"Intensified geopolitical conflicts and herding behavior: An evidence from selected Nifty sectoral indices during India-China tensions in 2020"

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BUSINESS PERSPECTIVES

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INTENSIFIED GEOPOLITICAL CONFLICTS AND HERDING BEHAVIOR: AN EVIDENCE FROM SELECTED NIFTY SECTORAL INDICES DURING INDIA-CHINA TENSIONS IN 2020

Abstract

The recent India-China geopolitical conflicts have presented enormous uncertainty to the investors in various sectoral indices of the Indian stock market. This empirical study aims to examine the impact of intensified India-China geopolitical conflicts 2020 on investors' herding behavior in the National Stock Exchange sectoral indices. The high-frequency data of three major NIFTY sectoral indices (Auto, Energy, and Pharma) are used in an intensified geopolitical event window to spot precisely the traces of the investors' herding behavior. Furthermore, multifractal detrended fluctuation analysis (MFDFA) is employed to obtain Hurst Exponent values (h(q)) for the NIFTY sectoral indices. The findings reveal that these NIFTY sectoral indices exhibited profound traces of herding behavior on the event day (t = 0) due to the heightened India-China geopolitical clashes. In addition, these indices depicted an overall higher level herding behavior with the (h(q)) values close to 0.72 throughout the intensified geopolitical event window. The study concludes that the sectors highly reliant on the Chinese supplies and with significant trade linkages with China depicted a higher level of herding behavior in their indices. Further, the presence of herding behavior in these sectoral indices is due to the operational and supply-chain risks posed by the geopolitical event.

INTRODUCTION

India-China ties had been securely deteriorating for the past few decades due to extreme misapprehensions and mistrust regarding each other's foreign affairs and global ambitions (Gokhale, 2021). However, their relations marked an implacable lowest point when the recent border disputes intensified to extreme tensions between both sides. On the intervening night of June 15-16, 2020, Chinese and Indian armed forces engaged in a fierce scuffle during the de-escalation process in the river valley of Galwan, India. This violent face-off that escalated between the two nations eventually caused the valuable lives of 20 Indian soldiers and undetermined Chinese casualties. Furthermore, it is documented as the worst phase that India and China perceived in their relationship after the 1962 war (Kumar, 2021). While the two nations continued to dissent about who was accountable for the violent face-off, the subsequent geopolitical tensions posed some serious concerns for their bilateral trade and economic relations.

Furthermore, China emerged as India's most crucial economic and trading partner only next to the United States in 2019–2020 (Kapoor,

2020). In addition, the current annual bilateral trade between India and China crossed the milestone figure of USD 100 billion (The Economic Times, 2021). Several sectors of the Indian economy are intertwined with China's economy. Among them, sectors such as automobiles, energy, power, and pharmaceuticals are substantially dependent on Chinese exports for their supply chain and operations. As a consequence of this violent geopolitical event, these sectoral indices of the Indian stock markets witnessed turbulent volatility in their trading patterns due to the panic-stricken trading activity of the market participants. For instance, on June 16, 2020, when the news affirmed that the tensions worsened into blood-spattered violence, the fifteen share index that benchmarks the Indian automobile sector, known as the Nifty Auto index, touched an intraday low of 6355.75 points (a fall of 205.45 points from its intraday open). Later, the index closed at 6451.05 points, wiping out all its gains of the day. Besides, the Nifty Energy and Nifty Pharma indices were also considerably trembled by the deadly geopolitical violence. Given this, the Nifty Energy index and the Nifty Pharma closed at 13780.55 points (–2%) and 9926.40 points (–1.35%), respectively, from its intraday open. In this regard, Dhall and Singh (2020) affirmed that investors in financial markets mimic the investment activities of others, principally during such times of turbulent volatility, panic, and uncertainty. Thus, they eventually exhibit their herding behavior (Mertzanis & Allam, 2018).

Therefore, against this backdrop, this study fundamentally attempts to examine the impact of intensified India-China geopolitical tensions in 2020 on the investors' herding behavior in three major dependent sectoral indices of the National Stock Exchange (NSE), namely the NIFTY AUTO, NIFTY ENERGY, and NIFTY PHARMA.

1. LITERATURE REVIEW

Literature in recent times has undoubtedly documented evidence that there exists a substantial impact of geopolitical uncertainties on financial markets globally (Noguera-Santaella, 2016; Antonakakis et al., 2017; Balcilar et al., 2018; Aysan et al., 2019; Baur & Smales, 2020).

Noguera-Santaella (2016) investigated the impact of global geopolitical events (1861–2011) such as armed and civil conflicts on the highly sensible oil markets. The study results documented that geopolitical events that occurred before 2000 positively impacted oil prices while those events post 2000 had little or no impacts on the actual oil prices. Antonakakis et al. (2017) conducted a study to check whether the returns of stock and oil markets are affected by geopolitical risks using the developed geopolitical risk index (GPI). Their study revealed that geopolitical risk negatively affects the returns and volatility of oil markets. Balcilar et al. (2018) examined the effect of geopolitical uncertainty in the stock markets of BRICS nations. They found a heterogeneous effect of geopolitical risks on the markets examined. Their findings also indicated that the Russian stock markets had borne the greater geopolitical risk while the Indian markets were the most resilient among the BRICS group. Aysan et al. (2019) examined the global geopolitical risks on daily returns and volatility of Bitcoin. They found that both volatility and returns of Bitcoin are positively and negatively related to the geopolitical risks, respectively. Most recently, Baur and Smales (2020) analyzed the relationship between geopolitical risks and the asset prices of precious metals and reported that the impact of the geopolitical risk could be lowered by holding the precious metals within a diversified portfolio. Further, it is concluded that precious metals hedge against the threat of geopolitical risks.

