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Investor Archetype Responses to Black Swan Event Severity: A Monte-Carlo Simulation Study

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Abstract. Black Swan events—rare but severe market shocks—pose significant challenges to traditional risk management frameworks, which often rely on average-case assumptions and fail to capture tail risk dynamics. This paper investigates how five types of investor behavior perform under such extreme conditions using a Monte Carlo jump-diffusion simulation framework. The model generates terminal wealth distributions across six stylized market scenarios, each representing different magnitudes of positive and negative price jumps. The investor heuristics studied include rational (mean-variance), loss-averse, momentum-based, contrarian, and leveraged strategies. Results reveal pronounced differences in tail risk exposure: loss-averse investors achieve the most robust downside protection, while leveraged and momentum strategies exhibit substantial vulnerability to large negative shocks. Contrarian and rational types fall between these extremes in both risk and reward potential. By comparing not only median outcomes but also the 5th and 95th percentiles, the analysis highlights trade-offs between downside containment and upside participation. These findings offer practical implications for behavioral modeling, stress-testing frameworks, and regulatory design aimed at improving portfolio resilience under low-probability, high-impact conditions.

Keywords: Black Swan, Monte Carlo simulation, Investor behavior, Jump-diffusion, Loss aversion

1. Introduction

The increasing frequency and impact of rare market disruptions—commonly known as Black Swan events—pose substantial challenges to portfolio management. Traditional investment strategies and risk models, typically built on normal return assumptions and average-case behavior, often fail to capture the asymmetric effects of such events. When these shocks occur, they can trigger sharp and nonlinear investor responses, especially when behavioral biases such as loss aversion, momentum chasing, or overconfidence are involved. Understanding how different investor types perform under extreme conditions is crucial not only for individual portfolio resilience but also for broader market stability. This research seeks to clarify the performance profiles of common investment heuristics when exposed to large, sudden price shocks, with a particular focus on the trade-offs between downside protection and upside potential.

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Prior studies have emphasized the importance of behavioral biases in financial decision-making. Prospect theory, introduced by Kahneman and Tversky, demonstrates that investors react more strongly to losses than to equivalent gains, a finding that has since influenced many extensions in behavioral asset pricing [1,2]. Models incorporating loss aversion, trend extrapolation, and contrarian behavior have been shown to generate patterns consistent with observed investor actions during crisis periods. However, while these models offer theoretical insight, relatively few studies have evaluated the performance of such behavioral strategies under explicitly simulated Black Swan conditions. The empirical performance distribution—particularly tail behavior—of these rules remains underexplored in simulation-based frameworks.

To address this gap, this paper uses a Monte Carlo jump-diffusion model to simulate investor outcomes across six stylized market scenarios, including both positive and negative extreme price shocks. Five representative investor types are analyzed: rational (fixed-weight), loss-averse (crash-sensitive), momentum-following, contrarian, and leveraged. For each scenario, 5,000 terminal wealth outcomes are generated and analyzed across median, 5th, and 95th percentiles. This design allows us to compare the distributional robustness of different behavioral rules without relying on prediction models or real-time data. The findings aim to inform both investor behavior modeling and policy-oriented risk disclosure, offering insight into how simple heuristics behave under conditions of rare but consequential market stress.

2. Methodology

2.1. Asset process and calibration

This study models asset prices using a discrete-time jump-diffusion process to better capture the fat tails and rare shocks observed in equity markets. The S&P 500 index is selected as the benchmark asset for its liquidity, representativeness, and long historical record. Daily price data from January 1, 2000, to May 5, 2025, are obtained from Stooq, yielding over 6,300 observations. Crash frequency is estimated by counting days with returns below –8%, resulting in a calibrated jump intensity of approximately λ equals to 0.5% per year. Drift and volatility are set to 8% and 15%, respectively, consistent with long-run U.S. market averages.

