

IT Sector Stock Performance Under Artificial Intelligence Disruption a Comparative Event Study of TCS, Infosys and HCL Technologies on the NSE

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Abstract

Purpose: This study examines equity-market responses to selected artificial intelligence (AI) announcements and compares market performance with financial resilience in Tata Consultancy Services (TCS), Infosys and HCL Technologies (HCL Tech). **Method:** A market model using the Nifty 50 covers 988 aligned trading sessions from July 2022 to June 2026. Six events are examined using ninety-session estimation windows, four event windows and Patell standardisation. Robustness checks vary the estimation window, exclude selected earnings sessions and substitute the Nifty IT benchmark. Quarterly institutional ownership and annual financial statements provide comparative evidence. **Findings:** The ChatGPT launch produced no statistically detectable abnormal response. Three-session cumulative average abnormal returns were -3.03% , -3.21% and -4.16% around the DeepSeek repricing session, Anthropic's COBOL modernisation publication and Accenture's guidance reduction, respectively, significant at the nominal 5% level under the reported test. Selected capability-event declines partly reversed. HCL Tech showed greater full-period market resilience but sharper reactions to selected announcements and weaker normalised margin performance. **Contribution:** The comparison separates market valuation, announcement sensitivity and realised profitability. It demonstrates how sectoral benchmarking changes measured abnormal returns and identifies a tension between resource-based expectations and accounting outcomes. Results remain exploratory because only three firms and one demand event are studied; cross-firm dependence, event selection and overlapping news limit inference. The evidence establishes associations around selected events, rather than the causal contribution of AI to the sector's entire decline.

Keywords: artificial intelligence; event study; abnormal returns; indian information technology; institutional ownership; resource-based view

1. Introduction

Indian information technology (IT) stocks declined after the Nifty IT peak of 13 December 2024 despite revenue growth. The study records an index fall from 45,995.80 to 26,299.05 by 30 June 2026. Financial year (FY) 2026 revenue grew by 4.58% for TCS, 9.61% for Infosys and 11.18% for HCL Tech (Table 1) raising questions about AI and expected earnings. AI may reduce billable engineering effort while creating demand for implementation, integration and oversight. An event study measures whether returns around dated announcements differ from

returns predicted by market exposure (Fama et al., 1969; MacKinlay, 1997). It cannot attribute the entire sector decline to AI, because client budgets, interest rates and other information also influence prices. The study distinguishes full-period stock performance, announcement sensitivity and realised profitability. HCL Tech software products suggest possible protection from labour substitution, yet market and accounting rankings differ. Six events, risk and returns, benchmarks, ownership and financial performance are compared.

2. Literature and Theoretical Framework

Automation displaces tasks but creates new work (Acemoglu & Restrepo, 2018). Exposure measures identify occupational and industry vulnerability (Felten et al., 2021; Eloundou et al., 2024). Exposure alone does not determine revenue loss or repricing: contracts complementary services and adjustment costs matter.

Event-study methods connect dated information with abnormal returns (Fama et al., 1969; Brown & Warner, 1985; MacKinlay, 1997). Patell (1976) accounts for uncertainty in estimated normal returns. Event-induced variance remains an additional concern (Boehmer et al., 1991). These issues are particularly relevant when several securities share an industry shock.

The efficient market hypothesis (EMH) predicts incorporation of public information into prices (Fama, 1970). Different announcement responses may reflect different information. The resource-based view (RBV) links advantage to valuable, difficult to replicate assets (Barney, 1991); dynamic capabilities concern their adaptation (Teece et al., 1997). Software products may protect revenue while remaining vulnerable to valuation revisions.

Creative destruction connects innovation with the erosion and replacement of incumbent advantages (Schumpeter, 1942). These perspectives motivate questions about abnormal return direction timing and firm-level differences without presuming that software ownership protects margins.

Null hypotheses address: H1, no abnormal response; H2, no cross-firm differences; H3, no early later event differences; H4, no capability demand differences; and H5, no association with lagged foreign portfolio investor (FPI) ownership. H2, H4 are exploratory: differences in individual significance do not establish significant differences.

3. Data and Methodology

The purposive sample comprises TCS, Infosys and HCL Tech, whose business mixes differ in their exposure to software products and engineering services. The period, 1 July 2022 to 30 June 2026, contains 988 aligned price observations and 987 daily returns. The abbreviated 12 November 2023 Muhurat session is excluded consistently.

