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Causal relationships between cryptocurrencies: the effects of sampling interval and sample size

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Abstract: For this paper, the relationship between seventeen popular cryptocurrencies was analyzed by multivariate Granger causality tests and simple linear regression, using data spanning the period 1 September 2020 to 8 December 2021. The novelty of this work is that it studies the effects of sampling interval and sample size in cryptocurrency markets, which can yield significantly different results. Minute-by-minute, hourly and daily data were collected to examine the Granger causality relationship between cryptocurrencies. It was found that all the currencies demonstrated a significant causality relationship when high frequency (such as minute-by-minute) data was used, in contrast to hourly and daily data. The bigger the sample size, the higher the probability of rejecting the null hypothesis. Hence, the null hypothesis for the Granger causality test can be rejected for minute-by-minute time series data because of too large a sample size. Granger causality test results for hourly and daily data indicated that Bitcoin, Ethereum Classic, and Neo were leading indicators among the cryptocurrencies included in the research. In addition, according to simple linear regression analysis, the short term marginal effect of Bitcoin plays an important role by creating significant impacts on other cryptocurrencies.

Keywords: cryptocurrency; multivariate Granger causality test; sample size; sampling interval; simple linear regression.

JEL Classification: C5; F3; G1.

1 Introduction

Digital platforms and globalization have made it necessary for the world to use virtual assets. Cryptocurrency markets emerged with Bitcoin (Nakamoto 2008), and there are now many coins that try to attract funds in large amounts in exchange markets. Cryptocurrencies create value by digital connection and energy resources (Yan et al. 2022). They are widely accepted in all countries even if they do not have a physical identity. There is a free market environment, and this gives both professionals and ordinary individuals easy access to cryptocurrencies. This is a revolution in the financial markets because these valuable virtual assets have expanded the concept of investments from conventional investments such as stock exchanges, foreign currencies, gold and bonds to cryptocurrencies. These new assets have become a reality and attracted a large amount of investments around the globe. Unlike conventional investments, cryptocurrency markets are open to spot sale for twenty four hours a week. Investors can connect to this market even via mobile phones. This has made it easy for people to invest their savings with many options, using cryptocurrencies not only for buying and selling, but also

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for earning interest, or being used for futures. Moreover, most of the companies are also engaged in this digital market for garnering funds by issuing coins. This market gives investors the opportunity to diversify their portfolios (Culjak et al. 2022). Cryptocurrencies can also serve as safe havens. It has been found that they behave as safe havens during panics in financial markets (Corbet et al. 2022). They can also be attractive for risk-appetite investors. Both individuals and firms have significant power to influence the market (Breidbach and Tana 2021). Returns and volatility can be explained by the attention of investors (Guindy 2021; Li et al. 2021a; Smales 2022). In addition, cryptocurrencies can behave as speculative assets. This means they cannot be predicted by conventional assets. Therefore, it is important to conduct a causal relationship analysis to predict their behaviors in the markets using a high frequency and big data sample.

The impact of conventional assets, commodities and stock exchanges on the cryptocurrencies, and also their impacts on these indicators, have been comprehensively analyzed (Caferra 2022; Cao and Ling 2022; Lahiani et al. 2021). Canh et al. (2019a) studied the diversification capability of seven cryptocurrencies against risks from the oil price, the gold price, interest rate, USD strength, and S & P500 by using weekly data between August 2014 and June 2018. It was found that causality between cryptocurrencies and economic factors was undirected. The results implied that cryptocurrencies could not be assumed as financial assets to hedge risks caused by economic factors. However, the causal relationship between cryptocurrencies has been neglected in terms of high frequency by using minute-by-minute data. When a large data sample is considered, it can be seen that research about how a change in one cryptocurrency can impact on those in others remains limited. This work is going to fill this gap in the research. For conventional empirical analysis, it is difficult to collect high frequency data, but for this digital market, it is easy to select minute-by-minute, hourly and daily data for analysis. The cryptocurrency markets have become important but there is not enough information on how these coins impact upon each other. Hence, this work is going to focus on a comparative analysis of the effects of sampling intervals and sample size between seventeen cryptocurrencies, listed in the tables. For the research, it was assumed that both a multivariate Granger causality test and simple linear regression can be used to examine the connection between the currencies. Twenty-four-hour markets are favorable for analyzing causality relationships by examining big data. The main questions of this work are as follows: First, what is the causal relationship between the currencies on a minute-by-minute, hourly and daily basis? Second, which is the leading currency – that which has the largest impact? This work is going to find answers to these questions.

It can be observed in the cryptocurrencies when the trend is downward, all currencies usually experience falling prices. It was estimated that there is connection between Bitcoin volume and returns and the volumes of other cryptocurrencies (Yarovaya and Zieba 2022). This indicates that the trading volume of Bitcoin can impact on changes of other players in the financial market. Moreover, it is expected that the Bitcoin price can be dominant, with a larger impact than other coins. Comparing sampling interval and sample size could help understand how movements can be differentiated. Most research is more limited with daily data. This paper goes beyond this by including minute-by-minute and hourly data. The world is becoming more connected to twenty-four-hour cryptocurrency markets and instant investments are crucial. Hence, this can help investors diversify their portfolios between currencies and decide how to invest. To our knowledge, this work is the first to analyze the relationship between cryptocurrencies by considering both different sampling intervals (data frequencies) and a large sample size for the comparison of minute-by-minute, hourly and daily data. Causal relationships analysis data were between seventeen cryptocurrencies. This research showed significant connections among cryptocurrencies when minute-by-minute data were in the analysis. However, the Granger causality test results for hourly and daily data indicated that Bitcoin, Ethereum Classic, and Neo could be leading indicators. In addition, simple linear regression analysis showed that Bitcoin could significantly affect other cryptocurrencies. According to the study, causal relationships can be present when the analysis employs high frequency data, even if there might not be any actual causal relationship. Henceforth, researchers, policy-makers, portfolio managers, and investors should consider alternative methods, sampling intervals, and sample sizes in big data analysis.

The paper is organized as follows: In Section 2, previous research and the novelty of current work were discussed. In Section 3, how data was collected explained. In Section 4, multivariate Granger causality test and simple linear regression analysis were conducted. Section 5 is discussion. In Section 6, the paper is concluded.

2 Previous research and the current work

2.1 Previous research

Research about the relationship between cryptocurrencies is more limited when high frequency is considered. Nevertheless, there are some recent works that have considered the relationship between coins. Naeem et al. (2022) investigated connectedness network of returns by using standard VAR and quantile vector autoregression (VAR) spillovers, focusing on daily data from 7 August 2015 to 31 October 2020. The research highlighted that Bitcoin, Litecoin and Ripple were dominant transmitters to return spillover. Moreover, it was found that Ethereum can be influenced by most cryptocurrencies. Bouri et al. (2021) applied quantile-based connectedness measures via a quantile VAR model using daily price data of seven cryptocurrencies for the period between 8 August 2015 and 31 December 2020. It was pointed out that extreme events caused stronger connectedness than calm periods. Li et al. (2021b) investigated MAX effects between cryptocurrencies for daily data between 1 January 2014 and 30 June 2020. It was estimated that higher daily returns create higher returns in the future. Moratis (2021) used Bayesian VAR analysis to investigate spillover effects in the cryptocurrency market using daily data between 10 October 2016 and 28 May 2020. It was found that Bitcoin dominates spillover in the market. Kim et al. (2021) implemented a Granger non-causality tests in quantiles to investigate causality relationships among eight popular cryptocurrencies by using daily data spanning from 23 July 2017 to 28 November 2019. The results of the non-causality tests indicated that there was a significant causal relationships in the tail quantiles. Hence, it was mentioned that it could be hard for investors to hedge risks in cryptocurrency markets. Schinckus et al. (2020) used a network analysis to explore interdependences among a large number of cryptocurrencies for daily period between 28 April 2013 and 14 July 2018. It was estimated that although Bitcoin is the older and the most famous cryptocurrency, it is not an influential asset on the virtual cryptocurrency market. Canh et al. (2019b) used cumulative sum test for parameter stability, Granger causality test, LM test for ARCH and DCC-MGARCH model to investigate structural breaks and volatility spillovers in seven largest cryptocurrencies including Bitcoin, Litecoin, Ripple, Stellar, Monero, Dash, and Bytecoin by using daily data between 5 August 2014 and 31 December 2018. It was mentioned that the structural breaks are universally presents in these cryptocurrencies, and the shifts spread from smaller cryptocurrencies to larger ones. Moreover, volatility spillovers exist with strong positive correlations among cryptocurrencies. Tu and Xue (2019) implemented Granger causality test and a BEKK-MGARCH model to analyze the return and volatility spillovers between Bitcoin and Litecoin by using daily data spanning from 28 April 2013 to 31 July 2017. This work indicated that shock-transmission being reversed from Litecoin to Bitcoin after bifurcation.

2.2 The current work and research gap

Previous studies are highly likely to ignore the causal relationships in different sampling intervals and sample sizes. These works are limited to daily data. Contrary to previous studies, this paper includes more leading cryptocurrencies with data in different frequencies, such as minute-by-minute, hourly and daily data. Our work proves that Granger causality can be present among cryptocurrencies in minute-by-minute analysis. In other words, sampling intervals and sample size affect causality analysis. In addition, previous works did not discover that high frequency data would lead to significant causal relationships between variables. In the big data world, this work highlights that the Granger causality test finds relationships among variables when high frequency data are in the analysis. In other words, the null hypothesis for the Granger causality test can be rejected because of the too-large sample size. This is a novelty for researchers to consider this situation when applying causality tests. This will help them create favorable discussions and meaningful results.

3 Data collection

Binance was used for the collection of variables because this data base makes data available at the three levels of frequency required for our statistical analysis. This cryptocurrency exchange application is widely used around the globe. Moreover, it is assumed that this database is an honest platform compared with other emerging crypto applications (Chen et al. 2022). It shows instant changes in the figures and provides the opportunity to compare with other cryptocurrencies. Vidal-Tomás (2022) examined several exchange platforms in cryptodatadownload.com for the underlying process of Bitcoin. It was found that this database is appropriate for the conduct of research. In this paper, the available data was collected for Binance exchange platform from cryptodatadownload.com for seventeen cryptocurrencies over the period between 1 September 2020 and 8 December 2021. These are described as follows: *Bnb* (Binance), *Btc* (Bitcoin), *Btt* (Bittorrent), *Cel* (Celsius), *Dash* (Dash), *Eos* (EOS), *Etc* (Ethereum Classic), *Eth* (Ethereum), *Link* (Chainlink), *Ltc* (Litecoin), *Neo* (Neo), *One* (One), *Qtum* (Qtum), *Trx* (Tronix), *Xlm* (Stellar), *Xmr* (Monero) and *Zec* (Zcash).

