Excel International Journal of Technology, Engineering and Management
2026; Volume -13, Issue-2_Page_295-305

Excel International Journal of
Technology, Engineering & Management
Journal homepage: exceljournals.org.in
ISSN ONLINE: https://portal.issn.org/resource/ISSN/2349-8455
ISSN PRINT: https://portal.issn.org/resource/ISSN/2348-0378

Structural Break Analysis of Indian IT Sector Stocks Using ARIMA: Evidence from the COVID-19 Pandemic

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DOI Link: https://doi.org/10.64971/j.cph.eijtem.v13.i2.29.2026

Abstract:

Five major NSE-listed Indian information technology companies — Infosys (INFY), HCL Technologies (HCLTECH), Tech Mahindra (TECHM), Wipro (WIPRO), and Tata Consultancy Services (TCS) — form the empirical focus of this investigation into structural breaks in stock price dynamics. The Autoregressive Integrated Moving Average (ARIMA) framework is applied across a decade-long horizon from January 2016 to January 2026. India's national lockdown on March 24, 2020, and the COVID-19 pandemic declared a global health emergency on March 11, 2020, together constitute the primary macro shock examined here. Drawing on the full Box-Jenkins methodology alongside the Chow test, Zivot-Andrews test, and Bai-Perron multiple structural break tests, the paper documents how the dynamics of Indian IT markets shifted permanently during the pandemic.

All five closing price series are confirmed as integrated of order one (I(1)) by Augmented Dickey-Fuller, KPSS, and Phillips-Perron tests, with log returns satisfying stationarity under all three criteria. AIC-guided ARIMA model selection produces ARIMA(2,1,2) for INFY and WIPRO, ARIMA(3,1,2) for HCLTECH, ARIMA(2,1,3) for TECHM, and ARIMA(0,1,0) for TCS — the last of these reflecting random walk behaviour in the most liquid stock. At both COVID event dates, Chow test F-statistics are strongly significant across all five stocks (all $p < 0.001$), while Bai-Perron PELT analysis turns up between 9 and 11 endogenous break points per stock, with a notable concentration in March-June 2020 and later pandemic waves. Mean prices rose 71% to 161% from pre-COVID to post-COVID, and Levene's test confirms statistically significant variance expansion across all stocks. On the out-of-sample window, ARIMA forecasts return negative R^2 values for every stock — a consequence of parameter instability after the structural break. Engle's ARCH-LM test further reveals significant conditional heteroskedasticity in all ARIMA residuals, pointing toward GARCH-family extensions for volatility modelling. Taken together, the results show that while ARIMA can detect these permanent regime shifts, it is ill-equipped to accommodate them fully — establishing a rigorous econometric baseline for more advanced forecasting work.

Keywords:
ARIMA; Structural Break; COVID-19; NSE India; IT Sector; Stock Price Forecasting; Bai-Perron; Pre-Post COVID Regime

1. Introduction

India's information technology sector holds a position of considerable strategic importance, both domestically and within global technology supply chains. With a contribution of roughly 7.5% to GDP and a workforce exceeding 5.4 million [1], the sector — led by Tata Consultancy Services, Infosys, Wipro, HCL Technologies, and Tech Mahindra — has delivered strong long-run growth while periodically exposing investors to sharp macro-driven corrections. The NSE Nifty IT Index captures this dynamic well: during the COVID-19 pandemic it traced one of the most dramatic boom-bust-boom arcs in its history, falling roughly 30% in early 2020 before surging to nearly three times that trough by 2021-2022, as the global pivot to digital infrastructure gathered pace.

Few macro shocks in recent decades have matched the COVID-19 pandemic for speed and geographic reach. Designated a Public Health Emergency of International Concern on January 30, 2020 and declared a pandemic on March 11, 2020 [2], it compressed into weeks what normal business cycles spread over years. India's announcement of a national lockdown on March 24, 2020 compounded the disruption further. For empirical researchers working in financial econometrics, this sequence of events is methodologically attractive: the dates are precisely known, the shock was clearly exogenous, and the before-and-after contrast is sharp — a near-ideal setting in which to test whether time series models detect and adapt to structural breaks.

Systematised by Box and Jenkins [3] and since refined through decades of empirical application [4, 5], the Autoregressive Integrated Moving Average (ARIMA) model retains its status as the default benchmark in time series forecasting, even as machine learning alternatives multiply [6, 7]. Its transparency, theoretical grounding, and well-developed diagnostic toolkit make it hard to displace as a reference point. That said, ARIMA rests on an assumption of parameter stability that becomes untenable once a structural break has altered the data-generating process — a limitation that financial crises, pandemics, and sharp policy interventions repeatedly expose [8, 9].

Against this backdrop, the paper asks: do the structural breaks triggered by COVID-19 fundamentally reshape the statistical processes governing Indian IT sector stock prices, and if so, how do ARIMA model behaviour and forecast accuracy differ across the pre-COVID and post-COVID regimes? Four specific contributions follow from this question.

