“A tick-by-tick level measurement of the lead-lag duration between cryptocurrencies: The case of Bitcoin versus Cardano”

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A TICK-BY-TICK LEVEL MEASUREMENT OF THE LEAD-LAG DURATION BETWEEN CRYPTOCURRENCIES: THE CASE OF BITCOIN VERSUS CARDANO

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Abstract

According to past research utilizing Bitcoin and other cryptocurrencies, Bitcoin has been shown to lead most other cryptocurrencies in terms of price movements. However, existing studies tend to focus on the direction of the lead-lag relationship instead of the duration of the lead-lag time. Furthermore, they are handicapped by the reliance on low-frequency data such as daily prices. This paper showcases the measurement of the lead-lag duration between cryptocurrencies using ultra-high-frequency tick-by-tick data, via the pair of Bitcoin and Cardano. Tick-by-tick data bring unique challenges in terms of methodology. The vast majority of time series econometrics methods are designed for use with data collected at regularly spaced time intervals, such as every hour, every day, etc. Tick-by-tick data, on the other hand, are not synchronized in any way and do not arrive at consistently spaced time intervals. Consequently, an asynchronous data integration methodology is utilized to estimate the Bitcoin price lead over Cardano price for each month beginning in January 2019 and continuing through May 2021. The length of the lead time ranges from 16 seconds to 118 seconds, with an average of around 57 seconds. Throughout the study period, the lengths of the lead time manifest a general trend of decline, which is shown to be statistically significant via non-parametric tests. Testing of seasonal patterns turns out to be not significant. The methodology and the findings of this paper have implications for both academics and practitioners, for example, when studying and implementing statistical arbitrage with cryptocurrencies.

Keywords cryptocurrency, asynchronous data integration, high frequency, price comovement, lead time, statistical arbitrage

JEL Classification G12, G14, G19

INTRODUCTION

Since the introduction of Bitcoin in 2009, cryptocurrencies have seen tremendous growth. Many now regard cryptocurrencies as a separate asset class for investment and trading. There are also numerous academic studies devoted to cryptocurrencies. However, existing lead-lag research on cryptocurrencies tends to focus on the direction of the lead-lag relationship, or in other words, on which cryptocurrencies lead and which cryptocurrencies lag. How long is the lead-lag time between two major cryptocurrencies? The answer is surprisingly lacking in the existing literature.

A reason for the void in the literature is that most lead-lag studies on cryptocurrencies employ daily prices or other low-frequency data. But the solution is not as easy as switching to high-frequency data. Ultra-high-frequency tick-by-tick data for cryptocurrencies are available. But utilizing them will require completely different methodology, be-

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cause of the asynchronous nature of the tick-by-tick data. This paper will showcase the measurement of the lead-lag duration between cryptocurrencies at the tick-by-tick level.

As of the beginning of 2023, Cardano is the ninth largest cryptocurrency by market capitalization. However, if one travels back in time to September 2021, they will find that Cardano was the third largest cryptocurrency by market capitalization. Cardano entered the world of cryptocurrencies in 2017, making it a relative latecomer. Remarkably, by September 2021, its market capitalization was smaller than only those of Bitcoin and Ethereum. Bitcoin and Ethereum both employ the proof-of-work protocol. Cardano employs a proof-of-stake system, which operates with a drastically reduced amount of energy. Furthermore, it improves upon earlier generations of cryptocurrencies in a number of ways. As a result, many individuals view Cardano as a cryptocurrency of the future, particularly in comparison to Bitcoin, Ethereum, and numerous other cryptocurrencies. Because of this, it was decided to focus on the lead-lag duration between Bitcoin and Cardano for this particular paper.

