Analysis of the high-frequency volume-price relationship of Bitcoin

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Abstract

In this paper, we present a comprehensive analysis of the high-frequency volume-price relationship of Bitcoin, we designed a systematic analyzing process from quantifying the information flow between price and volume with transfer entropy, filtering the linear conponents with VAR and investigating the trend inside the relationship from both directions and in different conponents. An increasing dominant non-linear information flow observed from volume to price, and a dominant linear infomation flow observed from price to volume, with the non-linear one decreasing by years. These results provide valuable insights into trading volume based price predictability, methodology for risk control and the construction of trading strategy in encryptocurrency market.

Keywords: Information flow, Transfer entropy, Cryptocurrency market, Volume-price relationship

1. Introduction

Research into the volume-price relationship provides insights into the underlying mechanisms of market efficiency and liquidity formation. By quantifying the extent to which volume influences or predicts price, analysts can develop more robust models for risk management, trading strategies, and regulatory assessments. As cryptocurrency becomes increasingly prevalent, Iits high volatility and non-interval trading mechanism making it one of the most profit but risky markets for investment, with **Bitcoin** being the highest trading activity and having the largest market share(about 60% currently) product in the whole market. The past few years has witnessed the rocket growth of Bitcoin in both price and rading volume calculated in USD, making it a fiercely competing and widely participating market. And several researches has been done on Bitcoin and the whole encrypto cryptocurrency market, and reached several useful Conclusions.
From the perspective of the feature and predictability of price or volume themselves, we got passimistic conclusion like nothing can predicte the return of BitcoinAalborg et al. (2019). Besides, evidence of informed trading were found in BitcoinFeng et al. (2018), which may cause volatility in the volume-price relationship of Bitcoin.
Thus in this paper, we designed a systematic process from quantifying the information flow to isolating different conponents, and further examed the trend inside those relationship on the high-frequent data to comprehensively describe the volume-price relationship of the centeral role of encryptocurrency, Bitcoin. and offer valuable insights on the interactivity of Bitcoin's volume & price, and provides with suggestions on the prediction of Bitcoin's returns and volatility.

2. Data and Software

The primary data source used in this study is the Gemini Exchange dataset available from `https://www.cryptodatadownload.com/data/gemini/`, which provides minute-level historical data from 2017 through the most recently available period for Bitcoin trading. This

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dataset includes timestamped open, high, low, close (OHLC) prices, and trading volume calculated in BTC and USD. The high-frequency nature of the data enables fine-grained temporal analysis and makes it particularly suitable for exploring information flow dynamics within short time intervals. The software implemented in our analysis is R with several well-verified packages mentioned in Section 3. The general view of our data is shown as below. We consider only days with over 90% minute-level data available as valid days for our analysis, and the number of them are shown by year in Table 1. The summary statistics of the high-frequency close price and trading volume are shown in Table 2 and Table 3 respectively. The data is then transformed into two log returns, and are denoted as $r^{(P)}$ and $r^{(V)}$ for price and volume respectively.

Table 1: Valid Days for Each Year in the Dataset

Year	Valid Days
2017	111
2018	94
2019	49
2020	195
2021	359
2022	314
2023	30
2024	140
2025	65

Table 2: Summary statistics of the high-frequency Close Price(calculated in USD)

Year	Mean	Std	Skewness	Kurtosis
2017	7323.06	4905.62	0.9181	-0.4115
2018	9681.76	2826.69	0.1143	0.0823
2019	9205.53	1968.58	-0.2179	-0.4777
2020	12762.69	5245.04	0.9788	0.4220
2021	47424.68	9802.02	-0.0576	-1.1365
2022	29678.15	10009.00	0.2697	-1.5421
2023	29687.64	7180.20	0.7205	-0.5403
2024	75431.92	17850.48	0.0627	-1.1986
2025	94123.43	7461.64	-0.2667	-1.0735

Table 3: Summary statistics of the high-frequency Trading Volume(calculated in BTC)

Year	Mean	Std	Skewness	Kurtosis
2017	8.96	28.97	34.32	2278.52
2018	6.10	13.52	10.60	259.67
2019	3.18	12.65	13.87	340.38
2020	2.04	7.71	16.00	463.17
2021	1.52	4.95	26.14	1770.81
2022	1.06	4.48	25.13	1253.53
2023	0.58	2.17	25.10	1381.38
2024	0.84	1.85	8.88	194.07
2025	0.78	1.64	7.94	143.46

