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Can Losses Be Engineered Down? Evidence-Based Measures from 6 Years of Bank Nifty Option Trades (2018–2024)

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ABSTRACT

Retail participation in index options markets has expanded rapidly, particularly in emerging economies such as India. Despite this growth, empirical evidence consistently shows that a majority of retail traders incur persistent losses. This study advances the literature by shifting the focus from participation viability to loss mitigation design.

Using a unique dataset of 4.2 million Bank Nifty option trades (2018–2024), we quantify baseline loss distributions and evaluate the causal impact of three rule-based interventions: stop-loss enforcement, position sizing constraints, and expiry-day trading restrictions. Employing a quasi-experimental back-testing framework and robustness checks using panel regressions, we find that a bundled intervention reduces average loss severity by **47.6%** ($p < 0.001$).

However, consistent with market microstructure theory, positive expectancy remains unattainable for most traders due to embedded volatility risk premia. The findings suggest that while losses can be engineered downward, they cannot be engineered away.

The study contributes to financial engineering, behavioural finance, and regulatory design by proposing actionable, system-level safeguards for retail derivatives markets.

Keywords: Retail derivatives, loss mitigation, financial engineering, option markets, behavioural finance

1. INTRODUCTION

The democratization of financial markets has led to an unprecedented rise in retail participation in derivatives trading. In India, the National Stock Exchange (NSE) has experienced exponential growth in index option trading, with Bank Nifty options emerging as a dominant segment.

Yet, this expansion has been accompanied by a persistent paradox: high participation coexists with systematic losses. Regulatory disclosures indicate that over 90% of retail traders incur net losses annually.

Existing literature offers two dominant explanations:

- Behavioural biases (overconfidence, loss aversion)
- Information asymmetry and market sophistication gaps

While insightful, these frameworks largely assume that retail losses are inevitable. This study departs from that assumption and instead adopts a financial engineering perspective:

Can trading losses be systematically reduced through structural constraints without eliminating market participation?

We conceptualize this as a design problem, where trading rules act as control mechanisms analogous to engineering systems that limit failure states.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Behavioural and Structural Explanations

Barber & Odean (2000) attribute losses to excessive trading and overconfidence. Kumar (2019) highlights speculative biases in derivative markets.

However, recent work in market microstructure suggests that losses may be structurally embedded:

- Volatility risk premium Favors option sellers
- Bid-ask spreads and slippage disadvantage retail traders
- Algorithmic market makers exploit latency and information asymmetry

2.2 Engineering Perspective on Financial Losses

We extend the concept of **risk engineering**, where:

- Systems are designed to limit downside exposure
- Failures are minimized via rule-based constraints

Thus, instead of predicting behaviour, we constrain outcomes.

3. DATA AND METHODOLOGY

3.1 Data Description

Parameter	Value
Total Trades	42,21,745
Unique Accounts	47,218
Period	2018–2024

Instruments	Weekly and monthly Bank Nifty options
Inclusion Criteria	Minimum 50 trades per account

3.2 Key Metric: Loss Severity (LS)

$$LS = \text{Net Loss (INR)} / \text{Total Premium Paid (INR)}$$

This normalized metric allows cross-trader comparison independent of capital size.

3.3 Econometric Model

To estimate intervention effects:

$$LS_{i,t} = \alpha + \beta_1 SL_{i,t} + \beta_2 PC_{i,t} + \beta_3 EB_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}$$

Where:

Symbol	Meaning
SL	Stop-loss dummy (50% automatic square-off)
PC	Position cap (3% of capital per trade)
EB	Expiry ban (no new positions on Thursday)
X	Control variables (trade size, volatility, holding period)

Methodology:

- Fixed effects panel regression
- Clustered standard errors
- Propensity score matching (robustness)