4 Empirical analysis

4.1 Unit root test results

To check the stationarity of the variables in a robust manner, two alternative unit root tests, Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP), were used. The unit root test results are reported in Table 1. Both ADF and PP unit root test results indicate that the integrated order of each variable is one for minute-by-minute, hourly, and daily data. These results show that all series are stationary in the logarithmic first difference.

4.2 Multivariate Granger causality tests

Causality was defined as in Granger (1969): a variable y causes a variable x if the variance of the forecast error of x obtained by using the past of y is smaller than the variance of the forecast error of x obtained without using the past of y. The Granger causality test is sensitive to a misspecified lag length, insufficiently frequent observations, too small a sample, or the lack of Granger causality even if philosophical causation occurs.

In empirical studies, the causal relationship between two variables is commonly estimated by applying the traditional Granger causality test proposed by Granger (1969). While the traditional Granger causality test is easy to carry out, it has its limitations. For instance, the test is sensitive to model specification and the number of lags included. In a multivariate time series, bivariate causality measures may estimate indirect causality from x to y stemming from intermediate interaction with another variable z, e.g., from the direct causal effect $x \to z$ and $z \to y$, the indirect causal effect $x \to y$ arises. Thus, bivariate analysis cannot distinguish between direct and indirect causal effects and may give erroneous results when applied to multivariate systems. Therefore, it is essential to account for the presence of the other observed variables of a multivariate time series when testing for directional relationships between two variables. Multivariate causality measures utilize all the

Table 1: Unit root test results.

Minute-by-minute data										
	Logarithmic level					Logarithmic first difference				
Variable	Lag	ADF	p-Value	PP	p-Value	Lag	ADF	p-Value	PP	p-Value
Bnb	36	−1.21	0.6723	−1.22	0.6693	35	−138.38	0.0001	−791.20	0.0001
Btc	28	−2.21	0.2030	−2.22	0.2008	27	−160.24	0.0001	−790.57	0.0001
Btt	48	−1.16	0.6951	−1.15	0.6985	47	−118.17	0.0001	−802.94	0.0001
Cel	10	−1.05	0.7381	−0.97	0.7643	9	−259.32	0.0001	−826.95	0.0001
Dash	28	−1.96	0.3063	−1.91	0.3263	27	−157.49	0.0001	−770.03	0.0001
Eos	28	−2.29	0.1756	−2.24	0.1938	27	−158.02	0.0001	−782.68	0.0001
Etc	37	−1.26	0.6524	−1.25	0.6557	36	−137.11	0.0001	−787.10	0.0001
Eth	38	−1.38	0.5933	−1.38	0.5922	37	−133.88	0.0001	−794.33	0.0001
Link	29	−2.06	0.2607	−2.03	0.2726	28	−156.24	0.0001	−783.19	0.0001
Ltc	29	−2.11	0.2413	−2.08	0.2511	28	−158.42	0.0001	−795.82	0.0001
Neo	29	−1.66	0.4498	−1.65	0.4583	28	−155.21	0.0001	−786.76	0.0001
One	29	−0.82	0.8136	−0.82	0.8139	28	−157.05	0.0001	−811.40	0.0001
Qtum	25	−1.36	0.6035	−1.34	0.6128	24	−166.23	0.0001	−779.89	0.0001
Trx	17	−1.24	0.6588	−1.21	0.6718	16	−193.12	0.0001	−777.02	0.0001
Xlm	31	−1.96	0.3040	−1.94	0.3121	30	−152.30	0.0001	−789.81	0.0001
Xmr	28	−2.51	0.1129	−2.48	0.1216	27	−158.22	0.0001	−772.62	0.0001
Zec	57	−1.84	0.3634	−1.88	0.3429	56	−114.44	0.0001	−764.40	0.0001
Hourly data										
Bnb	0	−1.17	0.6876	−1.17	0.6878	1	−77.50	0.0001	−107.17	0.0001
Btc	0	−1.78	0.3911	−1.78	0.3888	0	−105.92	0.0001	−105.96	0.0001
Btt	1	−0.94	0.7757	−0.95	0.7711	0	−111.87	0.0001	−111.75	0.0001
Cel	2	−0.76	0.8295	−0.76	0.8305	1	−78.58	0.0001	−107.10	0.0001
Dash	2	−1.74	0.4101	−1.79	0.3861	1	−78.19	0.0001	−108.34	0.0001
Eos	2	−2.16	0.2222	−2.24	0.1920	1	−78.08	0.0001	−108.92	0.0001
Etc	2	−1.00	0.7565	−1.02	0.7475	1	−79.30	0.0001	−111.70	0.0001
Eth	2	−1.02	0.7500	−1.02	0.7466	1	−77.54	0.0001	−104.29	0.0001
Link	0	−1.93	0.3185	−1.88	0.3443	1	−77.91	0.0001	−107.34	0.0001
Ltc	2	−1.68	0.4395	−1.71	0.4284	1	−79.76	0.0001	−112.09	0.0001
Neo	2	−1.58	0.4934	−1.57	0.4959	1	−78.75	0.0001	−109.85	0.0001
One	2	−0.58	0.8730	−0.58	0.8722	1	−78.67	0.0001	−109.02	0.0001
Qtum	0	−1.25	0.6546	−1.23	0.6621	1	−77.40	0.0001	−107.35	0.0001
Trx	2	−1.30	0.6338	−1.36	0.6046	1	−78.22	0.0001	−106.96	0.0001
Xlm	2	−1.68	0.4439	−1.71	0.4251	1	−79.68	0.0001	−112.61	0.0001
Xmr	2	−2.17	0.2171	−2.22	0.2000	1	−78.22	0.0001	−109.37	0.0001
Zec	1	−1.69	0.4386	−1.65	0.4544	0	−112.96	0.0001	−113.23	0.0001
Daily data										
Bnb	0	−1.19	0.6784	−1.19	0.6785	0	−23.41	0.0000	−23.35	0.0000
Btc	0	−1.79	0.3872	−1.79	0.3857	0	−22.44	0.0000	−22.42	0.0000
Btt	0	−0.92	0.7831	−0.93	0.7771	0	−21.12	0.0000	−21.13	0.0000
Cel	0	−0.69	0.8477	−0.63	0.8612	0	−21.68	0.0000	−21.72	0.0000
Dash	2	−1.77	0.3940	−1.73	0.4131	0	−25.15	0.0000	−24.89	0.0000
Eos	1	−1.96	0.3047	−2.16	0.2202	0	−25.25	0.0000	−25.14	0.0000
Etc	0	−1.02	0.7490	−1.07	0.7300	0	−20.41	0.0000	−20.51	0.0000
Eth	0	−1.05	0.7362	−1.03	0.7439	0	−23.38	0.0000	−23.34	0.0000
Link	1	−1.66	0.4514	−1.67	0.4446	0	−24.82	0.0000	−25.13	0.0000
Ltc	0	−1.70	0.4291	−1.68	0.4412	0	−22.28	0.0000	−22.28	0.0000

Table 1: (continued)

Minute-by-minute data										
	Logarithmic level					Logarithmic first difference				
Variable	Lag	ADF	p-Value	PP	p-Value	Lag	ADF	p-Value	PP	p-Value
Neo	0	−1.58	0.4923	−1.58	0.4923	0	−23.59	0.0000	−23.56	0.0000
One	0	−0.57	0.8736	−0.54	0.8812	0	−23.36	0.0000	−23.30	0.0000
Qtum	0	−1.24	0.6599	−1.22	0.6683	0	−22.27	0.0000	−22.26	0.0000
Trx	0	−1.37	0.5977	−1.29	0.6339	0	−24.13	0.0000	−24.13	0.0000
Xlm	0	−1.70	0.4292	−1.69	0.4375	0	−22.46	0.0000	−22.46	0.0000
Xmr	1	−1.94	0.3150	−2.03	0.2721	0	−27.13	0.0000	−27.19	0.0000
Zec	5	−1.90	0.3338	−1.69	0.4340	4	−9.88	0.0000	−24.40	0.0000

Exogenous variable is only constant. Appropriate lag length for ADF test has been selected using Schwarz information criterion (SC) while maximum lag for minute-by-minute, hourly, and daily data is 120, 48, and 12 periods, respectively. Appropriate Newey–West bandwidth for PP unit root tests is selected using Bartlett kernel

available information and aim to indicate only direct causality (Geweke 1982). Granger causality tests depend on which additional variables are included or excluded from a statistical model. If the model omits an important causal variable, the omitted variable bias can generate false conclusions about Granger causality (Lütkepohl 1982). The advantage of multivariate Granger tests over bivariate Granger tests is that they can help avoid spurious correlations and can aid in testing the general validity of the causation test. This is through adding additional variables that may be responsible for causing y or whose effects might obscure the effect of x on y (Lütkepohl 1982; Stern 2011). There may also be indirect channels of causation from x to y, which VAR modeling can uncover.

As already noted by Granger (1969), an important problem is the choice of the sampling interval for the Granger causality test. Data frequency is the sampling interval which is collected of time series data. In this study, as stated, causal relationships between seventeen cryptocurrencies were examined using minute-by-minute, hourly and daily data in a multivariate Granger causal test.

Park and Phillips (1989), Sims et al. (1990) and Toda and Phillips (1993) have shown that the standard asymptotic theory is not applicable to hypothesis testing in a level VAR model if the variables are integrated or cointegrated. Therefore, the usual Wald test statistics for Granger non-causality based on level VAR not only have non-standard asymptotic distribution, but depend on nuisance parameters in general if variables are non-stationary. In other words, if the variables in VAR are integrated of order one, F-statistics may not be used to jointly test the Granger causality since the test statistics do not have a standard distribution. According to unit root test results, the integrated order of each variable is one for all three data periods. These results show that all series are stationary in the logarithmic first difference. Also, Engle and Granger (1987) and Hansen (1992) cointegration tests were performed, and cointegrated relationships were not determined between cryptocurrencies at 5% level. Therefore, a VAR model in the logarithmic first differences of the variables can be estimated so that the standard asymptotic theory is valid for hypothesis testing in the VAR, since both integrated order for all variables is one and non-cointegrated with each other. Due to these reasons, multivariate Granger causality tests were performed by using the logarithmic first difference data.