1. LITERATURE REVIEW

There is a substantial amount of literature devoted to lead-lag examinations. Xu and Yin (2017) investigate the lead-lag relationship between the volume of index ETFs and stock market index volatility. Koutmos (2018) analyzes eighteen distinct cryptocurrencies utilizing the VAR approach proposed by Diebold and Yilmaz (2009). He discovers that Bitcoin has the biggest return spillover of all cryptocurrencies. In their study of Bitcoin and sixteen other cryptocurrencies, Ciaian et al. (2018) conclude that, in the near term, changes in the price of Bitcoin have an impact on the majority of the other cryptocurrencies' prices. Tolikas (2018) examines the lead-lag relationship between the stock and bond markets. Using a wavelet approach, Mensi et al. (2019) conclude that Bitcoin is in a better position than Ripple, Monero, and Dash in the temporal frequency space. According to a study by Corbet et al. (2018), "Bitcoin prices affect both Ripple (28.37%) and Lite (42.3%), whereas Ripple and Lite have limited influence on Bitcoin," and "inside the cryptocurrency market, Bitcoin is the undisputed leader." Marsh and Wagner (2016) and Ballester and Gonzalez-Urteaga (2020) study the lead-lag relationship between the credit default swap market and the stock market. According to Ji et al. (2019), who conducted research on six of the most important cryptocurrencies, Bitcoin and Litecoin have the most influential return shocks. Wang et al. (2022) examine the lead-lag relationship between the VIX of the S&P 500 index and the VIXs of individual stocks in their study. Anderson (2022) measures the duration of the lead-lag time between specific stocks tick-by-tick for each year from 2000 to 2022.

A lot of the lead-lag research overlaps with the price discovery literature. Frino and Garcia (2018) investigate the lead-lag connection between bank accepted bill futures contracts and Australian interest rate swaps. The lead-lag link between Chinese stock index and the index futures are studied by Zhou et al. (2021), Ren et al. (2019), Xiao et al. (2022), Jin et al. (2022), Miao et al. (2017), Liu and Qiao (2017), Huo and Ahmed (2018), Hou and Li (2020), Qu and Xiong (2019), Zhou and Wu (2016), Xu and Wan (2015), Hao et al. (2019), Gong et al. (2016), and Wang et al. (2017). The lead-lag relationship between stock index and stock index futures are researched, for Taiwan by Jiang et al. (2012), for DAX30 by Alemany et al. (2020), for FTSE/ATHEX-20 by Kavussanos et al. (2020), for the DJIA by Tse (1999), for Thailand by Judge and Reancharoen (2014), for Korea by Kang et al. (2013), for Malaysia by Sifat et al. (2021), and for Finland by Martikainen and Puttonen (1994). Kumar (2018) investigates price discovery in the emerging currency markets: South African rand, Indian rupee, and Brazilian real, in particular. Yang and Shao (2020) probe the lead-lag connection between VIX and VIX futures. Storhas et al. (2020) examine the lead-lag link between refined oil product and crude oil. Shao et al. (2019) study the lead-lag relationship between crude oil futures and spot markets. Li and Hayes (2017) investigate the lead-lag connection among soybean futures prices in different countries.

Although Cardano is occasionally studied among a group of cryptocurrencies, it is seldom studied specifically. We are aware of only one previous research that focuses on Cardano, a working paper by Johnson (2021), in which she discovers a high correlation between Cardano and Ethereum prices, using daily data. This paper examines the relationship between price movements of Bitcoin and Cardano on a market microstructure level, using ultra-high-frequency tick-by-tick data.

Besides being one of the first papers to study Cardano specifically, this study here fills two other gaps in the literature, in terms of fine time scale and novel methodology.

Most of the existing papers that have examined the price comovement of cryptocurrencies have used daily data. This paper uses tick-by-tick data to measure the lead time of Bitcoin over Cardano. We have not come across a study that actually measures the length of the lead-lag time between two cryptocurrencies at this fine time scale.