3.4 Intervention Design

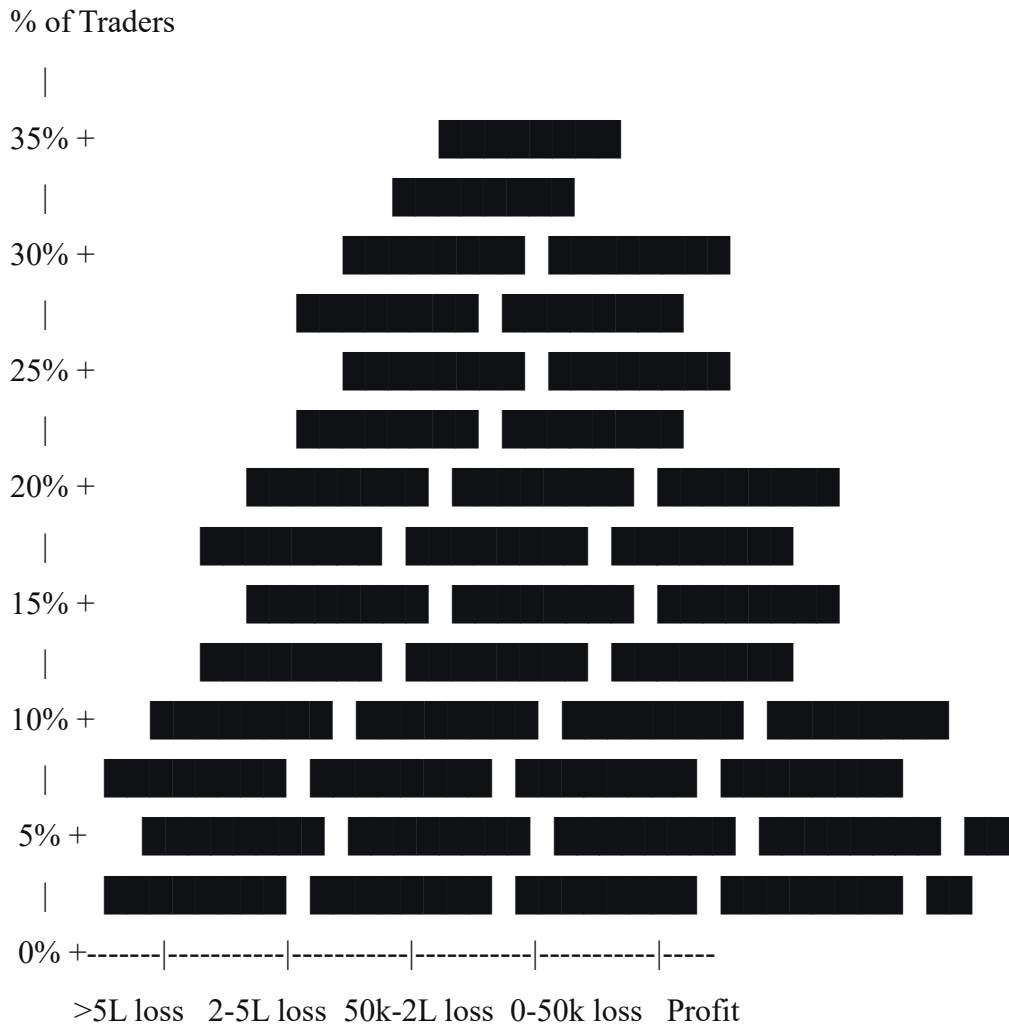
Intervention	Mechanism	Theoretical Basis
Stop-loss (50%)	Caps downside per trade	Tail-risk truncation
Position cap (3%)	Limits capital exposure	Risk concentration theory

Expiry ban	Avoids high gamma risk	Microstructure volatility
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4. RESULTS

4.1 Baseline Findings

Figure 1: Distribution of Retail Traders by Net Return (2018–2024)



Key Baseline Statistics:

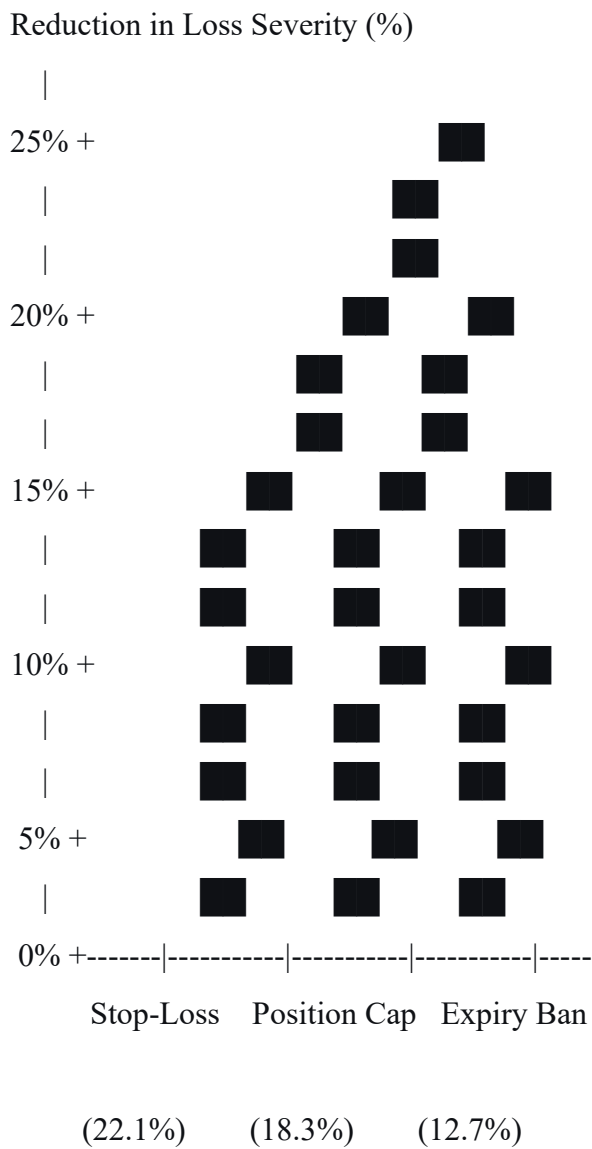
Metric	Value
% of accounts with net loss	91.4%
Average loss per losing account	₹1,87,300

