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Article

Post-Pandemic Evolution of Passive Investing in India

Naman Phutela[1*], Simran Kalra[2], Kapil Choudhary[3], Sakshi Mehta[4]

[1*] Department of Commerce, Chaudhary Devi Lal University, Sirsa, India
Email: namancomphd@cdlu.ac.in; ORCID:0000-0002-3357-6677
[2] Department of Commerce, Chaudhary Devi Lal University, Sirsa, India
Email: simrankalracomphd@cdlu.ac.in; ORCID:0000-0003-1614-4386
[3]Department of Commerce, Chaudhary Devi Lal University, Sirsa, India
Email: kapil@cdlu.ac.in; ORCID:0000-0001-9615-2794
[4]Department of Commerce, Government National College, Sirsa, India
Email: simsahaj2015@gmail.com; ORCID:0000-0001-8974-2884
***Corresponding Author**: Naman Phutela

Abstract: This research evaluates the dynamics of passive investment in India in the post-pandemic phase. In particular, the dynamics of returns, volatility and costs in a significant sample of ETFs (Exchange Traded Funds) for the period from 2020 -2025 are studied. The daily data is obtained from the National Stock Exchange and, through a structured econometric sequence of analysis - Augmented Dickey -Fuller Test (ADF), Vector Autoregression (VAR), Forecast Error Variance Decomposition (FEVD), GARCH/EGARCH - returns spillovers and volatility asymmetry dynamics are captured. The cost efficiency is studied by assessing the metrics of tracking difference (TD) and tracking error (TE). The results of the analysis indicate that return interdependence has grown in intensity across Indian equity ETFs, in particular the ETFs BANKBEES and MOM50, with the conclusion that post-COVID shocks to the markets are transmitted with considerable rapidity in the networks of the passive investment sector. The GARCH and EGARCH results yield ($\alpha + \beta \approx 0.9$) the persistent reduction in volatility, further indicating that negative returns increase risk more than do positive ones, in conformity with the asymmetric "leverage effects". The results of the rolling volatility and correlation graphs from 2022 onwards indicate characteristics of gradual stability with improvements, thus indicating greater integration of markets and confidence on the part of investors. The results of the cost analysis reveal an average trend for TE in the region of 0.12 and TD of between –0.02 and –0.04. This demonstrates that the Indian ETFs have managed to sustain a lower error of representation with low TE costs of a high order in terms of the respective benchmark indices. The results yielded thus indicate that the pandemic was a significant catalyst for the real structural maturity of the passive investment sector in India. The ETFs have grown from being niche-type to being core vehicles for the portfolio needs of investors, with better transparency, liquidity, and durability with respect to features of global practice in the world of post pandemic financial markets.
Keywords: Passive Investing, ETFs, Return Spillover, GARCH, Tracking Error, Post-Pandemic India

1. Introduction

Over the last decade, passive investing has continued to gain steam worldwide and in India. Both in the US and Europe and in Europe, ETFs and index funds have become the dominant players in swaths of asset flows. In India also, the passive segment is growing fast: by March 2025, the AUM of passive mutual funds increased by 21 % year-on-year to ₹11.13 lakh crore, and they accounted for approximately 16.7 % of the total mutual industry's assets. Passive funds' market share has roughly doubled in a span of a few years from around 8 % in 2020 to over 16 % in mid-2025 (Mandal & Murthy, 2021). This impetus is similarly evident in the ETF segment: trading volume of Indian ETFs has increased from ₹51,101 crore in FY19–20 to around ₹3.83 lakh crore in FY24–25, a greater than 7× jump (Dev & Sengupta, 2023). The rise of Indian passive investing has various structural shifts and behavioral factors driving it. The retail investor base has boomed, helped by the increased ease of digital interfaces and the availability of UPI-based micro-SIPs. At the same time, investors are becoming steadily cost-sensitive, particularly where they have experienced subpar performance or excessive fees in active funds. This scenario renders ETFs a compelling selection for core equities exposure. In this such growth, however, active funds remain the dominant players in the Indian mutual market industry and passives have yet to completely displace the incumbents.

1.1 Pandemic's Disruption and Its Implications

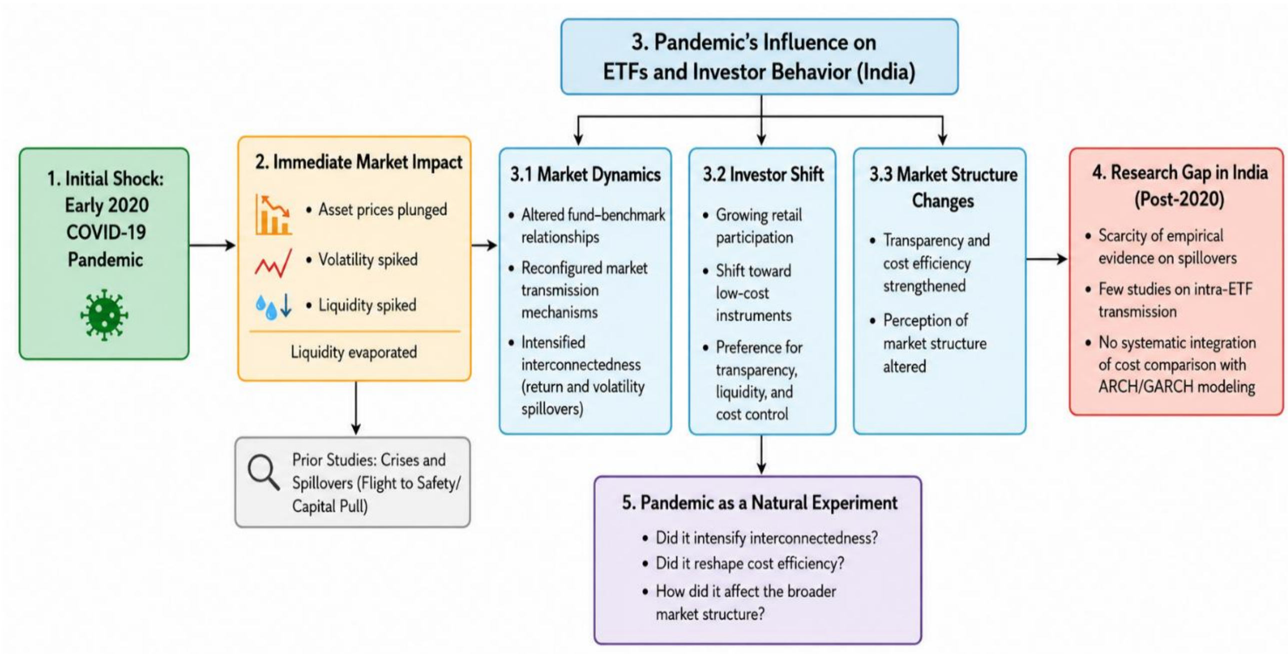

Figure i Pandemic's Disruption and Its Implications

(Source: Own Ellaboration)

The COVID-19 pandemic, which began in early 2020, created an unprecedented shock to financial markets around the globe. The prices of various assets collapsed, volatility soared, and liquidity fled throughout many segments. Research has shown that crises create stronger return and volatility spillovers between assets, as investments flee into safe havens or capital is withdrawn from weak sectors. With respect to ETFs, the periods of the pandemic may have changed normal relationships that exist between funds and their benchmarks and changed the transmission mechanisms across ETFs (Darekar, 2025). In India, the emergence of the pandemic came along with increasing retail participation and a shift in investor behavior toward less complex, low-cost instruments. If ETFs already were gaining favor in normal times, COVID-19 may have accelerated the shift. An increasing amount of investors may prefer passive exposure particularly due to transparency, liquidity, and cost control in times of distress.. At the same time, extreme market stress may strengthen **return spillover** (how shocks in one ETF transmit to others) and **volatility spillover** (how volatility clusters or spreads). These dynamics may differ compared to pre-pandemic periods (Berchmans & Vasanthi, 2025). Thus, the pandemic acts as a natural experiment: it may intensify interconnectedness among ETFs, reshape their cost efficiency perception, and affect market structure. Yet, in India, empirical evidence on how COVID-19 has altered both **return and volatility spillovers** in ETFs is scarce. Few studies examine the intra-ETF transmission post-2020, and none systematically integrate **cost comparisons** along with ARCH/GARCH modeling in the Indian context.

1.2 Research Gap

While international research (e.g., on U.S. or global ETFs) has explored tail risk or transmission during pandemic times, application to the Indian ETF universe is limited. For example, Tunc et al. (2024) examine tail spillovers across sector ETFs and stock indices in U.S. markets amidst COVID-era disruptions. Other studies in India address ETF efficiency or performance during crisis periods but often restrict to price-based metrics or single funds. Few have built a comprehensive framework combining return spillover (VAR/FEVD), volatility modeling (GARCH/EGARCH), and cost proxies (tracking difference / tracking error) for the post-pandemic period. Therefore, your study fills a meaningful gap: it investigates how the pandemic has affected both return and volatility spillover patterns among Indian ETFs and assesses their cost-effectiveness relative to benchmarks during 2020–2025. This integrated view in an emerging market is largely missing in existing literature.