Table 1. Firm Profiles for FY2026

Particulars	TCS	Infosys	HCL Tech	Basis
Revenue from operations (₹ crore)	2,67,021	1,78,650	1,30,144	Reported
Revenue growth over FY2025 (%)	4.58	9.61	11.18	Derived

Profit after tax, reported (₹ crore)	49,454	29,474	16,652	Reported
Profit after tax, normalised (₹ crore)	52,872	30,424	17,371	Derived
Normalised net profit margin (%)	19.80	17.03	13.35	Derived
Market capitalisation (₹ lakh crore)	8.95	4.79	3.25	Reported
Approximate headcount	6,07,979	3,23,788	2,23,420	Reported

Note. Financial year (FY) 2026 figures are in Indian rupees (₹). Sources: TCS, Infosys and HCL Tech annual reports (2026), India Brand Equity Foundation (2026) for market capitalisation and headcount. Normalised profit excludes specified exceptional items, Table 15 gives the adjustments.

Daily prices and both indices were obtained from Investing.com for National Stock Exchange of India (NSE) listings. Quarterly ownership comes from shareholding filings under Regulation 31 of the Securities and Exchange Board of India (SEBI, 2015) listing regulations. Annual reports supply financial information; the 364-day Treasury Bill yield supplies the risk free rate. TCS monthly closing highs and lows were compared with FY2023-FY2024 statutory disclosures (Tata Consultancy Services Limited, 2023, 2024). Adjustment discontinuities led to excluding April–June 2022. Later within-interval factors supported adjusted prices, without independently validating every security or observation.

Table 2. TCS Price Validation

Interval	Disclosed high (₹)	Vendor high (₹)	Adjustment factor	Treatment
Apr–Jun 2022	3,440.15	3,440.15	1.00000	Excluded
Jul–Dec 2022	3,475.65	3,390.93	1.02498	Retained
Jan–Dec 2023	3,861.00	3,843.19	1.00463	Retained
Jan 2024 onward	4,219.30	4,219.25	1.00001	Retained

Illustrative comparisons from TCS annual reports (2023, 2024) and Investing.com. Disclosed and vendor highs are in ₹; the factor is disclosed high divided by vendor high. The study reports comparisons over 24 months.

Table 3 retains six events: ChatGPT, GPT-4, DeepSeek repricing, Anthropic’s Common Business Oriented Language (COBOL) modernisation publication, OpenAI Deployment Company and Accenture guidance. The first five concern capability; the last concerns demand. Selection considered comparator-stock reactions, potentially favouring events already associated with visible price movements.

Day zero is the assigned NSE response session after an announcement. DeepSeek is an exception its 20 January 2025 release and the later 27 January repricing session are distinct the study uses the latter. This timing choice must be distinguished from a release-date test.

Table 3. Event Calendar

ID	Event	Announced	NSE day 0	Classification
E1	Public launch of ChatGPT by OpenAI	30 Nov 2022	1 Dec 2022	Capability shock
E2	Launch of GPT-4 by OpenAI	14 Mar 2023	15 Mar 2023	Capability shock
E3	DeepSeek-R1 global repricing session	24 Jan 2025	27 Jan 2025	Capability shock
E4	Anthropic publication on COBOL modernisation using Claude Code	23 Feb 2026	24 Feb 2026	Capability shock
E5	Launch of the OpenAI Deployment Company	11 May 2026	12 May 2026	Capability shock
E6	Reduction of Accenture plc financial year 2026 revenue guidance	18 Jun 2026	19 Jun 2026	Demand shock

Sources: OpenAI (2022, 2023, 2026), DeepSeek (2025), Anthropic (2026) and Accenture plc (2026). E3's 24 January entry denotes the selected repricing information date, not the model's 20 January release date.

3.1 Returns and Event Tests

Daily continuously compounded return is calculated from adjusted closing price P:

$$R_{it} = \ln (P_{it} / P_{i,t-1}) \quad \dots (1)$$

Subscripts i and t identify the firm and trading session. Logarithmic returns sum across sessions; percentages equal these returns multiplied by 100.

Normal returns follow the single-index market model:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \quad \dots (2)$$

Ordinary least squares (OLS) estimates the intercept α and market sensitivity β over $T = 90$ sessions ending at day -6 . R_{mt} is the Nifty 50 return and ε is the residual. The same window length is used for every event E1 lacks 120 clean pre-event sessions. Nifty 50 reduces sector concentration relative to Nifty IT but includes the studied firms and is not an untreated control.

