Price-Volume Relationship in Cryptocurrencies

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Abstract: The relationship between the volume and price of various cryptocurrencies remains largely unexamined. This paper uses a non-parametric causality-in-quantiles model to examine the Granger causality between volume and returns. I extend the existing literature by incorporating more exchanges and a larger sample size. This study finds that trading volume predicts returns during bull or bear markets and that trading volume predicts volatility throughout the majority of the conditional distribution.

JEL codes: C22, C5, G1, G15

Keywords: Time Series Analysis, Non-Parametric Causality-in-Quantiles, Bitcoin, Ethereum, Cryptocurrency, Efficient Market Hypothesis, Granger Causality

1. Introduction

In recent years, the presence of alternative currencies in the news has been increasing with more media attention surrounding cryptocurrencies such as Bitcoin and Ethereum. Its usage as a medium of exchange for goods and services, particularly in the black market, has enshrouded these digital currencies in controversy, but the speculative nature of these currencies echoes many other financial assets such as commodities, stocks, and bonds.

Understanding how returns and volume interact with each other is important in predicting how information disseminated throughout the market exchanges affect how price is determined. Modeling this relationship strengthens the forecasting power of these relationships and may help to better explain market rallies and crashes. For speculators, this information will aid in the recognition of trading strategies. The detection of crashes and booms is vital to speculators looking for an investment vehicle. Governing agencies looking to regulate or derive their own cryptocurrency will benefit in learning how a decentralized currency still follow patterns seen in other asset classes.

In this paper, I investigate the relationship between price and volume of Bitcoin and Ethereum across several exchanges. I use a non-parametric causality-in-quantiles method to estimate this relationship. I expand upon the existing literature by using data from multiple exchanges, a longer sample period, and applying the method onto other cryptocurrencies.

My paper proceeds as follows. I first discuss the history and mechanisms of the cryptocurrencies with high market capitalizations. Considering the growing literature and curiosity for cryptocurrencies, a fundamental understanding of its technology is crucial to accurately generalize models and ascertain its role in the financial economy. Then, I prepare an empirical model before the time series analysis. For consistency, I primarily focus on the

cryptocurrency Bitcoin throughout the paper. Empirical findings concerning other cryptocurrencies are discussed in the Appendices and when appropriate. I find statistically significant evidence that Bitcoin trading volume Granger causes returns and volatility dependent on market behavior.

2. Literature Review

The technology behind digital currencies such as Bitcoin and Ethereum seek to efficiently address issues inherent in virtual money. These problems include the double spending problem. This is the possibility of counterfeiting, where the digital currency may be duplicated or spent more than once. One proposed solution is to use a decentralized electronic payout system connected by a peer-to-peer network with open-source software. This solution which incorporates what is known as the blockchain was first developed by a person or group under the alias of (Nakamoto, 2008).

Cryptocurrencies utilizing blockchain technology have spawned far past the original Bitcoin developed by Nakamoto. Since January 2009, there are now 55 different cryptocurrencies with a market capitalization of over $100 million USD and 906 different cryptocurrencies with a market capitalization of over $1000. Bitcoin remains dominant in the world of cryptocurrency with its market capitalization being $238.6 billion, which is 62.5 percent of the total cryptocurrency market. Interestingly, other digital coins have challenged Bitcoin's dominance in recent months, as evidenced by Bitcoin's market dominance falling from 87.6 percent on January 1, 2017, to as low as 37.4 percent on June 20, 2017 (coinmarketcap.com).

Among the first notable uses of Bitcoin on an international scale was the Cyprus bailout of 2013. As detailed in Luther and Salter (2017), a significant levy was imposed on bank deposits, 6.75 percent for deposit balances under 100,000 euros and 9.9 percent for balances

above 100,000 euros. A spike in Bitcoin app downloads occurred in the week following the bailout announcement, even in countries outside of Cyprus. Spain, whose banking system was also under considerable pressure, had the largest percentage increase in bitcoin app downloads during the observed period. This study suggests how expectations shift given news and how changing policies may encourage those losing a sense of security with traditional bank deposits to transform their liquid assets into alternatives such as cryptocurrency.

Ethereum is the second most used cryptocurrency with a market capitalization of $44.2 billion. While not certainly as dominant as Bitcoin, Ethereum has climbed faster than Bitcoin's rise to prominence. Ethereum continues to utilize blockchain technology while extending its possible usages by incorporating an additional programming layer (Buterin, 2014).

One possible explanation as to why cryptocurrencies have not been widely accepted as a form of currency is proposed by Hendrickson, Hogan, and Luther (2016) in the context of network effects and switching costs. Even if all economic agents considering adopting cryptocurrencies view the currently accepted currency as inferior, the network effects and switching costs are enough to impede a broad adoption of the substitute. Either a severe distrust in financial institutions or prominent government support are necessary to instigate a major change.

The literature on the market characteristics of cryptocurrencies are sparse – even more so when including cryptocurrencies other than Bitcoin. To date, the only paper with a comprehensive analysis on a price-volume relationship in a cryptocurrency is by Balcilar et al. (2017). They use a novel non-parametric causality-in-quantiles test to measure the nonlinearity of the relationship between the trading price of Bitcoin and its trading volume. Their non-parametric causality-in-quantiles test addresses the significant kurtosis inherent in the Bitcoin

price and volume data. They find that the relationship between Bitcoin trading volume and returns is nonlinear and that volume can predict price during range-bound markets, but not during a bearish and bullish market -- where only previous prices are relevant. The market capitalization of Bitcoin at the endpoint of their observation period slightly exceeded 7 billion USD, which has since increased tenfold. Further concessions are included by the authors which I exploit, such as how they only study one exchange and how their bivariate model excludes robustness checks. Part of my findings refute their claims as I initially extend their sample period of their only exchange, and find that the Bitcoin trading volume does indeed Granger cause Bitcoin returns and volatility in both bull and bear markets. Furthermore, their assessment of the GARCH(1,1) model in their linear estimate of volatility would be disputed by both Katsiampa (2017) and Chu et al. (2017), who find that other GARCH-type models better fit volatility models for cryptocurrencies.

3. Empirical Methodology

3.1 Theoretical Prediction

Speculative assets are theoretically said to be fairly priced by the market by virtue of the market having knowledgeable investors. Asset prices are then priced according to all available information. This is the backbone of Fama's Efficient Market Hypothesis (1970). Considering the availability of publicly accessible information via the blockchain, cryptocurrencies backed by blockchain technology follow the paradigm of the Semi-Strong Form of the Efficient Market Hypothesis. While the complete transactional history of a particular cryptocurrency is easily obtainable via the blockchain, not all information pertaining to each transaction is available. Assuming a Strong Form of the Efficient Market Hypothesis is not possible, since deriving private information from blockchain users is infeasible, such as precisely determining how many

private keys are permanently lost, wallet owner location, and the total number of cryptocurrency users (Hileman and Rauchs, 2017). Evidence suggesting that cryptocurrencies follows the Efficient Market Hypothesis is presented by Bartos (2015) which confirm that cryptocurrency prices adjust relative to the dissemination of news.

If the cryptocurrency market is in fact traded by informed investors, then the Efficient Market Hypothesis would imply the spuriousness of forecasting cryptocurrencies and predict that neither volume nor returns can aid in the prediction of future cryptocurrency prices. Timmermann and Granger (2004) provide reasoning for developing econometric forecasts despite the satisfaction of the classical definition of the Efficient Market Hypothesis. The accumulation and usage of econometric variables that are not relevant to trading profit are not explained by the Efficient Market Hypothesis, since the efficiency is inherent in the common interest shared by investors to make profits. Because each potential variable initially has an uncertain usefulness in forecasting models, success in certain models will remain in the short run until its usage is made known to the adapting market, nullifying a new model's effectiveness.

