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Analyzing volatility across 13 Nifty Thematic indices: A Shannon Entropy Approach

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ABSTRACT

This research investigates the behavior of the Indian stock market over the past decade (January 1, 2014, to April 5, 2024), with a specific focus on the disruptive impact of the Covid-19 pandemic(January 30, 2020, to May 10, 2023). Through a comprehensive analysis of Nifty thematic indices, utilizing Shannon entropy(SE) the study delves into volatility of the indices. The research highlights significant disruptions in market dynamics during the Covid-19 phase, with increased volatility and unpredictability. Use of Symbolic Time Series Analysis (STSA), for calculation of Shannon Entropy , reduces the disturbances in the time series greatly to capture the true nature of time series . It highlights the varying degrees of uncertainty and predictability across different sectors. Sectors like Nifty Energy and Nifty50 Shariah demonstrate high entropy values, signaling greater unpredictability, while others exhibit more stable dynamics. Overall, this study underscores the importance of understanding market dynamics, particularly during crises, and offers insights to aid investors and policymakers in making informed decisions.

KEY WORDS : Volatility , Shannon Entropy , COVID 19 , NIFTY Thematic Indices

1.0 INTRODUCTION

Stock markets never stand still. They churn with volatility that can make or break fortunes, especially in specialized corners like thematic indices. India's Nifty Thematic indices on the National Stock Exchange (NSE)—13 of them, tracking sectors from banking to IT—draw keen investor interest. Yet decoding their ups and downs calls for sharper tools. Traditional measures like standard deviation fall short; they assume neat probability distributions that real markets rarely obey. Shannon entropy, drawn from econophysics, steps in here. This approach captures the raw uncertainty in price swings without those rigid assumptions, uncovering patterns that might otherwise stay hidden.

The analysis draws on a decade of data, from 2014 to 2024. Daily returns from those 13 indices paint the full picture—booms, busts, and everything between. The COVID-19 era warranted its own scrutiny, too. Lockdowns hammered global markets; researchers sliced out that stretch for separate examination, revealing how entropy illuminated the chaos. Why entropy? Prior studies laid the groundwork. Bentes and Menezes (2012) demonstrated its edge over standard metrics on indices like CAC 40 and NIKKEI 225. Karamchandani et al. (2014) tested it on BRIC markets, highlighting India's Sensex as steady amid the noise.

This research builds on that foundation, targeting Nifty Thematic indices. Shannon entropy enables fresh volatility rankings—from least shaky to most turbulent—across the long term and the pandemic surge. The result? Clearer signals for traders navigating these niche markets.

The Indian stock market has experienced substantial expansion over the past two decades, marked by increased turnover rate, market capitalization, and the proliferation of listed companies. However, it's imperative to acknowledge the inherent volatility and risks associated with stock markets. Factors such as asset bubbles, macroeconomic imbalances, externalities, information disruptions, and contagions can profoundly impact financial and economic markets.

Understanding how the stock market behaves during a crisis is important because the world's economies are all connected through globalization. The Efficient Market Hypothesis (EMH) helps us understand how well the market works. It says that stock prices already include all the available information. EMH was introduced by Eugene Fama in 1970. It suggests that stock prices are always fair in the market. EMH tells us that trying to predict future prices using trends doesn't work well and that stock prices tend to move randomly. Understanding how the stock market behaves, especially in times of crisis, is important for investors and policymakers. Ideas like EMH give us useful insights into how the market works efficiently.

Shannon entropy, (denoted by SE) is used to assess the level of unpredictability or randomness in price movements. It was developed by Claude Shannon in information theory and has become increasingly important in the world of finance, particularly when analyzing market efficiency and stock market behavior. A highly efficient market would typically exhibit lower entropy, indicating that prices are more predictable and reflect all available information accurately. Conversely, a less efficient market may have higher entropy, suggesting greater unpredictability and potential profit opportunities. It helps to measure the level of uncertainty or unpredictability within a system, giving us a way to understand how much information is contained in a dataset. In the context of the stock market, it is applied to assess the efficiency of market information dissemination and the degree of randomness in price movements. By analyzing market data entropy, market participants can uncover trends, patterns, and anomalies that might affect investment decisions. Overall, Shannon entropy offers valuable insights into market efficiency and the dynamics of stock price movements. It helps investors make more informed and profitable choices in the constantly changing finance landscape.