It is obivious that the price grows rapidly from 2017 to 2025, with its distribution much-flatter than normal, and slightly positive skewness. As for volume, the distribution is hight skewed and heavy-tailed, with the mean volume decreasing from 2017 to 2025. This indicates that in this fast, extensive market, the growth of trading scale of Bitcoin is imbalance with the increase of its price, which implies a non-linear relationship can be captured. Thus we inroduced transfer entropy as the main tool to capture this non-linear volume-price relationship, and designed a combination of TE captureer, VAR filter and MK trend examiner to investgate this delicate paradiam.

3. Method

3.1. Transfer entropy(TE) with Markov Block Bootstrap

Transfer entropy is used to capture the non-linear and directional information flow between time seriesDimpfl & Peter (2013), with that from $X = \{x_t\}$ to $Y = \{y_t\}$ defined as Eq. 1 Schreiber (2000).

$$TE_{y \to x} = \sum p(x_{t+1}, \mathbf{x}_t^{(k)}, \mathbf{y}_t^{(l)}) \log \frac{p(x_{t+1} \mid \mathbf{x}_t^{(k)}, \mathbf{y}_t^{(l)})}{p(x_{t+1} \mid \mathbf{x}_t^{(k)})} \tag{1}$$

where $\mathbf{x}_t^{(k)} = (x_{t-k+1}, \ldots, x_t)$ and $\mathbf{y}_t^{(l)} = (y_{t-l+1}, \ldots, y_t)$ denote the k-lag and l-lag historical state vectors of x and y respectively, with the number of states is determined as 4 by quantiles as Eq. 2. Besides, a 600-time Markov Block BootstrapBehrendt et al. (2019) is adopted to preserve the local dynamics between the series while eliminating the global dependency, the significance of the true TE is obtained from the surrogate distribution of the generated TEs, where the smaller the p-value, the more significant the information flow.

$$x_t^{'} = \begin{cases} s_1 & x_t \leq q_{0.1} \\ s_2 & x_t \in (q_{0.1}, q_{0.5}] \\ s_3 & x_t \in (q_{0.5}, q_{0.9}] \\ s_4 & x_t > q_{0.9} \end{cases} \tag{2}$$

3.2. VAR-based TE analysis

Given that VAR models are widely used to capture linear interdependencies, which can be expressed as Eq. 3:

$$\begin{bmatrix} r_t^{(P)} \\ r_t^{(V)} \end{bmatrix} = c + \sum_{i=1}^{3} A_i \begin{bmatrix} r_{t-i}^{(P)} \\ r_{t-i}^{(V)} \end{bmatrix} + \epsilon_t \tag{3}$$

Here, A_i represents the coefficient matrices capturing linear dependencies at lag i , and ϵ_t is a 2-dimensional residual vector, isolating the nonlinear parts of the $r^{(P)}$ and $r^{(V)}$ that cannot be explained by VAR. With the significance evaluated by the combination of JB test, Ljung-Box test and ARCH LM test, where smaller p-values for the JB and LM tests indicate better results, and larger p-values for the LB test indicate better results.

To analyze nonlinear components individually in the volume-price relationship, we design a implementation based on transfer entropy (TE) and vector autoregression (VAR):

1. Firstly, we compute the transfer entropy (TE) bidirectionally between $r^{(P)}$ and $r^{(V)}$, with the result denoted as $TE_{p \to v}$ and $TE_{v \to p}$. Based on these TE results, we put analysis on the directional dominance and higher moments of TE.