At the tick-by-tick level, price changes do not emerge at fixed-length time intervals. Unfortunately, most of the tools in time series econometrics are designed for data arriving at fixed-length time intervals, for examples, a data point every day, or a data point every hour, etc. Artificially casting asynchronous data into fixed-length time intervals could cause problems in analyses. This is discussed in Finucane (1999). Suppose Bitcoin always leads Cardano by half a minute, but the fixed-length time interval used in an analysis is 5 minutes. Very likely, a price change in Bitcoin and the corresponding price change in Cardano will fall into the same 5-minute interval. An analysis should show that there is no lead-lag relationship between the two cryptocurrencies. Therefore, this paper chooses to use an asynchronous multi-asset data integration approach pioneered by Finucane (1999), which does not require fixed-length time intervals. This method has been used before in lead-lag analyses for stock prices at the tick-by-tick level, for example, in Anderson (2016). To the best of our knowledge, no previous research has applied this methodology to study the price co-movements of cryptocurrencies.

2. METHODS

Tick-by-tick data are purchased from FirstRateData.com. The Cardano data are from February 2018 to May 2021. The data are a mixture of transactions from five exchanges: Coinbase, BitFinex, BitStamp, HitBTC, and Kraken. However, for the majority of the time period studied, only HitBTC and Kraken have data for Cardano. In the early part of the time period, HitBTC has much more Cardano transactions than Kraken. For example, in January 2020, HitBTC has 114,933 trades, but Kraken has only 24,733 trades. Therefore, only trades from HitBTC were used for this analysis, for both Cardano and Bitcoin. For Cardano, there is a drastic change in the number of trades recorded at the end of 2018. In January 2019, it is 45,278. But, in December 2018, it is only 5,063. As a result, the year 2018 is not included in the analysis.

C is used to denote the trade prices for Cardano. Denote C at time $t(C_0)$ as C_0. When the next C trade arrives at time $t(C_1)$, its price is C_1. $C_1 \neq C_0$ is required to consider it as a different price (see Figure 1).

Next, several prices of Bitcoin, B, are defined. B_0 denotes the price of B valid at time $t(C_1)$. B_{-1} is the price immediately before C_0, which satisfies $B_{-1} \neq B_0$. B_{-2} denotes the price of Bitcoin immediately before B_{-1}, with $B_{-1} \neq B_{-2}$.

Finally, the returns are defined:

$$\begin{aligned} r_{-2}^{B} &= \ln(B_{-1}) - \ln(B_{-2}), \\ r_{-1}^{B} &= \ln(B_{0}) - \ln(B_{-1}), \\ r^{C} &= \ln(C_{1}) - \ln(C_{0}). \end{aligned} \tag{1}$$

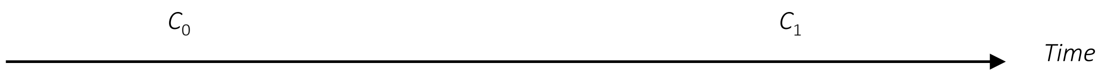

Figure 1. A simple illustration of the Cardano price sequence

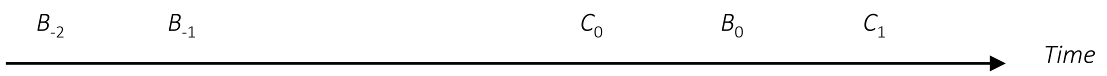

Figure 2. The asynchronous integration of Bitcoin and Cardano prices

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To measure the maximum amount of time by which Bitcoin leads Cardano, an artificial time gap of X seconds is introduced between B_{-1} and C_0. In other words, B_{-1} is now defined as the Bitcoin price immediately before X seconds before C_0, with $B_{-1} \neq B_0$. Note that in $r_{-2}^{B} = \ln(B_{-1}) - \ln(B_{-2})$, both B_{-1} and B_{-2} are before, or on the left side of, the artificial time gap of X seconds (see Figure 2). Also note that in $r^C = \ln(C_1) - \ln(C_0)$, both C_0 and C_1 are after, or on the right side of, the artificial time gap of X seconds. Hence, if X seconds is more than the maximum amount of time by which Bitcoin prices lead Cardano, β_2 will not be significantly different from zero in the following equation:

$$r^C = \alpha + \beta_1 r_{-1}^{B} + \beta_2 r_{-2}^{B} + \varepsilon. \qquad (2)$$