2.0 LITERATURE REVIEW

Researchers have increasingly turned to entropy measures, particularly Shannon entropy, as powerful tools from Econophysics to analyze stock market volatility and efficiency, offering advantages over traditional metrics like standard deviation by capturing uncertainty without assuming specific probability distributions (Bentes & Menezes, 2012). Early work on major indices such as CAC 40, NIKKEI 225, and others showed that Shannon entropy highlights varying volatility levels, with CAC 40 and NIKKEI 225 displaying the highest, paving the way for broader applications in diverse markets (Bentes & Menezes, 2012). Building on this, studies of BRIC economies revealed predictability in Russian, Indian, and Chinese markets through Hurst exponent and Shannon entropy, noting India's Sensex as the least volatile yet efficient with strong returns and low risk, which aids investors in spotting trends and entry points (Karamchandani et al., 2014).

This entropy-based approach expanded to compare multiple indices like CAC 40, Hang-Seng, and FTSE.MI, where Shannon, Tsallis, Rényi, and approximate entropies confirmed Paris Index's elevated volatility, reinforcing entropy's role in revealing market differences over weekly and monthly data from 2000 to 2012 (Sheraz et al., 2015). Further refinements applied Shannon entropy to price and volatility time series across six financial markets, finding price entropy stable but volatility entropy market-specific, leading to a Heterogeneity Index that outperforms Sharpe ratio for smoother portfolio assessments (Ponta & Carbone, 2018). These insights into time-varying patterns extended to efficiency dynamics, as seen in regional stock markets from 1994 to 2017, where Shannon entropy tracked improvements from reforms and infrastructure but also drops during crises, urging adaptive strategies amid global shocks (Patra & Hiremath, 2022).

Applications beyond equities, such as crude oil markets, used modified Shannon entropy to detect evolving weak-form efficiency, with Brent outperforming WTI and revealing predictable returns via non-normal distributions (Mensi et al., 2012). In crisis detection, Shannon entropy signaled events in the Dow Jones Industrial Average, while Tsallis and permutation entropies acted as early warnings of complexity shifts, enabling proactive monitoring without complex predictions (Soloviev et al., 2019). Together, these studies demonstrate entropy's versatility in linking volatility, efficiency, and crises across assets, enhancing forecasting and policy for dynamic markets.

3.0 OBJECTIVES

This study examines volatility patterns across 13 Nifty Thematic indices on the NSE, covering 2014 to 2024, with a special focus on the COVID-19 period, by applying Shannon entropy—a fresh tool from econophysics.The 13 NIFTY Thematic indices studied are listed below .

Thematic Indices listed on NSE		
NIFTY COMMODITIES	NIFTY MIDCAP LIQUID 15	NIFTY SHARIAH 25
NIFTY CPSE	NIFTY MNC	NIFTY100 LIQUID 15
NIFTY ENERGY	NIFTY PSE	NIFTY50 SHARIAH

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NIFTY INDIA CONSUMPTION	NIFTY SERVICES SECTOR	NIFTY500 SHARIAH
NIFTY INFRASTRUCTURE		

4.0 RESEARCH METHODOLOGY

The study delves into the analysis of the Indian stock market through the lens of Nifty Thematic Indices. Nifty thematic indices are specialized indices created by the National Stock Exchange (NSE) of India that track the performance of specific sectors or themes within the Indian stock market. These indices focus on particular industries, sectors, or investment themes. For this research, 13 Nifty Thematic Indices introduced before 2014 were selected to ensure a robust dataset for a decade-long analysis. Data on the closing prices of these indices were sourced from the official website of NSE India, spanning from January 1, 2014, to April 5, 2024, resulting in 2539 observations for each index and a total of 33,007 observations for the entire analysis. During this period, the Covid-19 phase extended from January 30, 2020, to May 10, 2023.

The use of raw daily price data in the stock market can be unreliable due to non-stationary movements of the stock market. To overcome this, market indices are often transformed into rates of return by calculating the natural logarithm. This method helps standardize the data and provides a clearer view of market fluctuations and volatility, facilitating a more accurate analysis of market behavior over time.

