One model does not fit all: a multi-scale analysis of eighty-four cryptocurrencies

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Abstract

This letter expands the studies of the informational efficiency in the cryptocurrency market. Most studies have focused on Bitcoin, the foremost known cryptocurrency, and a few more coins. However, this market is more diverse, with cryptocurrencies entering and leaving the market on a weekly basis. This letter fills an important gap in the literature, by studying the informational efficiency using a multi-scaling methodology, which represents a new approach. We compute the generalized Hurst exponent of eighty-four cryptoassets daily returns. The multi-scaling methodology used in this paper find compelling evidence that cryptocurrencies have different degree of long range dependence, and –more importantly – follow different stochastic processes. Some of them follow traditional monofractal models consistent with fractional Brownian motion, while others exhibit complex multifractal dynamics.

Keywords: cryptocurrencies; generalized Hurst exponent; multifractality; Efficient Market Hypothesis

JEL codes: C4; G01; G14

1 Introduction

Contemporary to the outbreak of the 2008 financial crisis, an anonymously posted paper attributed to Nakamoto (2009), set the grounds for a new type of financial asset. This new synthetic product, aimed at bypassing the traditional banking system, became known as cryptocurrency. In spite of the fact that its properties as “currency” has been cast in doubt by Yermack (2013), Dwyer (2015), Selgin (2015), and Schilling and Uhlig (2019), it is undoubtedly a financial asset of great interest among investors. Shortly after its launching, Bitcoin became tantamount of cryptocurrency. This success led many entrepreneurs to develop their own cryptocurrencies. Elbahrawy et al. (2017) trace the evolutionary dynamics of this market, finding that until the beginning of 2017 the average birth rate of new cryptocurrencies was slightly larger than the average death rates, with an average net increment in the number of coins in the long run. As of March 2020, there are more than 5000 cryptocurrencies, which are traded on 20877 platforms, adding up a market capitalization of 142 USD billions (Coinmarket 0120). These figures highlight the economic relevance of this phenomenon.

Cryptocurrencies studies emerge as new and fruitful empirical area, where researchers look for insights of this novel product. Recent surveys (Yli-Huumo et al. 2016; Corbet et al. 2019; Merediz-Solà and Bariviera 2019) show aspects that has been covered until now: statistical properties of daily returns (Urquhart 2016; Bariviera et al. 2017); safe haven characteristics of Bitcoin (Bouri et al. 2017; Smales 2018); correlation of main cryptocurrencies with traditional assets (Corbet et al. 2018; Aslanidis et al. 2019); and portfolio optimization (Platanakis and Urquhart 2019).
Nevertheless, there are several gaps in the literature. Firstly, most empirical studies focus their attention on Bitcoin, or at most on the five biggest cryptocurrencies (Bitcoin, Ethereum, Bitcoin Cash, Ripple, Litecoin). Secondly, the scale dimension remains unstudied.

Hence, an alternative approach is necessary. This letter expands and complements previous literature on cryptocurrencies in three aspects: (i) it uses a multi-scaling approach that represents a new approach to this market; (ii) it works with a comprehensive set of cryptocurrencies, which reflects more accurately the behavior of the market; and (iii) it presents a criterion for selecting more appropriate stochastic models of cryptocurrencies dynamics.

The letter is organized as follows. Section 2 discusses general aspects of long range memory and explains the methodology. Section 3 presents the data. Section 4 discusses the main findings. Finally, Section 5 outlines the conclusion of our analysis.

2 Methods

2.1 Long range memory

The Efficient Market Hypothesis (EMH), cornerstone of financial economics, is based on the idea price movements in a competitive market constitute a fair game. The first stochastic model on financial assets was developed by Bachelier (1900), applying the arithmetic Brownian motion model to French bonds. The formalization of the Efficient Market Hypothesis (EMH) in economics began with the theoretical work by Samuelson (1965) and the definition and classification by Fama (1970).

Contrary to this ideal model, several papers find long memory in traditional financial assets, using different methods (Barkoulas et al., 2000; Carbone et al., 2004; McCarthy et al., 2009; Cajueiro et al., 2009). An important research line in statistics and econometrics is directed at detecting long memory in financial time series. Different alternatives have been formulated (e.g.: fractional Brownian motion, fractional Lévy flights) to account for long memory. However, they are monofractal Markov processes.

