"Do all shocks produce embedded herding and bubble? An empirical observation of the Indian stock market"

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BUSINESS PERSPECTIVES

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DO ALL SHOCKS PRODUCE EMBEDDED HERDING AND BUBBLE? AN EMPIRICAL OBSERVATION OF THE INDIAN STOCK MARKET

Abstract

Herding has a history of igniting large, irrational market ups and downs, usually based on a lack of fundamental support. Intuitively, most herds start with an external shock. This empirical study seeks to detect shock-induced herding and the creation of nascent bubbles in the Indian stock market. Initially, the multifractal form of the detrended fluctuation analysis was applied. Then the Reformulated Hurst exponent for the Bombay stock exchange (BSE) was determined using Kantelhardt's calibration. The investigation found evidence of high-level herding and a bubble in 2012, with a high value of Hurst Exponent (0.7349). The other years of the research period (2011, 2013, 2016, 2018, 2020–2021) observed mild to significant herding with comparatively lower Hurst values. The results confirm that herding behavior occurs during a crisis and harsh situations emitting shocks. The study concludes that shock-based herding is prevalent in all six shocks: the economic meltdown, commodities and currency devaluation, geo-political problems, the Central Bank's decision on liquidity management, and the Pandemic. Additionally, the years following the Financial Crisis and the years of the Pandemic are when herding and bubble are prominent.

Keywords econophysics, multifractal, persistence, market shocks, Hurst exponent

JEL Classification D53, G14, G41

INTRODUCTION

Typically, shocks infuse panic in the asset price markets. When faced with such uncertainty, investors frequently mimic the actions of others, which is called herding. Herd behavior usually produces enormous levels of volatility in the stock markets – both on the upside and the downside. Most of the time, such shocks are received negatively. Therefore, a crash or anti-bubble becomes inevitable intuitively. However, sometimes, it infuses positivism as well, causing a bubble to build in quick time. The Central Bank of India, in its FY21 annual report, warned of a possible stock market bubble as the domestic stock market continued to touch a record high even as the country continued to face disruption due to the Pandemic. In the same year, the Centre for Monitoring Indian Economy Pvt. Ltd data of the listed companies revealed a rise in profits due to rationalization and cost-cutting. The share of non-institutional investors also increased significantly in 2021 despite the confusing fundamental, economic, and environmental parameters (Business Standard, 2022). All these indicators pointed to a stock market bubble. The loss of wealth for small investors due to the bubble burst could be the highest, like in the Housing bubble of 2008, which led to a severe global recession. The chaos and uncertainty in such times call for a study to measure herding behavior and detect

bubble if it exists, which is inevitable for investors and policymakers. Usually, there are six types of shocks that are imperative for market volatility to reach its extreme levels. Therefore, it would be rather interesting to check out those, namely economic meltdown, commodities, and currency devaluation, geo-political problems, the Central Bank's decision on liquidity management, and last but not least, a pandemic such as Covid-19.

1. LITERATURE REVIEW

Various events bring about market shocks and affect security prices for multiple reasons, including political, geo-political, economic, monetary, fiscal, and natural disasters. These events may bring about a positive or a negative effect on the stock markets. Many studies have shown how shocks cause panic among investors in stock markets. The political actions of governments may have a significant impact not only on the macroeconomic health of the entire economy but also on the microeconomic actions of individuals, including stock market investors. A recent study on emerging stock markets found that political shocks affect the efficiency levels in a stock market (Hkiri et al., 2021). State elections in any country also have an impact on stock prices. Wong and McAleer (2009) concluded that U.S. stock prices closely followed the Presidential Election cycle. Another study investigating a sample of twenty-seven countries found that stock market volatility increased during National Elections (Białkowski et al., 2008). Monetary policy shocks due to favorable or unfavorable policies also lead to accelerated asset prices and have a negative impact on stock market bubbles (Caraiani & Călin, 2020). It has been determined that there are complex, critical, and bidirectional links between monetary policy and stock market performance (Suhaibu et al., 2017). According to other research, the oil supply sector benefits from positive shocks while the oil consumer and finance sectors have adverse effects. (Akhtaruzzaman et al., 2021). Gopal and Munusamy (2016) investigated the links between gold, crude oil, U.S. dollar exchange rates, and stock market indexes. They discovered that emerging countries had a high level of stock market uncertainty and a significant impression on the stock market due to macroeconomic factors' volatility. Geo-political events like wars and terrorist attacks (Battaglia & Mazzuca, 2014) and Black swan events, such as epidemics, induce investors to experience anxiety and panic, resulting in quick panic selling (Aslam et al., 2020;

Taleb, 2007). Recent research shows that emerging stock markets are more vulnerable to pandemics than established ones because mature stock markets can provide better resilience in unpredictable circumstances (Salisu et al., 2020). Therefore, it is observed that the onset of different shocks causes panic and confusion among investors. One of the reasons this panic in stock markets may happen is when the less knowledgeable investors attempt to emulate the conduct of more informed agents, resulting in behavioral biases such as herding behavior. Herding occurs because agents desire to maintain their reputation (Trueman, 1994), as a rational choice (Devenow & Welch, 1996), or as a result of informational cascades (Bikhchandani et al., 1992).

