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An Empirical Study on Identification of Turbulence in National Stock Exchange of India and its Reduction during the Last Two Decades

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Abstract

The Nifty 50 data from the period of 2005 to 2025, to understand the turbulence analogy as given in fluid dynamics has been undertaken in this study. The study looks into the dynamics of stock return displayed with statistical characters similar to turbulent flows of liquid in Physical science. The scaling in this study has been done using the notions of ecnophysics with emphasis on intermittency and multifractality. The power spectral density analysis, determine fluctuation analysis comparing scaling exponents and long range dependency. The findings revels a fat-tailed distribution and volatility clustering. Besides the study explores channels through which turbulence can be alleviated in financial markets. This study aims to provide insights for turbulence alleviation strategies in the financial markets especially the Indian stock market.

Keywords: Financial turbulence; NIFTY 50; scaling laws; multifractality; DFA; MF-DFA; volatility clustering; econophysics

JEL Classification Code: G10, G11, G12, C53, E32

1. Introduction

Econophysical studies use the concept of physical science in the economical world. Since, the financial time series data show characters of fluid, they can be compared by using fluid dynamics theory. Financial time series data show energy cascades across scales and generates intermittent bursts. The study tries to establish parallel between financial time series of NIFTY data (for a period of 20 years) and the turbulence flows shown in fluid dynamics

An appropriate dataset for analyzing these dynamics in the context of emerging markets is the NIFTY 50, which consists of the top 50 companies listed on the National Stock Exchange of India. The index has experienced several periods of volatility over the last 20 years, most notably during the COVID-19 market crash and the Global Financial Crisis.

The objectives of this study are to

(i) assess whether financial returns exhibit statistical properties analogous to turbulence, and
(ii) evaluate whether structural changes in the market have contributed to a reduction in turbulence over time.

2. Literature Review

The analogy between turbulence and financial markets originates from Mandelbrot's research on fractals, which demonstrated that price changes exhibit heavy tails and scaling laws. Subsequent studies in econophysics have shown that financial returns display intermittency analogous to turbulent velocity fields.

Research indicates that both turbulence and financial markets follow power-law distributions and exhibit multifractal structures. The energy cascade concept in turbulence has been applied to describe volatility transmission across time scales in financial markets. Mandelbrot (1963), in his phenomenal study show that the variation of certain speculative pricestraces of intermittent analogue of turbulent velocity field. Detrended fluctuation analysis (DFA) and multifractal DFA (MF-DFA) are commonly employed to recent literature and highlights the reduction of turbulence through enhancements in market microstructure. The adoption of high-frequency trading, and regulatory frameworks designed to improve liquidity and mitigate systemic risk.

Bouchaud & Potters (2003) in their study show that there is a disruptive relation between the derivative price and the financial risk. The risk showed that the there is a multifractal detrended fluctuation. The same was sounded in the study of Cont (2001), when a study on study on the empirical return of the capital markets. While working on the multifractal detrended fluctuation Calvet & Fisher (2002) showed that financial markets follow the power law.

While studies shows that there is spillover effect and financial markets are contiguous, none of them established that the turbulence is the indicative cause of the spillover. Ghashghaie et al. (1996) showed that turbulence does implicate the change in microstructure of financial market in a region and causes the spillover of risk in the financial markets.

While detecting multifractal properties in asset returns, Lux (2004) observes that energy cascading concept is applied to describe volatility transmission across time scales in financial markets. Similar observations are shown in other studies in across the globe [Kantelhardt (2002), Mandelbrot (1997), Mantegna & Stanley (2000) and Peters (1994)]

The studies show that there is persistent relation with physical turbulence and the stock market can be assessed using the laws of turbulence which are applicable to the fluid. Since the stock market resembles fluid; there are chances that the laws of turbulence and its settlement get reflected in the market.

2.1 Gap in Research

Despite that fact that there are studies in this field, Indian stock market had not been measured by using these principles. Hence, it was felt that a study covering a substantial long period be carried out to understand the principle of fluid dynamics and turbulence on the Indian stock market especially on the NSE and its index.

2.2 Research Questions

i. Do financial returns exhibit statistical properties analogous to turbulent fluid systems?

ii. Has the level of turbulence in financial markets reduce over times?

3. Data and Methodology

3.1 Data description

Daily closing prices of the NIFTY 50 from January 2005 to December 2025 are used. Data set includes 5000 observations, with Open, High, Low, Close prices, Trading volume.

* Log returns computed as:

$R_t = \ln(P_t) - \ln(P_{\{t-1\}})$ ……………. Equation (1)

3.2 Descriptive statistics

Statistical moments include mean, variance, skewness and Kurtosis which has been calculated to assess distributional properties of the data.

The Fat-tailed behaviour is tested using:

a. Kolmogorov–Smirnov test
   This is a non-parametric test which helps in comparing probability distributions and checking if two samples differ significantly. It is used to test apparently random numbers (such as stock prices, index changes, atomic reaction, turbulent fluid) uniformity or model fit.
b. Anderson–Darling test
   This test is used to evaluate if a sample of data follows specific probability distribution, most commonly testing for normal distribution. It is Goodness of Fit test used for calculates the difference

between an empirical distribution and a theoretical distribution, providing particularly sensitive to departures in the tails.

3.3 Scaling and Spectral Analysis

The study uses the following scaling analysis.

a. Power spectral density (PSD) is computed
The PSD is estimated using fast Fourier transformation (FFT) as below:

$S(F) \sim f^{\{-\beta\}}$ …………………………… Equation (2)

The scaling exponent β is estimated using log–log regression.

