Physica A 593 (2022) 126983

Contents lists available at ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa

Sentiment spillover and price dynamics: Information flow in the cryptocurrency and stock market

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ARTICLE INFO

Article history:
Received 26 October 2021
Received in revised form 4 January 2022
Available online 1 February 2022

JEL classification:
C58
G15

Keywords:
Cryptocurrencies
Information diffusion
Sentiment
Financial market

ABSTRACT

This study examines the sentiment–returns relationship in both stock (S&P500) and cryptocurrency (Bitcoin) markets. An explorative wavelet analysis evidences period of episodic interconnectedness across different data frequencies. Therefore, Transfer Entropy (ET) measures remark the relative statistical significance, frequently outperforming traditional (VAR) estimates. In particular, ET methods successfully identify the mediating role of sentiments in connecting the two different markets. Hence, it is discussed how the potential cryptocurrencies indirect linkage with real economy moves through market sentiments.

1. Introduction

Cryptocurrencies are revolutionizing the financial landscape, attracting the attention of different investors and scholars. At least two relevant points have been addressed and not totally solved: (i) the dynamics underlying their price formation [1] and (ii) the connection of their "digital" world with the real economic and financial spheres [2]. Despite the huge amount of literature explaining the poor connection with external factors [3,4] and the high relevance of the crypto-specific inner dynamics [5,6], more efforts are required to identify potential linkage with the real economic scenario. This would be useful for both (i) investors, identifying and rediscussing the role of Bitcoin as portfolio diversifier [7–9], and (ii) policy-makers, shedding more light on the influence and the impact that cryptocurrencies might have on "traditional" financial markets. Since the direct relationship between cryptocurrencies and the stock market has evidence scarce connection in previous studies, in this letter we try to identify a potential mediating variable through which the two spheres are connected. As an ideal candidate, we consider the general impact that information (and sentiment) flow has in financial markets. It is well known that the cryptocurrencies market is influenced by social and press media sentiments [10–14], and this pattern has been also historically recurrent in the stock market [15]. Hence, the "digital" and the "real" world might reciprocally influence each other through sentiment spillovers between the two markets. From a methodological perspective, considering the episodic and non-constant nature of informative flow [16], we analyze such a relationship comparing traditional linear causality (VAR) models with entropy-based variants.

The remainder of the paper is organized as follow: Section 2 overviews the existing literature, while Section 3 introduces the data and the different methodologies employed, Section 4 outlines the main results and Section 5 concludes.

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https://doi.org/10.1016/j.physa.2022.126983

Table 1
Descriptive statistics.

	Mean	Standard deviation	Minimum	Maximum
BTC returns	0	0.041	−0.238	0.203
S&P500 returns	0	0.014	−0.041	0.048
Crypto Sentiment (CSI)	0	0.137	−0.472	0.401
Economic Sentiment (ESI)	0	0.015	−0.065	0.056

2. Sentiment flow in financial markets

Information and sentiments flow from the different economic and financial spheres impact investors' mood and preferences in the related market [15], as proved by the literature in different sectors, such as stock markets [17], banking [18], cryptocurrencies [19]. Therefore, different empirical strategies have been employed to estimate the causal relationship between sentiments and prices. We can (partially) disentangle the literature considering three different (but connected) categories: (i) econometric, ii) computational, and (iii) physical methods.

Mainstream existing model-based econometric techniques rely on regression models (e.g. [20]), time-series forecasting methods [21] or quantile and Granger causality techniques [22].

Computational methods are based on artificial intelligence (such as machine learning and deep learning techniques) constructing data-intensive sentiment variables to predict returns [10–12].