Given the studies that established empirical evidence concerning the impact of geopolitical uncertainties on the financial assets and markets worldwide, it is also further perceived that such tensions substantially influence participants' investment decisions in financial markets. Moreover, events associated with such geopolitical tensions mean greater volatility and higher risk to the investors in the financial markets (Schroders, 2019). In times of such higher unpredictability and greater volatility, they mostly mimic the investment activities of other investors to make quick investment decisions. Such mimicking propensity is also denoted as herding behavior (Naresh et al., 2019).

Herding behavior is a phenomenon in financial markets that stems from the arena of behavioral finance (Trueman, 1994; Hirshleifer et al., 1994). Behavioral finance studies delve into why investors make investment decisions contrary to the assumptions of rational investors (Liu et al., 2020). Concerning the same, the reasons for investors' herding behavior in financial markets can be numerous. Some of them include reputational reasons (Teh & de Bondt, 1997), social reasons (Ganesh et al., 2017), and psychological factors of greed and fear (Prechter, 1999). In addition, herding can also occur due to a widely known human behavioral bias named the loss aversion bias. Investors have a stronger desire to avoid losses than the probability of obtaining gains from their investments (Pompain, 2017).

Moreover, Espinosa-Méndez and Arias (2021) also indicated that uninformed investors under the influence of fear and uncertainty are more likely to incline towards the actions of well-informed investors, particularly during turbulent market conditions. Irrespective of the reason, herding is dangerous and disastrous both to the economy and financial markets of the nation (Ganesh et al., 2017). It can cause extremities such as asset mispricing, inefficiency in financial markets, and the formation of a market bubble, eventually weakening the financial markets (Avery & Zemsky, 1998; Hott, 2009; Kabir, 2018).

Furthermore, there exists evidence in the academic literature that events associated with risks and uncertainties accompany investors' herding behavior in financial markets (Indārs et al., 2019). In this regard, examining the existence of herding behavior in financial markets worldwide during the ongoing COVID-19 pandemic crises and uncertainties period emerged as one of the frontrunner topics for researchers in behavioral finance. Numerous research works have been undertaken in the most recent times to empirically extend and restore the evidence of herding behavior across financial markets during such crisis times. Dhall and Singh (2020) investigated the herding bias in the Indian industry indices of the National Stock Exchange (NSE). They established the traces of herding behavior during the post-event period of the COVID-19 pandemic. Bharti and Kumar (2021) examined the herd phenomenon in the

Indian stock markets amidst the COVID-19 period and identified herding at a significant level due to provoked market volatility. Fang et al. (2021) assessed the impact of the COVID-19 pandemic using a sample of six Eastern European stock markets. They determined that the pandemic has amplified the herding activity in all the stock markets evaluated. Very recently, Mishra and Mishra (2021) conducted a study to check for the presence of herding behavior amid the COVID-19 pandemic in Indian banking and financial services indices. The results of their study identified herding behavior in public banking and financial services indices under the bull market situation during the pandemic period.

Further, the pandemic period of COVID-19 holds significance in this study because the fresh geopolitical tensions between India and China originated and intensified in May-June 2020, and the same is accordingly in the timeline with the midst of the COVID-19 pandemic period. Thus, amidst the COVID-19 pandemic, intensified geopolitical tensions erupted between India and China. These tensions presented shock, panic, and uncertainty to the investors in the sectoral indices of the Indian stock markets. In addition, they have caused severe damage and harm to the India-China economic and trade relations, eventually affecting the short- to mid-short term performance of the sectoral indices. Therefore, the study presumed that due to the heightened level of uncertainties that prevailed, there could be the possibility of herding behavior in the sectoral indices of the Indian stock markets during the intensified days of India-China geopolitical tensions. Thus, this study aims to trace out the footprints of herding behavior in the selected Nifty sectoral indices during the intensified days of India-China geopolitical tensions.

2. METHODOLOGY

2.1. Event date and event window

This sub-section of the paper describes the dates of the intensified geopolitical events and their respective explanation with the event windows. An intensified India-China geopolitical event window 2020 consists of the event day, a day before the event day, and a day after the event day. Thus, the

Table 1. Intensified geopolitical event window for India-China tensions, 2020

Event date	Event window	Description of intensified geopolitical events
June 15, 2020	(t = –1)	On an intervening evening, Indian soldiers in the disputed LAC at Galwan valley dismantled illegal temporary establishments made by the Chinese PLA. Retaliation by the Chinese soldiers arose by attacking Indian troops that resulted in an unprecedented violent clash. This violent clash caused the death of 20 Indian soldiers, including a commanding officer, and undetermined causalities from the Chinese military.
June 16, 2020	(t = 0)	The news affirming that tensions worsened into violent attacks, causing the demise of 20 Indian soldiers, reached the Indian stock markets, eventually inducing fears of geopolitical uncertainties among the market participants. On the same day, major general level talks were held to release captive Indian soldiers.
June 17, 2020	(t = +1)	Indian Prime minister addressed the nation about the violent Galwan clash, and the Chinese foreign minister warned India.

first day of the intensified geopolitical event window, i.e., June 15, 2020, is called ($Day = –1$) or ($t = –1$). The event day, i.e., June 16, 2020, is indicated as ($Day = 0$) or ($t = 0$). And the third day, i.e., June 17, 2020, is called as ($Day = +1$) or ($t = +1$). These three days are very significant for the reason that the India-China tensions 2020 at the LAC border escalated into heightened violent clashes. Therefore, the same is employed to precisely examine the effect caused by the intensified level of India-China geopolitical tensions on the herding behavior in Nifty sectoral indices. The description concerning the intensified event window of India-China geopolitical tensions 2020 is exhibited in Table 1.

