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THE BREAK POINT-DEPENDENT CAUSALITY BETWEEN THE CRYPTOCURRENCY AND EMERGING STOCK MARKETS

Abstract. *The causal relationship between the cryptocurrency and emerging stock markets is investigated using the Granger causality test and Liang causality analysis, a state-of-the-art technique rigorously derived ab initio. On the whole, neither market is Granger causal to the other. But with Liang's causality analysis we identified a unidirectional short-run temporal causality from the cryptocurrency market to emerging stock markets, and a unidirectional long-run causality in the opposite direction. Application of the multiple structural break point test reveals that the causal relationship is dynamic. Specifically, during the turbulent periods, by Liang's causality analysis there is a unidirectional short-run temporal causality from the cryptocurrency market to emerging stock markets, but by the Granger test, the causality is not identified between both markets; during the tranquil periods, the inference based on Liang's technique yields a long-run causal relationship from emerging stock markets to the cryptocurrency market. These results have been justified with observations.*

Keywords*: Granger causality test, Liang's causality analysis, Break-point test, Cryptocurrency market, Emerging stock markets.*

JEL Classification: C32, C53, F39, G11

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1. Introduction

With the growing popularity of cryptocurrency market, greater attention is now being paid by governments, academics, and other stakeholders around the world. For example, the pricing mechanism has been studied by Urquhart (2016); the existence of frequent structural breaks in Bitcoin (BTC) returns has been investigated by Thies and Molnár (2018), and many other aspects of the cryptocurrency markets have been studied from the cross-correlation points of view (Bakar and Rosbi, 2018). Allowing for the volatility of financial assets in traditional markets, the time-varying volatility of cryptocurrencies has been highlighted by Baur and Dimpfl (2018), among others, and the volatility spillovers among cryptocurrencies have been examined by Ji et al (2019), Katsiampa et al (2019), and Moratis (2020).

Experiences have testified to the power of cryptocurrencies in turning around an economic meltdown and the leader towards the emerging markets' rebound (Baur et al, 2018). With an asymmetric Dynamic Conditional Correlation (DCC) model and a traditional DCC model, it has been shown that BTC is a strong hedge and a safe-haven against movements of commodity indices (Bouri et al, 2017), and that leading cryptocurrencies against equities offer significant time-varying diversification ability for investors (Bouri et al, 2020). On the other hand, Trabelsi (2018) does not find significant spillover effects between the cryptocurrency and other financial markets, such as stock markets and commodity markets. Like Trabelsi (2018), Aslanidis et al (2019) also observe that correlations between cryptocurrencies and traditional financial assets are negligible. These observations, nonetheless, are still very controversial.

Although in a substantial body of literature the relationship between the cryptocurrency and traditional financial markets has been examined, little is known about the interaction of the cryptocurrency market with emerging stock markets. Understanding the characteristics of emerging markets is important in that, along with the sustained growth and prosperity of emerging economies, they will exert a large effect on the global economy. So far, Aizenman and Hutchison (2012) have found clear evidence that emerging markets with higher total foreign liabilities have greater exposure and are much more vulnerable to the financial crisis; Basher and Sadorsky (2016) have modeled, using DCC, asymmetric DCC and generalized orthogonal GARCH (Generalized Autoregressive conditional Heteroskedasticity), the volatilities and conditional correlations between emerging market stock prices, oil prices, VIX, gold prices and bond prices; Akel and Torun (2017) have empirically investigated the role of stock market development on economic growth of the emerging markets listed in the Morgan Stanley Capital International (MSCI) Emerging Market Index, to name several. However, the absence of empirical works addressing the relationship, especially the causality between both markets, hampers the research progress along this line. This study is intended to fill this gap.