Physical methods provide an interesting class of data analysis, allowing for different time series multi-scale wavelet decomposition [23] and non-linear entropy based causality methods [24], having a more flexible approach in identifying complex patterns, such as those characterizing financial markets. This is why, we opt for the comparison of entropy based techniques with mainstream econometric Granger-causality model, in order to understand if specific events of sentiment flows might be better captured by physical methods, highlighting their overperformance. As reviewed in Scaramozzino et al. [16], information theory dated back to the pioneer work of Shannon [25] in 1948. From then on, we have waited different years to observe an application to the financial market contexts [26]. Such methodologies have been adapted to study stock markets [27] and the dynamics of the cryptocurrencies ecosystem [28]. Scaramozzino et al. [16] propose one of the first work considering the entropy methods to reconstruct the sentiment–price dynamics. To this end, we consider this methodology to address two important questions. Firstly (*H1*) we consider, the market-specific relationship between sentiments and returns. Secondly, (*H2*), we employ entropy method to check a direct causality relationship between stock and cryptocurrencies prices, shedding more light on the existing literature on the cryptocurrencies exposure to real economy [3]. Finally (*H3*), we consider a potential *indirect* relationship between cryptocurrencies and stock market that pass through sentiments spillovers.

3. Data and hypothesis

3.1. Data description

Different data sources have been employed. Specifically, daily data on financial time series (i.e. BTC and SP&500) have been sourced from yahoo finance, while the U.S. Economic sentiments [29] has been downloaded from the FRBSF.[1] The crypto sentiment index has been constructed by employing the Global Online News Coverage Dataset [20].[2] These indices have been used in previous studies, evidencing interesting stock markets [30] and cryptocurrencies [20] reactions. Financial returns have been computed as the log differences of the adjusted daily price, while the first differences of Crypto sentiments (CS) and Economic Sentiments (ES) are employed.[3] The period starts from the 01/01/2018 (after the peak of the Bitcoin bubble) and it ends with the advent of COVID-19[4] on the 20 of February 2020, obtaining 537 common observations per time series. Descriptive statistics (Table 1) remarks the high volatility of both Bitcoin returns and related sentiments variations.[5]

1 Federal Reserve Bank of San Francisco https://www.frbsf.org/economic-research/indicators-data/daily-news-sentiment-index/.

2 The word "cryptocurrency" has been searched in the GDelt Project worldwide articles database. Hence, the news daily tone has been weighted for the media incidence provided by the website https://www.gdeltproject.org/.

3 An augmented Dickey–Fuller test confirms the trend stationarity.

4 In this case, an iterative cumulative sum of square test-ICSS [31] detect a volatility break in SP500 on that date, signing the starts of the COVID-19 financial downturn.

5 For robustness, we conduct the analysis considering the Dow Jones index (DJI) and Ethereum, obtaining results of a similar spirit, even considering that DJI-SP500 are correlated at 98% and Bitcoin–Ethereum at 80%. To favor the readability of the paper, we omit these results that remain available upon request.

3.2. Methodology

The analysis consists of different steps, merging different methodologies. Firstly, a preliminary wavelet analysis is conducted to have graphical evidence of connections. After having observed and described the time series dynamics, formal tests will be compared. As mentioned above, traditional tests on connectivity and causality, such as the (i) Pearson correlation and the (ii) Vector Autoregressive Model (VAR) will be compared with the entropy-based variant, such as the (iii) mutual information and the (iv) Rényi Transfer entropy measures, comparing their performance. Here we briefly overview the salient methodological aspects.

Preliminary exploratory step: Wavelet Coherence Analysis

The wavelet coherence approach analyzes the co-movements between time series, both in the time and in the frequency domain. The comparison across frequencies can help to identify synchronization at different scales, from daily fluctuations to those on large scale. As discussed by Torrence and Compo [32], from the cross wavelet transform of two time-series x_t and y_t it is possible to calculate the wavelet coherence $R^2(u, s)$ at different u location (time) and s scale (frequency), where $0 \leq R^2(u, s) \leq 1$. Values close to 0 indicate the absence of coherence (correlation), while values close to 1 indicates a high coherence (correlation). It is also possible to identify local causality considering the phase disalignment of the two time series, studying whether one is lagging/leading the other.

Correlation Coefficient and VAR model

Evidence of time series co-movements are given by the Pearson's Correlation coefficient, which is the most common measure to study the similarity between different kind of assets.

Vector Autoregressive models (VAR) are generally used to inspect possible lag/leads effect across time series. For simplicity, considering the short memory of time series [24], we consider only one lag in this letter.