3.2 Data

This study uses Bitcoin daily price and volume data from www.bitcoincharts.com and exchange rankings are downloaded from data.bitcoinity.org. The primary exchange used is Bitstamp (based in Luxembourg), due to its longevity in comparison to other exchanges as well as its prevalence in existing literature. Bitstamp's sample period starts on July 17, 2010 and ends on November 25, 2017 (N = 2262). For robustness, results will be compared with data from other exchanges. Bitfinex (based in Taiwan) and GDAX (based in the United States) are other popular exchanges, with Bitfinex being the current most popular exchange. Additionally, the now defunct Russian exchange BTC-e and Japanese exchange Mt.Gox are included as they were

historically dominant exchanges. Mt.Gox went bankrupt in 2014 and BTC-e was shut down by U.S. authorities in July 2017. The data sample for BTC-e begin on October 26, 2012 because the data have a significant 50 day gap before that day. My sample for Ethereum is from March 8, 2016 to November 25, 2017 (N = 628) and was collected from www.cryptocompare.com.

The market capitalization of Bitcoin displayed in Fig. 1 illustrate the accelerated growth of Bitcoin, one of which can be evidenced by the Cyprus bailout of 2013 (Luther and Salter 2017). When Cyprus announced bank bailout and imposed banking restrictions, Bitcoin app searches significantly increased in the country and Spain who also had banking instabilities in 2013.

The distribution properties of each Bitcoin series is presented in the summary statistics table (Table 1). Daily Bitcoin price, volume, returns, and the detrended volume are shown. It is observed that the large standard deviation values for Bitcoin prices and volumes suggest that these series are highly deviated from the mean. Volume is shown to be much more volatile than returns. The skewness and kurtosis values imply non-normality of price and volume.

Table 1: Summary Statistics for Bitcoin (Exchange: Bitstamp)

	Price	**Volume**	**Returns**	**Detrended Volume**
Mean	664.0558	8546812	.3297877	7.01e-10
Median	338.9793	2405452	.2233982	-.1538981
Minimum	2.2475	1.2275	-76.02333	-7.217244
Maximum	8430.349	2.26e+08	72.44698	4.584148
Std. Dev.	1182.653	1.95e+07	5.202741	1.5829
Skewness	3.620129	4.864968	-2.610947	.1723076
Kurtosis	17.59635	34.63182	74.51483	3.057315

Notes: N = 2262. Std. Dev. is standard deviation.

Bitcoin prices and trading volume are non-stationary as evidenced by unit-root tests (Appendix B). Since our econometric analysis requires stationary series, Bitcoin prices are transformed into a logged difference series:

$$r_t = 100 * [\ln(p_t) - \ln(p_{t-1})] \tag{1}$$

where p_t is the daily closing price of Bitcoin at time t and r_t represents the computed Bitcoin returns. Trading volume is detrended by regressing its logarithmic form against other covariates and saving the residuals given by ϵ_t for my empirical method:

$$\ln(v_t) = \alpha + \beta\left(\frac{t}{T}\right) + c\left(\frac{t}{T}\right)^2 + \epsilon_t \tag{2}$$

where v_t is trading volume and T is the total size of each respective sample series.

There are multiple techniques for transforming data series into stationary form. Transforming prices via the logarithmic function is more deeply discussed in Lo and Wang (2000). The bid-ask spread in financial markets factor into trading costs which means the actualized costs expressed as a percentage are inversely related to price levels. My detrending technique for trading volume is motivated by multiple papers (Gallant, Rossi, and Tauchen 1992; Chuang, Kuan, and Lin 2009; Gebka and Wohar 2013). The quadratic detrending method is akin to a band limited filter which removes very low frequency behavior and thus removing long-run volume trends. The stationarity property of our variables of interest are confirmed through visual inspection (Figures 3b, 3d) and formal unit-root tests (Appendix B).

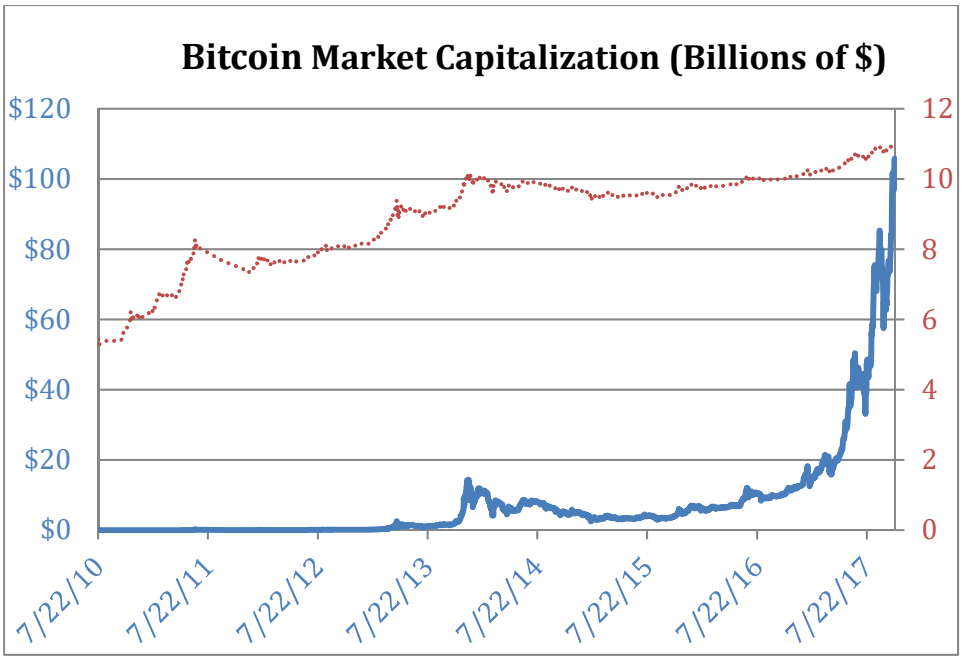

Fig 1. Market Capitalization of Bitcoin in USD (linear in blue, log in dotted red)

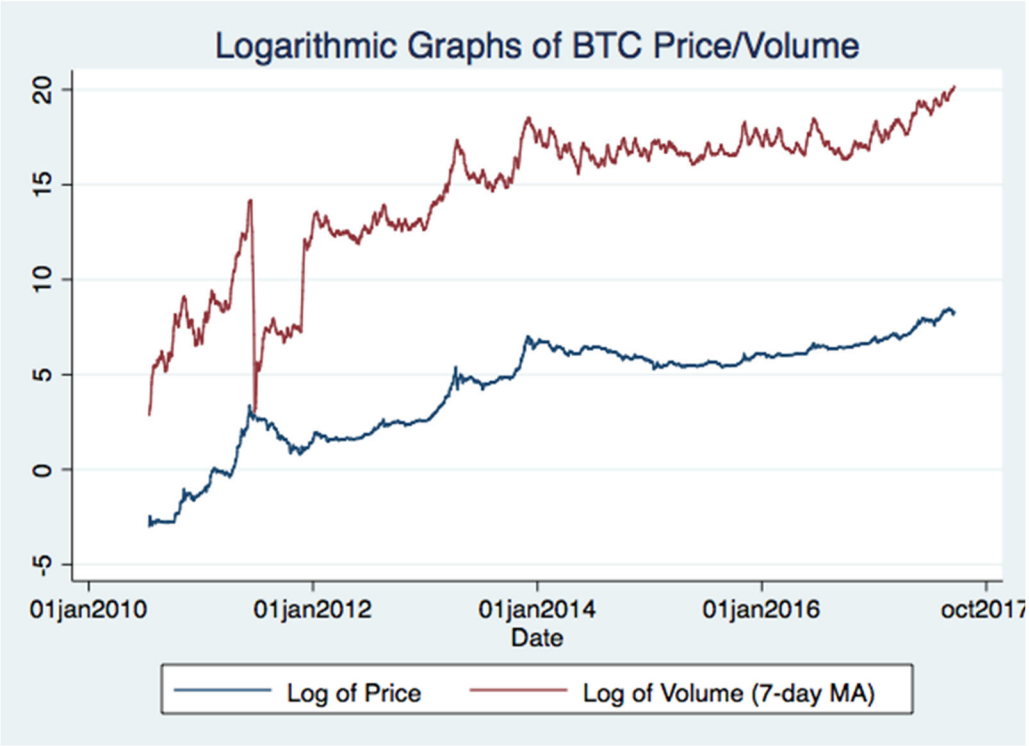

Fig 2. Logarithmic Price (bottom) and Volume of Bitcoin (top)