Abnormal return (AR) is realised return minus fitted normal return:

$$AR_{it} = R_{it} - (\hat{\alpha}_i + \hat{\beta}_i R_{mt}) \quad \dots (3)$$

Cumulative abnormal return (CAR) sums AR across the event window:

$$CAR_i(t_1, t_2) = \sum AR_{it} \quad \dots (4)$$

Cumulative average abnormal return (CAAR) is the arithmetic mean of the three firm CARs. Windows (-1,+1), (-2,+2), (-5,+5) and (0,+5) cover immediate adjustment, wider movement and post-event returns.

Following Patell (1976), prediction variance for a single-session AR is:

$$V_{it} = s_i^2 \left[1 + 1/T + (R_{mt} - \bar{R}_m)^2 / \sum (R_{mt} - \bar{R}_m)^2 \right] \quad \dots (5)$$

Here s_i^2 is estimation-residual variance and $\bar{R}_m$ is the estimation-period market mean. The summation in the denominator covers estimation sessions. Firm-level tests use 88 degrees of freedom. The reported aggregate statistic uses standardised cumulative abnormal returns (SCAR):

$$Z = \sum SCAR_i / \sqrt{[N(T-2)/(T-4)]} \quad \dots (6)$$

$N = 3$ firms. Standardising CAR requires the variance of the cumulative prediction error, including covariance between sessions, rather than treating daily prediction errors as independent. Reported significance is nominal and depends on distributional assumptions. Patell aggregation assumes cross-firm independence; common sector exposure weakens that assumption.

3.2 Ownership and Sensitivity Tests

Lagged FPI shareholding is related to event period CAR through:

$$CAR_{ie} = \gamma_0 + \gamma_1 FPI_{i,q-1} + \delta_e + u_{ie} \quad \dots (7)$$

The event effect δ_e absorbs shared event movements; $q-1$ denotes the preceding quarter and u the residual. Ownership availability restricts this regression to E3 and E6 are giving twelve observations. Lagging ownership limits simultaneity but does not establish causality. Sensitivity checks use 120 estimation sessions, omit three January 2025 earnings sessions, substitute Nifty IT and compare four event windows.

4. Descriptive Results

Table 4 reports annualised returns of -11.20% for TCS, -9.38% for Infosys and 2.44% for HCL Tech, compared with 11.19% for Nifty 50. All series exhibit negative skewness and excess kurtosis; Jarque Bera statistics reject normality (Jarque & Bera, 1987). Standardisation does not itself remove non normality.

Table 4. Daily Return Statistics

Series	Mean (%)	SD (%)	Ann. return (%)	Ann. volatility (%)	Skewness	Ex. kurtosis	Jarque-Bera
TCS	-0.0471	1.361	-11.20	21.60	-0.206	4.338	780.9
Infosys	-0.0391	1.609	-9.38	25.55	-0.397	4.511	862.8
HCLTech	0.0096	1.528	2.44	24.25	-0.700	6.297	1711.1
Nifty IT	-0.0066	1.339	-1.64	21.25	-0.155	2.689	301.3
Nifty 50	0.0421	0.809	11.19	12.85	-0.389	4.971	1041.2

Source: Investing.com, $n = 987$. Standard deviation (SD) measures daily dispersion. Annualised return = $\exp(252 \times \text{daily mean}) - 1$; annualised volatility = $\text{daily SD} \times \sqrt{252}$. The Jarque Bera 1% critical value is 9.21.