Herd behavior directly contradicts the Efficient Market Hypothesis (Fama, 1970), often known as the Random Walk Theory. The Efficient Market Hypothesis asserts that markets are efficient, investors behave rationally, and share prices always "fully represent" available information. There is substantial debate about the validity of EMH. Several studies have indicated that the traditional financial theory, associated with the efficient market, has significant deficiencies in predicting real-world stock returns implying that the theory does not hold up (Barber & Odean, 2001; Summers, 1986). In contrast, the Fractal Market Hypothesis states that stock market values resemble a random walk but have fractal qualities in that they have a similar structure when sampled at different periods (Peters et al., 1994). A fractal is a pattern that never ends. Fractals are infinitely intricate patterns that recur in different sizes. They are formed by repeatedly repeating an essential procedure in a continuous feedback loop. In Econophysics, prices in financial markets have a fractal behavior. Econophysics is a new branch of study which at least uses two subjects' concepts, i.e., physics and mathematics models, to examine economic events, notably financial markets. In Econophysics, financial markets are complex sys-

tems, and the price dynamics they follow are considered stochastic processes (Mantegna & Stanley, 1999). Econophysicists achieve simulations of stock price changes and provide alternate forecasts over financial economics models (Jovanovic & Schinckus, 2013). According to them, there is a connection between two well-known market phenomena: large tails in the distribution of stock market returns on the one hand and investor behavior in financial markets on the other (Cont & Bouchaud, 2000). High kurtosis indicates heavy tails. It is connected with high risk, since it shows a high likelihood of huge and minimal returns, which causes a power-law increase followed by bubbles forming, culminating in a crash (Sornette, 2003).

In Econophyiscs, the 'Hurst exponent' is often used to analyze financial market phenomena (Hurst, 1951). The Hurst exponent measure is a powerful tool for analyzing complex financial time series and is used to uncover various hidden patterns and events in financial markets. It is a potential tool for evaluating and measuring herding behavior and impending financial market bubbles. It has found appropriate applications in many domains, such as chaos theory, spectral analysis, fractals, and long memory processes, although its initial usage was for the water storage issue (Graves et al., 2017). Through extensive research, researchers in the field of Econophyiscs have identified that the Hurst exponent can be a valuable and robust tool for examining multiple occurrences in financial markets. These include forecasting (Fernández-Martínez et al., 2017), efficiency, market memory (Cajueiro & Tabak, 2006; Ghosh & Bouri, 2022; Lobato & Velasco, 2000; Suárez-García & Gómez-Ullate, 2014), bubbles (Johansen et al., 2000; Lux & Sornette, 2002) and herding behavior. The significance of such discoveries has been proved and established by investigations spanning several markets and asset kinds in various nations. The literature describes multiple ways of estimating the Hurst Exponent. García and Ramos (2019) offer a thoughtful evaluation of the Hurst exponent's methods in Econophysics.

Kantelhardt et al. (2002) proposed the Multifractal Detrended Fluctuation Analysis, commonly known as the MFDFA methodology. This technique is the most established and robust method

for analyzing Hurst's value. Multifractal is used everywhere, from biological series to stochastic series. Benoit B. Mandelbrot and two other scientists initially developed the MMAR (Multifractal Concept of Asset Returns) model to explain the variation in most financial asset closing prices. It demonstrated self-similarity, volatility clustering, fat tails, long-term memory, and other ideas (Mandelbrot et al., 1997). Mandelbrot expanded fractals from monitoring coasts to clarifying stock movement. He contended that these methodologies estimate the likelihood of stock price predictions before any Black Swan events (Mandelbrot, 1999). Mandelbrot's pioneering fractals were expanded upon by a team of distinguished experts (Kantelhardt, 2008; Kantelhardt et al., 2002), who gave an excellent structure to the complete process of determining the effect of multifractality in a noisy time series by providing a mathematical equation. Ihlen (2012) gave this equation a code in MATLAB.

Researchers have widely used this Fractal technique to study the multifractal features of numerous financial markets worldwide. Numerous stylized facts about financial markets, such as market efficiency, financial crisis, risk rating, and crash prediction, are investigated using the MFDFA approach (Ali et al., 2018; Hasan & Mohammad, 2015; Lee et al., 2016; Patil & Rastogi, 2020). This technique is the most established and robust method for analyzing Hurst's value. Hasan and Mohammad (2015) conducted fractal analysis in the U.S. and Asian stock markets during the financial crisis. They used MFDFA and discovered evidence of multifractality in all market indices. Aslam et al. (2021) recently examined the European financial exchanges during the COVID-19 pandemic and discovered that multifractality was common in those markets at the time. Milos et al. (2020) recently researched the discovery of multifractality in seven European Union stock markets. Using the MFDFA technique, these authors found that Bulgaria and the Czech Republic markets had the highest multifractality. Therefore, because of the MFDFA approach's reliability, analysts worldwide have recently used it. They have been highly influential in demonstrating the multifractal features of financial markets worldwide. As a result, the same method was used in this research to uncover embedded herding and nascent bubbles.

In recent years, India has seen various events that have caused shocks in its stock markets. Such market shocks are among the most severe market disruptors with which players will have to contend in the coming years. Several researchers investigated how these shocks affect the volatility and returns of financial assets and financial markets. However, there is less empirical research exploring the impact of various shocks on market players' behavior. Scarce data in empirical research for the Indian market opens the door to investigating and analyzing the influence of such market shocks, regardless of their magnitude, on the creation of bubbles or anti-bubbles generated by herding from market players, which forms the primary objective of the study. Hence, it is crucial to investigate whether herding behavior occurs and whether it has created a stock market bubble in India.

