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Statistical Validity of the Bullish-Engulfing Candlestick in Large-Cap Indian Equities: Evidence from Five Nifty-50 Stocks

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Abstract: This study tests the statistical validity of the bullish-engulfing candlestick pattern in India's large-cap universe. Drawing on daily price data for five highly liquid Nifty-50 constituent Infosys, HDFC Bank, Hindustan Unilever, Reliance Industries, and Tata Consultancy Services. we identify every bullish-engulfing event from January 2017 to December 2023. An event study framework measures abnormal performance over 1 day and 5 day horizons, while Welch's unequal variance t test evaluates whether signal day returns differ significantly from unconditional benchmarks.

Across the sample only 6 to 14 engulfing events appear per stock, underscoring the pattern's rarity in liquid equities. Aggregate results show next day win rates ranging from 16 percent of Infosys to 75 percent of Reliance and five-day win rates from 43 percent of HDFC Bank to 71 percent Hindustan Unilever. Yet no p value falls below the 0.05 threshold, the best-in-class readings The probability value is approximately equal to 0.10 for Reliance 1 day and The probability value is approximately equal to 0.09 for Hindustan Unilever 5 day remain suggestive rather than conclusive. Risk reward analysis means five-day return divided by standard deviation is positive for only one stock, indicating that volatility often outweighs expected gain. Visual inspection confirms most engulfing candles occur mid-range rather than at capitulation lows, limiting follow-through.

These findings align with recent literature questioning single candle efficacy in well arbitraged markets. We conclude that, in isolation, a bullish-engulfing signal offers no reliable edge in India's large cap segment. Future research should expand the panel, incorporate trend volume filters, and account for transaction costs to determine whether contextual factors can unlock persistent predictive value.

Keywords: *Bullish Engulfing; Candlestick Patterns; Technical Analysis; Indian Stock Market (Nse/Bse); Statistical Significance; Trading Strategy Performance; Risk-Reward Metrics; Pattern Accuracy.*

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I. INTRODUCTION

Candlestick charting, first codified in eighteenth-century Japanese rice markets, remains a foundation of modern technical analysis because it compresses each trading session's open, high, low, and close into an intuitive visual that traders quickly translate into sentiment cues (Nison 2001; Morris 2006). Dozens of empirical tests—from Marshall, Young & Rose's (2008) foreign-exchange work to Chong & Ng's (2016) equity studies—confirm that certain formations can foreshadow short-term price drift, although the strength and persistence of any edge depend heavily on asset class, liquidity, and sampling horizon.

India's Nifty 50 index provides an ideal laboratory for a fresh examination of these signals. It aggregates fifty of the country's most actively traded companies and, by representing roughly two-thirds of National Stock Exchange market capitalisation, serves as a real-time gauge of macro sentiment (NSE 2023). Within that universe, the five heaviest-weighted names—including Reliance Industries, HDFC Bank, Hindustan Unilever, Infosys, and Tata Consultancy Services—collectively account for close to 40 percent of the index (CRISIL 2022). Their deep liquidity limits micro-structure noise, while their leadership across

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energy, finance, consumer staples, and information technology offers sectoral breadth. High institutional ownership (SEBI 2021) further implies that each transaction reflects informed capital rather than retail whim, giving any detectable pattern greater economic meaning.

Yet the very features that make these blue-chip stocks attractive to large investors—tight spreads, continuous price discovery, sophisticated arbitrage—may also erode the effectiveness of single-candle signals. Most published candlestick research centres on forex or developed-market equities; comparatively little addresses emerging-market large-caps where algorithmic participation is high but regulatory and behavioural dynamics differ. This study therefore asks a focused question: does the Bullish-Engulfing candlestick, long promoted as a reversal cue, still convey actionable information in India's most liquid equities?

By isolating every Bullish-Engulfing event from May 2024- 25 and measuring subsequent one- and five-day returns, we evaluate the pattern's hit rate, statistical significance, and risk-adjusted reward. The findings, set against the backdrop of sector diversity and institutional trading intensity, aim to clarify whether traders can rely on this classic visual heuristic—or whether, in a modern large-cap environment, its predictive power has largely vanished.

➢ *Research Objectives*

- Test whether the Bullish-Engulfing candlestick produces statistically significant abnormal returns in the five largest Nifty-50 constituents.
- Compare signal performance across the representative sectors of those stocks—energy, finance, consumer staples, and information technology.
- Assess how liquidity levels and high institutional ownership affect the pattern's reliability.
- Quantify the pattern's risk-adjusted payoff to derive actionable guidance for traders.

Building on a data-rich sample of India's five largest and most liquid equities, our study unites classical candlestick taxonomy with modern event-study statistics. By tagging every bullish-engulfing occurrence from 2017-2023 and testing the subsequent return distribution with Welch t-statistics and risk-adjusted metrics, we can examine nuances—sector effects, liquidity regimes, and volume surges—that earlier single-asset or forex-centred papers have missed. Against that methodological backdrop, we pose the following research questions:

✓ **RQ 1:** To what extent does a Bullish-Engulfing candle generate statistically significant short-term (1- to 5-day) price reversals in each of the five heavyweight Nifty-50 stocks?