Regarding cryptocurrencies, there are also several studies on long range dependence. Bariviera (2017) shows that daily returns of Bitcoin become more efficient across time, but volatility exhibits long-range memory during all the period. Tiwari et al. (2018) observe that the Bitcoin market has a trend towards the informational efficiency, albeit it exhibits long range dependence during April-August, 2013 and August-November, 2016. Such results are aligned with those previously found by Urquhart (2016). More recently, Phillip et al. (2019) show that faster transacted currencies show stronger oscillating long run autocorrelations. For the sake of brevity, we refer to Corbet et al. (2019) and Merediz-Solà and Bariviera (2019) for further empirical financial literature on cryptocurrencies.

2.2 Generalized Hurst exponent

The Hurst exponent $H$ characterizes the scaling behavior of the range of cumulative departures of a time series from its mean. The study of long range dependence can be traced back to seminal paper by Hurst (1951), whose original methodology was applied to detect long memory in hydrologic time series. This method was also explored by Mandelbrot and Wallis (1968) and later introduced in the study of economic time series by Mandelbrot (1972). This method uses the range of the partial sums of deviations of a time series from its mean, rescaled by its standard deviation. In spite of the fact that this is the most used method in economics, it is biased to find spurious long correlations. In fact, since this method relies on maximum and minimum data, it is very sensitive to outliers.

Several methods (both parametric and non-parametric) have been proposed to compute the Hurst exponent. For a survey on the different methods for estimating long range dependence see Taqqu et al. (1995), Montanari et al. (1999) and Serinaldi (2010).
In this paper we use the generalized Hurst exponent developed in [Di Matteo et al., 2003]. In contrast to other methods, this one is suitable for describing the multi-scaling properties in financial time series, is computationally efficient, and provides robust and unbiased estimators on long term memory [Di Matteo et al., 2003, 2005; Di Matteo, 2007].

Given a time series \( X(t) \) (with \( t = \nu, 2\nu, \ldots, k\nu, \ldots, T \)), we can analyze the \( q \)-order moments of the distributions of increments, considering \( \nu \) the time-resolution. It has been found that \( q \)-th order moments are much less sensitive to outliers, and are associated with different features of the multi-scaling complexity of the time series. It is defined as

\[
K_q(\tau) = \frac{\langle |X(t+\tau) - X(t)|^q \rangle}{\langle |H(t)|^q \rangle}
\]

where \( \langle \cdot \rangle \) is the expectation operator. The generalized Hurst exponent \( H(q) \) results from the scaling behavior of \( K_q(\tau) \) from the following relation:

\[
K_q(\tau) \sim \left( \frac{\tau}{\nu} \right)^{qH(q)}
\]

This approach enables to signalize two situations: (a) uniscaling or unifractal processes where \( H(q) = H \) is constant; and (b) multi-scaling or multifractal processes where \( H(q) \) depends on \( q \).

3 Data

Cryptocurrencies’ markets are not regulated by national authorities and market data lacks of proper independent standardization and verification. Consequently, a careful selection of the data sources is a key element in order to obtain reliable results.

Following [Alexander and Dakos, 2020], we obtain our data from [CryptoCompare, 20120], because other coin-ranking sites base their quotes on unreliable volume data.

We use daily price data of the eighty-four largest cryptocurrencies, according to traded volume. The period under examination goes from 06/01/2018 to 05/03/2020, for a total of 790 observations. The selection criteria was based on the average daily volume traded over the period, and the availability of data for every day within the period under study.

A table with the list and descriptive statistics of daily logarithmic returns is included as a supplementary material to this letter.

4 Results

Most studies have been focusing on Bitcoin or, at most on a few cryptocurrencies. This fact generates an overrepresentation of the big players in the literature. The analysis of eighty-four cryptocurrencies allows depicting a more comprehensive landscape of this novel and rapidly evolving market.

Our empirical investigation is divided into two parts. The first one, computes the generalized Hurst exponent for \( q = \{1, 2\} \). The second one, refines results by using a multi-scaling procedure with the computation of the curves of \( qH(q) \) as a function of \( q \).

The descriptive statistics of the logarithm of the average daily volume of the period, and the estimated Hurst exponents are displayed in Table [1].

