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Working Papers

KAIST 문술미래전략대학원
Moon Soul Graduate School of Future Strategy

2020-03

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After the Splits: Information Flow between Bitcoin and Bitcoin Family

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Draft (April 2020)

ABSTRACT

This paper investigates the information flow between new and old forks after the Bitcoin splits. Particularly, we estimate the transfer entropy between Bitcoin and Bitcoin Cash as an information-theoretic approach. We find that the data, when symbolic analysis is applied, exhibit an asymmetric information flow from Bitcoin to Bitcoin Cash. Further investigation suggests that the reason relates to the role of liquidity in price leadership. Our results imply that the information flow between the cryptocurrency and its split coin, which has not realized its value, exists at least on the rise–fall price pattern.

Keywords: Bitcoin; Hard fork; Symbolic time series analysis; Transfer entropy

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1. Introduction

Since 2010, new tradeable digital currencies based on blockchain technology have emerged. This cryptography-based currency, i.e., cryptocurrency, is intrinsically transacted from peer to peer, so users can effectively form an opinion on any aspect. If they fail to reach a consensus, an occasional separation may occur (Islam et al., 2019). This is not a simple transformation or division, such as a monetary reform or a stock split, but a unique phenomenon not seen in traditional assets, in that new cryptocurrency could have the same role and status as the original. Physical or technological changes do not necessarily lead to the creation of new cryptocurrencies (soft fork and hard fork). Particularly, Bitcoin has maintained its preponderant position in terms of market capitalization, trading volume, and recognition among thousands of cryptocurrencies while precipitating "splits of Bitcoin" into various contexts. Just as a living organism grows through cell division, examining Bitcoin's split legacy and its market characteristics can meaningfully provide insights into the evolution and the future direction of the cryptocurrencies.

The fundamental reason for the cryptocurrency splitting is that their existence is rooted in technology. With Bitcoin, technical deficiencies related to scalability and security issues have been discovered over time, but Bitcoin users have not reached a workable consensus. The first separation of Bitcoin occurred with the birth of Bitcoin Cash, conducted by Bitmain, one of the cryptocurrency mining pools in 2017 (Islam et al., 2019). Since then, each group of mining pools has progressed its own split according to its respective goals. Bitcoin Gold and Bitcoin Diamond are such examples, separating from Bitcoin over decentralization and the evolution of better blockchain technology, respectively. Our study defines the cryptocurrencies created from the Bitcoin split as the "Bitcoin Family." The members are Bitcoin Cash (August 1, 2017),[1] Bitcoin Gold (October 24, 2017),[2] Bitcoin Diamond (November 24, 2017),[3] and Bitcoin SV (August 16, 2018),[4] which was repartitioned from Bitcoin Cash. Since Bitcoin SV is a secondary derivative coin, this study focuses on the former three coins that are directly separated, especially "Bitcoin Cash," which ranks fifth in overall market share.

Specifically, we discuss the information flow between markets, the new and the old forks, while referencing the literature on the characteristics of the cryptocurrency market. Gajardo et al. (2018) found that Bitcoin has a greater multifractality and asymmetry than other major fiat currencies, after conducting a cross-correlation analysis between Bitcoin and other asset markets (DJIA, gold, and WTI) by applying the Asymmetric Multifractal Detrended Cross-Correlation Analysis method. Drozdz et al. (2019) confirmed this cross-correlation in the relationship between Bitcoin and other cryptocurrency markets, e.g., Ethereum. Similarly, Erdaş and Çağlar (2018) argued that information flows asymmetrically from Bitcoin to other assets, such as stock, gold, oil, and the US dollar, by identifying a causal relation using the Hatemi-J test. Conversely, Jang et al. (2019) analyzed the causality between Bitcoin and asset markets using transfer entropy, finding that information flows from each asset to the Bitcoin market. However, previous studies only discussed the flow of information between the cryptocurrency and conventional asset markets such as gold, oil, and stock, or between Bitcoin and major altcoins, which have a fairly large market capitalization (Drozdz, 2019). By examining the information flow between the original and its split coins, this study thus fills the gap in the literature. Furthermore, considering the possibility that splitting, due to technological development, will continue in the cryptocurrency market, our study provides helpful information for stakeholders and policymakers.