2.2. Data and sources

Three major Nifty sectoral indices of the National Stock Exchange (NSE), India, representing the Auto, Energy, and Pharma sectors, were considered to examine the herding behavior under the impact of the intensified India-China geopolitical event window. Table 2 exhibits the details of the Nifty sectoral indices listed in the NSE.

Table 2. Nifty sectoral indices and their description

Sectoral indices	Constituents	No. of stocks represented
NIFTY AUTO	The stocks of automobiles including 2, 3 and 4 wheelers, auto ancillaries and tires	15
NIFTY ENERGY	The stocks of Petroleum, Gas, and Power sector	10
NIFTY PHARMA	The stocks of Pharmaceutical companies	10

This study employed the high-frequency data of the aforesaid Nifty sectoral indices for all three days

in the intensified geopolitical event window. High-frequency data is also known as tick-by-tick data. Tick-by-tick data is employed in financial analysis, mainly when an intra-day observation is made to understand the market behavior at a micro-level. This study employs tick-by-tick data of the sectoral indices to investigate the traces of herding behavior during the intensified India-China geopolitical events of 2020. The high-frequency trading data of the three Nifty sectoral indices for the event period was procured from NSE DotEx (also known as NSE data and analytics limited).

Initially, all the tick-by-tick values of the considered Nifty sectoral indices (per second frequency) during the regular market hours between 09:15 to 15:30 for all three days in the intensified geopolitical event window were considered individually. In the second stage, all the repeated tick-by-tick index values of the trading days were removed, and only the unique index prices were taken for the final dataset. The list containing the number of tick-by-tick unique observations for each sectoral index as per the intensified geopolitical event window is presented in Table 3.

Table 3. Number of intraday tick-by-tick unique observations considered for analysis

Event date and event window / Nifty sectoral indices	June 15, 2020 and (t = –1)	June 16, 2020 and (t = 0)	June 17, 2020 and (t = +1)
NIFTY AUTO	2866	3590	2667
NIFTY ENERGY	5163	6329	3207
NIFTY PHARMA	4527	4673	1989

2.3. Model description

To examine the herding behavior traces in the three Nifty sectoral indices during the intensified India-China geopolitical tensions of 2020, this paper applies the Kantelhardt et al. (2002) model of Multifractal Detrended Fluctuation Analysis (MFDFA). This model generates the values of Hurst (1951), enabling measuring the level of herding behavior in the sectoral indices. Kumar and Deo (2009), Ghosh et al. (2020), and Mnif and Jarboui (2021) have established that the most prominent method to estimate the Hurst exponent value for any non-stationary time series in finance is the Kantelhardt et al. (2002) MFDFA model. The following summarizes the steps involved in the MFDFA methodology proposed by Kantelhardt et al. (2002).

Firstly, the normal log returns for the sectoral index prices in its tick-by-tick frequency are estimated as:

$$T(i) = \ln\left(\frac{R_t}{R_{t-1}}\right), \tag{1}$$

here, $T(i)$ indicates the tick-by-tick time series of the Nifty sectoral indices which is non-stationary by its nature, R_t denotes the sectoral index price on tick t and R_{t-1} depicts the index price on tick $t-1$. The key formulas for the Kantelhardt et al. (2002) model of MFDFA analysis consist of five steps as outlined below:

Step 1: Construction of the profile, $Y(p)$:

$$Y(p) \equiv \sum_{i=1}^{P}\left[T(i) - \overline{T}\right], \quad i = 1,\dots,N. \tag{2}$$

In the above equation, $T(i)$ for $i = 1, \dots, N$ represents the possible non-stationary time series that resulted from the sectoral index returns of equation (1), in which N denotes the series length and $\overline{T}$ being its mean.

Step 2: The second step in the MFDFA analysis involves the division of the above-constructed profile $Y(p)$ into N_s. Here, $N_s \equiv \text{int}(N/s)$, i.e., non-overlapping segments of the equal length s. As the entire series length $\boldsymbol{N}$ is generally not a multiple of the considered length s. Therefore, a short part of the profile $Y(p)$ is disregarded, and the sub-division is also realized from the opposite end side.

Thus, totally, $2N_s$ segments are obtained as a result of this step.

Step 3: The third step in the analysis involves the computation of the local trend for individually obtained $2N_s$ segment by a least-square fit of the series. This is performed by fixing a polynomial of degree m to estimate the profile in each of the $2N_s$ windows. Further, the variance is determined through the formulas:

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

for each segment v, $v = 1, \dots, N_s$ and

$$F^2(s,v) \equiv \frac{1}{s}\sum_{p=1}^{s}\{Y[(v-N_S)s+p] - y_{v(p)}\}^2, \tag{4}$$

for $v = N_{s+1}, \dots, 2N_s$. Here, $y_{v(p)}$ is the polynomial fit in segment v.

Step 4: The fourth step in the analysis includes averaging all the segments from the step (2) to get the qth – order fluctuation functions.

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

here, the variable q can take any real value except zero.