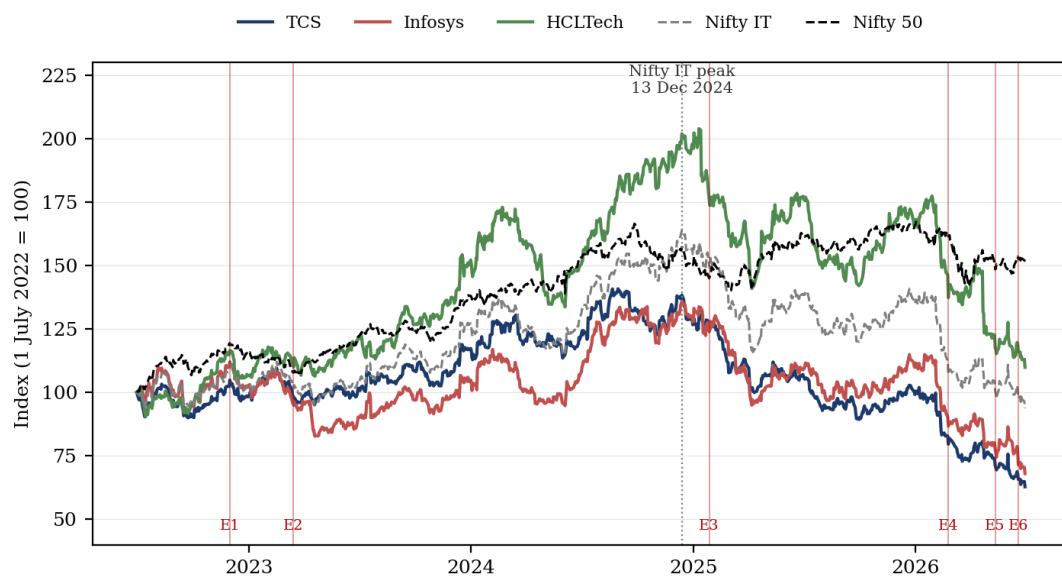


Figure 1. Indexed Prices from July 2022

Source: Investing.com and National Stock Exchange India Limited, Base: 1 July 2022 = 100. Vertical markers identify Table 3 events and the sectoral peak.

Figure 1 shows the divergence after the sectoral peak. Table 5 separates the two sub-periods. Post-peak annualised returns range from -33.19% to -40.76% for the firms, against -2.43% for Nifty 50. The peak-based split is descriptive, not an independently estimated structural break.

Table 5. Sub-period Returns and Volatility

Series	Pre-peak return (%)	Pre-peak volatility (%)	Post-peak return (%)	Post-peak volatility (%)
TCS	14.42	19.81	-40.76	24.00
Infosys	13.59	23.74	-36.83	28.07
HCLTech	33.86	21.63	-33.19	27.75
Nifty IT	22.77	19.34	-30.98	23.85
Nifty 50	20.67	12.31	-2.43	13.64

Source: Investing.com, Pre-peak 4 July 2022–13 December 2024, 607 returns. Post-peak 16 December 2024, 30 June 2026, 380 returns.

Table 6 reports Nifty 50 betas below one, with coefficients of determination around 0.21–0.23. Nifty IT explains substantially more daily variation. Thus, the choice of benchmark changes whether common sector movements remain in abnormal returns.

Table 6. Market Model Estimates

Firm	Alpha	Beta	Std. error of beta	t (beta = 1)	R-squared
Benchmark: Nifty 50					
TCS	-0.000805	0.7936	0.0472	-4.37	0.2227
Infosys	-0.000788	0.9433	0.0558	-1.02	0.2250
HCLTech	-0.000267	0.8617	0.0535	-2.58	0.2084
Benchmark: Nifty IT					
TCS	-0.000413	0.8893	0.0157	-7.05	0.7654
Infosys	-0.000318	1.0970	0.0157	6.19	0.8328
HCL Tech	0.000157	0.9265	0.0212	-3.46	0.6591

Note. Source: Investing.com and National Stock Exchange India Limited, OLS on 987 daily log returns. Alpha is a daily decimal return. R-squared is the coefficient of determination.

Table 7 compares excess return per unit of total volatility (Sharpe ratio) per unit of market beta (Treynor, 1965), and the excess-return regression intercept (Jensen, 1968). All rank HCL Tech above Infosys and TCS, although all three firms have negative excess performance.

Table 7. Risk-adjusted Performance

Series	Ann. excess return (%)	Sharpe ratio	Treynor ratio	Jensen's alpha (%)
TCS	-18.40	-0.852	-0.2320	-21.64
Infosys	-16.38	-0.641	-0.1737	-20.22
HCLTech	-4.12	-0.170	-0.0479	-7.64
Nifty IT	-8.19	-0.385	-0.0896	-11.92
Nifty 50	4.08	0.317	0.0408	Benchmark

Note. Sources: Investing.com and Reserve Bank of India (n.d.). Annual Treasury Bill inputs for 2022-2026 are 4.62%, 7.24%, 7.08%, 6.54% and 5.90%, converted to daily equivalents. Jensen's alpha is annualised.

Figure 2 and Table 8 show declining FPI stakes and rising domestic institutional investor (DII) stakes. FPI reductions were 340, 651 and 390 basis points for TCS, Infosys and HCL Tech. Ownership percentages describe holdings, not directly measured transaction flows.