3. RESULTS

To estimate the lead time X, we first experiment with different X values at 10-second intervals: X = 10, 20, 30, … For each X, Equation (2) is estimated with heteroscedasticity and autocorrelation consistent covariance estimators. The r^C time series is pre-whitened with AR(2). For sufficiently small X, both β_1 and β_2 coefficients in equation (2) are significantly different from zero at the 5% level. But eventually, when the value of X experimented is large enough, β_2 will stop being significant.

Let us suppose, for example, for X = 10, 20, and 30, both β_1 and β_2 are significantly different from zero, but for X = 40, β_2 is no longer significant. It means the length of the lead time is between 30 and 40

Table 1. Estimation steps for the lead time of Bitcoin over Cardano, for January 2020

X (seconds)	α	β_1	β_2
10	−3.0236e−06	0.4755**	0.2655**
	(3.8907e−06)	(0.0627)	(0.0166)
20	−2.4724e−06	0.4199**	0.1935**
	(3.5924e−06)	(0.0468)	(0.0170)
30	−2.7797e−06	0.3609**	0.1616**
	(3.4779e−06)	(0.0389)	(0.0230)
40	−1.4636e−06	0.3151**	0.1400**
	(3.4007e−06)	(0.0356)	(0.0201)
50	−9.0501e−07	0.2718**	0.1174**
	(3.4490e−06)	(0.0328)	(0.0212)
60	−7.9795e−07	0.2474**	0.0948**
	(3.4381e−06)	(0.0309)	(0.0157)
70	−1.4987e−06	0.2196**	0.0719**
	(3.5589e−06)	(0.0290)	(0.0171)
80	−1.8121e−06	0.1996**	0.1029**
	(3.6215e−06)	(0.0262)	(0.0194)
90	−2.0468e−06	0.1888**	0.0636**
	(3.6757e−06)	(0.0245)	(0.0222)
100	−2.0325e−06	0.1794**	0.1312**
	(3.6179e−06)	(0.0238)	(0.0279)
110	−2.2044e−06	0.1714**	0.0747**
	(3.6374e−06)	(0.0229)	(0.0158)
120	−1.7405e−06	0.1559**	0.0284
	(3.6744e−06)	(0.0221)	(0.0167)
130	−1.5086e−06	0.1400**	0.0156
	(3.6700e−06)	(0.0223)	(0.0164)
115	−2.0018e−06	0.1638**	0.1101**
	(3.6280e−06)	(0.0220)	(0.0297)
117	−1.8736e−06	0.1611**	0.0358**
	(3.6453e−06)	(0.0220)	(0.0152)
119	−1.7946e−06	0.1573**	0.0386
	(3.6704e−06)	(0.0221)	(0.0218)
118	−1.8639e−06	0.1587**	0.0581**
	(3.6559e−06)	(0.0222)	(0.0233)

Note: Newey-West standard errors are reported in parentheses beneath the estimates. ** Significant at the 5% level.

seconds. From here on, the interval is halved in each iteration, until the lead time estimate is narrowed down to a particular second.

The lead time of Bitcoin over Cardano is estimated, for each month from January 2019 to May 2021. An example of the estimation process is shown in Table 1, for the month of January 2000. The estimation results are reported in Table 2.