Step 5: The fifth step is the last one in the MFDFA model that determines the scaling exponent of the fluctuation function for each q to get the relation between $F_q(s)$ and s. If $f_q(s)$ is power-law correlated, the series are in log-log scale for that particular q.

$$f_q(s) \sim s^{h(q)}. \tag{6}$$

In equation (6), $h_{(q)}$ is referred to as the generalized form of Hurst exponent (Hurst, 1951). The Hurst values generally range from 0.5 to 1.00. The same is employed to measure the degree of herding behavior in the time series. The 5th order Hurst exponent, i.e., $H_q(5)$, is computed in this study through the MFDFA analysis for each sectoral index accordingly to the intensified event window. Further, the MFDFA codes established by Ihlen (2012) were applied in the MATLAB software and run to obtain the Hurst values, i.e., $H_q(5)$. Table 4 represents the Hurst exponent value range and their respective interpretation for herding **behavior.**

Table 4. Hurst exponent value range

Hurst exponent range	Interpretation for herding behavior level
$0 < H_q < 0.5$	No herding behavior (or) Anti-herding behavior
$H_q = 0.5$	Random-walk
$0.5 < H_q < 0.64$	Mild herding behavior
$0.65 < H_q < 0.71$	High level herding behavior
$0.72 < H_q < 1$	Higher level herding behavior

3. RESULTS

This section of the study demonstrates the results obtained from Multifractal detrended fluctuation analysis. The 5th order generalized Hurst exponent values, i.e., $H_q(5)$ for all the three Nifty sectoral indices are computed through the MFDFA method, and their results are exhibited respectively for each trading day as per the intensified geopolitical event window.

Table 5. Illustrating results of Hurst exponent (H_q) from MFDFA analysis

S. No.	Event date and event window — Nifty sector indices	June 15, 2020 and ($t = -1$)	June 16, 2020 and ($t = 0$)	June 17, 2020 and ($t = +1$)
1.	NIFTY AUTO	0.70203	0.71314	0.71542
2.	NIFTY ENERGY	0.73492	0.73680	0.62697
3.	NIFTY PHARMA	0.54452	0.72378	0.71739

Figures 1-9 illustrate the MFDFA output figures of the 5th order Hurst exponents $H_q(5)$ for each Nifty sectoral index as per the event window.

S. No. 1 of Table 5 reports the Hurst values of the Nifty Auto index. The day ($t = -1$) in the intensified geopolitical event window recorded a Hurst value (H_q) of 0.70203 as seen in Figure 1, depicting a high-level herding behavior. Subsequently, its Hurst value increased marginally to 0.71314 on ($t = 0$) i.e. event day (see Figure 2) and remained at 0.71542 on the day ($t = +1$) (see Figure 3). The overall average Hurst exponent value of the index throughout the event window being 0.71019 demonstrates that the investors in the Nifty Auto index exhibited the highest-level herding behavior during the intensified days of India-China geopolitical tensions.

S. No. 2 of Table 5 provides the Hurst exponent (H_q) results of the Nifty Energy index. Figure 4
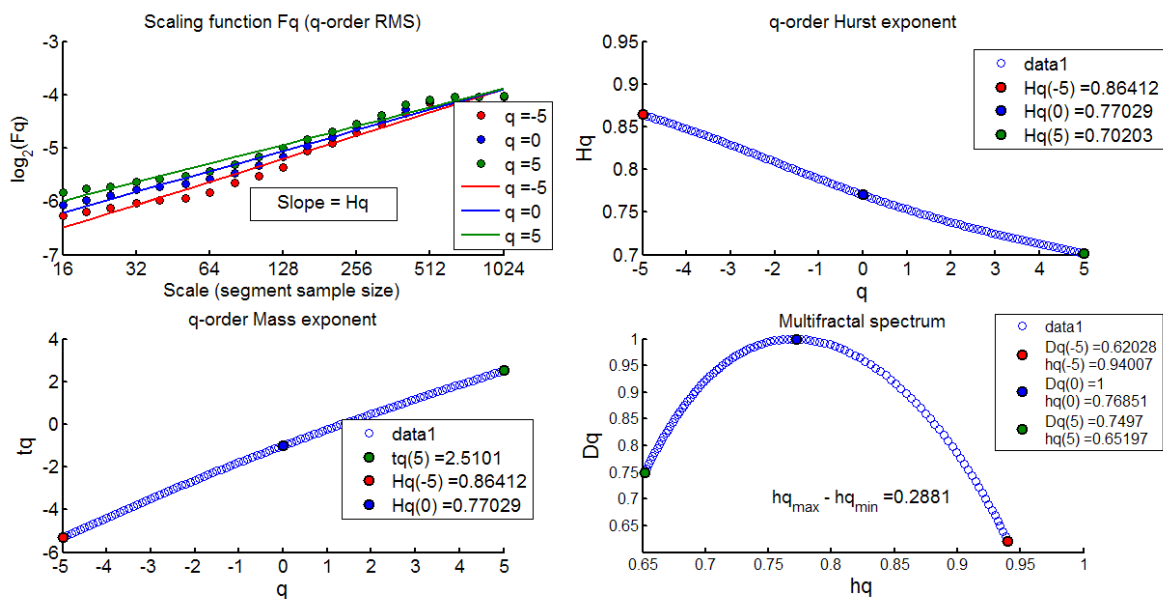
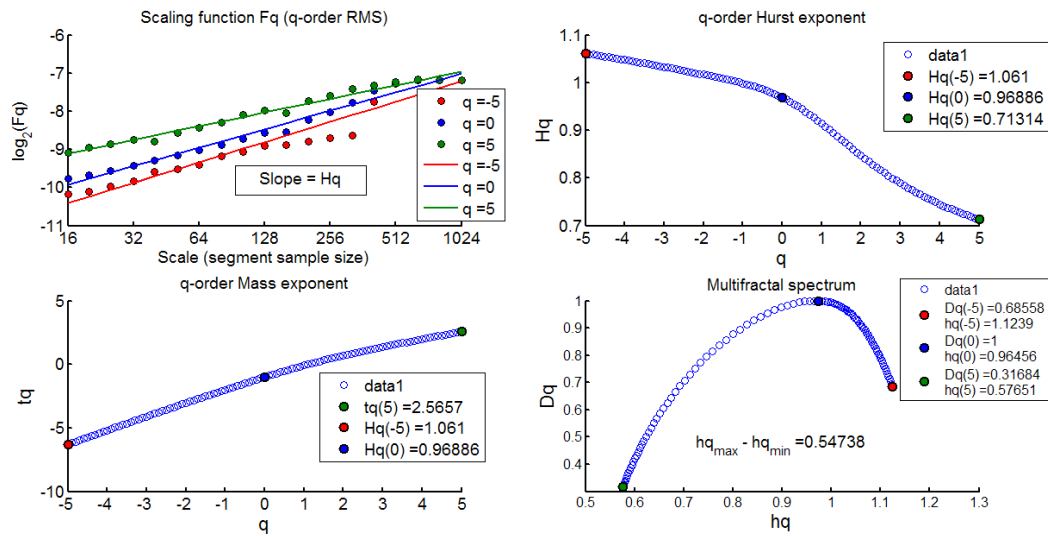**Figure 1.** The $H_q(5)$ of Nifty Auto index on June 15, 2020, i.e., ($t = -1$)

