Risk Tolerance and the Adoption of Stop-Loss Strategies among Retail Investors in the Indian Stock Market

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Abstract
This paper examines the association between risk tolerance and the usage of stop-loss strategies by retail investors in the Indian stock market. The paper uses primary data collected from 72 investors using a structured questionnaire with five-point Likert scales and employs correlation analysis and ordinal logistic regression to examine the hypotheses. The results indicate that higher risk as a predictor of stop-loss usage is significant, but self-identified risk profile is not significant. Moreover, behavioral response to market downturns is identified as a robust predictor of disciplined stop-loss strategy, accounting for a larger variance than general risk tolerance metrics. The results indicate that dynamic behavioral responses to market volatility have a more significant impact on the adoption of formal risk management strategies than static risk identity. This paper makes a contribution to the literature on behavioral finance by indicating that disciplined protective action is linked to active risk engagement rather than risk tolerance.

Keywords: Risk Tolerance, Stop-Loss Strategy, Retail Investors, Behavioural Finance, Adoption

1. INTRODUCTION

The growth of digital trading platforms together with financial inclusion programs and reduced transaction fees has enabled retail investors in emerging markets to participate in equity markets more than ever before during the last ten years which includes India as an emerging market. The market depth improves with increased participation, yet it creates problems because individual investors lack proper risk management skills. Retail investors lack the same advanced hedging tools that institutional investors possess, so they depend on basic methods for risk management which include stop-loss orders to handle potential losses (Chang et al., 2016; Hoffmann & Post, 2016). The risk tolerance of an individual determines which investments they select and how they construct their investment portfolio. The research demonstrated that individual risk preferences had a direct impact on investors' asset distribution choices and their trading activity levels together with their decision to use protective measures (Grable, 2016; Nguyen et al., 2019). Active investors who want to take more risks choose high risk assets, but they use fewer protective measures, while conservative investors establish more risk control procedures (Aren & Zengin, 2016; Pak & Mahmood, 2015). People who study market behavior have shown that market participants who self-report their risk tolerance do not always practice effective risk management methods during times of market volatility (Kumar & Goyal, 2016; Bouri et al., 2017).
Retail investors frequently use stop-loss strategies as their primary tool for managing investment risk because these methods automatically close positions when market losses reach predetermined thresholds according to Duong et al. 2019. Theoretical frameworks of risk tolerance raise questions about human behavior because research shows mixed results about whether people who self-identify as high-risk investors use these methods or depend on their own judgment according to Hoffmann et al. 2017 and Toma 2015. Market downturns produce two different investor responses because people either sell their assets during moments of distress or they seek safe investments which can replace or work together with structured stop-loss systems according to Baker et al. 2020 and Statman 2019.
The current research investigates how Indian stock market investors use stop-loss strategies based on their level of risk tolerance. The research explores human behavior through its study of risk management methods which help advance the existing knowledge base about household financial behavior and risk management in developing economies.