It is well known that the Granger causality test is sensitive to the choice of lag length. If the chosen lag length is less than the true lag length, the omission of relevant lags can cause bias. If the chosen lag length is high, irrelevant lags in the equation cause the estimates to be inefficient (Clarke and Mirza 2006). To avoid this problem, Alternative lag selection criteria[1] were used for optimum lag length selection.

1 LR: Sequential modified LR test statistic at 5% level, FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion.

While the maximum lag length for minute-by-minute data is 60, the appropriate lag length is estimated at 60 by LR, AIC and FPE, 4 by SC and 27 by HQ. The maximum lag is 48, while the appropriate lag for hourly data is 48 with LR testing, 13 by AIC, 2 by FPE and HQ and 1 by SC. For daily data, the LR test determined the appropriate lag length to be 12, with a maximum lag of 12, while the appropriate lag length was determined as 1 by other lag selection criteria. Sawa (1978) has argued that the AIC tends to choose models of higher order than the true model, but states that the bias is negligible when the appropriate lag length is less than (Number of observations/10), as in this study. Therefore, the appropriate lag lengths for minute-by-minute, hourly, and daily data, using AIC, were taken as 60, 13 and 1, respectively.

Multivariate Granger causality test results for all data frequencies are given in Table 1A in Appendix. Those for minute-by-minute data indicate that each cryptocurrency is the cause of the other cryptocurrencies at 1% significant level in the Granger sense. In other words, there is a causal relationship between the seventeen cryptocurrencies, minute-by-minute in the sense of Granger.

The appropriate lag length for minute-by-minute data was selected as 4 by SC and 27 by HQ. In these lags, Granger causality tests were performed and the results remained the same. In addition, bivariate Granger causality tests were performed for the same data and it was determined that the results remained the same at the 1% significant level. These results show that Granger causality tests for minute-by-minute data are not sensitive to lag order and definition by VAR model as bivariate or multivariate. A major obstacle to detecting causality is temporal aggregation. Low frequency financial data such as that garnered monthly or weekly may mask the true causal relationship between variables since aggregation may make the relationship between x and y simultaneous. High frequency data such as hourly and minute-by-minute thus offer an opportunity to analyze causal effects (Dufour et al. 2012). On the other hand, as the sample size increases, standard errors will decrease, thereby greatly improving the value of the test statistics. The number of observations for minute-by-minute data was 645.768, and it is too large a sample size. Thus, the null hypothesis, where x is not a Granger cause of y, can be rejected for minute-by-minute time series data because of the over-large sample size. In other words, the bigger the sample size, the higher the probability of rejecting the null hypothesis. Therefore, for minute-by-minute data, each cryptocurrency may have been determined as the cause of other cryptocurrencies in the Granger sense.

The results of how many of the cryptocurrencies for the other sixteen currencies are Granger causes at 1% and 5% levels using hourly and daily data are given in Table 2. At 5% significant level for hourly data, *Zec* was found to be the cause for the other sixteen cryptocurrencies in the Granger sense. In addition, at 5% level, *Link*, *Btc*, *One* and *Etc* cryptocurrencies were determined as Granger causes of 14, 13, 13 and 10 of the other crypto currencies, respectively. However, the results show that *One* cryptocurrency is not the cause of Granger of any of the other cryptocurrencies at both 5% and 1% significant level for daily data, *Zec* is also Granger cause of one cryptocurrency. However, in daily frequency, it was determined that the cryptocurrencies that stand out in sense of Granger causality are *Neo*, *Btc*, and *Etc*. Maddala and Kim (1998) argue that a better term for Granger causality would be precedence. Hence, Granger causality test results can be used to determine the leading cryptocurrencies. Cryptocurrencies which can be the leading indicators for hourly data are *Link*, *Btc*, *One* and *Etc*, while those for daily frequency are *Neo*, *Btc*, *Btt* and *Etc*. When both hourly and daily data frequencies are taken into account, it is seen that the cryptocurrencies that stand out are *Btc*, *Etc* and *Neo*. Thus, these cryptocurrencies are the ones that will be used as leading indicators among the cryptocurrencies included in the research.

4.3 Simple linear regression results

Using high frequency data increases the chance of detecting causal links since temporal aggregation may make the relationship between cryptocurrencies simultaneous. On the other hand, the sample size for minute-by-minute and hourly data is too large. The bigger the sample size, the higher the probability of rejecting the null

Table 2: Granger causality numbers between cryptocurrencies.

Cryptocurrency	Hourly data		Daily data	
	Granger causality numbers (1% level)	Granger causality numbers (5% level)	Granger causality numbers (1% level)	Granger causality numbers (5% level)
Bnb	1	7	0	0
Btc	9	13	1	3
Btt	4	5	2	4
Cel	2	5	0	1
Dash	2	3	0	2
Eos	2	8	1	2
Etc	6	10	2	4
Eth	0	5	0	0
Link	10	14	0	1
Ltc	1	3	1	1
Neo	3	8	2	7
One	9	13	0	0
Qtum	0	3	0	1
Trx	6	8	0	0
Xlm	4	5	0	1
Xmr	0	1	0	0
Zec	13	16	1	1

hypothesis. The fact that the Granger non-causality null hypothesis between crypto coins for daily data cannot be mostly rejected indicates that the relationships between cryptocurrencies can be simultaneous in daily frequency. The instantaneous causality can be explained by either temporal aggregation or missing causal variables (Granger 1988). For example, variables which are Granger causal based on hourly data may not be Granger causal based on daily data (Breitung and Swanson 2002). Therefore, the results obtained from simple linear regression analysis for daily data are informative about the simultaneous relationships between cryptocurrencies. Namely, simple linear regression with daily data will uncover which cryptocurrency has a higher marginal impact on other cryptocurrencies. In other words, the instantaneous response of other cryptocurrencies to the change in any cryptocurrency in the daily period will be determined.

If the relationship between two cryptocurrencies is cointegrated, there is a long term equilibrium relationship between them. If two cryptocurrencies are not cointegrated, then simple linear regression at a logarithmic level would be spurious. In this study, both Engle and Granger (1987) and Hansen (1992) cointegration tests were performed, and cointegrated relationships were not obtained between cryptocurrencies at 5% level. Therefore, simple linear regression analyses were carried out to determine short term relationships between daily cryptocurrencies using series with logarithmic first-order differences. The results of simple linear regression in logarithmic first difference for daily data are given in Table 2A in Appendix.

The results of simple linear regression indicate that all slope coefficients are statistically significant at 1% level. The values of the estimated slope coefficients range from 0.19 to 1.26. This indicates a positive and statistically significant simultaneous relationship between cryptocurrencies. The R-square, which is the explanation power of the model, yielded values ranging from 0.165 to 0.708. While the highest R-squared value was determined in the regressions between *Dash* and *Zec*, the lowest R-squared value was obtained from regressions between *Etc* and *One*. When the mean R-square results are examined, the cryptocurrencies that explain 50% of the total change in other cryptocurrencies are *Neo* and *Ltc*, while the cryptocurrencies with the lowest explanatory power were found to be *Cel* and *One*, with values of 28% and 24%.

Table 3: The average marginal effect of any cryptocurrency on other cryptocurrencies and the average R-square coefficients.

Independent variable	Ordered mean coef.	Independent variable	Ordered mean R-sq
Btc	1.12	*Neo*	0.499
Eth	0.88	*Ltc*	0.498
Ltc	0.79	*Eos*	0.477
Xmr	0.73	*Link*	0.464
Trx	0.72	*Dash*	0.463
Neo	0.71	*Zec*	0.463
Dash	0.66	*Eth*	0.460
Link	0.66	*Qtum*	0.430
Eos	0.66	*Etc*	0.419
Zec	0.65	*Trx*	0.412
Etc	0.62	*Btc*	0.407
Bnb	0.59	*Xmr*	0.393
Xlm	0.58	*Xlm*	0.374
Qtum	0.54	*Bnb*	0.345
Btt	0.48	*Btt*	0.313
Cel	0.39	*Cel*	0.278
One	0.36	*One*	0.244

Table 4: Descriptive statistics for cryptocurrencies in logarithmic first order difference.

Cryptocurrency	Mean	Ordered std. deviation
Btc	0.3172	4.0288
Eth	0.4957	5.4677
Xmr	0.1725	6.0088
Ltc	0.2109	6.2439
Trx	0.2433	6.3682
Bnb	0.6952	6.9546
Neo	0.0806	7.0257
Dash	0.1020	7.1412
Etc	0.3875	7.2323
Link	0.0652	7.2739
Xlm	0.2341	7.3054
Zec	0.1726	7.3398
Eos	0.0009	7.3530
Btt	0.4551	8.1469
Qtum	0.2593	8.4025
Cel	0.4265	9.4209
One	0.6428	9.6290

Based on the results obtained from simple linear regression analysis, the mean marginal effects (slope coefficients) and the mean of the R-square values are given in Table 3. The marginal effect of *Btc* on other cryptocurrencies has always been greater than other marginal impacts in each regression equality. The marginal effect of *Btc* on other cryptocurrencies ranges from approximately 1.00 to 1.26. The mean marginal effect of *Btc* was estimated to be 1.12. Another cryptocurrency with a large marginal effect is *Eth*. The mean marginal effect of this cryptocurrency on the others was estimated at 0.88. The slope coefficients corresponding to the marginal effects of cryptocurrencies on other cryptocurrencies were determined to be less than 1, with the exception of

Btc. In addition, the cryptocurrency with the lowest marginal effect on the other cryptocurrencies, was usually *One*. The slope coefficients for *One* ranged from 0.19 to 0.68. The average marginal impact of this cryptocurrency was found to be 0.36. These results show that the cryptocurrency with the greatest marginal effect on the others is *Btc*, while that with the lowest marginal effect is *One*.

