Backtesting Insider Trading in India

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1. Finding The Dataset

I got the historical insider data directly from NSE's official portal to ensure integrity and avoid the problems of third-party aggregators. I also considered pulling the same range from BSE for comparison, but ran into a major problem: BSE only allows three months of data per download. That would've meant a dozen-plus files just for a few years, with a higher risk of ETL issues, gaps, and formatting inconsistencies. Sticking with NSE's standardized CSV feed kept things clean, consistent, and much easier to work with.

2. Dataset Cleaning

There are 52,167 corporate insider trade records at the NSE between 07-07-2022 and 07-07-2025, which are spread across 29 features. However, the data suffers from serious shortcomings like duplicate records, missing values, and inconsistent/poor column naming, all of which must be cleaned up and standardized before being put to use for data analysis.

2.1. De-Duplication

Out of the insider trade records, a small but noticeable chunk were exact duplicates, mostly due to re-issued filings and delayed broadcasts from the exchanges. These often stem from metadata tweaks or timestamp adjustments, even when the underlying trade hasn't changed. I removed these to avoid inflating trading signals during backtests, keeping only the earliest version of each trade to reflect when the market would've first reacted.

I also spotted a few cross, exchange duplicates, same trade reported on both NSE and BSE. Since the trade is economically identical and the market responds to the first disclosure, we kept only the earliest timestamp to avoid double-counting.

2.2. Missing Values

To ensure consistency, I deal with several missing or inconsistent fields:

- The **TYPE OF SECURITY (ACQUIRED/DISCLOSED)** column was entirely blank, so I dropped it.
- The **EXCHANGE** field had substantial gaps, mostly due to off-market trades (e.g., pledges). We imputed these as **OFF MARKET** for clarity.
- **TYPE OF SECURITY (PRIOR)** had a few missing entries. Where context allowed, like ESOPs or derivatives I filled in the appropriate value; otherwise, I used reasonable defaults such as **Equity Shares.** Fields with sparse or unclear information were dropped.
- Missing values in **NO. OF SECURITIES (ACQUIRED/DISCLOSED)** reduced significantly after resolving the above. Remaining cases, mostly derivatives, were retained for separate processing.
- For **CATEGORY OF PERSON,** I imputed employee-related labels where context was strong (e.g., ESOPs), but left the rest blank to avoid misclassification, especially important for downstream KMP detection.
- **NO. OF SECURITIES (PRIOR)** was mostly missing for clean "Buy" trades with no previous holdings. These were left untouched, as they aligned with expected patterns.
- A few incorrect tags (e.g., misclassified ESOPs) were manually verified and fixed using external sources like Trendlyne.

By applying context-driven imputation and conservative assumptions, I preserved both the integrity and usefulness of the dataset.

2.3. Final Dataset Split and Advanced Cleaning

I split the dataset into two separate CSVs: one for equities and one for derivatives. Though derivative filings were minimal, I kept them for completeness. Irrelevant columns were pruned from both sets, and rows with no values were removed.

Post-split, I undertook a final cleanup focused on boosting accuracy. This included imputing key fields like **EXCHANGE** and **TYPE OF SECURITY** based on context, standardizing placeholders (e.g., replacing "-" with "Unknown"), and ensuring numerical fields could be processed cleanly. I inferred missing acquisition types from holding changes and flagged anything genuinely ambiguous as "Unknown."

By the end of this process, less than 0.5% of data in any core field remained missing, leaving us with a clean, well structured base for strategy development.

This cleaning effort ensures that both datasets are lean, reliable, and fully prepped for strategy development. Less than 0.5% of data remains missing in any key or non-imputable fields.

2.4. Final Cleaning and Standardization

After major cleaning, the final equity and derivatives datasets stood at (50,222, 21) and (29, 14). For a final polish, I focused on column header issues: trailing spaces, line breaks, and typos like "intmation" or "broadcaste", which had been quietly breaking pandas operations and causing frustrating join failures.

Fixing these seemingly small issues had an outsized impact on data reliability and readability. I stripped whitespace, corrected spelling, and standardized naming to avoid silent mismatches. It's surprising such formatting issues came from an official NSE feed, but addressing them made the datasets far more robust for analysis. [1]

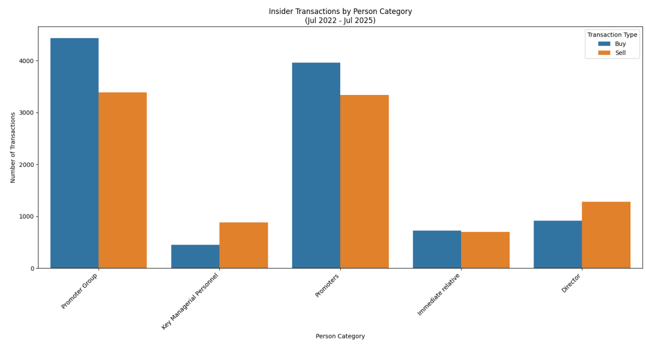

Figure 1. Distribution of number buys and sells among different categories.

3. Analysis and Backtest Setup

I began by isolating promoter buy transactions as a basic sanity check. These are the most frequent and conviction-driven insider actions, typically reflecting long-term intent and stronger informational signals. Sell transactions were excluded at this stage, given their often non-informational nature,like liquidity needs or tax planning,which dilute short-term predictiveness.