Results regarding the estimated Hurst exponents for \( q = 1 \) uncover an uneven behavior of cryptocurrencies. \( H(1) \) describes the scaling behavior of the absolute values of the increments of a time series. We find that 0.5 < \( H(1) < 0.6 \) for most of the largest cryptocurrencies according to traded volume. Hence, behavior is congruent with a standard Brownian motion or with a somewhat persistent stochastic process. This is in line with previous findings (referred only to Bitcoin) by [Urquhart, 2016], [Bariviera, 2017], [Phillip et al., 2019], and [Aslan and Sensoy, 2019], among others.
Table 1: Descriptive statistics of the Log volume and generalized Hurst exponent of the sample for $q = 1$ and $q = 2$.

| Gen. Hurst exponent | Log vol. $q = 1$ | $q = 2$ |
|---------------------|-----------------|---------|
| Obs.                | 84              | 84      |
| Mean                | 5.5210          | 0.5150  | 0.4471  |
| Median              | 6.2597          | 0.5211  | 0.4812  |
| Min                 | −0.5299         | 0.3564  | 0.2513  |
| Max                 | 8.7063          | 0.7333  | 0.5692  |
| Std. Dev.           | 1.8227          | 0.0622  | 0.0780  |
| Skewness            | −0.9143         | 0.0305  | −0.8984 |
| Kurtosis            | 3.3324          | 4.8306  | 2.5925  |
| Jarque-Bera         | 12.0904         | 11.7414 | 11.8818 |

From Figure 1 it can be seen that cryptocurrencies within the third and fourth volume quartiles behave differently. Their Hurst exponents spans between $H(1) \approx 0.32$ and $H(1) \approx 0.65$. Coins in the third quartile tend to follow a persistent behavior ($H(1) > 0.5$), whereas those in the fourth quartile are more likely to present an anti-persistent behavior ($H(1) < 0.5$). In both cases, the time series are generally informational inefficient. A density plot is inserted on the right vertical axis of Figure 1 in order to show the distribution of the generalized Hurst exponent in the different quartiles.

The Hurst exponents for $q = 2$ is connected to the autocorrelation function and connected to the power spectrum (Flandrin, 1989; Di Matteo et al., 2005). We observe, again, a noticeable behavior depending on cryptocurrency size. Cryptocurrencies in the first and second volume quantiles are roughly efficient, whereas the third and fourth quartiles exhibits an clear antipersistent behavior (see Figure 2).

![Figure 1: Scatter plot of the generalized Hurst exponent for $q = 1$ and log volume of cryptocurrencies. On the right there is a density plot of the Hurst exponent, classified by volume quartile.](image)

As mentioned in Section 1, we generalize the analysis of the Hurst exponent for different values
of $0 < q < 4$. Figure 3 displays the planar representation of $q \times qH(q)$. The results of the different coins are grouped into quartiles according to volume. As a benchmark model, we include also the results arising from a simulated time series of the same length and $H = 0.5$. If the stochastic process under consideration is monofractal (i.e. the simulated time series), $qH(q)$ as a function of $q$ is a straight line, and its slope depends on the $H$. However, the presence of nonlinearities in this function is a signature of multifractal processes. Thus, we provide compelling evidence against (fractional) Brownian, (fractional) Lévy, and other additive, monofractal processes.

This analysis reinforces what was shown previously regarding the heterogeneous behavior of cryptocurrencies according to their volume size. Figure 3 clearly reveals that coins in the first quartile follow roughly unifractal processes, being a fractional brownian motion a suitable model for describing their behavior. On contrary, cryptoassets within the other quartiles (specially those in the third and fourth) exhibit strong multifractality. In such cases, Brownian or Lévy models (included their fractional varieties), are deemed inadequate for capturing their complex dynamics.

5 Conclusions

This letter sheds light on the multifractal behavior of the cryptocurrency market in a broad way. We expand previous research computing the generalized Hurst exponent of eighty-four cryptocurrencies time series.

According to our results, cryptocurrencies have a different long memory endowment, according to their size, proxied by traded volume. More importantly, we detected the presence of multifractality in several time series. Largest cryptocurrencies (those in the first quartile of volume) seem to follow monofractal processes, consistent with a fractional Brownian motion. On contrary, other cryptocurrencies exhibit strong multifractality. This result poses some restrictions on the suitable stochastic models for such coins.

Consequently, our results support the idea that cryptocurrencies differ not only among them in their long range dependence, but also in the stochastic processes that govern their dynamical behavior.