Mutual Information Index and Rényi Transfer entropy

Here, the readers can refer to He and Shang [24] for a detailed overview of the methodology. Information theory Shannon [25] has been introduced in the past to describe financial time series processes, especially to understand the pattern of connections in a globalized world [2]. Essentially, such methodology is based on the analysis of uncertainty that different states of the world might generate, and then, on the different probabilities that different events might occur. The related entropy (H) increases with the higher heterogeneity (i.e. uncertainty) at which different events (x) occur, measured by the related probability (p):

$$H_x = -\sum_{x} p(x) log(p(x)) \tag{1}$$

Such methodologies, as the ones introduced above, can be used to explain both: instantaneous connectivity (similarly to the correlation) and dynamic causal relationship (such as models based on Granger causality).

Mutual information I(X,Y) among two different processes (X and Y) is a measure of the relevance of the dependence among the two processes, expressed in the joint distribution of X and Y, related to the marginal distribution of X and Y, approaching to 0 when the two events are independent and the joint distribution is exactly equal to the multiplication of individual probabilities. Differently from correlation, it has only positive value. After some algebra, the formula can be expressed as:

$$I(X, Y) = \sum_{x \in X} \sum_{y \in Y} p(x, y) \log \frac{p(x, y)}{p(x)p(y)} \tag{2}$$

where x and y are events (i.e. observations) of the two time series generated by X and Y processes, while p is the associated probability. Considering the lower limit (x), it is easy to demonstrate that, when the events are independents and, then, $p(x, y) = p(x)p(y)$, the logarithm of 1 is 0.[6]

The same framework has been applied to identify the directed information flow from one process to the other. Transfer entropy (TE) can effectively detect the direction of interaction between the two processes. As it happens for the lag introduced in the VAR model, here it is assumed that y_{t+1} is influenced by the former state of the process itself (y_t) and the former state of the other process x_t. The transfer entropy, from the sequence X to the sequence Y, defines the uncertainty of Y that X could reduce. Reapplying the formula of mutual information, we can obtain the Shannon Transfer Entropy (TE) formula:

$$TE_{X \to Y} = \sum p(y_{t+1}, y_t, x_t) \log \frac{p(y_{t+1}, y_t, x_t)p(y_t)}{p(y_{t+1}, y_t)p(y_t, x_t)} \tag{3}$$

Rényi [33] modified the Shannon formula, weighting the uncertainty at which events might occur. Introducing a parameter q, it is possible to weigh more rare (0<q<1) or frequent (q>1) events. For q = 1, the formula coincides with

[6] In this letter, the Jackknife bias corrected MI estimate (BCMI) is proposed, calculating the p-value from the z-score returned by the statistical software (*mpmi* R package).

Table 2
Test results.P-values are in parentheses. BCMI indicates the Bias Corrected Mutual index estimates.

X	Y	Correlation	Mutual Information (BCMI)	VAR Causality (p-value)	
				X → Y	Y → X
CSI	BTC	0.099 (0.02)	0.124 (0.000)	0.586	0.107
CSI	SP500	−0.001 (0.98)	0.100 (0.000)	0.334	0.289
BTC	SP500	0.005 (0.89)	0.135 (0.000)	0.09	0.931
ESI	BTC	−0.07 (0.07)	0.109 (0.000)	0.513	0.891
ESI	SP500	0.03 (0.47)	0.041 (0.05)	0.563	0.001
ESI	CSI	0.101 (0.02)	0.12 (0.000)	0.586	0.11

the Shannon Entropy:

$$RE_{x,q} = \frac{1}{1-q} log(\sum_{x} p(x)^{q}) \tag{4}$$

The transfer entropy equation should be modified accordingly. For completeness, the readers can find below the formula, but, once again, they can refer to other papers that analyze the subject in an exhaustive manner. Using the escort distribution (i.e. a one parameter q deformation of the original probability formula, see Beck and Schögl, 1993) $\phi_q(x) = \frac{p^q(y)}{\sum_y p^q(y)}$, Jizba et al. (2012) derived the Rényi transfer entropy measure as:

$$RTE_{X\rightarrow Y} = \frac{1}{1-q} log\left(\frac{\sum_y \phi_q\left(y_t^{(1)}\right) p^q\left(y_{t+1}|y_t^{(1)}\right)}{\sum_{x,y} \phi_q\left(x_t^{(1)}, y_t^{(1)}\right) p^q\left(y_{t+1}|y_t^{(1)}, x_t^{(1)}\right)}\right) \tag{5}$$

where $^{(1)}$ indicates the number of former states considered. Once again, here we have only positive value, without distinguishing between negative and positive effects.