1. It offers the first decade-long (2016-2026) ARIMA-based structural break analysis conducted at the individual stock level for NSE-listed IT companies, rather than relying on the broad index or cross-sectoral aggregates used in prior work [9, 10].
2. It brings together three structural break tests — Chow [11], Zivot-Andrews [12], and Bai-Perron [8, 13] — allowing triangulated confirmation of break dates that no single-test approach can provide.
3. It captures stock-specific heterogeneity in how COVID-19 break patterns manifest across five companies spanning the full range of Indian IT business models, surfacing nuances that aggregate index studies tend to obscure [14, 15].
4. It produces a statistically validated ARIMA baseline for Indian IT stocks that incorporates post-2020 data, against which LSTM, Transformer-based, and hybrid forecasting architectures can be rigorously compared in subsequent research [16, 17].

Section 2 surveys the relevant literature. Section 3 describes the data, preprocessing steps, technical indicators, and normalisation procedure. Section 4 sets out the ARIMA and structural break methodology. Section 5 presents and interprets the empirical results. Section 6 draws conclusions and outlines directions for future work.

2. Literature Review

2.1 ARIMA Models in Stock Market Forecasting: Recent Evidence

ARIMA-based stock market forecasting has a well-established track record in financial econometrics. Senol and Ozturk [7] showed that ARIMA retains its competitiveness as a short-horizon benchmark across several emerging market indices. Within India specifically, Dadhich et al. [14] — in a Springer-published contribution — fitted ARIMA models to both BSE and NSE index data, arriving at ARIMA(0,1,4) for NSE and ARIMA(3,1,2) for BSE. The BSE order, interestingly, matches the range of orders obtained in the present study for individual IT stocks.

Varshney and Srivastava [18] set ARIMA against ANN models for NSE index prediction and found ARIMA held its own at shorter horizons, though its inability to capture nonlinear patterns remained a recurring concern. A Springer benchmark study [15] pitting ARIMA against Facebook Prophet and stacked LSTM found ARIMA delivered dependable baseline accuracy for blue-chip IT stocks. More recently, Rahi et al. [17], writing in Springer's Innovations in Data Analytics series, combined ARIMA with option-chain data and technical indicators for NSE stocks and reported around 92% accuracy — a result that highlights ARIMA's value as a building block in hybrid systems even where its standalone performance reaches a ceiling.

Looking beyond India, Fang et al. [16] argued that ARIMA continues to serve as an indispensable reference point in financial time series forecasting precisely because its failure modes are well understood, while He et al. [6] found that ensemble architectures incorporating ARIMA components routinely outperform purely data-driven deep learning models on financial data.

Both observations reinforce the case for establishing a careful ARIMA baseline before moving to more complex methods.

2.2 COVID-19 Structural Breaks in Financial Markets

COVID-19 left a heavy imprint on the structural break literature across both developed and emerging markets. Applying Bai-Perron tests to U.S. daily data from January 2019 to June 2020, Yong and Cao [19] in Springer's Financial Innovation journal pinpointed a single significant break in price volatility for both the S&P 500 and DJIA, placing it on February 21, 2020 — weeks before the WHO pandemic declaration. Ndako et al. [20], working across 16 countries, documented 10 to 12 structural break dates per market using the same Bai-Perron framework, with COVID-related breaks prominent across Asian economies.

Indian market evidence points in the same direction. Bhatia [9] applied multiple structural break tests to NIFTY and SENSEX and found lasting reductions in market efficiency around pandemic break periods. Maiti [10] used an event study design on NIFTY50 and its sectoral components, reporting that IT and pharmaceutical stocks diverged sharply from financial services and consumer goods in how they absorbed the shock — an observation that directly motivates the stock-level, rather than sector-index, focus adopted here. Manu and Shetty [21] modelled NSE sectoral indices with EGARCH and documented asymmetric volatility patterns and structural persistence that were particularly pronounced in technology stocks.

Guru and Das [22] tracked uncertainty spillovers across Indian stock markets and found elevated volatility transmission persisting well past the initial lockdown — a pattern consistent with the multiple Bai-Perron breaks identified in the present study running through 2020-2022. Methodological corroboration comes from Bariviera et al. [23], whose Springer-published analysis of NSE sector responses to pandemic uncertainty confirmed heterogeneous sectoral transitions and provided a direct precedent for the multi-break approach taken here.

2.3 Structural Break Testing: Methodological Framework

Three tests underpin the structural break battery used in this paper, each addressing a distinct identification challenge. The Chow [11] test handles situations where the candidate break date is known in advance — here, both the WHO declaration and India's lockdown qualify. The Zivot-Andrews [12] test drops the requirement for a pre-specified date, instead identifying a single unknown break endogenously by minimising the ADF t-statistic across all candidate points. Bai and Perron [8, 13] extended this logic to settings — such as a multi-wave pandemic — where more than one break is plausible, providing confidence intervals around each estimated break date.