Traditionally Granger causality test (Granger, 1969) has been widely used to study the causal relationship in economics and finance. With it recently Huynh

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(2019) finds that Ethereum is likely to be independent coin in the cryptocurrency market, while BTC tends to be the spillover effect recipient; Rehman and Apergis (2019) identify a significant unidirectional causality from cryptocurrencies to commodity futures in terms of quantile Granger causality tests. Extensive studies in this regard can be found in asserting the existence and direction of causality in emerging markets (Lin, 2012). For example, based on MSCI G7 and emerging stock markets indices, Çevik et al (2018) employ the time-varying Granger causality tests in mean and in variance to examine the causal relationship between oil price movements and global stock returns; they find a significant causal link in mean tests, but no causal link in variance tests, from oil prices and G7 countries' stock returns to MSCI emerging countries' stock returns. These ambiguous results indicate that the Granger causality testing alone may not be enough for one to arrive at conclusive statements. It is well known that the Granger formalism is just a statistical hypothesis test, which provides only a yes-or-no judgment; moreover, as demonstrated by Smirnov (2013), it may lead to spurious causality inference in a wide range of situations. In order to arrive at more certain conclusions, we henceforth will re-examine the causal relationship between the cryptocurrency and emerging stock markets the Granger causality test in tandem with a newly developed rigorous causal inference technique, the Liang's causality analysis.

Different from previously empirical/half-empirical formalisms, Liang (2014, 2016) realizes that causality can be quantitatively evaluated with information flow, and, since the latter is a real physical notion, causality analysis therefore can be rigorously derived from first principles, rather than axiomatically proposed; see Liang (2016) for details. In the case of two time series, Liang (2014) establishes under the linear assumption that the maximum likelihood estimator of the measure is rather concise; with the formula, the causality between two time series can be quantitatively evaluated. We henceforth investigate the causality between the cryptocurrency and emerging stock markets with the two techniques, namely, the Granger causality test, and the Liang's causality analysis. We will particularly focus on the causal relations based on structural break points. A vast amount of evidence from the worldwide financial markets indicates the existence of multiple structural breaks and regime changes in price series of financial assets (e.g., Ewing and Malik, 2013, among others), which are also found in the cryptocurrency and emerging stock markets (Bouri, et al, 2019). In short, this study investigates the overall causality between the cryptocurrency and emerging stock markets using the Granger causality test and the Liang causality analysis, and its variability in regimes for the four sub-intervals obtained by Bai and Perron's structural break-point test (Bai and Perron, 1998). Toward the end of this study, one will see that, there is no significant Granger causality between the two markets, while, surprisingly, by Liang's causal inference there is a unidirectional short-run temporal causality from the cryptocurrency market to emerging stock markets, and a unidirectional long-run causality from the other way around. We will also see soon that this remarkable finding is consistent with observations.

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The remainder of this study is organized as follows. Section 2 is a brief introduction of the methodologies, and section 3 a description of the data and summary statistics. The results are presented in section 4. This study is concluded in Section 5.

2. Methodology

The main logic behind the Granger causality test is that if a series X is useful in predicting another series Y, then there is causality from X to Y. In economics and finance this is a well-known approach; the detailed procedure is referred to Granger (1969).

Completely different from the Granger causality test is the rigorous causality analysis developed by Liang (e.g., Liang, 2014, 2016), where causality is measured with information flow (or information transfer as called). As the latter is a real physical notion, causality analysis hence can be put on a rigorous footing. Liang (2016) proves that, for an *n*-dimensional dynamical system, which has a form like

$$d\mathbf{X} = \mathbf{F}(\mathbf{X},t)dt + \mathbf{B}(\mathbf{X},t)d\mathbf{W} \tag{1}$$

where $\mathbf{W}$ is a vector of standard Wiener processes, $\mathbf{F}$ a vector of drift coefficients (any nonlinear operator), and $\mathbf{B}$ a matrix of perturbation coefficients (volatility; could be any function of $\mathbf{X}$ and t), the information flow from component X_j to X_i (in nats per unit time) proves to be

$$T_{j\to i} = -E\left[\frac{1}{\rho_i}\int_{\Re^{n-2}} \frac{\partial(F_i\rho_{\tilde{j}})}{\partial x_i} d\mathbf{x}_{\tilde{i}\tilde{j}}\right] + \frac{1}{2}E\left[\frac{1}{\rho_i}\int_{\Re^{n-2}} \frac{\partial^2(g_{ii}\rho_{\tilde{j}})}{\partial x_i^2} d\mathbf{x}_{\tilde{i}\tilde{j}}\right] \tag{2}$$