Our study estimates the information flow between Bitcoin and the Bitcoin Family and interprets it by linking the liquidity and price discovery based on the relative market capital and the transaction volume of each coin. We mainly employ transfer entropy on the basis of information theory applying both histogram-based analysis and symbolic time series. Our results suggest that Bitcoin and Bitcoin Cash do not exchange information at the level of log returns but have information flow in terms of the price rise–fall pattern.

The remainder of this paper is structured as follows: Section 2 describes the data and introduces the methodology; Section 3 discusses the results, whereas Section 4 concludes.

2. Data and Methodology

2.1. Data

We retrieved the daily trading data from CoinMarketCap (https://coinmarketcap.com). We collected the data from when the hard fork of each Bitcoin split was "activated" (user-activated, initial release,

[1] In the case of Bitcoin Cash, the actual split event, i.e., user activated hard fork of Bitcoin, was conducted in Aug 1, 2017, while the transaction history existed in the previous period (Jul 23 – Jul 31, 2017) (Islam et al., 2019).
Source: CoinMarketCap. Bitcoin Cash. https://coinmarketcap.com/currencies/bitcoin-cash [accessed March 13, 2020]

[2] Source: CoinMarketCap. Bitcoin Gold. https://coinmarketcap.com/currencies/bitcoin-gold [accessed March 13, 2020]

[3] Source: CoinMarketCap. Bitcoin Diamond. https://coinmarketcap.com/currencies/bitcoin-diamond [accessed March 13, 2020]

[4] Source: CoinMarketCap. Bitcoin SV. https://coinmarketcap.com/currencies/bitcoin-sv [accessed March 13, 2020]

or officially launched) until January 31, 2020.[5] Since the Bitcoin exchange operates 24 h a day, we selected the closing price to be 19:00 EST. We transformed the price series into log returns to guarantee stationarity of the time series data. Table 1 summarizes the descriptive statistics of each daily log return series.

Table 1. Summary statistics of the log returns.

	Obs.	Min.	Max.	Mean	Std.	Skewness	Kurtosis
Bitcoin	922	−0.20	0.22	1.33×10^{-3}	4.25×10^{-2}	−0.01	3.46
Bitcoin Cash	922	−0.44	0.43	1.03×10^{-4}	7.91×10^{-2}	0.63	7.36
Bitcoin Gold	830	−1.25	0.71	4.58×10^{-3}	9.02×10^{-2}	−1.76	56.61
Bitcoin Diamond	798	−1.17	1.43	5.91×10^{-3}	1.28×10^{-1}	1.10	35.20

Note: Bitcoin & Bitcoin Cash (Jul 23, 2017 – Jan 31, 2020), Bitcoin Gold (Oct 23, 2017 – Jan 31, 2020), Bitcoin Diamond (Nov 24, 2017 – Jan 31, 2020)

The descriptive statistics show that Bitcoin and Bitcoin Cash are quite distinct from the other two splits. Bitcoin and Bitcoin Cash have a relatively small difference between the maximum and the minimum, and have a small kurtosis (about 1 of 10 scale), implying that they have a relatively low frequency with extreme values of daily return. The standard deviation shows that Bitcoin has a lower volatility, indicating that the early split market has relatively lower uncertainty and risk. Particularly, the Bitcoin and Bitcoin Cash have a skewness close to zero, unlike the other two.

2.2. Methodology

As an information-theoretic approach, transfer entropy estimates the information flow between two different coins.[6] Assume that X_i and Y_i are two discrete random processes. The length of each, i.e., k and l, defines $X_i^{(k)} = (X_i, X_{i-1}, \cdots, X_{i-k+1})$ and $Y_i^{(l)} = (Y_i, Y_{i-1}, \cdots, Y_{i-l+1})$ (Sensoy, 2014). Then, the transfer entropy can be expressed as follows (Schreiber, 2000):

$$TE_{Y\to X}(k,l) = H\left(X_{i+1}|X_i^{(k)}\right) - H\left(X_{i+1}|X_i^{(k)}, Y_i^{(l)}\right) = \sum p\left(x_{i+1}, x_i^{(k)}, y_i^{(l)}\right) \log \frac{p\left(x_{i+1}|X_i^{(k)}, Y_i^{(l)}\right)}{p\left(x_{i+1}|x_i^{(k)}\right)},$$

where $H\left(X_{i+1}|X_i^{(k)}\right)$ stands for the degree of uncertainty for predicting X_{i+1} for a given $X_i^{(k)}$ and $H\left(X_{i+1}|X_i^{(k)}, Y_i^{(l)}\right)$ is the degree of uncertainty considering both $X_i^{(k)}$ and $Y_i^{(l)}$ in predicting X_{i+1}. Thus, $TE_{Y\to X}$ shows the effect of $y_i^{(l)}$ on predicting X_{i+1}.