A recent application by Bui et al. [24] to ASEAN stock markets is directly relevant: they found COVID-19 produced more breaks per market than either the 2008 global financial crisis or the 2013 taper tantrum, with Asian markets averaging 8 to 12 endogenous breaks over 2019-2022. That range sits squarely alongside the 9 to 11 breaks per stock identified in the present study, offering independent validation of both the methodology and the order of magnitude of the results.

2.4 Research Gap and Positioning

Prior literature has addressed ARIMA forecasting [14, 15, 18], COVID-19 market impacts [10, 21, 22], and structural break testing [19, 20, 24] as largely separate lines of enquiry. What remains absent is work that pulls all three together at the individual stock level for the Indian IT sector, across a full decade that spans the pre-pandemic phase, the crisis, and the subsequent recovery. Existing studies tend to rely on broad index data, limit their temporal scope to 2020-2021, or employ a single break test. The present study fills this gap through stock-level, multi-method analysis covering five of India's most economically consequential IT companies over ten years.

3. Data and Methodology

3.1 Data Description

Daily historical closing price data are drawn for five NSE-listed IT companies: Infosys Limited (INFY), HCL Technologies Limited (HCLTECH), Tech Mahindra Limited (TECHM), Wipro Limited (WIPRO), and Tata Consultancy Services Limited (TCS). Between them, these firms dominate the NSE Nifty IT Index and span the full range of large-cap Indian IT operations. The sample runs from January 11, 2016 to January 8, 2026, yielding approximately 2,460 to 2,468 trading-day observations per stock — a ten-year window that covers the pre-COVID growth phase (2016-2019), the crisis and initial recovery (2020-2021), and the post-pandemic normalisation period (2022-2026) [1]. Table 1 sets out the key dataset characteristics.

Table 1: Dataset Description — NSE IT Sector Stocks

Stock	Company	Exchange	Period	Observations	Variables
INFY	Infosys Ltd.	NSE India	Jan 2016 - Jan 2026	2,466	Open, High, Low, Close, Volume
HCLTECH	HCL Technologies Ltd.	NSE India	Jan 2016 - Jan 2026	2,468	Open, High, Low, Close, Volume
TECHM	Tech Mahindra Ltd.	NSE India	Jan 2016 - Jan 2026	2,465	Open, High, Low, Close, Volume
WIPRO	Wipro Ltd.	NSE India	Jan 2016 - Jan 2026	2,465	Open, High, Low, Close, Volume
TCS	Tata Consultancy Services	NSE India	Jan 2016 - Jan 2026	2,460	Close

3.2 Data Preprocessing

Before analysis, each series went through a standard quality protocol. Duplicate date entries were identified and removed. Trading holidays create gaps in daily data; these were addressed through forward-fill imputation, a method well established in high-frequency financial time series work [5]. The daily closing price serves as the primary analytical variable throughout. Where distributional properties or stationarity are examined, log returns are computed as $r_1 = \ln(P_1 / P_{1-1})$.

3.3 Technical Indicators

For the four stocks with complete OHLCV records — INFY, HCLTECH, TECHM, and WIPRO — a set of technical indicators was also computed. These include EMA-9 and EMA-21 with crossover signals; MACD using the conventional 12/26/9 parameterisation; standard Pivot Points with first and second support and resistance levels; Heiken Ashi candle transforms; and volume metrics comprising a 20-day moving average and On-Balance Volume (OBV). At present these serve mainly as supplementary market-structure context, consistent with recent hybrid modelling practice [17], and are earmarked as features for extended multivariate work in future studies.

3.4 Normalization

Min-Max normalisation maps each feature onto [0, 1] via $x_{no^rm} = (x - x_{min}) / (x_{ma^x} - x_{min})$. Scaling parameters are estimated on the training set alone and carried forward to the test set — an important discipline that prevents any look-ahead information from leaking into evaluation [4]. Log return series used in stationarity testing are left un-normalised, since the statistical tests require the original scale to be intact.

3.5 ARIMA Methodology

The ARIMA(p, d, q) framework, first systematised by Box and Jenkins [3] and later extended by Box et al. [25], models a time series through three interlocking components: an autoregressive part of order p, a differencing operator of order d, and a moving average part of order q. For a series $\{Y_1\}$, the model takes the form $\phi(B)(1-B)^d\, Y_1 = \theta(B)\varepsilon_1$, where $\phi(B)$ and $\theta(B)$ are the AR and MA lag polynomials, B is the backshift operator, and ε_1 is white noise with zero mean and constant variance σ^2.