In simple linear regression, the least squares estimator of the slope coefficient is $\widehat{Cov}(X,Y)/\widehat{V}(x)$, so in equations where the independent variable is Bitcoin, the value $\widehat{V}(x)$ corresponds to the variance value for Bitcoin. For daily data, the marginal influence of Bitcoin on other cryptocurrencies is high. In other words, the variance of this cryptocurrency is lower than that of other cryptocurrencies. The mean and variance values for the cryptocurrencies included in the research are in Table 4. The lowest variance value is in Bitcoin. This finding also indicates that the volatility for Bitcoin is at a lower level than other cryptocurrencies. Volatility is known to be high for percentage changes in the price of cryptocurrencies. The low volatility in Bitcoin compared to other cryptocurrencies causes less uncertainty in this cryptocurrency. Thus, Bitcoin can be considered a leading indicator cryptocurrency. It has the highest marginal effect on other cryptocurrencies.

5 Discussion

Big data analysis has gained importance in every field in the global and digital world. Deriving high frequency and large data samples is much easier than before. One of the prominent econometric analyses using a large data sample has been performed via Granger causality tests. Many scientific fields can study the causal relationships between variables. In analysis, the sampling intervals and sample size should be appropriate to obtain favorable results. To our knowledge, this is the first work that considered sampling intervals and sample size in cryptocurrencies. This research highlights that "the bigger the sample size, the higher the probability of rejecting the null hypothesis. Therefore, the null hypothesis for the Granger causality test can be rejected for minute-by-minute time series data because of too large a sample size". This work indicates that researchers, policymakers, portfolio managers, and investors should be cautious about the instantaneous changes in cryptocurrencies in big data analysis. Cryptocurrencies are open to investments for every moment in digital platforms. Hence, it is easy for investors to connect to this market. Nevertheless, choosing a currency that could have a hedge effect is challenging. In other words, investors may not diversify their investments among cryptocurrencies to avoid risks. When Granger causality tests utilize high frequency data, there were significant relationships between all cryptocurrencies. Therefore, the analyses should use low frequency data or different sampling intervals and sample sizes. It cannot be favorable to conduct causality tests with high frequency data because it is already clear that researchers would always find significant relationships between cryptocurrencies.

It is not easy to know which cryptocurrency can help reduce risks in the market. Therefore, the changes in leading cryptocurrencies should be monitored. Granger causality test results for hourly and daily data indicated that Bitcoin, Ethereum Classic, and Neo were leading currencies. In addition, according to the simple linear regression analysis, the short term marginal effect of Bitcoin on other cryptocurrencies always had a more powerful impact than others. When researchers analyze using a large data sample, they must be aware that the null hypothesis for the Granger causality test can be rejected. Thus, they should select an alternative method or alternative sampling intervals and sample size. This work employed an alternative method to discuss the results using simple linear regression analysis, different sampling intervals, and sample sizes. Canh et al. (2019b) pointed out that there could be a high degree of non-diversifiable risk within seven popular cryptocurrencies. This work is limited to causality analysis using daily data, similar to the study by Tu and Xue (2019). They found that smaller cryptocurrencies are indicators of changes in larger ones. Our work showed that larger capitalized cryptocurrencies could also be leading indicators such as Bitcoin. Kim et al. (2021) also pointed out that it is difficult for investors to hedge risks among cryptocurrencies. Similarly, our research proves that selecting cryptocurrencies for diversification is challenging, specifically in minute-by-minute analysis. However, when different sampling intervals and sample sizes are considered, the leading cryptocurrencies can be detected. Schinckus et al. (2020) reported that Bitcoin is not an influential asset on other cryptocurrencies. Nevertheless, our work proves that the short term marginal impact of Bitcoin on other cryptocurrencies is always more profound. This information can provide an opportunity to reduce risks. Hence, researchers, policymakers, portfolio managers, and investors should consider results from different sampling intervals and sample sizes in big data analysis.

6 Conclusions

In this work, the effects of the sampling interval and sample size on the causal relationships between seventeen popular cryptocurrencies were examined by comparing minute-by-minute, hourly and daily data for the period from September 1, 2020 to December 8, 2021. Multivariate Granger causality tests were used to determine the leading cryptocurrencies for both different sampling intervals and sample sizes. Linear simple regression by daily data was conducted to indicate the simultaneous relationships between cryptocurrencies.

Multivariate Granger causality test results showed that each cryptocurrency is the cause of the other cryptocurrencies at 1% significant level in the Granger sense using minute-by-minute data. In other words, there is a minute-by-minute causal relationship between all cryptocurrencies in the sense of Granger. The bigger the sample size, the higher the probability of rejecting the null hypothesis. Therefore, each cryptocurrency may be determined as the cause of other cryptocurrencies for minute-by-minute data in the Granger sense.

As the sampling interval changes, the causality relationship also produced different results. When the sampling interval changed hourly or daily, the causal relationship in the sense of Granger between some cryptocurrencies could not be rejected. However, the most causal relationships between cryptocurrencies emerged with Bitcoin, Ethereum Classic, and Neo. For this reason, Bitcoin, Ethereum Classic, and Neo may be used as leading indicators among the cryptocurrencies included in the research.

In addition, high frequency data increases the chance of detecting causal links because temporal aggregation can create simultaneous relationship between cryptocurrencies. Hence, daily data for simple linear regression analysis was conducted, and may indicate a simultaneous relationship. The result showed that the short term marginal effect of Bitcoin on other cryptocurrencies always had a larger impact compared with those of others. As a result, sampling intervals and sample size are crucial for Granger causality tests, and Bitcoin plays a leading role as an indicator for other currencies.

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Appendix A

Table 1A: Multivariate Granger causality test results.

Dependent variable is *Bnb*

X	Minute-by-minute data		Hourly data		Daily data	
	χ^2	Prob.	χ^2	Prob.	χ^2	Prob.
Btc	381.0	0.000*	34.4	0.001*	0.6	0.4331
Btt	334.4	0.000*	41.9	0.000*	1.9	0.1685
Cel	363.0	0.000*	25.6	0.019**	0.0	0.9715
Dash	317.2	0.000*	14.7	0.328	0.3	0.5831
Eos	445.5	0.000*	19.2	0.117	0.3	0.6085
Etc	322.9	0.000*	23.9	0.032**	0.0	0.8604
Eth	415.1	0.000*	24.5	0.027**	1.1	0.2851
Link	296.2	0.000*	23.2	0.040**	1.9	0.1668
Ltc	465.4	0.000*	9.1	0.766	0.0	0.8660
Neo	420.7	0.000*	22.0	0.055	0.6	0.4347
One	164.7	0.000*	32.3	0.002*	2.2	0.1367
Qtum	886.0	0.000*	12.7	0.474	0.1	0.8140
Trx	196.4	0.000*	37.0	0.000*	0.3	0.5677
Xlm	286.2	0.000*	11.2	0.596	0.2	0.6783
Xmr	434.7	0.000*	20.9	0.075	0.2	0.6398
Zec	451.9	0.000*	29.4	0.006*	1.0	0.3121
All	8752	0.000*	418	0.000*	16.0	0.4501

Dependent variable is *Btc*

X	Minute-by-minute data		Hourly data		Daily data	
	χ^2	Prob.	χ^2	Prob.	χ^2	Prob.
Bnb	17,356.8	0.000*	17.4	0.180	0.1	0.7959
Btt	478.0	0.000*	24.8	0.024**	0.2	0.6559
Cel	603.5	0.000*	10.7	0.633	0.6	0.4306
Dash	3243.9	0.000*	12.3	0.503	0.1	0.7718
Eos	4876.8	0.000*	11.1	0.604	1.9	0.1730
Etc	4655.0	0.000*	21.0	0.073	0.0	0.9801
Eth	16,388.1	0.000*	25.4	0.021**	0.4	0.5494
Link	5620.2	0.000*	29.6	0.006*	0.8	0.3658
Ltc	1906.5	0.000*	12.7	0.474	1.6	0.2122
Neo	2087.8	0.000*	16.7	0.214	3.0	0.0825
One	508.9	0.000*	20.7	0.080	0.9	0.3556
Qtum	1736.9	0.000*	7.2	0.893	0.5	0.4779
Trx	2175.2	0.000*	14.9	0.317	0.4	0.5497
Xlm	1769.6	0.000*	29.7	0.005*	3.8	0.0509
Xmr	249.4	0.000*	20.1	0.094	0.5	0.4920
Zec	3653.4	0.000*	24.0	0.031**	1.1	0.3013
All	747,551	0.000*	338	0.000*	29.4	0.0215**

Dependent variable is *Btt*

X	Minute-by-minute data		Hourly data		Daily data	
	χ^2	Prob.	χ^2	Prob.	χ^2	Prob.
Bnb	1293.7	0.000*	21.0	0.073	0.1	0.7731
Btc	1082.5	0.000*	30.6	0.004*	2.9	0.0910
Cel	164.4	0.000*	40.7	0.000*	1.4	0.2426
Dash	766.2	0.000*	12.8	0.460	1.0	0.3177
Eos	372.0	0.000*	39.7	0.000*	0.0	0.8916
Etc	1462.7	0.000*	26.4	0.015**	0.8	0.3684
Eth	2991.9	0.000*	16.1	0.243	0.0	0.9106
Link	2198.2	0.000*	29.3	0.006*	0.8	0.3608
Ltc	1465.8	0.000*	18.1	0.154	0.2	0.6370
Neo	507.2	0.000*	18.2	0.149	2.8	0.0950
One	326.6	0.000*	21.0	0.074	0.5	0.4654
Qtum	713.1	0.000*	24.3	0.029**	0.5	0.4667
Trx	7271.0	0.000*	13.3	0.427	0.2	0.6861
Xlm	722.5	0.000*	13.7	0.399	0.0	0.9552
Xmr	628.3	0.000*	10.5	0.651	1.7	0.1873
Zec	307.9	0.000*	26.8	0.013**	0.1	0.8000
All	68,725	0.000*	423	0.000*	21.0	0.1773