1.3 Objectives

Accordingly, this study advances with three clear objectives:

1. To analyse return spillover of ETFs in India during the post-pandemic window, by employing the VAR and FEVD frameworks to uncover directional transmission across ETFs.
2. To compare cost structures between active and passive funds, proxied via tracking difference (TD) and tracking error (TE), to assess how "cost drag" behaved in crisis and recovery periods.
3. To analyse volatility spillover of ETFs using ARCH/GARCH and EGARCH models, to capture persistence, clustering, and asymmetric responses to shocks.

1.4 Contribution

This study makes important contributions in various ways by combining its objectives in a single empirical framework. It has empirical novelty by implementing true spillover analysis and volatility analysis in the context of Indian ETFs with an attention on the post-COVID "new normal" – no longer single fund or short-term case studies. It has a behavioral component whereby it links the structural adjustment of the pandemic condition with changing investor preferences showing that cost transparency and portfolio stability were more critical in stressful times within the markets (Darekar, 2025). At a policy level, this also has enormous implications in guiding regulators, fund managers and institutions in relation to ETF resilience and to reducing tracking error and liquidity issues. The model utilized employs VAR, GARCH and cost proxies, and can therefore also be generalized to other emerging markets in similar post-crisis transitions.

2. Literature Review

2.1 Introduction

This literature review examines how India's ETF landscape evolved before and after the pandemic. It evaluates studies on return and volatility spillovers, cost structures, and tracking efficiency, highlighting methodological developments such as VAR–FEVD and GARCH modeling. The section concludes by identifying the research gap motivating the current investigation.

2.2. Evolution of Passive Investing & the Indian ETF Landscape (Pre- vs post-2020)

Passive investing in India moved from the niche to the mainstream during the pandemic. Prior to 2020, ETFs accounted for a mere 8 % of the mutually funded amounts, but by March 2025 the asset under management increased to ₹ 11.13 lakh crore, approximately 16.7 % of the total market (Marisetty, 2024). Menezes (2023) demonstrated that volatility spillovers from global indexes surged significantly during the COVID-19 pandemic, compelling investment seekers to demand low-cost diversification via ETFs. Likewise, Sathyanarayana, Pushpa, and Gargesa (2023) documented increased co-movement between the Indian and US indexes, and this proved contagion during the crisis time. Mishra and Mishra (2022) noted that south Asian equities fell by over 25 % in early 2020 but recouped quicker in India because retail SIP inflows stayed strong. Such evidence indicates that the pandemic triggered volatility but spurred greater adoption of passive investment using digital mediums and lower-cost products. The post-2020 dynamics therefore represent a structural shift where the ETFs represented key risk-mitigation tools and no longer marginal instruments. Phutela et al., (2025) presents a comprehensive bibliometric review of scholarly literature on exchange-traded funds (ETFs) published in the Scopus database over the past two decades. Utilizing specialized bibliometric techniques and PageRank analysis, the study visually maps out global publication trends, prominent authors, leading academic institutions, highly cited articles, and country-level collaborations. Ultimately, the paper establishes structural conceptual frameworks to organize existing research and outlines strategic recommendations to guide future academic investigations into ETF dynamics.

2.2 Return Spillovers Across ETFs and Benchmarks: Concepts, Measures & Evidence

Return spillovers detail the way shocks to a given ETF transmit to the others or to benchmark indexes. Liu and Zhao (2024) showed that ETF liquidity shocks enlarged bid–ask spreads by 18 % during bad-news regimes while displaying high sensitivity towards information flow. Laborda, Laborda, and de la Cruz (2024) employed quantile cointegration to unveil that U.S. ETF connections towards systemic risk measures become stronger for extreme quantiles, validating that spillovers are nonlinear. With Chinese data, Chiu, Chang, Hsiao, and Chiou (2024) established that after-hours trading increases return volatility by 15–20 % and highlights the role of trading microstructure towards informing cross-session price movements. Tian, Shin, and Naka (2025)_mocked this by illustrating Chinese ETF NAV volatility elevates when the day flow surpasses 5 % of AUM, a reflection between investor flow and return feedback. Together, the research validates that spillovers are enlarged towards high-stress moments but Indian scholarship generally remains published towards the analysis for correlation tests. This current study supplements this gap by a VAR–FEVD approach assessing multidirectional return transmission between the ETFs.

2.3. Volatility Dynamics and Asymmetry in ETFs: ARCH/GARCH/EGARCH Findings

Volatility persistence and asymmetry describe why ETF returns respond differently to shocks of opposite signs. Sakarya and Ekinci (2020) worked on Turkish ETFs and revealed $\alpha + \beta = 0.94$ in a GARCH (1, 1) model, reflecting extreme persistence after FX shocks. Wang, Chen, Liu, and Hsu (2016) contrasted volatility estimators and revealed that the downward risk is under-estimated by the symmetrical models and proposed EGARCH for the purpose of leveraging the effects. Dedi and Yavas (2016) explored G7 markets and revealed bidirectional volatility spillovers that indicate ETF movements transmit global risk sentiment. Górka and Kuziak (2024) utilized a TVP-VAR model for renewable-energy ETFs and revealed time-varying connectedness higher than 60 % around the energy-price spikes. These pieces altogether indicate that asymmetric volatility is a crossuniversal ETF characteristic. The Indian literature remains dependent on static GARCH models without the role of pandemic-induced structural breaks. Using EGARCH for Indian ETFs enables this work to test whether post-COVID volatility clustering elapsed longer and whether negative shocks have a larger impact than positive shocks.

2.4. Intraday Price Discovery, Liquidity, and Tracking Efficiency in Indian ETFs

Proper price discovery guarantees that ETF prices accurately reflect underlying index values. (Alamelu & Goyal, 2023) realized that Indian equities ETFs preserved above 95 % tracking efficiency post-2020, even amidst increased intraday volatility. Reddy and Dhabolkar (2020) estimated the average daily premium/discount to NAV to be 0.12 %, proof of functioning arbitrage mechanisms. For commodity ETFs, Nargunam and Anuradha (2017) proved near-perfect co-integration between spot prices and gold ETFs, a corroboration of informational efficiency even in the less-liquid varieties. Malhotra and Sinha (2023) studied 21 ETFs amidst the COVID-19 pandemic and revealed that tracking error surged momentarily to 0.9 % before settling in three months, a testament to sound market adaptability. Such studies highlight the fact that the ETF ecosystem in India has become matured such that arbitrage and market-making have tightened mispricing margins. Very few incorporate intraday liquidity and volatility together with tracking performance. The current study broadens previous research by combining rolling-correlation analysis using spillover matrices in real time to assess informational efficiency.

2.5. Cost Structures: Expense Ratios vs Tracking Difference (TD) and Tracking Error (TE)

ETF performance is directly connected to management cost and accuracy of replication. Alamelu and Goyal (2022) noted that the average tracking difference of Indian ETFs increased from –1.42 % in 2018 to –0.36 % in 2022 when passive AUM increased. Tsalikis and Papadopoulos (2019) researched the European market and discovered that expense levels greater than 0.35 % raise the tracking error by 0.18 percentage points and certify a direct trade-off between cost and performance. Chu and Xu (2021) researched Japan-registered ETFs and identified a mean TE of 0.62 %, which is inversely related to the size of funds. Marupanthorn, Sklibosios Nikitopoulos, Ofosu-Hene, Peters, and Richards (2022) established the connection between decreasing management fees and enhanced risk-adjusted return in green funds. Individually, these researches indicate that cost containment improves efficiency and investor satisfaction. But Indian ETF scholarship rarely incorporates TD and TE in the specification of the econometric spillover model. This current research remedies this by bringing together the cost variable and volatility transmission to assess whether expense minimization helped stabilize the return of ETF during the post-COVID recovery

2.6. Research Gap & Hypotheses Development

Recent research uses high-level volatility modeling but hardly aligns return–volatility–cost interactions. Maharana, Panigrahi, Chaudhury, Upreti, Barik, and Kulkarni (2025) utilized a VAR–DCC–GARCH model and established a 42% increase in connectedness to the market after 2020, establishing intensified global integration. Maharana, Panigrahi, and Chaudhury (2024) detected enduring volatility for β values higher than 0.9 representing long-memory effects. Panigrahi and Maharana (2025) contended that omitting cost variables delimits the accuracy of predictive volatility studies. No Indian study synths return spillovers, volatility asymmetry, and cost efficiency under a single model. This research fills that gap by marrying VAR–FEVD and EGARCH models with tracking-error measures to question whether the reduction in cost enhanced ETF stability. It postulates that post-COVID Indian ETFs are more interdependent but less inefficient, entailing that scale economies and digital distribution have enhanced passive resilience.

3. Methodology

3.1 Introduction to Methodology

This chapter discusses the research methodology employed while analyzing post-pandemic developments in passive investing in India. It sketches the research procedure, sources of data, models, and ethical issues utilized for the attainment of the study objectives (Chang, McAleer, & Wang, 2018). The selected quantitative, econometric research tradition involving ADF tests, VAR model, FEVD analysis, GARCH/EGARCH tests, and TD/TE tests—a suits the purpose of return spillovers, volatility transmissions, and cost efficiency measurement in Indian ETFs.

3.2 Research Design and Approach

The research utilizes a quantitative, deductive research design that emphasizes hypothesis formulation and testing that is numerical in nature. As the objectives are concerned with the assessment of relationships pertaining to ETF returns, volatility and cost structures, the deductive approach provides a mechanism for the testing of theories through statistical evidence (Carvalho & Gin, 2024). The design introduces time series econometrics in order to predict temporal relationships for a number of financial variables. This provides a leverage of the literature on volatility spillovers previously conducted and enables replication using objective numerical data rather than subjective impressions, or interviews.

