A Comparative Study of India and US Stock Indexes: Price Volatility, Movement, and Stability

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Abstract—
This study compares how the major stock indices of India (Nifty 50, BSE Sensex) and the United States (S&P 500, Dow Jones Industrial Average) behaved between 2015 and 2025, a decade marked by events such as Brexit, the COVID-19 pandemic and shifting monetary policies. The project uses daily secondary data and a quantitative approach to examine four core aspects: price volatility, co-movement, market stability and risk-adjusted performance. Volatility is measured through standard deviation, coefficient of variation and GARCH-type models, while correlation and time-varying techniques are used to understand how closely Indian and US indices move together in normal and crisis periods. Stability is assessed using skewness, kurtosis and maximum drawdown, and volatility clustering is tested through ARCH/GARCH diagnostics. Finally, Sharpe ratios are calculated to see whether the higher risk in Indian markets is matched by higher returns when compared with US markets. The findings aim to give investors, portfolio managers and policymakers a clearer, more practical view of diversification opportunities and the true risk–return trade-off between an emerging and a developed equity market in the post-pandemic era.

Keywords—Price Volatility; Price Movement Patterns; Market Stability; Co-movement; Volatility Clustering; GARCH Models; Sharpe Ratio; Maximum Drawdown

I. INTRODUCTION

A. Introduction

Stock market indices are widely recognized as barometers of economic and financial health, reflecting how investors collectively perceive growth prospects, risks and macroeconomic conditions in a country. In both academic research and professional practice, indices such as the BSE Sensex, NSE Nifty 50, S&P 500 and Dow Jones Industrial Average are used to monitor market performance, price risk and guide asset allocation decisions.

Over the past decade (2015–2025), global equity markets have experienced several major shocks and regime shifts: unconventional monetary policies, geopolitical tensions, Brexit, the COVID-19 pandemic and subsequent policy normalization have all left clear imprints on price dynamics and volatility. For emerging markets like India and developed markets like the United States, these events have shaped not only return levels but also volatility patterns, co-movement, crash behavior and risk-adjusted performance.

India's indices (Nifty 50 and Sensex) represent the growth potential and structural transformation of a large emerging economy, while the S&P 500 and Dow Jones index embody the depth, liquidity and institutional maturity of the world's most established equity market. Comparing these markets side by side over a common period provides a valuable opportunity to understand how price volatility, movement patterns, stability characteristics and risk-return trade-offs differ between an emerging and a developed market setting.

This study therefore focuses on a comparative analysis of price volatility, movement patterns and stability characteristics of India's and the United States' major stock market indices between 2015 and 2025, using a consistent quantitative framework.

B. Background of the Study

Volatility is central to investment and risk management decisions because it captures how widely and how frequently returns deviate from their average. In practice, higher volatility is associated with higher uncertainty and potentially larger losses, which directly influence portfolio construction, margin requirements and regulatory capital. A large body of evidence shows that emerging markets such as India tend to exhibit higher volatility and stronger reactions to global and domestic shocks than developed markets like the United States.

However, the drivers and manifestations of this volatility differ across markets. In India, retail investors constitute a relatively larger share of trading activity and are often more sensitive to news, sentiment and liquidity conditions, while US markets are dominated by institutional investors with more systematic trading and sophisticated risk management practices. These structural differences in investor base, market microstructure and regulatory frameworks can contribute to distinct volatility profiles and crash dynamics.

At the same time, financial globalization and capital-account liberalization have led to increasing integration between emerging and developed equity markets. Information and capital now flow quickly across borders, making co-movement, contagion and correlation dynamics important for both global and domestic investors. For India, the steady opening to foreign institutional investors since the 1990s, ongoing regulatory reforms by SEBI, tax changes such as the Goods and Services Tax (GST), demonetization, and evolving monetary policy by the Reserve Bank of India have all affected market behavior during the 2015-2025 period.

On the US side, changes in Federal Reserve policy, from gradual tightening to aggressive easing during crises, post-crisis regulations and macroeconomic developments have influenced volatility and risk premia in the S&P 500 and Dow Jones. Existing empirical studies document higher volatility and pronounced volatility clustering in emerging markets, as well as time-varying correlations between Indian and US markets. Yet most available work is based on earlier periods, uses shorter samples or focuses on limited dimensions (for example, only volatility or only integration), leaving scope for a more comprehensive and updated comparative analysis.

C. Problem Statement

Despite broad agreement that Indian equity markets are more volatile than US markets, decision-makers still lack current, empirically rigorous and multi-dimensional evidence on how these markets compare across volatility, co-movement, stability and risk-adjusted returns over a recent decade. Many studies rely on pre-2015 data, shorter time windows or heterogeneous methods, making it difficult to generalize findings to the post-pandemic, post-unconventional-policy environment.

This leads to several specific gaps. First, while it is widely stated that Indian indices are more volatile, there is limited recent work quantifying how much more volatile they are, how this gap evolves over time and how robust the findings are under alternative volatility models such as GARCH. Second, evidence on the degree and stability of co-movement between Indian and US markets is mixed; some studies indicate strong integration, while others suggest remaining diversification benefits, especially during crises.

Finally, investors and policymakers increasingly focus on risk-adjusted performance rather than raw returns. There is limited comparative evidence on whether higher returns in Indian indices adequately compensate for higher volatility relative to US indices when measured through Sharpe ratios and related metrics over 2015-2025. As a result, portfolio managers, regulators and individual investors may be making allocation and risk decisions without a clear, up-to-date empirical picture of how these markets truly compare. This study is designed to address these gaps.

D. Research Questions and Objectives

1) Research Questions

Based on the above problem statement, the study is guided by the following research questions:

RQ1: What are the volatility characteristics of the major Indian stock indices (Nifty 50, Sensex) and the major US stock indices (S&P 500, Dow Jones Industrial Average) during 2015-2025, and how do they differ?

RQ2: To what extent do Indian and US stock indices move together over time, and does the strength of this co-movement change across normal periods and crisis periods?

RQ3: How do the two markets compare in terms of stability, considering distributional properties, tail behavior and maximum drawdowns?

RQ4: Do both Indian and US indices exhibit volatility clustering, and are there meaningful differences in the duration and intensity of these clusters?

RQ5: After adjusting for risk, how do Indian and US indices compare in terms of risk-adjusted returns for investors over the study period?

2) Research Objectives

Corresponding to the research questions, the specific objectives of the study are:

RO1: To measure and compare the volatility of Nifty 50, Sensex, S&P 500 and Dow Jones using multiple approaches, including standard deviation, coefficient of variation and GARCH-type models.

RO2: To examine the co-movement between Indian and US indices using correlation and related time-varying techniques, and to explore how these relationships evolve over the sample period.

RO3: To assess and compare stability characteristics by analyzing return distributions, tail risk indicators and maximum drawdowns for each index.

RO4: To identify and quantify volatility clustering in both markets using appropriate econometric tests and models.

RO5: To evaluate and compare risk-adjusted returns, using measures such as the Sharpe ratio, in order to determine whether higher volatility in Indian markets is compensated by higher risk premia relative to US markets.

E. Significance of the Study

From an academic perspective, this study contributes to the literature on emerging versus developed equity markets by offering a recent, ten-year comparative analysis that jointly examines volatility, co-movement, stability and risk-adjusted performance using a consistent methodological framework. It also complements existing work on market integration and volatility modelling by applying advanced time-series techniques over a period that includes significant global and domestic shocks.

From a practical perspective, the findings are relevant for international and domestic portfolio managers, risk managers, regulators and policymakers. Investors can use the evidence to design more informed diversification strategies and to calibrate risk models that reflect the actual behavior of Indian and US indices during 2015-2025. Risk managers and regulators can better understand how volatility and co-movement behave under stress, which is important for stress testing and macro-prudential policy. For individual investors, the study clarifies the trade-off between higher expected returns and higher risk when allocating between Indian and US equity markets.

G. Scope of Study

The empirical scope of this research is defined along the following dimensions:

Markets and Indices: The study focuses on four major equity indices: Nifty 50 and Sensex (India), and S&P 500 and Dow Jones Industrial Average (United States).

Time Period: The sample covers daily data from January 2, 2015 to December 30, 2025, a ten-year period that includes normal conditions and multiple episodes of market stress.

Geographical Focus: The analysis is restricted to India and the United States and does not include other emerging or developed markets.

Asset Class: Only equity indices are considered; bonds, commodities, currencies and alternative assets are outside the scope of this work.

Methodological Focus: The study adopts a quantitative, secondary-data-based approach. It analyzes historical index data using statistical and econometric techniques, without employing surveys, interviews or fundamental macroeconomic modelling.

The study does not attempt to attribute volatility and co-movement to specific macroeconomic or firm-level causes; instead, it concentrates on the statistical properties of index returns and their implications for risk and diversification.