2. Secondly, we fit a VAR with order up to 3 between $r^{(P)}$ and $r^{(V)}$, and evaluating the significance of VAR with a combination of JB test(Eq. 4), Ljung-Box test(Eq. 5) and ARCH LM test(Eq. 6) on each residual respectively, and a primal idea towards the different components in the price-volume relationship will be obtained from the result.

$$JB = \frac{n}{6} \left(S^2 + \frac{(K-3)^2}{4} \right) \tag{4}$$

$$Q = n(n+2) \sum_{k=1}^{h} \frac{\hat{\rho}_k^2}{n-k} \tag{5}$$

$$LM = n(n+2) \sum_{k=1}^{h} \frac{\hat{\rho}_k^2}{n-k} \tag{6}$$

In these equations, S, K, n, h, and $\hat{\rho}_k$ denote skewness, kurtosis, length of the residual observed, lag order, and autocorrelation at lag k, respectively. The significance of the residuals is assessed via the Jarque-Bera (JB) test for normality and the Ljung-Box (Q) test for autocorrelation. The corresponding p-values are computed under the null hypotheses of normality (χ^2_2 distribution) and white noise (χ^2_h distribution), respectively.

3. We then recompute bidirectional TE on the residuals to measure the information flow of the nonlinear components.By comparing TE before and after filtering, we can model the relative strength of linear and nonlinear causality and distinguish their respective roles in market dynamics.

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3.3. Mann-Kendall Trend

To further evaluate trend inside the TE calculated, we applied the Mann-Kendall (MK) test to the daily TE series, The definition of the MK test contains two parts as Eq. 6 and Eq. 7, where the satistics S represent both the direction of the trend, with its average on each day-pair denoted as τ, and p-value obtained from the location of Z in the normal distribution.

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathrm{sign}(x_j - x_i) \tag{7}$$

$$\text{where } sign(x) = \begin{cases} 1 & x > 0 \\ 0 & x = 0 \\ -1 & x < 0 \end{cases} \tag{8}$$

$$\tau = \frac{2S}{(n(n-1)x_j - x_i)} (n \text{ represent the length of the series}) \tag{9}$$

$$Z = \begin{cases} \frac{S-1}{\sqrt{\mathrm{Var}(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\mathrm{Var}(S)}} & \text{if } S < 0 \end{cases} \tag{10}$$

4. Results

4.1. Volume-price relationship of high-frequency data

Based on the transfer entropy (TE) calculated for each day, we compute Annual Summaries of TE for both direction, which are offered in Tab. 4 and Tab. 5. hype skewness and kurtosis are observed in 2017, 2021, 2022 and 2025, showing that the price-volume relation tend to get more significant when the market is in drastic volatility. By comparing the $\bar{p}$ of TE betwen the two direction, the one from price to volume is much lower, which means the information flow from price to volume is more significant, indicating the market is generally driven more by price than volume, however, On the TE value it self, We found the average of $TE_{v\to p}$ is slightly higher than $TE_{p\to v}$, which indicates that though the information flow from volume to price is less significant, a stable part of non-linear information flow from volume to price is coverd by the the dominant bidirectional linear one.(Details in Sec. 4.2).

Table 4: Moments & Significance of TE from Price to Volume ($TE_{P\to V}$)

Year	Mean	Std	Skewness	Kurtosis	$\bar{p}$
2017	0.0226	0.0052	0.2346	0.0073	0.1234
2018	0.0238	0.0111	**5.0787**	**32.0705**	0.1284
2019	0.0229	0.0056	0.9319	0.7630	0.2129
2020	0.0220	0.0054	0.5658	0.1045	0.2020
2021	0.0212	0.0251	**17.8038**	**330.1464**	0.2575
2022	0.0238	0.0267	**11.8465**	**145.9301**	0.2354
2023	0.1545	0.2303	1.2866	-0.1367	0.2873
2024	0.0920	0.1670	2.1809	3.2453	0.2624
2025	0.0373	0.0785	**5.7141**	**32.5258**	0.2614

Table 5: Moments & Significance of TE from Volume to Price ($TE_{V\to P}$)

Year	Mean	Std	Skewness	Kurtosis	$\bar{p}$
2017	0.0284	0.0066	0.6172	-0.0201	0.3550
2018	0.0299	0.0154	**6.8460**	**57.5926**	0.3710
2019	0.0257	0.0061	0.0381	-0.2896	0.3893
2020	0.0257	0.0066	0.4806	-0.0247	0.4033
2021	0.0243	0.0188	**16.3237**	**293.5880**	0.4673
2022	0.0259	0.0174	**10.6488**	**134.4553**	0.3987
2023	0.1433	0.2221	1.7369	2.1892	0.3688
2024	0.0911	0.1634	2.3158	4.2528	0.3461
2025	0.0397	0.0888	**5.5911**	**30.6203**	0.3084

Consequently, we did another comparison over the TE value pairly in a day, with the results shown in fig 1. We found that from a synchronized perspective, the ininformation flow from price to volume is still dominant the price-volume relationship. But the dominance is showing a noticable decreasing trend in recent years, showing a paradiam shift we'd describe in Sec. 4.2.