Model building follows the Box-Jenkins iterative cycle: (1) Identification — the differencing order d is set using unit-root tests [26, 27, 28], after which ACF and PACF plots of the differenced series guide the choice of p and q; (2) Estimation — parameters are obtained by maximum likelihood; (3) Diagnostic checking — the Ljung-Box Q-test probes for residual autocorrelation, Jarque-Bera tests residual normality, and Engle's ARCH-LM [29] screens for conditional heteroskedasticity; (4) Forecasting — out-of-sample predictions are generated with associated confidence intervals. Final model selection minimises AIC over a grid of p, q ∈ {0,...,5} [4], with BIC and HQIC recorded alongside.

3.6 Train-Test Split and Evaluation Metrics

Data are split chronologically at the 80/20 mark. Temporal order is preserved throughout — random splitting would allow future observations to inform the model, invalidating any evaluation of genuine forecasting ability [4]. Out-of-sample accuracy on the held-out test set is measured with RMSE, MAE, MAPE, MSE, Mean Error (ME, reflecting directional bias), Mean Percentage Error (MPE), and R^2.

3.7 Structural Break Testing

Three structural break tests are used in sequence, following the testing battery recommended in the recent COVID-19 break literature [19, 20, 24].

(i) Chow test [11]: An F-test of parameter equality across two sub-samples defined by a known candidate date — here the WHO declaration (March 11, 2020) and India's lockdown announcement (March 24, 2020).

(ii) Zivot-Andrews test [12]: Rather than requiring the researcher to nominate a break date, this test searches endogenously for a single unknown break by minimising the ADF t-statistic over all candidate dates. Three model variants are estimated in parallel: one allowing an intercept shift only, one allowing a trend shift only, and one allowing both.

(iii) Bai-Perron test [8, 13]: Where a single break may be insufficient — as in a multi-wave pandemic — the PELT algorithm searches for multiple unknown break points simultaneously, using BIC to settle on the optimal number and placing confidence intervals around each estimated date. This approach has become the standard reference for multi-break contexts in the recent literature.

4. Results and Discussion

4.1 Descriptive Statistics

Table 2 summarises descriptive statistics for all five stocks across the full sample. At INR 2,684.43, TCS records the highest mean closing price, reflecting its position as India's largest IT company by market capitalisation; Wipro's mean of INR 181.13 sits at the other end. Relative price variability is widest for HCLTECH (CV = 50.60%) and narrowest for INFY (CV = 31.24%), pointing to meaningful differences in price cycle behaviour even within the same industry segment. None of the five series approximates a normal distribution: Jarque-Bera statistics run from 96.60 for INFY to 214.43 for HCLTECH, with all p-values at 0.000. Log return distributions carry excess kurtosis ranging from 4.14 to 11.11, in line with the fat-tailed behaviour widely documented for emerging-market financial returns [30] and consistent with earlier descriptive findings for Indian IT stocks [14, 18].

Table 2: Descriptive Statistics — NSE IT Sector Stocks (Jan 2016 – Jan 2026)

Stock	Mean (INR)	Std Dev	Min	Max	Skewness	Ex. Kurtosis	JB Stat	JB p-val	CV (%)
INFY	640.29	200.01	235.66	1,012.90	-0.185	-0.896	96.60	0.000	31.24
HCLTECH	906.60	458.78	354.38	1,995.10	0.505	-1.033	214.43	0.000	50.60
TECHM	963.47	404.34	376.30	1,806.10	0.316	-1.161	179.49	0.000	41.97
WIPRO	181.13	74.08	81.18	360.75	0.376	-1.133	189.87	0.000	40.90
TCS	2,684.43	955.94	1,050.58	4,553.75	-0.132	-1.211	157.39	0.000	35.61

4.2 Stationarity Tests

Table 3 reports ADF [26], KPSS [27], and Phillips-Perron [28] results for both price levels and log returns. Because ADF and KPSS test opposite null hypotheses — unit root versus stationarity — their combined verdict is particularly informative. For HCLTECH, TECHM, WIPRO, and TCS, ADF fails to reject the unit root null (p-values of 0.081, 0.220, 0.492, and 0.992 respectively) while KPSS simultaneously rejects stationarity: clear I(1) evidence. INFY's ADF result is borderline ($p = 0.027$), but KPSS contradicts stationarity ($p < 0.01$), tipping the combined judgement to I(1) as well. For log returns, the picture is unambiguous: ADF t-statistics range from -11.32 to -51.07 and every p-value reads 0.000. These findings sit comfortably alongside the random walk hypothesis [31] and match conclusions drawn in prior NSE-focused ARIMA studies [14, 18].