where $d\mathbf{x}_{\tilde{i}\tilde{j}}$ stands for $d\mathbf{x}$ but with $d\mathbf{x}_i$ and $d\mathbf{x}_j$ excluded, E for mathematical expectation, $g_{ij} = \sum_{k=1}^{n} b_{ik}b_{jk}$, $\rho_i = \rho_i(x_i)$, and $\rho_{\tilde{j}} = \int_{\Re}\rho(\mathbf{x})dx_j$. If $T_{j\to i} = 0$, then X_j is NOT causal to X_i; otherwise it is causal; and the magnitude of $T_{j\to i}$ measures the size of the causality from X_j to X_i. It has been proved that the causal relations in any nonlinear systems (e.g., the Lorenz system) can be precisely recovered. Besides, $T_{j\to i}$ proves to be invariant upon nonlinear coordinate transformation.

The above formula is rigorously derived from first principle, but it relies on a model, and hence to some extent is difficult to apply. However, with a linear assumption, Liang (2014) proves that, for two time series X_1 and X_2, the maximum likelihood estimator of the rate of information flowing from X_2 to X_1, $T_{2\to 1}$ has a very concise form:

$$T_{2\to 1} = \frac{C_{11}C_{12}C_{2,d1} - C_{12}^2 C_{1,d1}}{C_{11}^2 C_{22} - C_{11}C_{12}^2} \tag{3}$$

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where $C = (C_{ij})$ is the sample covariance matrix between X_i and X_j, and $C_{i,dj}$ the sample covariance between X_i and a series derived from X_j using Euler forward differencing scheme:

$$\dot{X}_{j,n} = \left(X_{j,n+1} - X_{j,n} \right) / \Delta t \quad (4)$$

where Δt is the time step size. Ideally when $|T_{2\to1}| > 0$, X_2 is causal to X_1; if $T_{2\to1} = 0$, X_2 is not causal to X_1; but in practically applications, statistical significance must be tested. This formula has been applied in many different fields with remarkable success. An immediate corollary is that causation implies correlation, but correlation does not imply causation.

Besides the above causal inference technique, we also adopt the break-point test proposed by Bai and Perron (1998) to determine the multiple structural breaks in the prices of financial assets. Suppose there are m breaks (m+1 regimes) in the following regression model:

$$Y_t = k_t + \delta_i X_t + \varepsilon_t, t = T_{j-1} + 1, \cdots, T_j \quad (5)$$

where T is the number of observations, and $T_0 = 0$. For example, T_1 and T_2 denote the last observations in regimes 1 and 2, respectively. The equality of the δ_i across multiple regimes need to be tested based on the F test statistic. The null hypothesis states no break points against the alternative hypothesis of k breaks.

3. Data and Descriptive Statistics

The CRIX is selected as a proxy of the cryptocurrency data, which is provided by Humboldt-Universität zu Berlin, and can be found from https://thecrix.de/. It is composed of 30 main cryptocurrencies in the cryptocurrency market, representing well the cryptocurrency market. The MSCI Emerging Market Index (priced in US dollars) is chosen as a proxy of the emerging stock markets data; it is provided by MSCI and can be downloaded from https://www.investing.com/. Up to now, the MSCI Emerging Market Index covers more than 800 securities across large and mid-cap size segments and across style and sector segments in 26 emerging markets; it is hence appropriate to represent the emerging stock markets. The dataset consists of daily closing prices, covering the period from July 31, 2014 through September 31, 2019. The sample therefore is composed of 1370 observations for each time series after matching the timestamps of price series in both markets. In the following, we denote respectively by p_t^{CRIX} and p_t^{MSCI} the closing prices of CRIX and MSCI Emerging Market Index at time t, and by $r_t^{CRIX} = \ln\left(p_t^{CRIX}\right) - \ln\left(p_{t-1}^{CRIX}\right)$ and $r_t^{MSCI} = \ln\left(p_t^{MSCI}\right) - \ln\left(p_{t-1}^{MSCI}\right)$ the log-returns of each index, respectively.