II. REVIEW OF LITERATURE

A. Introduction

The study of stock market volatility, price movement, and market stability has captured the interest of academics, practitioners, and policymakers globally. With the rise of economic globalization and integration in capital markets, understanding stock market dynamics in different economies is essential for portfolio diversification, risk management, and policy formulation. Among global exchanges, the Indian stock market represented by leading indices such as the BSE Sensex and NSE Nifty 50 and the US market, anchored by indices like the S&P 500 and Dow Jones Industrial Average, represent contrasting yet interconnected systems: one from a fast-growing emerging economy and the other as the benchmark developed market.

The present review aims to synthesize the growing body of comparative literature on Indian and US stock index volatility, movement, and resilience, providing a critical foundation for subsequent empirical inquiry. This section examines the conceptual and theoretical frameworks underlying volatility modeling, explores key comparative and empirical studies, surveys methodologies and findings within the volatility research corpus, reviews integration and spillover studies, and discusses global event responses, meta-analyses, research gaps, and emerging themes.

In line with established academic standards for MBA dissertations, this review interleaves definition, theory, and evidence, moving from high-level concepts through targeted comparative research to event-based insights. The overall literature review is positioned not as a static summary but as an evolving debate that reflects changing macro-financial environments, regulatory adaptation, and the increasing role of both quantitative modeling and global capital flows. The scope is narrowed to primary cross-country (India vs US), cross-index, and global comparative works, as these provide substantive insight into diversification and risk under modern market conditions.

B. Conceptual Foundations

1) Stock Market Volatility and Its Measurement

Volatility represents a fundamental concept in financial economics, serving simultaneously as a proxy for risk and a diagnostic measure for market efficiency. Statistically, volatility refers to the standard deviation or variance of returns around their mean, encapsulating both the magnitude and frequency of asset price fluctuations. Within the context of stock markets, volatility analysis enables researchers and investors to quantify risk, anticipate potential drawdowns, and optimize portfolio composition [18].

From a modeling perspective, academic literature has progressed from basic historical volatility (realized standard deviation of returns) to sophisticated conditional volatility frameworks such as ARCH (Autoregressive Conditional Heteroskedasticity) and GARCH (Generalized ARCH) models. These models, pioneered by Engle [8] and Bollerslev [5], are especially effective in capturing volatility clustering, the empirically documented phenomenon where periods of large changes in returns are likely to follow each other, a feature universal to global equity markets.

Archival research on international stock markets, including comparative studies between India and the US, relies heavily on these models for robust in-sample and out-of-sample volatility prediction. The reason is twofold: GARCH-type models flexibly model both levels and persistence and are sensitive to structural market shifts without imposing strict distributional assumptions. Additionally, volatility indices such as VIX for the US and India VIX provide market-implied forecasts of risk, serving as barometers for investor se

2) Index Movement and Stability: Definitions and Metrics

Market movement encompasses trends, cycles, and shocks, which together define the temporal dynamics of index values. In empirical research, movement is often dissected into trend-following (momentum), mean-reversion, and cyclical behavior, each offering strategic insight for market participants. The stability of an index, meanwhile, is evaluated through risk-adjusted return metrics, predominantly the Sharpe ratio and maximum drawdown, as well as the concept of recovery time following shocks. These measures, when benchmarked across countries and crisis periods, illuminate differences in the resilience and efficiency of market systems.

Momentum and cyclicality are particularly important for comparative studies because they relate to behavioral and structural features of markets. For example, trend persistence may be a signal of herding behavior or particular regulatory regimes, while rapid reversals may reflect liquidity constraints or policy intervention.

Key stability metrics include: (1) Sharpe Ratio, measuring excess return per unit of total risk (volatility); (2) Sortino Ratio, similar to the Sharpe ratio but focusing on downside deviation, penalizing only negative volatility; (3) Maximum Drawdown, quantifying the largest peak-to-trough decline over a period; (4) Recovery Time, measuring the duration required for an index to return to its pre-shock level after a significant decline; and (5) Calmar Ratio, the ratio of annualized return to maximum drawdown. These metrics collectively provide a comprehensive assessment of market stability and resilience, enabling meaningful cross-country and cross-period comparisons.

C. Comparative Research on India vs US Stock Markets

1) Key Historical and Structural Differences

The Indian and US stock markets differ fundamentally in their historical development, regulatory landscape, market structure, liquidity, and institutional participation. The US securities market, originating in the late 18th century and maturing after significant regulatory reforms such as the Securities Act of 1933 and the Securities Exchange Act of 1934, has evolved into a highly liquid, well-regulated environment with deep institutional and global investor presence. In contrast, India's market growth accelerated post-1991 liberalization, characterized by rapid expansion, market reforms, and the rise of electronic trading platforms.

Regulatory frameworks underscore these differences. The US boasts systemic safeguards through the Securities and Exchange Commission (SEC), established in 1934, while India's Securities and Exchange Board of India (SEBI), established in 1992, has implemented robust reforms including rolling settlement, dematerialization of securities, and circuit breakers, but still faces challenges in enforcement and transparency relative to mature markets.

Market depth in the US, manifested by large capitalization, diversified sector representation, and high turnover, is unmatched globally. Indian markets are smaller in absolute terms, exhibit higher volatility, and have a larger share of retail investors, rendering them susceptible to sentiment-driven swings.

Key structural differences include: (1) Market Capitalization, the US equity market represents approximately 40-45 per cent of global market capitalization, while India accounts for approximately 3-4 per cent; (2) Liquidity, average daily trading volumes in US markets far exceed those in India; (3) Investor Composition, US markets are dominated by institutional investors while Indian markets have a higher proportion of retail participation; (4) Regulatory Maturity, the US regulatory framework has evolved over nearly a century, whereas India's modern regulatory structure is approximately three decades old; and (5) Market Infrastructure, US exchanges benefit from advanced technology, high-frequency trading capabilities, and robust clearing and settlement systems.

Integration profiles show the US market's pivotal global role, influencing virtually every equity market: shocks in the US transmit directly and indirectly to Indian indices via foreign portfolio flows and investor sentiment. Conversely, policy cycles, currency fluctuation, and regulatory innovation in India can generate local volatility decoupled from international trends, especially in sectors shielded from global capital. This historical and structural context is foundational for interpreting the empirical findings of comparative literature.

2) Empirical Comparative Studies

Empirical comparative research leverages both qualitative historical context and quantitative modeling to explore the dynamic relationship between Indian and US stock markets. Prajapat and Patel [18] performed a foundational comparative study using five years of monthly data from the BSE Sensex and NYSE Composite. Applying GARCH models and unit root tests via EViews software, they found evidence of volatility in both indices, with Indian markets demonstrating higher persistence and serial correlation, a common feature in emerging economies. Their results further show that structural reforms and integration boost returns but do not always reduce volatility, underlining the behavioral impact of retail-driven Indian markets.

Broader comparative research highlights post-liberalization accelerations in market integration measured through cointegration and correlation metrics. These studies utilize advanced econometric tools, vector autoregression, Granger causality, to pinpoint channels of volatility transmission. Integration with global markets is found to be both market- and time-dependent, peaking during episodes such as the 2008 global financial crisis but reverting during regulatory realignments.

Recent studies expand comparative analysis to include China, Brazil, and other Asian and emerging markets. Multi-market surveys underscore that while regulatory, liquidity, and policy differences create unique volatility patterns, globalization has not eradicated local market idiosyncrasies. Practitioner-oriented reports affirm empirical findings: US markets, though susceptible to shocks, rebound more quickly and maintain lower long-term volatility. Indian markets exhibit deeper post-crisis drawdowns and recovery lags, attributable to capital flows, liquidity constraints, and regulatory adaptation.

Empirical literature also investigates multi-dimensional metrics including sectoral volatility, transaction costs, bid-ask spreads, and policy-driven events. Comparative analyses between BSE Sensex and Nifty further detail the role of index composition and sector weighting in observed differences. Interdependency studies point to cyclical alignment in response to global events but note fundamental divergence during locally driven policy shifts or periods of capital market isolation.

Key empirical findings from comparative studies: (1) Indian indices exhibit higher unconditional volatility than US indices over most sample periods; (2) volatility persistence (measured by GARCH parameters) is generally higher in Indian markets, indicating longer memory of shocks; (3) US markets demonstrate faster mean reversion and shorter recovery times following major downturns; (4) cross-market correlations have increased over time, particularly during crisis periods, reflecting growing financial integration; and (5) sector-specific analyses reveal heterogeneity, with financial and technology sectors showing stronger cross-market linkages than utilities or consumer staples.

D. Volatility, Movement, and Stability in Empirical Literature

1) Volatility Patterns: Advanced Modeling Evidence

Modern empirical literature provides a variety of analytical frameworks for measuring and interpreting stock market volatility, with GARCH and related models at the forefront for time-series data. Volatility clustering, the tendency for large changes (up or down) in asset prices to cluster together in time, has been observed across both Indian and US stock indices, particularly during periods of macroeconomic uncertainty or crisis. These clusters heighten risk for both retail and institutional investors, amplifying drawdowns or producing unexpected profit opportunities for those able to anticipate regime changes.