2. LITERATURE REVIEW

Risk tolerance has been identified as a basic driver of investment decisions for a long time. Modern studies stress that risk tolerance is not only a personality characteristic but a dynamic construct influenced by financial literacy, market experience, income certainty, and psychological characteristics (Grable, 2016; Nguyen et al., 2019). Empirical evidence shows that investors with higher risk tolerance allocate more of their portfolio to stocks and are more actively involved in trading activities (Baker et al., 2020). However, increased risk tolerance does not always mean effective risk management; in fact, it is often associated with speculative activities and lower dependence on formal risk protection instruments (Aren & Zengin, 2016). In the context of household finance studies, behavioral biases further distort the relationship between risk tolerance and sound portfolio management. Overconfidence, disposition effect, and loss aversion play a significant role in shaping investor reactions to market uncertainty (Hoffmann & Post, 2016; Kumar & Goyal, 2016). Investors tend to stray from optimal portfolio rebalancing and instead tend to act emotionally during market downturns, either through panic selling or holding on to losers for too long. Such behavioral patterns may offset or interact with systematic risk protection methods such as stop-loss orders, Stop-loss strategies are a risk management approach that aims to limit potential losses by automatically selling assets once a certain price level is breached. While such strategies are widely accessible through contemporary trading platforms, there is a lack of empirical research on their usage by retail investors. Duong et al. (2019) suggest that mechanical trading rules can improve risk management in turbulent markets, although their efficiency requires strict adherence to the rules. Hoffmann et al. (2017) point out that retail investors tend to overstate the usage of protective strategies while neglecting their implementation in times of market stress. This observation points to a possible mismatch between risk preferences and actual behaviour. Recent research on emerging markets indicates that the usage of formal risk management tools is affected by investor demographics and market development (Baker et al., 2020). In emerging markets, retail investors tend to make more decisions based on heuristics rather than on risk assessment models. Furthermore, market reactions in times of market stress, such as rebalancing portfolios towards less risky assets, may point to reactive risk management rather than strategic risk discipline (Statman, 2019). Notwithstanding the rising interest in the field of behavioural finance, there is a dearth of empirical research that focuses on whether investors' self-assessed risk tolerance is predictive of the structured application of stop-loss strategies, especially in the Indian setting. It is imperative to fill this research void to determine whether retail investors are able to convert risk attitudes into risk management practices, thereby adding to the existing debate on risk management in emerging equity markets.

Objectives

- To examine the influence of retail investors' risk tolerance on the adoption of stop-loss strategies in equity investments.
- To analyse whether behavioural reactions to market downturns are associated with structured stop-loss usage among retail investors.

Hypothesis

H1: Risk tolerance has a significant influence on the level of stop-loss usage among retail investors.
H2: Behavioural reaction during market downturns significantly influences the adoption and structured use of stop-loss strategies among retail investors.

3. METHODOLOGY

The research study employs a cross-sectional design with quantitative methods to investigate how risk tolerance affects retail investors in the Indian stock market to use stop-loss strategies. The researchers collected primary data by administering a structured questionnaire to retail equity investors who were selected through non-probability convenience sampling. The survey instrument used standardized Likert-scale items that measured investment risk profile and willingness to take higher risk for higher returns and behavioural response during market downturns and regular use of stop-loss strategies and predefined stop-loss criteria and perceived effectiveness of stop-loss techniques through five-point scale ranging from strongly disagree to strongly agree. The researchers pre-tested the questionnaire to determine its clarity and content validity. The researchers coded the data and analyzed it with SPSS software. The researchers used Cronbach's alpha to measure the reliability of multi-item constructs which confirmed their internal consistency. The researchers used non-parametric correlation analysis with Spearman's rho to measure relationships between constructs because the variables were assessed through ordinal Likert scales. The researchers used ordinal logistic regression analysis to examine the hypotheses while determining how risk tolerance and behavioural reaction influenced stop-loss adoption with stop-loss usage serving as the dependent variable and risk-related indicators acting as independent variables. The researchers conducted statistical tests at the 5 percent level of significance. The current methodological framework permits researchers to study how behavioural risk traits predict investor behavior in structured risk management routines used by retail investors.

4. RESULTS AND ANALYSIS

Demographic profile

Variable	Category	Frequency
City	Jaipur	54
	Kota	18
	Total	**72**
Age	Less than 30 Years	13
	31–40 Years	24
	41–50 Years	27
	51–60 Years	2
	More than 60 Years	1
	Total	**72**
Annual Income	Rs. 1,00,000–5,00,000	12
	Rs. 5,00,000–10,00,000	31
	Rs. 10,00,000–25,00,000	19
	Above Rs. 25,00,000	10
	Total	**72**
Occupation	Private Employee	47
	Business	6
	Self-Employed	5
	Government Employee	3
	Student	2
	Total	**72**
Qualification	PhD	22
	Postgraduate	22
	Professional (CA/CMA/CS/Doctor etc.)	13
	Graduate	10
	XII Pass	2
	Total	**72**

The demographic profile indicates that the majority of respondents are from Jaipur (54 out of 72), suggesting a stronger representation of investors from this city. Most participants fall within the 31–50 years age bracket, particularly 41–50 years, reflecting a mature and financially active investor group. In terms of income, the largest segment earns between Rs. 5,00,000 and Rs. 10,00,000 annually, indicating a middle-income dominance. The sample is primarily composed of private employees, followed by business owners and self-employed individuals. Educationally, respondents are highly qualified, with a substantial proportion holding PhD and postgraduate degrees, indicating informed investment decision-making capacity.