Figure 1 plots the closing prices of the CRIX and MSCI Emerging Markets Index considered in this study. As can be seen, they fluctuate over time, showing similar trends and patterns in some periods, such as the remarkable price increase

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from the third quarter of 2017 until the first quarter of 2018, followed by a plummet in the beginning of 2018. This similarity implies some potential correlation between the two time series.

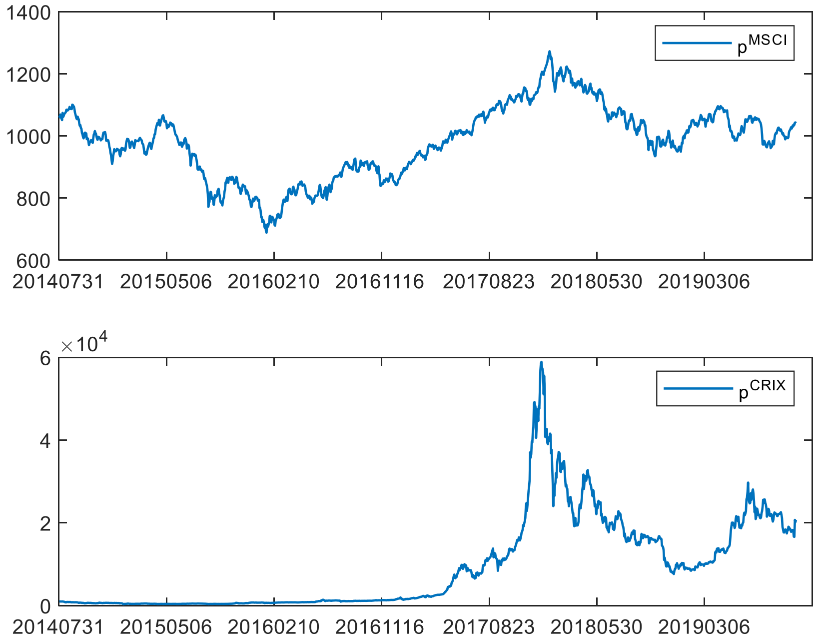

Figure 1. Closing prices of the cryptocurrency and emerging stock markets

Figure 2 depicts log-returns of the two markets. The volatility clustering of log-returns is quite evident. That is, groups of large or small changes persist for a number of periods. More frequent periods of turbulence are exhibited from the second quarter of 2017 to the third quarter of 2018.

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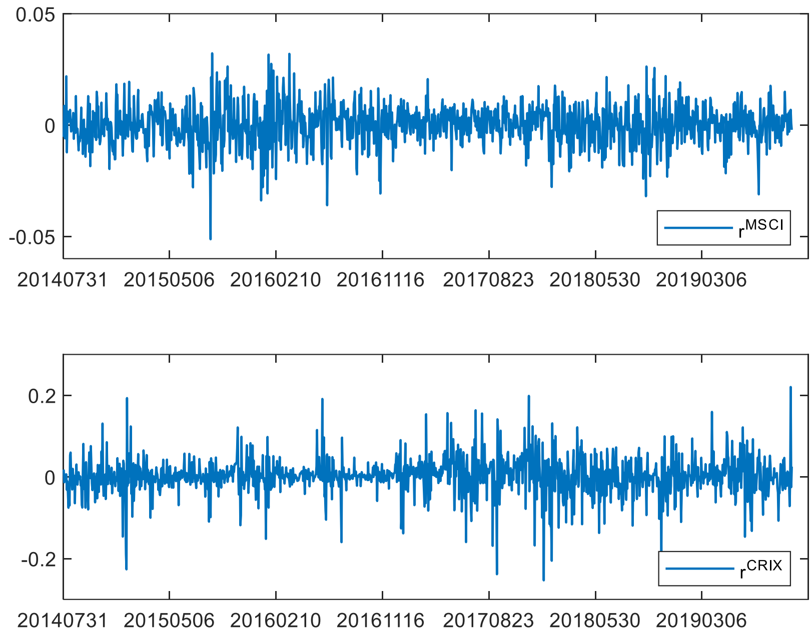