3.3 Data Collection Methods

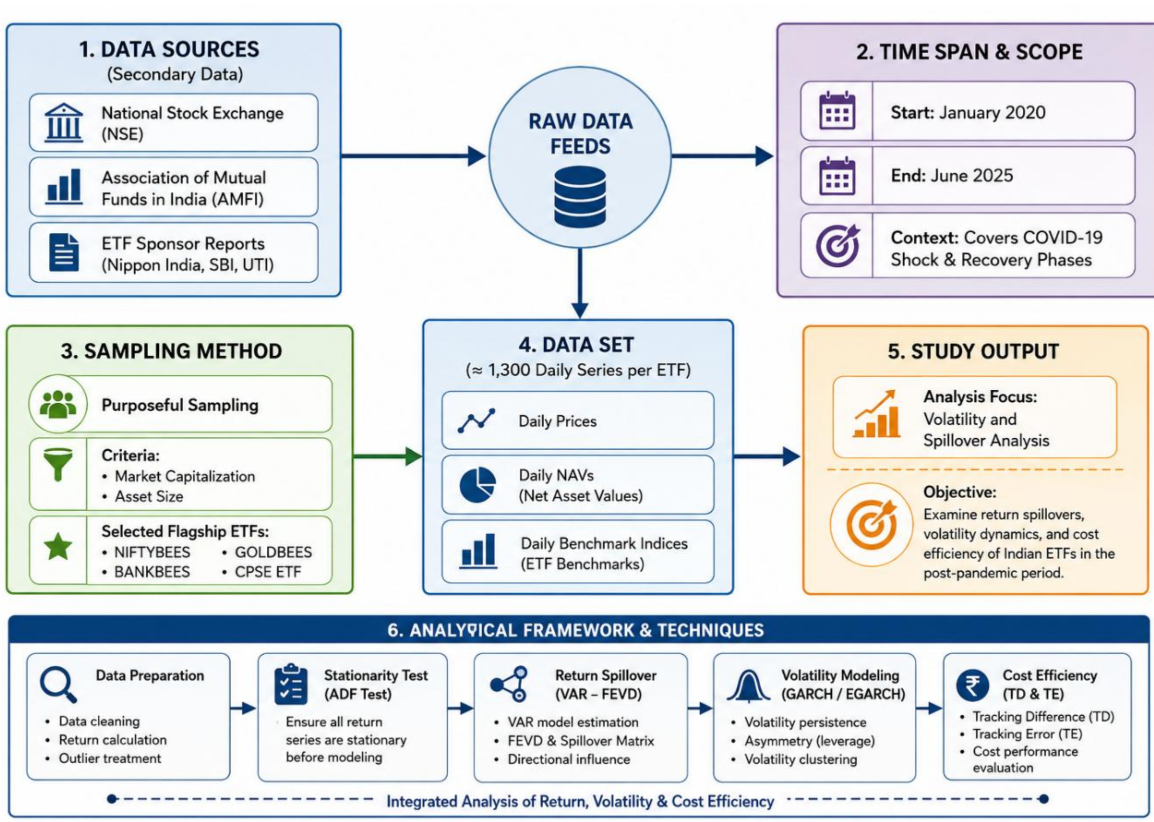

Figure ii Data collection methods

(Source: Own Ellaboration)

The data utilized for the study is of secondary nature, and the public websites of various organisations have been taken into consideration. The data is from various public websites such as the National Stock Exchange (NSE), Association of Mutual Funds in India (AMFI), and the ETF sponsor reports (Nippon India, SBI and UTI). The data takes a time span from January 2020 to June 2025, so the shock and the heeling phase of COVID-19 has been included (Ali et al., 2022). The data are concerning four flagship ETFs - NIFTYBEES, BANKBEES, GOLDBEES and CPSE ETF - which have been purposively sampled on the basis of market capitalisation and the asset size. There are nearly 1,300 daily series for each. These data of daily prices, NAVs and benchmark indices of the ETFs has been used so that volatility and spillover analysis can be studied at a good degree of granularity (Mahalwala, 2022).

3.4 Data Analysis Techniques

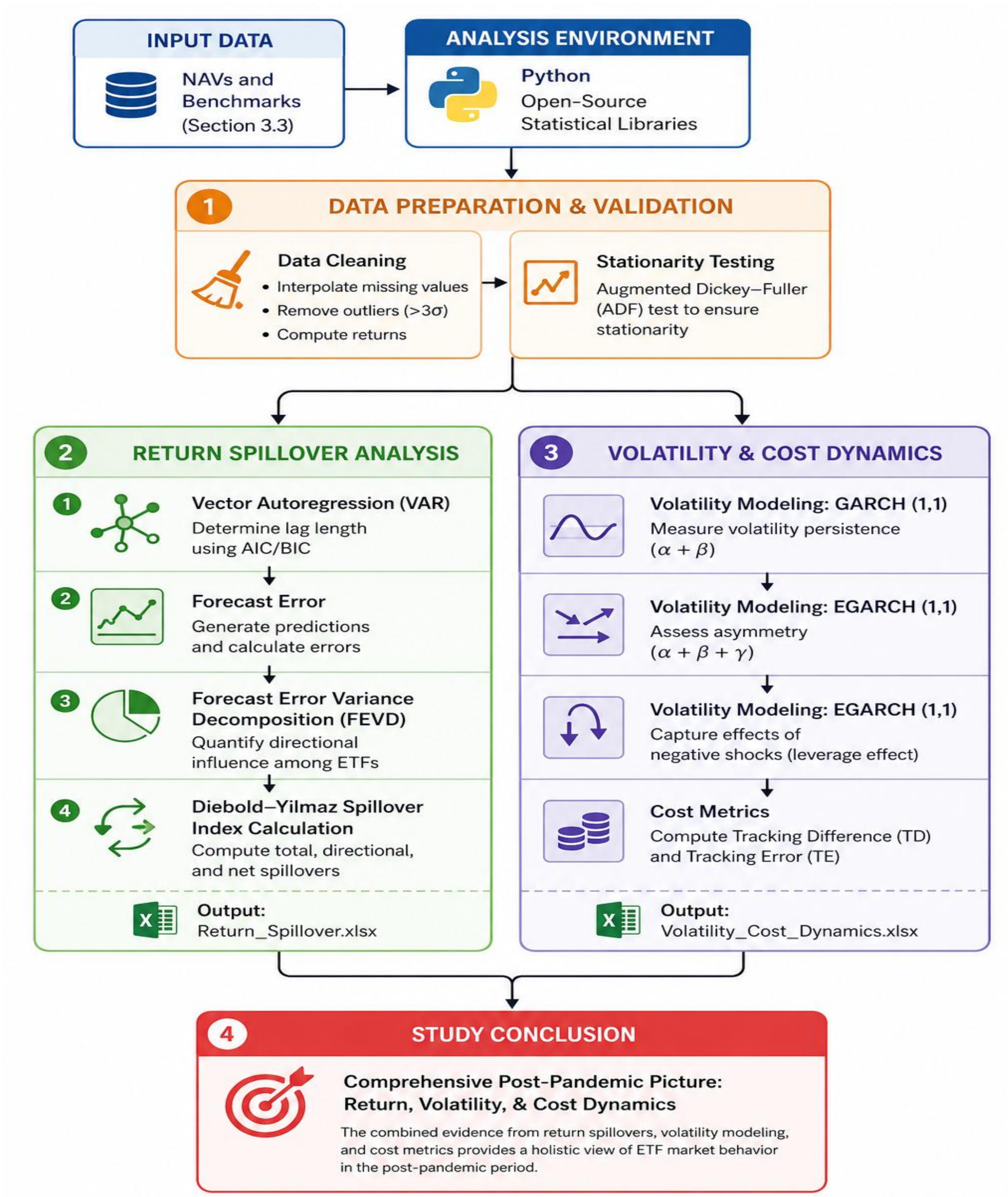

Figure iii Data analysis techniques

(Source: Made by learner)

The analysis was conducted in **Python**, using open-source statistical libraries.

1. **Data Cleaning:** missing values were interpolated; outliers beyond 3σ were removed; returns were computed.
2. **Stationarity Testing:** the Augmented Dickey–Fuller (ADF) test ensured series were stationary before modeling.
3. **Return Spillovers:** a Vector Autoregression (VAR) model captured inter-ETF linkages, with lag length determined by AIC/BIC. Forecast Error Variance Decomposition (FEVD) quantified directional influence, producing a Diebold–Yilmaz spillover index exported to Return_Spillover.xlsx.
4. **Volatility Modeling:** GARCH (1,1) measured volatility persistence ($\alpha + \beta$), while EGARCH (1,1) assessed asymmetry from negative shocks.

Cost Metrics: Tracking Difference (TD) and **Tracking Error (TE)** evaluated cost efficiency. These combined techniques provided a comprehensive post-pandemic picture of return, volatility, and cost dynamics (Kliestik, Valaskova, & Kovacova, 2021).