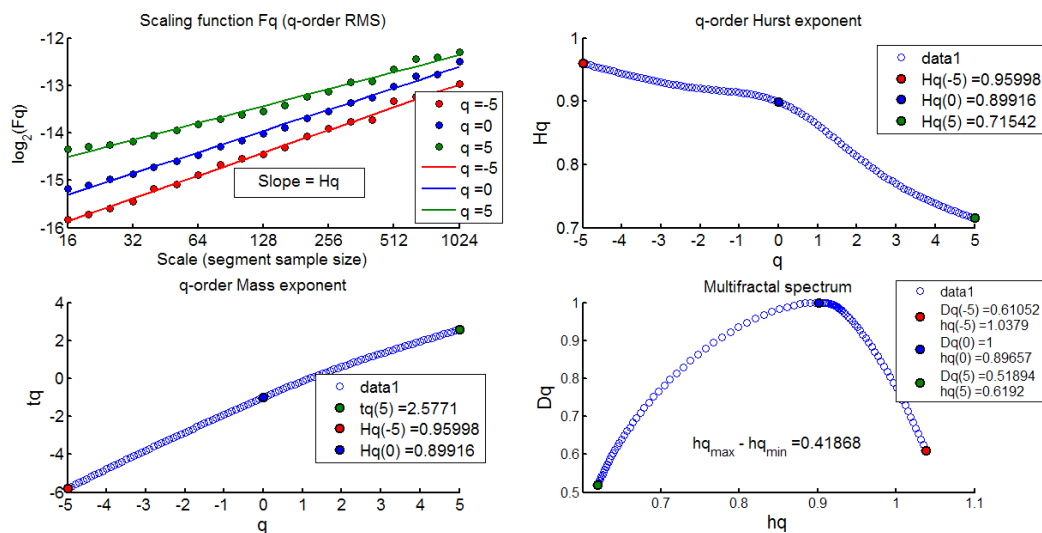**Figure 2.** The $H_q(5)$ of Nifty Auto index on June 16, 2020, i.e., ($t = 0$)

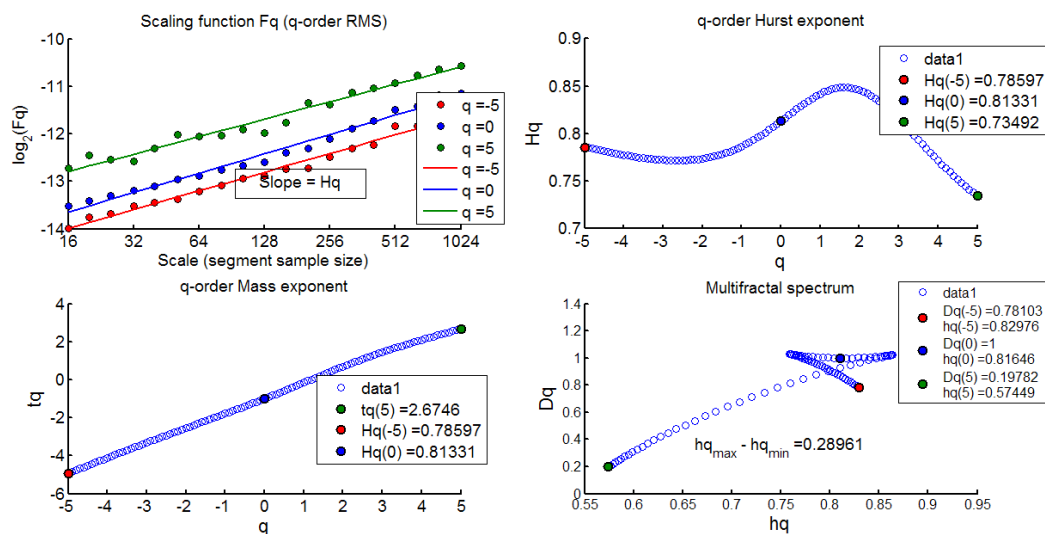**Figure 3.** The $H_q(5)$ of Nifty Auto index on June 17, 2020, i.e., ($t = +1$)