Figure 2. Log-returns of the cryptocurrency and emerging stock markets

Table 1 provides the summary statistics for both daily closing prices and log-returns. p^{MSCI} , r^{MSCI} and r^{CRIX} are slightly left-skewed, while p^{CRIX} is obviously right-skewed. p^{CRIX} , r^{MSCI} and r^{CRIX} have the characteristics of peakedness and fat tails. Jarque-Bera statistics show that all four variables reject the normal hypothesis. The augmented Dickey–Fuller test (ADF) statistics show that p^{CRIX} and p^{MSCI} have unit roots, indicating that they are non-stationary, while r^{CRIX} and r^{MSCI} significantly reject the null hypothesis; that is, they are stationary. The Pearson correlation coefficient of p^{CRIX} and p^{MSCI} shows a high positive correlation between the closing prices of cryptocurrency and emerging stock markets, while that of r^{CRIX} and r^{MSCI} shows a low positive correlation between closing log-returns.

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Table 1. Summary statistics for CRIX and MSCI Emerging Market Index

	p^{CRIX}	p^{MSCI}	r^{CRIX}	r^{MSCI}
Mean	9337.12	981.88	0.0022	-1.68e-5
Std. Dev	11202.02	115.19	0.0447	0.0089
Max	58899.68	1273.07	0.2203	0.0322
Min	342.07	688.52	-0.2533	-0.0513
Skewness	1.4436	-0.1614	-0.4223	-0.3249
Kurtosis	5.0905	2.5615	7.8388	4.7704
JB stat	725.3254^{***}	16.926^{***}	1376.289^{***}	202.8685^{***}
ADF	-0.6427	-0.2403	-35.7172^{***}	-30.3191^{***}
Corr	0.7157		0.0139	

*** indicates significance at the 1% level.

4. Results

With the above data we now make causal inferences. Both the traditional Granger causality test and Liang's causal inference are performed, along with the multiple structural break point test. As stationarity is required, the log-returns of both markets are used.

As shown in Table 2, there is no statistically significant Granger causality between the cryptocurrency and emerging stock markets at the 5%, even 10% significance levels. That means, the null hypothesis that CRIX does not Granger cause MSCI is not be rejected, and vice versa. However, with Liang's causality analysis, a unidirectional causality from the cryptocurrency to emerging stock markets is identified; it is significant at a 10% level when lag order 1 of CRIX is considered as a causal variable of MSCI. Also identified is a unidirectional causality from emerging stock markets to the cryptocurrency market (significant at a 5% level) when lag order 5 of MSCI is considered as a causal variable of CRIX. That is to say, there is a unidirectional short-run causal relationship from CRIX to MSCI, and a unidirectional long-run causality from MSCI to CRIX. These remarkable findings are not seen from the Granger causality test results.

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Table 2. Causality tests for CRIX and MSCI Emerging Market Index

	lag	0	1	2	3	4	5	6
Liang/T	MSCI→CRIX	0.00027	-0.00009	0.00014	-0.00058	0.00022	0.00090**	0.00098
	CRIX→MSCI	0.00013	0.00053*	0.0019	0.00008	-0.00015	0.00012	-0.00036
Granger/F	MSCI→CRIX		0.506563	0.298394	0.662974	0.684081	0.60965	1.44554
	CRIX→MSCI		0.129976	1.42488	1.63429	1.22901	0.95444	1.15436

* stands for significance at the 10% level, ** for the 5% levels, and *** for the 1% level. Liang's causality test gives the T values, while the Granger causality test uses F statistics to test the null hypothesis. X→Y indicates the resulting causal measure from X to Y.

Allowing for the existence of multiple structural breaks and regime changes in price series of financial assets, we here employ the break-point test by Bai and Perron (1998) to reveal whether there are regime changes in the cryptocurrency and emerging stock markets. It is necessary to emphasize that political, economic, social or environmental events may coincide with the detected break points. However, markets may anticipate some events in advance or may take some extra time to respond to other events. As Ewing and Malik (2013), we do not attempt to identify the causes of the breaks, but instead focus on how these empirically detected break points influence return and volatility dynamics. Shown in Table 3 are the test results. According to the Bayesian Information Criterion (BIC), under the minimum segment size of 15% of each group, there are three optimal break points: July 24, 2015, May 3, 2017 and August 10, 2018. The minimum BIC values are 18128.61. By F statistics the three break points are significant, testifying the validity of Bai and Perron's approach.