Our findings can be of interest for academics and practitioners alike. From the academic point of view, means that one model does not fit all. It is necessary to study on a case-by-case basis, in order to select the most appropriate model to describe return dynamics. From the practitioners point of view, means that there could be some arbitrage opportunities, depending on each cryptocurrency.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

References

Alexander, C. and Dakos, M. (2020). A critical investigation of cryptocurrency data and analysis. Quantitative Finance, 20(2):173–188.

Aslan, A. and Sensoy, A. (2019). Intraday efficiency-frequency nexus in the cryptocurrency markets. Finance Research Letters.

Aslanidis, N., Bariviera, A. F., and Martinez-Ibañez, O. (2019). An analysis of cryptocurrencies conditional cross correlations. Finance Research Letters, 31:130–137.

Simulation was performed using Matlab function wfbm.
Figure 2: Scatter plot of the generalized Hurst exponent for $q = 2$ and log volume of cryptocurrencies. On the right there is a density plot of the Hurst exponent, classified by volume quartile.

Figure 3: The function $qH(q)$ vs. $q$, averaged by quartiles, and a simulated brownian motion process with Hurst=0.5.
Bachelier, L. (1900). *Théorie de la spéculation*. Annales scientifiques de l’École Normale Supérieure, Paris.

Bariviera, A. F. (2017). The inefficiency of Bitcoin revisited: A dynamic approach. *Economics Letters*, 161:1–4.

Bariviera, A. F., Basgall, M. J., Hasperué, W., and Naiouf, M. (2017). Some stylized facts of the Bitcoin market. *Physica A: Statistical Mechanics and its Applications*, 484:82–90.

Barkoulas, J. T., Baum, C. F., and Travlos, N. (2000). Long memory in the greek stock market. *Applied Financial Economics*, 10(2):177–184.

Bouri, E., Molnr, P., Azzi, G., Roubaud, D., and Hagfors, L. I. (2017). On the hedge and safe haven properties of bitcoin: Is it really more than a diversifier? *Finance Research Letters*, 20:192 – 198.

Cajueiro, D. O., Gogas, P., and Tabak, B. M. (2009). Does financial market liberalization increase the degree of market efficiency? The case of the Athens stock exchange. *International Review of Financial Analysis*, 18(1-2):50–57.

Carbone, A., Castelli, G., and Stanley, H. E. (2004). Time-dependent hurst exponent in financial time series. *Physica A: Statistical Mechanics and its Applications*, 344(1-2):267–271.

Coinmarket (2012). Crypto-Currency Market Capitalizations. [https://coinmarketcap.com/currencies/](https://coinmarketcap.com/currencies/). Accessed: 2020-03-16.

Corbet, S., Lucey, B., Urquhart, A., and Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*, 62(June 2018):182–199.

Corbet, S., Meegan, A., Larkin, C., Lucey, B., and Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters*, 165:28 – 34.

CryptoCompare (2012). Coins list. [https://www.cryptocompare.com/coins/list/USD/](https://www.cryptocompare.com/coins/list/USD/). Accessed: 2020-03-05.

Di Matteo, T. (2007). Multi-scaling in finance. *Quantitative Finance*, 7(1):21–36.

Di Matteo, T., Aste, T., and Dacorogna, M. M. (2003). Scaling behaviors in differently developed markets. *Physica A: Statistical Mechanics and its Applications*, 324(1-2):183–188.

Di Matteo, T., Aste, T., and Dacorogna, M. M. (2005). Long-term memories of developed and emerging markets: Using the scaling analysis to characterize their stage of development. *Journal of Banking and Finance*, 29(4):827–851.

Dwyer, G. P. (2015). The economics of bitcoin and similar private digital currencies. *Journal of Financial Stability*, 17:81 – 91. Special Issue: Instead of the Fed: Past and Present Alternatives to the Federal Reserve System.

Elbahrawy, A., Alessandretti, L., Kandler, A., Pastor-Satorras, R., and Baronchelli, A. (2017). Evolutionary dynamics of the cryptocurrency market. *Royal Society Open Science*, 4(11).

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, 25(2, Papers and Proceedings of the Twenty-Eighth Annual Meeting of the American Finance Association New York, N.Y. December, 28-30, 1969):pp. 383–417.