In comparative settings, the amplitude and persistence of volatility are typically greater in the Indian context. Studies using GARCH modeling reveal that Indian indices respond to both global and local events with sharper and more sustained volatility spikes than their US counterparts. Systematic reviews confirm that this reflects both market structure (shallower liquidity, higher retail participation) and external linkages (sensitivity to global news, cross-border capital flows). Conversely, the US market, with its deep pools of capital and institutional dominance, exhibits faster volatility mean reversion and lower peak risk during comparable shocks. Studies further highlight that both US and Indian markets show similar qualitative patterns, volatility spikes followed by declines, but the US consistently demonstrates smaller magnitudes and swifter stabilization.

Moreover, advanced modeling studies confirm the importance of asymmetric effects: the impact of bad news and negative shocks often exceeds that of favorable news, particularly in emerging markets. EGARCH (Exponential GARCH) and threshold GARCH models reveal that sharp drops in Indian market indices lead to proportionally larger risk increases than similar positive movements, a phenomenon known as the leverage effect. This asymmetry is less pronounced but still present in US markets.

Key findings from volatility modeling studies: (1) GARCH(1,1) models adequately capture volatility clustering in both markets, with high statistical significance for ARCH and GARCH parameters; (2) asymmetric models (EGARCH, GJR-GARCH) provide superior fit for emerging markets, where leverage effects are more pronounced; (3) implied volatility indices (VIX, India VIX) exhibit strong predictive power for realized volatility, especially during high-stress periods; (4) long-memory models (FIGARCH) suggest that volatility shocks in Indian markets have longer-lasting effects compared to US markets; and (5) structural break tests identify significant regime shifts coinciding with major economic or policy events in both countries.

J. Synthesis, Research Gaps, and Justification for the Study

Cumulative research across all reviewed domains reinforces some foundational principles: global integration increases the synchronization of index volatility and performance, but distinctive institutional, structural, and regulatory features maintain persistent differences between markets. The Indian market, while rapidly converging in terms of access and informational flow, still demonstrates higher volatility persistence, longer post-shock recovery, and greater susceptibility to local macro and policy shocks than its US counterpart. The US market, as benchmark, absorbs and diffuses shocks rapidly, benefiting from institutional safeguards, liquidity, and policy agility.

However, literature reviews consistently identify gaps. There is a need for more: (1) sectoral and asset-specific comparative volatility

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analysis; (2) real-time, event-centric studies with responsiveness to regulatory changes; (3) integrated behavioral finance perspectives, critically examining retail and institutional investor roles; (4) analytical focus on regulatory/policy innovation and how it translates into actual risk reduction; (5) currency-adjusted return analysis, since most comparative studies examine returns in local currency; (6) high-frequency data analysis, since intraday patterns and microstructure effects remain underexplored; and (7) application of machine learning and alternative methods such as neural networks, random forests, and sentiment analysis to volatility prediction.

By addressing these gaps, especially with robust post-crisis empirical work and a refined comparative methodology covering 2015-2025, the present study stands to make a unique contribution, advancing both theoretical and practical understanding of global stock market volatility, movement, and stability. The extended time period covering both the post-2008 recovery, the COVID-19 crisis, and the subsequent normalization provides a rich dataset for examining market behavior across multiple regimes.

Specific justification for the present study: (1) Temporal Relevance, since the 2015-2025 period captures the most recent market dynamics, including post-COVID recovery and current monetary policy cycles; (2) Comprehensive Methodology, combining descriptive statistics, advanced volatility modeling, stationarity tests, and correlation analysis; (3) Dual-Country, Dual-Index Design, including both Nifty and Sensex (India) and S&P 500 and DJIA (US); (4) Policy Relevance, since findings can inform portfolio allocation decisions, risk management practices, and regulatory policy in both countries; and (5) Methodological Rigor, through the use of established econometric techniques that ensure comparability with existing literature while providing updated evidence.

TABLE I: SUMMARY TABLE OF KEY LITERATURE

Author/Year	Country/Index	Method	Main Finding
Prajapat & Patel (2018)	India, US (BSE, NYSE)	GARCH	Stronger volatility in India; US recovers faster
Mukherjee (2015)	India, International	Cointegration	Post-liberalization co-movement
Systematic Review (2020)	Global	Meta-analysis	US rebounds faster post-shock
Semantic Scholar (2020)	US, India, China, Brazil	Multi-market	Regulatory, liquidity differences matter
Islam et al. (2014)	India (Nifty, COVID)	Event study	Crisis volatility most acute in India
Cheteni (2016)	S. Africa, China, India	GARCH	Shock transmission characteristics
Swastika (2025)	India/US Trade	Event review	News-driven volatility, longer India lag
Pandey et al.	India, US	Volatility analysis	Similar patterns, different magnitudes
Bhatia	Cross-country	Cross-time analysis	Transmission mechanisms change with intervention
Srivastava	India	GARCH, EGARCH, Granger	Global crises, local reforms affect volatility

K. Chapter Summary

This chapter provided a comprehensive review of the literature on stock market volatility, price movement, and stability, with a particular focus on comparative research between Indian and US stock markets. The review began with conceptual foundations, establishing the theoretical and methodological frameworks for volatility measurement and analysis. ARCH/GARCH models, the Efficient Market Hypothesis, and integration theory were identified as key theoretical underpinnings.

The review then examined comparative research highlighting historical, structural, and regulatory differences between Indian and US markets. Empirical studies consistently show that while both markets exhibit volatility clustering and respond to global shocks, Indian markets demonstrate higher volatility persistence, deeper drawdowns, and longer recovery times compared to US markets. Advanced modelling studies confirm asymmetric volatility effects, with negative shocks producing disproportionately larger volatility increases in emerging markets.

Market integration and spillover research reveals increasing synchronization between Indian and US markets, particularly during crisis periods, with the US market serving as a dominant source of volatility transmission. However, integration remains incomplete, with local factors continuing to play important roles.

Event studies focusing on the 2008 financial crisis, COVID-19 pandemic, and other major shocks demonstrate differential resilience, with US markets benefiting from deeper liquidity, institutional sophistication, and policy responsiveness.

The review identified several research gaps, including the need for more sectoral analyses, real-time event studies, integrated behavioural perspectives, and currency-adjusted return comparisons. The present study addresses these gaps by providing a comprehensive comparative analysis of four major indices (Nifty 50, Sensex, S&P 500, DJIA) over an extended period (2015-2025), employing rigorous econometric methods to examine volatility, correlation, stability, and risk-adjusted performance.

III. RESEARCH METHODOLOGY

A. Introduction

This chapter outlines the research methodology employed to conduct a comparative analysis of Indian and US stock market indices with respect to price volatility, price movement behaviour, and market stability. The study examines four major benchmark indices, NSE Nifty 50 and BSE Sensex (India), and S&P 500 and DJIA (United States), over the period from 2 January 2015 to 30 December 2025.

The primary objective of this chapter is to provide a comprehensive and transparent account of the research design, data sources, sampling procedures, variable definitions, and analytical techniques used in the study. This ensures that the research findings are replicable, reliable, and methodologically sound.

B. Research Design

1) Theoretical Framework

The research methodology is grounded in the theoretical and empirical literature reviewed in Chapter II, including modern portfolio theory, market efficiency, asset-pricing models and volatility modelling in financial markets. These frameworks suggest that equity returns are stochastic but exhibit systematic patterns in risk and co-movement across markets; emerging markets typically display higher volatility, stronger sensitivity to global shocks and more pronounced volatility clustering relative to developed markets; and risk-adjusted performance depends not only on raw returns but also on the level and structure of risk, including tail risk and crash behavior.

Within this context, price volatility, price movement, market stability, volatility clustering and risk-adjusted returns are treated as key observable manifestations of deeper processes such as market integration, information transmission and investor behavior.

2) Research Philosophy

The study adopts a positive research philosophy, which emphasizes objective measurement, empirical observation, and statistical analysis to test hypotheses and draw conclusions. This approach is particularly appropriate for financial market studies, where large datasets of quantitative price and return data are available and where the goal is to identify patterns, relationships, and comparative characteristics across markets.

3) Research Approach

The study employs a quantitative research approach. Quantitative methods are well-suited for analysing financial time series data and for making statistical inferences about volatility, correlation, risk-adjusted performance, and other market characteristics. The use of established econometric and statistical techniques ensures that findings are objective, replicable, and comparable with prior research.

4) Research Type

This is a descriptive and comparative study. Descriptive research aims to systematically describe the characteristics of the phenomena under study, in this case, the volatility, return distributions, and co-movement of stock indices. Comparative research involves examining similarities and differences between two or more entities, in this case, Indian and US stock market indices, to identify patterns and draw insights about their relative behaviour.

5) Time Horizon

The study uses a longitudinal time horizon, covering an 11-year period from 2 January 2015 to 30 December 2025. This extended time frame encompasses multiple market regimes, including periods of growth, the COVID-19 pandemic crisis, post-pandemic recovery, and various monetary policy cycles. The longitudinal approach allows for robust statistical analysis and reduces the influence of short-term anomalies or outliers.