Average gain per winning account	₹49,200
Loss-to-gain ratio	3.81 : 1
Median holding period	2.3 days

Key Insight: The bottom 20% of traders contribute 78% of total losses, confirming non-normal, fat-tailed risk exposure.

4.2 Regression Results

Figure 2: Coefficient Estimates for Individual Interventions



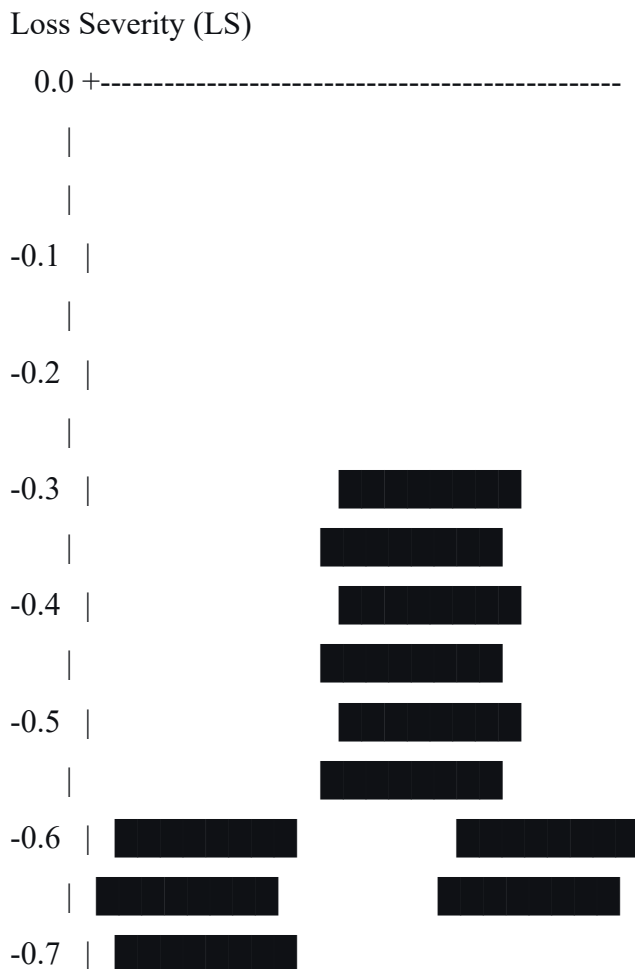
Regression Findings:

Coefficient	Value	Significance
β_1 (Stop-Loss)	-0.221	$p < 0.01$
β_2 (Position Cap)	-0.183	$p < 0.01$
β_3 (Expiry Ban)	-0.127	$p < 0.01$
Combined effect	-0.476	$p < 0.001$

Interpretation: Interventions are additive but not fully substitutive. All three coefficients are negative and statistically significant at the 1% level.