Reliability Analysis

Table 1: Reliability Statistics

Cronbach's Alpha	N of Items
0.797	6

The internal consistency of the six-item scale was evaluated using Cronbach's alpha. The alpha value of 0.797 is greater than the acceptable level of 0.70, signifying high internal consistency of the scale. This implies that the items representing investment risk profile, risk-taking willingness, behavioral response to downturns, stop-loss application, stop-loss criteria, and perceived effectiveness are highly consistent to be considered as a set of consistent constructs. Hence, the scale has adequate psychometric properties for inferential purposes.

Objective 1: To examine the influence of risk tolerance on the adoption of stop-loss strategies.

Correlation Analysis

Variables	Investment_Risk_Profile	Willingness_Higher_Risk	StopLoss_Usage
Investment_Risk_Profile	1	-0.161	-0.262*
Willingness_Higher_Risk	-0.161	1	0.333**
StopLoss_Usage	-0.262*	0.333**	1

Table 2: Correlation Matrix

*Significant at 0.05 level
**Significant at 0.01 level*
N = 72

The findings show a statistically significant negative correlation between Investment Risk Profile and Stop-Loss Usage (r = -0.262, p = 0.026). This implies that investors who associate themselves with higher risk profiles are less likely to use stop-loss strategies. The strength of the correlation is moderate but significant, suggesting that higher risk tolerance is associated with lower stop-loss usage.

On the other hand, Willingness to Take Higher Risk is positively and significantly correlated with Stop-Loss Usage (r = 0.333, p = 0.004). This implies that investors who are willing to take higher risks for higher rewards are more likely to use stop-loss strategies. This finding implies that risk-takers are likely to use stop-loss strategies as a calculated risk management approach rather than avoiding risk management altogether.

Ordinal Logistic Regression

Table 3: Model Fitting

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	121.351			
Final	108.714	12.637	5	0.027

The model chi-square of 12.637 (p = 0.027) shows that the final model is a significant improvement on the intercept-only model. This means that the predictors together account for variation in stop-loss use.

Goodness-of-Fit

Table 4: Goodness-of-Fit

Test		Chi-Square	df	Sig.
Pearson		90.092	55	0.002
Deviance		80.334	55	0.015

Both the Pearson and Deviance statistics are significant, indicating that there is some discrepancy between the observed and predicted values. Although this is an indication of problems with model fit, ordinal regression is still possible due to the significance of the model chi-square.

Pseudo R-Square

Table 5: Pseudo R-Square

Measure	Value
Cox & Snell	0.161
Nagelkerke	0.174
McFadden	0.067

The Nagelkerke value of 0.174 means that the variance in stop-loss usage explained by the risk tolerance variables is about 17.4%. While this is a small percentage, it is acceptable in research on behavioural finance because investor behaviour is driven by unobserved variables.

Parameter Estimates

Analysis of the regression output shows that the Willingness_Higher_Risk variable is statistically significant (β = 0.471, p = 0.010). The positive sign of the coefficient shows that the greater the willingness to take risk, the higher the probability of adopting higher stop-loss usage categories. The odds ratio (exp(0.471) ≈ 1.60) shows that for every unit increase in willingness to take risk, the odds of adopting higher stop-loss usage are approximately 60% higher. On the other hand, the results show that the categorical levels of Investment_Risk_Profile are not statistically significant (p > 0.05). This implies that the self-reported investment profile does not have a statistically significant relationship with stop-loss adoption, controlling for the willingness to take risk. The hypothesis is partially accepted. Although the willingness to take higher risk has a statistically significant relationship with stop-loss adoption, the self-reported investment risk profile does not have a statistically significant relationship with stop-loss adoption in the regression model.

Objective 2: To analyse whether behavioural reaction during market downturns influences structured stop-loss discipline.