Table 3: Stationarity Test Results — Closing Price and Log Returns

Stock	Series	ADF Stat	ADF p-val	ADF Decision	KPSS Stat	KPSS Decision	PP Stat	Combined Decision
INFY	Close	-3.633	0.027	Borderline	0.394	Non-Stat.	-3.633	I(1)
INFY	Log Returns	-11.323	0.000	Stationary	0.023	Stationary	-11.323	I(0)

HCLTECH	Close	-3.215	0.081	Non-Stat.	0.690	Non-Stat.	-3.215	I(1)
HCLTECH	Log Returns	-15.282	0.000	Stationary	0.046	Stationary	-15.282	I(0)
TECHM	Close	-2.741	0.220	Non-Stat.	0.190	Non-Stat.	-2.741	I(1)
TECHM	Log Returns	-17.735	0.000	Stationary	0.048	Stationary	-17.735	I(0)
WIPRO	Close	-2.196	0.492	Non-Stat.	0.398	Non-Stat.	-2.196	I(1)
WIPRO	Log Returns	-49.724	0.000	Stationary	0.079	Stationary	-49.724	I(0)
TCS	Close	-0.156	0.992	Non-Stat.	0.970	Non-Stat.	-0.156	I(1)
TCS	Log Returns	-51.068	0.000	Stationary	0.103	Stationary	-51.068	I(0)

4.3 ARIMA Model Selection

With d = 1 confirmed for all series, ACF and PACF correlograms of the first-differenced data guided the initial (p, q) search. Exhaustive AIC-minimising grid search [4] over all ARIMA(p,1,q) specifications then yielded the models shown in Table 4. INFY and WIPRO settle on ARIMA(2,1,2). HCLTECH requires a higher autoregressive order — ARIMA(3,1,2) — in keeping with its more complex price cycles and the highest coefficient of variation in the sample (50.60%). TECHM lands on ARIMA(2,1,3). TCS is a particularly interesting case: its optimal specification is ARIMA(0,1,0), a pure random walk, consistent with TCS trading at a level of liquidity and information efficiency where past price movements carry no linear predictive content [31]. The fact that five companies operating in the same sector require quite different ARIMA orders is itself a substantive finding: it suggests that sectoral aggregation conceals important firm-level dynamics and reinforces the case for the stock-level approach adopted in this study [10].

Table 4: ARIMA Model Selection — AIC Grid Search Results

Stock	Selected Order	AIC	BIC	HQIC	Log-Likelihood	Sigma²	Train Period	Test Period
INFY	ARIMA(2,1,2)	14,133.39	14,161.32	14,143.66	-7,061.70	75.77	Jan 2016 - Jan 2024	Jan 2024 - Jan 2026
HCLTECH	ARIMA(3,1,2)	15,638.23	15,671.76	15,650.55	-7,813.12	161.12	Jan 2016 - Jan 2024	Jan 2024 - Jan 2026
TECHM	ARIMA(2,1,3)	16,621.28	16,654.80	16,633.60	-8,304.64	267.43	Jan 2016 - Jan 2024	Jan 2024 - Jan 2026
WIPRO	ARIMA(2,1,2)	9,746.11	9,774.05	9,756.38	-4,868.06	8.18	Jan 2016 - Jan 2024	Jan 2024 - Jan 2026
TCS	ARIMA(0,1,0)	19,899.56	19,905.14	19,901.61	-9,948.78	1,447.82	Jun 2016 - Jun 2024	Jun 2024 - Jan 2026

4.4 ARIMA Coefficient Estimates

Table 5 sets out the coefficient estimates for each fitted model. INFY's ARIMA(2,1,2) yields four highly significant parameters (all $p < 0.001$). Both AR terms are negative (ar.L1 = -0.487, ar.L2 = -0.949), signalling mean-reverting autoregressive dynamics, while the positive MA terms (ma.L1 = 0.516, ma.L2 = 0.934) capture the correction structure. The picture for HCLTECH's ARIMA(3,1,2) is different: individual AR and MA coefficients are statistically insignificant despite acceptable overall model fit. One plausible explanation is near-cancellation between roots of the AR and MA polynomials, a phenomenon documented in higher-order ARIMA models [25] that does not undermine the model selection itself. TECHM's ARIMA(2,1,3) produces significant AR(1), MA(1), and MA(3) terms. WIPRO's ARIMA(2,1,2) coefficients are uniformly non-significant ($p > 0.05$), consistent with the near-random-walk character implied by the low AIC value for WIPRO. TCS, fitted as ARIMA(0,1,0), has no AR or MA terms to report beyond the innovation variance.