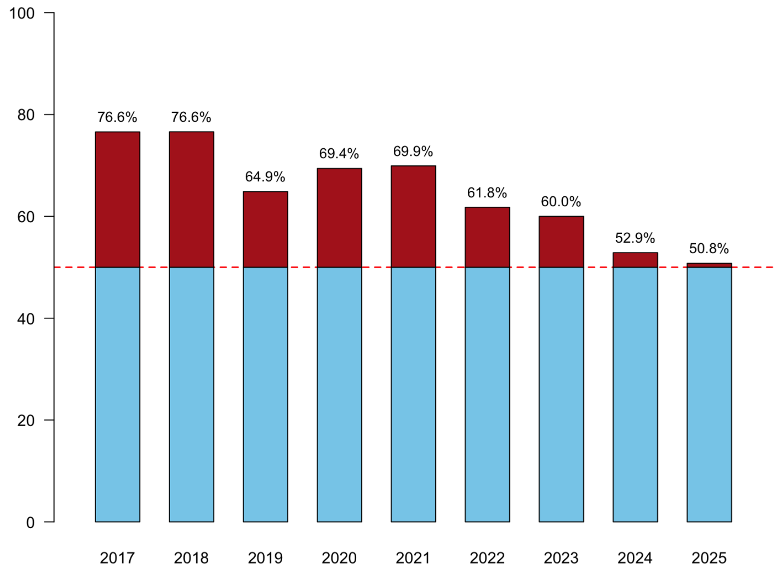

Figure 1: Ratio of Days that $TE_{p\to v} > TE_{v\to p}$ across years.

Besides, we observed specially higher upper quantiles of TE in 2023 and 2024(as shown in Tab. 6), which might be caused by certain market maniputation like The Merge of ETH, showing a complex and strong connection was formed between price and volume in that period.

Table 6: 95% and 99% Quantiles of TE from Both Directions

Year	$Q_{0.95}^{P\to V}$	$Q_{0.99}^{P\to V}$	$Q_{0.95}^{V\to P}$	$Q_{0.99}^{V\to P}$
2017	0.0317	0.0339	0.0404	0.0457
2018	0.0315	0.0798	0.0435	0.0632
2019	0.0339	0.0369	0.0348	0.0388
2020	0.0318	0.0358	0.0374	0.0419
2021	0.0286	0.0345	0.0340	0.0411
2022	0.0314	0.0379	0.0358	0.0465
2023	**0.5931**	**0.6572**	**0.5638**	**0.7595**
2024	**0.5195**	**0.5941**	**0.4698**	**0.6575**
2025	0.0343	0.4505	0.0374	0.5187

4.2. Analysis of VAR filtered volume-price relationships

I this process, we firstly check the results of theVAR itself, with the average lag selected with minium AIC for each day, and p-values of JB test, LB test and ARCH LM test shown in Table 7. The results indicate:

1. From the period from 2017 to 2020 exhibits strong autocorrelation and significant non-normality in the VAR residuals, reflecting a volatile and structurally complex market.

2. In contrast, from 2021 onward, both the trading volume (Vr) and price (Pr) residuals display diminishing Ljung-Box and ARCH effects, with Jarque-Bera tests suggesting convergence toward normality.

3. This reflects a structural simplification of the market dynamics, with the VAR model capturing most of the linear dependencies — a potential signal of increased market efficiency or post-regime stabilization.

Moreover, we observe a consistent asymmetry between the Ljung-Box p-values of volume and price residuals, where the residual autocorrelation in trading volume is significantly stronger than that in price across most years, indicating volume series contains more linear conponents that may not be clearly explained by only volume-price relationship. But generally, the results indecating our VAR models are relatively well fitted on these data and non-linear conponents are well extracted, with residuals shown weak non-normality, ARCH effects on both series and autocorrelation at least on $r^{(P)}$.