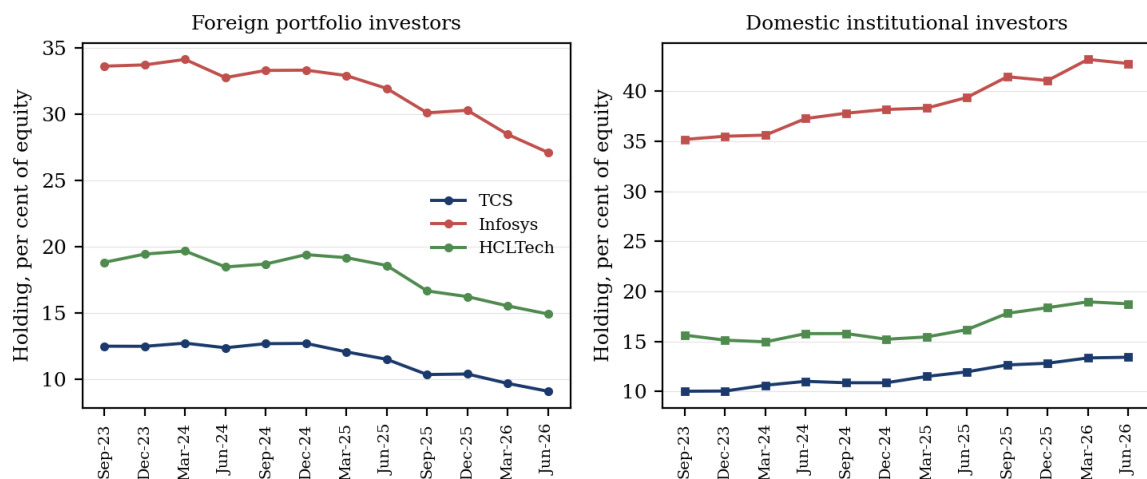


Figure 2. Institutional Shareholding

Source: Company quarterly shareholding disclosures under SEBI (2015), September 2023-June 2026.

Table 8. Institutional Shareholding Changes

Firm	FPI Sep-23 (%)	FPI Jun-26 (%)	Change (bps)	DII Sep-23 (%)	DII Jun-26 (%)	Change (bps)
TCS	12.47	9.07	-340	10.01	13.41	+340
Infosys	33.60	27.09	-651	35.19	42.78	+759
HCLTech	18.80	14.90	-390	15.62	18.75	+313

Note. Source: Company shareholding disclosures. FPI = foreign portfolio investors; DII = domestic institutional investors, bps = basis points. One percentage point equals 100 basis points.

5. Event Results

Table 9 and Figure 3 report the event-window averages. ChatGPT's three-session CAAR is 0.43%; the reported test does not distinguish it from zero. DeepSeek repricing, Anthropic's publication and Accenture guidance have CAARs of -3.03%, -3.21% and -4.16%, respectively, significant at the nominal 5% level.

Table 9. Event CAARs (%)

ID	Event	CAAR (-1,+1)	CAAR (-2,+2)	CAAR (-5,+5)	CAAR (0,+5)
E1	ChatGPT launch	0.43	0.36	-0.49	-0.28
E2	GPT-4 launch	-1.57	-1.18	-3.51*	-2.73*
E3	DeepSeek-R1	-3.03**	-2.25	-2.76	-4.30**
E4	Claude Code COBOL	-3.21**	-4.01**	-0.84	1.04
E5	OpenAI Deployment Co.	-2.12	-2.93	3.06	1.35
E6	Accenture guidance cut	-4.16**	-4.82*	-0.84	-3.33

Note. Source: Investing.com and report from www.nseindia.com, Nifty 50 market model 90 session estimation ending at -6. Patell significance: *** $p < .01$, ** $p < .05$, * $p < .10$.