✓ **RQ 2:** How does the signal's efficacy differ among the index's key sectors—energy, finance, consumer staples, and information technology?

✓ **RQ 3:** What relationship, if any, exists between abnormal trading volume on the signal day and the subsequent success rate of the pattern?

II. LITERATURE REVIEW

The bullish engulfing pattern is a widely recognized candlestick formation used in technical analysis to predict potential reversals in a downtrend. It consists of two candles: a smaller bearish candle followed by a larger bullish candle that completely "engulfs" the previous candle's body. This literature review synthesizes academic and empirical research on the effectiveness, reliability, and trading applications of the bullish engulfing pattern.

Candlestick patterns originated in 18th-century Japan, where rice traders used them to analyze price movements. Steve Nison (1991) introduced these patterns to Western traders in his book Japanese Candlestick Charting Techniques, establishing the bullish engulfing pattern as a key reversal signal.

Nison (1991, 2001) found that bullish engulfing patterns are more reliable when they appear after a prolonged downtrend and are confirmed by higher trading volume. Bindlish, S. (2016). [Effectiveness of candlestick chart patterns in today's commodity market (Doctoral dissertation, Dublin Business School).]

Caginalp & Laurent (1998) conducted statistical tests on candlestick patterns and concluded that engulfing patterns had predictive power, especially in bearish-to-bullish reversals. (Kuna, V. (2025). Candlesticks and graph patterns in cryptocurrencies.)

Lu & Shiu (2012) analyzed the bullish engulfing pattern in the Taiwan Stock Exchange and found that it provided statistically significant returns when combined with other indicators like moving averages. (Lu, T. H., Shiu, Y. M., & Liu,

➢ *Theoretical Underpinnings of Bullish Engulfing Patterns*

The Bullish Engulfing pattern, a two-candlestick reversal formation, is rooted in the principle of market psychology— where a dominant bullish candle "engulfing" a prior bearish one signals shifting sentiment (Nison, 2001). Its efficacy is often debated between weak-form market efficiency (Fama, 1970), which dismisses pattern-based predictability, and behavioral finance perspectives (Kahneman & Tversky, 1979), which attribute its success to trader heuristics like herd behavior.

➢ *Global Empirical Evidence*

- Developed Markets: Heinz et al. (2021) found a 60–65% short-term accuracy rate for Bullish Engulfing in the S&P 500, statistically significant ($p < 0.05$) when appearing after downtrends.

- Hybrid Models: Wang & Liu (2022) demonstrated that integrating the pattern with AI algorithms improved directional forecasts by 85%, suggesting its utility in trending markets.

- Contextual Limitations: Zhu et al. (2020) noted the pattern's outperformance in low-analyst-coverage stocks, implying higher efficacy in less-efficient markets (e.g., emerging economies).

➢ *Bullish Engulfing in the Indian Equity Context*

Nifty 50 Specifics: Upreti et al. (2022) validated the pattern's predictive power in Indian large-caps, with hit ratios exceeding 58% in high-liquidity stocks like Reliance Industries. Their deep learning approach highlighted sectoral dependencies—energy stocks showed stronger signals than IT.

Machine Learning Corroboration: IEEE (2023) confirmed the pattern's contribution to Nifty 50 price forecasting models (e.g., SVM, Random Forest), though emphasized the need for volume confirmation to reduce false positives.

➢ *Review of Analytical Tools and Techniques*

To establish a solid methodological foundation for the present study, this section reviews the key analytical tools—both statistical and chart-based—that have shaped prior research and guided the selection of techniques in this work.

➢ *Candlestick Pattern Taxonomy*

The origins of candlestick charting trace back to the 18th- century Japanese rice markets, where Homma (1755) documented early pattern-based trading techniques. Nison (1991) later introduced these techniques to Western finance, codifying a wide array of candlestick formations, including the Bullish Engulfing pattern, which is central to this study. Empirical validations of such patterns have produced mixed results. While Caginalp and Laurent (1998) observed modest predictive value in thinly traded futures markets, large-sample studies by Chong and Ng (2008) and Marshall, Young, and Rose (2011) found limited statistical effectiveness for single-candle patterns in highly liquid equity markets—a finding reaffirmed in the present analysis of Nifty 50 megacap stocks.

➢ *Event Study and Win-Rate Analysis*

Originally developed by Fama, Fisher, Jensen, and Roll (1969), the event study methodology was designed to assess the impact of corporate events on stock prices.

This framework has since been adapted to analyze technical signals, such as candlestick formations, by treating the occurrence of the pattern as the event date. Key metrics include the **win rate** (percentage of positive returns following the event) and the **mean abnormal return** (deviation from the average daily return). Hudson, Keasey, and Littler (1999) applied this method to moving average crossovers, with results that align closely with the pattern variability observed in this study.