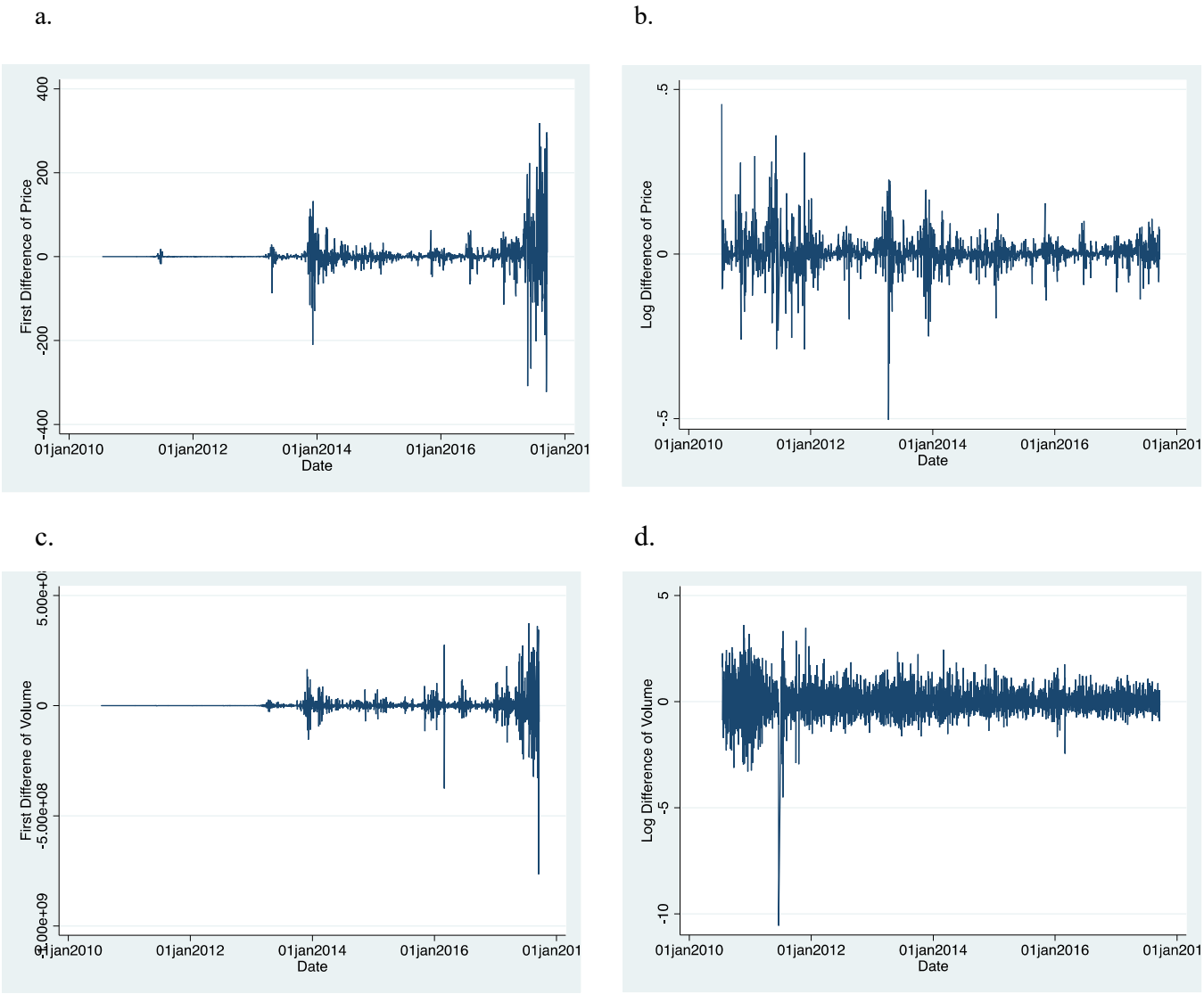

Fig 3. a) First difference of closing price of Bitcoin. b) Log difference of closing price of Bitcoin.

c) First difference of Bitcoin trading volume. d) Log difference of Bitcoin trading volume.

4. Empirical Model

I use the non-parametric, causality-in-quantiles test of Balcilar et al. (2016, 2017) to analyze the causal relationship between price and volume of cryptocurrencies. Their model extends the distance function utilized by Jeong, Härdle, and Song (2012) and the non-parametric Granger quantile causality model by Nishiyama et al. (2011). This newly developed technique addresses the nonlinearity of the price-volume relationship of Bitcoin and other cryptocurrencies. Nonlinearity in these data are established by Balcilar, otherwise these Granger causality tests could have been performed using a vector autogression (VAR) model or a vector error correction model (VECM).

If x_t does not cause y_t in the θth quantile, then the following equation is held:

$$Q_\theta\left(y_t \middle| y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\right) = Q_\theta(y_t | y_{t-1}, \dots, y_{t-p}) \tag{3}$$

where $Q_\theta(y_t| \dots)$ is the θth quantile of y_t dependent on t and $0 < \theta < 1$. Based on Equation (2), the following hypotheses tests are derived:

$$H_o : P\left\{F_{(y_t|Z_{t-1})}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1 \tag{4}$$

$$H_1 : P\left\{F_{(y_t|Z_{t-1})}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1 \tag{5}$$

where $Z_t = (X_t, Y_t) \ni X_{t-1} \equiv \left(x_{t-1}, \dots, x_{t-p}\right)$ *and* $Y_{t-1} \equiv \left(y_{t-1}, \dots, y_{t-p}\right)$. $F_{(y_t|Z_{t-1})}\{y_t|Z_{t-1}\}$ represents the conditional distribution function of y_t given Z_{t-1}. It follows after denoting $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$ and $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ then $F_{(y_t|Z_{t-1})}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$ with probability one. In addition to interpreting the causality-in-means, the higher order can be modelled in order to test the volatility causality of cryptocurrencies between volume and price:

$$H_o : P\left\{F_{\left(y_t^k|Z_{t-1}\right)}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1 \; \forall \; k \in [1, \dots, K] \tag{6}$$

$$H_1 : P\left\{F_{\left(y_t^k|Z_{t-1}\right)}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1 \; \forall \; k \in [1, \dots, K] \tag{7}$$

x_t Granger causes y_t in the θth quantile up to the K-th moment. I may then gather test statistics from each horizon k. Since each test statistic k are mutually correlated and cannot be combined into a joint null hypothesis, the sequential test devised by Nishiyama et al. (2011) and modified by Balcilar et al. (2016) must be used to allow for testing in higher moments. It should be noted that a failure to reject the null in quantile causality-in-means does not necessarily also reject the null for quantile causality-in-variance.

To measure return volatility, the GARCH(1,1) series and squared values of returns and are used separately to estimate the variance in Bitcoin price. These variance series are then used in the causality-in-quantiles computation.

5. Results

Preliminary results for the causality-in-quantiles test for Bitcoin returns and volatility from volume are presented in Figures 4 and 5 in the 0.01 – 0.99 quantile range. These figures account for all Bitcoin exchanges in our data sample. The null hypothesis (t-statistic of 1.96) is that volume does not Granger cause returns/volatility. I find that the null hypothesis of volume not Granger causing returns is rejected at the five percent significance level over the quantile ranges of 0.03 – 0.35 and 0.55 – 0.98. This suggests that Bitcoin trading volume can predict returns over the majority of the conditional distribution except for the middle quantiles. These findings refute the main findings of Balcilar et al. (2017), who concluded that volume has no predictive power during bear and bull markets. My results align more towards the similarity between Bitcoin and equities where trading volume is connected with high or low values of returns. The null hypothesis of volume not Granger causing volatility is rejected throughout the majority of the quantile range, with the exception of the extremities. This is supported by Figure

6, where I use the variance calculated from the GARCH(1,1) model to achieve similar results. Thus, I conclude that Bitcoin volume does indeed predict volatility except during extremely low or extremely high volatility. These findings also directly refute those of Balcilar et al. (2017). Additional individual graphical results for each exchange can be found in Appendix C. While there are similar statistically significant results supporting Granger causality between Bitcoin volume and returns for Bitfinex and BTC-e, the rejected quantile ranges differ for GDAX and Mt. Gox. For example, the null hypothesis of volume not Granger causing returns for GDAX is rejected for the entire quantile range over 0.08. Also, there are failures to reject the null for Mt. Gox from 0 to 0.08 and all quantiles above 0.47.