The asset price St evolves according to the jump-diffusion process:

$$S_{t+1} = S_t \cdot exp\left[\left(\mu - \frac{1}{2}\sigma^2\right)\Delta t + \sigma\sqrt{\Delta t} \cdot z_t\right] \cdot \left(1 + J_t \cdot I_t\right) \quad (1)$$

Where z_t ~N (0,1), I_t ~ Bernoulli (λ· Δt), and J_t is the jump magnitude drawn from the fixed set {–45%, –35%, –25%, –15%, +10%}. To supplement these fixed-shock scenarios, a sixth scenario samples jumps from a truncated Pareto distribution over the same set with weights [0.50, 0.25, 0.15, 0.08, 0.02]. This construction preserves fat-tailed behavior while matching the historical average jump size.

2.2. Investor archetypes

The model includes five investor archetypes, each defined by a simple decision rule:

First, five investor types are modeled using rule-based heuristics that capture widely observed behavioral patterns. The rational investor maintains a fixed 60% equity allocation, serving as a benchmark consistent with classical portfolio theory. The loss-averse investor dynamically reduces exposure in response to an exponentially smoothed estimate of crash probability. The momentum

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investor increases equity weight following a positive 20-day return, while the contrarian investor takes the opposite approach, increasing exposure after losses and reducing it after gains. Finally, the leveraged investor maintains a constant 150% equity allocation through margin, amplifying both upside and downside outcomes.

All weights are constrained within [0, 1.5] to prevent excessive leverage. These heuristics are based on well-documented behavioral patterns observed in both academic studies and real-world trading.

These five investor types are designed to reflect widely documented behaviors in financial literature and market practice. The rational investor follows a mean-variance optimization framework, as in Merton, and serves as a baseline [3]. The loss-averse investor adapts to crash signals, based on the notion of asymmetric risk preferences introduced in prospect theory [1]. Momentum strategies have been shown to yield short-term return persistence, while contrarian behaviors are often observed in deep-value investing [4,5]. Finally, the leveraged strategy mimics the risk-taking behavior of margin users or leveraged ETF holders, who are known to amplify both gains and losses [6]. By grounding these archetypes in theoretical and empirical precedent, it can be ensured that the simulation results are interpretable within realistic behavioral finance contexts.

2.3. Simulation design and validation

Monte Carlo simulation is suitable for modeling complex financial dynamics, especially when closed-form solutions are infeasible. Its effectiveness in simulating path-dependent and rare-event processes has been well established [7,8].

Each investor is simulated over 5,000 Monte Carlo paths per scenario, with a one-year horizon consisting of 252 trading days. At each step, investor wealth W_t evolves recursively according to:

$$W_{t+1} = W_t \cdot [1 + w_t \cdot R_{t+1} + (1 - w_t) \cdot r] \tag{2}$$

Where R_{t+1} is the return of the risky asset, w_t is the time-varying equity weight determined by the heuristic, and r is the daily risk-free rate.

Simulations are implemented using vectorized Python code (NumPy) for computational efficiency. Model validation includes three checks: (i) simulated drift and volatility converge to target values within ±0.1 percentage points; (ii) the average number of jumps matches the calibrated λ; and (iii) investor weights respond logically to market conditions, such as loss-averse exposure declining on crash days and momentum rising after rallies.

3. Empirical results

3.1. Median wealth outcomes

Figure 1 summarizes the median terminal wealth for each investor type under six market shock scenarios. Across the fixed negative jump scenarios (–15%, –25%, –35%, –45%), loss-averse and contrarian investors consistently rank among the highest performers in terms of capital preservation. Their medians remain clustered around 1.03–1.05. Leveraged and momentum strategies generally produce lower medians, especially under large downward shocks. In the +10% shock case, leveraged investors clearly outperform, reflecting their amplified exposure to upside events. However, no investor type shows a consistently increasing or decreasing trend across scenarios, confirming that performance is highly sensitive to the nature of the shock.