Table 3. Break point specification of multiple structural changes

Break point	F-statistic	P-value
0vs.1	1268.082	0.0000
1vs.2	836.9196	0.0000
2vs.3	216.4812	0.0000
Break dates	July 24, 2015 May 3, 2017 August 10, 2018	

According to the break points, the data are hence divided into four sub-intervals, or four regimes. Figure 3 depicts the closing prices of both series in light of the break points. It is obvious that MSCI prices fluctuate dramatically in the first and second intervals, yet CRIX prices are relatively stable at low level. In the third interval, both MSCI and CRIX experience huge fluctuations, like a rollercoaster

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ride and exhibit similar trends and patterns. In the fourth stage, the two markets tend to be stable again, while their co-movement weakens.

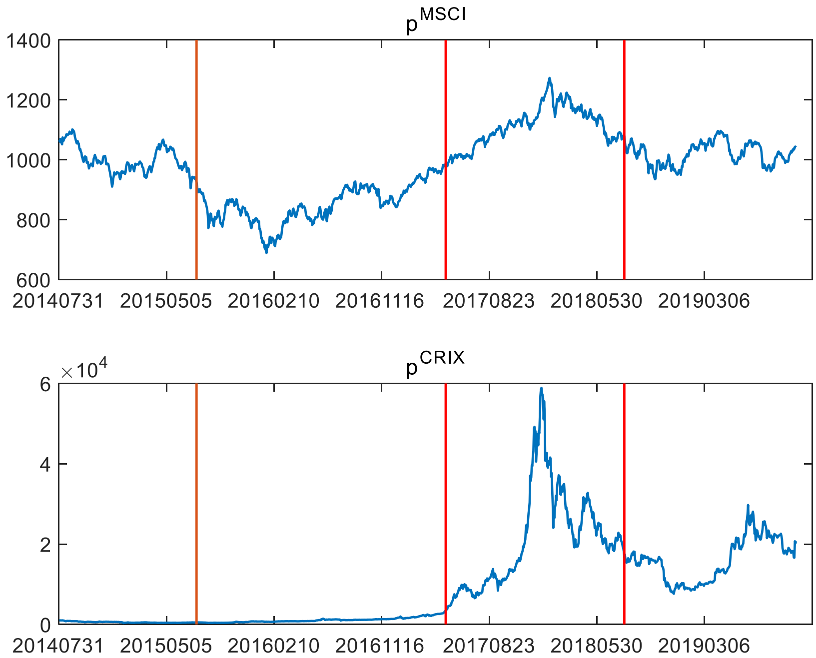

Figure 3. Closing prices of the cryptocurrency and emerging stock markets in light of the break points

The Granger causality test and Liang's causality analysis are applied one by one to these four sub-intervals. The results are shown in Table 4. In the first sub-interval, the two approaches yield consistent results; no significant causality exists between the two markets. This may be because, compared with traditional financial markets, the cryptocurrency market in its infancy has less influence on the worldwide financial markets and different market participants. Therefore, both markets seem to be relatively independent of each other. This reconfirms what is observed in previous studies, e.g., Huynh, 2019; Trabelsi, 2018, among others. In the second sub-interval, the lag orders 3 and 4 of CRIX are significantly Granger causal to MSCI, while in the opposite direction no significant Granger causality is identified. This implies that the cryptocurrency market is Granger causal to emerging stock markets over short run and long run, but not the other way around. In contrast, by Liang's causality analysis not only the lag order 2 of CRIX is causal

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Table 4. Causality tests for the four sub-intervals