Table 7: Annual Significance of multi-test in VAR residuals

Year	k_{AIC}	$p_{\mathrm{JB}}^{(\mathrm{Vr})}$	$p_{\mathrm{JB}}^{(\mathrm{Pr})}$	$p_{\mathrm{LB}}^{(\mathrm{Vr})}$	$p_{\mathrm{LB}}^{(\mathrm{Pr})}$	$p_{\mathrm{ARCH}}^{(\mathrm{Vr})}$	$p_{\mathrm{ARCH}}^{(\mathrm{Pr})}$
2017	3.000	**4.21e-13**	**0.0000**	**2.87e-11**	0.2444	**0.0093**	**0.0070**
2018	3.000	**1.09e-03**	**1.35e-04**	**5.44e-05**	0.3390	**0.0165**	**0.0220**
2019	3.000	**6.20e-07**	**0.0000**	**5.48e-12**	0.1455	**0.0331**	**0.0285**
2020	3.000	**5.08e-04**	**5.46e-18**	**2.48e-14**	0.2462	**0.0208**	**0.0202**
2021	2.994	**1.99e-03**	**1.06e-03**	**1.49e-04**	0.2556	**0.0101**	**0.0146**
2022	2.997	**2.20e-03**	**2.67e-03**	**1.70e-03**	0.2427	**0.0141**	**0.0121**
2023	2.633	1.49e-01	1.82e-01	1.55e-01	0.3418	0.1666	0.1917
2024	2.771	8.15e-02	8.91e-02	7.30e-02	0.2776	0.1008	0.0895
2025	2.938	**1.16e-02**	**1.05e-02**	**3.74e-03**	0.1781	**0.0284**	**0.0297**

After obtaining the residuals, we recompute the TE on the residuals, It is notable that the $\bar{p}$ of both directions degenerate to nearly the same level, with $\bar{p}$ for $TE_{Pr\to Vr}$ higher than before(Tab. 4) and $\bar{p}$ for $TE_{Vr\to Pr}$ lower than before(Tab. 5), indecating that linear components dominates the information flow from price to volume, while non-linear components dominates the information flow from volume to price. Furthermore, the more significant direction shifted from $TE_{p\to v}$ to $TE_{vr\to pr}$ in 2017 & 2020.Meanwhile, the dynamic remains almost the same on moments of the bidirectional TE, with only slight difference from those in Tab. 4 and Tab. 5, thus we put details in Appendix.

Table 8: Average p-values of TE for Residuals

Year	$\bar{p}_{Pr\to Vr}$	$\bar{p}_{Vr\to Pr}$
2017	0.2522	0.1496
2018	0.2552	0.3227
2019	0.2436	0.2734
2020	0.3914	0.3671
2021	0.3795	0.4743
2022	0.3619	0.4330
2023	0.4007	0.4486
2024	0.3118	0.3743
2025	0.2276	0.3205

Table 9: 95% and 99% Quantiles of Residual TE from VAR

Year	$Q_{0.95}^{Pr\to Vr}$	$Q_{0.99}^{Pr\to Vr}$	$Q_{0.95}^{Vr\to Pr}$	$Q_{0.99}^{Vr\to Pr}$
2017	0.0335	0.0392	0.0869	0.1455
2018	0.0373	0.0650	0.0394	0.0585
2019	0.0339	0.0372	0.0397	0.0517
2020	0.0335	0.0378	0.0325	0.0375
2021	0.0310	0.0369	0.0286	0.0331
2022	0.0309	0.0428	0.0315	0.0365
2023	0.5399	0.6538	0.5670	0.6928
2024	0.5471	0.6291	0.5268	0.6531
2025	0.0388	0.5075	0.0350	0.4129