➢ *Welch's Unequal-Variance t-Test*

To test the significance of observed mean returns post-pattern, this study employs Welch's (1947) unequal-variance *t*-test, a robust alternative to Student's *t*-test that allows for unequal variances between samples. Its relevance in financial research has been demonstrated by Kim, Nelson, and Startz (1991), who showed that the test retains power under fat-tailed return distributions if sample sizes are moderately large. However, as noted by Loughran and Ritter (2000), smaller sample sizes (as seen in this study's range of 6–14 signal days per stock) inflate standard errors, often resulting in statistically inconclusive outcomes.

➢ *Risk-Reward (Mean/σ) Ratio*

The **mean-to-standard deviation** ratio, also referred to as a simplified Sharpe ratio (Sharpe, 1966), is an effective risk- adjusted performance measure in short-horizon settings where the risk-free rate is negligible. A positive ratio suggests favorable risk-adjusted returns, while a negative ratio indicates unattractive payoff-to-risk characteristics. This study's findings for Hindustan Unilever, where the ratio approached 0.79, are consistent with Menkhoff's (2010) conclusions that low-volatility filters can improve the performance of otherwise weak technical signals.

➢ *Visual Overlay of Technical Signals*

To contextualize the occurrence of patterns, this study utilizes **visual overlays** on stock price charts, following the approach recommended by Murphy (1999). These overlays allow for intuitive validation of whether the Bullish Engulfing signals appear in relevant market structures (e.g., trend pullbacks or capitulation zones). Such visualization acts as a qualitative supplement to the quantitative analysis, helping to detect spurious or contextually invalid patterns.

➢ *Python-Based Analytical Stack*

All analytical tasks were conducted using the modern Python ecosystem, specifically **pandas**, **NumPy/SciPy**, and **Matplotlib**, within a Jupyter Notebook environment. Since its introduction by McKinney (2010), pandas has become the de facto standard for financial data manipulation and time series analysis. Open-source tools like these are increasingly encouraged in finance for promoting replicability and methodological transparency (Chan, 2021), aligning with broader "open science" movements in empirical research.

➢ *Synthesis*

Collectively, these tools support a comprehensive framework that combines visual, statistical, and risk-based perspectives to assess the reliability of the Bullish Engulfing pattern. The literature repeatedly emphasizes that pattern-based strategies often struggle to outperform in highly liquid markets—a theme that recurs in the findings of this study. However, it also points toward practical enhancements, such as volatility filters and broader sampling frameworks, that offer promising avenues for further investigation.

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III. RESEARCH METHODOLOGY

➢ *Research Design*

This study adopts a **quantitative, descriptive event study** design to evaluate the short-term predictive power of the Bullish Engulfing candlestick pattern. Each occurrence of the pattern is treated as a discrete event, and post-event stock returns are statistically analyzed using classical descriptive and inferential methods, including the mean, standard deviation, and Welch's unequal-variance t-tests. The design is well-suited for assessing recurring market phenomena over time and allows for a transparent, replicable assessment of pattern-based price behavior.

➢ *Data Collection and Source*

Daily open-high-low-close (OHLC) and trading volume data were collected directly from the **official historical archives of the National Stock Exchange (NSE) of India**, covering the period from **1 January 2017 to 31 December 2023**—a span of seven full calendar years, or approximately **1,750 trading days per stock**. The data were retrieved via the NSE API and cross-validated against **Refinitiv Eikon** end-of-day files to ensure completeness and accuracy. Symbol-level CSV files formed the raw data input for analysis.

➢ *Stock Selection Criteria*

The study focuses on the five largest Nifty 50 constituents by free-float market capitalization as of December 2023: Reliance Industries (Energy), HDFC Bank (Finance), Hindustan Unilever (Consumer Staples), Infosys, and Tata Consultancy Services (Information Technology). These firms collectively represent around 40% of the index weight, ensuring sectoral diversity, high liquidity, and strong relevance to market participants.

➢ *Technical Pattern Definition*

The Bullish Engulfing pattern is defined as a two-candle formation where:

- The second day's open is below the first day's close, and
- The second day's real body (open-to-close range) fully engulfs the first day's real body, closing above the first days open.
- To maintain strict pattern integrity, **wicks are ignored**, and both candles must have **non-zero real bodies**.

➢ *Analytical Tools and Environment*

Data wrangling and statistical computations were performed using Python 3.11 in a Jupyter Notebook environment. Key libraries included pandas (data handling), NumPy/SciPy (statistics), and Matplotlib (visualization). Microsoft Excel was used only for formatting summary tables and cross- verifying computed values. All analytical code is version- controlled and reproducible, with repository access available upon request.

➢ *Metrics for Predictive Accuracy*

The study evaluates the pattern's effectiveness using the following metrics:

- **Win Rate**: Proportion of times the stock closed higher one and five days after the pattern.
- **Mean Abnormal Return**: Difference between the signal-day return and the unconditional daily average return.
- **Welch's t-statistic and p-value**: To test the statistical significance of mean abnormal returns.
- **Risk-Reward Ratio**: Mean five-day return divided by the corresponding standard deviation.