Table 2. Estimated lead time for each month

Time	Month	Year	Lead time (seconds)
1	January	2019	68
2	February	2019	71
3	March	2019	80
4	April	2019	64
5	May	2019	61
6	June	2019	56
7	July	2019	86
8	August	2019	46
9	September	2019	75
10	October	2019	70
11	November	2019	62
12	December	2019	98
13	January	2020	118
14	February	2020	88
15	March	2020	27
16	April	2020	68
17	May	2020	21
18	June	2020	30
19	July	2020	30
20	August	2020	21
21	September	2020	29
22	October	2020	16
23	November	2020	62
24	December	2020	73
25	January	2021	75
26	February	2021	38
27	March	2021	40
28	April	2021	41
29	May	2021	25

From Table 2, it can be seen that the lead time of Bitcoin over Cardano varies from month to month, with the maximum being 118 seconds and the minimum being 16 seconds, with a mean of 56.5 and a median of 62 seconds. The standard deviation is 26.

A question is: In general, does the lead time increase or decrease over time? A nonparametric approach can answer that question. The Pearson correlation coefficient is calculated between the estimated monthly lead time and the Time index (Time =1, 2, 3, …). The Pearson correlation coefficient is –0.4747, with a p-value of 0.0093. Hence, there is a significant down trend. However, it may or may not be linear. Spearman's rho is thus calculated, which is –0.4601 with a p-value of 0.0120. Because of the small sample size, we also calculate Kendall's tau, with tau-a = –0.2882, and tau-b = –0.2900, with a p-value of 0.0294. From these calculations, it can be concluded that the lead time tends to decrease over time, and that this down trend is statistically significant.

Lastly, it is examined if there are seasonality patterns in the estimated monthly lead time series. An unobserved-components model is fitted with a stochastic seasonal component of 12 months a year. The output from Stata is reported in Table 3. The variance of the seasonal component is estimated to be 234.57. However, the 95% confidence interval for the variance contains 0, which implies that deterministic seasonal components are appropriate. An unobserved-components model with deterministic seasonal components of 12 months a year is therefore fitted with the estimated monthly lead time series. The output from Stata is reported in Table 4. Among the 11 free seasonality parameters estimated via the model, only 3 are significantly different from 0 at the 5% level, and none are significant at the 1% level. Hence, it can be concluded that there are no significant season-

Table 3. Stata output from fitting the first unobserved-components model

Sample: 2019m1 – 2021m5
Number of obs = 29
Log likelihood = –95.021932

Lagt	OIM					
	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
			Variance			
Level	74.63115	59.60169	1.25	0.105	0	191.4483
Seasonal	234.5687	120.9817	1.94	0.026	0	471.6885

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Table 4. Stata output from fitting the second unobserved-components model

Sample: 2019m1 – 2021m5
Log likelihood = –122.71269
Number of obs = 29
Wald chi2(11) = 24.04
Prob > chi2 = 0.0126

Lagt	OIM					
	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Month						
1	10.60937	12.61699	0.84	0.400	–14.11948	35.33823
2	–10.98438	15.71677	–0.70	0.485	–41.78867	19.81992
3	–27.91146	17.89433	–1.56	0.119	–62.98369	7.160775
4	–19.50521	19.46173	–1.00	0.316	–57.6495	18.63908
5	–41.76563	20.55901	–2.03	0.042	–82.06055	–1.470697
6	–40.15625	21.47319	–1.87	0.061	–82.24293	1.93043
7	–25.54688	21.60063	–1.18	0.237	–67.88333	16.78958
8	–50.4375	20.95569	–2.41	0.016	–91.50989	–9.365106
9	–32.32812	19.46173	–1.66	0.097	–70.47242	5.816168
10	–41.71875	16.89502	–2.47	0.014	–74.83237	–8.605128
11	–23.10938	12.61699	–1.83	0.067	–47.83823	1.619481
12	0	(empty)				
Variance						
Level	351.3127	93.89226	3.74	0.000	167.2872	535.3381

ality patterns. However, the length of the time series fitted into the model is limited. In a few years, with more data available, perhaps this issue should be revisited.