4.3. Trend analysis

With the results from MK test put on all TE series , we further investigate the trend inside the price-volume relationship. we put visual analysis on the direction of accumulative trend(by rolling up the τ year by year) and the significance of the trend in those TEs, and found out that the accumulative trend of infomation flow from volume to price keeps incresing with that from price to volume showing a evident decrease(in Fig. 2). Besides, it is noticable that the trend of information flow from volume to price shares its pattern with that of its non-linear residuals, while that from price to volume shows drastiv volativity and only its residuals shows steady decreasiing trend. Following by our observation in Section 4.2, we are more confident with our assumption that the non-linear conponents dominates the information flow from volume to price, and the linear conponents dominates that from price to volume. with the former has shown a strengthening trend over the years, whereas the latter gradually weakens. And for significance analysis, we found that the p-value pattern was almost shared between $v \to p$, $p \to v$ and $vr \to pr$, with only $pr \to vr$ less significant(in Fig. 3), indicating that the former 3 information flow are in a general psttern of whole market, while the pattern of $pr \to vr$ deviates from the general market status. This indecates a

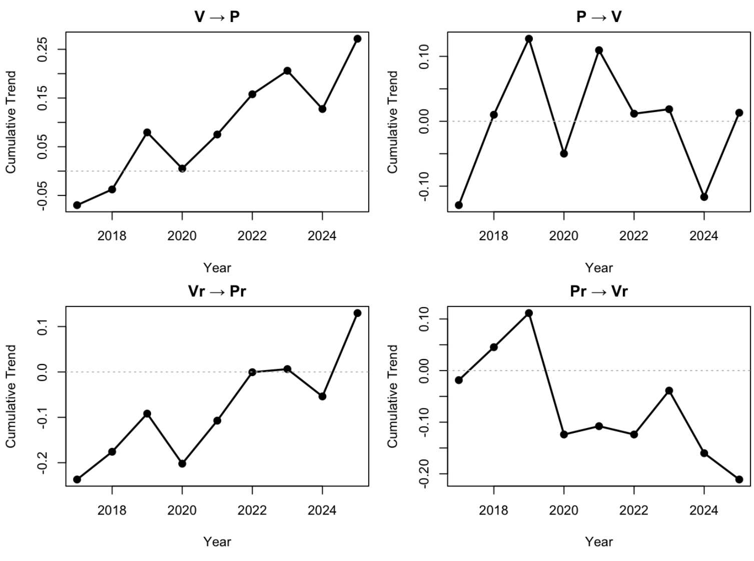

Figure 2: Cumulative Trend of TE across years.

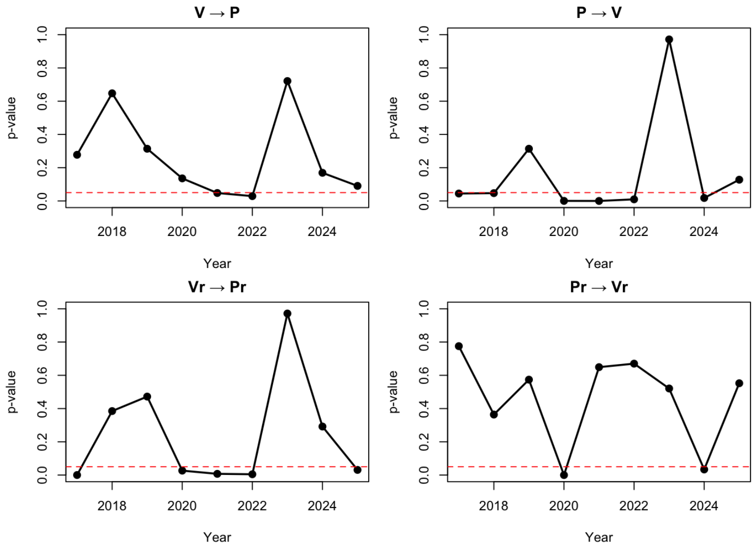

Figure 3: Significance of Trend across years.

5. Conclusions

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CRediT authorship contribution statement

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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. No conflict of interest have been declared by the authors.