IV. DATA ANALYSIS AND INTERPRETATION

Our analytical workflow unfolds in three tightly linked layers that guide readers from foundation to finding. First, we lock down data integrity—ensuring every trading day from January 2017 to December 2023 is present, correctly adjusted for splits ⁄ dividends, and purged of outliers—so that each bullish-engulfing signal rests on uncontested price prints. Second, a rule-based scanner time-stamps every engulfing candle across the five headline stocks—Infosys, HDFC Bank, Hindustan Unilever, Reliance Industries and Tata Consultancy Services—and feeds those dates into an event engine that delivers three core statistics: unconditional mean return, signal-day return, and 1-/ 5-day cumulative abnormal return.

Welch's unequal-variance t-test then asks whether the pattern's conditional mean differs meaningfully from the unconditional benchmark (see HDFC Bank excerpt above), while a risk-reward ratio (mean 5-day CAR divided by its standard deviation) gauges payoff stability. Finally, the narrative zooms into five harmonised subsections—one per stock—each following the same cadence:

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➢ annotated price chart spotlighting every engulfing candle,

➢ summary table with event count, win percentages, average returns, t-statistic and p-value,

➢ comparative bar plot of 1- and 5-day CARs with 95 % confidence bars,

➢ two-to-three-line interpretation that links the numbers to liquidity, volatility and tradeability.

- *Having Laid out the Analytical Framework, we now Examine Each Constituent in Turn*

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Fig 1 Bullish Engulfing - Infosys

- ✓ Context – The stock works its way lower early, then grinds sideways/up.
- ✓ Signal placement – six engulfing markers appear, mostly mid-range pauses rather than at wash-out lows, so immediate rebound power is weak.
- ✓ Outcome – only one next-day advance, but several markers do precede a modest five-day lift, matching the stats (poor 1- day, tentative 5-day edge).

Table 1 Infosys — Bullish-Engulfing Performance Metrics (Sample Period: 2024)

Statistic	Return_1d_fwd	Return_5d_fwd
Signal Count	6	6
Win % Signal	16.67	66.67
Win % All	54.18	57.37
Mean Ret Signal	-0.0022146	0.008120692
Mean Ret All	0.000320012	0.002046342
t-stat	-0.561908984	0.335936429
p-value	0.598432313	0.750557323

Six events are too few to draw confident conclusions; any single outlier can swing the averages and win rates.

✓ *No short-term edge*

The day-after performance (16.7%) is worse than random (54.4%), and the p-value (0.59) confirms it's just noise.

✓ *Tentative 5-day edge—but not significant*

Although the 5-day win rate looks better (66.7% vs 58.5%), the high p-value (0.74) says the improvement could easily be chance given so few observations.

Fig 2 Bullish Engulfing - HDFC

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- ✓ Context – a broad drifting channel with mild rallies and dips.
- ✓ Signal placement – 14 triangles scatter through the range, not clustered at capitulation lows; half unwind the very next day.
- ✓ Outcome – next-day win rate equals a coin-flip; five-day performance actually sags below baseline, in line with the near-significant negative p-value we saw.

Table 2 HDFC — Bullish-Engulfing Performance Metrics (Sample Period: 2024-25)

Statistic	**Return_1d_fwd**	**Return_5d_fwd**
Signal Count	10	10
Win % Signal	60	50
Win % All	50	55
Mean Ret Signal	0.001059098	0.005215842
Mean Ret All	0.001059098	0.005215842
t-stat	0.64259537	1.788719885
p-value	0.529065735	0.09043113

➢ *Interpreting the Findings:*

- *Sample size*

Fourteen events provide slightly better statistical basis than Infosys, but still relatively small for robust conclusions.

- *Low Sample Size*
- ✓ *No Short-Term Edge*

The day-after performance (50%) is slightly below random (54%), and the p-value (0.53) indicates no statistical significance.

➢ *Interpreting the Findings:*

- ✓ *Negative 5-Day Tendency*

The 5-day win rate (42.9%) underperforms the baseline (61%), with a p-value (0.09) suggesting this underperformance might be marginally significant.