The interesting point – which will be used in the empirical section – is the possibility to study the relationship between sentiments and price dynamics simultaneously understanding if such relationship exists and, therefore, if it is driven by rare or frequent episodes of interconnection.

4. Results discussion

Figures below report the wavelet coherence analysis. X-axis reports the time domain, while the Y-axis reports the frequency domain, from the high frequency (low scale) of daily variations to the low frequency (high scale) of variations of higher timing. The colored areas indicate differences in the magnitude of the wavelet coherence, ranging from low (blue) to high (yellow) levels, while arrows indicate phase differences, which underlines the synchronization between the two series. On the one hand, arrows pointing to the right (left) indicate time series that are in-phase (out of phase), i.e. they are positively (negatively) correlated. On the other hand, arrows pointing upward indicate that the first time series leads the second; whereas downward pointing arrows indicate that the second time series is leading the first.[7]

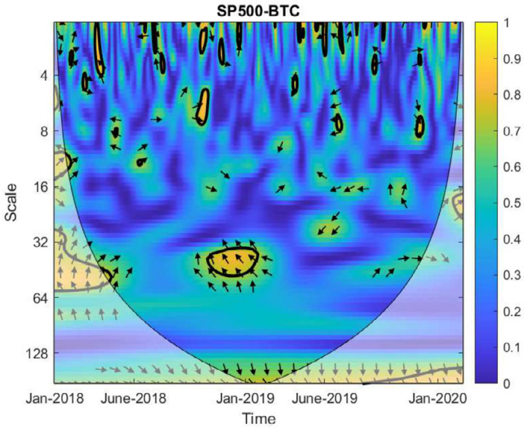
Considering the Wavelet analysis (Fig. 1), it can be inferred a general disconnection (prevalence of blue areas) between the sentiment metrics used and the relative financial returns series. The disconnection is more evident at daily frequencies (i.e. lower scales), while some market-specific sentiments–returns connections can be observed at lower frequencies. The intermittence of the relationship between sentiments factor and returns can be attributed to specific attention-driven changes in market regimes [13]. Indeed, at higher scale (lower frequencies) there are greater yellow area within the ESI-S&P500 and CSI-BTC relationship. However – validating the methodology proposed – at lower scale (i.e. higher frequencies) different points of scattered and bidirectional (arrows pointing in different opposite directions) causality are evident. Hence, the different weight (q) of infrequent events might successfully identify non-linear and non-constant causality patterns.

Following the methodological steps proposed, we test both correlation and causality using traditional metrics and entropy based variants. In particular, we compare the correlation values with the mutual information index, testing the VAR (1 lag) causality method (Table 2). All these results are reported in Table 2, while Rényi Transfer entropy (RTE) is studied across a wide range of weights ($0.1 < q < 2$), and a graphical representation of the results (Fig. 2) is offered.

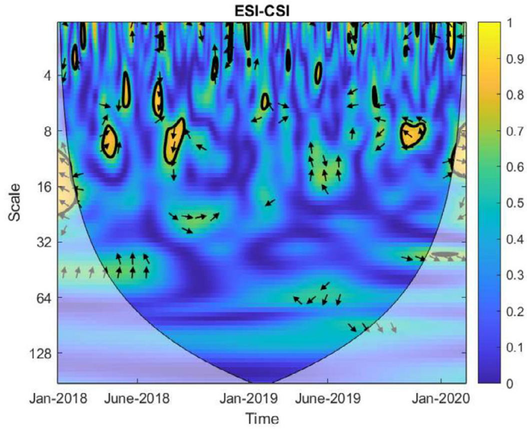
Table 2 outlines the main test results. At a glance, it is possible to observe how mutual information methods (always statistically significant) outperform Pearson's correlation in identify connectivity. Furthermore, both Correlation and Mutual Information are statistically significant in the Bitcoin relationship with both economic and crypto mood, evidencing the sensitivity and volatility of this instrument [20,34]. VAR coefficients are inconclusive[8] Here, we introduce the RTE

[7] The black contours indicate regions with significance at the five percent level.