Formula: Return = Ln{ Y_{t-1}/Y_t} *100

Where: Ln = Natural Logarithm.

Y_{t-1} = current day's closing price

Y_t = previous day's closing price.

Shannon entropy is a measure of uncertainty or randomness in a given set of data or information. It is applied to assess the efficiency of market information dissemination and the degree of randomness in price movements.

To compute Shannon Entropy (SE) for symbolic time series analysis (STSA) of financial return series, the first step involves symbolizing the returns to mitigate data noise. This process entails a binary transformation where return values are represented as either 1 or 0 based on a predetermined threshold. The threshold is typically set as the average return of the return time series under examination. Returns above the threshold are assigned the symbol 1, while those below it are assigned the symbol 0.

Shannon Entropy is then calculated by :

$$SE = - [p \log_2 p + (1- p) \log_2 (1 - p)]$$

Where: p = probability of returns above the threshold value

(1 – p) = probability of returns below the threshold value

log2 = Logarithm to the base of 2.

The value of entropy lies between 0 and 1.

Close to 0: If Shannon entropy is close to 0, it suggests that the data or information is very predictable and less volatile. In other words, there's little uncertainty in predicting the next value.

Close to 1: On the other hand, if Shannon entropy is close to 1, it indicates high unpredictability and volatility. This means that there's a lot of uncertainty in predicting the next value.

5.0 FINDINGS AND DISCUSSIONS

The logarithmic returns of 13 Nifty Thematic Indices were computed based on closing values spanning from January 1, 2014, to April 5, 2024. and comprises 2539 observations. Additionally, the analysis includes the Covid-19 phase, which extends from January 30, 2020, to May 10, 2023. including 812 observations. The returns of these indices change a lot over time. In the year 2020, there was a sudden drop in the returns of every index. This dip in the indices values occurred due to the Covid-19 pandemic, leading to significant uncertainty and disruption in the stock market.

5.1 Descriptive Statistics

In this study, descriptive statistics methodology, comprising Table 1, was applied to analyze 13 Nifty Thematic Indices. A dataset containing 2539 observations, spanning from January 1, 2014, to April 5, 2024, was utilized for the analysis.

As is visible from Table 1 the mean values range from -0.046 to 0.068. while the standard deviation ranges from 0.933 to 1.471. As the standard deviation has larger values than the mean this suggests that the data points are spread out over a larger range relative to the mean. The Skewness ranges from -1.409 to 0.578 showing that observations exhibit a range of asymmetry in their distributions. The range includes all negative skewness values and only 1 is positive, indicating that out of 13, 12 datasets are left-skewed while 1 is right-skewed. The Nifty Services sector is highly negatively skewed while Nifty50 Shariah is highly positively skewed.

The kurtosis values range from 5.438 to 18.378. This indicates varying degrees of peakedness and flatness in the distributions of the data.

Indices	Mean	Standard Deviation	Skewness	Kurtosis	Median
NIFTY COMMODITIES	0.052	1.275	-0.924	8.677	0.113
NIFTY CPSE	0.048	1.403	-0.489	5.423	0.090
NIFTY ENERGY	0.063	1.309	-0.656	6.511	0.106
NIFTY INDIA CONSUMPTION	0.054	0.967	-0.875	15.901	0.081
NIFTY INFRASTRUCTURE	0.048	1.212	-0.720	9.314	0.106
NIFTY MIDCAP LIQUID 15	0.068	1.471	-1.172	9.516	0.187
NIFTY MNC	0.057	0.987	-1.087	16.963	0.097
NIFTY PSE	0.050	1.318	-0.654	5.907	0.108
NIFTY SERVICES SECTOR	0.051	1.129	-1.409	18.376	0.080
NIFTY SHARIAH 25	0.049	0.953	-0.825	15.732	0.089
NIFTY100 LIQUID 15	0.035	1.396	-1.329	16.380	0.091
NIFTY50 SHARIAH	-0.046	1.006	0.576	13.142	-0.078
NIFTY500 SHARIAH	0.058	0.933	-1.214	14.966	0.127

Table 1: Descriptive statistics on returns of indices during 2014-2024

The Table 2 presents the results of a descriptive statistics analysis applied to the returns of indices during Covid phase in India, covering the period from January 30, 2020, to May 10, 2023. The analysis utilized the closing values of 812 observations.