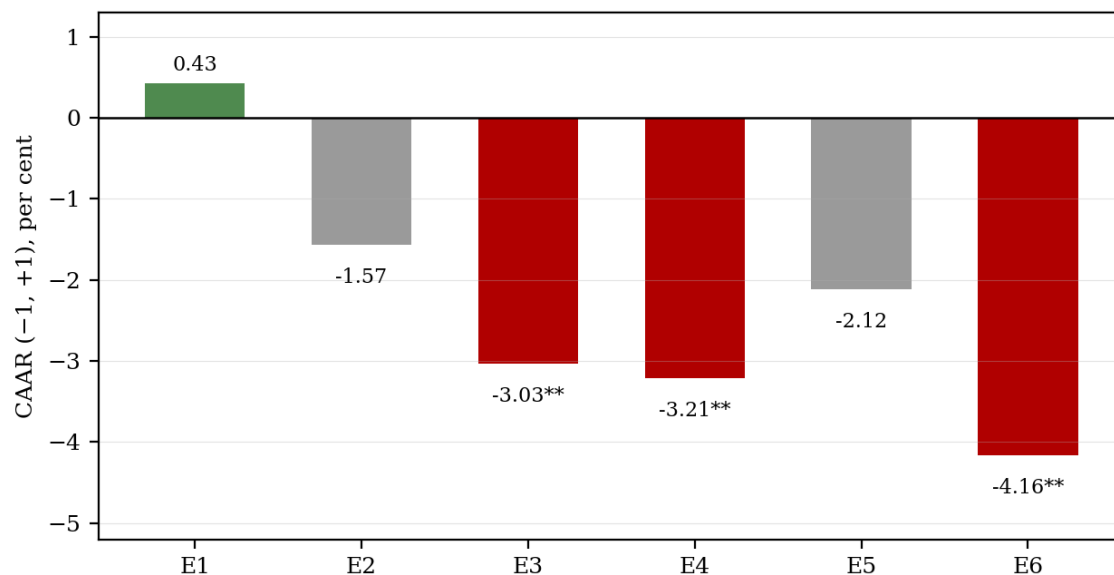


Figure 3. Three-session CAARs

Note. Source: Investing.com and National Stock Exchange India Limited, dark bars denote nominal $p < .05$ under the reported Patell test.

GPT-4's eleven-session CAAR is -3.51% , significant at 10%. Later selected events show larger immediate declines. This sequence is consistent with changing assessments, but does not isolate delayed learning from differences in announcement content. It therefore does not independently establish a rejection of H3.

Table 10 and Figure 4 show firm-level differences. At DeepSeek repricing, HCL Tech's CAR is -6.01% , compared with -1.69% for TCS and -1.39% for Infosys. At Anthropic's event, HCL Tech's -3.86% is marked significant at 10%, not 5%. These rankings motivate H2 without constituting a direct equality test.

Table 10. Three-session Firm CARs (%)

ID	Event	TCS	Infosys	HCLTech	CAAR
E1	ChatGPT launch	0.99	0.27	0.04	0.43
E2	GPT-4 launch	-2.21	-0.80	-1.71	-1.57
E3	DeepSeek-R1	-1.69	-1.39	-6.01**	-3.03**
E4	Claude Code COBOL	-1.51	-4.27	-3.86*	-3.21**
E5	OpenAI Deployment Co.	-2.50	-2.29	-1.59	-2.12
E6	Accenture guidance cut	-3.31	-7.17*	-1.98	-4.16**

Note. Source: Investing.com. Reported firm level tests use 88 degrees of freedom. *** $p < .01$, ** $p < .05$, * $p < .10$; nominal significance.

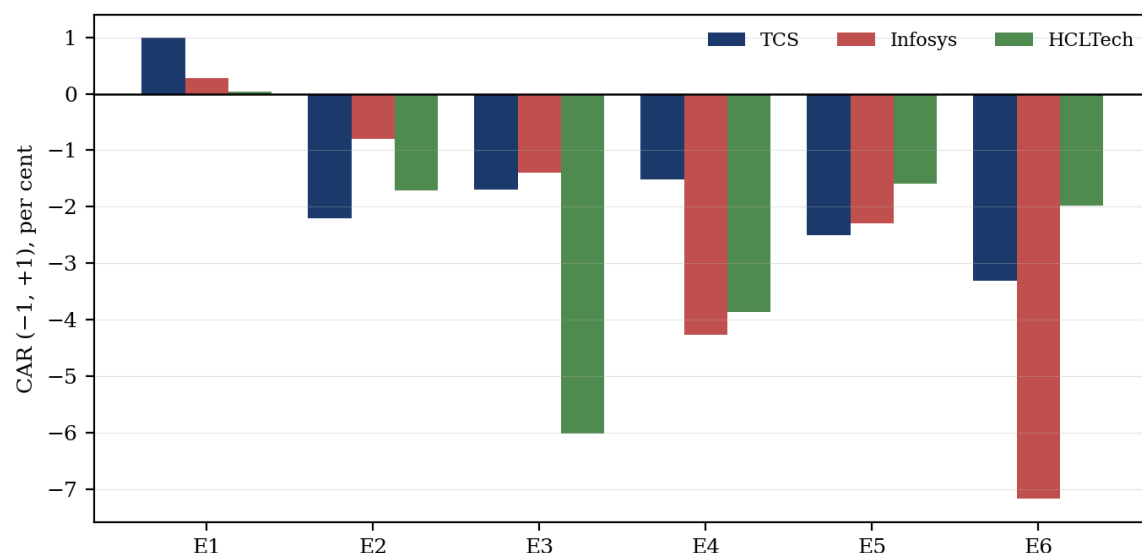


Figure 4. Firm CARs by Event

Source: Investing.com and National Stock Exchange India Limited, firm level three session CARs correspond to Table 10.