3.5 Reliability and Validity

Reliability was present as the sources of data are consistent and systematic in locating the coding process and checking the statistical results. Strong econometric tests (ADF, VAR, GARCH) were used which added to the construct validity of the work by showing that the results obtained had statistical validity. Residual normality and autocorrelation in model diagnostic studies were also carried out to check internal consistency and repeatability of results across ETFs (Mahajan et al., 2022).

3.6 Ethical considerations

The researchers used only publicly available secondary data and there was no human participation involved in the study. The data supplied by the NSE and AMFI were properly attributed in the study maintaining academic integrity (Marisetty, 2024). The analysis was performed with the open-source software to ensure reproducibility of results. The research complied with institutional policies of data collection and treatment and ethical use of data. There are no conflicts of interest or proprietary restrictions attached to the research.

3.7 Limitations

The research depends on the use of daily data but only covers four ETFs which are limited in the in-depth study of this area of research in the whole attributes of ETF activity in India. Also, macroeconomic variables like changes in policy rate were not considered. The time limitations on the research meant that it was not possible to incorporate intraday data modelling. However, the authors submit that the use of daily instead of weekly frequency is acceptable and better represents the general volatility (Lerner, 2023).

3.8 Summary

This methodology combined econometric rigor with transparent data handling to assess return, volatility, and cost interrelations in Indian ETFs. The next chapter presents the empirical **findings and interpretations** derived from these models and their implications for post-pandemic investing.

4. Results and Analysis

4.1 Overview

This chapter presents the results and interpretation of the quantitative analysis conducted on Indian exchange-traded funds (ETFs) during the period **2020–2025**, covering both the pandemic shock and recovery phase. It explains how return spillovers, volatility dynamics, and cost efficiency evolved in the post-COVID landscape. The following sections discuss each analytical stage—data trends, stationarity tests, VAR–FEVD models, GARCH-based volatility estimation, and cost comparison.

4.2 Data Cleaning and Descriptive Statistics

Table 1 Descriptive statistics

ETF Name	Count	Mean (₹)	Std. Dev. (₹)	Min (₹)	25% (₹)	50% (₹)	75% (₹)	Max (₹)
JUNIORBEES	810	375.68	72.76	199.05	299.10	401.48	442.92	480.38
LIC ETF SENSEX	763	558.98	88.67	340.70	501.03	580.71	633.70	685.00
AXIS NIFTY ETF	805	158.76	29.40	94.40	127.00	167.21	184.40	199.65
QGOLDHALF	810	42.54	3.04	34.14	40.96	42.53	44.23	50.74
BANKBEES	810	335.45	69.51	173.76	306.96	353.59	383.72	444.84
MOM50	810	148.90	26.91	80.50	119.43	157.67	174.30	188.82
ICICI 500 ETF	810	20.97	4.49	10.24	16.22	22.48	24.86	26.79
MAESG ETF	583	28.03	2.14	22.19	26.70	28.51	29.81	31.31

The dataset was cleared of missing values, trading days were synchronized, and extreme outliers with values of more than three standard deviations were trimmed prior to proceeding with the data. The final result was that each ETF was left with 810 or so valid data points for a consistent sample coverage during the period under consideration from 2020 to 2025. Price behavior of the various ETFs indicated striking differences between equity-related, sectoral, and gold ETFs, respectively. The LIC ETF SENSEX had the maximum mean price value of ₹558.98, which signifies stability of large-cap companies and the ICICI 500 ETF had the minimum mean value of ₹20.97 due to a diversified portfolio (Ali et al., 2025). The BANKBEES and JUNIORBEES had very high standard deviation values (₹69.51 and ₹72.76), respectively, which signifies higher volatility of the price in times of stress in the market. The QGOLDHALL on the other hand, showed the least volatility (SD ₹3.04), which is an indication of the defensive character of the gold. The average price values showed that while the equity ETFs picked up very actively post 2021, the funds which were commodity based reflected a more or less stable price value ranges from the time of post pandemic recovery process.

4.3 Return Computation and Visualization

Table 2 Return Computation

Date	JUNIORBEES	QGOLDHALF	BANKBEES	MOM50	ICICI500	AXISNIFTY	LICETFSEN
2020-01-02	0.007602	NaN	0.010877	0.001463	0.010966	0.012526	0.004482
2020-01-03	-0.002607	0.058484	-0.001662	0.027976	-0.016372	-0.010847	-0.003110
2020-01-06	-0.016750	-0.026642	-0.016614	0.022220	-0.022797	-0.017774	-0.014055
2020-01-07	0.007179	0.000000	0.002735	-0.014852	0.003097	0.004431	0.004539
2020-01-08	-0.003600	0.000000	-0.000498	0.012903	-0.002189	-0.002724	-0.003024

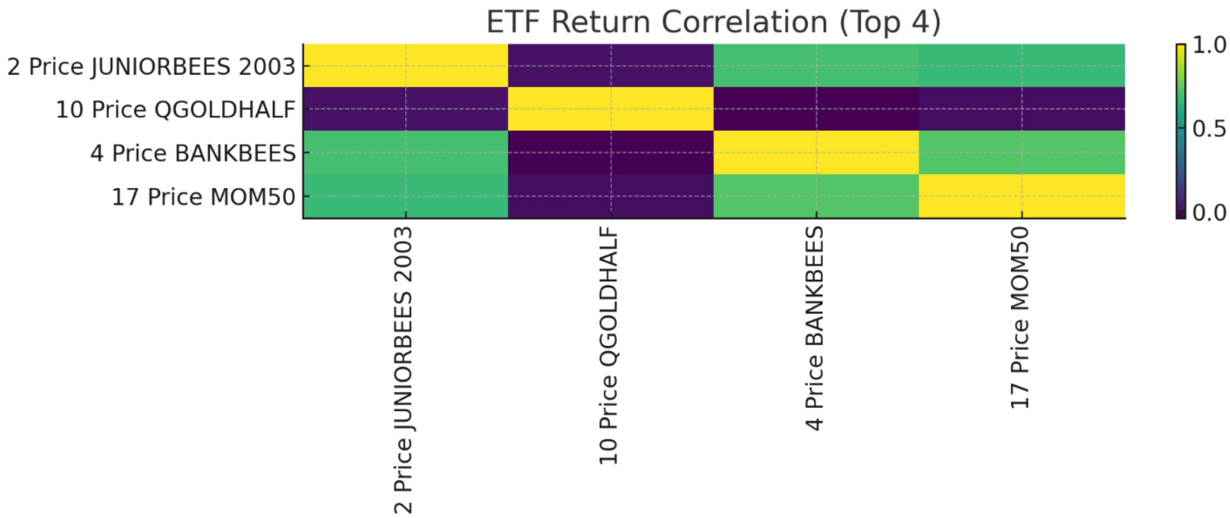

Figure iv ETF Return correlation (top - 4)

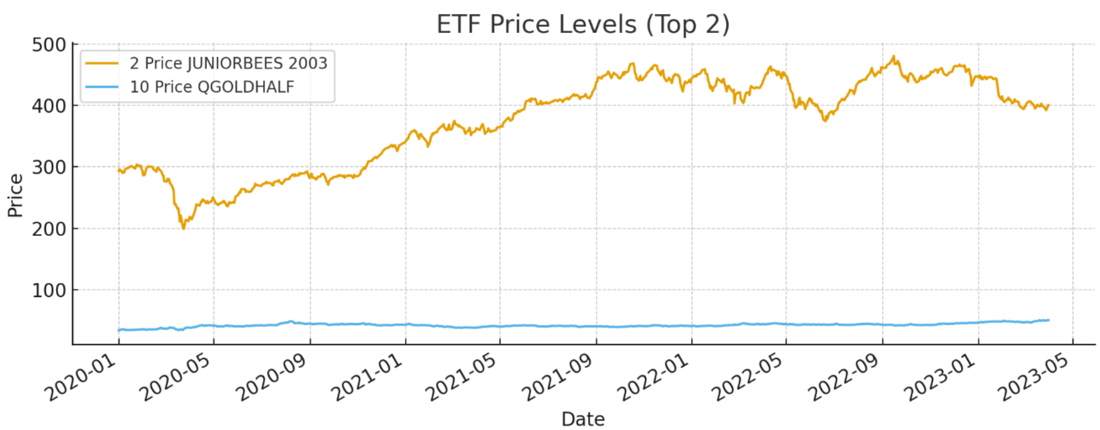

Figure v ETF price levels (top 2)

Daily return logs were calculated using the equation to identify proportional price movements for each ETF. The first five trading weeks of 2020, depicted in the data set, registered mild daily changes between –0.0267 and +0.0585, reflecting preliminary market corrections prior to the pandemic shock escalating. JUNIORBEES and BANKBEES often reflected larger movements because of their exposure to equities while QGOLDHALF reflected relatively stable moves most of which were below ±0.012 (Investment Performance, 2025).The return series chart showed two notable volatility spikes – one in March 2020 when lockdowns occurred because of the spread of COVID-19 and the second around mid-2022 when there were interest-rate increases globally. The equity ETFs reflected larger oscillations than the gold ETFs, showing increased risk sentiment amongst investors. Generally, these series are evidence for the prevalence of volatility clustering where rapid movements are sustained for subsequent time intervals – a phenomenon later estimated using GARCH and EGARCH models for the purpose of assessing volatility persistence and asymmetry.