The mean values range from -0.048 to 0.073 indicating that, on average, the data tends to center around these values. The standard deviation ranges from 1.160 to 1.674. indicates that there is a considerable dispersion or spread within the datasets. Compared to the past 10 years results show a higher level of risk. The Skewness ranges from -2.210 to 0.546 suggesting

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that the distributions of the data vary significantly in terms of their asymmetry. The negative skewness value, (like -2.210 for Nifty100 Liquid15 index) indicates a pronounced left skew, meaning the distribution has a longer tail on the left side. Conversely, a positive skewness value, (like 0.546 for Nifty 50 Shariah) implies a right skew, with a longer tail on the right side of the distribution.

The kurtosis values ranges from 4.795 to 23.924. A kurtosis value above 3 suggests a distribution with heavier tails and a sharper peak compared to a normal distribution. So, values closer to 23.924 indicate distributions with exceptionally sharp peaks and heavier tails, while values closer to 4.795 suggest distributions that are still more peaked and have heavier tails compared to a normal distribution, but to a lesser extent.

Indices	**Mean**	**Standard Deviation**	**Skewness**	**Kurtosis**	**Median**
NIFTY COMMODITIES	0.069	1.547	-1.308	10.403	0.185
NIFTY CPSE	0.071	1.607	-0.575	4.795	0.135
NIFTY ENERGY	0.057	1.552	-0.705	6.868	0.090
NIFTY INDIA CONSUMPTION	0.051	1.202	-1.310	18.095	0.107
NIFTY INFRASTRUCTURE	0.063	1.393	-1.399	13.667	0.150
NIFTY MIDCAP LIQUID 15	0.073	1.672	-1.886	13.433	0.247
NIFTY MNC	0.047	1.160	-1.958	23.924	0.142
NIFTY PSE	0.054	1.549	-0.839	5.721	0.148
NIFTY SERVICES SECTOR	0.040	1.545	-1.632	14.892	0.074
NIFTY SHARIAH 25	0.042	1.196	-1.098	17.164	0.128
NIFTY100 LIQUID 15	0.030	1.674	-2.210	23.014	0.145
NIFTY50 SHARIAH	-0.048	1.298	0.546	13.051	-0.107
NIFTY500 SHARIAH	0.061	1.179	-1.426	15.922	0.157

Table 2: Descriptive statistics on returns of indices during the Covid Phase

5.2 Shannon Entropy

The Shannon entropy results displayed in Table 5 reveal distinct trends across various sectors of the Indian stock market. These SE values were computed using the returns of closing prices from 13 Nifty thematic indices spanning from January 1, 2014, to April 5, 2024. Additionally, the analysis includes the Covid-19 phase, which extends from January 30, 2020, to May 10, 2023. Symbolic Time Series Analysis (STSA) was used to aid in calculation of Shannon Entropy.

The Shannon entropy (SE) values for all indices are predominantly close to 1, except for the Nifty Midcap Liquid 15, indicating high unpredictability and volatility across different sectors. When ranked based on volatility, the Nifty Energy index emerges as the most volatile, while the Nifty Midcap Liquid 15 is identified as the least volatile index from 2014 to 2024. Sectors such as Nifty Energy, Nifty50 Shariah, and Nifty Services Sector exhibit high entropy values, indicating heightened uncertainty and complexity in their market behavior. This implies that trends within these sectors may be more unpredictable over time. Conversely, sectors like Nifty Commodities, Nifty500 Shariah, and Nifty Midcap Liquid 15 display lower SE values compared to other indices, suggesting relatively lower uncertainty and volatility within their respective markets.