The five capability-related events average -1.90% over three sessions; the single demand event records -4.16% . Post-event CAARs for E4 and E5 are positive, at 1.04% and 1.35% , while E6 remains negative at -3.33% . These patterns suggest different adjustment paths, but one demand event cannot support a general category comparison or a formal rejection of H4. Accenture's broader earnings information also prevents treating E6 as a pure AI shock.

6. Robustness and Ownership

Table 11 compares 90- and 120-session estimation windows. Signs remain unchanged for five events, with differences of 0.07-0.40 percentage points. This supports estimate stability but does not resolve all inference concerns.

Table 11. Estimation-window Sensitivity

Event	90-session window	120-session window	Difference	Inference
E1	0.43	Not estimable	NA	Unchanged
E2	-1.57	-1.73	-0.16	Unchanged
E3	-3.03	-2.96	0.07	Unchanged
E4	-3.21	-3.10	0.11	Unchanged
E5	-2.12	-2.33	-0.21	Unchanged
E6	-4.16	-4.55	-0.40	Unchanged

Note. Source: Investing.com and National Stock Exchange India Limited, E1 has insufficient clean data for 120 sessions. Differences use unrounded estimates.

Table 12 removes the 9, 13 and 16 January 2025 earnings sessions from E3's estimation sample. CARs change little, although this check cannot exclude other overlapping news or resolve the choice of repricing date.

Table 12. E3 Excluding Earnings Sessions

Firm	CAR including (%)	t	CAR excluding (%)	t	Beta change
TCS	-1.69	-0.81	-1.68	-0.82	0.732 → 0.772
Infosys	-1.39	-0.60	-1.41	-0.60	0.680 → 0.704
HCLTech	-6.01	-2.24	-6.01	-2.24	0.635 → 0.673

Sources: Investing.com and company earnings filings. "Including" and "excluding" refer to selected earnings sessions in the estimation sample.

Table 13 and Figure 5 compare benchmarks. Mean CAAR changes from -2.28% using Nifty 50 to -0.17% using Nifty IT, a 2.11 percentage-point difference. A sector index absorbs shared

sector movements; it answers a relative-performance question. Neither benchmark by itself identifies an AI causal effect.

Table 13. Benchmark Sensitivity

Event	Benchmark: Nifty 50	Benchmark: Nifty IT	Absorbed by the benchmark
E1	0.43	-1.42	-1.85
E2	-1.57	-0.09	1.48
E3	-3.03	-0.06	2.97
E4	-3.21	0.97	4.18
E5	-2.12	0.38	2.50
E6	-4.16	-0.76	3.39
Mean	-2.28	-0.17	2.11

Note. Source: Investing.com and NSE India The final column equals Nifty IT CAAR minus Nifty 50 CAAR.