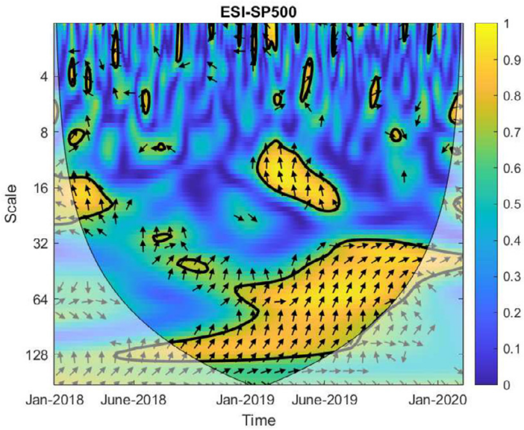
[8] They only identify a scarce and low statistically significant connection between Bitcoin and Standard and Poor's index.



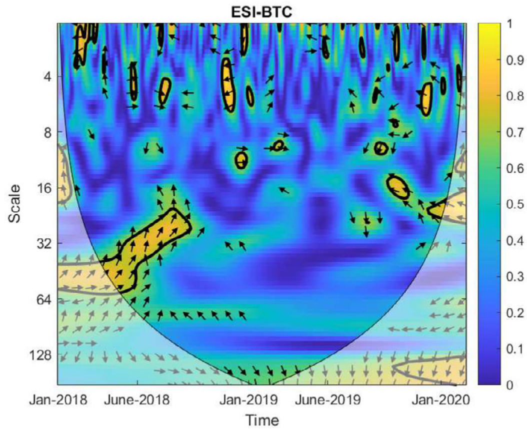
(a) S&P500-Bitcoin



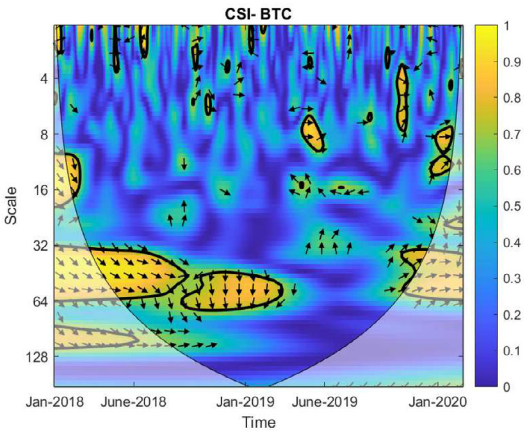
(b) Economic Sentiment Index-Crypto Sentiment Index



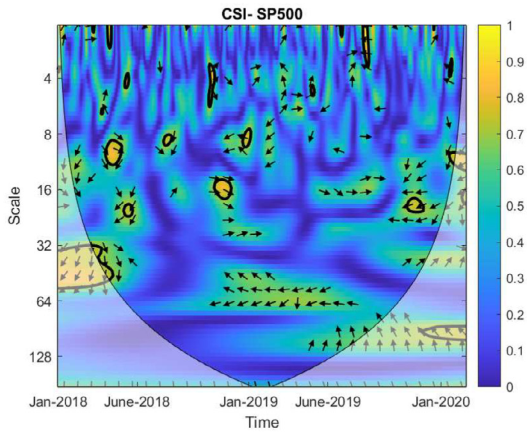
(c) Economic Sentiment Index-S&P500



(d) Economic Sentiment Index-Bitcoin



(e) Crypto Sentiment Index-Bitcoin



(f) Crypto Sentiment Index-S&P500

Fig. 1. Explorative Wavelet Analysis. The titles report the order in which time series have been included to properly infer, from the direction of arrows, leads/lags among time series.

results (Fig. 2), including variations in the outcome due to the different weights attributed to specific infrequent events (i.e. q).