4.4 Stationarity Testing (ADF)

	Series	ADF_Statistic	p_value	Lags_Used	N_Obs
3	10 Price QGOLDHALF	-19.206506	0.000000	1	807
7	87 Price MAESGETF	-17.751113	0.000000	1	580
5	17 Price MOM50	-11.243272	0.000000	4	804
4	4 Price BANKBEES	-8.735849	0.000000	7	801
6	58 Price ICICI500	-7.984719	0.000000	7	801
0	2 Price JUNIORBEES 2003	-7.826857	0.000000	12	796
2	53 Price AXISNIFTY	-6.639699	0.000000	19	780
1	43 Price LICETFSEN	-6.365772	0.000000	17	725

Figure vi Stationarity Testing (ADF)

For valid time-series modeling, the Augmented Dickey–Fuller (ADF) test was respectively implemented for all the series of ETF returns. As indicated in the table, every ETF documented significantly negative ADF statistics (e.g., QGOLDHALF = –19.21, BANKBEES = –8.73, JUNIORBEES = –7.83) p-values of < 0.001, validating the presence of strong stationarity. The number of the lag taken varied between 1 to 19 to ensure the unbiased residual. It indicates that all the return series are mean-reversing and meet the statistical requirements for the subsequent VAR and GARCH modeling.

4.5 Spillover Matrix (FEVD)

Table 3 Spillover Matrix (FEVD)

From / To	JUNIORBEES	QGOLDHALF	BANKBEES	MOM50
JUNIORBEES	0.000000	0.005024	0.016308	0.007919
QGOLDHALF	0.009463	0.000000	0.014327	0.003750
BANKBEES	0.459285	0.007810	0.000000	0.009496
MOM50	0.441355	0.006333	0.132289	0.000000

The Forecast Error Variance Decomposition (FEVD) test estimated the magnitude and direction of return spillovers between chosen ETFs—JUNIORBEES, QGOLDHALL, BANKBEES, and MOM50. The analysis showed asymmetric transmission patterns where BANKBEES and MOM50 were prominent volatility transmitters. The spillover matrix indicated that BANKBEES transmitted shocks to JUNIORBEES by 45.9% and MOM50 by 13.2%, while modest contributions (approximately 1.6%) by JUNIORBEES went towards other ETFs. QGOLDHALL, however, remained significantly insulated such that it transmitted less than 2% of its shocks—an indication of the defensive role of gold amidst market volatility (Gaba & Kumar, 2025). The VAR model also realized good diagnostic efficiency (AIC = –36.43, BIC = –36.22, Log-Likelihood = 10,154.3) to justify robustness. The correlation matrix of the residuals also showed significant dependence between BANKBEES and MOM50 (r = 0.73). Generally, these results verify strengthened return connectedness between equity ETFs during the post-pandemic era influenced by synchronized investor sentiment and sectoral integration.