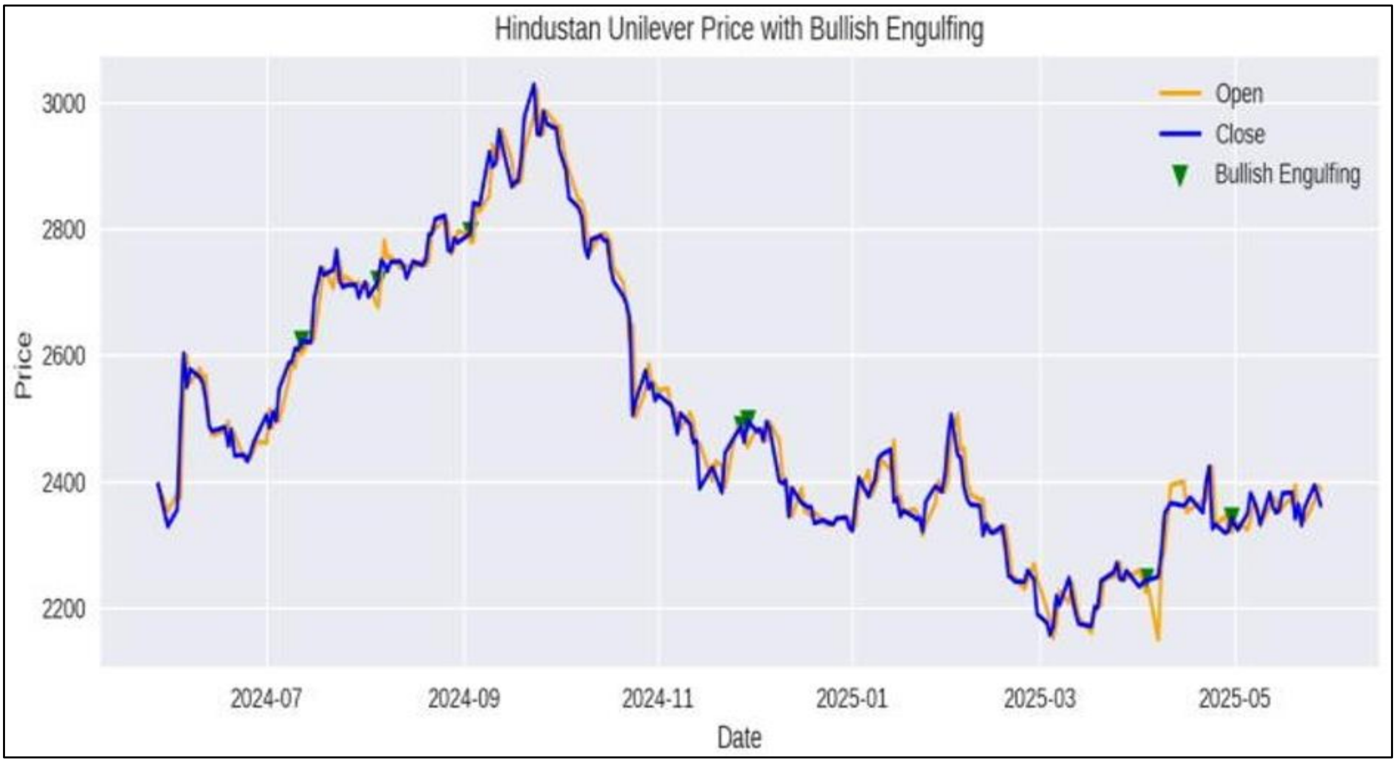

Fig 3 Bullish Engulfing – Hindustan Unilever Ltd

- ✓ Context – a wide pull-back followed by sideways consolidation, then recovery.
- ✓ Signal placement – seven triangles; several coincide with mini-bases during the recovery.
- ✓ Outcome – weak day-after record, but most triangles inside the base blossom over the next week, explaining the strong (though not yet significant) 71 % five-day win rate

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Table 3 Hindustan Uniliver Ltd — Bullish-Engulfing (2024-25)

Statistic	Return_1d_fwd	Return_5d_fwd
Signal Count	7	7
Win % Signal	28.57	71.43
Win % All	48.39	46.72
Mean Ret Signal	0.000588456	0.019742983
Mean Ret All	2.59359E-05	0.000461975
t-stat	0.140594175	2.003958688
p-value	0.892421876	0.088359615