2. METHODS

This study employs the Multifractal Detrended Fluctuation Analysis model developed by Kantelhardt et al. (2002) to explore the herding behavior and bubble patterns from January 1, 2011, to December 3, 2021. It is the period immediately following the recovery from the 2008 recession and includes several economic and political events and natural disasters such as Demonetization, the change of the ruling party as the Central government, and the Covid-19 pandemic. This model produces the Hurst (1951) values, making it possible to gauge the degree of herding behavior in the index. This study examines the behavior of BSE 100 investors. BSE 100 is India's most widely followed stock market benchmark index. As a result, this would aid in providing a better understanding of investor behavior.

In MFDFA, pure loud time series must initially be modified to resemble 'random walk.' Persistent sounds are converted to pure 'random walk' series by removing the mean and incorporating the same. The root means square (RMS) variation is computed. RMS and the many samples demonstrate their 'power law' link. This procedure is the well-known "monofractal detrended fluctuation analysis," or DFA. The 'Hurst exponent' is the coefficient for this special relationship. This procedure is extended to the qth order. It is called MFDFA or "multifractal detrended fluctuation analysis." Fractal

features and coefficient values shift from mono to multi, with the latter being more accurate.

The following are the five phases of the MFDFA approach as proposed by Kantelhardt et al. (2002):

Firstly, the normal log returns are calculated. Following is the calculation of the index prices' normal log returns:

$$x(t) = \ln\left(\frac{p_t}{p_{t-1}}\right), \text{ of length } N, \quad (1)$$

where p_t denotes the index price on the day (t), p_{t-1} represents the index price on the day $(t-1)$, and $x(t)$ is the nonstationary time series of the market index for a trading day (t).

Step 1: Profile estimation:

$$Y(i) = \sum_{k=1}^{i}\left[x(t) - \bar{x}\right], \quad i = 1,..,N, \quad (2)$$

when N is the length of the whole time series in this case, and $\bar{x}$ is the mean of the initial time series $x(t)$.

Step 2: N_s, the non-overlapping segments of length s, are used to partition the profile Y(i), where $N_s =$ int(N/s). A minor portion of the time series remains because the entire time series length N might be a non-multiple of the considered time scale s. The identical procedure is repeated beginning on the opposite end side. Consequently, getting $2N_s$ segments overall.

Step 3: By fitting the time series using a least-squares algorithm, one may determine the local trend for separately generated $2N_s$ portions. The following is how variance is determined:

$$F^2(s,v) \equiv \frac{1}{s}\sum_{i=1}^{s}\left\{Y\left[(v-1)s+i\right] - y_{v(i)}\right\}^2. \quad (3)$$

For each part v, $v = 1...N_s$ and

$$F^2(s,v) \equiv \frac{1}{s}\sum_{i=1}^{s}\left\{Y\left[(N-(v-N_s)S+i\right] - y_{v(i)}\right\}^2. \quad (4)$$

Step 4: By averaging all the components from step 2, where the variable q can take any real value other than zero, one can obtain the qth order fluctuation functions.

$$F_q\left(s\right) \equiv \left\{ \frac{1}{2N_s} \sum_{v=1}^{2N_s} \left[F^2\left(S,V\right) \right]^{q/2} \right\}^{\frac{1}{q}}. \qquad (5)$$

Step 5: By looking at the log-log plot of F_q(s) versus s for each value of q; one may determine the scaling behavior of the fluctuation functions. F_q(s) rises for a considerable value of s as a power law if the time series $x(t)$ are long-range power-law correlated, where $h(q)$ is the Hurst exponent used in the financial literature (Hurst, 1951).

$$f_q\left(s\right) \sim s^{h(q)}. \qquad (6)$$

The Hurst exponent typically has values between 0 and 1. The values of the Hurst exponent were calculated using the above-described MFDFA analysis, precisely the 5th order Hurst exponent, for each trading day. The 5th order Hurst exponent findings were examined for the market index using MATLAB software and the Ihlen (2012) coding.

Table 1 shows the range of Hurst values and their associated interpretations.

**Table 1.** Hurst values and their associated interpretations

Hurst values	Interpretation
$0 < H < 0.5$	Herding – free, Bubble – free, Anti - persistent
$H = 0.5$	No predictability, Random Walk
$0.5 < H < 0.64$	High predictability, Mild Herding, Mild Bubble
$0.65 < H < 0.71$	Impending crisis, High-level Herding, High Bubble
$0.72 < H < 1$	The Crisis phase, Higher level Herding, Higher bubble

The dataset includes daily stock data from the BSE website. Daily stock prices helped to analyze herding behavior on an annual basis. The annual computation offered exact conclusions for the study and helped identify events that affected the stock market throughout the study period. The data is open source and reliable, making it a trustworthy source of research. The dataset is cleaned before being loaded into MATLAB. The data is organized as follows: Multifractal for current pricing, Monofractal for lag one information, and Whitenoise for lag two data. The MFDFA codes are used to generate the results. The obtained results are examined and investigated for existing herding behavior, and the Hurst exponent explains stock market volatility.

3. RESULTS

This study section presents the findings from the Multifractal detrended fluctuation analysis. The values of the 5th order Hurst exponent, or Hq (5), for the BSE 100 index are calculated using the MFDFA method. The Hq (–5), Hq (0), and Hq (5) result from each year are displayed.