Correlation Analysis

Table 6: Correlation Matrix

Variables	Sell_Risky_in_Downturn	StopLoss_Usage	StopLoss_Criteria	StopLoss_Effectiveness
Sell_Risky_in_Downturn	1	0.355**	0.366**	0.437**
StopLoss_Usage	0.355**	1	0.645**	0.490**

StopLoss_Criteria	0.366**	0.645**	1	0.737**
StopLoss_Effectiveness	0.437**	0.490**	0.737**	1

All the correlation values are positive, and they are significant at the 1% significance level. The use of stop-loss is moderately correlated with selling risky investments during downturns (r = 0.355), the criteria used in stop-loss (r = 0.366), and perceived effectiveness (r = 0.437). This shows that the reactive defensive strategy is consistent with the risk control mechanism.

It is important to note that there is a strong positive correlation between StopLoss_Criteria and StopLoss_Effectiveness (r = 0.737), indicating that investors who set clear criteria for stop-loss perceive higher levels of effectiveness of the strategy.

Ordinal Logistic Regression

Table 7: Model Fitting

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	100.187			
Final	73.455	26.732	4	0.000

The model fitting output reveals that the final ordinal logistic regression model is significantly better than the intercept-only model in terms of predicting stop-loss discipline. The change in -2 Log Likelihood from 100.187 to 73.455 indicates that the addition of the predictor variable, behavioural reaction, has improved the model's explanatory power. The chi-square of 26.732 with 4 degrees of freedom is statistically significant (p = 0.000), which suggests that the independent variable set, as a whole, makes a significant contribution to the prediction of differences in stop-loss usage categories. This suggests that behavioural reaction in market downturns has a significant positive effect on the model's explanatory power regarding structured stop-loss usage among retail investors.

Goodness-of-Fit

Table 8: Goodness-of-Fit

Test	Chi-Square	df	Sig.
Pearson	31.848	32	0.474
Deviance	31.906	32	0.471

The Pearson (χ^2 = 31.848, p = 0.474) and Deviance (χ^2 = 31.906, p = 0.471) chi-square statistics are non-significant, and this implies that the model is a good fit for the observed data. In ordinal logistic regression analysis, non-significant goodness-of-fit statistics imply that there are no significant differences between the observed and predicted frequencies of the dependent variable. The results imply that the predicted probabilities produced by the model are valid and that there is no evidence of mis-specification or poor fit of the model. This further enhances the validity of the regression results, implying that the behavioural reaction to market downturns is a statistically significant predictor of stop-loss discipline.

Pseudo R-Square

Table 9: Pseudo R-Square

Measure	Value
Cox & Snell	0.310
Nagelkerke	0.317
McFadden	0.098

The Nagelkerke value of 0.317 shows that about 31.7% of the variation in stop-loss discipline is accounted for by the behavioural reaction during downturns. This is a moderate level of explanatory power in a behavioural study.

Parameter Estimates

The regression coefficients for the Sell_Risky_in_Downturn categories are statistically significant (p < 0.001), which shows that the behavioural reaction during market decline is a strong predictor of structured stop-loss usage.

The coefficients are positive, which shows that investors who actively move to safe assets are significantly more likely to use disciplined stop-loss strategies.

The hypothesis is accepted. The behavioural reaction during downturns is a significant predictor of structured stop-loss discipline, with good model fit and substantial explanatory power.

Overall Interpretation

The results show that behavioral variables have a more significant impact on the adoption of stop-loss strategies than static self-classified risk profiles. Active risk-taking attitude promotes structured risk management, and reactive defensive behavior in bear markets is a strong predictor of prudent stop-loss strategy adoption. The findings show that retail investors who are consciously aware of market risk are more likely to adopt structured risk management approaches, whereas simply being classified as a high-risk investor does not necessarily ensure the adoption of structured protection strategies.

5. DISCUSSION

The results show that the behavioural aspects of risk engagement are more influential in the adoption of stop-loss than static self-assessments of risk investment profile. Although self-assessed risk profile failed to show a significant predictive relationship with the adoption of stop-loss in the regression analysis, risk tolerance showed a positive and significant relationship. This implies that investors who deliberately take risks as a matter of choice are more likely to adopt structured risk management strategies than avoid risk protection mechanisms altogether. In other words, calculated risk-taking seems to be compatible with disciplined risk protection.