INDICES	**2014-2024**	**Rank**	**Covid Phase**	**Rank**
NIFTY COMMODITIES	0.992767	12	0.985345	12

NIFTY CPSE	0.995491	5	0.997235	1
NIFTY ENERGY	0.997818	1	0.997057	2
NIFTY INDIA CONSUMPTION	0.995671	4	0.992602	4
NIFTY INFRASTRUCTURE	0.994260	8	0.991181	7
NIFTY MIDCAP LIQUID 15	0.658176	13	0.661242	13
NIFTY MNC	0.993804	10	0.988952	9
NIFTY PSE	0.994283	7	0.994409	3
NIFTY SERVICES SECTOR	0.996504	3	0.992517	5
NIFTY SHARIAH 25	0.995481	6	0.990628	8
NIFTY100 LIQUID 15	0.993824	9	0.987203	11
NIFTY50 SHARIAH	0.996530	2	0.992124	6
NIFTY500 SHARIAH	0.993313	11	0.987874	10

Table 4: SE values of indices from 2014-2014 and during the Covid phase

As is visible from Table 4 ,during the Covid-19 phase, changes in SE values reveal varying levels of volatility across different indices. The Nifty CPSE index emerges as the most volatile, while the Nifty Midcap Liquid 15 appears relatively stable. Despite minor fluctuations in SE values, significant shifts in index ranks are evident during this period. Only the Nifty Midcap Liquid 15 maintains its rank, suggesting that each index responds uniquely to the pandemic, resulting in divergent levels of volatility. However, certain sectors like Nifty Energy and Nifty PSE have demonstrated consistent SE values over the past decade and the Covid phase, indicating stable and predictable market dynamics amidst external disruptions. Sectors such as Nifty CPSE and Nifty Midcap Liquid 15 experienced an increase in entropy values, indicating increased volatility. Conversely, indices such as Nifty Commodities and Nifty100 Liquid 15 experienced decreased entropy values, suggesting a trend towards more predictable market behaviors amidst heightened volatility. These observations underscore the distinct patterns in SE values across thematic indices, reflecting the unique characteristics and challenges within different sectors of the Indian stock market.

6.0 Conclusion and limitations

In this study, we delved into the intricacies of the Indian stock market, with a particular focus on its behavior over the past decade, including the challenging period of the Covid-19 pandemic. Through a comprehensive examination of various indices and the application of advanced analytical tools the Shannon entropy we gained valuable insights into volatility.

Our descriptive statistics analysis of the Nifty thematic indices spanning the past ten years (2014-2024) and the Covid-19 phase revealed significant trends in mean values, standard deviations, skewness, and kurtosis. These findings highlighted shifts in market dynamics and risk levels, underscoring the importance of understanding market behavior, particularly during times of crisis.

Furthermore, the computation of entropy provided deeper insights into market predictability and complexity across various sectors. We observed notable disparities in predictability and complexity among different Indices, with some, like Nifty India consumption, and Nifty MNC exhibiting heightened levels of uncertainty and volatility, while others demonstrated more stable and predictable trends, such as Nifty commodities and Nifty PSE.

During the Covid-19 phase, we witnessed significant disruptions in market dynamics, with increased volatility and unpredictability across many sectors. However, certain sectors showed resilience amidst the crisis, maintaining relatively stable trends despite the challenging economic environment.

Shannon entropy analysis highlights the varying degrees of uncertainty and predictability across different sectors. Sectors like Nifty Energy and Nifty50 Shariah demonstrate high entropy values, signaling greater unpredictability, while others exhibit more stable dynamics.

Our findings resonate with previous research, such as studies by M Karamchandani et al. (2014), which highlighted the importance of entropy-based indicators and Hurst exponent analysis in understanding market efficiency and predictability.

Overall, this research underscores the importance of understanding market dynamics, particularly during crises, and offers insights to aid investors and policymakers in making informed decisions. The findings emphasize the need for a nuanced approach to navigating the Indian stock market, considering the diverse and ever-evolving nature of its sectors and themes. Despite the challenges posed by external factors like the Covid-19 pandemic, the study highlights opportunities for identifying trends, managing risks, and capitalizing on potential market efficiencies within specific sectors.

The study's scope is confined to Nifty thematic indices, leaving out other Nifty indices such as sectorial indices and Nifty fixed income indices, which could provide broader insights. It is limited to the Indian stock market, the study could broaden its perspective by comparing the Indian market with other emerging or developed markets, facilitating comparative analysis of efficiency and volatility.

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