Table 2 reports the Hurst exponent values for each year. The Bolded values indicate the presence of herding as the Hurst exponent Hq (5) value is above 0.5. The Multifractal Detrended Fluctuation Analysis codes from MATLAB by Ihlen (2012) were applied. The first three years (2011–2013) witnessed consistent bubbles and herd. 2016, 2018, 2020–2021 observed a similar trend (see Table 2 and Figure 1).
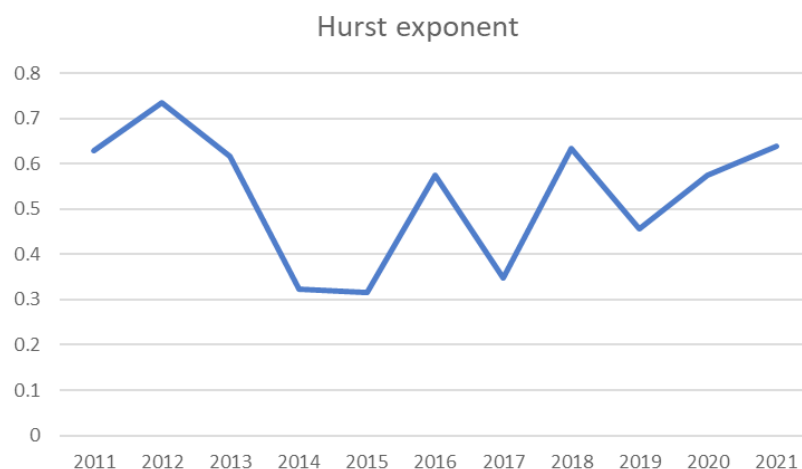
Figure 1. Hurst exponent values of BSE 100 from January 1, 2011 to December 31, 2021

Table 2. Illustrating the results of Hurst for BSE 100

Year	Hq (−5)	Hq (0)	Hq (5)
2011	0.7137	0.6714	0.6297
2012	0.9004	0.8155	0.7349
2013	0.8967	0.7733	0.6164
2014	0.4464	0.3915	0.3242
2015	0.6334	0.5131	0.3165
2016	0.7626	0.6839	0.5758
2017	0.7626	0.6839	0.3483
2018	0.7202	0.6765	0.6351
2019	0.8205	0.7006	0.4567
2020	1.1474	0.9916	0.5757
2021	1.0423	0.8219	0.6380

Table 3. Summary of events during periods of High Hurst Exponent

Year	Event
2011	Inflation causes market declines; global signals caused a significant correction, with crude oil prices rising, Significant interest rate increases in the United States
2012	Flash crash on October 5, 2012, due to erroneous trade orders, Market players anticipated budgets
2013	Allowed Foreign Direct Investment (FDI) in retail, aviation, and broadcasting sectors. Opinion polls hinting at a change in Government, Sudden liquidity tightening measures by the Central bank, Devaluation of the Rupee
2016	Brexit, Demonetization, Passing of the GST (Goods and Services Tax) bill, Uri attack followed by surgical strike, U.S Presidential elections
2018	LTCG (Long term Capital Gain) tax in the budget proposal, US-China trade war, Crude oil price rise followed by rupee rise, M.F. (Mutual Fund) reclassification, Local Bank fraud and scams, Surprise resignation by Central bank Governor, Economic slowdown
2020	First case of Covid-19 reported in the country, Lockdown announcements, Covid-19 cases crossed the 1 lakh mark, announcement of economic stimulus, India and China border tensions escalated, Rise in gold prices
2021	Rally in stock markets, increase in domestic retail investors, Delta wave of Covid-19, Banning of Chinese applications by India, Covishield and Covaxin get approval as vaccinations

4. DISCUSSION

The study spotted inconsistent herd and bubbles (see Table 2 and Figure 1). The first three years (2011–2013) witnessed consistent bubbles and herd as the aftermath of the Global Financial Crisis (GFC-2008). 2016, 2018, and 2020–2021 recorded a similar pattern (see Table 3 for justification). Apparently and qualitatively, no visible shocks were there on BSE 100 in 2014; therefore, it is consistently anti-persistent. However, the following year shows a mixed bag as some shocks induced bubble and herd, albeit partially. The last two years of consideration (2020–2021) are understandably persistent, owing to Covid-19 (SARS-COV, Delta & Omicron).

Most of the indicators in Table 3 point to six major events: the economic meltdown, commodities and currency devaluation, geo-political problems, the Central Bank's decision on liquidity management, and the Pandemic. The global economy issues were considered a key factor for the stock market's decline in 2011 and 2012. Worries about domestic economic

expansion, a state of policy uncertainty, and a slowdown in the business sector added to the uncertainties. Therefore, a high level of herding activity was detected this time, as shown by the Hurst values 0.6297 and 0.7349 in Table 2. While, markets for the majority of the year in 2013 succumbed to depressing economic growth, inflation, high-interest rates, a widening current account deficit, and a weak rupee. Several optimistic factors, including FII inflows and expectations of a change in the regime, caused sentiment to shift later. High Hurst exponent values during this time frame indicate herding behavior and a bubble, consistent with Makololo and Seetharam (2020), who discovered that political and economic risks affect herding behavior.

Equity investors experienced a roller-coaster in 2016, as the Indian stock market hit a record low at year's end due to domestic and international factors. On August 3, 2016, the Goods and Services (GST) Tax Bill was enacted, which led to a spike in the equities markets. The Indian government announced the "demonetization" on November 8 of the same year, a

step that involved the outlawing of currency notes with values of 500 and 1,000. The unexpected prohibition reduced peoples' purchasing power, negatively impacting Indian stock markets. The local stock market crashed on September 29, 2016, when the Director General of Military Operations announced that the Indian Army had done surgical strikes on terror launch sites on Pakistani soil. Through the analysis, the Hurst exponent value in 2016 was found to be 0.5758, indicating herding and bubble.