Dependent variable is *Cel*

X	Minute-by-minute data		Hourly data		Daily data	
	χ^2	Prob.	χ^2	Prob.	χ^2	Prob.
Bnb	1389.6	0.000*	20.3	0.089	1.7	0.1859
Btc	610.5	0.000*	29.5	0.006*	1.7	0.1978
Btt	456.9	0.000*	38.8	0.000*	7.2	0.0072*
Dash	697.6	0.000*	8.5	0.809	0.1	0.7401
Eos	681.0	0.000*	31.4	0.003*	1.4	0.2437
Etc	887.9	0.000*	20.0	0.096	0.7	0.3953
Eth	2511.4	0.000*	14.5	0.340	0.0	0.9649
Link	2465.0	0.000*	51.1	0.000*	0.0	0.9792
Ltc	1023.5	0.000*	20.0	0.095	0.8	0.3598
Neo	621.5	0.000*	28.1	0.009*	5.5	0.0188**
One	1330.4	0.000*	56.6	0.000*	0.3	0.5886
Qtum	871.8	0.000*	11.5	0.573	0.1	0.7644
Trx	839.9	0.000*	27.0	0.012**	0.1	0.8068
Xlm	355.4	0.000*	10.8	0.628	1.7	0.1948
Xmr	364.6	0.000*	9.2	0.760	0.4	0.5428
Zec	488.9	0.000*	30.6	0.004*	0.5	0.4784
All	63,999	0.000*	450	0.000*	24.0	0.0897

Table 1A: (continued)

Dependent variable is *Dash*						
	Minute-by-minute data		Hourly data		Daily data	
X	χ^2	Prob.	χ^2	Prob.	χ^2	Prob.
Bnb	293.5	0.000*	23.5	0.036**	9.9	0.627
Btc	377.5	0.000*	25.6	0.019**	23.2	0.027**
Btt	185.7	0.000*	8.6	0.803	14.9	0.246
Cel	218.0	0.000*	14.0	0.376	15.5	0.214
Eos	359.1	0.000*	6.2	0.940	25.1	0.014**
Etc	430.0	0.000*	37.8	0.000*	14.4	0.274
Eth	463.9	0.000*	12.8	0.465	11.0	0.526
Link	279.2	0.000*	32.6	0.002*	13.0	0.368
Ltc	721.5	0.000*	14.9	0.313	15.4	0.219
Neo	279.1	0.000*	11.3	0.585	24.2	0.019**
One	169.0	0.000*	28.9	0.007*	8.9	0.711
Qtum	1023.7	0.000*	10.2	0.680	11.5	0.486
Trx	178.6	0.000*	11.9	0.538	7.5	0.825
Xlm	256.0	0.000*	32.0	0.002*	14.3	0.280
Xmr	380.5	0.000*	15.6	0.271	7.6	0.814
Zec	523.2	0.000*	41.5	0.000*	11.2	0.512
All	8037	0.000*	370.8	0.000*	263.8	0.001*

Dependent variable is *Eos*						
	Minute-by-minute data		Hourly data		Daily data	
X	χ^2	Prob.	χ^2	Prob.	χ^2	Prob.
Bnb	353.4	0.000*	26.5	0.014**	0.0	0.8882
Btc	474.6	0.000*	30.8	0.004*	3.7	0.0545
Btt	319.0	0.000*	19.7	0.103	0.2	0.6905
Cel	245.1	0.000*	18.2	0.148	2.1	0.1440
Dash	202.4	0.000*	22.8	0.044**	1.6	0.2102
Etc	632.0	0.000*	42.4	0.000*	5.1	0.0237**
Eth	379.2	0.000*	9.3	0.751	0.1	0.6994
Link	531.6	0.000*	36.3	0.001*	0.7	0.3977
Ltc	1146.1	0.000*	23.1	0.041**	1.0	0.3121
Neo	408.6	0.000*	13.5	0.408	6.7	0.0098*
One	160.1	0.000*	34.7	0.001*	0.0	0.9330
Qtum	1344.6	0.000*	19.8	0.100	0.8	0.3582
Trx	234.3	0.000*	32.3	0.002*	3.6	0.0585
Xlm	473.2	0.000*	36.5	0.001*	2.9	0.0875
Xmr	399.4	0.000*	24.2	0.029**	1.1	0.3035
Zec	592.0	0.000*	32.0	0.002*	0.1	0.8220
All	10,471	0.000*	454	0.000*	32.9	0.0077*

Dependent variable is *Etc*						
	Minute-by-minute data		Hourly data		Daily data	
X	χ^2	Prob.	χ^2	Prob.	χ^2	Prob.
Bnb	352.8	0.000*	17.6	0.172	0.2	0.6796
Btc	423.6	0.000*	25.7	0.018**	0.0	0.8721
Btt	321.0	0.000*	10.8	0.624	0.7	0.4092
Cel	296.7	0.000*	23.9	0.033**	2.8	0.0932
Dash	319.1	0.000*	22.3	0.050***	3.3	0.0688
Eos	708.8	0.000*	16.2	0.239	5.2	0.0230**
Eth	631.8	0.000*	22.9	0.043**	0.0	0.8976
Link	326.4	0.000*	25.9	0.018**	0.0	0.9763
Ltc	763.5	0.000*	19.0	0.125	5.0	0.0250**
Neo	370.8	0.000*	23.3	0.038**	8.0	0.0047*
One	227.2	0.000*	29.8	0.005*	0.4	0.5378
Qtum	1025.1	0.000*	23.7	0.034**	0.6	0.4220
Trx	389.6	0.000*	36.9	0.000*	0.4	0.5381
Xlm	352.3	0.000*	14.2	0.361	0.8	0.3627
Xmr	452.8	0.000*	11.6	0.559	2.5	0.1155
Zec	454.3	0.000*	60.7	0.000*	0.1	0.7928
All	9441	0.000*	416	0.000*	36.8	0.0022*

Dependent variable is *Eth*						
	Minute-by-minute data		Hourly data		Daily data	
X	χ^2	Prob.	χ^2	Prob.	χ^2	Prob.
Bnb	2537.0	0.000*	15.1	0.299	0.2	0.6538
Btc	560.8	0.000*	37.0	0.000*	6.0	0.0146**
Btt	1294.0	0.000*	8.2	0.833	0.2	0.6674
Cel	274.7	0.000*	10.5	0.649	2.9	0.0900
Dash	1085.6	0.000*	11.0	0.611	0.9	0.3391
Eos	1085.4	0.000*	16.6	0.218	0.7	0.3887
Etc	2564.6	0.000*	18.5	0.139	0.1	0.7087
Link	7385.1	0.000*	32.5	0.002*	0.1	0.7569
Ltc	1742.5	0.000*	18.2	0.151	1.1	0.2851
Neo	747.4	0.000*	24.2	0.029**	4.7	0.0299**
One	491.1	0.000*	29.4	0.006	0.0	0.9676
Qtum	1396.9	0.000*	7.6	0.871	1.0	0.3144
Trx	1019.1	0.000*	13.9	0.382	0.3	0.6046
Xlm	1208.1	0.000*	19.2	0.118	1.0	0.3220
Xmr	865.3	0.000*	11.1	0.598	0.1	0.8093
Zec	1239.6	0.000*	31.3	0.003*	1.1	0.2968
All	100,348	0.000*	342.0	0.000*	31.8	0.0106**

Table 1A: (continued)

	Dependent variable is *Link*							Dependent variable is *Ltc*					
	Minute-by-minute data		Hourly data		Daily data			Minute-by-minute data		Hourly data		Daily data	
X	χ^2	**Prob.**	χ^2	**Prob.**	χ^2	**Prob.**	**X**	χ^2	**Prob.**	χ^2	**Prob.**	χ^2	**Prob.**
Bnb	219.2	0.000*	12.8	0.465	0.0	0.9603	*Bnb*	2617.1	0.000*	9.5	0.734	0.1	0.7654
Btc	394.2	0.000*	37.3	0.000*	3.9	0.0495**	*Btc*	498.6	0.000*	35.8	0.001*	8.8	0.0031*
Btt	212.7	0.000*	11.8	0.541	0.2	0.6523	*Btt*	413.7	0.000*	15.4	0.281	0.2	0.6965
Cel	253.9	0.000*	14.1	0.368	2.6	0.1036	*Cel*	516.1	0.000*	22.0	0.056	6.0	0.0145**
Dash	281.3	0.000*	18.2	0.150	0.5	0.4714	*Dash*	2960.5	0.000*	15.1	0.301	0.2	0.6686
Eos	362.6	0.000*	8.3	0.826	0.7	0.4199	*Eos*	5939.7	0.000*	17.3	0.187	2.1	0.1456
Etc	335.4	0.000*	18.3	0.146	3.9	0.0497**	*Etc*	4294.3	0.000*	17.6	0.174	1.7	0.1895
Eth	379.3	0.000*	13.2	0.436	0.4	0.5162	*Eth*	609.6	0.000*	17.9	0.163	0.0	0.8589
Ltc	487.8	0.000*	13.3	0.428	0.5	0.4638	*Link*	5791.4	0.000*	24.6	0.026**	0.0	0.8284
Neo	322.5	0.000*	23.3	0.039**	5.5	0.0186**	*Neo*	1045.3	0.000*	31.6	0.003*	4.2	0.0406**
One	202.1	0.000*	38.1	0.000*	0.0	0.8744	*One*	463.8	0.000*	28.0	0.009*	0.0	0.9179
Qtum	1011.8	0.000*	17.3	0.186	0.1	0.7514	*Qtum*	1563.4	0.000*	8.2	0.830	0.0	0.8373
Trx	290.3	0.000*	16.7	0.212	0.0	0.9226	*Trx*	778.2	0.000*	8.0	0.841	2.0	0.1612
Xlm	226.9	0.000*	11.4	0.578	0.4	0.5037	*Xlm*	4491.9	0.000*	13.2	0.433	0.9	0.3557
Xmr	310.7	0.000*	15.1	0.300	0.2	0.6291	*Xmr*	1853.0	0.000*	21.1	0.070	2.4	0.1187
Zec	438.8	0.000*	32.0	0.002*	0.4	0.5282	*Zec*	2032.0	0.000*	23.3	0.038**	1.0	0.3139
All	8314	0.000*	344	0.000*	23.2	0.1087	All	235,899	0.000*	388	0.000*	40.2	0.0007*