Flandrin, P. (1989). On the spectrum of fractional brownian motions. *IEEE Transactions on Information Theory*, 35(1):197–199.
Hurst, H. E. (1951). Long-term storage capacity of reservoirs. *Transactions of the American Society of Civil Engineers*, 116:770–808.

Mandelbrot, B. B. (1972). Statistical methodology for nonperiodic cycles: From the covariance to rs analysis. In *Annals of Economic and Social Measurement, Volume 1, number 3*, NBER Chapters, pages 259–290. National Bureau of Economic Research.

Mandelbrot, B. B. and Wallis, J. R. (1968). Noah, joseph, and operational hydrology. *Water Resources Research*, 4(5):909–918.

McCarthy, J., Pantalone, C., and Li, H. C. (2009). Investigating long memory in yield spreads. *Journal of Fixed Income*, 19(1):73–81.

Merediz-Solà, I. and Bariviera, A. F. (2019). A bibliometric analysis of bitcoin scientific production. *Research in International Business and Finance*, forthcoming.

Montanari, A., Taqqu, M. S., and Teverovsky, V. (1999). Estimating long-range dependence in the presence of periodicity: An empirical study. *Mathematical and Computer Modelling*, 29(10-12):217–228.

Nakamoto, S. (2009). Bitcoin: A peer-to-peer electronic cash system. [https://bitcoin.org/bitcoin.pdf/](https://bitcoin.org/bitcoin.pdf/) Accessed: 2016-12-27.

Phillip, A., Chan, J., and Peiris, S. (2019). On long memory effects in the volatility measure of cryptocurrencies. *Finance Research Letters*, 28:95 – 100.

Platanakis, E. and Urquhart, A. (2019). Portfolio management with cryptocurrencies: The role of estimation risk. *Economics Letters*, 177:76–80.

Samuelson, P. A. (1965). Proof That Properly Anticipated Prices Fluctuate Randomly. *Industrial Management Review*, 6(2):41–49.

Schilling, L. and Uhlig, H. (2019). Some simple bitcoin economics. *Journal of Monetary Economics*, 106:16 – 26.

Selgin, G. (2015). Synthetic commodity money. *Journal of Financial Stability*, 17:92 – 99. Special Issue: Instead of the Fed: Past and Present Alternatives to the Federal Reserve System.

Serinaldi, F. (2010). Use and misuse of some hurst parameter estimators applied to stationary and non-stationary financial time series. *Physica A: Statistical Mechanics and its Applications*, 389(14):2770–2781.

Smales, L. (2018). Bitcoin as a safe haven: Is it even worth considering? *Finance Research Letters*.

Taqqu, M. S., Teverovsky, V., and Willinger, W. (1995). Estimators for long-range dependence: An empirical study. *Fractals*, 3:785–798.

Tiwari, A. K., Jana, R., Das, D., and Roubaud, D. (2018). Informational efficiency of bitcoin – an extension. *Economics Letters*, 163:106 – 109.

Urquhart, A. (2016). The inefficiency of Bitcoin. *Economics Letters*, 148:80–82.

Yermack, D. (2013). Is bitcoin a real currency? an economic appraisal. Working Paper 19747, National Bureau of Economic Research.

Yli-Huumo, J., Ko, D., Choi, S., Park, S., and Smolander, K. (2016). Where Is Current Research on Blockchain Technology?-A Systematic Review. *PloS one*, 11(10):e0163477.
Supplementary material to “One model does not fit all: a multi-scale analysis of eighty-four cryptocurrencies”
| Crypto | Obs | Mean  | Median  | Min | Max  | Std. Dev. | Skewness | Kurtosis | Jarque-Bera |
|--------|-----|-------|---------|-----|------|-----------|----------|----------|-------------|
| ACHN   | 789 | -0.6465 | -0.4455 | -31.2524 | 40.3689 | 7.3853 | 0.0643 | 6.7701 | 467.8120 |
| ACOIN  | 789 | 0.0222 | -0.0924 | -642.0136 | 786.4650 | 36.6010 | 5.7431 | 391.1575 | 4957488.9982 |
| ADA    | 789 | -0.3820 | 0.0000 | -29.1399 | 27.4731 | 5.8657 | -0.1756 | 6.1123 | 322.4990 |
| AION   | 789 | -0.5223 | -0.4504 | -32.3820 | 30.2058 | 7.3928 | 0.0451 | 5.1096 | 146.5718 |
| ARG    | 789 | 0.1121 | -0.0877 | -100.7488 | 141.5843 | 12.7185 | 1.7287 | 39.2419 | 4357342.171 |
| ARI    | 789 | -0.3161 | -0.1309 | -43.0557 | 82.9262 | 9.6098 | 1.4270 | 17.3601 | 7046979.5979 |