However, is that the behavioural response to market downturns was found to be a stronger predictor of stop-loss discipline, accounting for a much larger proportion of variance. Investors who tend to make behavioural transitions to safer investments during market downturns were significantly more likely to adopt predefined stop-loss rules and find them effective. This implies that defensive behavioural tendencies are associated with formalized risk protection strategies. The greater explanatory power of the behavioural response suggests that situational responses may be more influential in risk management decisions than risk identity.

6. CONCLUSION

This paper investigates the correlation between risk tolerance and the usage of stop-loss strategies in the Indian stock market among retail investors. The results show that the behavioural aspects of risk engagement are more effective than static risk types in predicting structured risk management practices. Although the self-reported risk profile of investment did not have a significant effect on stop-loss strategy usage, higher risk tolerance had a positive effect on the adoption of stop-loss strategies. This shows that investors who voluntarily take risks are also more likely to adopt systematic approaches to manage potential risks.

Moreover, the behavioural response to market downturns was found to be a strong and significant predictor of stop-loss strategy discipline. Investors who move towards risk-free assets during a declining market are more likely to follow defined stop-loss rules and rate the strategy as effective. The greater explanatory power of this behavioural variable indicates that investors' dynamic responses to market conditions have a greater influence on risk management practices than static risk identity.

This paper shows that structured risk management practices among retail investors are not simply a result of their self-reported risk tolerance but are significantly influenced by their behavioural responses to market risks.

REFERENCES

1. Aren, S., & Zengin, A. N. (2016). Influence of financial literacy and risk perception on choice of investment. *Procedia – Social and Behavioral Sciences, 235*, 656–663.
2. Baker, H. K., & Ricciardi, V. (2016). Understanding behavioral aspects of financial planning and investing. *Journal of Financial Planning, 29*(3), 22–26.
3. Baker, H. K., Kumar, S., Goyal, N., & Gaur, V. (2020). How financial literacy and demographic variables relate to behavioral biases. *Managerial Finance, 46*(6), 771–794.
4. Barber, B. M., & Odean, T. (2017). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *The Journal of Finance, 72*(2), 773–806.
5. Bouri, E., Gupta, R., & Roubaud, D. (2017). Herding behaviour in cryptocurrencies. *Finance Research Letters, 20*, 1–8.
6. Chang, T. Y., Solomon, D. H., & Westerfield, M. M. (2016). Looking for someone to blame: Delegation, cognitive dissonance, and the disposition effect. *The Journal of Finance, 71*(1), 267–302.
7. Duong, T. H., Kalev, P. S., & Krishnamurti, C. (2019). The impact of stop-loss strategies on trading performance. *Journal of Behavioral and Experimental Finance, 23*, 100–112.
8. Grable, J. E. (2016). Financial risk tolerance: A psychometric review. *Journal of Financial Service Professionals, 70*(2), 59–66.
9. Hoffmann, A. O. I., & Post, T. (2016). How does investor confidence lead to trading? Linking investor return experiences, confidence, and investment beliefs. *Journal of Behavioral and Experimental Finance, 12*, 65–78.
10. Hoffmann, A. O. I., Post, T., & Pennings, J. M. E. (2017). Individual investor perceptions and behavior during the financial crisis. *Journal of Banking & Finance, 80*, 1–16.
11. Kumar, S., & Goyal, N. (2016). Evidence on rationality and behavioural biases in investment decision making. *Qualitative Research in Financial Markets, 8*(4), 270–287.
12. Nguyen, L., Gallery, G., & Newton, C. (2019). The joint influence of financial risk perception and risk tolerance on individual investment decision-making. *Accounting & Finance, 59*(1), 747–771.

13. Statman, M. (2019). Behavioral finance: The second generation. *CFA Institute Research Foundation*.
14. Toma, F. M. (2015). Behavioral biases of the investment decisions of Romanian investors on the Bucharest Stock Exchange. *Procedia Economics and Finance, 32*, 200–207.