4. DISCUSSION

Before this work, it was not even clear what the order of magnitude of the duration of the lead time of Bitcoin over Cardano is. Is it a number of weeks, a number of days, a number of hours, a number of minutes, or a number of seconds? Using ultra-high-frequency tick-by-tick data, this work answered that question definitively. It also shows how the length of the lead-lag time can vary over time. The variation of the length of the lead-lag time can provide insight into the relation and correlation between Bitcoin and Cardano. The shortest monthly lead-lag time measured is 16 seconds, and the longest monthly lead-lag time measured is 118 seconds. In the months when the lead-lag time is at the longer end of the range, it could mean that the two cryptocurrencies are more driven by different market forces, and therefore are less related and correlated. On the other hand, when the lead-lag time is relatively short for a particular month, the same or similar market forces are probably driving both the Bitcoin price changes and the Cardano price changes, although maybe to a different extent and with a slightly different time effect. In that case, Bitcoin and Cardano are more related and correlated.

The lead time of Bitcoin over Cardano has a general trend of decline over time. We establish this via non-parametric approaches. It is not just established for the linear possibilities (the Pearson correlation coefficient). It is also established for the nonlinear possibilities via Spearman's rho. Even the small sample size is taken into account via Kendall's tau. Bitcoin has certainly always been the leader among cryptocurrencies. Hence the shrinkage of the lead time is most likely due to Cardano gaining recognition and significance. It is certainly not a deterministic linear trend of decline. Hence, market sentiment could play a role here, too. Market sentiment can fluctuate and change, which helps to explain why it is not a deterministic linear trend of decline. When the market sentiment for Cardano gets stronger, the lead time of Bitcoin over Cardano declines. Sometimes, the market sentiment goes the other way, and there could be a temporary increase of the lead time of Bitcoin over Cardano. But as time progresses, the general trend is that Cardano gradually gains more significance and recognition, and therefore the general trend of decline of the lead time of Bitcoin over Cardano. Given that the Bitcoin has always been the leader among the cryptocurrencies, this general trend of decline of the lead time also shows that Cardano is in general getting more influential as the months and years pass.

An in-depth study investigating the lead-lag relationship between Bitcoin and Cardano should pique the curiosity of both academics and industry experts. After a lead-lag link has been established, for instance, field experts and academics may study the possibility of statistical arbitrage. If, for instance, Bitcoin price fluctuations consistently lead Cardano price changes by sixty seconds, then arbitrage opportunities exist. It is feasible to generate a profit by purchasing Cardano whenever the price of Bitcoin increases, waiting sixty seconds until the price of Cardano increases as well, and then selling the Cardano acquired. The reality will not be quite as perfect as this. In actuality, if Bitcoin price changes lead Cardano price changes by an average of sixty seconds, this indicates that there will be instances in which the lead time will be greater than sixty seconds, instances in which the lead time will be less than sixty seconds, and instances in which the Cardano price will not increase in response to a Bitcoin price increase. This will be a statistical arbitrage opportunity as opposed to a risk-free arbitrage opportunity in the traditional sense. If one still buys Cardano whenever the Bitcoin price goes up, wait till the Cardano price also goes up to sell the Cardano for a profit, or wait till some terminal condition to liquidate the Cardano position at a loss, although one will not make a profit for each and every trade, over time one should still be able to accumulate a profit. That is the statistical arbitrage.

There could be many other factors that influence the duration of the lead-lag time, such as news and market events. It must be kept in mind that cryptocurrencies, even the ones as established as Bitcoin or Cardano, are highly volatile and unpredictable, and rapid and perhaps unexplained price changes can occur and may happen often. These may seem noises that can be ignored when establishing a theoretical framework. But when implementing a statistical arbitrage trading strategy based on the lead-lag time measured and presented in this paper, one needs to take into account the highly volatile and unpredictable nature of both the Bitcoin prices and the Cardano prices. There certainly could be returns that can be generated via statistical arbitrage, but the risk inherit in this process cannot be and should not be taken lightly either.