I also apply these same time series procedures to Ethereum data. Interestingly, the null hypothesis that volume does not Granger cause Ethereum returns is rejected throughout the entire conditional distribution, whereas the null for causality-in-variance is rejected in the quantile range of 0.15-0.86.

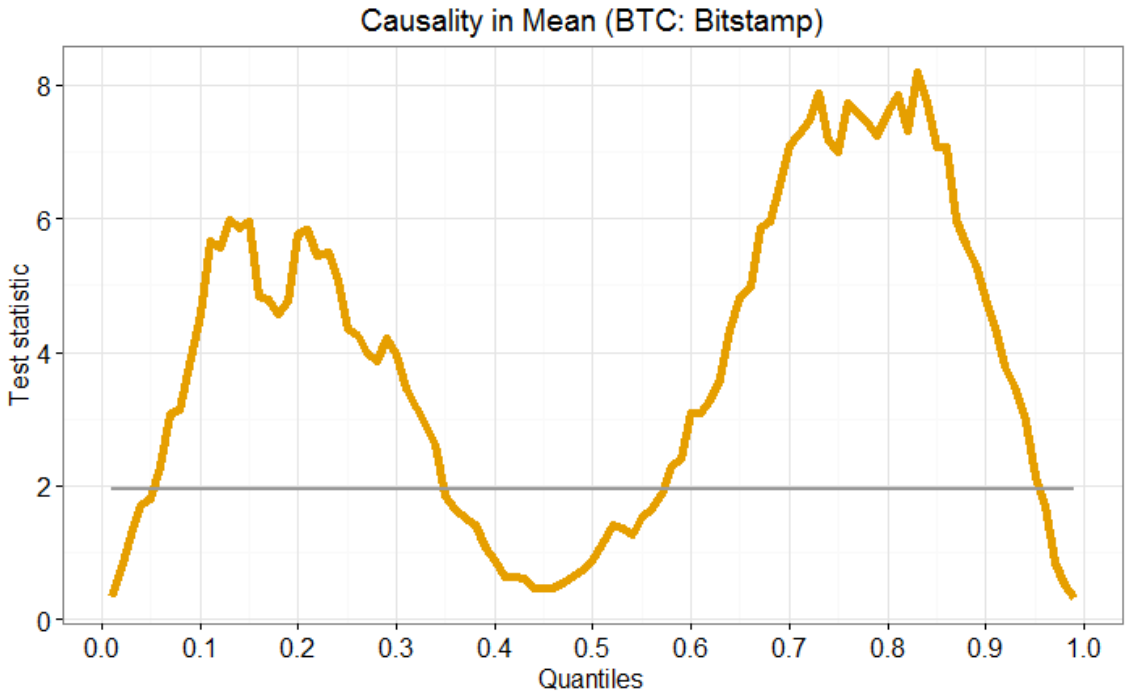

Fig 4. Causality-in-Quantiles. H_o: Volume does not Granger cause Bitcoin Returns.

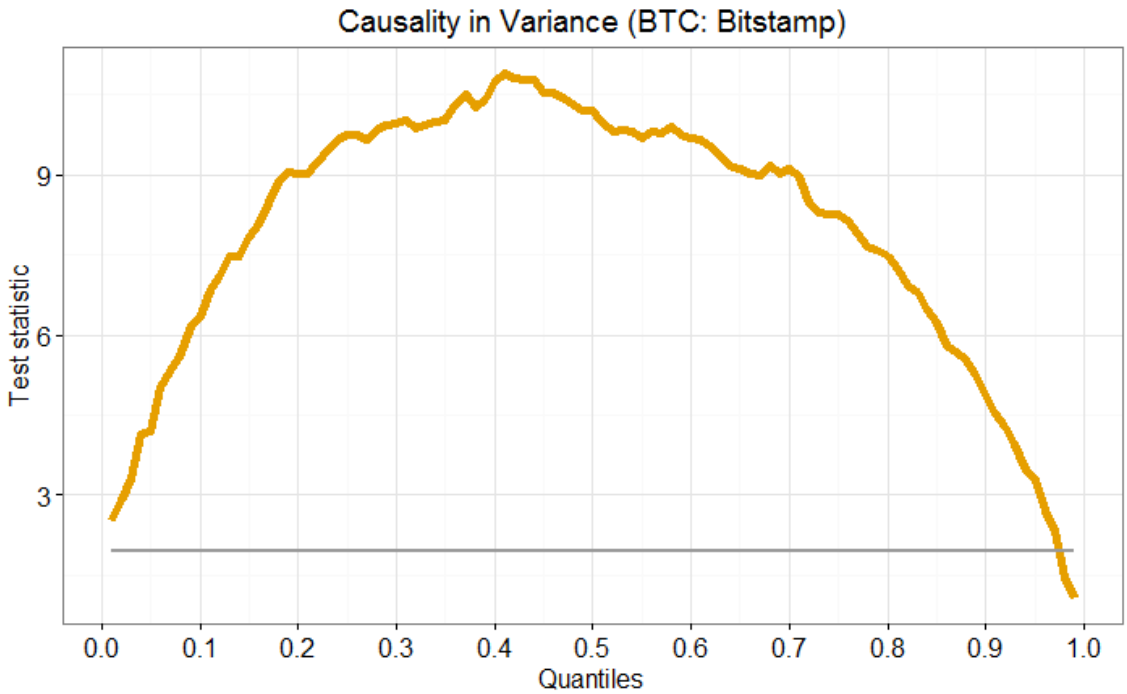

Fig 5. Causality-in-Quantiles. H_o: Volume does not Granger cause Bitcoin Volatility.

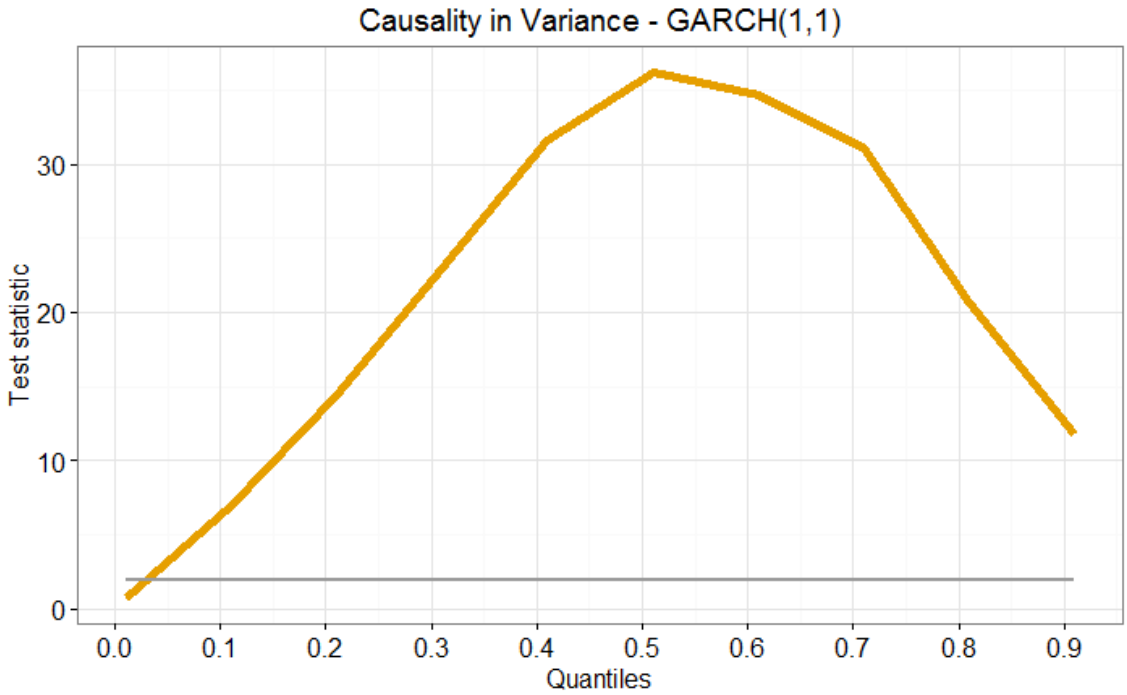

Fig 6. Causality-in-Quantiles. H_o: Volume does not Granger cause Bitcoin GARCH-based Volatility.