Table 5: ARIMA Coefficient Estimates — Selected Models

Stock	Model	Parameter	Coefficient	Std Error	z-stat	p-value
INFY	ARIMA(2,1,2)	AR(1)	-0.487	0.020	-24.553	0.000***
INFY	ARIMA(2,1,2)	AR(2)	-0.949	0.019	-50.320	0.000***
INFY	ARIMA(2,1,2)	MA(1)	0.516	0.022	23.642	0.000***
INFY	ARIMA(2,1,2)	MA(2)	0.934	0.021	44.139	0.000***
HCLTECH	ARIMA(3,1,2)	AR(1)	-0.039	2.490	-0.016	0.987
HCLTECH	ARIMA(3,1,2)	AR(2)	0.543	1.951	0.278	0.781
HCLTECH	ARIMA(3,1,2)	MA(1)	0.069	2.490	0.028	0.978
TECHM	ARIMA(2,1,3)	AR(1)	0.992	0.238	4.160	0.000***
TECHM	ARIMA(2,1,3)	MA(1)	-0.945	0.238	-3.976	0.000***
TECHM	ARIMA(2,1,3)	MA(3)	0.080	0.021	3.754	0.000***
WIPRO	ARIMA(2,1,2)	AR(1)	0.431	0.281	1.532	0.126
WIPRO	ARIMA(2,1,2)	AR(2)	0.400	0.237	1.689	0.091
TCS	ARIMA(0,1,0)	—	—	—	—	Random Walk

*Note: *** p < 0.001; ** p < 0.01; * p < 0.05. Coefficients represent Maximum Likelihood Estimates.*

4.5 Residual Diagnostics

Table 6 collects the residual diagnostic tests. Ljung-Box Q-statistics at lags 5, 10, 15, and 20 are insignificant for all five stocks, establishing that the fitted models have absorbed the serial correlation in the data and leave behind residuals that behave as white noise. INFY's Q-statistics of 2.55, 8.38, 12.00, and 20.52 at those lags (p-values 0.768, 0.592, 0.679, 0.426) are representative of this pattern. Residual normality, on the other hand, is firmly rejected in every case: Jarque-Bera statistics run into the millions — from roughly 3.4 million for INFY to 7.2 million for WIPRO — driven by the extreme excess kurtosis that characterises financial return residuals [30].

Where the diagnostics raise a clear red flag is in the ARCH-LM test [29]. F-statistics at lag 10 range from 86.39 for TCS to 217.34 for TECHM, and every p-value is 0.000 — unanimous evidence of conditional heteroskedasticity and volatility clustering in the ARIMA residuals. In practical terms, this means the models handle the conditional mean adequately but leave the time-varying conditional variance entirely unmodelled. Given the asymmetric volatility responses that Manu and Shetty [21] have specifically documented for Indian IT stocks, EGARCH or similar extensions appear warranted as a natural next step.

Table 6: Residual Diagnostic Tests — Ljung-Box, Jarque-Bera, and ARCH-LM

Stock	LB(5) p-val	LB(10) p-val	LB(20) p-val	JB Stat	JB p-val	ARCH(5) F	ARCH(10) F	GARCH Needed
INFY	0.768	0.592	0.426	3,387,389	0.000	134.64	200.74	Yes
HCLTECH	0.900	0.997	0.995	4,446,917	0.000	90.87	128.30	Yes
TECHM	0.999	0.990	0.999	3,704,953	0.000	149.66	217.34	Yes
WIPRO	0.973	0.904	0.610	7,189,668	0.000	81.70	120.54	Yes
TCS	0.512	0.695	0.779	5,496,170	0.000	47.08	86.39	Yes

Note: LB = Ljung-Box Q-test; JB = Jarque-Bera normality test; ARCH = Engle ARCH-LM test [29]. All ARCH-LM p-values = 0.000.

4.6 Structural Break Analysis

Table 7 presents the structural break results, which constitute the central empirical contribution of this paper. The Chow test [11] at both COVID event dates — the WHO pandemic declaration on March 11, 2020 and India's national lockdown on March 24, 2020 — produces strongly significant F-statistics for all five stocks (all p = 0.000). The magnitudes are striking: HCLTECH records F = 625.61 and F = 642.98 at the two dates, and TCS reaches F = 428.36 and F = 463.91. Values of this size are rarely encountered in Indian equity research and leave no ambiguity — the COVID-19 shock produced a profound and statistically unambiguous break in the data-generating process of every stock examined.

The Bai-Perron PELT algorithm [8, 13] uncovers between 9 and 11 endogenous break points per stock over the full ten-year window. For INFY, the break chronology runs through April 2017, April 2018, March 2019, March 17, 2020 — six days after the WHO pandemic declaration — and June 2020, with the COVID cluster standing out clearly. HCLTECH's break sequence shifts mostly into the pandemic and recovery period, with major dates in January 2018, July 2020, December 2020, August 2021, and April 2022, tracking India's successive COVID waves. WIPRO accumulates the most breaks overall (11), with COVID-period clustering in March 2020, July 2020, December 2020, and April 2021. A tally of 9 to 11 breaks per stock aligns closely with Ndako et al. [20], who found 10 to 12 breaks per market across Asian economies using the same Bai-Perron method, and with Bui et al. [24] for the ASEAN region.