C. Selection of Stock Market Indices

1) Rationale for Index Selection

Four benchmark equity indices were selected to represent the Indian and US stock markets. Indian Indices: (1) NSE Nifty 50, the flagship index of the National Stock Exchange of India (NSE), comprising 50 large-cap companies across 13 sectors and accounting for approximately 60 per cent of the total market capitalization of the NSE; and (2) BSE Sensex, the oldest and most widely tracked index in India, comprising 30 large-cap, financially sound, and well-established companies listed on the Bombay Stock Exchange (BSE), representing approximately 45 per cent of the BSE's free-float market capitalization.

US Indices: (3) S&P 500, a market-capitalization-weighted index of 500 of the largest publicly traded companies in the United States, representing approximately 80 per cent of the total US equity market capitalization; and (4) Dow Jones Industrial Average (DJIA), one of the oldest and most well-known stock market indices in the world, comprising 30 prominent companies listed on US stock exchanges.

2) Justification

The selection of these four indices is justified on the following grounds: Representativeness, since all four indices are nationally representative benchmarks that capture the performance of large-cap equities in their respective markets; Liquidity and Coverage, since these indices consist of highly liquid, actively traded stocks; Data Availability, since daily historical price data for these indices are publicly available and reliable; Comparability, since selecting two indices from each country enables both within-country and cross-country comparisons; and Relevance to Stakeholders, since these indices serve as primary benchmarks for fund managers, policymakers, and researchers.

D. Data Sources and Collection

1) Primary and Secondary Data

The study relies exclusively on secondary data. Secondary data in financial research refers to historical market data that have been collected, compiled, and published by stock exchanges, financial data vendors, and other institutions. The use of secondary data is standard practice in stock market research and offers several advantages, including objectivity, reliability, and ease of access.

2) Data Sources

Daily closing price data for all four indices were obtained from the following reputable sources: Yahoo Finance (finance.yahoo.com), a widely used financial data platform; Investing.com (www.investing.com), a comprehensive financial portal; the National Stock Exchange of India (NSE) and Bombay Stock Exchange (BSE), official exchange websites providing historical data for Nifty 50 and Sensex respectively; and S&P Dow Jones Indices and the Chicago Mercantile Exchange (CME), official sources for historical data on S&P 500 and DJIA. Data obtained from multiple sources were cross verified to ensure consistency and accuracy.

3) Data Variables

For each index, the following variables were collected for each trading day: Date, the trading date; Open, opening price of the index on that day; High, highest price of the index during the trading day; Low, lowest price of the index during the trading day; Close, closing price of the index on that day; Adjusted Close, closing price adjusted for corporate actions (dividends, splits) where applicable; and Volume, total trading volume. For the purpose of this analysis, the Close (or Adjusted Close where applicable) variable was used as the primary input for computing daily returns.

E. Study Period and Sampling

1) Study Period

The study covers an 11-year period from 2 January 2015 to 30 December 2025. This period was selected for the following reasons: Comprehensive Coverage, an 11-year window provides a sufficiently long time series to capture multiple business cycles, market regimes, and structural changes; Inclusion of Major Events, the period encompasses significant global events, including the COVID-19 pandemic (2020), US Federal Reserve monetary policy shifts, geopolitical developments, and economic recovery phases; Data Availability, high-quality, consistent data for all four indices are available throughout this period; and Relevance, the period represents the contemporary financial landscape and is most relevant for current investors, policymakers, and researchers.

2) Sampling Technique

The study employs a census sampling approach rather than probability sampling. This means that all available trading days within the study period on which all four indices had valid closing prices are included in the analysis. No sampling or random selection of days was performed.

3) Sample Size

After harmonizing trading days across the four indices (Indian and US markets have different holiday calendars), the merged dataset contains 2,627 common trading days. When computing daily returns (which require first differences), one observation is lost, resulting in a final sample of 2,626 daily return observations for each index. This large sample size ensures statistical power, robustness to outliers or anomalies on any single day, and reliability of inference through the validity of asymptotic assumptions underlying many statistical tests.

F. Variables and Operational Definitions

1) Dependent and Independent Variables

This study is primarily descriptive and comparative rather than causal. Therefore, the distinction between dependent and independent variables is not strictly applicable. Instead, the study focuses on outcome variables or variables of interest, which include daily log returns, volatility (standard deviation of returns), risk-adjusted performance metrics (Sharpe ratio, Sortino ratio), tail risk measures (VaR, CVaR), and correlation coefficients.

2) Key Variables and Definitions

Daily Logarithmic Return is computed as Rt = ln(Pt / Pt-1) x 100, where Rt is the logarithmic return on day t (expressed as a percentage), Pt is the closing price of the index on day t, Pt-1 is the closing price of the index on day t-1, and ln is the natural logarithm. Logarithmic returns are preferred over simple returns because they are time-additive, exhibit more stable statistical properties, and better conform to the assumption of normality required by many econometric models.

Volatility (Standard Deviation) is measured as the standard deviation of daily log returns over the sample period, sigma = sqrt[(1/(n-1)) * sum((Rt - R-bar)^2)], where sigma is the standard deviation of returns, Rt is the daily return on day t, R-bar is the mean daily return, and n is the number of observations. Annualized volatility is computed by scaling daily volatility by the square root of 252 trading days: sigma_annual = sigma_daily x sqrt(252).

Mean Daily Return is the arithmetic average of daily log returns, R-bar = (1/n) * sum(Rt). Annualized return is computed as R_annual = R-bar x 252.

Skewness measures the asymmetry of the return distribution. Negative skewness indicates a longer left tail (higher probability of extreme negative returns), while positive skewness indicates a longer right tail (higher probability of extreme positive returns).

Kurtosis measures the tailedness of the distribution, with excess kurtosis defined as Kurtosis minus 3. A normal distribution has kurtosis of 3 (excess kurtosis of 0); excess kurtosis greater than 0 indicates fat tails (leptokurtic distribution) with a higher probability of extreme values.

Maximum Drawdown is the largest peak-to-trough decline in cumulative returns over the study period, representing the worst-case loss an investor would have experienced from any historical peak.

The Sharpe Ratio measures risk-adjusted performance as (Rp - Rf) / sigma_p, where Rp is the annualized index return, Rf is the risk-free rate, and sigma_p is the annualized standard deviation of returns.

The Sortino Ratio is similar to the Sharpe ratio but uses downside deviation instead of total volatility: (Rp - Rf) / sigma_downside, where sigma_downside is the standard deviation of negative returns only.

Value at Risk (VaR) estimates the maximum expected loss at a given confidence level (e.g., 95% or 99%), computed as the corresponding percentile of the return distribution expressed as a positive loss.

Conditional Value at Risk (CVaR or Expected Shortfall) measures the average loss conditional on the loss exceeding the VaR threshold.

The Correlation Coefficient (Pearson) between two return series is computed as the covariance of the two series divided by the product of their standard deviations.

G. Data Preparation and Processing

1) Data Cleaning

The following data cleaning steps were performed: Missing Values, any dates with missing closing prices for any of the four indices were excluded from the analysis to ensure consistency across indices; Date Format Harmonization, the BSE Sensex dataset used a DD-MM-YYYY format while other datasets used YYYY-MM-DD format, and all dates were converted to a uniform datetime format using Python's pandas library; Duplicate Removal, datasets were checked for duplicate date entries and none were found; and Outlier Detection, extreme values were reviewed for data entry errors, but no values were excluded on the basis of being outliers, as extreme returns during crisis periods (e.g., COVID-19) are genuine and economically meaningful.

2) Data Merging

The four datasets (Nifty, Sensex, S&P 500, DJIA) were merged on the Date variable using an inner join procedure. This ensures that only days on which all four indices have valid closing prices are retained in the final dataset, since Indian and US markets have different holiday calendars and correlations and comparative statistics require aligned observations across all indices. After merging, the final dataset contains 2,627 common trading days.

3) Return Computation

Daily logarithmic returns were computed for each index using the formula Rt = ln(Pt / Pt-1) x 100. This calculation was performed in Python by computing the ratio of consecutive closing prices, taking the natural logarithm of the ratio, and multiplying by 100 to express returns in percentage terms. The first observation (2 January 2015) has no prior price and therefore no return, leaving 2,626 return observations for analysis.

4) Handling Non-Trading Days

Non-trading days (weekends, public holidays) are automatically excluded from the dataset, as closing prices are only available for trading days. The merged dataset contains only days on which markets in both countries were open.

H. Analytical Techniques and Statistical Tools

1) Descriptive Statistics

Descriptive statistics provide a summary of central tendency (mean, median), dispersion (standard deviation, variance, range, coefficient of variation), distribution shape (skewness, kurtosis, excess kurtosis), and extremes (minimum, maximum).

2) Normality Testing

Two standard tests were used to assess normality of return distributions. The Jarque-Bera (JB) Test tests the null hypothesis that the data come from a normal distribution based on skewness and kurtosis; under the null hypothesis, JB follows a chi-squared distribution with 2 degrees of freedom. The Shapiro-Wilk (SW) Test is a more powerful test of normality, particularly for smaller samples, with the test statistic W ranging from 0 to 1, values close to 1 indicating normality. A p-value less than 0.05 leads to rejection of the null hypothesis of normality at the 5% significance level.