	Dependent variable is *Neo*							Dependent variable is *One*					
	Minute-by-minute data		Hourly data		Daily data			Minute-by-minute data		Hourly data		Daily data	
X	χ^2	**Prob.**	χ^2	**Prob.**	χ^2	**Prob.**	**X**	χ^2	**Prob.**	χ^2	**Prob.**	χ^2	**Prob.**
Bnb	275.0	0.000*	24.4	0.028**	0.4	0.5229	*Bnb*	2118.3	0.000*	24.3	0.028**	0.6	0.4240
Btc	554.5	0.000*	33.7	0.001*	2.2	0.1408	*Btc*	987.2	0.000*	17.7	0.171	2.2	0.1404
Btt	302.0	0.000*	14.0	0.372	4.8	0.0291**	*Btt*	534.7	0.000*	39.6	0.000*	9.6	0.0020*
Cel	187.2	0.000*	23.0	0.041**	0.1	0.7479	*Cel*	448.0	0.000*	28.6	0.007*	1.3	0.2457
Dash	349.3	0.000*	7.0	0.903	0.1	0.7211	*Dash*	1032.5	0.000*	17.2	0.188	0.3	0.5632
Eos	416.5	0.000*	23.2	0.040**	7.9	0.0048*	*Eos*	867.7	0.000*	25.6	0.020**	1.5	0.2136
Etc	666.1	0.000*	29.7	0.005*	11.7	0.0006*	*Etc*	1549.4	0.000*	23.5	0.036**	3.1	0.0800
Eth	496.1	0.000*	10.2	0.679	0.3	0.5684	*Eth*	2563.5	0.000*	16.8	0.206	0.2	0.6897
Link	417.3	0.000*	47.5	0.000*	0.1	0.7408	*Link*	3034.2	0.000*	35.6	0.001*	0.7	0.4164
Ltc	710.8	0.000*	30.5	0.004*	0.0	0.8871	*Ltc*	2059.1	0.000*	19.5	0.107	0.4	0.5069
One	175.3	0.000*	22.4	0.049**	0.9	0.3477	*Neo*	939.4	0.000*	17.5	0.179	1.9	0.1733
Qtum	2355.7	0.000*	9.5	0.738	0.0	0.9678	*Qtum*	823.4	0.000*	15.7	0.265	0.0	0.9898
Trx	267.4	0.000*	31.0	0.003*	0.0	0.9024	*Trx*	1038.6	0.000*	6.8	0.910	1.3	0.2494
Xlm	517.2	0.000*	9.5	0.735	2.3	0.1284	*Xlm*	544.7	0.000*	10.3	0.668	2.5	0.1173
Xmr	454.5	0.000*	15.0	0.306	0.5	0.4800	*Xmr*	681.7	0.000*	8.9	0.777	0.3	0.5915
Zec	528.7	0.000*	68.5	0.000*	1.0	0.3231	*Zec*	481.4	0.000*	29.6	0.005*	0.8	0.3742
All	12,221	0.000*	441	0.000*	28.4	0.0285**	All	73,582	0.000*	360	0.000*	26.2	0.0512

Table 1A: (continued)

Dependent variable is *Qtum*						
	Minute-by-minute data		Hourly data		Daily data	
X	χ^2	Prob.	χ^2	Prob.	χ^2	Prob.
Bnb	251.8	0.000*	30.5	0.004*	0.1	0.7320
Btc	357.4	0.000*	26.2	0.016**	1.8	0.1848
Btt	162.6	0.000*	21.8	0.059	1.1	0.3050
Cel	179.6	0.000*	12.1	0.520	1.4	0.2359
Dash	259.9	0.000*	7.9	0.850	4.6	0.0316**
Eos	532.0	0.000*	20.0	0.095	1.0	0.3062
Etc	640.3	0.000*	44.0	0.000*	9.6	0.0019*
Eth	322.0	0.000*	8.3	0.825	0.2	0.6186
Link	266.2	0.000*	32.7	0.002*	0.1	0.6986
Ltc	480.2	0.000*	22.1	0.053	0.1	0.7170
Neo	472.0	0.000*	24.1	0.030**	0.6	0.4454
One	185.3	0.000*	26.5	0.014**	1.0	0.3122
Trx	216.0	0.000*	41.5	0.000*	0.4	0.5504
Xlm	341.9	0.000*	17.2	0.190	0.1	0.7466
Xmr	296.1	0.000*	10.2	0.678	2.6	0.1089
Zec	459.3	0.000*	54.6	0.000*	0.2	0.6419
All	7396	0.000*	431	0.000*	21.0	0.1768

Dependent variable is *Trx*						
	Minute-by-minute data		Hourly data		Daily data	
X	χ^2	Prob.	χ^2	Prob.	χ^2	Prob.
Bnb	230.8	0.000*	17.6	0.174	2.7	0.1012
Btc	374.3	0.000*	43.9	0.000*	0.8	0.3848
Btt	1074.4	0.000*	45.7	0.000*	4.2	0.0402**
Cel	227.7	0.000*	20.3	0.088	0.5	0.4998
Dash	251.8	0.000*	15.0	0.305	0.7	0.3982
Eos	488.1	0.000*	26.2	0.016**	4.3	0.0374**
Etc	503.9	0.000*	31.2	0.003*	1.0	0.3130
Eth	283.8	0.000*	24.9	0.024**	0.0	0.8928
Link	259.1	0.000*	29.7	0.005*	0.1	0.7428
Ltc	708.6	0.000*	16.5	0.222	0.3	0.6168
Neo	266.2	0.000*	23.7	0.034**	9.5	0.0020*
One	158.6	0.000*	20.2	0.092	0.4	0.5303
Qtum	843.4	0.000*	12.8	0.467	3.9	0.0484**
Xlm	292.7	0.000*	59.5	0.000*	0.6	0.4531
Xmr	287.5	0.000*	6.4	0.929	0.8	0.3762
Zec	315.3	0.000*	32.4	0.002*	0.2	0.6264
All	8958	0.000*	455	0.000*	27.3	0.0379**

Dependent variable is *Xlm*						
	Minute-by-minute data		Hourly data		Daily data	
X	χ^2	Prob.	χ^2	Prob.	χ^2	Prob.
Bnb	1344.5	0.000*	25.2	0.022**	0.2	0.6725
Btc	301.8	0.000*	17.2	0.192	0.4	0.5227
Btt	128.0	0.000*	5.2	0.971	0.2	0.6941
Cel	398.4	0.000*	15.2	0.293	0.7	0.4035
Dash	1744.5	0.000*	5.4	0.966	0.0	0.9610
Eos	3192.8	0.000*	23.1	0.041**	3.6	0.0562
Etc	2997.9	0.000*	34.1	0.001*	0.6	0.4252
Eth	585.1	0.000*	25.4	0.020**	2.6	0.1055
Link	4327.4	0.000*	21.0	0.073	1.8	0.1848
Ltc	7863.3	0.000*	14.6	0.333	0.0	0.8540
Neo	1488.2	0.000*	29.6	0.005*	2.2	0.1389
One	424.6	0.000*	22.7	0.045**	0.0	0.9200
Qtum	1455.8	0.000*	24.5	0.027**	0.3	0.6159
Trx	751.3	0.000*	27.9	0.009*	0.5	0.4595
Xmr	1608.9	0.000*	12.6	0.482	1.3	0.2579
Zec	1411.1	0.000*	39.4	0.000*	0.0	0.9386
All	162,926	0.000*	410	0.000*	20.6	0.1960

Dependent variable is *Xmr*						
	Minute-by-minute data		Hourly data		Daily data	
X	χ^2	Prob.	χ^2	Prob.	χ^2	Prob.
Bnb	3084.9	0.000*	20.3	0.089	0.7	0.3909
Btc	302.1	0.000*	23.2	0.040**	1.7	0.1954
Btt	159.7	0.000*	9.0	0.774	0.9	0.3490
Cel	742.4	0.000*	18.7	0.133	0.2	0.6683
Dash	4312.4	0.000*	31.3	0.003*	0.9	0.3466
Eos	3188.4	0.000*	24.7	0.025**	0.0	0.9366
Etc	2779.7	0.000*	17.5	0.177	2.0	0.1523
Eth	687.7	0.000*	21.6	0.062	0.3	0.6097
Link	4176.6	0.000*	22.0	0.056	1.8	0.1836
Ltc	10,032.9	0.000*	26.6	0.014**	0.4	0.5033
Neo	1529.9	0.000*	19.5	0.109	0.6	0.4401
One	637.7	0.000*	33.3	0.002*	1.8	0.1828
Qtum	1906.9	0.000*	8.7	0.798	0.4	0.5200
Trx	595.0	0.000*	25.1	0.023**	0.1	0.8078
Xlm	3971.7	0.000*	8.8	0.788	1.1	0.2928
Zec	4332.3	0.000*	66.8	0.000*	0.2	0.6485
All	225,132	0.000*	397	0.000*	16.6	0.4093

Table 1A: (continued)

Dependent variable is *Zec*						
	Minute-by-minute data		Hourly data		Daily data	
X	χ^2	Prob.	χ^2	Prob.	χ^2	Prob.
Bnb	306.8	0.000*	25.5	0.020**	0.1	0.7528
Btc	506.9	0.000*	20.7	0.079	0.8	0.3654
Btt	230.2	0.000*	12.6	0.475	0.5	0.4823
Cel	197.5	0.000*	14.4	0.346	1.3	0.2563
Dash	1001.3	0.000*	38.1	0.000*	1.5	0.2205
Eos	537.5	0.000*	24.0	0.031**	0.0	0.9072
Etc	474.4	0.000*	23.9	0.032**	0.5	0.4872
Eth	585.7	0.000*	14.8	0.320	0.0	0.9588
Link	352.5	0.000*	22.8	0.044**	1.2	0.2648
Ltc	715.4	0.000*	18.6	0.136	0.5	0.4647
Neo	282.8	0.000*	15.2	0.296	5.3	0.0213**
One	216.3	0.000*	24.6	0.026**	0.0	0.8898
Qtum	941.7	0.000*	15.2	0.294	2.8	0.0942
Trx	258.6	0.000*	21.9	0.056	0.0	0.9377
Xlm	273.8	0.000*	24.7	0.026**	0.4	0.5273
Xmr	397.3	0.000*	21.4	0.065	1.4	0.2406
All	9701.9	0.000*	410.4	0.000*	17.3	0.3664

*Indicate significance at the 1% level. **Indicate significance at the 5% level.

Table 2A: Results of simple linear regression in logarithmic first difference for daily data.