The first case of Covid-19 was reported on January 30, 2020. As a result, the government implemented several measures and restrictions to protect the public and lessen pandemic fear, including the announcement of multiple lockdowns for approximately 54 days and the temporary closure of educational and commercial establishments. All key activities and operations were stopped; as a result, resulting in business losses. The financial markets were affected, and many investors experienced fear. The Indian stock market had its greatest decline on March 12, 2020, after the WHO recognized the outbreak as an epidemic. The BSE Sensex saw its worst decline of 8.18%, or 2,919 points, in 23 months. This period's high Hurst exponent values (0.5757 and 0.6380) indicate excessive herding behavior and a bubble in line with Aslam et al. (2021), who found

that herding behavior increased during a health crisis. Surprisingly, despite the Pandemic and economic downturn, a stock market rally was observed in late 2020 and early 2021, when the index peaked before moving downwards. Domestic individual investors propelled the stock market rise in 2021. 27.4 million new Demat accounts were established, proving that the stock market rise had relatively little help from foreign investors (Hindustan Times, 2021). It is challenging for investors to demonstrate their rational investing behavior in the face of such uncertainties. Consequently, encouraging them to engage in panicked herding eventually protects their financial assets from likely unpredictability produced by such market shocks.

Therefore, it is observed that the analysis corresponds to the events. The findings are consistent with a similar study in Iberia by Ferreruela and Mallor (2021), proving the link between extreme shocks and herd behavior by market participants. The higher value of the Hurst exponent showed more chances of herding and bubble patterns in the market's time series and high-risk elements. The investigation has been kept consistent with the existing literature keeping the Hurst exponent as 5, i.e., 5th order. However, there are also opportunities to investigate values between 2-4.

CONCLUSION

The study aims to find herding and bubble in the BSE 100 Index from January 1, 2011, to December 31, 2021, using the Hurst Exponent (HE) measure. The study's findings effectively exposed the hidden imprints of herding and bubble. The results exhibited that shock-based herding has been prevalent in all six kinds of shocks: the economic meltdown, commodities and currency devaluation, geo-political problems, the Central Bank's decision on liquidity management, and the Pandemic. The Hurst values serve as an illustration of the relationship between herding behavior and actual events. Furthermore, the results show that the Hurst value is more significant after the Financial Crisis and during the Pandemic, indicating a higher degree of herding and bubble in those years.

This study is helpful to policymakers, market operators, and individual investors. In this context, the study's findings might be a crucial motivator for stock market players to purchase or sell in Indian stock markets during unpredictable events. Furthermore, these findings will aid them in making risk-adjusted investing decisions. Investors might devise proper hedging techniques to protect their portfolios from future hazards. It might also help market analysts understand investor mindsets and how markets respond collectively. Hurst exponent tool, if appropriately used, can anticipate future market effects and provide valuable trading strategy assistance. Research on herding in stock markets and detection of bubbles in important sectoral indices of uncertain markets is urged strongly as a future field of study. Future studies may use High-Frequency Trading (HFT) data to analyze events in detail. Researchers can also conduct a thorough event-based investigation.