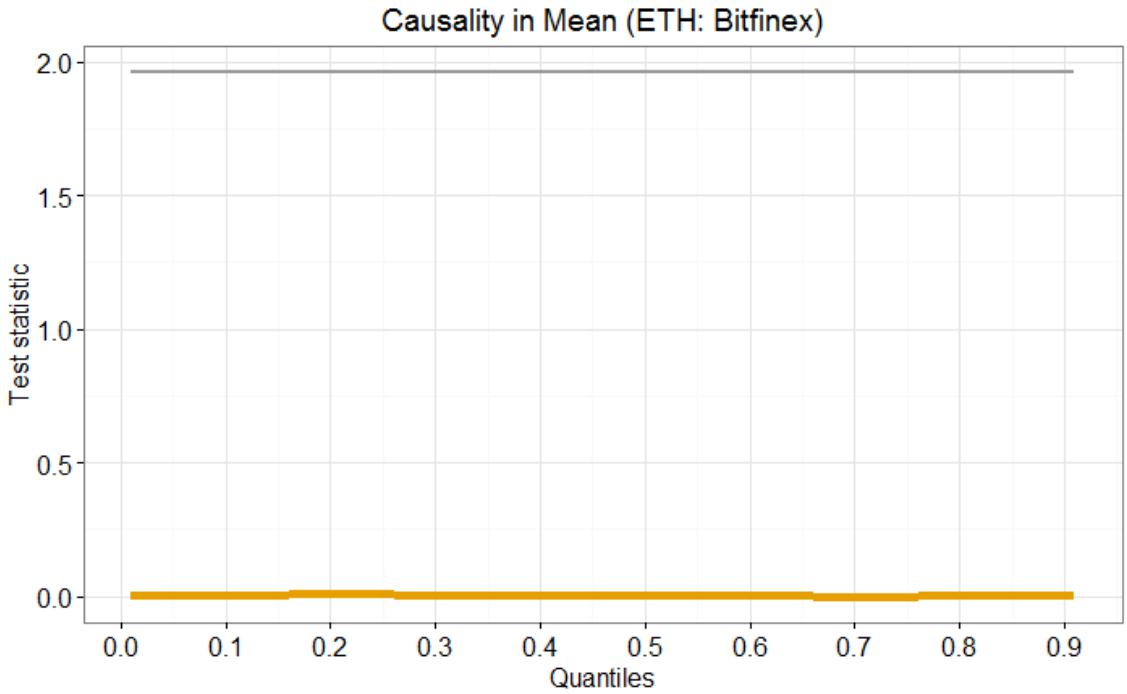

Fig 7. Causality-in-Quantiles. H_o: Volume does not Granger cause Ethereum Returns.

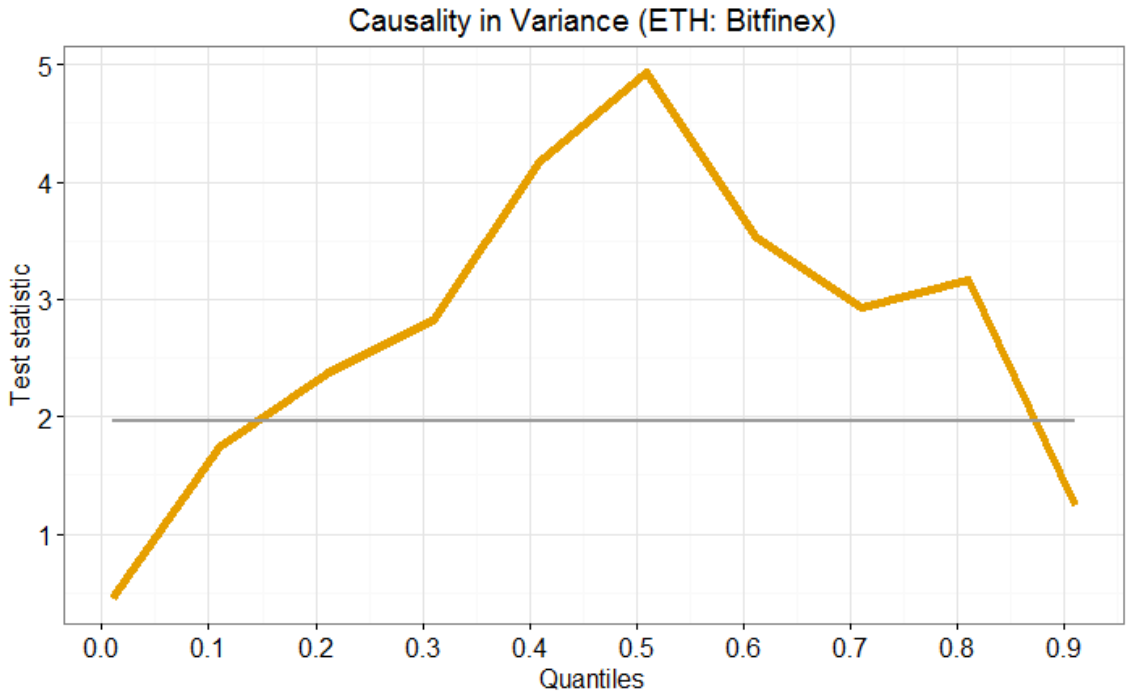

Fig 8. Causality-in-Quantiles. H_o: Volume does not Granger cause Ethereum Volatility.

6. Conclusion

This paper explores the application of time series modelling of cryptocurrencies by evaluating the forecasting power of trading volume in predicting returns and volatility. After confirming the data series for stationarity through standard unit-root tests, I apply the non-parametric quantile-in-causality tests developed by Balcilar et al. (2016) to study the Granger causality of cryptocurrency trading volume on returns and volatility. I reject the null hypothesis that volume Granger causes returns at the quantile ranges of 0.03 – 0.35 and 0.55 – 0.98. Additionally, the hypothesis that volume Granger causes volatility is rejected over the majority of the conditional distribution. Finally, I apply the same method on Ethereum data and find that while causality-in-variance is established throughout most of the quantile range, causality-in-means fails to reject the null entirely.

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Appendix A

One informal method for testing stationarity in a series is by inspecting the autocorrelation of each variable. For example, by comparing the autocorrelations between Bitcoin prices and returns, it is clear that the nonstationary price declines extremely slowly, whereas the stationary returns decline extremely rapidly.

a. b.