Table 7: Structural Break Test Results — Chow Test and Bai-Perron Multiple Breaks

Stock	Chow F (WHO Mar 11)	p-val	Chow F (Lockdown Mar 24)	p-val	BP Breaks (Total)	Key COVID-Period Break Dates
INFY	224.68	0.000***	195.66	0.000***	10	2020-03-17, 2020-06-17
HCLTECH	625.61	0.000***	642.98	0.000***	9	2020-07-21, 2020-12-11, 2021-08-12
TECHM	29.99	0.000***	32.35	0.000***	10	2020-03-18, 2020-08-13, 2020-12-01
WIPRO	161.08	0.000***	188.63	0.000***	11	2020-03-03, 2020-07-16, 2020-12-22, 2021-04-22
TCS	428.36	0.000***	463.91	0.000***	11	2020-09-15, 2021-01-04, 2021-08-12

*Note: *** p < 0.001. BP = Bai-Perron PELT algorithm with BIC break-number selection [8, 13]. Full break date lists available in supplementary materials.*

4.7 Pre-COVID versus Post-COVID Regime Comparison

Table 8 presents the pre-COVID and post-COVID comparative statistics. The split follows the India national lockdown date of March 24, 2020, consistent with established practice in Indian COVID market studies [9, 10]. Post-COVID mean prices rose dramatically across the board: INFY climbed 71% from INR 453.45 to INR 775.55; HCLTECH gained 161%, moving from INR 468.34 to INR

1,224.28; TECHM and WIPRO each roughly doubled; and TCS increased by exactly 100%. Independent-samples t-tests confirm these shifts are statistically significant in every case (all |t| > 65, all p = 0.000).

Variance widened substantially alongside the mean shifts. HCLTECH's standard deviation ballooned more than five-fold, from INR 62.94 to INR 346.30; WIPRO's tripled, moving from INR 15.70 to INR 55.66. Levene's test rejects equal variances for all five stocks (all $p < 0.05$), confirming a genuine change in the risk profile — not just the price level — of Indian IT stocks after the pandemic. These findings echo Guru and Das [22], who found elevated uncertainty spillovers persisting well beyond the initial lockdown, and Bhatia [9], who documented enduring efficiency changes in Indian indices following pandemic break periods.

Table 8: Pre-COVID vs. Post-COVID Comparative Analysis

Stock	Pre Mean (INR)	Post Mean (INR)	Change	Pre Std	Post Std	t-stat	t p-val	Levene p-val	Regime Shift
INFY	453.45	775.55	+71%	117.22	124.70	-65.39	0.000***	0.038*	Confirmed
HCLTECH	468.34	1,224.28	+161%	62.94	346.30	-80.74	0.000***	0.000***	Confirmed
TECHM	593.10	1,231.57	+108%	137.05	311.63	-68.75	0.000***	0.000***	Confirmed
WIPRO	110.94	232.07	+109%	15.70	55.66	-78.08	0.000***	0.000***	Confirmed
TCS	1,655.34	3,311.60	+100%	407.54	576.52	-83.06	0.000***	0.000***	Confirmed

*Note: *** p < 0.001; * p < 0.05. Pre-COVID: Jan 2016 – Mar 23, 2020. Post-COVID: Mar 25, 2020 – Jan 8, 2026.*

4.8 Forecast Accuracy

Table 9 reports out-of-sample forecast error metrics computed on the 20% chronological hold-out test set. Among the five models, INFY's ARIMA(2,1,2) performs best in relative terms (MAPE = 9.56%), followed by HCLTECH at 11.64% and WIPRO at 13.13%. TCS's random-walk specification posts the weakest result (MAPE = 20.58%), which is unsurprising given how difficult it is to forecast a highly efficient, large-capitalisation stock in levels [31].

More telling than the individual MAPE values is the sign on R^2: every stock returns a negative figure, ranging from -0.155 for INFY to -2.960 for TECHM. A negative R^2 means the ARIMA forecast is beaten even by the sample mean as a predictor — a stark result, but one that makes sense once the structural break context is kept in view. Models estimated largely on pre-COVID data carry parameter values calibrated to a regime that no longer exists in the test window, and their predictions systematically drift from the post-break reality. In other words, the forecast failure is not a verdict on ARIMA in general; it is the econometric footprint of the COVID-19 structural break documented in Section 4.6. Yong and Cao [19] reached an analogous conclusion for U.S. markets, and Bhatia [9] made the same observation for Indian indices.

Positive ME values for INFY (+37.25), HCLTECH (+186.86), TECHM (+260.12), and WIPRO (+35.61) indicate systematic under-prediction — the models are consistently too conservative relative to actual prices. The source of this bias is the secular post-COVID uptrend in Indian IT valuations, a trajectory that pre-COVID-trained models simply cannot extrapolate [21, 22]. TCS is the exception: its negative ME (-365.78) reflects over-prediction on a more recently declining price path.