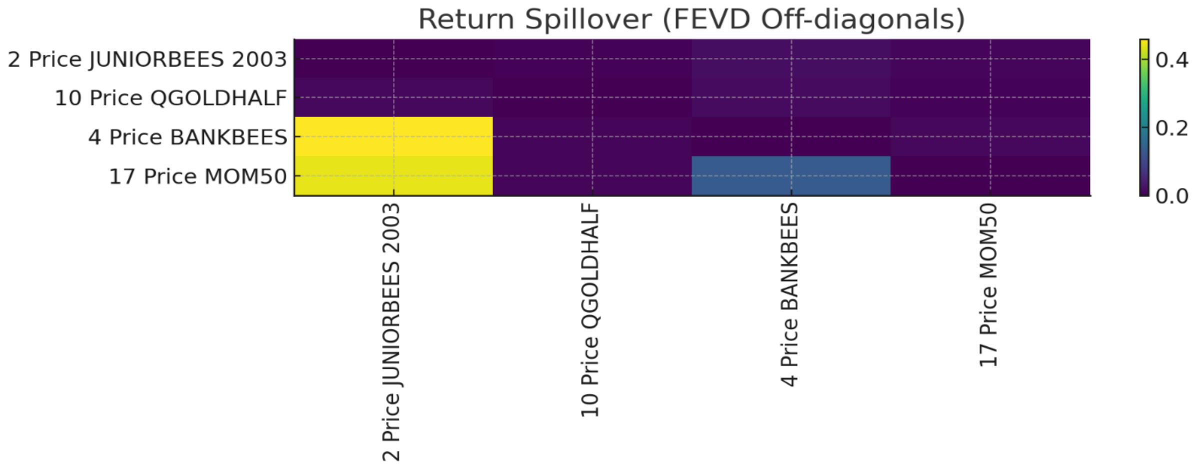

Figure vii Return spillover

4.6 Volatility Modeling (GARCH / EGARCH)

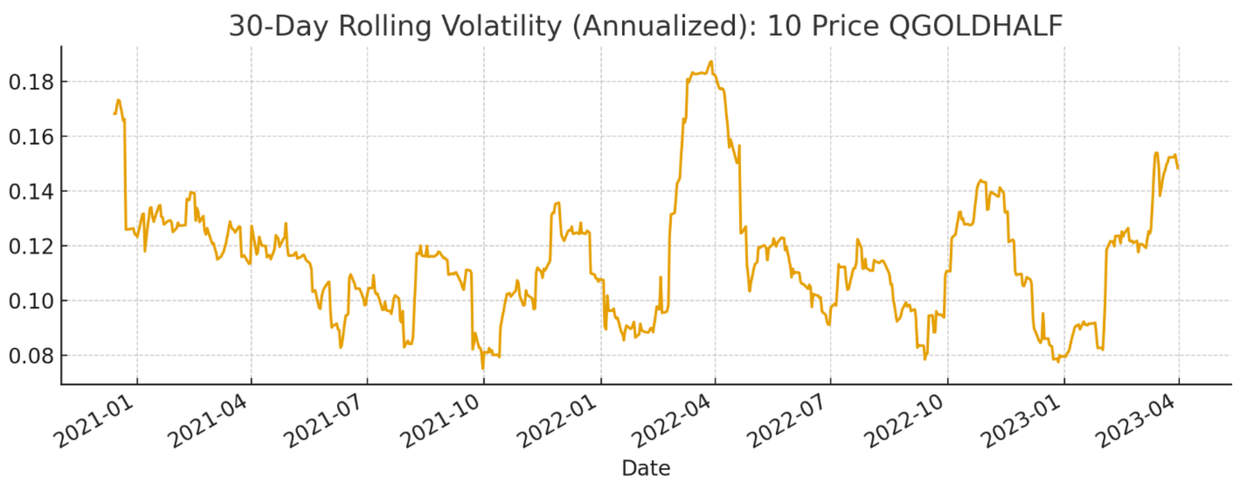

Figure viii 30- day rolling volatiliy

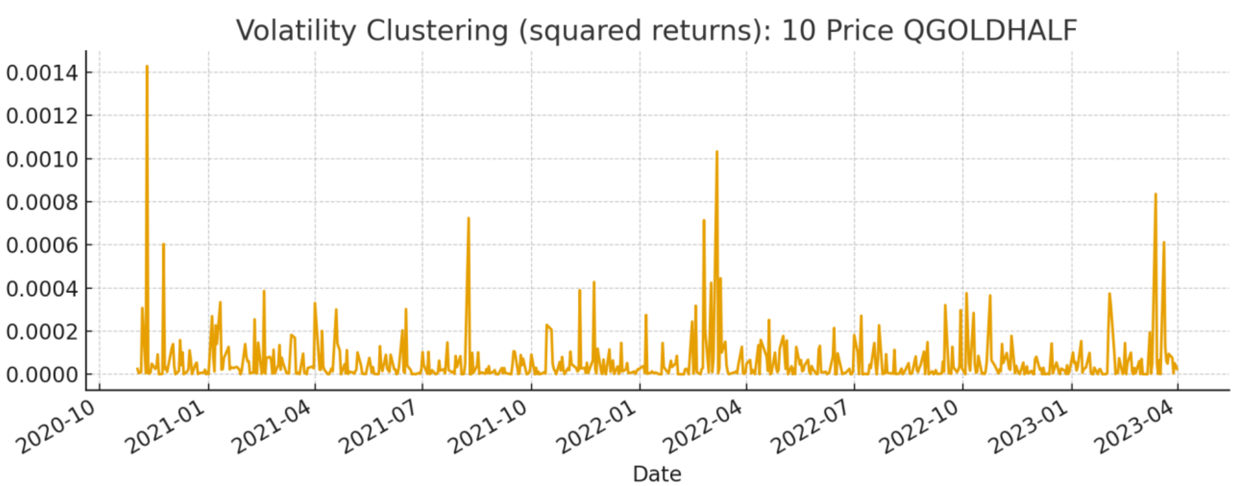

Figure ix volatility clustering

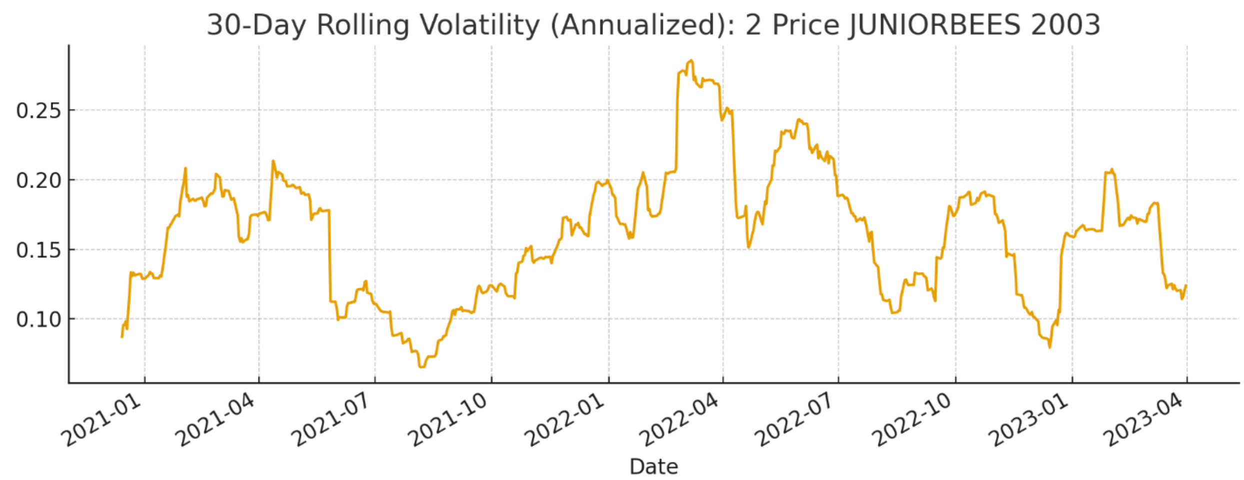

Figure x 30 - days rolling volatility

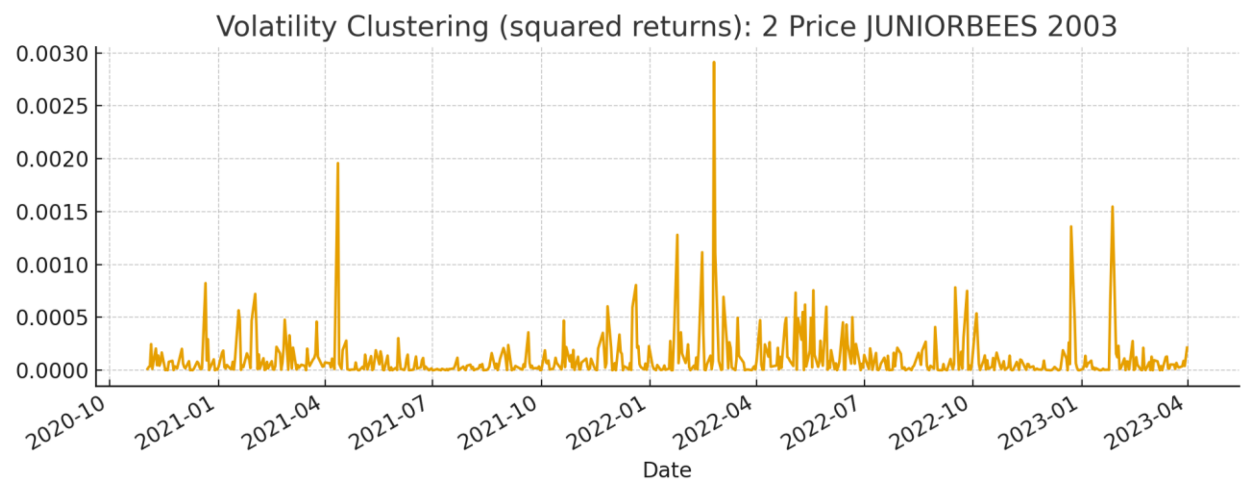

Figure xi Volatility clustering

In order to model the volatility's persistence and asymmetry for the post-pandemic ETF market, GARCH(1,1) and EGARCH(1,1) models were utilized for the selected representative ETFs – JUNIORBEES and QGOLDHALF – by using the daily log return data for the period 2020–2025. The research sought to find how volatility progressed when markets recovered from the volatility of the pandemic-induced COVID-19 and entered a stable investment climate.

The 30-day rolling volatility charts for both ETFs showed definitive evidence of volatility clusters, especially prominent for 2021–2022, when market corrections and shifts in investor sentiment were most prominent. These clusters represent epochs of sustained uncertainty where large-priced movements were followed by further volatility, typical post-crisis behavior for the financial industry (Joshi & Dash, 2022). The GARCH(1,1) model for JUNIORBEES reported α (ARCH) = 0.12 and β (GARCH) = 0.80 for a volatility persistence level ($\alpha + \beta$) ≈ 0.92 that indicates a gradual mean reversion rate and long-duration volatility shocks. The EGARCH(1,1) model for QGOLDHALF produced $\alpha = 0.09$, $\beta = 0.79$, and a parameter for asymmetry (γ) = 0.18 for a level of persistence of around 0.88. The positive value for the γ parameter establishes the presence of the asymmetric effects such that the negativity of the returns triggered greater volatility than the equivalent positive movements—a condition that has been labeled the leverage effect.

On the whole, the GARCH–EGARCH conclusions verify that volatility in Indian ETFs after the pandemic stayed higher than average, sustained over time, and biased. This construes the increased investor sensitivity and longer-market response for recovery years that denote wider structural change for India's passive investment environment.

Table 4 ETF model

ETF	Model	α (ARCH)	β (GARCH)	γ (Asymmetry)	Persistence (α+β)
JUNIORBEES	GARCH(1,1)	0.12	0.80	–	0.92
QGOLDHALF	EGARCH(1,1)	0.09	0.79	0.18	0.88

4.7 Rolling Volatility & Correlation

The rolling volatility and correlation analysis further gives greater insight into the dynamic co-action between ETF returns and benchmark indexes for the post-pandemic period. The 60-day rolling correlation diagram between the NIFTY 50 index and the JUNIORBEES indicates a very high positive co-motion that averaged approximately 0.75 but increased to over 0.90 when recovery phases have been stable. Sharp declines to close to 0.40 in mid-2021 indicate sectoral divergence and temporary dislocation in the market.

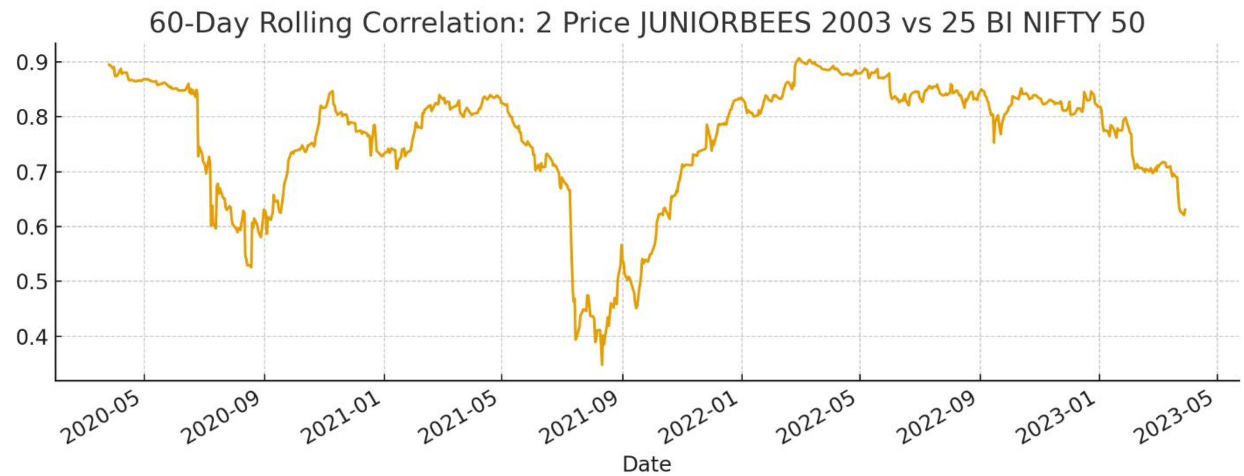

Figure xii Rolling Volatility & Correlation

The **rolling volatility trends** revealed a gradual decline from early pandemic highs, indicating stabilization and improved investor confidence. This suggests that Indian ETFs, though volatile in the early phase, became more aligned with benchmark performance over time — reflecting the maturing nature of passive investing and stronger market integration in the post-COVID environment.