AUTHOR CONTRIBUTIONS

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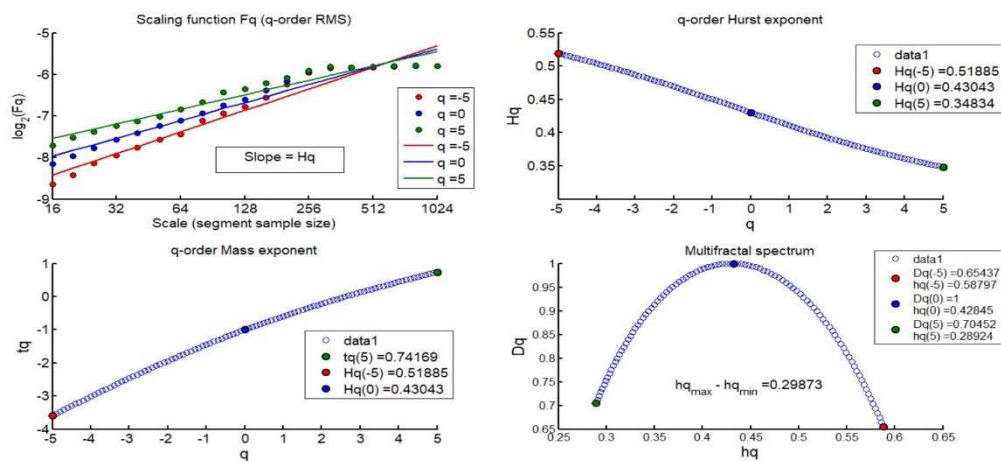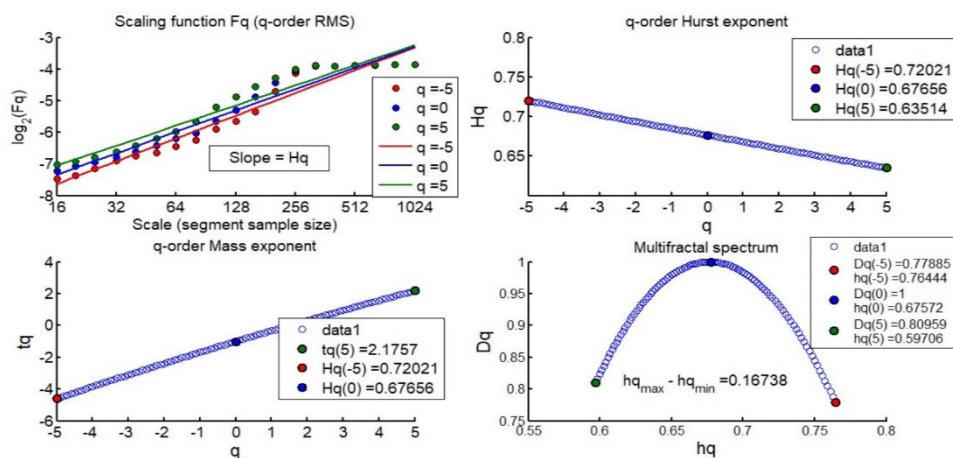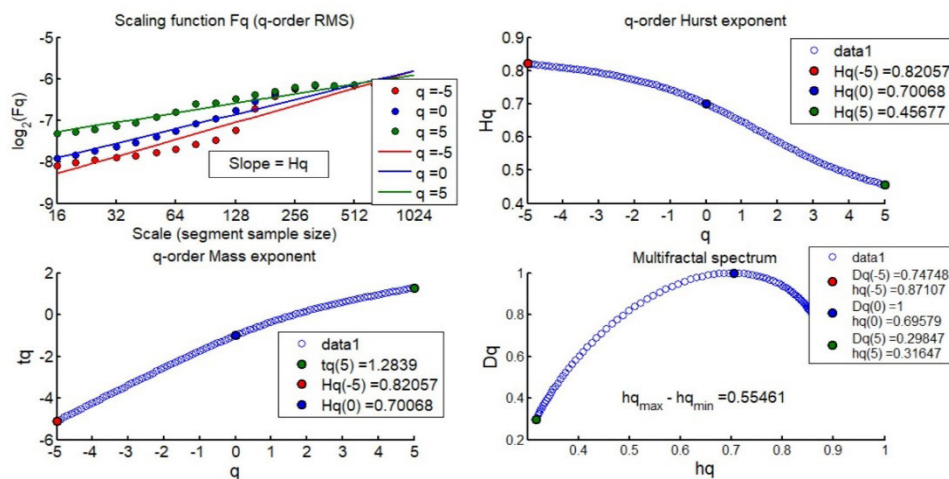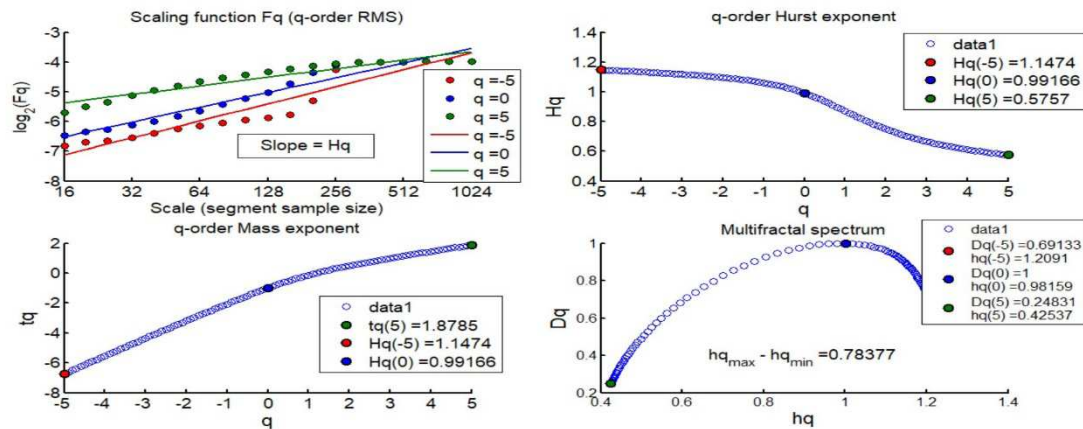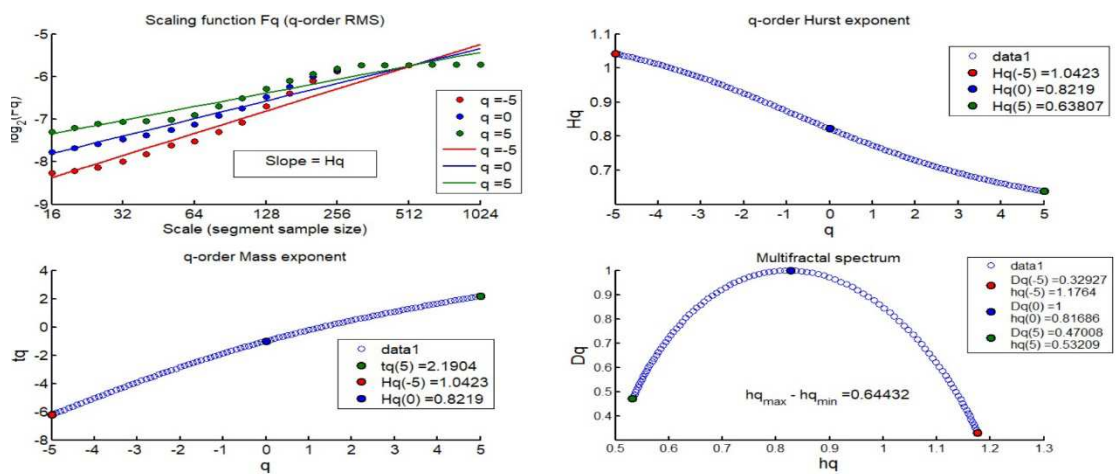
APPENDIX A
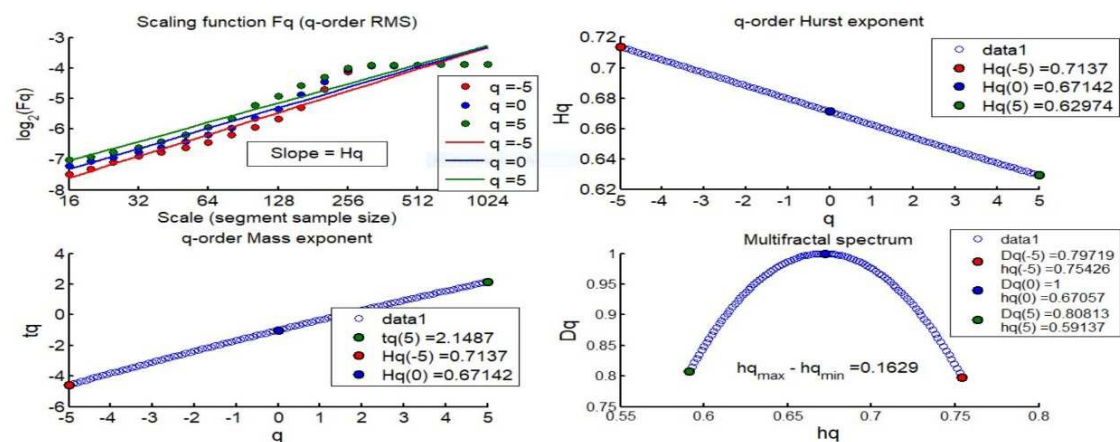