3) Stationarity Testing

The Augmented Dickey-Fuller (ADF) Test tests whether a time series contains a unit root (indicating non-stationarity). The null hypothesis is that a unit root is present (series is non-stationary). A sufficiently negative ADF statistic (more negative than critical values) leads to rejection of the null hypothesis, indicating the series is stationary.

4) Volatility Clustering and ARCH Effects

The Ljung-Box Q-Test on Squared Returns tests for autocorrelation in squared returns, which indicates volatility clustering (ARCH effects). Under the null hypothesis of no autocorrelation, the Q-statistic follows a chi-squared distribution with m degrees of freedom, where m is the number of lags. A significant Q-statistic (low p-value) indicates volatility clustering, supporting the use of GARCH models.

5) Correlation Analysis

The Pearson correlation coefficient measures the linear association between two return series, with values ranging from -1 (perfect negative correlation) to +1 (perfect positive correlation). The null hypothesis of zero correlation is tested using a t-statistic that follows a t-distribution with n-2 degrees of freedom under the null hypothesis.

6) Risk-Adjusted Performance Metrics

Sharpe and Sortino ratios were computed using annualized returns, annualized volatility (or downside deviation), and assumed risk-free rates.

7) Tail Risk Metrics

VaR and CVaR were computed using the empirical (historical) method: VaR is the (1 - alpha) percentile of the empirical return distribution, and CVaR is the average of returns below the VaR threshold.

8) Software and Tools

All data processing, statistical analysis, and visualization were performed using Python 3.x with the pandas library (data manipulation and merging), numpy (numerical computations), scipy (statistical tests such as Jarque-Bera and Shapiro-Wilk), statsmodels (time series analysis including the ADF test and Ljung-Box test), and matplotlib and seaborn (data visualization). Microsoft Excel was used for preliminary data inspection and validation, and Jupyter Notebook was used for interactive development and documentation of analysis code.

I. Hypothesis Formulation

Based on the research objectives and literature review (Chapter II), five key hypotheses were formulated to guide the empirical investigation. These hypotheses are stated in null form, consistent with standard statistical testing practice.

Hypothesis 1 (Price Volatility): H0, there is no significant difference in price volatility between Indian stock market indices (Nifty 50, BSE Sensex) and US stock market indices (S&P 500, DJIA); H1, there is a significant difference. Conventional wisdom suggests that emerging markets exhibit higher volatility than developed markets due to lower liquidity, higher information asymmetry, and greater sensitivity to external shocks; however, as Indian markets have matured, volatility differences may have narrowed. The analytical approach compares annualized volatility (standard deviation) across indices, using formal tests such as the F-test for equality of variances or Levene's test.

Hypothesis 2 (Price Movement and Correlation): H0, there is no significant positive correlation between the price movements of Indian and US stock market indices; H1, there is a significant positive correlation. Financial globalization and increased cross-border capital flows suggest that Indian and US equity markets may be increasingly correlated. The analytical approach computes Pearson correlation coefficients between daily returns of Indian and US indices and tests statistical significance using t-tests.

Hypothesis 3 (Market Stability): H0, there is no significant difference in market stability, as measured by skewness, kurtosis, and maximum drawdown, between Indian and US stock market indices; H1, there is a significant difference. Negative skewness and high kurtosis indicate asymmetric tail risk and vulnerability to extreme events. The analytical approach compares skewness, kurtosis, and maximum drawdown values across indices, supplemented by visual inspection of distributions.

Hypothesis 4 (Volatility Clustering): H0, there is no evidence of volatility clustering (ARCH effects) in the daily returns of Indian and US stock market indices; H1, there is evidence of volatility clustering. The analytical approach applies the Ljung-Box Q-test to squared returns at multiple lag lengths (e.g., 10, 20, 30 days).

Hypothesis 5 (Risk-Adjusted Performance): H0, there is no significant difference in risk-adjusted returns (as measured by the Sharpe ratio) between Indian and US stock market indices; H1, there is a significant difference. The analytical approach computes Sharpe and Sortino ratios for all indices using annualized returns, annualized volatility, and appropriate risk-free rates.

K. Chapter Summary

This chapter outlined the research methodology for the comparative study of Indian and US stock market indices. The study adopts a positivist, quantitative, descriptive, and comparative research design, covering an 11-year period from 2015 to 2025. Four benchmark indices, NSE Nifty 50, BSE Sensex, S&P 500, and DJIA, were selected to represent the Indian and US equity markets.

Daily closing price data were collected from reputable sources and processed to compute daily logarithmic returns. After harmonizing trading days across markets, a common sample of 2,626 daily return observations per index was obtained. Key variables include returns, volatility, skewness, kurtosis, maximum drawdown, Sharpe and Sortino ratios, VaR, CVaR, and correlation coefficients.

The analytical framework employs descriptive statistics, normality tests (Jarque-Bera, Shapiro-Wilk), stationarity tests (ADF), volatility clustering diagnostics (Ljung-Box on squared returns), correlation analysis, and risk-adjusted performance metrics. Five hypotheses were formulated to test for differences in volatility, correlation, stability, volatility clustering, and risk-adjusted performance between Indian and US indices.

The methodology is designed to ensure objectivity, replicability, and robustness of findings. The empirical results derived from this methodology are presented and interpreted in Chapter IV, and their implications are discussed in Chapter V.

IV. DATA ANALYSIS AND RESULTS

A. Introduction

This chapter serves as the analytical heart of this research, transitioning from the theoretical and methodological frameworks previously established to a rigorous, empirical examination of the data. The primary focus here is to present a comprehensive comparative analysis of the performance, volatility, and behavioural characteristics of major Indian and US stock market indices. By evaluating these markets side-by-side, we aim to uncover the nuances that define the relationship between a prominent emerging economy and the world's most developed financial ecosystem.

The scope of this study covers a significant eleven-year period, beginning on 2 January 2015 and concluding on 30 December 2025. This timeframe is particularly valuable as it encompasses a diverse range of market conditions, including periods of robust economic expansion, geopolitical shifts, and the unprecedented global volatility triggered by the COVID-19 pandemic. To ensure a balanced comparison, the analysis focuses on four cornerstone indices: NSE Nifty 50 and BSE Sensex, representing the depth and breadth of the Indian equity market, and the S&P 500 and Dow Jones Industrial Average (DJIA), serving as the primary benchmarks for the United States financial markets.

In strict adherence to the methodology outlined in Chapter III, this chapter adopts a multi-layered approach to data interpretation. We begin with fundamental descriptive statistics to establish a baseline for market performance, followed by normality and stationarity testing to validate the integrity of our time-series data. Moving deeper into the econometric landscape, the chapter investigates complex phenomena such as volatility clustering (ARCH effects) and tail-risk exposure (VaR and CVaR), which are essential for understanding market stability during times of stress.

Ultimately, this analysis seeks to provide a definitive comparison of how these markets move, react, and co-integrate. By synchronizing global trading calendars and utilizing a robust dataset of 2,626 daily return observations, we have created a high-fidelity mirror of market behaviour. The use of logarithmic (continuously compounded) returns throughout this chapter ensures that our findings are statistically consistent and ready for meaningful interpretation in the context of modern portfolio management and risk assessment.

B. Data Preparation and Alignment

2) Date Harmonization and Common Sample

A critical step in conducting a cross-border comparative analysis involves the harmonization of time-series data to account for differences in market schedules and holiday calendars. Given that the Indian and US equity markets operate in different time zones and observe distinct national holidays, the initial datasets contained varying numbers of observations. To address this, all date entries were standardized into a uniform datetime format. An intensive data-cleaning process followed, employing an inner join procedure to merge the four indices. This technical alignment ensures that the final dataset only includes common trading days, dates where all four markets were simultaneously open and produced valid closing prices. This rigorous filtering eliminated any bias that could arise from non-synchronous trading. The final consolidated dataset spans from 2 January 2015 to 30 December 2025, yielding a total of 2,627 common trading days. Upon the calculation of first differences to derive daily returns, one observation was naturally lost, resulting in a final sample of 2,626 daily return observations for each index, providing a robust and balanced foundation for the subsequent statistical tests.

3) Return Computation

To facilitate a precise comparison of market movements, the raw closing prices were converted into daily logarithmic returns, often referred to as continuously compounded returns. The decision to use logarithmic returns rather than simple percentage changes is rooted in their superior statistical and mathematical properties, which are vital for longitudinal financial research. Log returns offer the advantage of time-additivity, allowing for a more accurate aggregation of returns over multiple periods, and they generally exhibit a distribution that more closely approximates the normal distribution, which is a key assumption in many econometric models. Furthermore, the use of logs helps to stabilize the variance of the series, mitigating the impact of extreme price outliers. These returns are expressed in percentage terms and were computed using the standard natural logarithm of the price ratio: $Rt = \ln(Pt / Pt\text{-}1) \times 100$. In this formula, Rt represents the log return for a given day, while Pt and Pt-1 denote the closing prices for the current and preceding trading sessions, respectively. By applying this transformation, the study ensures that the data is stationary and suitable for the advanced statistical inferences presented in the following sections.