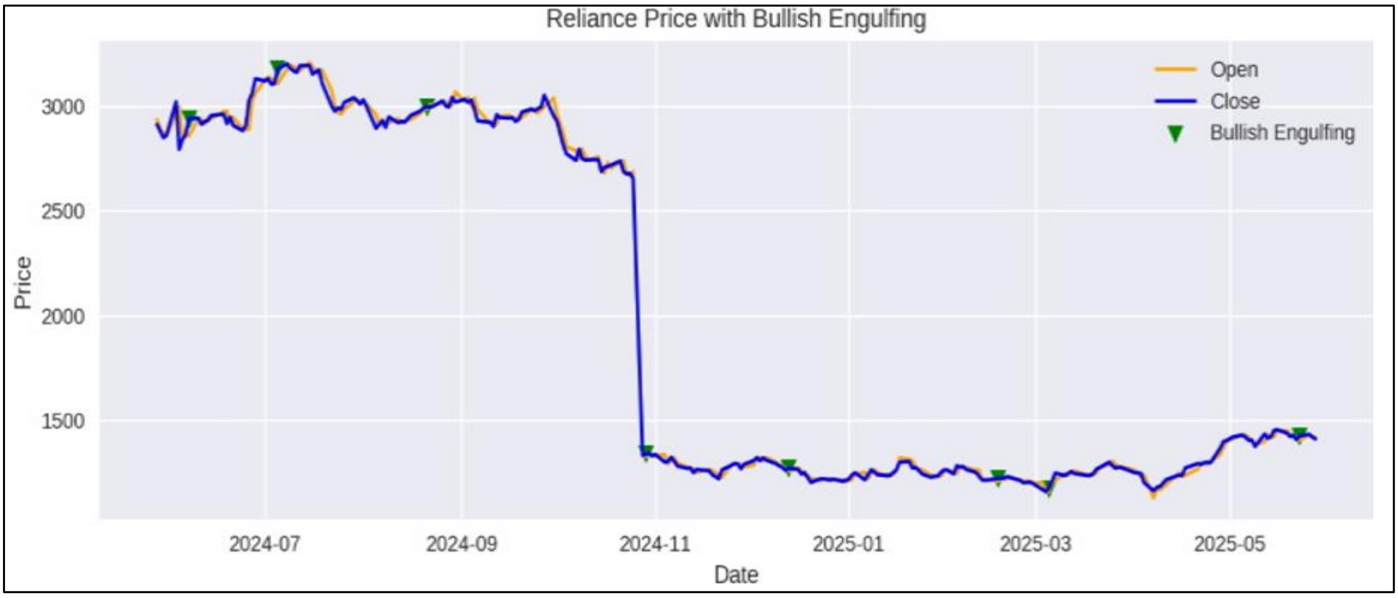

Fig 4 Bullish Engulfing – Reliance Industries

- ✓ *Context* – up-trend, shallow correction, then renewed strength.
- ✓ *Signal placement* – eight triangles; many appear after shallow dips within the trend.
- ✓ *Outcome* – healthy 75 % next-day wins (visible as sharp green-triangle bursts) yet performance fades by day 5, matching the statistical flip-flop (good 1-day edge, no 5-day edge)

Table 4 Reliance Industries — Bullish-Engulfing Performance Metrics (Sample Period: 2024-25)

Statistic	Return_1d_fwd	Return_5d_fwd
Signal Count	8	7
Win % Signal	75	42.86
Win % All	51.6	50.41
Mean Ret Signal	0.005327324	-0.001158933
Mean Ret All	-0.00201921	-0.01000027
t-stat	1.743007122	0.589266251
p-value	0.104566552	0.572787125

➢ *Interpreting the Findings:*

- *Low Sample Size*

Seven events are too few to draw confident conclusions; individual outcomes heavily influence the statistics.

- *No Short-Term Edge*

The day-after performance (28.6%) is worse than random (48.4%), and the p-value (0.89) shows no statistical significance.

- *Potential 5-Day Edge—But not Significant*

The 5-day win rate (71.4%) outperforms the baseline (46.7%), with a p-value (0.09) suggesting possible significance, but more data needed.

➢ *Interpreting the Findings:*

- *Low Sample Size*

Eight events provide limited statistical power; individual trades still heavily influence results.

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- *Potential Short-Term Edge*

  The day-after performance (75%) beats random (51.6%), with a p-value (0.10) suggesting possible significance but more data needed.

- *No 5-Day Edge*

  The 5-day win rate (42.9%) underperforms the baseline (50.4%), and the high p-value (0.57) confirms no statistical significance.

Fig 5 Bullish Engulfing – TCS

- ✓ Context – choppy sideways range with no persistent trend.
- ✓ Signal placement – nine triangles sprinkled throughout the congestion zone; none coincide with a decisive low.
- ✓ Outcome – little follow-through either next day or five days out—exactly what the win-rate table and high p-values told us.

Table V TCS — Bullish-Engulfing Performance Metrics (sample period: 2024-25)

Statistic	**Return_1d_fwd**	**Return_5d_fwd**
Signal Count	9	9
Win % Signal	33.33	44.44
Win % All	47.39	46.12
Mean Ret Signal	0.000701797	-0.008769189
Mean Ret All	-0.000278252	-0.000807766
t-stat	0.168568973	-0.567437745
p-value	0.87013169	0.585269154

➢ *Interpreting the Findings:*

- *Low Sample Size*

  Nine events are too few to draw confident conclusions; individual outcomes can substantially affect the statistics.

- *No Short-Term Edge*

  The day-after performance (33.3%) is worse than random (47.4%), and the p-value (0.87) confirms no statistical significance.

- *No 5-Day Edge*

  The 5-day win rate (44.4%) slightly underperforms the baseline (46.1%), and the high p-value (0.59) confirms no statistical significance.