Figure 4. The $H_q(5)$ of Nifty Energy index on June 15, 2020, i.e., ($t = -1$)
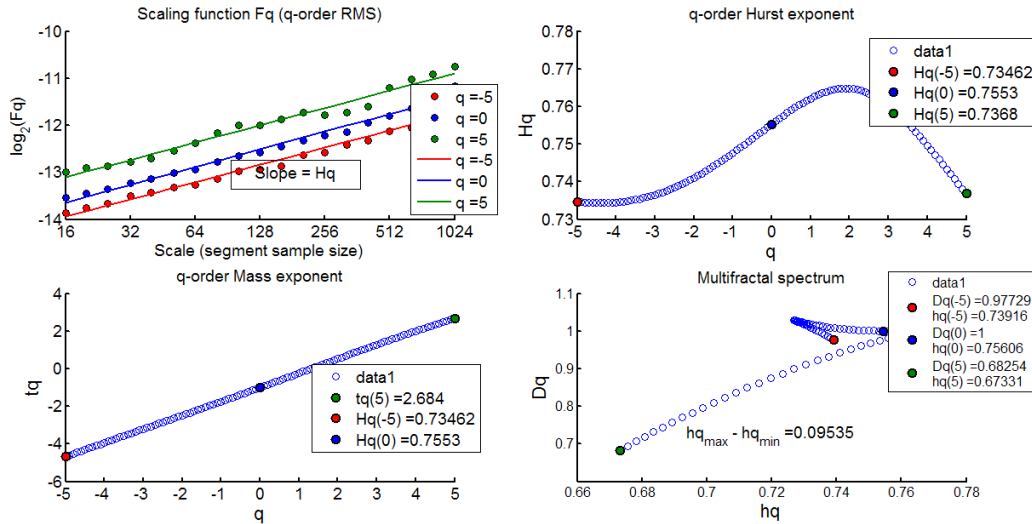
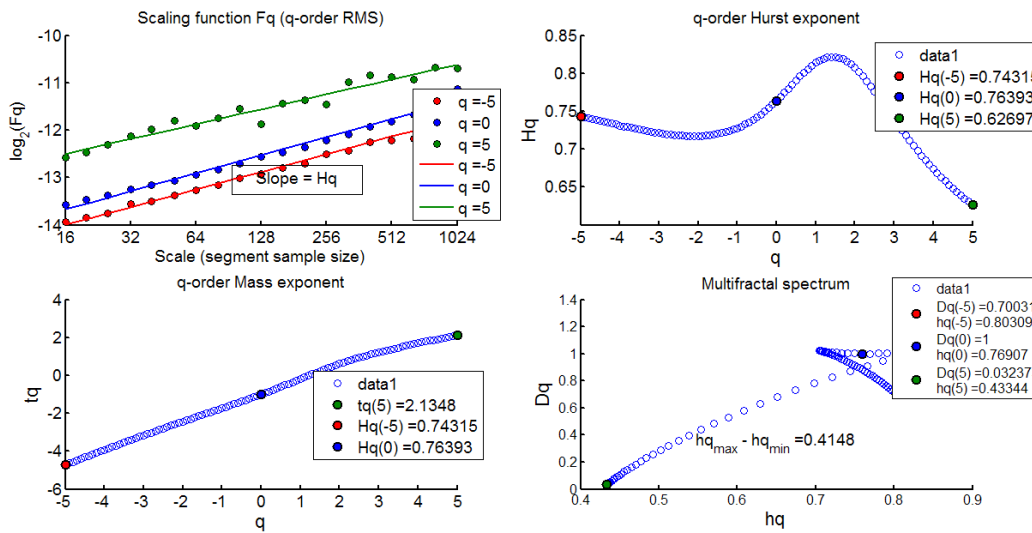**Figure 5.** The $H_q(5)$ of Nifty Energy index on June 16, 2020, i.e., ($t = 0$)

Figure 6. The $H_q(5)$ of Nifty Energy index on June 17, 2020, i.e., ($t = +1$)
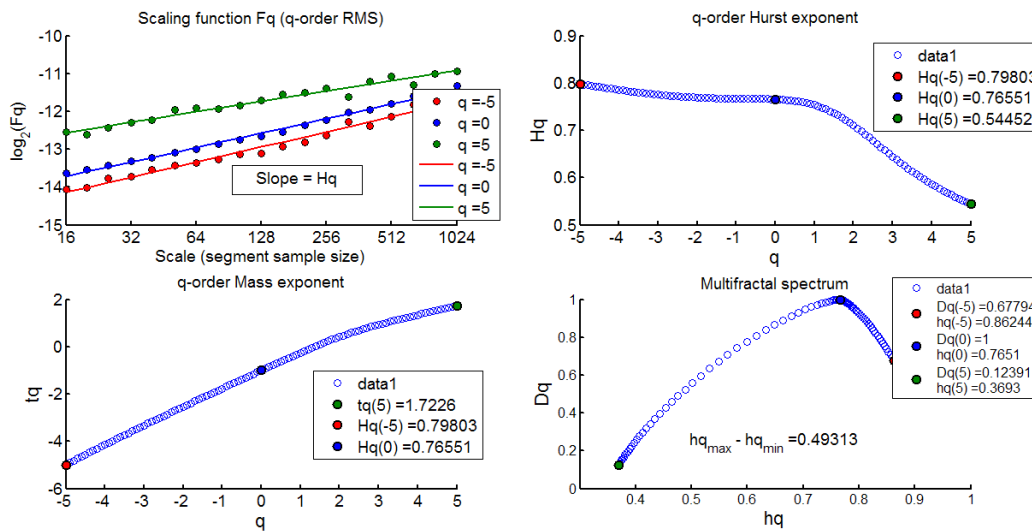