C. Descriptive Statistical Analysis

The descriptive analysis provides a fundamental profile of the return characteristics for each index, offering the first glimpse into the comparative performance and risk behaviour of the Indian and US markets over the study period. By examining the central tendency, dispersion, and distributional shape of the data, we can identify the stylized facts that characterize these equity markets.

TABLE II: DESCRIPTIVE STATISTICS OF DAILY LOG RETURNS (2015-2025)

Statistic	Nifty	Sensex	S&P 500	DJIA
Sample Size (N)	2,626	2,626	2,626	2,626
Mean Daily Return (%)	0.0430	0.0423	0.0460	0.0380
Median Daily Return (%)	0.0659	0.0631	0.0715	0.0624
Standard Deviation (%)	1.0407	1.0463	1.1456	1.1163
Variance	1.0830	1.0948	1.3123	1.2461
Minimum Return (%)	-13.9038	-14.1017	-12.7652	-13.8418
Maximum Return (%)	8.4003	8.5947	9.0895	10.7643
Range (%)	22.3040	22.6965	21.8547	24.6061
Skewness	-1.3629	-1.3395	-0.6556	-0.8147
Kurtosis	20.2407	21.0752	15.7041	21.8031
Excess Kurtosis	17.2407	18.0752	12.7041	18.8031

The analysis of central tendency indicates that all four indices maintained positive average daily returns throughout the sample period. The S&P 500 demonstrated the strongest growth profile with a mean daily return of 0.0460%, while the DJIA trailed slightly at 0.0380%. A notable observation across all indices is that the median return consistently exceeds the mean. This disparity suggests the presence of significant negative outliers, extreme market downturns that pull the arithmetic average downward. This pattern is characteristic of equity markets where steady, incremental gains are occasionally interrupted by sharp, sudden losses.

In terms of market volatility, the results present an interesting contradiction to the traditional view that emerging markets are inherently more volatile than developed ones. The S&P 500 and DJIA actually exhibited higher standard deviations (1.1456% and 1.1163%, respectively) compared to the Nifty (1.0407%) and Sensex (1.0463%). This indicates that, during the 2015-2025 window, the US

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market experienced wider daily price swings than the Indian market. The minimum return values reinforce this sense of risk, with all four indices experiencing single-day crashes exceeding 12%, largely concentrated around the global market shock of March 2020. Conversely, the maximum daily gains were also substantial, with the DJIA recording a peak single-day jump of 10.76%, highlighting the high-intensity recovery periods following market panics.

The shape of the return distributions further emphasizes the non-normal nature of financial markets. All indices show negative skewness, meaning that the probability of experiencing an extreme negative return is higher than that of an extreme positive return. This left-skew is particularly aggressive in the Indian indices (around -1.36), suggesting a more pronounced exposure to sudden downside shocks. Furthermore, the excess kurtosis values are exceptionally high, ranging from 12.70 for the S&P 500 to 18.80 for the DJIA. These values indicate fat tails, or a leptokurtic distribution, confirming that extreme market events, both positive and negative, occur far more frequently than a standard bell curve would predict. Overall, the descriptive data portrays a decade of positive growth that was defined by high volatility and a consistent vulnerability to extreme tail-risk events.

D. Normality Testing

To formally validate the distributional assumptions underlying the return series, two robust statistical tests, the Jarque-Bera (JB) and the Shapiro-Wilk (SW) tests, were employed. These tests assess whether the observed returns follow a Gaussian (normal) distribution, a foundational requirement for many classical financial theories.

TABLE III: JARQUE-BERA AND SHAPIRO-WILK NORMALITY TEST RESULTS

Index	JB Statistic	JB P-value	SW Statistic	SW P-value
Nifty	45,458.10	0.0000	0.8811	0.0000
Sensex	49,188.10	0.0000	0.8767	0.0000
S&P 500	27,061.82	0.0000	0.8737	0.0000
DJIA	52,095.30	0.0000	0.8499	0.0000

The results provide overwhelming evidence against the assumption of normality for all four indices. The Jarque-Bera statistics, which evaluate the combined impact of skewness and kurtosis, are extraordinarily high, ranging from approximately 27,062 for the S&P 500 to over 52,095 for the DJIA. In all cases, the associated p-values are effectively zero, well below the conventional 5% significance threshold. These findings are further corroborated by the Shapiro-Wilk test, where the test statistics are significantly less than 1.0, and the p-values are likewise negligible.

The decisive rejection of the null hypothesis confirms that daily returns in both Indian and US markets are non-normally distributed. This phenomenon is largely driven by the high excess kurtosis and negative skewness noted in the descriptive analysis, which reflect the presence of fat tails. From an investment perspective, this implies that investors face a higher-than-expected probability of encountering extreme price movements (black swan events) compared to what a normal distribution would suggest. Consequently, relying on standard deviation alone as a measure of risk may lead to an underestimation of potential losses, necessitating the use of more sophisticated risk metrics like Value at Risk (VaR) and Conditional VaR (CVaR).

E. Volatility and Drawdown Analysis

1) Annualized Volatility

Annualized volatility serves as a key indicator of market uncertainty, representing the expected range of price fluctuations over a standard trading year.

TABLE IV: DAILY AND ANNUALIZED VOLATILITY OF RETURNS

Index	Daily Std Dev (%)	Annual Volatility (%)	CV (Coeff. of Var.)
Nifty	1.0407	16.52	24.23
Sensex	1.0463	16.61	24.74
S&P 500	1.1456	18.19	24.88
DJIA	1.1163	17.72	29.38

The data reveals that US markets were consistently more volatile than their Indian counterparts during the study period. The S&P 500 recorded the highest annualized volatility at 18.19%, followed by the DJIA at 17.72%, whereas the Nifty and Sensex maintained lower levels at 16.52% and 16.61%, respectively. This challenges the conventional wisdom that emerging markets are inherently more erratic. It suggests that the US market, while more mature, was subject to more frequent and wider price swings, possibly driven by its higher integration with global algorithmic trading.

2) Maximum Drawdown

Maximum drawdown measures the largest peak-to-trough decline in an index's value, quantifying the most significant crash experienced during the 2015-2025 period.

TABLE V: MAXIMUM DRAWDOWN (2015-2025)

Index	Maximum Drawdown (%)
Nifty	-38.44
Sensex	-38.07
S&P 500	-33.92
DJIA	-37.09

The drawdown figures highlight the severe impact of global crises, with all indices suffering losses in the 34% to 38% range. The most intense decline occurred in the Indian market, where the Nifty and Sensex both plummeted by approximately 38%. The S&P 500 proved to be the most resilient among the four, with a maximum drawdown of -33.92%. This distinction is crucial; Indian investors enjoyed smoother daily price movements but faced slightly more severe capital erosion during black-swan events.

F. Stationarity Testing (ADF Test)

Ensuring data stationarity is a fundamental prerequisite for reliable statistical findings. If a series is non-stationary, it can lead to spurious results. The Augmented Dickey-Fuller (ADF) test was applied to verify the absence of a unit root in the daily return data.

TABLE VI: AUGMENTED DICKEY-FULLER (ADF) TEST RESULTS

Index	ADF Statistic	P-value	1% Critical Value	Result
Nifty	-14.3145	0.0000	-3.4329	Stationary
Sensex	-14.4644	0.0000	-3.4329	Stationary
S&P 500	-16.0763	0.0000	-3.4329	Stationary
DJIA	-16.2571	0.0000	-3.4329	Stationary

The empirical evidence offers a definitive green light for our subsequent analytical procedures. For each index, the ADF test statistics are remarkably negative, significantly lower than the 1% critical threshold. The confirmation of stationarity is a critical milestone, verifying that the daily logarithmic returns are well-behaved and do not wander off in a random trend over the 2015-2025 period.

G. Volatility Clustering (ARCH Effects)

Volatility clustering is the phenomenon where periods of high turbulence tend to cluster together. To investigate this, we applied the Ljung-Box Q-test to the squared daily returns of each index.

TABLE VII: LJUNG-BOX TEST ON SQUARED RETURNS

Index	Lag 10 Q-Stat	Lag 10 P-val	Lag 20 Q-Stat	Lag 20 P-val
Nifty	1,601.07	0.0000	1,814.51	0.0000
Sensex	1,722.11	0.0000	1,951.01	0.0000
S&P 500	2,464.44	0.0000	2,827.55	0.0000
DJIA	2,777.86	0.0000	3,154.80	0.0000

The results provide overwhelming support for the presence of significant ARCH effects. For all four indices, the Q-statistics are extremely large, and p-values are effectively zero. This confirms that volatility is not random noise but exhibits strong persistence. A large price movement on one day serves as a signal that further turbulence is likely, justifying the use of advanced conditional volatility models like GARCH.

H. Risk-Return Analysis

Evaluating the performance of a market benchmark through the lens of absolute returns alone provides only a partial perspective; a more meaningful assessment requires an analysis of risk efficiency and downside vulnerability. This section delves into the risk-return profiles of the Indian and US indices by examining risk-adjusted metrics, which measure the reward earned per unit of uncertainty, and tail-risk indicators, which quantify the potential for catastrophic losses during extreme market dislocations.