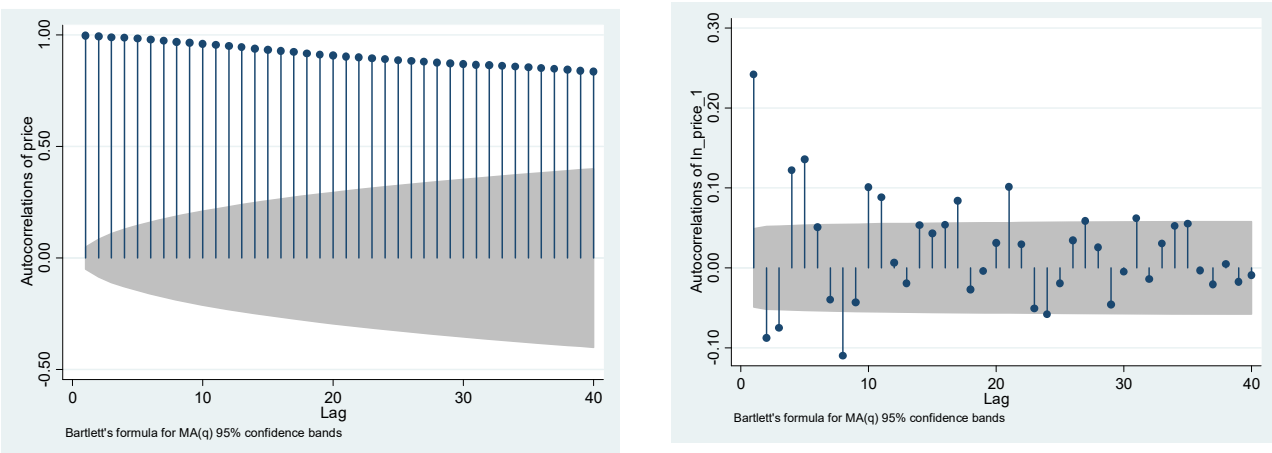

Fig 3. a) Autocorrelations of Bitcoin price (all exchanges). b) Autocorrelations of Bitcoin returns.

Appendix B

Table 2: Summary of Bitcoin Stationarity Tests

	ADF	KPSS	PP	DF-GLS
Price	No	No	No	No
Volume	Yes	No	Yes	No
$Price_{t-1}$	Yes	No	Yes	No
$Volume_{t-1}$	Yes	Yes	Yes	No
Log Price	No	No	No	No
Log Volume	Yes	No	Yes	No
Returns	Yes	Yes	Yes	Yes
Detrended Volume	Yes	N/A	Yes	N/A

The Augmented Dickey-Fuller (ADF) test for unit root is the usual starting point in determining time series stationarity. However, ADF tests are generally considered to have low statistical power due to the near observation equivalence problem, where the test fails to distinguish between true unit-root processes and near unit-root processes. The Kwiatkowski–Phillips–Schmidt–Shin (KPSS; 1992) test assesses time series stationarity around a deterministic trend. Since detrended volume already has its deterministic trend removed, the KPSS test cannot be performed. The Phillips–Perron (PP; 1988) test, unlike the ADF test, adds trend terms and only includes one lag in its regression estimation. Lastly, the DF-GLS test is a modification of the Dickey-Fuller test (Elliott, Rothenberg, and Stock 1996). There is an initial detrending step via a GLS method.

Appendix C

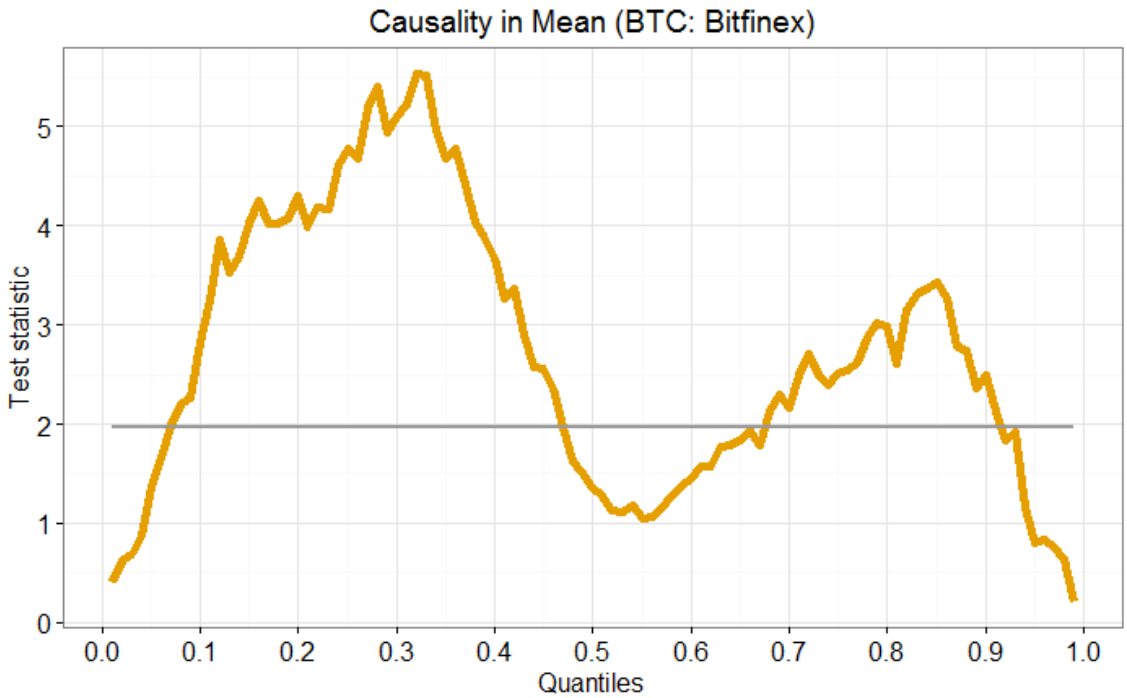

Fig 9. Causality-in-Quantiles. H_o: Volume does not Granger cause Bitcoin Returns.

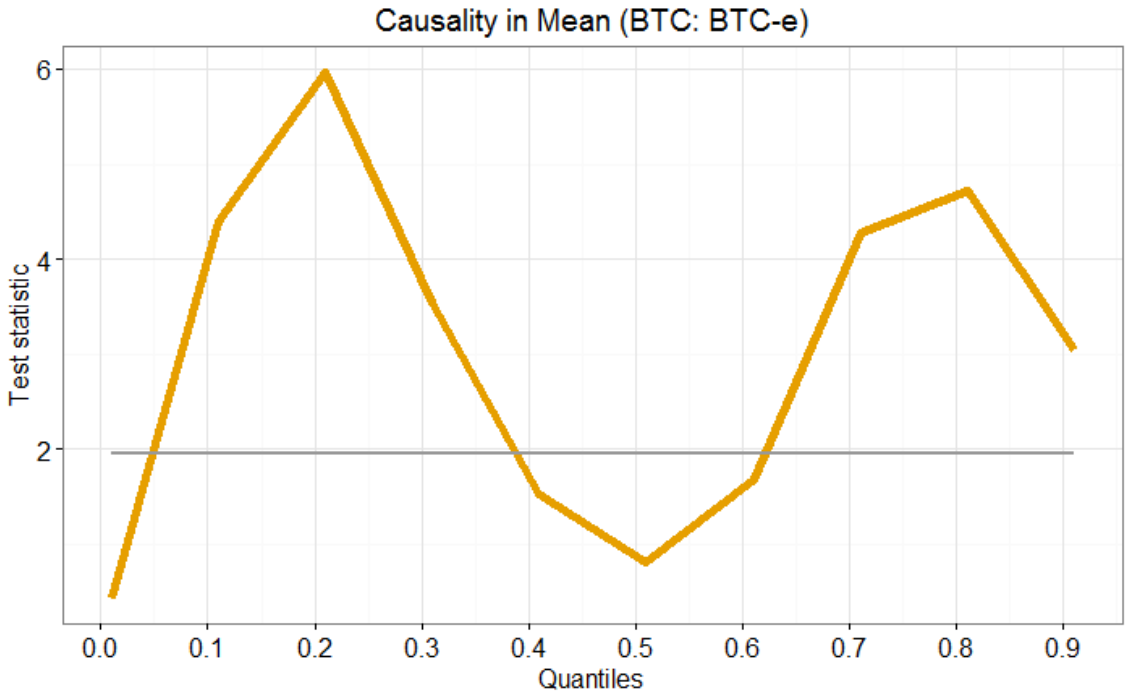

Fig 10. Causality-in-Quantiles. H_o: Volume does not Granger cause Bitcoin Returns.