Figure 7. The $H_q(5)$ of Nifty Pharma index on June 15, 2020, i.e., ($t = -1$)
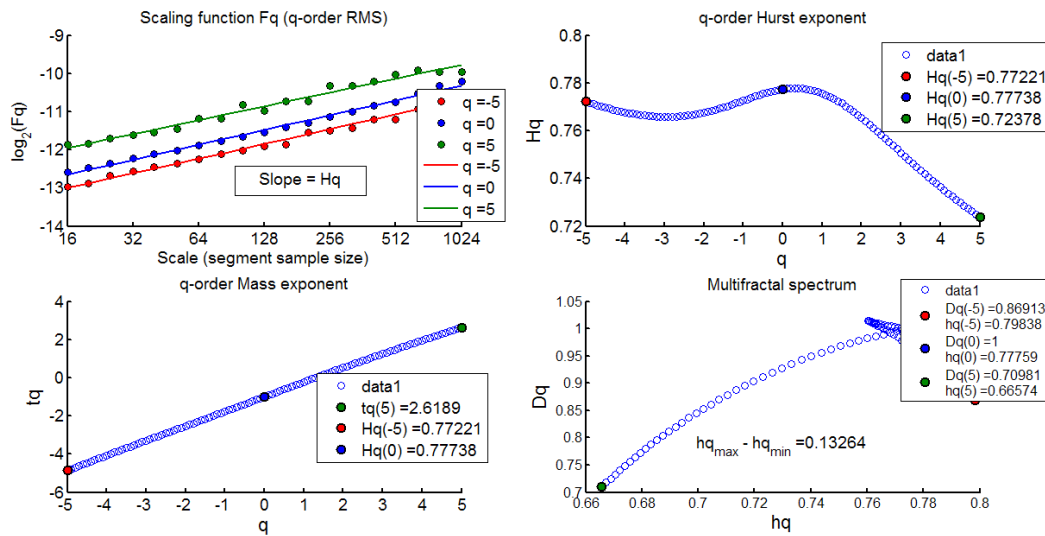
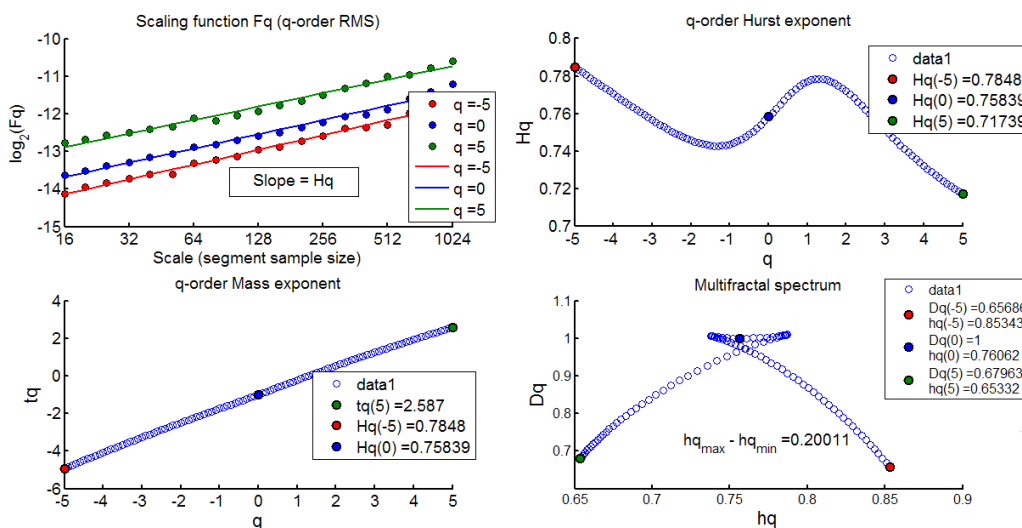**Figure 8.** The $H_q(5)$ of Nifty Pharma index on June 16, 2020, i.e., ($t = 0$)

Figure 9. The $H_q(5)$ of Nifty Pharma index on June 17, 2020, i.e., ($t = +1$)

illustrates the 5th order Hurst value of the index, i.e., 0.73492 depicting a higher trace of herding behavior on day ($t = -1$). The Hurst value of the index remained at 0.73680 even on the event day ($t = 0$) as seen in Figure 5, denoting the profound presence of higher-level herding behavior. Gradually, the level of herding in this index reduced to its mildest form with a Hurst exponent of 0.62697 on the subsequent day of the event, i.e., ($t = +1$) as shown in Figure 6. The average Hurst exponent of 0.69956 (close to 0.70) in the intensified geopolitical event window for this index indicates high-level herding behavior.

S. No. 3 of Table 5 exhibits the herding behavior results of the Nifty Pharma index. Figure 7 displays that the Hurst value of 0.54452 in the index indicated only mild herding bias on day ($t = -1$). Further, as seen in Figure 8 and Figure 9, the Hurst values of the index rapidly jumped to 0.72378 on the event day ($t = 0$) and 0.71739 on ($t = +1$), respectively. This shows that the herding level of the index significantly increased from the mild level to the higher level herding behavior. The overall average Hurst exponent value of the index throughout the intensified event window being 0.66189 demonstrates that the investors in the Nifty Pharma index exhibited only high-level herding in the event period.

4. DISCUSSION

The results of the MFDFA analysis for the Nifty sectoral indices in the intensified geopolitical event window obtained from the empirical investigation are analyzed.

The rationale of the herding presence in the Nifty Auto sector index is that the Indian automobile sector is a major industry that is substantially dependent on Chinese supplies. About 24% of the specific auto components that feed the Indian vehicle manufacturing industry are imported from China. In addition, China holds a significant share of 24% in auto tires and tubes imports (Mudgill, 2020). The Nifty Auto index represents stocks of the companies that are directly into the manufacturing of automobiles, including two, three, and four wheelers. In addition, it also includes stocks of auto ancillaries and tires, etc. The disturbances regarding supply chain factors and instabilities in the sectors' trade policies with china due to this extreme geopolitical event severely impacted the performance of this index and the investment behavior of the market participants. Therefore, the massive traces of herding activity with the Hurst values of 0.71314 on the event day, i.e., ($t = 0$) in a profound manner was traced out in this index during the intensified geopolitical event period.