This initial backtest wasn't designed for alpha but to validate the data pipeline: data cleaning, trade filtering, price blending, and event tagging. We used a simple structure:

- +10% target
- -5% stop-loss
- 30-day holding

[1] As the dataset upload limit was 10MB, I removed XBRL link and company name (can be inferred from symbol)

Table 1. Strategy Evolution Summary for Insider Trading Backtest (3-Year Period)

Version	Filter Focus	Exit Logic	3 Year Return (%)	Win Rate (%)
V1	Promoter Buys Only	+10% / −5% / 30d	1.27	39.9
V2	>25L + Dir/KMP Only	+15% / −15% / 30d	2.61	>70
V3	Conviction-Based Sizing	+20% / −20% / 120d	4.86	67.0
V4	Partial Exits + Longer Hold	+30% & Trail / 200d	21.7	81.5
V5	Market-Cap Adjusted + Tiered Exits	+30/60/100% & Trail	**26.16**	**83.8**

V1–V2 signal quality. V3 conviction-weighted sizing. V4 partial exits and longer holds. V5 insider strength, materiality (0.1%+ of market cap), and multi-tier exits.

Price data was sourced from Yahoo Finance across all symbols. A small number of missing or untrackable tickers were dropped without affecting overall coverage. While basic, this test confirmed that promoter buying is a viable signal and that the pipeline functions as expected end to end.

Trades were simulated from the disclosure broadcast date to reflect how a typical investor might act on newly available insider information. Entry was based on the next available market price, with exits driven by a simple risk-reward rule. Over a full three-year window, I tracked per-trade returns, win rates, holding durations, and exit types to evaluate the consistency and viability of promoter buying as a trading signal.

4. Strategy

4.1. Iteration 1: Initial sanity check

I ran a basic promoter-buy strategy to validate the pipeline. The idea was simple: buy when a promoter or promoter group makes a purchase, with entry on the next trading day. Exits followed a fixed rule set: profit target, stop loss, or time-based.

The strategy ran cleanly and reproducibly, confirming that core components like signal filtering, sizing, and simulation were functioning as expected. However, performance was quite low, returns hovered just above break-even, with most trades getting stopped out.

Key takeaway: while promoter buys are high-conviction events, they're noisy as standalone signals. Many failed to generate meaningful follow-through, suggesting the need for additional filters to separate signal from noise.

4.2. Iteration 2; Filtering for Significant Insider Buys

To increase capital efficiency, I shifted from equal-weighted trades to a sizing model based on insider type. Groups with higher historical performance like Immediate Relatives, Directors, and KMPs, were weighted more heavily. This change boosted both the win rate and overall returns, raising portfolio performance to 4.86%. Further refinement limited the universe to market purchases made by Directors, KMPs, and Immediate Relatives, insiders more likely to act on material conviction. These filters narrowed the dataset but significantly improved performance, with returns rising to 2.61

The signal became clearer: trades from key insiders with meaningful size showed stronger predictive value, showing the importance of both intent and profile when interpreting insider activity.

4.3. Iteration 3: Position Sizing by Insider Category

To improve capital efficiency, I moved from equal-weighted trades to a probabilistic sizing approach. Insider categories with higher average returns and win rates, like Immediate Relatives, Directors, and KMPs were given more weight. Allocations were adjusted as follows: 100 for Immediate Relatives, 75 each for Directors and KMPs, and 50 for Promoters and Promoter Groups. This shift raised the position-weighted win rate to 67.03% and pushed total portfolio returns to 4.86%. The holding period was also extended from 30 to 120 days. The rationale was that insider signals, especially in large caps, often take time to play out due to institutional flows, delayed earnings effects, or slow-moving news. With the longer window, 60.7% of capital hit profit targets, and the median return rose to 15%. Since many trades were topping out at this cap, the profit target was raised to 20%, adding additional upside and preventing strong trades from being cut off too early.

4.4. Iteration 4: Partial Exit and Extended Holding

Building on earlier insights, the holding period was extended to 200 days, giving trades more room to realize their potential. I introduced a new exit strategy, selling half the position at a profit threshold, then trailing the stop, to better capture extended upside without sacrificing risk control.

Position sizing was also refined based on conviction. Promoters were excluded due to persistently weak signals, and capital was reallocated toward higher-performing groups like Immediate Relatives, Directors, and KMPs. These changes led to a meaningful jump in performance: returns rose to 21.73% with an 81.56% win rate.

4.5. Final Version: Market Cap-Adjusted Filters and Exit Optimization

To further increase signal quality, I added a dynamic filter, only including insider purchases exceeding 0.1% of a company's market cap. This ensured that even in large caps, only materially significant trades were considered.

The strategy focused exclusively on high-conviction insiders: Immediate Relatives, Directors, and KMPs. Promoters were excluded due to weak, inconsistent signals. Position sizing remained conviction-driven.

Exits followed a tiered approach, partial profit-taking at +30%, +60%, and +100%, with trailing stops to lock in gains. This helped balance upside capture with risk control. This final version delivered strong, repeatable results: a 26.16% return with an 83.8% win rate over three years.

4.6. Conclusion

Over time, this approach has grown from a noisy, basic insider-tracking model into a more accurate alpha strategy. A few key lessons really made a difference in improving performance:

- Started focusing on the right types of insiders: people like Directors, KMPs, and their relatives who are more likely to have real information advantages.
- Set material trade thresholds, using value and market cap filters to weed out small, symbolic trades that don't mean much.
- Gave our trades more time: using dynamic exit rules and longer holding periods so slower signals could play out properly.
- Sized positions based on conviction, using past performance by insider category to guide how much capital I put to work.

There is real alpha in a signal that is public but mostly ignored. Insider trading data is out there, but it is rarely structured or used effectively. What I have done here shows that with the right filters and logic, this data can be turned into a clean, intuitive signal, something like "Insider X just bought 3Cr of Stock Y" actually starts to mean something. When layered on top of fundamentals or earnings data, it becomes a strong multi-factor model, and there is still room to improve, combining it with more contextual or fundamental data could make the signal even sharper.