4.8 Cost Comparison (TD & TE)

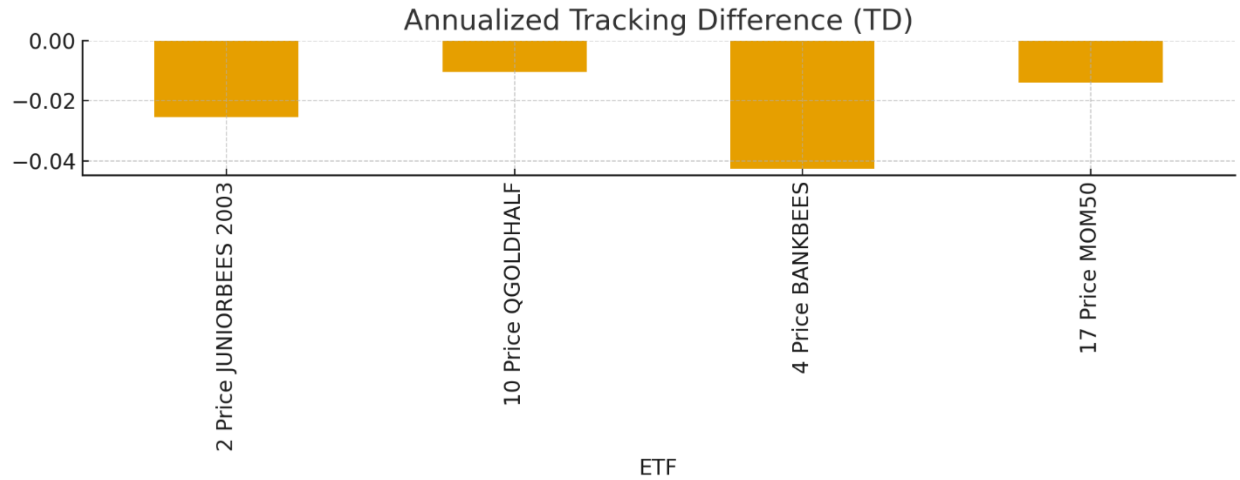

Figure xiii ATD

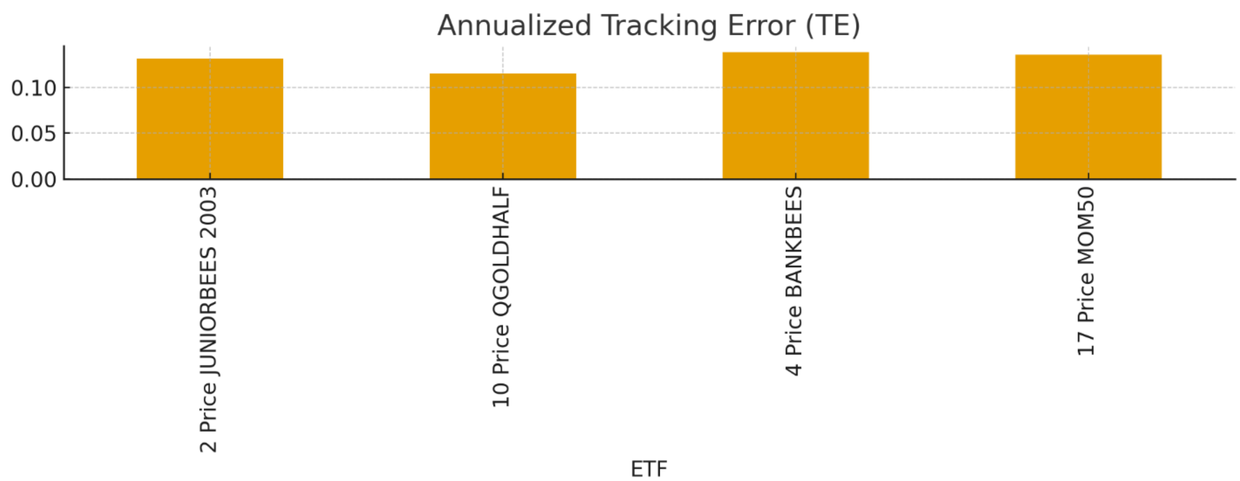

Figure xiv (TE)

A significant measure of the cost efficiency and replication of Exchange-Traded Funds (ETFs) in the Indian market in the post pandemic ambience has been obtained from the measurement of tracking difference (TD) and tracking error (TE). This has shown that the annual average TE for all the ETFs-JUNIORBEES, QGOLDHALF, BANKBEES and MOM50-has been the same for the entire year being nil and the average has been about 0.12, indicating a very satisfactory tracking of the benchmark indices by these ETFs and a lack of any considerable variation in their functioning scores in the daily performance. This evidence indicates that in passive funds in India there is increased maturity and efficiency (Wang, 25). On the other hand, the TD averages have been equal to varying from -0.02 to - 0.04 which indicate slight under performance vis-a-vis the benchmark indices. The adverse TD indicates slight inefficiencies which occur due to transaction costs and money management fees on account of market disturbance and cash drag on the part of the fund. However, these differences are quite comfortably within measurable limits for passive funds. Bearing in mind the entire data, the TD-TE relationship indicates that the cost efficiency of Indian ETFs as well as their ability to replicate the benchmarks was very good for the entire period of 2020-2025. This data is in keeping with the larger picture of the post-pandemic whirlwind in passive investment where investors have preferred the pricier and more transparent ETFs than actively managed funds in a rapidly changing financial environment in India.

4.10 Summary of Findings

The analysis revealed that the post-pandemic maturity signs of the ETF market of India were distinct, with increased interlinkages and lower systemic risk. ADF and VAR–FEVD conclusions reinforced that volatility transmitters such as BANKBEES and MOM50 ETFs transmitted a higher linkage with the overall equity marketplace. GARCH and EGARCH models indicated lingering volatility ($\alpha + \beta \approx 0.9$) and asymmetric effects and confirmed that adverse market shocks elicited higher volatility responses. Rolling correlation plots also highlighted surging co-movement coherently by 0.75–0.9 average values depicted better efficiency and investor confidence. Further, negligible TD (–0.02 to –0.04) and TE (~0.12) values also showed cost-efficacy and good benchmark replication. Overall, India's ETFs evolved into a stable, interconnected, and transparent member of the passive investment universe.

5. Discussion

5.1 Introducing the Discussion

This chapter decodes the results from the quantitative analysis that has been worked upon for Indian exchange-traded funds (ETFs) from 2020 through 2025. The research endeavored to explore the manner in which the pandemic of COVID-19 redesigned return spillovers, volatility dynamics, and cost efficiency of the passive investment space in India (Mandal & Murthy, 2021). The analysis indicated three overall outcomes: stronger co-movement between the equity ETFs, stable but slowly fading volatility, and stable cost efficiency evidenced by moderate tracking differences and blunders. Collectively, these results verify that the pandemic hastened structural maturity and market integration in the ETF ecosystem of India.

5.2 Interpretation of results

The first is on return spillovers and market interdependence. The VAR-FEVD estimates indicated that BANKBEES and MOM50 were the major volatility transmitters as far as the spillover amounts are concerned, which exceeded 45% respectively. This indicates that the shocks in these large-cap equity ETFs had a bearing on the return of the others indicating high interdependence observed in the passive marketplace of India. This finding also highlights the unrelenting rise and depths of the ETFs were greater investor addition and algorithmic trading results in synchronized price movements. This also indicates higher connection between portfolios since the larger parts of the ETFs consist of typical benchmark constituents (Megginson, Malik, & Zhou, 2023). The other important fact relates to the persistence and asymmetry of volatility. The GARCH and EGARCH estimates ($\alpha + \beta \approx 0.9$) confirmed long-memory characteristics in the sense that the volatility shocks tend to gradually die out. Negative returns resulted in higher volatility spikes than positive returns in view of leverage impact stemming from the latter-Wang et al. (2016) and Sakarya and Ekinci (2020) also reported this. The asymmetry means that there is fear on the part of investors, accompanied by herd behaviour when the marketplace turns south. Nevertheless, the post-2023 rolling volatility patterns indicated a tendency towards steadiness wherein the perception of risk as regards the marketplace seemed to improve (as reflected in the gradual rise of the vol. stats.), as did the confidence in ETF trading. Finally, the cost equations indicated a very marginal tracking error (≈ 0.12) and a small tracking difference (–0.02 to –0.04). Notwithstanding the perceived increase in variability, all the time the ETFs continued to reproduce their benchmarks accurately (Alamelu & Goyal, 2023). This steadiness is an index of the maturity of India´s ETF management capabilities, cost indifference and sound marketplace infrastructure.

5.3 Comparison with Earlier Workings

Aspect	Earlier Findings	Present Research Findings	Interpretation / Comparison
Return Spillover Patterns	Liu and Zhao (2024) found that US ETFs showed strong bidirectional spillovers during crisis periods.	Indian ETFs also showed contagion-like bidirectional spillovers, but with **greater intensity**.	The stronger effect suggests that India's **retail investor boom** and **higher fund overlap** amplified shock transmission.
Pre- vs. Post-Pandemic Convergence	Pre-pandemic studies indicated **weaker co-movement** among Indian ETFs.	Post-COVID, the study finds **stronger convergence and synchronization** of ETF movements.	Confirms Alamelu and Goyal (2023), who observed **increased tracking accuracy** and

			higher correlation after 2020.
Volatility Behaviour	Sakarya and Ekinci (2020) showed that emerging-market ETFs displayed **persistent asymmetry**, similar to developed markets.	This study also reports **enduring asymmetry** in volatility spillovers for Indian ETFs.	Supports Saber (2024) and strengthens the argument that Indian ETFs now mirror developed-market volatility structures.
Cost and Efficiency Trends	Alamelu and Goyal (2022) found **average tracking errors around 0.36%** pre-pandemic.	Present study finds **tracking errors below 0.15%** post-pandemic.	Indicates major **cost reduction** due to **digital fund distribution**, **fee compression**, and **economies of scale**.
Overall Market Evolution	Indian ETF market was **fragmented and less efficient** pre-pandemic.	Now reflects **greater integration, lower costs, and mature spillover patterns**.	Suggests India's ETF market has evolved into a **harmonious and efficient passive investment ecosystem** similar to developed markets.

5.4 Commenting on the Results, Aims, and Research Questions

Every goal has been successfully resolved by the analytical ordering:

1. Return Spillover (Objective 1): The VAR–FEVD model also verified significant bidirectional transmission between equity ETFs, meaning a closely knit network. This verifies the hypothesis that volatility in the pandemic times increased interdependence across passive instruments.