We further consider the effective transfer entropy (ETE) to redress sample bias. The ETE is calculated as (Sandoval, 2014):

$$ETE_{Y\to X} = TE_{Y\to X}(k,l) - \frac{1}{M}\sum_{i=1}^{M} TE_{Y_{(i)}\to X}(k,l),$$

where $Y_{(i)}$ denotes the variable Y which is shuffled randomly. Therefore, ETE can be considered as a subtraction of the arithmetic average of the randomized transfer entropy from the estimated value of transfer entropy.

[5] Bitcoin and Bitcoin Cash (July 23, 2017, to January 31, 2020); Bitcoin Gold (October 23, 2017, to January 31, 2020); and Bitcoin Diamond (November 24, 2017, to January 31, 2020)
[6] Transfer entropy is an advantageous alternative when the assumption of the Granger causality does not hold. Moreover, transfer entropy reduces to Granger causality for vector autoregressive processes (Barnett et al., 2009).

We calculate the transfer entropy via a histogram analysis (the most common method to deal with discrete random variables). To estimate the number of bins—an equally spaced interval of sample range, we use the mean squared error criterion (Larson, 1974; Scott, 1979; Freedman and Diaconis, 1981).

Next, we use the symbolic time series analysis (STSA) to alternatively estimate the transfer entropy. Because of its robustness to noise, STSA is widely used in a variety of fields, including physics, information theory, and finance (Ruiz et al., 2012; Risso, 2018). We use the log return data to convert each value to 0 or 1, reflecting the rise–fall pattern of the price series. Given the consecutive binary sequence, we then convert into decimal numbers X^S, with window size S. The transfer entropy is finally obtained through the probability assigned to each state X^S (Ahn et al., 2019a).

3. Results and Discussion

3.1. Granger Causality

To examine the information flow between Bitcoin and Bitcoin Cash, we perform a Granger causality test (Granger, 1969). Table 2 presents the results on the basis of the bivariate VAR(p) model. The optimal lag length p of the VAR model was obtained by the Akaike information criterion, Hannan Quinn information criterion, Schwarz criterion, and the final prediction error (Akaike, 1969; Hanna, 1979; Burnham, 2004). The result with an optimal lag of $p = 2$ rejects the null hypothesis that Bitcoin (Bitcoin Cash) does not Granger cause Bitcoin Cash (Bitcoin): there are significant bi-directional relationships between the two. We further perform the Granger causality test with a lag of $p = 1$ and conclude that there is no qualitative difference from the optimal lag of $p = 2$.

Table 2. Granger Causality test.

Lag	Null Hypothesis	F-Statistics
$p = 1$	BTC $\nrightarrow$ BCH	7.2276***
	BCH $\nrightarrow$ BTC	9.8333***
$p = 2$	BTC $\nrightarrow$ BCH	10.933***
	BCH $\nrightarrow$ BTC	5.2037***

Note: The notation "A$\nrightarrow$B" denotes the null hypothesis that "A does not Granger cause B". *** indicates significance at the 1% level. BTC and BCH represent Bitcoin and Bitcoin Cash, respectively.

To ensure the adequacy of the Granger causality test, the assumption that the residuals of the VAR(p) model are Gaussian white noise must be satisfied. We conduct a normality test on the residuals of the VAR(p) model. Table 3 indicates that the null hypothesis is rejected at the 1% significance level for all three test statistics. The result suggests that the assumption, *Residuals of VAR(p) model are normally distributed*, is not satisfied, which leads to the conclusion that the Granger causality test is too naïve to grasp the causal link between Bitcoin and Bitcoin Cash.

Table 3. Normality tests on the residuals of bivariate VAR(p) model.