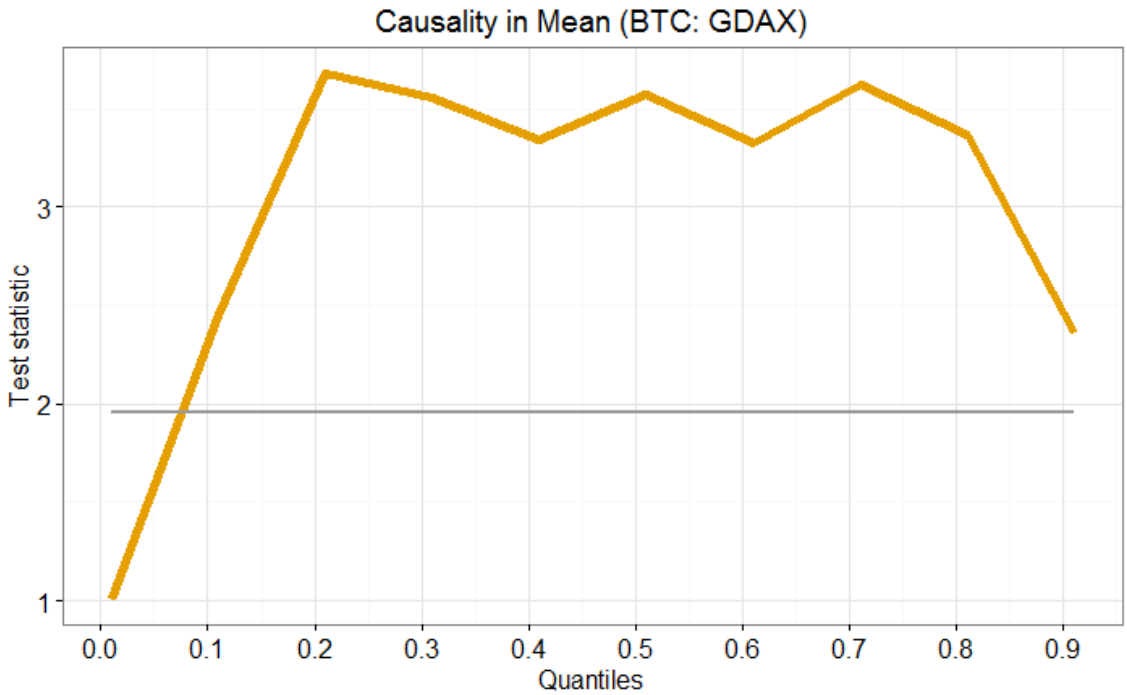

Fig 11. Causality-in-Quantiles. H_o: Volume does not Granger cause Bitcoin Returns.

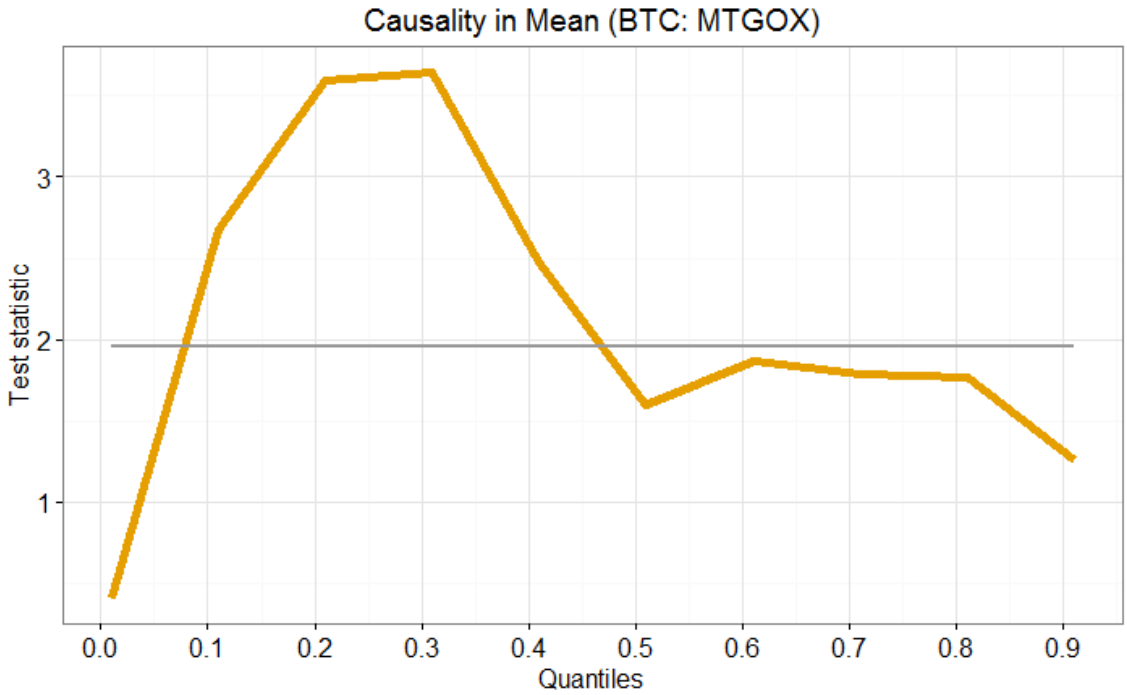

Fig 12. Causality-in-Quantiles. H_o: Volume does not Granger cause Bitcoin Returns.

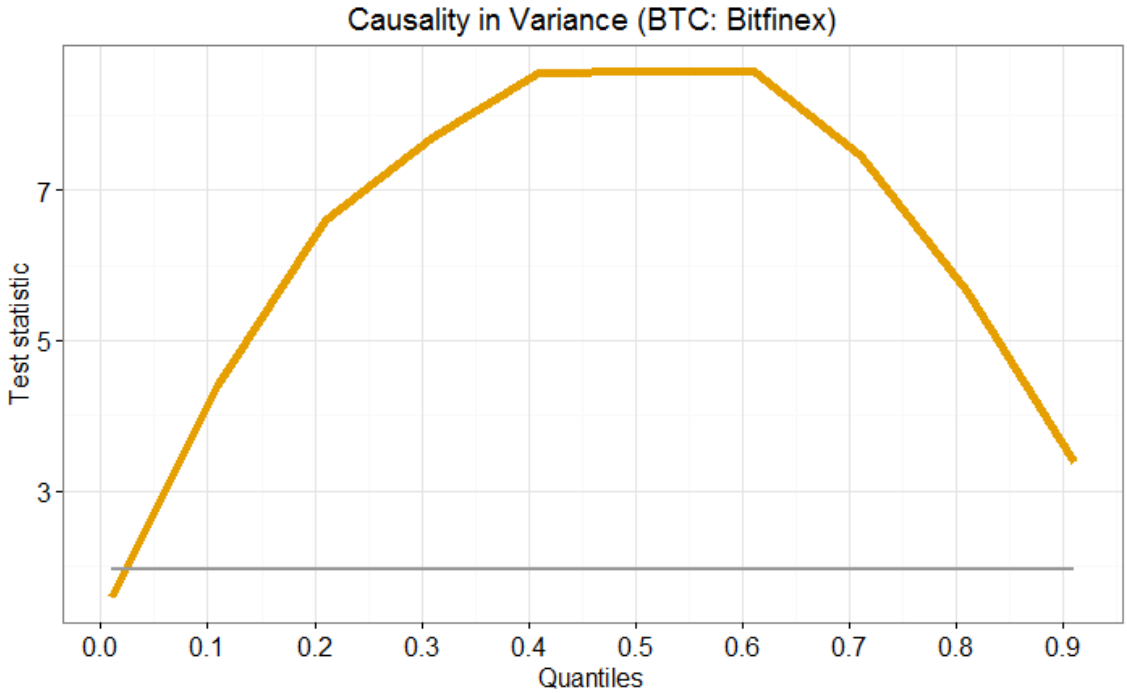

Fig 13. Causality-in-Quantiles. H_o: Volume does not Granger cause Bitcoin Volatility.