Interestingly, the weights attributed to such events are crucial in defining the intensity and the significance of information spillovers. Wavelet coherence suggests the episodic nature of the relationship, and the higher weights

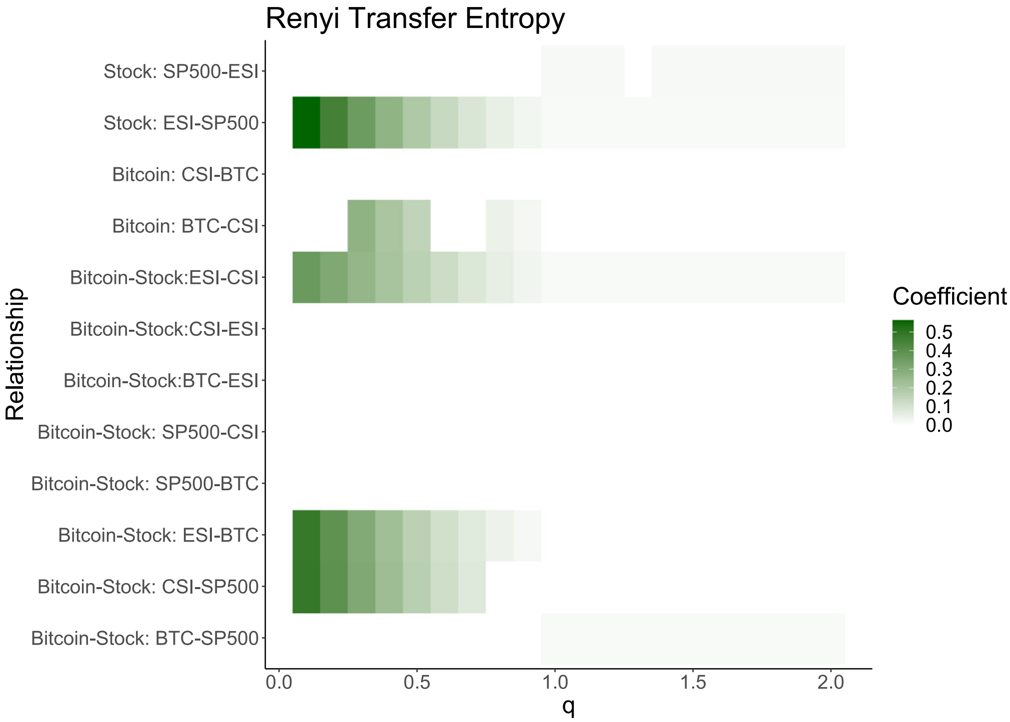


Fig. 2. Renyi Transferred Entropy across weights (x-axis). Coefficients with a p-value >0.10 are considered not statistically different from 0, then 0 is reported as estimate.

attributed to infrequent events evidence the temporal linkage of the relationship. This is observable from the decrease of TE as q increases.

Considering *H1*, we observe that crypto sentiments and Bitcoin prices co-move, with the latter influencing investors preferences (similarly to [35]). S&P500 is influenced by economic sentiments (*R1*). Even if mutual information suggests low co-movements between the market indices (the coefficient is 0.04), transfer entropy methods denote no direct evident causality (*R2*). *H3* reports the most interesting intuition. Economic sentiments influence Bitcoin dynamics, while "Crypto" sentiments affect stock market returns (Fig. 2). From here, it can be inferred a sort of "mediating" role of sentiment in shaping and transmitting investors' beliefs across markets (*R3*).

5. Discussion and conclusions

This study has analyzed the sentiment–returns relationship within and between stock and cryptocurrencies markets, through a mixture of techniques. Rényi Transfer Entropy significantly identifies the episodic connections among the real and digital sphere outperforming linear VAR model. Fig. 3 summarizes the RTE results. It is evident how the two markets influence each other through sentiments spread among investors. Then, investments' strategies seem to be influenced by sentiments, rather than price dynamics.

Results are useful for both (i) investors, entering the discussion of Bitcoin hedging properties [9], and (ii) policy-makers, evidencing the linkage and the influence of cryptocurrencies on "traditional" financial and economic instability [36]. Future researches might identify and analyze the sign of the specific indirect transmission channel supposed in the paper and the impact during specific financial market periods, identifying whether crypto and economic sentiments become more relevant and more connected in specific periods of market distress.

This letter acts as a magnifier on the crypto and real world, proposing them as two distinct but interconnected spheres.