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Table 10: Moments of $TE_{Pr \to Vr}$ (Residuals)

Year	Mean	Std	Skewness	Kurtosis
2017	0.0248	0.0054	0.4983	0.6252
2018	0.0273	0.0200	8.2555	75.2433
2019	0.0258	0.0055	0.1479	-0.6447
2020	0.0224	0.0060	0.8790	1.8067
2021	0.0222	0.0132	13.7429	229.5683
2022	0.0243	0.0255	11.6713	141.2074
2023	0.1271	0.1917	1.7327	2.0264
2024	0.0935	0.1726	2.3455	4.1877
2025	0.0407	0.0845	5.5176	29.5499

Table 11: Moments of $TE_{Vr \to Pr}$ (Residuals)

Year	Mean	Std	Skewness	Kurtosis
2017	0.0412	0.0292	2.8593	11.8731
2018	0.0256	0.0100	2.7837	11.6623
2019	0.0270	0.0090	1.0267	1.8689
2020	0.0226	0.0057	0.3192	0.1847
2021	0.0205	0.0149	16.2695	292.4390
2022	0.0230	0.0238	11.6990	143.4347
2023	0.1401	0.2128	1.5154	1.0093
2024	0.0933	0.1708	2.2114	3.4608
2025	0.0364	0.0755	6.0254	37.3487

Table 12: Mann–Kendall Test Results on Transfer Entropy from **Volume to Price** ($TE_{V \to P}$)

Year	Z-stat	p-value	S	Var(S)	τ
2017	-1.0856131	0.27765018	-427	153981.667	-0.06994267
2018	0.4572779	0.64747130	141	93733.667	0.03225806
2019	1.0070739	0.31389929	78	5846.000	0.11711712
2020	-1.4917860	0.13575525	-1237	686473.667	-0.07428091
2021	1.9788126	0.04783711	4497	5162300.333	0.06998024
2022	2.1827774	0.02905221	4059	3456250.333	0.08259905
2023	0.3568206	0.72122610	21	3141.667	0.04827586
2024	-1.3745703	0.16926471	-764	308116.667	-0.07852004
2025	1.6927542	0.09050227	300	31200.000	0.14423077

Table 13: Mann–Kendall Test Results on Transfer Entropy from **Price to Volume** ($TE_{P \to V}$)

Year	Z-stat	p-value	S	Var(S)	τ
2017	-2.00812947	0.04462954	-789	153981.667	-0.129238329
2018	1.98589269	0.04704524	609	93733.667	0.139327385
2019	1.00707385	0.31389929	78	5846.000	0.117117117
2020	-3.55807860	0.00037358	-2949	686473.667	-0.177085210
2021	4.50866467	0.00000652	10245	5162300.333	0.159427958
2022	-2.58619855	0.00970410	-4809	3456250.333	-0.097861256
2023	0.03568206	0.97153590	3	3141.667	0.006896552
2024	-2.36901689	0.01783544	-1316	308116.667	-0.135251799
2025	1.52291261	0.12778060	270	31200.000	0.129807692

Table 14: Mann–Kendall Test Results on Transfer Entropy from **Volume to Price** (Residuals, $TE_{Vr \to Pr}$)

Year	Z-stat	p-value	S	Var(S)	τ
2017	-3.68496854	0.00022873	-1447	153981.667	-0.237018837
2018	0.86882805	0.38494119	267	93733.667	0.061084420
2019	0.71933847	0.47193240	56	5846.000	0.084084084
2020	-2.21595397	0.02669465	-1837	686473.667	-0.110310455
2021	2.68213613	0.00731537	6095	5162300.333	0.094847575
2022	2.82072071	0.00479159	5245	3456250.333	0.106733685
2023	0.03568206	0.97153587	3	3141.667	0.006896552
2024	-1.05389725	0.29192996	-586	308116.667	-0.060226105
2025	2.15698775	0.03100662	382	31200.000	0.183653846

Table 15: Mann–Kendall Test Results on Transfer Entropy from **Price to Volume** (Residuals, $TE_{Pr \to Vr}$)

Year	Z-stat	p-value	S	Var(S)	τ
2017	-0.2854194	0.7753228	-113	153981.667	-0.01850942
2018	0.9080233	0.3638659	279	93733.667	0.06382979
2019	0.5623919	0.5738490	44	5846.000	0.06606607
2020	-4.7264029	0.00000229	-3917	686473.667	-0.23521287
2021	0.4550917	0.6490433	1035	5162300.333	0.01610619
2022	-0.4260127	0.6700986	-793	3456250.333	-0.01613724
2023	0.6422771	0.5206933	37	3141.667	0.08505747
2024	-2.1240083	0.03366945	-1180	308116.667	-0.12127441
2025	-0.5944454	0.5522142	-106	31200.000	-0.05096154