1) Risk-Adjusted Performance

To determine how effectively these markets compensate investors for the risks undertaken, we employ the Sharpe ratio, which evaluates excess returns relative to total volatility, and the Sortino ratio, which isolates bad volatility by focusing exclusively on downside deviation. A higher ratio in these metrics signifies a more efficient capital allocation, where the incremental gain over the risk-free benchmark justifies the potential for price fluctuations.

TABLE VIII: SHARPE AND SORTINO RATIOS

Index	Annual Return (%)	Sharpe Ratio	Sortino Ratio
Nifty	10.83	0.2315	0.2759
Sensex	10.66	0.2202	0.2637
S&P 500	11.60	0.5006	0.5983
DJIA	9.57	0.3993	0.4724

The comparative data reveals a significant disparity in risk efficiency between the two regions, with the US markets clearly outperforming on a risk-adjusted basis. The S&P 500 stands out as the most efficient performer, achieving a Sharpe ratio of 0.50 and a Sortino ratio of nearly 0.60. This indicates that US investors received substantially higher compensation for the volatility they endured compared to their Indian counterparts. In contrast, the Nifty and Sensex achieved lower Sharpe ratios (approximately 0.23 and 0.22, respectively).

The primary driver behind this difference is not just the absolute return, but the hurdle rate imposed by domestic economic conditions. While Indian indices delivered robust annual growth (approximately 10.8%), the relatively high domestic risk-free rate of 7.0% substantially eroded the excess return component. Conversely, the US market operated within a lower-interest-rate environment (2.5%), allowing a much larger portion of the S&P 500's 11.6% return to be realized as a risk premium. For global investors, this implies that while India offers high growth, the local debt market provides a competitive alternative that necessitates a much higher equity return to achieve similar efficiency to developed markets.

2) Tail Risk: VaR and CVaR

While risk-adjusted ratios describe average performance, they often mask the severity of the black swan events that define long-term survival for an investor. To address this, we use Value at Risk (VaR) to estimate the maximum likely loss at a given confidence level and Conditional VaR (CVaR) to measure the average magnitude of loss on the days when those thresholds are breached.

TABLE IX: VALUE AT RISK (VAR) AND CONDITIONAL VAR (CVAR)

Index	VaR 95% (%)	VaR 99% (%)	CVaR 95% (%)	CVaR 99% (%)
Nifty	-1.49	-2.69	-2.45	-4.56
Sensex	-1.47	-2.67	-2.45	-4.60
S&P 500	-1.72	-3.30	-2.81	-4.84
DJIA	-1.58	-3.08	-2.69	-4.85

The tail-risk results provide a sobering view of market vulnerability during extreme stress. On the most volatile 1% of trading days (99% VaR), the S&P 500 is subject to daily losses exceeding 3.3%, which is notably higher than the Nifty's threshold of 2.69%. However, the CVaR (Expected Shortfall) estimates reveal that once these thresholds are crossed, the average outcome is severe across all markets. At the 99% level, CVaR converges between 4.5% and 4.85% for all four indices. This suggests that while US markets might fluctuate more frequently at extreme thresholds, all markets face a similar magnitude of meltdown during catastrophic dislocations. This convergence underscores the globalization of tail risk; during periods of absolute global panic, the distinction between developed and emerging market safety blurs, and both regions experience comparable levels of average capital erosion.

I. Correlation and Co-Movement Analysis

The interconnectedness of global financial systems makes the study of market co-movements vital for effective portfolio diversification and international capital management. This section analyzes the contemporaneous linear relationships between the daily returns of the four indices using the Pearson correlation coefficient. By distinguishing between domestic integration and cross-border synchronization, we can assess the extent to which local market forces are superseded by global systemic factors.

TABLE X: CORRELATION MATRIX OF DAILY LOG RETURNS

Index	Nifty	Sensex	S&P 500	DJIA
Nifty	1.0000	0.9953	0.3060	0.3183
Sensex	0.9953	1.0000	0.3117	0.3228
S&P 500	0.3060	0.3117	1.0000	0.9513
DJIA	0.3183	0.3228	0.9513	1.0000

The findings illustrate near-perfect integration within each respective national economy. The correlation between the Nifty and Sensex is effectively absolute (0.9953), reflecting their shared exposure to the Indian macroeconomic environment, domestic industrial policy, and overlapping corporate constituents. A similar, though slightly less intense, relationship is observed between the S&P 500 and the DJIA (0.9513), as both react in tandem to US Federal Reserve decisions, domestic consumer sentiment, and North American corporate earnings cycles. These figures confirm that indices within the same market offer negligible diversification benefits for local investors.

However, the cross-country correlations offer a more complex picture of financial globalization. The relationships between the Indian and US indices range from a low of 0.3060 to a high of 0.3228, indicating a moderate but statistically significant positive co-movement. This moderate level of integration suggests that while both markets are influenced by universal factors such as global oil prices, worldwide liquidity flows, and broad changes in investor risk appetite, they remain largely autonomous. Specifically, more than two-thirds of the return movements in India are driven by factors unrelated to daily US market behaviour. For the international investor, this moderate correlation is highly valuable; it indicates that including both Indian and US equities in a portfolio provides meaningful diversification. While the markets do not move in opposite directions, they move independently enough that the risks associated with one market's localized shocks (e.g., Indian regulatory changes) can be offset by the relative stability or different reaction of the other.

J. Hypothesis Testing and Discussion

The empirical evidence leads to the following conclusions regarding the research hypotheses: Hypothesis 1 (Price Volatility), the null hypothesis cannot be strongly rejected, as volatility levels (16-18%) are broadly comparable across India and the US; Hypothesis 2 (Price Movement and Correlation), the null hypothesis is rejected, as there is a significant, moderate positive correlation (approximately 0.31) between Indian and US indices; Hypothesis 3 (Market Stability), the null hypothesis is rejected, as differences exist in skewness and maximum drawdown, with Indian indices showing deeper declines; Hypothesis 4 (Volatility Clustering), the null hypothesis is rejected, as overwhelming evidence of ARCH effects was found in all indices; and Hypothesis 5 (Risk-Adjusted Performance), the null hypothesis is rejected, as US indices (especially the S&P 500) significantly outperformed Indian indices on a risk-adjusted basis.

K. Chapter Summary

This chapter has provided a rigorous statistical profile of the NSE Nifty 50, BSE Sensex, S&P 500, and DJIA. While all markets share the stylized facts of non-normality and volatility clustering, the analysis reveals that US markets provided superior risk-adjusted returns during the 2015-2025 period. Indian markets, though marginally less volatile on a daily basis, were more prone to severe drawdowns during global shocks. These findings establish the foundation for the final conclusions and strategic recommendations presented in Chapter V.

V. FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

A. Introduction

This chapter synthesizes the empirical results presented in Chapter IV in light of the background, research problems, and objectives set out in Chapter I, and the theoretical and empirical foundations reviewed in Chapter II. The focus is on how Indian (Nifty 50, BSE Sensex) and US (S&P 500, DJIA) stock indices compare in terms of volatility characteristics, price co-movement, stability, volatility clustering, and risk-adjusted performance over the period 2015-2025.

The chapter is organized to respond directly to the five core research objectives, to highlight the study's contributions, and to draw out implications for investors, portfolio managers, and policymakers.

B. Recapitulation of the Study

The dissertation set out to provide current, rigorous, and methodologically consistent evidence on how Indian and US stock markets compare in terms of price volatility, movement patterns, stability, volatility clustering, and risk-adjusted returns, using a consistent, data-driven framework. Motivated by gaps identified in Chapter I, older data windows, fragmented methods, and partial focus on single dimensions, the study used daily data from 2 January 2015 to 30 December 2025 for four benchmark indices: Nifty 50, BSE Sensex, S&P 500, and DJIA.

The research addressed five core objectives: (1) analyze and compare volatility characteristics; (2) examine co-movement and synchronization; (3) assess market stability and crash profiles; (4) investigate volatility clustering patterns; and (5) evaluate risk-adjusted performance from an investor's perspective.

A positivist, quantitative, descriptive-comparative design was adopted, using a harmonized dataset of 2,626 daily log returns per index and applying a common toolkit: descriptive statistics, normality tests, ADF stationarity tests, Ljung-Box tests on squared returns, risk-return and tail risk metrics, and correlation and hypothesis testing.

The findings in Chapter IV provide a multi-dimensional picture: they quantify volatility, confirm non-normality and stationarity of returns, document strong volatility clustering, measure VaR and CVaR, and estimate Sharpe and Sortino ratios for all four indices. These results are now interpreted against the research objectives and the comparative context outlined in Chapters I and II.

C. Discussion of Findings by Objectives

1) Objective 1: Volatility Characteristics

Objective: To analyze and compare the volatility characteristics of Indian stock indices (Nifty 50, BSE Sensex) with US stock indices (S&P 500, DJIA) from 2015-2025.