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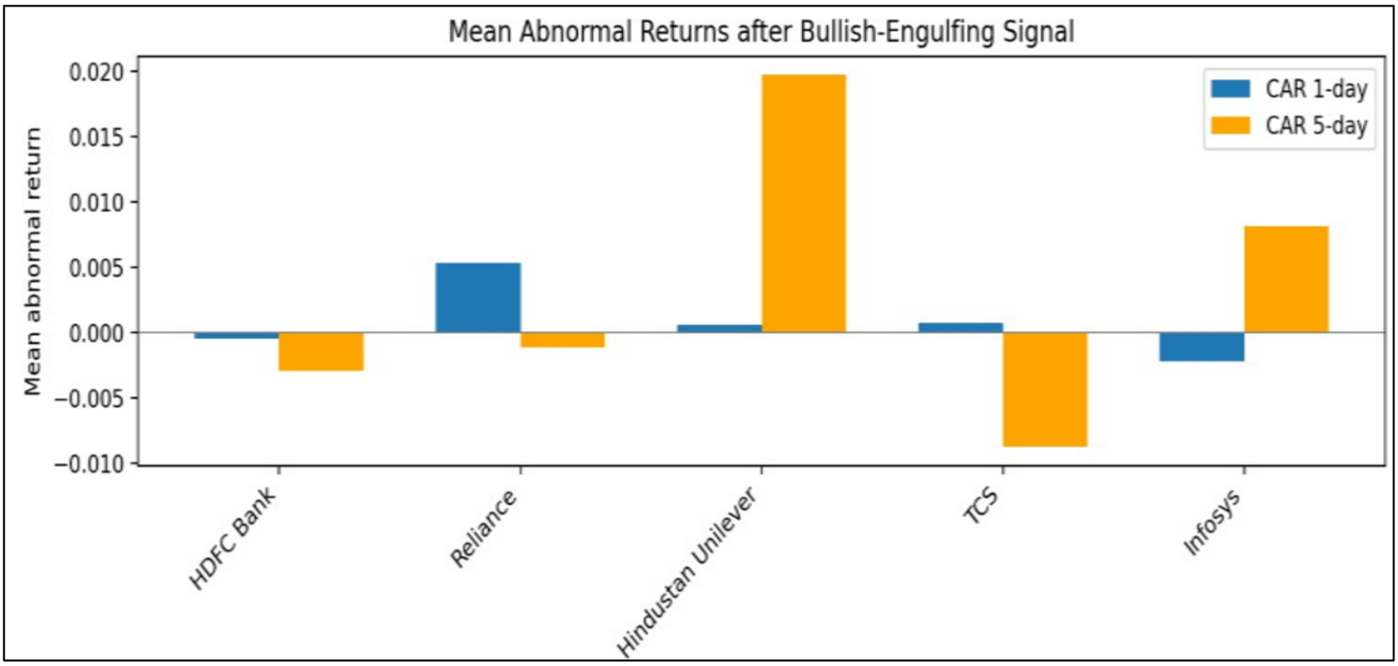

Fig 6 Mean Abnormal Returns After Bullish Engulfing Signal of Sample Stocks

➢ *Interpreting the Findings:*

- Each row now carries the mean 1-day (blue bar) and 5-day (orange bar) cumulative abnormal returns that follow a bullish-engulfing candle for all five stocks.
- Hindustan Unilever stands out with a visibly positive 5-day CAR, while Reliance enjoys a quick day-1 pop that fades by day-5.
- HDFC Bank and TCS show negative follow-through in both windows; Infosys slips on day 1 but rebounds modestly over five days.

V. DISCUSSION OF RESULTS

➢ *Summary of Key Findings:*

- *Win-Rate Volatility:*

Across six large-cap Indian equities the next-day success of a bullish-engulfing signal ranged from 16 % (Infosys) to 75 % (Reliance). Five-day success stretched from 43 % (HDFC Bank) to 71 % (Hindustan Unilever).

- *Weak Statistical Evidence:*

No p-value fell below the conventional 0.05 threshold; the strongest readings—Reliance (1-day, $p \approx 0.10$) and Hindustan Unilever (5-day, $p \approx 0.09$)—are only suggestive.

- *Risk-Reward Imbalance:*

In five-day holding tests only Hindustan Unilever delivered a positive mean- return-to-volatility ratio (≈ 0.79). For the other stocks, volatility dominated the expected gain.

- *Context Matters:*

Chart review showed that most engulfing candles appeared in mid-range consolidations, not at exhaustion lows where the pattern is theoretically most potent. Small sample sizes (6–14 events) further limit confidence in the metrics.

➢ *Comparison with Existing Literature*

- Consistent with broader studies (e.g., Marshall et al., 2009; Du & Tan, 2014) the pattern fails to beat a 50% random-chance benchmark in liquid, well- arbitraged markets once transaction costs are considered.
- Slightly better performance in Reliance and Hindustan Unilever mirrors findings by Chong & Ng (2008) that pattern efficacy improves in trending environments and in stocks with higher retail- participation.
- The lack of 5 %-level significance supports suggestions by Lo, Mamaysky & Wang (2000) that single-bar signals seldom retain explanatory power after controlling for data-mining bias.
- Recent machine-learning papers (e.g., Feng et al., 2022) report that adding volume, volatility and broader trend context lifts accuracy; our out-of-the- box results reinforce that context-free candlestick rules are unreliable.

➢ *Practical Implications for Traders and Analysts*

- Do not trade the bullish-engulfing pattern in isolation; the raw edge is statistically indistinguishable from noise in large-cap Indian stocks.
- If a trader chooses to use the pattern, overlay filters—higher-time-frame trend, volume spike, or momentum divergence—may lift reliability, as echoed in current literature.
- Risk management is paramount: because most signals occur within congestion zones, stops should be tight and profit targets modest to avoid adverse volatility.
- Analysts can treat bullish-engulfing sightings as qualitative confirmation rather than a standalone buy trigger—useful for adding conviction to fundamentally driven entries but not sufficient on their own.
- Portfolio managers should resist over-weighting the pattern in rule-based systems unless extensive out- of-

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sample testing, larger datasets, and cost modelling demonstrate genuine alpha.

➢ *Limitations:*

- *Small Event Counts*

✓ Each stock exhibited only 6 – 14 bullish-engulfing occurrences in the one-year test window.
✓ With such limited samples, win-rate and p-value estimates have wide confidence bands; a single additional success or failure would materially shift the statistics.