Dependent variable is *Bnb*

Variable	Coef.	p-Value	R-sq
Btc	**1.06**	0.0000	0.379
Btt	0.46	0.0000	0.286
Cel	**0.33**	0.0000	**0.200**
Dash	0.60	0.0000	0.374
Eos	0.58	0.0000	0.372
Etc	0.50	0.0000	0.273
Eth	0.82	0.0000	0.417
Link	0.61	0.0000	0.408
Ltc	0.70	0.0000	0.400
Neo	0.66	0.0000	**0.444**
One	0.34	0.0000	0.227
Qtum	0.51	0.0000	0.378
Trx	0.62	0.0000	0.323
Xlm	0.50	0.0000	0.281
Xmr	0.71	0.0000	0.372
Zec	0.59	0.0000	0.384

Dependent variable is *Btc*

Variable	Coef.	p-Value	R-sq
Bnb	0.36	0.0000	0.379
Btt	0.30	0.0000	0.380
Cel	0.21	0.0000	0.237
Dash	0.37	0.0000	0.430
Eos	0.36	0.0000	0.437
Etc	0.33	0.0000	0.343
Eth	**0.56**	0.0000	0.586
Link	0.37	0.0000	0.451
Ltc	0.51	0.0000	**0.615**
Neo	0.39	0.0000	0.458
One	**0.19**	0.0000	**0.211**
Qtum	0.29	0.0000	0.364
Trx	0.39	0.0000	0.371
Xlm	0.34	0.0000	0.373
Xmr	0.45	0.0000	0.445
Zec	0.36	0.0000	0.428

Dependent variable is *Btt*

Variable	Coef.	p-Value	R-sq
Bnb	0.63	0.0000	0.286
Btc	**1.06**	0.0000	0.380
Cel	0.43	0.0000	0.242
Dash	0.64	0.0000	0.309
Eos	0.67	0.0000	0.366
Etc	0.58	0.0000	0.260
Eth	0.85	0.0000	0.324
Link	0.61	0.0000	0.298
Ltc	0.74	0.0000	0.317
Neo	0.70	0.0000	0.369
One	**0.39**	0.0000	**0.210**
Qtum	0.53	0.0000	0.300
Trx	0.90	0.0000	**0.495**
Xlm	0.56	0.0000	0.249
Xmr	0.74	0.0000	0.293
Zec	0.62	0.0000	0.311

Dependent variable is *Cel*

Variable	Coef.	p-Value	R-sq
Bnb	0.61	0.0000	0.200
Btc	**1.14**	0.0000	0.237
Btt	**0.57**	0.0000	0.242
Dash	0.65	0.0000	0.240
Eos	0.68	0.0000	0.280
Etc	0.60	0.0000	0.210
Eth	0.97	0.0000	0.314
Link	0.80	0.0000	0.384
Ltc	0.84	0.0000	0.310
Neo	0.73	0.0000	0.293
One	0.68	0.0000	**0.480**
Qtum	0.58	0.0000	0.265
Trx	0.80	0.0000	0.292
Xlm	0.62	0.0000	0.233
Xmr	0.70	0.0000	**0.198**
Zec	0.67	0.0000	0.268

Dependent variable is *Dash*

Variable	Coef.	p-Value	R-sq
Bnb	0.63	0.0000	0.374
Btc	**1.16**	0.0000	0.430
Btt	0.49	0.0000	0.309
Cel	0.37	0.0000	0.240
Eos	0.73	0.0000	0.571
Etc	0.76	0.0000	0.596
Eth	0.89	0.0000	0.465
Link	0.68	0.0000	0.477
Ltc	0.89	0.0000	0.601
Neo	0.77	0.0000	0.574
One	**0.35**	0.0000	**0.224**
Qtum	0.57	0.0000	0.457
Trx	0.75	0.0000	0.445
Xlm	0.61	0.0000	0.395
Xmr	0.88	0.0000	0.550
Zec	0.82	0.0000	**0.708**

Dependent variable is *Eos*

Variable	Coef.	p-Value	R-sq
Bnb	0.65	0.0000	0.372
Btc	**1.21**	0.0000	0.437
Btt	0.55	0.0000	0.366
Cel	0.41	0.0000	0.280
Dash	0.78	0.0000	0.571
Etc	0.78	0.0000	0.593
Eth	0.94	0.0000	0.491
Link	0.74	0.0000	0.532
Ltc	0.92	0.0000	**0.610**
Neo	0.82	0.0000	0.609
One	**0.36**	0.0000	**0.221**
Qtum	0.67	0.0000	0.585
Trx	0.84	0.0000	0.531
Xlm	0.74	0.0000	0.537
Xmr	0.77	0.0000	0.393
Zec	0.72	0.0000	0.511

Dependent variable is *Etc*

Variable	Coef.	p-Value	R-sq
Bnb	0.54	0.0000	0.273
Btc	**1.05**	0.0000	0.343
Btt	0.45	0.0000	0.260
Cel	0.35	0.0000	0.210
Dash	0.78	0.0000	**0.596**
Eos	0.76	0.0000	0.593
Eth	0.90	0.0000	0.463
Link	0.67	0.0000	0.451
Ltc	0.86	0.0000	0.556
Neo	0.77	0.0000	0.564
One	**0.30**	0.0000	**0.165**

Dependent variable is *Eth*

Variable	Coef.	p-Value	R-sq
Bnb	0.51	0.0000	0.417
Btc	**1.04**	0.0000	0.586
Btt	0.38	0.0000	0.324
Cel	0.32	0.0000	0.314
Dash	0.52	0.0000	0.465
Eos	0.52	0.0000	0.491
Etc	0.51	0.0000	0.463
Link	0.61	0.0000	**0.650**
Ltc	0.70	0.0000	0.641
Neo	0.57	0.0000	0.539
One	**0.28**	0.0000	**0.237**

Dependent variable is *Link*

Variable	Coef.	p-Value	R-sq
Bnb	0.67	0.0000	0.408
Btc	**1.21**	0.0000	0.451
Btt	0.49	0.0000	0.298
Cel	0.48	0.0000	0.384
Dash	0.70	0.0000	0.477
Eos	0.72	0.0000	0.532
Etc	0.68	0.0000	0.451
Eth	1.07	0.0000	**0.650**
Ltc	0.90	0.0000	0.595
Neo	0.80	0.0000	0.590
One	**0.41**	0.0000	**0.294**

Table 2A: (continued)

Dependent variable is *Etc*				Dependent variable is *Eth*				Dependent variable is *Link*			
Variable	Coef.	p-Value	R-sq	Variable	Coef.	p-Value	R-sq	Variable	Coef.	p-Value	R-sq
Qtum	0.63	0.0000	0.528	*Qtum*	0.44	0.0000	0.449	*Qtum*	0.61	0.0000	0.496
Trx	0.74	0.0000	0.425	*Trx*	0.57	0.0000	0.446	*Trx*	0.76	0.0000	0.441
Xlm	0.62	0.0000	0.386	*Xlm*	0.48	0.0000	0.419	*Xlm*	0.67	0.0000	0.455
Xmr	0.75	0.0000	0.390	*Xmr*	0.59	0.0000	0.423	*Xmr*	0.77	0.0000	0.404
Zec	0.70	0.0000	0.501	*Zec*	0.53	0.0000	0.504	*Zec*	0.70	0.0000	0.498

Dependent variable is *Ltc*				Dependent variable is *Neo*				Dependent variable is *One*			
Variable	Coef.	p-Value	R-sq	Variable	Coef.	p-Value	R-sq	Variable	Coef.	p-Value	R-sq
Bnb	0.57	0.0000	0.400	*Bnb*	0.67	0.0000	0.444	*Bnb*	0.66	0.0000	0.227
Btc	**1.21**	0.0000	0.615	*Btc*	**1.18**	0.0000	0.458	*Btc*	**1.10**	0.0000	0.211
Btt	0.43	0.0000	0.317	*Btt*	0.52	0.0000	0.369	*Btt*	0.54	0.0000	0.210
Cel	0.37	0.0000	0.310	*Cel*	0.40	0.0000	0.293	*Cel*	0.71	0.0000	**0.480**
Dash	0.68	0.0000	0.601	*Dash*	0.75	0.0000	0.574	*Dash*	0.64	0.0000	0.224
Eos	0.66	0.0000	0.610	*Eos*	0.75	0.0000	0.609	*Eos*	0.62	0.0000	0.221
Etc	0.64	0.0000	0.556	*Etc*	0.73	0.0000	0.564	*Etc*	**0.54**	0.0000	**0.165**
Eth	0.91	0.0000	**0.641**	*Eth*	0.94	0.0000	0.539	*Eth*	0.86	0.0000	0.237
Link	0.66	0.0000	0.595	*Link*	0.74	0.0000	0.590	*Link*	0.72	0.0000	0.294
Neo	0.68	0.0000	0.586	*Ltc*	0.86	0.0000	0.586	*Ltc*	0.80	0.0000	0.268
One	**0.34**	0.0000	**0.268**	*One*	**0.38**	0.0000	**0.271**	*Neo*	0.71	0.0000	0.271
Qtum	0.53	0.0000	0.517	*Qtum*	0.67	0.0000	**0.637**	*Qtum*	0.55	0.0000	0.230
Trx	0.65	0.0000	0.443	*Trx*	0.81	0.0000	0.536	*Trx*	0.73	0.0000	0.236
Xlm	0.57	0.0000	0.438	*Xlm*	0.66	0.0000	0.467	*Xlm*	0.56	0.0000	0.183
Xmr	0.73	0.0000	0.489	*Xmr*	0.81	0.0000	0.476	*Xmr*	0.73	0.0000	0.208
Zec	0.65	0.0000	0.579	*Zec*	0.72	0.0000	0.572	*Zec*	0.64	0.0000	0.236