Jarque-Bera test	Skewness test	Kurtosis test
7.077×10^3 ***	2.665×10^2 ***	6.810×10^3 ***

Note: Jarque-Bera, skewness, and kurtosis were tested using χ^2 statistics. *** indicates significance at the 1% level.

3.2. Transfer Entropy

We use transfer entropy as an information-theoretic approach to identify the information flow between the two markets of the original and its split. Histogram-based transfer entropy posits no significant information flow between Bitcoin and Bitcoin Cash. This is quite different from the results of the Granger causality test: the causal relationship between the Bitcoin and Bitcoin Cash markets has not been found. Particularly, the values of the ETE, which was used to overcome the sample bias, are all zero, suggesting that the transfer entropy might more likely be due to noise, i.e., a random process (Sandoval, 2014). Table 4 summarizes the results.

Table 4. Information flow between Bitcoin and Bitcoin Cash.

	Transfer Entropy		Effective Transfer Entropy	
(A) Histogram	BTC → BCH	BCH → BTC	BTC → BCH	BCH → BTC
	1.663	1.719	0.000	0.000
(B) STSA	BTC → BCH	BCH → BTC	BTC → BCH	BCH → BTC
	0.064 **	0.046	0.015	0.000

Note: The arrow indicates the direction, and the number denotes the estimated value of transfer entropy and effective transfer entropy. The significance level is evaluated by bootstrapping the underlying Markov process (Horowitz, 2003; Dimpfl and Peter, 2013). ** indicates significance at the 5% level.

Meanwhile, the STSA uses the log return series differently with histogram analysis: it further processes data by symbolizing the rise and fall pattern of the sample series. The STSA-based transfer entropy reveals an asymmetric information flow between the original and its split. When the window size is 3 (number of bins = 8), the information flow is found from BTC to BCH at the 5% significance level. The result is also robust with the window size 4 (number of bins = 16) at the significance level of 10%. Particularly, the ETE is positive, implying that the information flow from Bitcoin to Bitcoin Cash is not an accidental event; i.e., the information flow palpably exists at a level exceeding the randomized transfer entropy or noise (Sandoval, 2014).

Our analysis, concentrating on the information flow between Bitcoin and its representative split, not only addresses the problem to apply each test but also introduces a higher-level proxy: a fluctuation pattern of the series, to ascertain the underlying link between the two, not obvious at first glance. Specifically, our study ensures the asymmetric dependencies between the structurally identical but non-identically coupled systems by estimating the transfer entropy through symbolizing data (Matthaus and Klaus, 2008; Staniek, 2008). Put differently, STSA, the domain of "value change" rather than "realized value" itself, comports well with our case: Bitcoin and its split, whereby a technology upgrade caused the change.

3.3. Liquidity and Price Discovery

We argue that the asymmetric information flow could be explained by the role of liquidity in price leadership. As shown in Figure 1, Bitcoin's market capitalization is about 40 times larger than that of Bitcoin Cash. Likewise, on average, the transaction volume of Bitcoin is nine times greater than that of Bitcoin Cash.[7] This indicates that investors' preference for Bitcoin is much higher than for Bitcoin Cash. Our findings thus imply that a market with more trading activities and less uncertainty (as can be seen in Table 1) is conducive to having a prominent role in price discovery (Chakravarty et al., 2004; Ahn et al., 2019b; Jang et al., 2019).

[7] Source: CoinMarketCap. https://coinmarketcap.com/currencies/bitcoin-cash [accessed March 10, 2020]