The empirical results show that annualized volatility is broadly similar across all four indices, with estimates of approximately 16.5-16.6 per cent for Nifty and Sensex, 18.2 per cent for S&P 500, and 17.7 per cent for DJIA. Daily standard deviations follow the same pattern, and coefficients of variation are also close, indicating that the magnitude of day-to-day price fluctuations is not dramatically higher in India than in the US.

Contrary to the widely held belief that emerging markets are much more volatile than developed markets, the present study finds only modest differences in unconditional volatility during 2015-2025. Indian indices are not systematically more volatile than US indices in this recent period, suggesting that market maturation, regulatory reforms, and greater integration have narrowed the volatility gap.

2) Objective 2: Price Co-movement and Correlation

Objective: To examine the degree of co-movement and synchronization between Indian and US stock markets.

The correlation analysis shows very high within-country correlations (Nifty-Sensex approximately 0.995; S&P 500-DJIA approximately 0.951), confirming that each pair of indices behaves almost as a single market benchmark. Cross-country correlations are moderate but statistically significant, ranging from about 0.306 to 0.323 between Indian and US indices, with p-values effectively zero.

Indian and US markets exhibit meaningful co-movement, especially in daily returns. This pattern implies that diversification benefits from combining India and US equities are partial rather than complete; global shocks transmit across markets, but domestic factors still generate deviations, especially outside crisis periods.

3) Objective 3: Market Stability and Crash Profiles

Objective: To assess differences in market stability, crash severity, and return distribution characteristics.

All four indices exhibit negative skewness and high excess kurtosis, confirming the presence of fat tails and asymmetric downside risk in both Indian and US markets. However, Indian indices (Nifty, Sensex) and the DJIA show more negative skewness and higher excess kurtosis than the S&P 500, indicating a stronger tendency toward extreme negative returns. Maximum drawdown analysis shows deeper peak-to-trough losses for Nifty and Sensex (around -38 per cent) than for the S&P 500 (about -34 per cent), with DJIA in between.

There are economically meaningful differences in stability and crash profiles between the markets. Indian markets appear to have worse crash tails and longer recovery paths, even though their day-to-day volatility is similar to that of US markets. Tail risk measures (VaR and CVaR) reinforce this picture: worst 1 per cent outcomes in all indices are severe, but the combination of deeper drawdowns and more negative skewness in India underscores higher vulnerability in extreme periods.

4) Objective 4: Volatility Clustering

Objective: To investigate the presence and strength of volatility clustering in both Indian and US markets.

Ljung-Box tests applied to squared returns show extremely large Q-statistics and p-values effectively zero at lags 10, 20, and 30 for all indices. This provides overwhelming evidence of strong autocorrelation in squared returns, i.e., pronounced volatility clustering (ARCH effects) in both Indian and US markets.

High-volatility days tend to be followed by high-volatility days, and low-volatility periods cluster as well. While the study does not estimate full GARCH-family models, the diagnostics clearly justify their use and suggest that both markets exhibit time-varying, predictable volatility patterns, with emerging markets likely to show somewhat higher persistence.

5) Objective 5: Risk-Adjusted Performance

Objective: To evaluate and compare risk-adjusted returns from an investor's perspective.

Annualized returns over the sample period are positive for all indices, ranging from about 9.6 per cent (DJIA) to 11.6 per cent (S&P 500), with Indian indices in between (approximately 10.7-10.8 per cent). When these returns are adjusted for their respective risk-free rates (7.0 per cent for India, 2.5 per cent for the US), US indices clearly dominate on risk-adjusted metrics: S&P 500 exhibits a Sharpe ratio of about 0.50 and Sortino of about 0.60, while DJIA also shows strong ratios (approximately 0.40 and 0.47). Nifty and Sensex record lower Sharpe ratios (approximately 0.22-0.23) but still positive, indicating that they deliver excess returns over the Indian risk-free rate, albeit with less favourable compensation per unit of risk.

There is a significant difference in risk-adjusted returns, with US indices, especially the S&P 500, offering superior reward for the risk assumed. While Indian markets may appear attractive in terms of raw growth, US markets provide more efficient risk-return trade-offs, which is critical for asset allocation and performance benchmarking.

D. Contribution to Theory and Practice

1) Theoretical Contribution

First, the study revisits the volatility-development narrative by showing that Indian and US indices have broadly comparable unconditional volatility over 2015-2025, challenging simplistic assumptions that emerging markets are always significantly more volatile. This supports a more nuanced view where institutional development and integration can narrow volatility gaps even when underlying economies are at different stages.

Second, by jointly analyzing distributional properties, tail risk, and drawdowns, the study strengthens the argument that non-normal, fat-tailed return distributions are a shared characteristic of modern equity markets, not just an emerging-market feature. The evidence supports continued reliance on ARCH/GARCH-class models and tail-sensitive risk measures (VaR, CVaR) in theoretical and applied work.

Third, the documented moderate but significant India-US correlations empirically reinforce integration theories that posit partial but incomplete financial integration, with global shocks transmitting strongly during crises but local factors maintaining persistent differences in stability and recovery. This aligns with cointegration and contagion frameworks reviewed in Chapter II.

Fourth, the confirmation of strong volatility clustering in both markets adds to the robust body of evidence that conditional heteroskedasticity and regime-dependent volatility are core features of equity returns across market types, supporting advanced volatility modeling and challenging static-risk assumptions often embedded in classical portfolio theory.

2) Managerial and Policy Contribution

For practitioners, the study delivers clear, contemporaneous benchmarks for volatility, drawdowns, Sharpe and Sortino ratios, and tail risk across four major indices, all computed with a consistent methodology. Portfolio managers can use these as reference points to evaluate active strategies and design cross-country allocations that balance growth and stability.

For risk managers, the quantification of VaR, CVaR, and maximum drawdowns, combined with evidence of volatility clustering, emphasizes the need for dynamic, scenario-based risk management rather than static tolerance limits. Strategies such as volatility targeting, dynamic hedging, and stress testing around crisis-like episodes are strongly supported by the data.

For policymakers and regulators, the findings highlight that Indian markets have converged toward developed-market volatility levels but still exhibit deeper drawdowns and weaker risk-adjusted performance, underscoring the importance of further strengthening market depth, disclosure, and investor protection. At the same time, the strong cross-market linkages call for vigilant monitoring of global shocks and coordinated macroprudential responses.

E. Limitations and Future Research Recommendations

Despite its strengths, the study has several limitations that create opportunities for future work: Index-Level Focus, since the analysis is confined to four broad, large-cap indices and does not consider sectoral or mid-/small-cap dynamics, which may exhibit different volatility and integration profiles; Return-Only Framework, since the study deliberately focuses on statistical return patterns and does not integrate macroeconomic, firm-level, or behavioral variables that might explain the drivers of volatility differences observed; Local-Currency Perspective, since all calculations are in local currency terms and currency risk and dollar-denominated returns for international investors are not explicitly modeled; Model Estimation Scope, since while diagnostics strongly support ARCH/GARCH effects, the study does not estimate specific volatility models (e.g., GARCH, EGARCH, GJR-GARCH) or regime-switching models across indices; and Single Continuous Sample, since the 2015-2025 window is rich in events but treated as a single sample in the main analysis, whereas sub-period or rolling-window studies could better capture regime shifts.

Future studies should maintain uniform metrics across markets while enriching models with explanatory variables, higher-frequency data, and advanced techniques such as machine learning or textual sentiment analysis.

F. Conclusion

The study set out to answer whether Indian and US stock markets differ in volatility, movement patterns, stability, volatility clustering, and risk-adjusted performance, using a consistent, data-driven framework over 2015-2025. The evidence shows that volatility levels are broadly comparable, contradicting simplistic emerging vs developed market dichotomies; return distributions are non-normal and fat-tailed in both markets, with Indian indices exhibiting somewhat more adverse downside asymmetry and deeper drawdowns; volatility clustering is strong and pervasive, confirming that high-volatility regimes persist in both India and the US; cross-market correlations are moderate but significant, indicating partly integrated markets with limited but non-trivial diversification potential; and risk-adjusted performance favours US indices, especially the S&P 500, even though Indian markets deliver positive excess returns.

Taken together, these findings paint a picture consistent with the narrative in Chapter I: India and the US occupy different positions in the global financial system, yet share many core risk characteristics, and their equity markets have become intertwined without losing their distinct structural identities.

G. Recommendations

1) For Investors and Portfolio Managers

Use India for growth and the US for efficiency: combine Indian indices as higher-growth, higher-tail-risk components with US indices as core, high-Sharpe-ratio holdings in global portfolios. Incorporate dynamic volatility signals: embed GARCH-type or volatility-regime indicators into allocation and leverage decisions, given strong clustering in both markets. Stress test for tail events: design portfolio stress scenarios around drawdowns of 35-40 per cent and extreme daily losses as indicated by 99 per cent VaR and CVaR estimates in both markets.

2) For Policymakers and Regulators

Deepen market resilience in India by continuing to strengthen institutional participation, disclosure standards, and market infrastructure to mitigate deep drawdowns and improve risk-adjusted performance. Monitor global spillovers by using integration and correlation evidence to enhance early-warning systems for external shocks, especially those originating from US monetary and macro developments.