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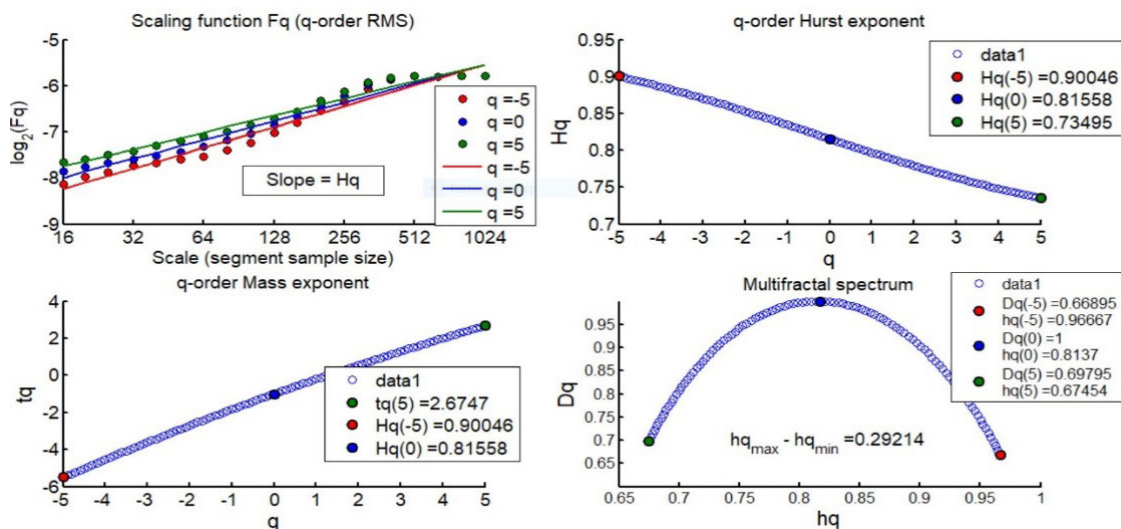
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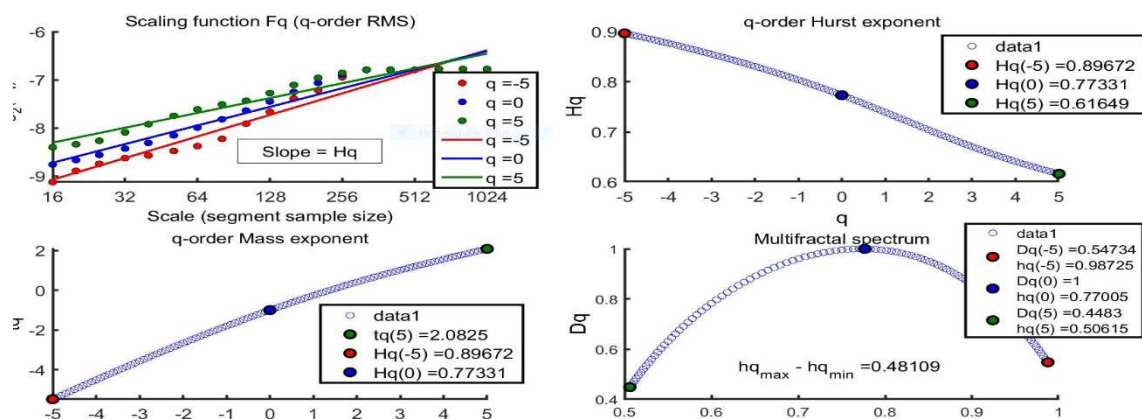
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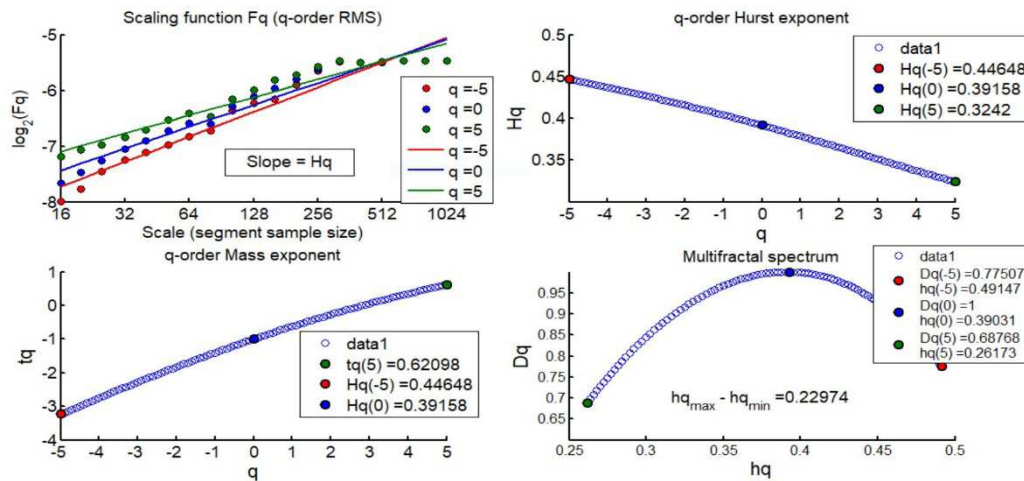
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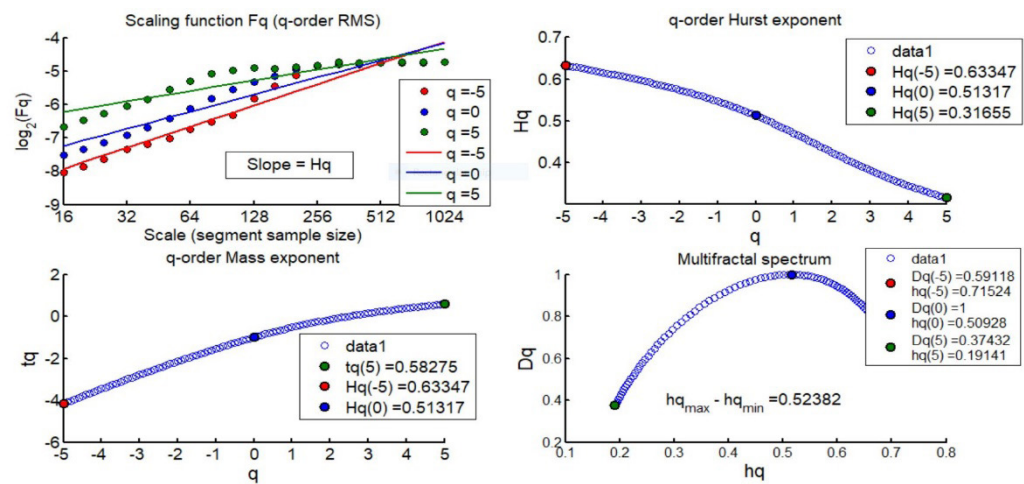