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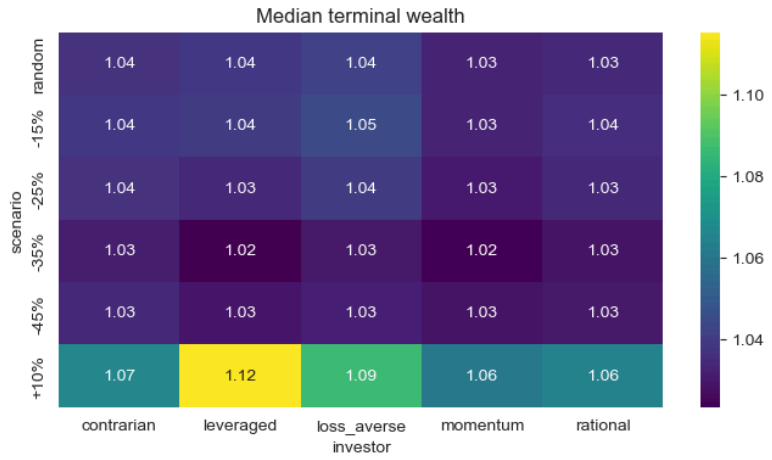

Figure 1: Median terminal wealth by investor archetype (columns) and jump severity (rows). Darker shades denote lower medians

3.2. Tail risk comparison: 5th and 95th percentiles

Figure 2 presents the 5th percentile of terminal wealth, reflecting the lower-bound outcomes for each investor strategy under six market scenarios. This metric captures downside risk, showing how severely a strategy can perform in the worst 5% of simulated outcomes. Leveraged investors exhibit the most extreme losses, with terminal wealth dropping below 0.5 under large negative shocks. In contrast, loss-averse strategies maintain tighter tails, often remaining above 0.7, highlighting the effectiveness of dynamically reducing exposure in response to perceived crash risk. Momentum and contrarian investors fall between these two extremes, with their downside performance varying depending on jump size and direction.

Figure 2: 5th Percentile of terminal wealth across scenarios

Figure 3 shows the 95th percentile of terminal wealth, which reflects the best-case outcomes for each strategy. Here, leveraged and momentum investors clearly outperform during positive jump scenarios, with 95th percentile wealth exceeding 1.4 in the +10% case. However, these same strategies also demonstrated the highest downside risk in Figure 3, emphasizing the asymmetric nature of their return distributions. Loss-averse and contrarian investors, while sacrificing some upside potential, deliver more stable performance by limiting exposure to extreme market moves. These findings illustrate the trade-off between convex upside participation and left-tail protection embedded in different behavioral investment rules.

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Figure 3: 95th Percentile of terminal wealth across scenarios

3.3. Full distributional shapes

Figure 4's violin plot displays the entire distribution of terminal wealth for each archetype. The leveraged strategy produces the broadest, most stretched violin: its density stretches down towards 0.3 times the initial wealth and flares upward beyond 2.5, signaling a pronounced downside ruin risk coupled with a small but tangible chance of outsized gains. On the contrary, the loss-averse violin is narrow and compact in all scenarios, having the most probability mass tightly gathered around 1.0-1.1. The thin whiskers also illustrate how the dynamic risk-avoiding rule suppresses both extreme losses and considerable profits. Momentum and contrarian distributions occupy the middle ground. Momentum's violin is slightly right-skewed, which reflects upside convexity when positive jumps occur, but still shows a noticeable lower tail bulge, denoting vulnerability to sharp downturns. Contrarian shapes are approximately symmetric and moderately wide, indicating balanced exposure, avoiding the deepest drawdowns yet foregoing the highest earnings. Finally, the rational benchmark sits almost exactly at the plot's center, whose violin is slimmer than those of momentum and contrarian but noticeably broader than loss aversion, portraying a classical mean-variance trade-off without behavioral damping or leverage enhancement.

