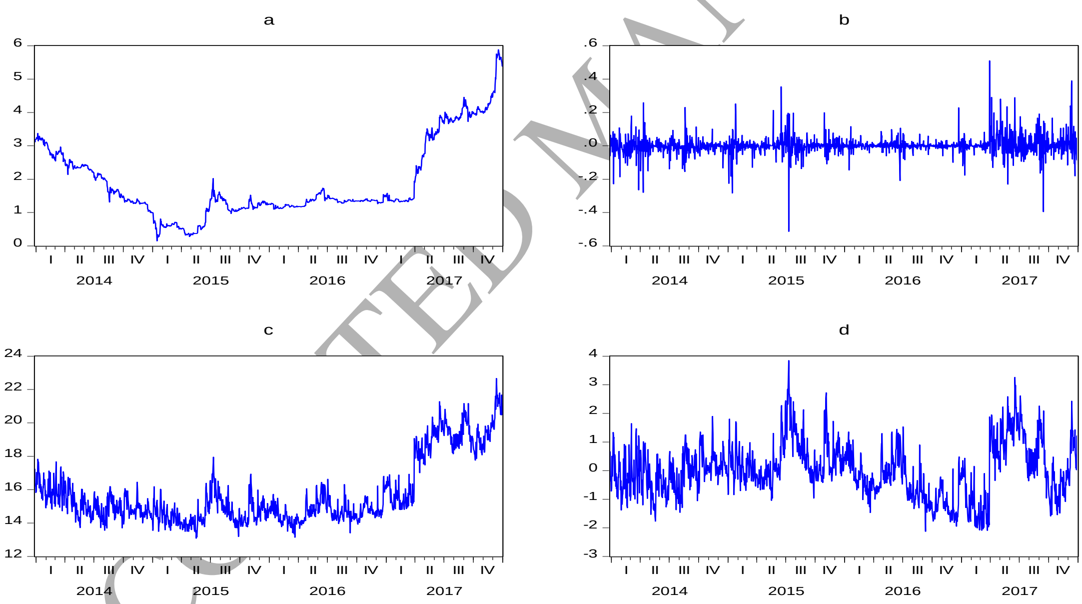

Figure 4: Litecoin: a) Natural logarithm of closing price of Litecoin. b). Litecoin returns. c). Natural logarithm of volume traded. D). Detrended volume.

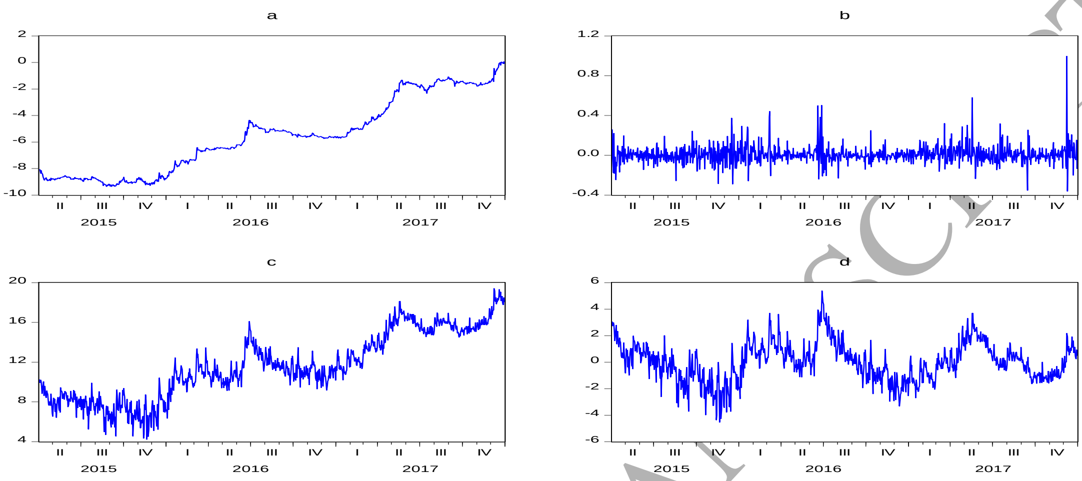

Figure 5: Nem: a) Natural logarithm of closing price of Nem. b). Nem returns. c). Natural logarithm of volume traded. D). Detrended volume.