Figure A5. Hurst exponent value Hq(5) in 2015
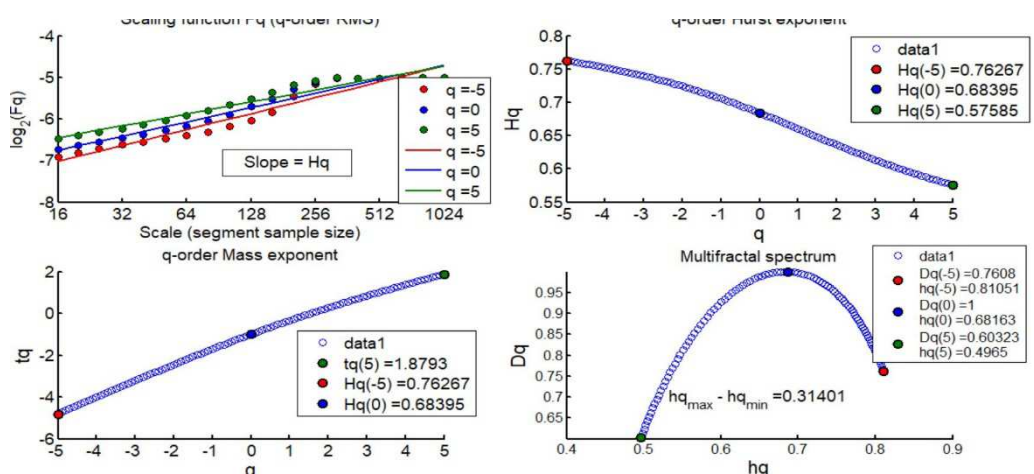
Figure A6. Hurst exponent value Hq (5) in 2016

Figure A7. Hurst exponent value Hq (5) in 2017

Figure A8. Hurst exponent value Hq (5) in 2018

Figure A9. Hurst exponent value Hq (5) in 2019

Figure A10. Hurst exponent value Hq (5) in 2020

Figure A11. Hurst exponent value Hq (5) in 2021