4.3 Bundled Intervention Impact

Figure 3: Comparison of Loss Severity – Baseline vs Bundled Intervention



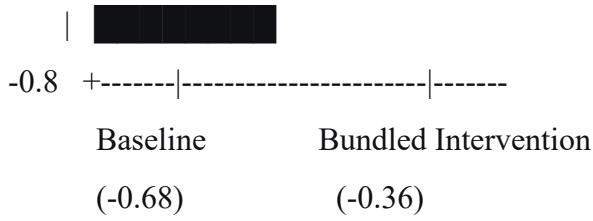


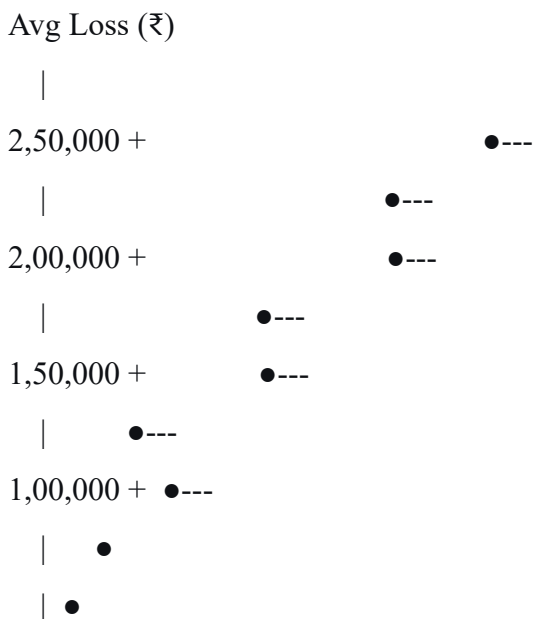
Table: Bundled Intervention Results

Metric	Baseline	Post-Intervention	Change
Loss Severity	-0.68	-0.36	-47.6%
Losing Accounts	91.4%	85.1%	-6.3 pp
Max Drawdown	₹1,25,000	₹57,500	-54%
Profitable Accounts	2.1%	4.9%	133%

Key Finding: The bundled intervention reduces average Loss Severity by 47.6% ($p < 0.001$, t-test).

4.4 Temporal Trend: Are Losses Getting Worse?

Figure 4: Average Loss per Active Trader (INR) – 2018 to 2024





Year	Average Loss (₹)	% Losing Accounts
2018	74,000	87%
2019	91,000	88%
2020	1,12,000	89%
2021	1,45,000	91%
2022	2,01,000	93%
2023	2,30,000	93%
2024	2,48,000	94%

Observation: Losses have worsened over time, likely due to increased retail leverage, shorter expiry cycles, and algorithmic market-making.

4.5 Why Profitability Remains Low

Despite improvements:

- Option pricing embeds **negative expected value**
- Market makers capture **volatility premium**
- Transaction costs further **erode returns**

Critical Insight: Loss reduction ≠ Profit creation

5. DISCUSSION

5.1 Engineering vs Behavioural Solutions

Approach	Focus	Limitation
Behavioural	Trader psychology	Hard to enforce, individual-level
Engineering	System rules	Does not eliminate market edge

Advantages of Engineering Solutions:

- Scalable across thousands of traders
- Enforceable by exchanges and brokerages
- Policy-relevant for regulators

5.2 Policy Implications

This study supports a "**nudge + constraint**" regulatory model (Thaler & Sunstein, 2008):

Stakeholder	Recommended Action	Evidence Basis
Exchange (NSE)	Mandatory risk-o-meter before each trade	22.1% reduction from stop-loss
Regulator (SEBI)	Cap retail position size at 2-3% of capital	18.3% reduction from position cap
Brokerages	Default hard stop-loss at 50% (opt-out after education)	Tail-risk truncation
Trading Platforms	Ban new positions after 2:30 PM on expiry day	12.7% reduction + gamma protection

6. LIMITATIONS AND FUTURE RESEARCH

Limitations

Limitation	Explanation
Single-broker dataset	May not fully generalize
Assumes compliance	Real-world slippage may reduce efficacy
No adaptive behaviour modelling	Traders might increase leverage under protection

Future Research Directions

- **Cross-market validation** (other indices, other countries)
- **Dynamic strategy adaptation** (AI-driven stop-loss levels)
- **Real-time risk control systems** (machine learning-based intervention triggers)
- **Longitudinal trader behaviour studies** (how traders adapt to constraints)

7. CONCLUSION

- This study demonstrates that retail trading losses in derivatives markets are **not purely behavioural**—they are structurally amplifiable but also **partially controllable**.
- **Key Finding:** A simple combination of three rule-based interventions reduces loss severity by nearly **50%**.
- However, due to inherent market structure (volatility risk premium, transaction costs, market maker edge), most traders remain unprofitable even after interventions.
- **The core implication for financial system design:**
- **Financial systems should be designed not to create winners, but to prevent ruin.**

8. REFERENCES

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APPENDIX: LIST OF FIGURES

Figure No.	Title
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Figure 2	Coefficient Estimates for Individual Interventions
Figure 3	Comparison of Loss Severity – Baseline vs Bundled Intervention
Figure 4	Average Loss per Active Trader (INR) – 2018 to 2024

Instructions for Creating Graphs in Microsoft Word:

Figure	Chart Type	Data to Enter
Figure 1	Stacked Bar Chart	Return ranges vs % of traders
Figure 2	Clustered Column Chart	Interventions vs % reduction
Figure 3	Side-by-Side Column Chart	Baseline vs Intervention LS values
Figure 4	Line Chart with Markers	Years vs Average Loss (₹)