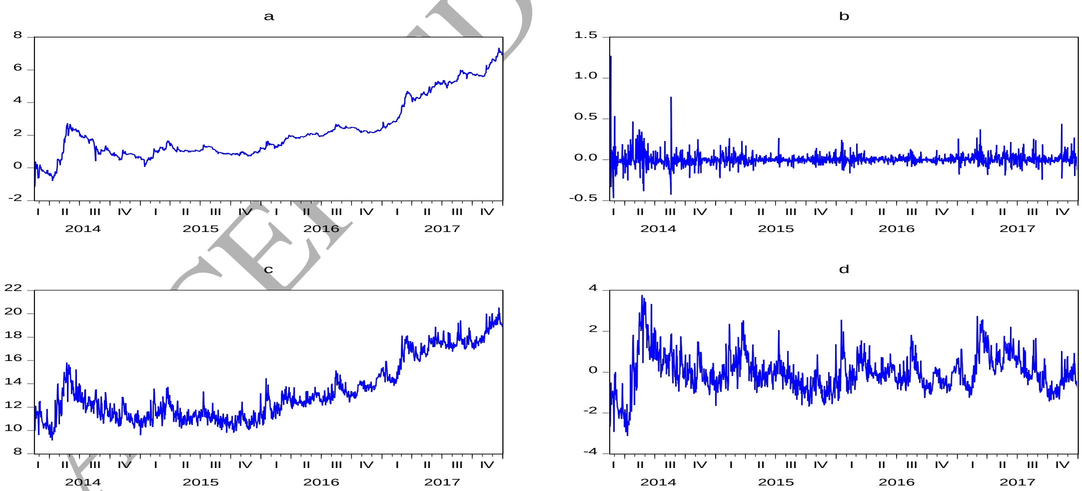

Figure 6: Dash: a) Natural logarithm of closing price of Dash. b). Dash returns. c). Natural logarithm of volume traded. D). Detrended volume.

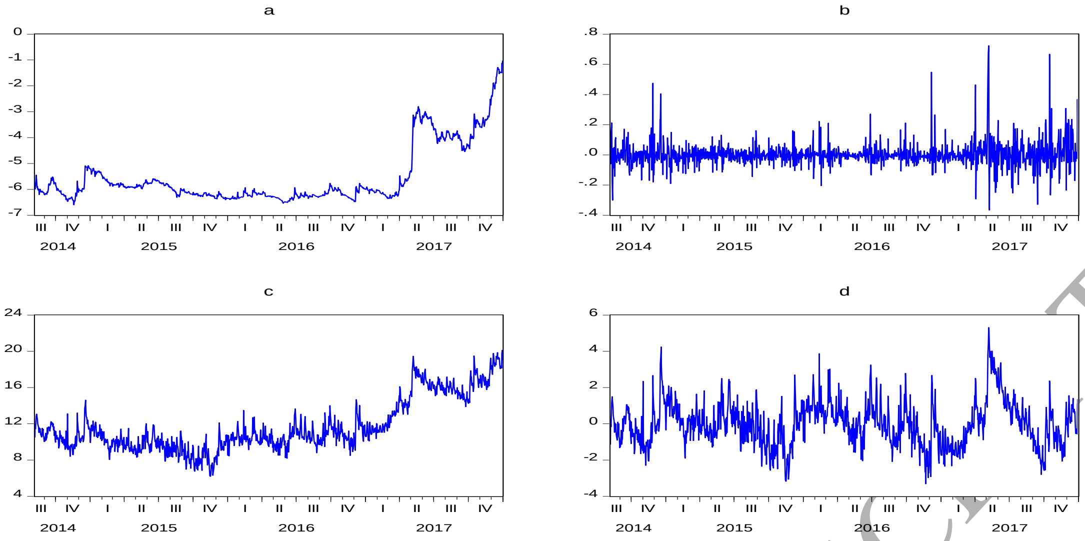

Figure 7: Stellar: a) Natural logarithm of closing price of Stellar. b). Stellar returns. c). Natural logarithm of volume traded. D). Detrended volume.

Table 1: Summary Statistics.

	Bitcoin		Ripple		Ethereum		Litecoin	
Statistic	Returns	Volume	Returns	Volume	Returns	Volume	Returns	Volume
Mean	0.0020	0.0000	0.0031	0.0000	0.0064	0.0000	0.0015	0.0000
Median	0.0018	-0.0160	-0.0030	-0.0882	-0.0005	-0.0725	0.0000	-0.0776
Maximum	0.2251	2.1673	1.0274	3.4202	0.4123	3.2524	0.5103	3.8472
Minimum	-0.2376	-2.0732	-0.6163	-3.7164	-1.3021	-2.5502	-0.5139	-2.1274
Std. Dev.	0.0387	0.6071	0.0714	1.2115	0.0852	1.1858	0.0598	0.9457
Skewness	-0.3875	0.0956	2.8438	0.0864	-3.7234	0.1085	0.5799	0.4061
Kurtosis	9.7907	2.9677	45.8138	3.1010	67.5562	2.2285	17.8437	3.1853
Jarque-Bera	2853.4530	2.2977	113942.9000	2.4488	154313.8000	23.4728	13541.0400	42.4014
Probability	0.0000	0.3170	0.0000	0.2939	0.0000	0.0000	0.0000	0.0000
ADF Test Statistics	-29.1316	-5.4396	-24.6602	-4.1029	-32.2963	-3.5008	-37.9492	-5.4008
p-value	0.0000	0.0000	0.0000	0.0010	0.0000	0.0082	0.0000	0.0000
Sample period	29 April, 2013-31 December 2017		5 August, 2013-31 December 2017		8 August, 2015-31 December 2017		29 April, 2013-31 December 2017	