Table 9: Out-of-Sample Forecast Error Metrics (Test Set: 20% Chronological Holdout)

Stock	Model	Test Obs.	RMSE	MAE	MAPE (%)	MSE	ME (Bias)	R^2
INFY	ARIMA(2,1,2)	494	101.62	85.39	9.56	10,326.71	+37.25	-0.155
HCLTECH	ARIMA(3,1,2)	494	241.91	198.92	11.64	58,518.88	+186.86	-1.479
TECHM	ARIMA(2,1,3)	493	300.93	262.03	16.56	90,557.78	+260.12	-2.960
WIPRO	ARIMA(2,1,2)	493	41.96	35.70	13.13	1,760.54	+35.61	-2.576
TCS	ARIMA(0,1,0)	492	732.68	622.01	20.58	536,819.45	-365.78	-0.332

Note: Negative R^2 indicates ARIMA underperforms the mean-prediction baseline on the out-of-sample test window, attributable to post-structural-break parameter instability [8, 13, 19]. ME positive = systematic under-prediction; ME negative = over-prediction.

5. Conclusion

Drawing on a decade of daily NSE data and a three-test structural break battery, this study has assembled comprehensive empirical evidence on the scale and character of COVID-19-induced breaks in Indian IT sector stock prices within an ARIMA modelling framework. Four main conclusions emerge.

First, complementary ADF [26] and KPSS [27] tests confirm that all five price series are integrated of order one (I(1)), while first-differenced log returns satisfy stationarity uniformly. AIC-guided model selection [4] produces orders ranging from ARIMA(0,1,0) for the most efficiently priced stock (TCS) to ARIMA(3,1,2) for the most volatile (HCLTECH). Ljung-Box diagnostics confirm that residual white noise holds for all five fitted models.

Second, the structural break tests converge on a consistent picture: COVID-19 induced a permanent regime shift across all five stocks. Chow test F-statistics are large and overwhelmingly significant ($p < 0.001$) at both event dates. Bai-Perron PELT analysis [8, 13] places 9 to 11 endogenous break points in each series, with a marked concentration in March-June 2020 and later pandemic waves — a pattern that mirrors global emerging market evidence from Ndako et al. [20] and ASEAN findings from Bui et al. [24].

Third, the pre-COVID to post-COVID subsample comparison reveals rises in mean prices of 71% to 161%, significant variance expansion (Levene's test $p < 0.05$ across all stocks), and shifted distributional characteristics — all pointing to a structural rather than transitory change. These results extend and reinforce index-level findings from Bhatia [9] and Maiti [10] to the stock-by-stock level of the individual IT company.

Fourth, out-of-sample evaluation shows that ARIMA models fitted across the structural break underperform consistently (all negative R^2, MAPE spanning 9.56% to 20.58%) and carry systematic directional bias. The universal ARCH-LM significance [29] adds a further caveat: complete characterisation of these series requires GARCH-family extensions to handle the time-varying conditional variance.

5.1 Implications

For portfolio managers, the systematic under-prediction documented here is a practical warning: models calibrated on pre-crisis data will generate overly conservative price forecasts in post-crisis markets, potentially distorting allocation decisions. Risk managers should note that the five-fold volatility expansion in HCLTECH and the three-fold expansion in WIPRO signal a materially higher-risk environment that static risk models built on pre-2020 data will understate. For the research community, this paper provides the first decade-long ARIMA baseline with explicit structural break treatment at the individual stock level for NSE IT companies — a foundation against which LSTM [16], Transformer-based, and hybrid forecasting architectures [6, 17] can now be benchmarked on a like-for-like basis.

5.2 Limitations and Future Directions

A few caveats deserve mention. The Zivot-Andrews test [12] ran into implementation constraints that prevented complete reporting across all five stocks; replication using the strucchange package in R or a dedicated econometric platform would strengthen this aspect of the analysis. More fundamentally, ARIMA's linearity assumption [3] makes it a poor fit for the sentiment-driven, algorithmic dynamics increasingly present in post-COVID IT markets [7, 16], and neither intraday data nor options market signals nor news sentiment enter the current dataset.

Future work will build on the baseline established here in two stages. The next step is to run Long Short-Term Memory (LSTM) neural networks on the same five-stock dataset and compare their forecasting performance directly against the ARIMA results above, with the training data design explicitly accounting for the structural break [6, 16]. Beyond that, a hybrid architecture merging LSTM with Transformer self-attention mechanisms and FinBERT-based financial news sentiment is planned, targeting state-of-the-art predictive performance for NSE IT sector stocks and engaging with the nonlinear and sentiment dimensions that lie outside ARIMA's reach.

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How do I cite this article?

Kulkarni Parag.M, et.al, Structural Break Analysis of Indian IT Sector Stocks Using ARIMA: Evidence from the COVID-19 Pandemic, Excel International Journal of Technology, Engineering and Management, 2026; Volume -13, Issue-2_Page_295-305.
DOI Link: https://doi.org/10.64971/j.cph.eijtem.v13.i2.29.2026