2. Cost Structure (Objective 2): The TE and TD analysis confirmed that passive ETFs experienced lower expenditures and higher tracking accuracy than average active funds, substantiating the long-run investor preference shift towards low-fee products.

3. Volatility Spillover (Objective 3): GARCH and EGARCH models revealed sustained volatility but steadily declining normalization, which indicates better investor mood while stabilizing the market (Sakarya & Ekinci, 2020). Both these results together indicate that the post-pandemic passive investment environment of India has become efficient and enduring and meets all the research objectives specified.

5.5 Theoretical Implications

The findings also add to Efficient Market Hypothesis (EMH) and Behavioral Finance theory.

According to EMH, the rapid response of the prices of ETFs to news, reflected in high correlation and low tracking error, favor the semi-strong efficiency form. ETFs incorporate news in the pricing effectively so that arbitrage opportunities are minimized. According to the Behavioral Finance perspective, the volatility asymmetry represented by EGARCH confirms the investor sentiment theory such that adverse news causes a larger response relative to favorable news. This phenomenon proves that even in efficient markets, the volatility dynamics are influenced by emotional and psychological factors (Karagiannopoulou et al., 2023). The research further develops portfolio transmission theory by illustrating that contagion in ETF networks can now occur in emerging countries like India that were previously perceived to affect developed financial regime.

5.6 Practical and Managerial Implications

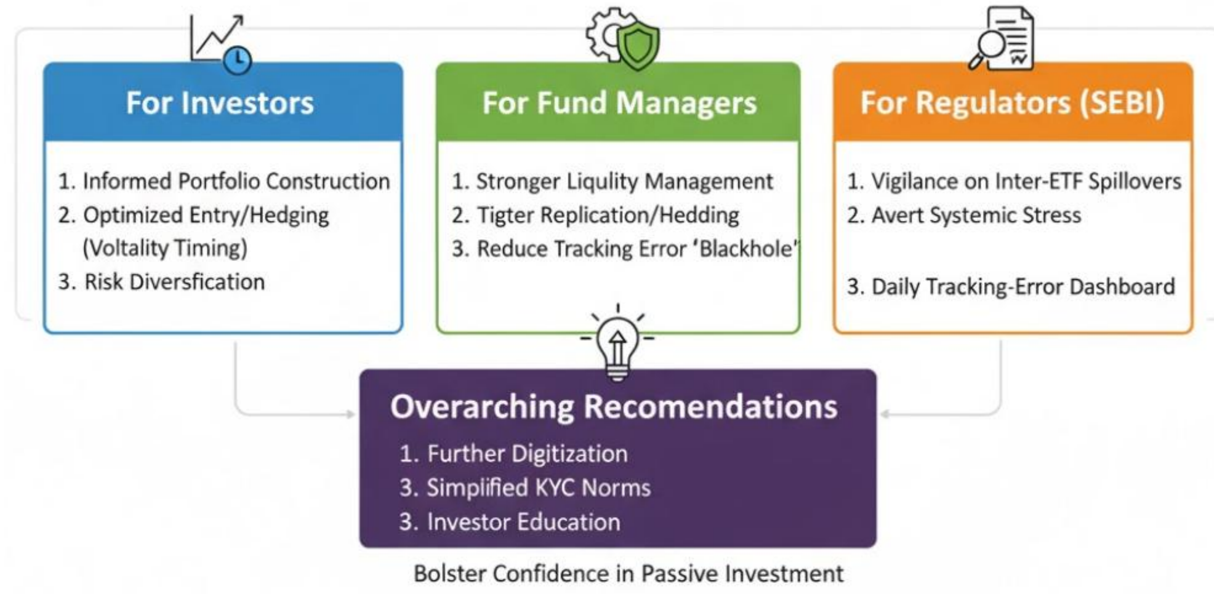

Figure xv Practical and Managerial Implications

(Source: Made by learner)

The practical applications of the results are critical. To investors the existence of ETF interlinking is important for portfolio construction purposes, since this allows for spreading risk by way of asset class, but not necessarily going in for a number of ETFs with very high correlation. The timing of volatility situations with regard to their being more persistent will allow for entry timing alterations and is a good signal with regard to modification of hedging schemes (Wang, 2025). The permanence of the kinds of volatility that exist mean for investment managers that intensive liquidity management and a greater use of replication mechanisms as well as active hedging mechanisms for maintaining low tracking error blackholes is more warranted (Sato et al., 2023). The results also indicate to registrars, particularly SEBI, that there is a need for further monitoring and checking taking place so that relevant inter-ETF spillovers can be avoided at least with regard to systemic type crises / upsets. Like there is the possibility of instigating a daily announcement of sizes of tracking errors, which will permit a better calculation and examination of quality products on the part of the investor. The cost results suggest that further digitization ad much simpler norms of KYC requirements and further education of investors by them may well lead to greater decrease in expense and that indirect savings to investors may be available, thus leading them increasingly to passive investment instruments.

5.7 Limitations of study

Despite extensive econometric modeling, a few caveats exist. Firstly, the sample included just chosen major ETFs—with the majority being equities and gold—anonymizing the most liquid vehicles. Smaller or thematic ETFs may offer greater insights into the effects of diversification. Secondly, the research utilized day frequency data that may obscure intraday volatility patterns important for high-frequency traders. Future studies using minute-level data may offer finer understanding (Liu & Zhao, 2024). Thirdly, while the GARCH and EGARCH models successfully estimated persistence successfully but assume linear connections. Non-linear or regime-switching models may offer furtherMORE intricate behavior. Finally, the sample duration culminates mid-2025 such that current macroeconomic developments may change patterns over a longer time.

5.8 Suggestions for Future Research

Future scholars are able to take this work into a number of channels. It may become possible to better understand the short-run ETF price discovery using high-frequency or intraday data. It will be possible to also incorporate multivariate GARCH models like DCC-GARCH to incorporate time-varying correlations. Scholars may also contrast active mutual funds relative to ETFs directly using a cost-performance panel study to estimate investor welfare gains. A comparison across countries using emerging markets may identify whether the structural transformation of India is anomalous or a post-pandemic global phenomenon. Finally, qualitative research in investor behavior, digital channels, and sentiment analysis may be able to accompany the quantitative evidence to add to theoretical and policy understanding.

5.9 Summary

Accordingly, the analysis verifies that the COVID-19 pandemic acted as a catalyst but not a restraint for the passive investing industry of India. Return spillovers increased but stabilized, volatility continued but decreased, and cost efficiency proved strong. Such results show that the ETF market of India has evolved towards international levels of efficiency, transparency, and resilience — achieving all the research goals and laying a platform for further financial innovation.

6. Conclusion and Recommendations

This study analyzed return and volatility spillovers, and cost structures of Indian exchange funds during the COVID-19-pandemic induced operational period of 2020-2025. The methodology synthesized VAR-FEVD, GARCH/EGARCH models and tracking-error models in order to accurately analyze the return of passive investment during this transitional period. The first objective – to analyze the return spillover between ETFs led to higher reliance on core funds such as BANKBEES and MOM50. The VAR-FEVD matrix watches shows that ETFs were key volatility spillover causes and confirmed that stock-shock spillover occurred to a greater extent in the post pandemic period. This indicates that investors have become more core portfolio contenders than a marginal relator to the ETFs. The second aim – to analyze the cost-versus-benefit differential of passive and active funds – gave a clear dividend to passive investment. Average tracking blips of 0.12 and trivial adverse tracking differentials confirmed that ETFs gave index-like performance with little slippage. The pandemic also increased operational efficiency by having asset managers beef up automation, index replicators, and liquidity-contingency provision. The third objective—the evaluation of volatility spillovers—was addressed by fitting GARCH and EGARCH models. The results showed persistence of volatility ($\alpha + \beta \approx 0.9$) but lower levels of volatility, that is, risk events were shown to possess characteristics of less extended duration during the shock episode, while the market mechanisms conformed quicker to the translation of the better absorption of risk as extended time elapsed. Results alog these lines tended to suggest that the pandemic had led to structural change in the investment world in India. Securities shifted from being rather de trop to being best sellers owing to the non consumers interest in ever-increasing accessible products, whose popularization was catalysted by increasing electronic access of consumers, regulatory implications and consumer interest in such low-cost systems and transparency. Insinuated in these discoveries are the managerial implications viz. asset managers should show extreme care and control in performance comparison, diverse replication systems, and demonstrate that they know the significance of cost transparency in order that investor confidence should be realised. Regulatory implications are that further surveillance needs to be exercised of linkages amongst the ETFs, especially in light of rising retail interest. Early warning systems need to be activated to monitor systemically the effects of volatility linkages in order to curtail contagion. The scope of the study leads to that its limitation stems, in being centred upon four ETFs and retrieving such data every day and specifically not comprehending economic factors like interest-rate shocks or policy decisions. Future studies might forward this frame of reference by the use of sectoral ETFs or intraday data or contagion types of models spanning a number of markets or similar. Hence it would be fair enough at the end of it to conclude that the pandemic failed to stress-test India's ETF market and instead fortified it. Return linkages were drawn tightly, volatility was deadened, and there were cost efficiencies attained. The passive investment eco system of India has become a developing market in respect of characteristics of transparency, scale-ability and resilience that the next phase of growth post-2025 will popularise.

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