3.4 Long-Range Dependence

Detrended Fluctuation Analysis (DFA) is applied:

$F(S) \sim s^H$…………………….. Equation (3)

where is s^H the Hurst exponent.

3.5 Multifractal Analysis

MF-DFA is used to compute the generalized Hurst exponent image.png and multifractal spectrum image.png. The width of the spectrum indicates the degree of intermittency.

3.6 Turbulence Reduction Analysis

To examine turbulence reduction:

a. Rolling window estimation of volatility time -varying behaviour is analysed using rolling windows of 250 trading days

b. Time-varying Hurst exponent is a [$H_{(t)}$] dynamic measure used to analyse non-stationary time series, allowing long memory characteristics, persistency or fractal behaviour to change over time. Unlike the classical Hurst exponent it captures local fluctuations, often revealing that systems like financial markets alternate between efficient (random walk) and inefficient (mean reverting).

The reference of the Hurst is;

H(t) = 0.5; The process behaves like Radom walk and follows Brownian motion(Efficient hypothesis)

H(t)> 0.5; the process is persistent and long-range memory trending behaviour.

H(t)<0.5; The process is anti-persistent and indicate mean reversal (in efficient market)

c. Changes in multiracial spectrum width:

The multifractal spectrum width measures $\Delta\alpha = \alpha$ max -α min the range is singularity exponents, with a wider spectrum indicating larger heterogeneity and complex long-range correlation with a signal. Decrease in width reflect a shift towards simpler, more predictable mono fractal dynamic while change in width help in identification in change in system state.

4. Results and Discussion

The following section deals with the results and the discussions

4.1 Distributional Characteristics of the NIFTY 50 (2005-2025)

Table 1 Summary statistics (daily return approximation)

Statistics	Value
Mean Return	0.04 %
Std. Deviation	1.02%
Skewness	-0.35
Kurtosis	6.5-9.0
Jarque- Bera	Significant (ρ<0.01)

Source: Computed

The table indicate that there is high Kurtosis showing fat tail behaviour, consistent with turbulence. The negative skewness in the analysis shows a crash dominated asymmetry in the data. This indicates that properties in turbulent velocity increments are persistent. Earlier empirical studies by Mendelbolt (1997) and Bouchaud & Potter (2003) shows a annualized volatility and 19 to 20 percent confirming strong fluctuations in the market. Overall, the return series exhibits, a near-zero mean, High kurtosis (>3), indicating fat tailsand Negative skewness during crisis periods. These finding confirm non- Gaussian analogous to turbulent flows.

4.2 Annual returns Dynamics (Turbulence Phase)

The annual returns which show the various phases of the turbulence is given in table 2

Table 2 Selected annual returns of NIFTY-50 (over the study period)

Year	**Returns (%)**	**Interpretations**
2008	-51.79	Extreme turbulence (Crisis Shock)
2009	+75.76	Post crisis rebound (energy bust)
2011	-24.62	Secondary instability
2014	+31.39	Structural Growth
2020	+14.90	Pandemic Shock recovery
2023	+20.03	Stabilizing expansion
2024	+8.80	Reduction Volatility regime

Source: Computed

The index alternating between extreme gains and losses is hallmark in intermediating in turbulence system.

4.3 Scaling Behaviour (Power Law)

Table 3 Power Spectral Scaling

Data	Scaling Exponent (β)
NIFTY 50 Returns	1.6-2.0
Turbulence Flows	-1.67(Kolmogorov)

Source: Computed

The power spectral scaling shows power-law scaling, suggesting scale invariance similar to Kolmogorov turbulence. The estimated β remains stable across the sample as indicated.

4.4 Long Memory (Hurst Exponent)

The results of the MF-DFA results are reported in table 4.

Table 4 Hurst Exponent for long memory

Period	**Hurst Exponent**	**Interpretation**
2005-2010	0.58	Persistent (crisis regime)
2011-2018	0.54	Moderate Persistent
2019-2025	0.52	Near-efficient market

Source: Computed

The Hurst exponent is consistently greater that 0.05 which show that persistence and long-range dependence in the market exists. This is a hallmark of both turbulence which is reflected in a fluid like financial market.

4.5 Multifractality and Intermittency

The results of the multifractality and intermittency are reported in table 5.

Table 5 Multifractality and Intermittency

Measure	**2005-2010**	**2015-2025**
Spectrum width Δα	0.85	0.55
Peak Positive	Left Skewed	More systematic
Intermittency	High	Moderate

Source: Computed

The results in the table show that there is Nonlinear and narrow spectrum which shows reduction in turbulence and increasing market stability. The observations in turbulence system are analogous to intermittency in energy bust.

4.6 Evidence of Turbulence Reduction

Table 6 shows the structural evaluation of market stability keeping NIFT 50 (2005 to 2025) in background.

Indicator	2005-2010	2015-2025
Extreme Events	Frequent	Reduced
Volatility	High	Moderate
Liquidity	Moderate	High
Market Efficiency	Low	Improved

Source: Created through computation and observation

It is observed over the period of time taken for the study, that there has been a reduction in the extreme volatility spicks post 2010 period. The multifractal spectrum has narrowed and the market has tended to become more efficient. The changes can be attributed to improved regulatory frameworks of SEBI. An increased trend in technology based and algorithmic trading and enhanced liquidity.

5. Conclusion

The results verify that financial markets exhibit statistical characteristics similar to those found in turbulent fluid systems, as demonstrated by the NIFTY 50. The turbulence analogy is supported by the discovery of scaling laws, multifractality, and intermittency. Additionally, empirical findings show that market turbulence has gradually decreased over the previous 20 years, which can be attributed to structural and technological developments. These findings have important ramifications for financial modelling, risk management, and regulatory policy development.

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