The Literature Review section of this paper covered important past studies in lead-lag research. Among them, the studies on cryptocurrency leads and lags use daily data and focus on the direction of the lead-lag relationship instead of the duration of the lead-lag time. This paper stands out in that it uses ultra-high-frequency tick-by-tick data and that it focuses on measuring the duration of the lead-lag time between two cryptocurrencies: Bitcoin and Cardano. The paper that is the closest to this work is Anderson (2022), in which tick-by-tick data are used to measure the duration of the lead-lag time between stocks. This study finds that the duration of the lead-lag time between Bitcoin and Cardano tends to decrease over time. Interestingly, in Anderson (2022), the duration of the lead-lag time between stocks is also found to decline over time. The length of the lead-lag time between stocks obtained in Anderson (2022) is much shorter than the length of the cryptocurrency lead-lag time measured in this paper. Perhaps it reflects the fact that the stock market is more mature, sophisticated, and more liquid than the relatively new cryptocurrency market.

CONCLUSION

The main purpose of this study is to fill a void in the literature by measuring the lead-lag duration between cryptocurrencies. Most of the lead-lag studies in the literature can reveal which assets lead and which assets lag, but they fail to measure the duration of the lead-lag time.

Another purpose of this study is to not only measure the length of the cryptocurrency lead-lag time, but also carry out the quantification using ultra-high-frequency tick-by-tick data. Most of the existing stud-

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ies in the cryptocurrency lead-lag literature are conducted using daily data. Introducing ultra-high-frequency tick-by-tick data brings its own challenges in terms of methodology. Most of the traditional time series econometrics methods are developed for regularly-spaced time intervals, for example, a data point every month. Ultra-high-frequency tick-by-tick data do not conform to any regularly spaced time intervals. In fact, they arrive asynchronously. The challenges can be overcome by using a multi-asset asynchronous data integration technology. This study is the first to utilize this technology to estimate the duration of lead-lag time in cryptocurrencies. Bitcoin has been the leader in cryptocurrencies. Cardano, with an energy-saving proof-of-stake protocol and other improvements over earlier generations of cryptocurrencies, has been considered by many as a cryptocurrency of the future. Because of these, the pair of Bitcoin versus Cardano is used to showcase the methodology with tick-by-tick data.

In conclusion, the lead time of Bitcoin over Cardano is found to vary from month to month. For the two and a half years studied here, the shortest lead time is 16 seconds and the longest 118 seconds. Another conclusion obtained is that the lead time tends to decrease as time progresses. The majority of current research focuses on which cryptocurrency is in the lead, rather than analyzing the exact duration of lead-lag time. It is vital for researchers to determine how lengthy the lead time is, but the ramifications and uses of this research's findings in statistical arbitrage may also benefit hedge funds and other high-frequency trading organizations.

Due to the fact that Cardano is still a relative newcomer to the world of cryptocurrencies, it was not possible to detect seasonality trends. Cardano is still in its infancy; therefore, this may be due to the small sample size. This effort should be repeated in a few years, when we have access to more data, to determine whether or not a seasonal pattern can be established. The findings of this paper indicate that Bitcoin's edge over Cardano has been shrinking over time. The causes that may have led to this drop may be the subject of additional research in the future.

AUTHOR CONTRIBUTIONS

Conceptualization: Bing Anderson.
Data curation: Bing Anderson.
Formal analysis: Bing Anderson.
Investigation: Bing Anderson.
Methodology: Bing Anderson.
Project administration: Bing Anderson.
Resources: Bing Anderson.
Software: Bing Anderson.
Supervision: Bing Anderson.
Validation: Bing Anderson.
Visualization: Bing Anderson.
Writing – original draft: Bing Anderson.
Writing – review & editing: Bing Anderson.

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