Dependent variable is *Qtum*				Dependent variable is *Trx*				Dependent variable is *Xlm*			
Variable	Coef.	p-Value	R-sq	Variable	Coef.	p-Value	R-sq	Variable	Coef.	p-Value	R-sq
Bnb	0.74	0.0000	0.378	*Bnb*	0.52	0.0000	0.323	*Bnb*	0.56	0.0000	0.281
Btc	**1.26**	0.0000	0.364	*Btc*	**0.96**	0.0000	0.371	*Btc*	**1.11**	0.0000	0.373
Btt	0.56	0.0000	0.300	*Btt*	0.55	0.0000	0.495	*Btt*	0.45	0.0000	0.249
Cel	0.46	0.0000	0.265	*Cel*	0.36	0.0000	0.292	*Cel*	0.37	0.0000	0.233
Dash	0.80	0.0000	0.457	*Dash*	0.59	0.0000	0.445	*Dash*	0.64	0.0000	0.395
Eos	0.87	0.0000	0.585	*Eos*	0.63	0.0000	0.531	*Eos*	0.73	0.0000	**0.537**
Etc	0.84	0.0000	0.528	*Etc*	0.57	0.0000	0.425	*Etc*	0.63	0.0000	0.386
Eth	1.03	0.0000	0.449	*Eth*	0.78	0.0000	0.446	*Eth*	0.86	0.0000	0.419
Link	0.81	0.0000	0.496	*Link*	0.58	0.0000	0.441	*Link*	0.68	0.0000	0.455
Ltc	0.97	0.0000	0.517	*Ltc*	0.68	0.0000	0.443	*Ltc*	0.77	0.0000	0.438
Neo	0.95	0.0000	**0.637**	*Neo*	0.66	0.0000	**0.536**	*Neo*	0.71	0.0000	0.467
One	**0.42**	0.0000	**0.230**	*One*	**0.32**	0.0000	**0.236**	*One*	**0.32**	0.0000	**0.183**
Trx	0.84	0.0000	0.408	*Qtum*	0.48	0.0000	0.408	*Qtum*	0.57	0.0000	0.437
Xlm	0.76	0.0000	0.437	*Xlm*	0.55	0.0000	0.403	*Trx*	0.73	0.0000	0.403
Xmr	0.87	0.0000	0.385	*Xmr*	0.63	0.0000	0.348	*Xmr*	0.68	0.0000	0.310
Zec	0.77	0.0000	0.450	*Zec*	0.58	0.0000	0.442	*Zec*	0.64	0.0000	0.419

Table 2A: (continued)

Dependent variable is *Xmr*				Dependent variable is *Zec*			
Variable	**Coef.**	**p-Value**	**R-sq**	**Variable**	**Coef.**	**p-Value**	**R-sq**
Bnb	0.53	0.0000	0.372	*Bnb*	0.65	0.0000	0.384
Btc	**1.00**	0.0000	0.445	*Btc*	**1.19**	0.0000	0.428
Btt	0.40	0.0000	0.293	*Btt*	0.50	0.0000	0.311
Cel	**0.28**	0.0000	**0.198**	*Cel*	0.40	0.0000	0.268
Dash	0.62	0.0000	0.550	*Dash*	0.87	0.0000	**0.708**
Eos	0.51	0.0000	0.393	*Eos*	0.71	0.0000	0.511
Etc	0.52	0.0000	0.390	*Etc*	0.72	0.0000	0.501
Eth	0.71	0.0000	0.423	*Eth*	0.95	0.0000	0.504
Link	0.52	0.0000	0.404	*Link*	0.71	0.0000	0.498
Ltc	0.67	0.0000	0.489	*Ltc*	0.89	0.0000	0.579
Neo	0.59	0.0000	0.476	*Neo*	0.79	0.0000	0.572
One	0.28	0.0000	0.208	*One*	**0.37**	0.0000	**0.236**
Qtum	0.44	0.0000	0.385	*Qtum*	0.59	0.0000	0.450
Trx	0.56	0.0000	0.348	*Trx*	0.77	0.0000	0.442
Xlm	0.46	0.0000	0.310	*Xlm*	0.65	0.0000	0.419
Zec	0.63	0.0000	**0.600**	*Xmr*	0.95	0.0000	0.600

Standard errors are corrected for autocorrelation and/or heteroscedasticity with the Newey–West HAC. The bold values indicate the explanatory power.

References

Breidbach, C. F., and S. Tana. 2021. “Betting on Bitcoin: How Social Collectives Shape Cryptocurrency Markets.” *Journal of Business Research* 122: 311–20.

Breitung, J., and N. R. Swanson. 2002. “Temporal Aggregation and Spurious Instantaneous Causality in Multiple Time Series Models.” *Journal of Time Series Analysis* 23 (6): 651–65.

Bouri, E., T. Saeed, X. V. Vo, and D. Roubaud. 2021. “Quantile Connectedness in the Cryptocurrency Market.” *Journal of International Financial Markets, Institutions and Money* 71: 101302.

Caferra, R. 2022. “Sentiment Spillover and Price Dynamics: Information Flow in the Cryptocurrency and Stock Market.” *Physica A* 593: 126983.

Canh, N. P., N. Q. Binh, and S. D. Thanh. 2019a. “Cryptocurrencies and Investment Diversification: Empirical Evidence from Seven Largest Cryptocurrencies.” *Theoretical Economics Letters* 9: 431–52.

Canh, N. P., U. Wongchoti, S. D. Thanh, and N. T. Thong. 2019b. “Systematic Risk in Cryptocurrency Market: Evidence from DCC-MGARCH Model.” *Finance Research Letters* 29: 90–100.

Cao, G., and M. Ling. 2022. “Asymmetry and Conduction Direction of the Interdependent Structure between Cryptocurrency and US Dollar, Renminbi, and Gold Markets.” *Chaos, Solitons & Fractals* 155: 111671.

Chen, J., D. Lin, and J. Wu. 2022. “Do Cryptocurrency Exchanges Fake Trading Volumes? An Empirical Analysis of Wash Trading Based on Data Mining.” *Physica A* 586: 126405.

Clarke, J. A., and S. Mirza. 2006. “A Comparison of Some Common Methods for Detecting Granger Noncausality.” *Journal of Statistical Computation and Simulation* 76 (3): 207–31.

Corbet, S., Y. G. Hou, Y. Hu, C. Larkin, B. Lucey, and L. Oxley. 2022. “Cryptocurrency Liquidity and Volatility Interrelationships during the COVID-19 Pandemic.” *Finance Research Letters* 45: 102137.

Culjak, M., B. Tomic, and S. Zikovic. 2022. “Benefits of Sectoral Cryptocurrency Portfolio Optimization.” *Research in International Business and Finance* 60: 101615.

Dufour, J. M., R. Garcia, and A. Taamouti. 2012. “Measuring High-Frequency Causality between Returns, Realized Volatility, and Implied Volatility.” *Journal of Financial Econometrics* 10 (1): 124–63.

Engle, R. F., and C. W. Granger. 1987. “Co-Integration and Error Correction: Representation, Estimation, and Testing.” *Econometrica: Journal of the Econometric Society* 55 (2): 251–76.

Geweke, J. 1982. “Measurement of Linear Dependence and Feedback between Multiple Time Series.” *Journal of the American Statistical Association* 77 (378): 304–13.

Granger, C. W. 1969. “Investigating Causal Relations by Econometric Models and Cross-Spectral Methods.” *Econometrica: Journal of the Econometric Society* 37 (3): 424–38.

Granger, C. W. 1988. “Some Recent Development in a Concept of Causality.” *Journal of Econometrics* 39 (1–2): 199–211.

Guindy, M. A. 2021. “Cryptocurrency Price Volatility and Investor Attention.” *International Review of Economics & Finance* 76: 556–70.

Hansen, B. E. 1992. “Testing for Parameter Instability in Linear Models.” *Journal of Policy Modeling* 14 (4): 517–33.

Kim, M. J., N. P. Canh, and S. Y. Park. 2021. “Causal Relationship Among Cryptocurrencies: A Conditional Quantile Approach.” *Finance Research Letters* 42: 101879.

Lahiani, A., A. Jeribi, and N. B. Jlassi. 2021. “Nonlinear Tail Dependence in Cryptocurrency-Stock Market Returns: The Role of Bitcoin Futures.” *Research in International Business and Finance* 56: 101351.

Li, R., S. Li, D. Yuan, and H. Zhu. 2021a. “Investor Attention and Cryptocurrency: Evidence from Wavelet-Based Quantile Granger Causality Analysis.” *Research in International Business and Finance* 56: 101389.

Li, Y., A. Urquhart, P. Wang, and W. Zhang. 2021b. “MAX Momentum in Cryptocurrency Markets.” *International Review of Financial Analysis* 77: 101829.

Lütkepohl, H. 1982. “Non-Causality Due to Omitted Variables.” *Journal of Econometrics* 19 (2–3): 367–78.

Maddala, G. S., and I. Kim. 1998. *Unit Roots, Cointegration, and Structural Change*. New York: Cambridge University Press.

Moratis, G. 2021. “Quantifying the Spillover Effect in the Cryptocurrency Market.” *Finance Research Letters* 38: 101534.

Naeem, M. A., S. Qureshi, M. U. Rehman, and F. Balli. 2022. “COVID-19 and Cryptocurrency Market: Evidence from Quantile Connectedness.” *Applied Economics* 54 (3): 280–306.

Nakamoto, S. 2008. *Bitcoin: A Peer-To-Peer Electronic Cash System*. Also available at https://bitcoin.org/bitcoin.pdf.

Park, J. Y., and P. C. B. Phillips. 1989. “Statistical Inference in Regressions with Integrated Process: Part 2.” *Econometric Theory* 5 (1): 95–132.

Sawa, T. 1978. “Information Criteria for Discriminating Among Alternative Regression Models.” *Econometrica: Journal of the Econometric Society* 46 (6): 1273–91.

Schinckus, C., D. P. T. Duy, and N. P. Canh. 2020. “Interdependences between Cryptocurrencies: A Network Analysis from 2013 to 2018.” *Journal of Interdisciplinary Economics* 33 (2): 1–10.

Sims, C. A., J. H. Stock, and M. W. Watson. 1990. “Inference in Linear Time Series Models with Some Unit Roots.” *Econometrica* 58 (1): 113–44.

Smales, L. A. 2022. “Investor Attention in Cryptocurrency Markets.” *International Review of Financial Analysis* 79: 101972.

Stern, D. I. 2011. “From Correlation to Granger Causality.” In *Crawford School Research Paper 13*.

Toda, H. Y., and P. C. B. Phillips. 1993. “Vector Autoregression and Causality.” *Econometrica* 59: 229–55.

Tu, Z., and C. Xue. 2019. “Effect of Bifurcation on the Interaction between Bitcoin and Litecoin.” *Finance Research Letters* 31: 382–5.

Vidal-Tomás, D. 2022. “Which Cryptocurrency Data Sources Should Scholars Use?” *International Review of Financial Analysis* 81: 102061.

Yan, L., N. Mirza, and M. Umar. 2022. “The Cryptocurrency Uncertainties and Investment Transitions: Evidence from High and Low Carbon Energy Funds in China.” *Technological Forecasting and Social Change* 175: 121326.

Yarovaya, L., and D. Zieba. 2022. “Intraday Volume-Return Nexus in Cryptocurrency Markets: Novel Evidence from Cryptocurrency Classification.” *Research in International Business and Finance* 60: 101592.

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