In the case of the Nifty Energy index, the index consists of the stocks of those companies predominantly engaged in power generation and production of petroleum and gas, etc. However, the power generation companies, including Power Grid India Ltd., NTPC Ltd., Adani Green Energy Ltd., and Tata Power, constitute a significant weightage in the index. The Indian power generation sector is considerably dependent on Chinese imports for its power plant inputs and equipment supplies. Chinese equipment was used in the last ten years to construct 12,540 MW out of 22,420 MW supercritical power plants in India (Samsani, 2021). In addition, the power sector is also significantly reliant on China for the equipment used in the construction of solar and thermal plants. India sources around 80% of its solar module necessities from China (Motilal Oswal, 2020). The trading pattern of the Nifty Energy index was impacted significantly when the Ministry of Power canceled deals and supplies from Chinese firms. Therefore, the

highest level of herding behavior with the Hurst values of 0.73492 and 0.73680 was traced in the Nifty Energy index on the ($Day = -1$) and ($Day = 0$), respectively. This is again due to the impact of the intensified geopolitical violent clashes between India and China.

Moving on to the case of Nifty pharmaceutical index, the Indian Pharma sector is largely dependent on Chinese supplies for most of its key ingredients used in drug making. Some of the largest Indian drug makers, including Sun pharmaceuticals and Lupin limited that form part of the Nifty Pharma index are incredibly dependent on Chinese exports for Active Pharmaceutical Ingredients (APIs). China holds a non-negligible share of 70% in API imports (Hindustan Times, 2020). In addition, more than 90% of the products like antibiotics and penicillin in Indian pharmaceutical industries are highly dependent on imports from China.

Further, some stringent trade regulations and prohibition of Chinese imports in the pharmaceutical sector due to the geopolitical tensions resulted in a hike in raw material costs for domestic drug makers. Thus, impacting the standard behavior of the Nifty Pharma's index. Therefore, the index exhibited its highest level of herding behavior on the event day ($t = 0$), and also the same remained on its subsequent day ($t = +1$).

In response to China's aggressive behavior with the Indian forces at the Galwan valley, the government of India reviewed trade policies and imposed stringent checks on Chinese trade, commerce, and imports. Several ministries, including the Ministry of Railways and Power, canceled deals and supplies from Chinese firms. In addition, the Indian government launched several strategic measures to cut down the dependency level on Chinese supplies and drive self-dependence in various aspects, including economy, technological sovereignty, and security (Chandrasekhar, 2020). India also banned essential imports from China for several sectors and imposed duties on the same, citing the availability of technology and infrastructure to manufacture domestically. This eventually caused panic and astonished the investors of the Nifty sectoral indices. Under such heightened levels of geopolitical uncertainties, it becomes highly challenging for the inves-

tors to exhibit their rational investment behavior. Therefore, eventually instigating them to follow the panic-stricken herding behavior to safeguard their financial investments from probable uncertainties aroused due to the intensified geopolitical tensions. Moreover, the market analysts and experts suggest that diplomatic talks between the two nations and the potential de-escalation process in the disputed Line of Actual control (LAC) could resolve the tensions. Thereby, it can reduce the level of panic and uncertainty among the market participants and help the markets come back to normality. Besides, diplomatic talks could also emerge as a solution to decrease the operational and supply-chain risks in the sectors which are highly exposed to Chinese imports.

CONCLUSION

The impulsive flare-up of geopolitical clashes between India and China has triggered unprecedented volatility and suppressed the rational investment behavior of the investors in key sectoral indices of the Indian stock markets. In this setting, this study investigated the traces of herding behavior in the Nifty sectoral indices of Auto, Energy, and Pharma during the intensified days of India-China geopolitical conflicts of 2020. It employed the Hurst exponent scale to examine the herding behavior level in sectoral indices under an intensified geopolitical event window. The results exhibited evidence of high-level herding behavior in the Nifty sectoral indices probed during the intensified geopolitical conflict period. In addition, the Hurst values in the Nifty sectoral indices examined, inched close to 0.72, indicating the highest form of the herding behavior on the event day, i.e., ($t = 0$). The study concludes that the presence of the panic-stricken herding behavior in the sectoral indices is due to the intense dependency of these sectors on the Chinese imports for its supply chain and raw materials.

Further, this study provides significant implications for investors in the market and foreign trade policymakers during extreme events like geopolitical tensions. Understanding of herd behavior at the sectoral level assists the investors in making rational, realistic, and sound financial decisions in times of geopolitical uncertainty. In addition, the awareness about the presence of herding levels will help them make informed investment decisions, particularly during such extreme events. Besides, the study suggests that the investors with a low-risk appetite stay away from investing rather than senselessly following the crowd behavior during the increased geopolitical uncertainties. It also recommends short-term market participants quit their stock holding positions to prevent losses due to the heightened levels of geopolitical severity. The unanticipated intensity of India-China geopolitical clashes and consequent containment measures of Chinese imports increased the herding levels in affected sectoral indices. Therefore, the policymakers of foreign trade should strengthen the reforms to de-risk the supply chain from Chinese firms so that the markets regain normalcy. It currently appears that the trade scenario between India and China is still blooming even after close to 1.5 years of deadly clash at the Galwan valley. Furthermore, market experts and analysts suggest that India will still continue to witness a substantial dependence on China for its supplies even in the foreseeable future.

AUTHOR CONTRIBUTIONS

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