Figure 4: Kernel smoothed violin densities of terminal wealth; width reflects probability mass. Split colors distinguish jump scenarios

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3.4. Interpretation of results

Collectively, Figures 1-4 illustrate key trade-offs across investor strategies under rare-event stress. The loss-averse heuristic consistently limits downside risk, effectively functioning as a form of behavioral insurance. Momentum and leveraged strategies exhibit strong performance in positive shock scenarios but suffer from pronounced left-tail risk. The contrarian strategy offers moderate stability across scenarios and achieves outperformance only in the most extreme case (−45% shock).

4. Policy implications

The results of this simulation suggest several policy-relevant implications for investor protection and systemic risk mitigation.

First, dynamic de-risking rules, such as the one used by the loss-averse investor, prove effective at containing tail losses under extreme events. Rather than imposing fixed exposure limits, regulatory frameworks could support investor dashboards that adapt exposure based on recent volatility or crash indicators—echoing the principles discussed in prospect theory and operationalized in recent loss-aware trading frameworks [1,2].

Second, leveraged strategies, while offering upside potential, exhibit disproportionate exposure to left-tail events. This supports ongoing proposals for volatility-responsive leverage caps, where brokers adjust maximum margin levels in periods of heightened market stress [9]. Given that the leveraged archetype in the model produced the lowest 5th percentile outcomes, even under modest shocks, such controls could enhance system-wide resilience.

Third, momentum-based trading, while popular, demonstrates fragility in crash scenarios. Institutional investors and retail platforms may benefit from implementing tail-risk overlays or temporary de-risking triggers, especially during rapid downward moves. Although momentum can enhance returns in trending markets, findings confirm its underperformance during dislocations, aligning with prior observations by Daniel and Moskowitz [10].

Finally, regulators and fintech platforms could promote the use of distributional risk metrics—such as 5th/95th percentile wealth outcomes—rather than relying solely on average performance or Sharpe ratios. Results show that median outcomes can mask meaningful asymmetries in risk profiles.

5. Conclusion

This paper analyzes how five types of investors—rational, loss-averse, momentum-based, contrarian, and leveraged—perform under extreme market shocks, known as Black Swan events. Using Monte Carlo simulation, it becomes possible to model their behavior across six jump scenarios involving both positive and negative price movements. While median wealth outcomes across strategies are similar, their risk outcomes vary widely. Loss-averse investors consistently avoid severe losses, while leveraged strategies carry the most tail risk and volatility. Momentum investors benefit in rising markets but suffer more during downturns, and contrarian investors remain comparatively stable.

By comparing not only median outcomes but also the 5th and 95th percentiles of wealth distributions, the paper can provide a better understanding of strategy robustness. However, the model still has several limitations. It considers only a single risky asset and assumes fixed behavioral rules with no learning or adaptation. Jump sizes are also manually set rather than empirically estimated. Future research could include multi-asset portfolios, adaptive strategies, and

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historical crash-based jump calibrations. These additions would make the model more realistic and suitable for broader risk management applications.

References

[1] Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263–291.
[2] Barberis, N., Huang, M., & Santos, T. (2001). Prospect theory and asset prices. Quarterly Journal of Economics, 116(1), 1–53.
[3] Merton, R. C. (1971). Optimum consumption and portfolio rules in a continuous-time model. Journal of Economic Theory, 3(4), 373–413.
[4] Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance, 48(1), 65–91.
[5] De Bondt, W. F. M., & Thaler, R. (1985). Does the stock market overreact? Journal of Finance, 40(3), 793–805.
[6] Barber, B. M., Huang, X., & Odean, T. (2009). Do retail traders move markets? Review of Financial Studies, 22(1), 151–186.
[7] Glasserman, P. (2003). Monte Carlo methods in financial engineering. Springer.
[8] Boyle, P. P. (1977). Options: A Monte Carlo approach. Journal of Financial Economics, 4(3), 323–338.
[9] Adrian, T., & Shin, H. S. (2010). Liquidity and leverage. Journal of Financial Intermediation, 19(3), 418–437.
[10] Daniel, K., & Moskowitz, T. (2016). Momentum crashes. Journal of Financial Economics, 122(2), 221–247.