CRediT authorship contribution statement

Rocco Caferra: Conceptualization, Methodology, Software, Data curation, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

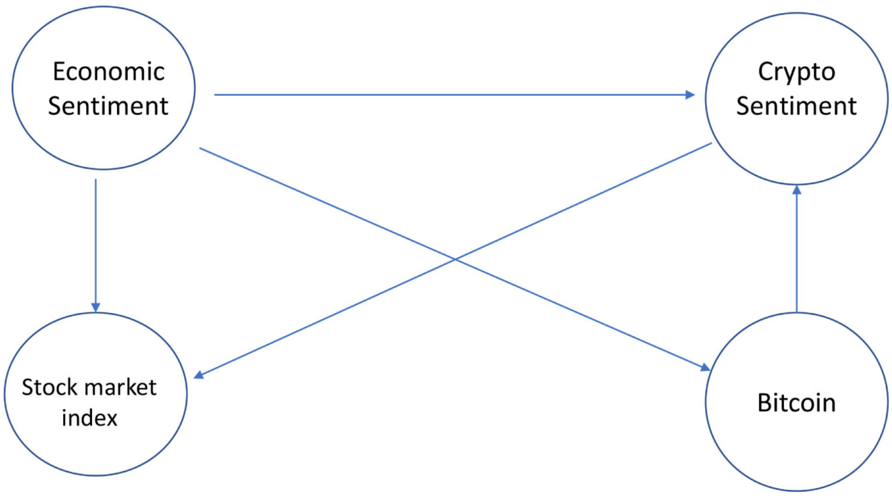


Fig. 3. Causality: Summary scheme.

Appendix. Point estimates

Points estimate of RTE results (see Fig. 4).

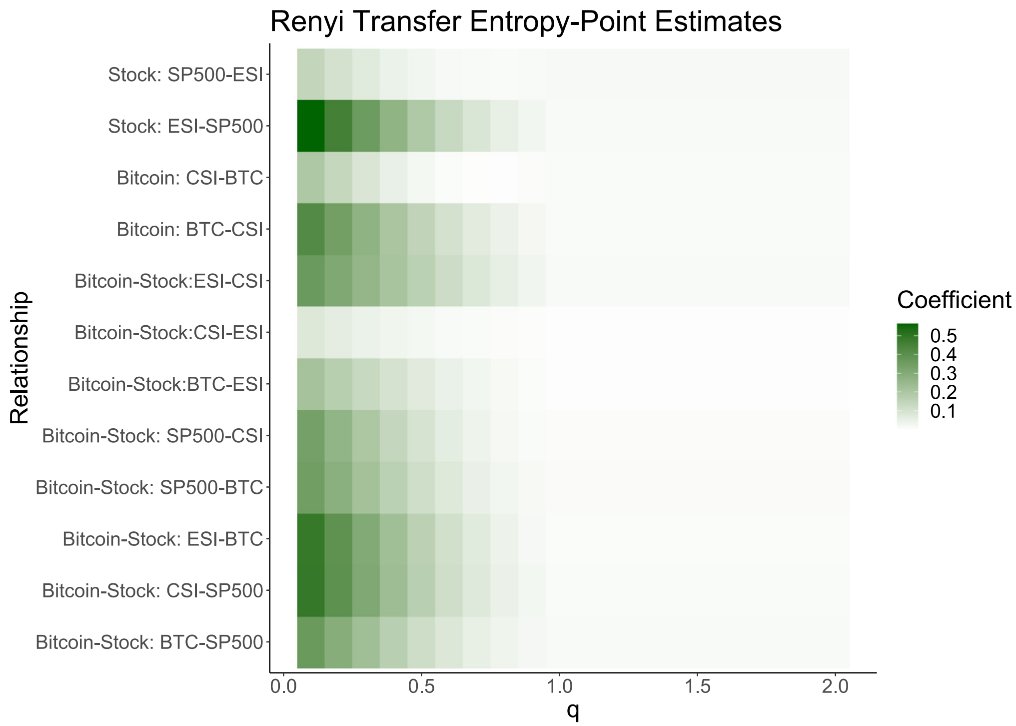


Fig. 4. Renyi Transferred Entropy across weights (x-axis).

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