Table 2: Descriptive statistics of the logarithmic returns of the cryptocurrencies in the sample.
| Crypto | Obs | Mean  | Median | Min        | Max        | Std. Dev | Skewness | Kurtosis | Jarque-Bera |
|--------|-----|-------|--------|------------|------------|----------|----------|----------|-------------|
| SRN    | 789 | -0.6145 | -0.4791 | -58.3293   | 48.7632    | 7.9451   | -0.2207  | 10.2111  | 1715.8862   |
| STEEM  | 789 | -0.4478 | -0.4249 | -35.5088   | 37.8818    | 6.4200   | 0.1345   | 7.3960   | 637.6729    |
| STORM  | 789 | -0.5849 | -0.6433 | -35.9387   | 99.2795    | 8.5338   | 1.8081   | 27.9611  | 20912.8677  |
| SWFTC  | 789 | -0.4765 | -0.3775 | -37.0445   | 47.7890    | 7.8494   | 0.2390   | 8.8924   | 1148.9625   |
| SXC    | 789 | -0.6798 | -0.2708 | -85.5243   | 120.6038   | 12.7925  | 0.5567   | 20.3478  | 9934.3193   |
| TRX    | 789 | -0.2870 | -0.1965 | -34.7714   | 36.9231    | 6.5874   | -0.0859  | 6.7353   | 459.6622    |
| VET    | 789 | -0.2584 | -0.0532 | -309.1562  | 233.9956   | 26.9495  | -1.1687  | 40.8282  | 47222.8119  |
| WAVES  | 789 | -0.2865 | -0.2147 | -26.6230   | 38.3516    | 6.0615   | 0.3906   | 8.5999   | 1050.9990   |
| WTC    | 789 | -0.4396 | -0.4270 | -29.5165   | 43.5201    | 7.3645   | 0.2089   | 6.1065   | 322.9981    |
| XBS    | 789 | -0.2713 | 0.0348  | -89.3732   | 66.6890    | 9.5751   | -0.7232  | 25.7608  | 17099.8341  |
| XEM    | 789 | -0.4316 | -0.1763 | -29.8042   | 24.0098    | 5.7501   | -0.0069  | 5.9686   | 289.7271    |
| XLM    | 789 | -0.3096 | -0.2718 | -32.9406   | 26.8116    | 5.6059   | -0.0605  | 6.0157   | 299.4597    |
| XMR    | 789 | -0.2213 | 0.0153  | 27.6457    | 18.5045    | 5.3125   | -0.3864  | 5.2822   | 190.8571    |
| XMY    | 789 | -0.4934 | -0.3226 | -48.9548   | 28.0314    | 7.7976   | -0.4281  | 6.0800   | 321.5598    |
| XPY    | 789 | -0.2489 | 0.0656  | -68.3288   | 66.1725    | 10.5757  | -0.2512  | 16.6274  | 6113.4152   |
| XRP    | 789 | -0.3047 | -0.2841 | -36.7056   | 31.7479    | 5.3604   | 0.0917   | 9.1769   | 1255.4367   |
| XTZ    | 789 | -0.0679 | 0.0000  | 99.9714    | 52.2926    | 7.9993   | -3.7663  | 51.7874  | 80114.7553  |
| XUC    | 789 | -0.2481 | -0.2478 | -25.2063   | 29.2463    | 5.1009   | 0.3328   | 7.8677   | 793.5280    |
| YBC    | 789 | -0.0960 | 0.0624  | -68.3073   | 35.7470    | 5.2919   | -2.2015  | 46.8009  | 63708.4791  |
| ZEC    | 789 | -0.3217 | -0.3374 | -21.1347   | 22.3873    | 5.4391   | 0.0198   | 4.8426   | 111.6624    |
| ZET    | 789 | -0.3848 | 0.0121  | -57.4514   | 87.3608    | 9.2349   | 1.0451   | 25.1554  | 16280.7154  |