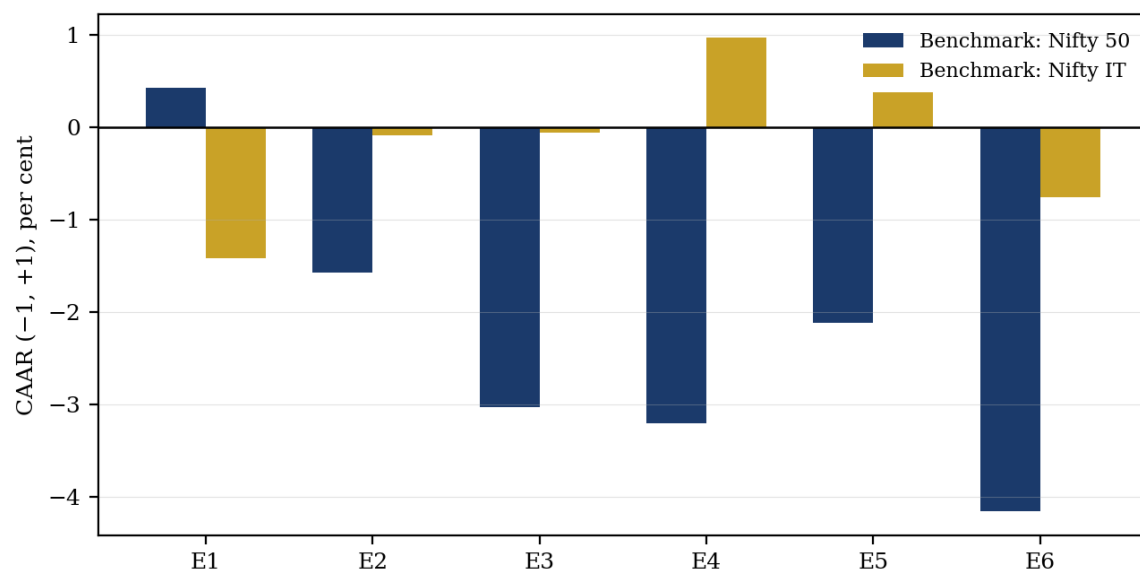


Figure 5. CAARs by Benchmark

Source: Investing.com. Alternative-benchmark estimates correspond to Table 13.

Table 14 retains the ownership regressions. Both slopes are negative but statistically insignificant: -0.0649 under pooled OLS and -0.0685 with event effects. A ten-point ownership difference corresponds to approximately -0.65 percentage points of CAR in the pooled estimate. H5 is not rejected; twelve observations provide limited power.

Table 14. CAR and Lagged FPI Ownership

Specification	Slope	Std. error	t statistic	R-squared
Pooled ordinary least squares	-0.0649	0.0654	-0.99	0.0898
With event fixed effects	-0.0685	0.0720	-0.95	NA

Note. Sources: Investing.com and quarterly company disclosures. Dependent variable: three session CAR (%). FPI ownership is in percentage points; n = 12, E3–E6.

7. Discussion and Financial Comparison

HCL Tech performs best over the full period but responds sharply to selected capability announcements. Table 15 adds a different comparison: normalised profit growth is -0.16% for HCL Tech, 8.35% for TCS and 13.73% for Infosys. HCL Tech's normalised margin falls from 14.86% to 13.35%, while TCS's rises from 19.11% to 19.80%.

Table 15. Normalised Financial Performance

Particulars	TCS	Infosys	HCLTech	Basis
Revenue growth (%)	4.58	9.61	11.18	Derived from reported
Reported profit growth (%)	1.35	10.18	-4.29	Derived from reported
Normalised profit growth (%)	8.35	13.73	-0.16	Derived from reported
Net margin, FY2025 (%)	19.11	16.41	14.86	Derived from reported
Normalised net margin, FY2026 (%)	19.80	17.03	13.35	Derived from reported

Sources: Company annual reports (2026). Normalisation removes pre-tax New Labour Codes charges recognised under Indian Accounting Standard 19, TCS ₹2,128 crore, Infosys ₹1,289 crore and HCL Tech ₹956 crore. TCS also excludes restructuring ₹1,388 crore and legal provision ₹1,010 crore. HCL Tech's normalised profit is ₹17,371 crore. Profit adjustments reflect their applicable tax effects.

The measures concern different horizons, cumulative expectations, specific revisions and realised profitability. Software assets may support future earnings while exposing a valuation premium to adverse news. This is consistent with RBV and dynamic capabilities but three firms

cannot isolate product ownership from client mix pricing or costs (Barney, 1991; Teece et al., 1997).

8. Conclusion and Limitations

Selected later announcements coincide with larger negative abnormal returns than ChatGPT's launch. HCL Tech combines stronger full period performance with sharper selected event declines and weaker normalised margins. Substantial benchmark sensitivity supports distinguishing valuation expectations from realised resilience.

Investors should examine contracts cash generation and valuation alongside technological exposure. Managers need to explain productivity effects on revenue and margins. No profitable trading strategy or preferred managerial response is established.

The study covers only three firms and six selected events. Cross firm dependence non normal returns event induced volatility and multiple testing qualify nominal significance. Firm-level degrees of freedom do not eliminate these concerns. There is only one demand event, event selection partly reflects observed comparator reactions, the ownership regression has twelve observations. Vendor validation is limited, and index and adjusted-stock dividend treatment may differ.

Coincident earnings, macroeconomic developments and announcement timing can affect event returns. No direct tests of all cross-firm or event-category differences are reported. The findings establish event related associations, not the proportion of the sector decline caused by AI. Extending the sample to all Nifty IT constituents testing cross sectional dependence and examining quarterly revenue per employee would strengthen inference.

Data

The study uses public price histories, annual reports and quarterly shareholding disclosures. I remain responsible for the data, calculations, references and submission.

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