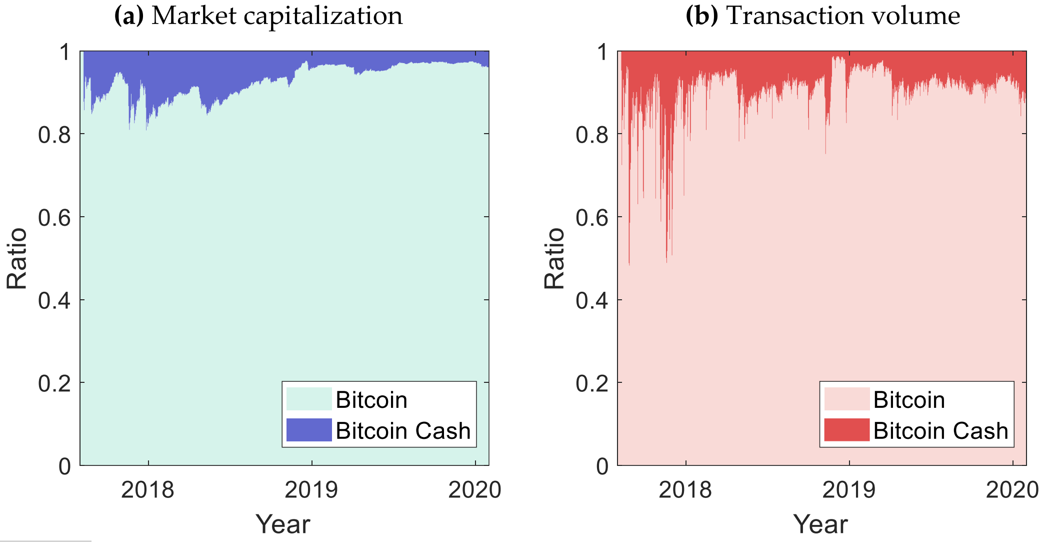

Figure 1. Market capitalization and transaction volume. We display the relative ratio of market capitalization and the transaction volume for each coin during the collection period, August 1, 2017, to January 31, 2020.

We further investigate the information flow between Bitcoin and the other split markets, such as Bitcoin Gold and Bitcoin Diamond. As shown in Table 5, it is difficult to assert statistically significant causality or information flow for both cases, even on price fluctuation. Unlike Bitcoin Cash, Bitcoin Gold and Bitcoin Diamond do not have sufficient market capitalization and transaction volume,[8] so we cannot exclude the possibility that the transfer entropy originated from noise rather than information flow. Our argument is bolstered by the fact that the value of ETE is nearly zero and that the transfer entropy is not statistically significant. We conjecture that the lack of information flow could be due to the small market size and the consequent low liquidity of the two split markets. This comports with the existing literature that the cross-correlation between cryptocurrencies exists only with a large enough market size (Drozdz, 2019). Accordingly, we conclude that as the entire cryptocurrency market becomes more mature, and the market capitalization of each altcoin increases, the information flow could be identified accordingly.

Table 5. Information flow between Bitcoin and its split: Bitcoin Gold and Bitcoin Diamond.

Transfer entropy		Effective Transfer Entropy	
BTC → BTG	BTG → BTC	BTC → BTG	BTG → BTC
0.051	0.058	0.002	0.008
BTC → BCD	BCD → BTC	BTC → BCD	BCD → BTC
0.040	0.045	0.000	0.000

Note: The arrow indicates the direction, and the number denotes the estimated value of transfer entropy and effective transfer entropy. The significance level was evaluated by bootstrapping the underlying Markov process (Horowitz, 2003; Dimpfl and Peter, 2013). BTC, BTG, and BCD represent Bitcoin, Bitcoin Gold, and Bitcoin Diamond, respectively.

[8] Compared to the Bitcoin Gold and Bitcoin Diamond, the Bitcoin market is approximately 890 times and 1,300 times larger in capitalization, 1,600 times and 2,700 times in transaction volume, respectively.

4. Conclusions

This study analyzes the information flow between Bitcoin and its split markets. The rise and fall pattern, on the basis of symbolic analysis, confirms that an asymmetric information flow exists from the original to its split. Moreover, we can affirm the hypothesis that a market with larger liquidity is likely to play a leading role in price discovery, and specifically, the Bitcoin market, with a larger transaction volume and less uncertainty, has leadership over Bitcoin Cash. Accordingly, we argue that the characteristics exhibited by the original coin could begin to emerge in the maturing split markets. Our results empirically substantiate the information flow according to the change of liquidity of each split coin market.

Moreover, our study offers insights about the relationship between the original and split coins in the upcoming hard fork phenomenon, such as Bitcoin SV, which has recently separated from Bitcoin Cash. Further research should be conducted through a number of different approaches to identify the flow of information between complex systems having a non-linear relationship rather than transfer entropy.

Funding: This research was funded by *Yonsei University* through (1) Seed Funding Grant for New Faculty (K.A.) and (2) Future-leading Research Initiative (Grant Number: 2019-22-0200; K.A.), and by *KAIST* through DELTA Research Center (E.Y.).

Conflicts of Interest: The authors in this study declare no conflict of interest.

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