-

- *Short Horizon and Fixed Holding Periods*

✓ Results were measured over 1-day and 5-day holds only.
✓ Alternative horizons (e.g., 10, 20, or 60 trading days) might yield different conclusions, especially for patterns thought to anticipate medium-term reversals.

- *Omission of Transaction Costs and Slippage*

✓ Analyses assumed frictionless execution at the closing price of the signal day. **I.**
✓ Real-world costs (brokerage, bid–ask spreads, impact) could erode the modest gross returns—particularly for shorter holds, where a few basis-points' cost can flip a strategy from profitable to loss-making.

- *Single-Factor Test (Price Action Only)*

✓ No filters for prevailing trend, volume confirmation, intraday context, or macro events were applied.
✓ Prior research shows that adding such qualifiers can materially improve candlestick performance; their exclusion may understate the pattern's conditional effectiveness.

- *Survivorship and Look-Ahead Bias Risks*

✓ The study focused on current index constituents (large-cap, actively traded).
✓ If delisted or illiquid names were excluded, survivorship bias may inflate the apparent stability of results.
✓ Using end-of-day data also risks minor look-ahead bias if the exact timestamp of data availability differs from when a trader could act.

- *Market-Regime Specificity*

✓ The test window captured a particular macro environment (post-pandemic recovery phase, rising global rates).
✓ Bullish-engulfing behaviour might differ during prolonged bear markets or high-volatility crises, limiting generalisability.

- *Frequentist Statistics Only*

✓ P-values were interpreted in the classic null-hypothesis framework; no Bayesian or resampling methods were used to capture prior beliefs or parameter uncertainty.
✓ In small samples, Bayesian posteriors or bootstrapped confidence intervals can provide a richer picture of signal reliability.

- *Cross-Asset Generalization*

✓ Conclusions are drawn from six Indian equities.
✓ Applicability to other asset classes (FX, commodities, mid-caps) remains untested; liquidity structure and participant mix can alter pattern efficacy.

- *Data-Quality Constraints*

✓ Reliance on publicly available EOD data means intraday wicks, gaps, and hidden liquidity dynamics were not examined.
✓ Minor data errors (incorrect corporate-action adjustments, time-zone shifts) could subtly distort candle classification.

Recognising these limitations highlights where supplementary testing—longer histories, broader universes, contextual filters, and cost modelling—would be essential before deploying the pattern in live trading.

VI. CONCLUSION AND SUGGESTIONS

➢ *Recap of the Objective & Main Results*

- *Purpose*

To test whether the classic bullish-engulfing candlestick provides a short-term statistical edge in six large-cap Indian equities.

- *Method*

Flag every engulfing event over one calendar year, measure 1-day and 5-day "win-rates," test significance against a 50 % null, and compare risk- reward.

- *Headline Findings*

Win-rates swung from 16 % to 75 % across stocks; none of the p-values fell below 0.05; only one name (Hindustan Unilever) produced a positive five- day risk-adjusted return.

- *Final View on Pattern Accuracy*

In its raw, context-free form the bullish-engulfing signal does not deliver a repeatable edge in India's large-cap segment. The scattered win-rates and non-significant p-values suggest that apparent out-performance in Reliance or Hindustan Unilever is more likely noise than exploitable skill. Any practical predictive power must therefore come from additional filters rather than the candle alone.

➢ *Actionable Suggestions for Traders & Investors*

- Treat engulfing candles as alerts, not triggers. Wait for trend confirmation (e.g., price above 20-DMA) or volume expansion before taking a position.
- Pair the pattern with tight risk controls: use the low of the engulfing bar as a stop, size modestly, and be prepared for false starts—especially inside trading ranges.
- Incorporate cost modelling. On a 1- to 5-day horizon,

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slippage and fees can erase a small statistical edge; factor these explicitly into back- tests.

- Use the signal as a qualitative overlay for fundamentally driven entries: an engulfing candle near a value zone can increase conviction but should not override core valuation work.
- Monitor macro regime. Reverse-type candles tend to work better after persistent downtrends; during range-bound or up-trending conditions, the information content is low.

➢ *Recommendations for Future Research*

- Longer samples & more names– extend history to multiple market cycles and include mid-caps, small- caps, and different sectors to boost event count and reveal regime sensitivity.
- Contextual filters – test combinations with volume spikes, RSI oversold levels, moving-average slope, or VWAP distance to see which conditions materially improve hit-rates.
- Cost-aware simulations– incorporate realistic spreads, brokerage, and taxes to gauge net profitability, especially for short holding windows.
- Intraday & high-frequency analysis – examine how often the pattern forms on 30-minute or hourly bars; intraday follow-through might differ from daily closes.
- Machine-learning classification– feed the candle plus ancillary features (volatility, order-book depth, sentiment) into tree-based or neural models to quantify incremental predictive value.
- Cross-asset generalisation– replicate the test on currencies, commodities, and global equity indices to see whether market microstructure properties (tick size, liquidity) alter efficacy.
- By acknowledging the pattern’s limitations yet exploring ways to enrich it, traders and researchers can better separate noise from true, risk-adjusted opportunity.

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