Interval 1	Liang/T							Granger/F					
lag	0	1	2	3	4	5	6	1	2	3	4	5	6
MSCI→ CRIX	-0.0039	-0.0035	-0.0022	0.0033	-0.0013	0.0018	0.0063	2.34276	1.70504	1.71513	1.45008	1.23354	1.47587
CRIX→ MSCI	0.000007	-0.00062	0.0022	-0.0023	-0.0022	0.0040	0.0003	0.000008	0.524878	0.500457	0.512998	0.732844	0.946611
Interval 2	Liang/T							Granger/F					
lag	0	1	2	3	4	5	6	1	2	3	4	5	6
MSCI→ CRIX	-0.0003	-0.0001	0.00054	-0.00052	0.00024	0.0022**	0.0066	0.052539	0.086462	0.392593	0.332497	0.300605	1.03533
CRIX→ MSCI	-0.00013	0.00007	0.0067**	-0.0051	0.00005	0.000169	-0.0013	0.010019	1.02933	2.44242*	2.04894*	1.61736	1.38184
Interval 3	Liang/T							Granger/F					
lag	0	1	2	3	4	5	6	1	2	3	4	5	6
MSCI→ CRIX	0.0017	-0.00078	-0.000032	-0.00068	-0.00005	-0.000018	-0.000506	0.740164	0.46109	0.34695	0.376884	0.304765	0.441759
CRIX→ MSCI	0.0026	0.0071*	0.0056	0.0048	0.0048	-0.0011	0.0003	1.71539	1.90088	1.41542	1.17704	1.00247	0.881181
Interval 4	Liang/T							Granger/F					
lag	0	1	2	3	4	5	6	1	2	3	4	5	6
MSCI→ CRIX	0.0020	-0.0017	0.00043	-0.00097	-0.00047	0.00035	-0.0021	1.20296	0.782081	0.562286	0.756106	0.665677	0.547069
CRIX→ MSCI	-0.0014	-0.0012	-0.00006	-0.00015	0.0017	0.0029	-0.0059	0.622824	0.48992	0.346545	0.482601	0.423549	0.522405

* stands for significance at the 10% level, ** for that at the 5% level, and *** for that at the 1% level.

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to MSCI, but also the lag order 5 of MSCI is causal to CRIX. That is to say, by the Liang's causality analysis, the cryptocurrency market is causal to emerging stock markets in short run, while emerging stock markets are causal to the cryptocurrency market in long run. These results imply that the cryptocurrency market is gradually connected with the traditional financial markets in that it is growing exponentially, attracting the attention of traditional investors and gaining popularity. In the third sub-interval, no significant Granger causality between the cryptocurrency and emerging stock markets is identified. However, By Liang's causality analysis, there is a significant unidirectional causality from CRIX to MSCI at the 10% significance level. Note that, as shown in Figure 3, in this period, the cryptocurrency and emerging stock markets have experienced drastic fluctuation. The indices of both markets reach their respective peaks and then plummet. This means that, during the period of violent market swings, a short-run causality tends to increase from the cryptocurrency market to emerging stock markets. Finally, in the fourth sub-interval, no significant causality is identified between both markets again, similar to the scenario in the first sub-interval. This can also be easily understood. After a drastic fluctuation of the cryptocurrency market, market participants may be more rational and more skeptical of cryptocurrencies than before; they, therefore, hold more bearish than bullish positions. As a result, the relationship between the two markets becomes weak for the time being.

5. Conclusions

This study employs the Granger causality test and Liang's causal inference to examine the causal relationship between the cryptocurrency and emerging stock markets. It is found that there is no significant Granger causal relationship between the two markets, while by Liang's causality analysis there is a unidirectional short-run temporal causality from the cryptocurrency market to emerging stock markets, and a unidirectional long-run causality from emerging stock markets to the cryptocurrency market. Application of the multiple structural break point test further reveals that the causal relationship varies with sub-intervals or regimes. Specifically, in the beginning, the cryptocurrency market is relatively independent of emerging stock markets. As it grows exponentially, it is gradually connected with the traditional financial markets. As it enters a period of violent market swings, significant unidirectional causal relationship from the cryptocurrency market to emerging stock markets emerges by Liang's causality analysis. After a drastic fluctuation, the two markets tend to be stabilized. They again become relatively independent of each other again. In a word, the results with Liang's causality analysis are justified; the causal relationship thus-inferred appears to be consistent with observations.

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