	Nem		Dash		Steller	
Mean	0.0083	0.0000	0.0056	0.0000	0.0040	0.0000
	0.0000	-0.0063	-0.0017	-0.0781	-0.0031	-

Median						0.0612
Maximum	0.9956	5.3808	1.2706	3.7682	0.7231	5.3104
Minimum	-0.3615	-4.5298	-0.4676	-3.1135	-0.3664	-3.3137
Std. Dev.	0.0931	1.4608	0.0859	0.9388	0.0836	1.2459
Skewness	2.0218	0.1681	3.1540	0.4723	2.1357	0.4869
Kurtosis	19.7902	3.3103	44.5391	4.2835	18.7611	3.8057
Jarque-Bera	12489.7200	8.7637	104151.8000	149.8431	13821.6100	82.8066
Probability	0.0000	0.0125	0.0000	0.0000	0.0000	0.0000
ADF Test Statistics	-26.0045	-4.0587	-37.9488	-5.2226	-32.3501	-6.1889
p-value	0.0000	0.0012	0.0000	0.0000	0.0000	0.0000
	2 April, 2015-31 December 2017		15 February, 2014-31 December 2017		6 August, 2014-31 December 2017	

Note: The null hypothesis for Augmented Dicky Fuller (ADF) test is that the variable contains a unit root.

Table 2. Testing for CGCQ (Return)

Quantile	1%	5%	10%	20%	30%	40%	50%	60%	70%	80%	90%	95%	99%
Bitcoin	0.000	0.000	0.000	0.000	0.000	0.000	0.120	0.763	0.009	0.000	0.000	0.000	0.000
Ripple	0.000	0.000	0.000	0.000	0.007	0.263	0.554	0.000	0.000	0.000	0.000	0.000	0.000
Ethereum	0.000	0.000	0.000	0.001	0.020	0.105	0.165	0.215	0.000	0.000	0.000	0.000	0.000
Litecoin	0.000	0.000	0.000	0.000	0.000	0.000	0.378	0.015	0.000	0.000	0.000	0.000	0.000
Nem	0.000	0.000	0.000	0.000	0.000	0.219	0.648	0.098	0.000	0.000	0.000	0.000	0.000
Dash	0.000	0.000	0.000	0.000	0.001	0.083	0.540	0.000	0.000	0.000	0.000	0.000	0.000
Stellar	0.000	0.000	0.000	0.000	0.005	0.379	0.503	0.000	0.000	0.000	0.000	0.000	0.000

Notes: We compute the quantile forecasts by inverting the parametric conditional copula distribution. We use six copulas (Gaussian, Frank, Clayton, Clayton Survival, Gumbel and Gumbel Survival). The check loss functions are compared to evaluate the predictive ability of different quantile forecasting using different copula models. The benchmark quantile forecasts are computed using the independent copula such that there is no CGCQ. Reported are the bootstrap p-values for testing the null hypothesis that none of these six copula models (which model CGCQ) produces a better quantile forecast than the independent copula (which gives no CGCQ). The small p-values of the reality check indicate the rejection of the null hypothesis, indicating that there is a copula function to model CGCQ and produce a better quantile forecast.

Table 3. Testing for CGCQ (GARCH volatility)

Table 3. Testing for CGCQ (GARCH volatility).

Quantile	1%	5%	10%	20%	30%	40%	50%	60%	70%	80%	90%	95%	99%
Bitcoin	0.495	0.494	0.496	0.501	0.498	0.502	0.502	0.502	0.498	0.501	0.496	0.493	0.491
Ripple	0.507	0.507	0.507	0.507	0.507	0.507	0.507	0.507	0.507	0.507	0.507	0.508	0.507
Ethereum	0.498	0.508	0.503	0.495	0.501	0.501	0.501	0.501	0.501	0.498	0.503	0.508	0.498
Litecoin	0.494	0.494	0.494	0.494	0.494	0.494	0.494	0.494	0.494	0.494	0.494	0.494	0.494
Nem	0.507	0.508	0.506	0.508	0.505	0.502	0.502	0.502	0.505	0.508	0.506	0.508	0.507
Dash	0.518	0.513	0.513	0.513	0.515	0.513	0.517	0.513	0.518	0.513	0.513	0.514	0.518
Stellar	0.504	0.504	0.501	0.499	0.499	0.502	0.503	0.502	0.501	0.499	0.501	0.502	0.505

See notes to Table 2.