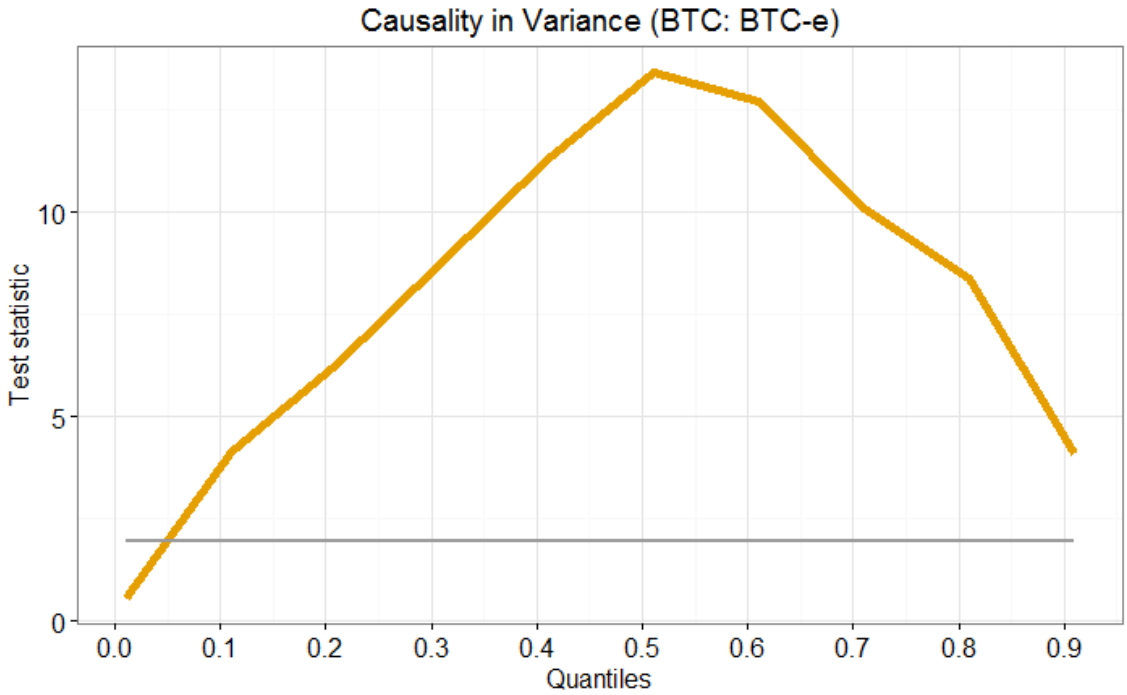

Fig 14. Causality-in-Quantiles. H_o: Volume does not Granger cause Bitcoin Volatility.

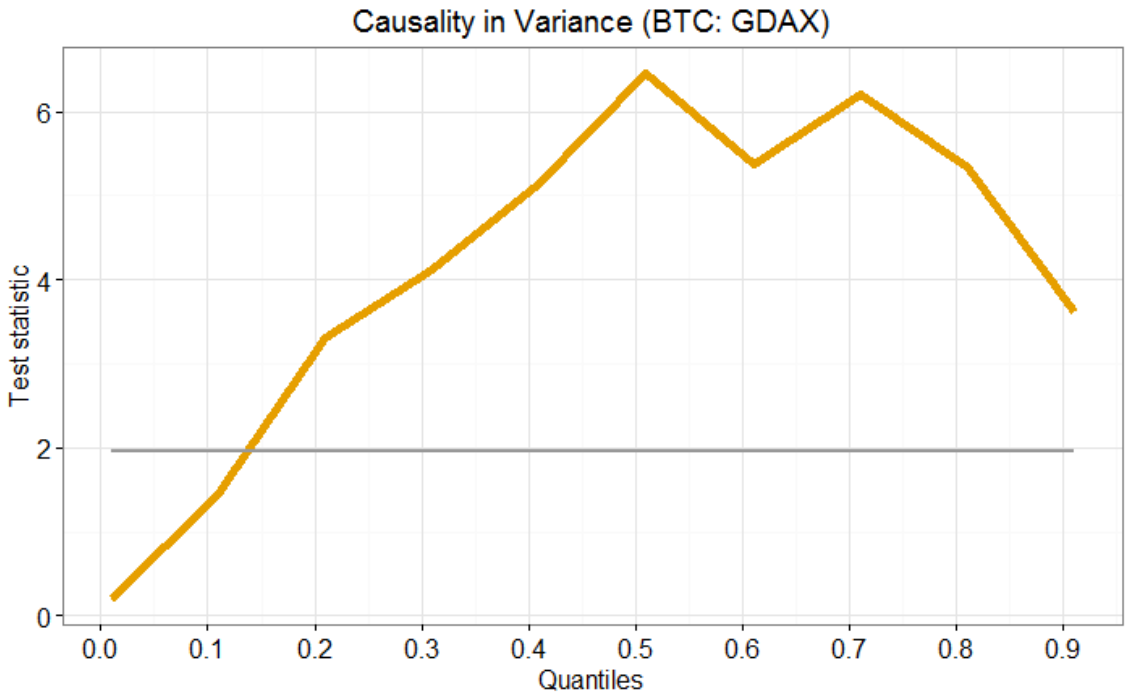

Fig 15. Causality-in-Quantiles. H_o: Volume does not Granger cause Bitcoin Volatility.

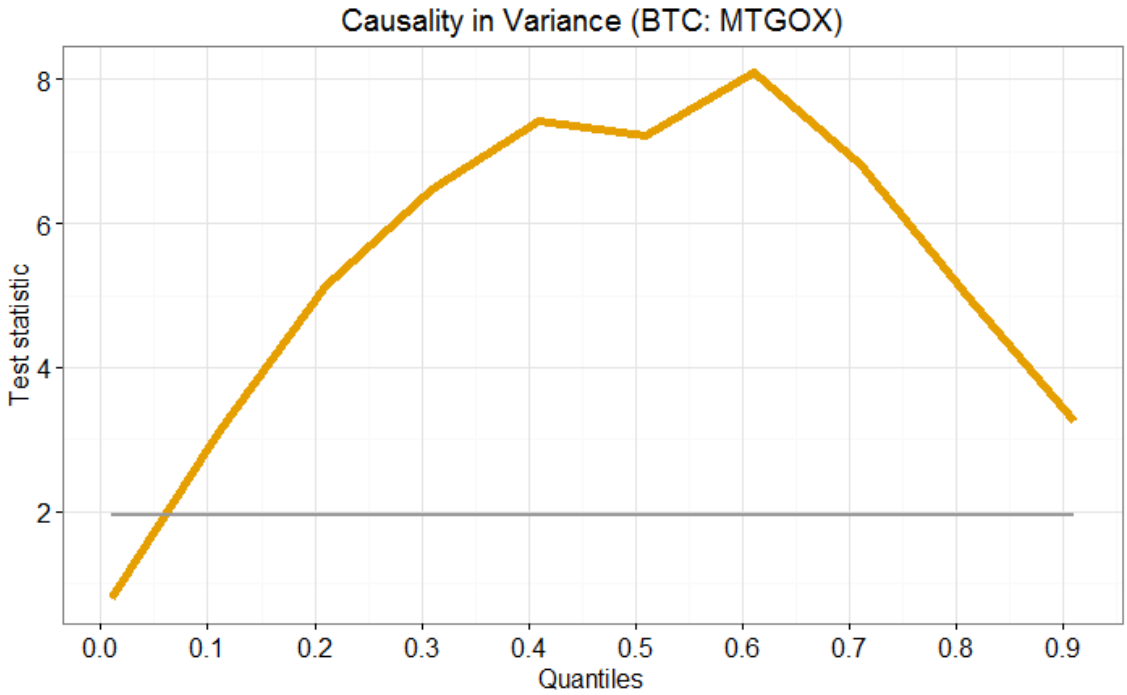

Fig 16. Causality-in-Quantiles. H_o: Volume does not Granger cause Bitcoin Volatility.