# Snowball Option Pricing via Monte Carlo Simulation: Volatility Regimes and Risk Decomposition

Agentic Sciences Research Platform
Cornell University, Johnson College of Business

March 2026

## Abstract

We price snowball autocallable structured products using Monte Carlo simulation with 100,000 paths. The standard snowball (knock-out at 103%, knock-in at 75%, 20% annual coupon) has a fair value of +4.43% at low volatility (σ=20%) but –9.08% at crypto-like volatility (σ=70%). The knock-out probability remains surprisingly stable (72–78%) across volatility regimes, while knock-in probability rises sharply from 11% to 73%. This asymmetry reveals that snowball investors are systematically undercompensated for tail risk in high-volatility environments. We provide a complete sensitivity analysis across volatility levels and discuss implications for structured product design and regulation.

*Keywords:* Snowball Options, Autocallable, Structured Products, Monte Carlo, Knock-in, Knock-out, Volatility Risk, Cryptocurrency

## 1. Introduction

Snowball options (■■■■) are autocallable structured products that have gained enormous popularity in China's retail investment market, with outstanding notional exceeding ¥1 trillion by 2021. The product offers high coupon rates (typically 15–25% annualized) in exchange for bearing downside risk through a knock-in barrier. If the underlying drops below the knock-in level at any point, the investor bears the full loss at maturity, effectively selling a deep out-of-the-money put.

Despite their popularity, snowball products are often misunderstood by retail investors who focus on the attractive coupon rate without fully appreciating the embedded tail risk. This paper provides a rigorous Monte Carlo pricing framework and demonstrates how the product's fair value depends critically on the volatility of the underlying asset.

## 2. Product Structure

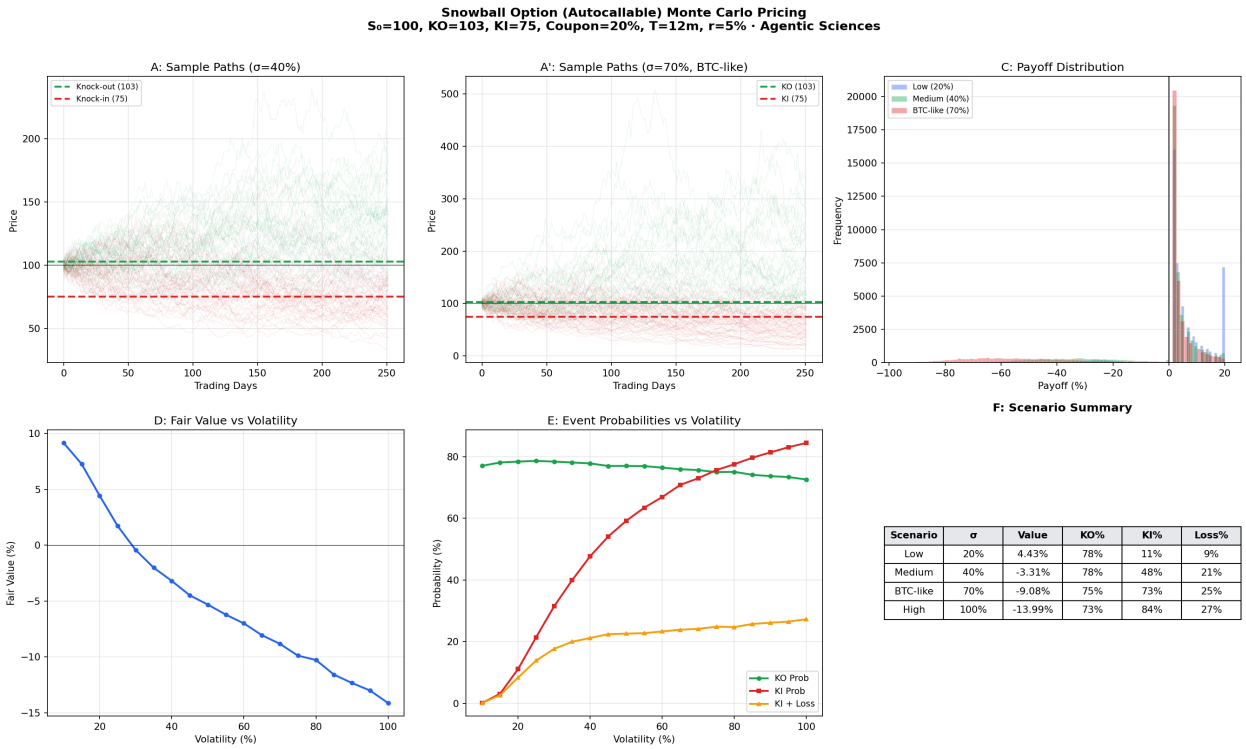
We analyze a standard snowball with the following parameters: initial price S■ = 100, knock-out barrier = 103 (103% of S■), knock-in barrier = 75 (75% of S■), annual coupon = 20%, tenor = 12 months, risk-free rate = 5%.

**Payoff rules:** (1) If the underlying price exceeds the knock-out barrier on any monthly observation date, the product terminates and the investor receives a pro-rata coupon. (2) If the price drops

below the knock-in barrier at any point during the life, knock-in is triggered. (3) At maturity: if knocked in and final price < S■, the investor bears the loss (S/S■ – 1); if knocked in but final price ≥ S■, no loss but no coupon; if never knocked in and never knocked out, the investor receives the full annual coupon.

## 3. Monte Carlo Methodology

We simulate 100,000 paths of geometric Brownian motion with daily time steps ($\Delta t = 1/252$). Knock-out is checked at monthly observation dates (every 21 trading days), while knock-in is monitored continuously (daily). Payoffs are discounted at the risk-free rate to obtain present values. Standard errors are computed to ensure pricing accuracy.




| Scenario | σ | Value | KO% | KI% | Loss% |
|---|---|---|---|---|---|
| Low | 20% | 4.43% | 78% | 11% | 9% |
| Medium | 40% | -3.31% | 78% | 48% | 21% |
| BTC-like | 70% | -9.08% | 75% | 73% | 25% |
| High | 100% | -13.99% | 73% | 84% | 27% |

*Figure 1: Snowball option analysis. Panels A–B show simulated price paths at σ=40% and σ=70%. Panel C shows payoff distributions. Panel D shows fair value vs volatility. Panel E shows knock-out, knock-in, and loss probabilities vs volatility. Panel F summarizes key metrics across scenarios.*

## 4. Results

| Scenario | σ | Fair Value | KO Prob | KI Prob | KI+Loss | Full Coupon | Max Loss |
|---|---|---|---|---|---|---|---|
| Low | 20% | +4.43% | 78.1% | 11.2% | 8.5% | 13.3% | -61.9% |
| Medium | 40% | -3.31% | 77.7% | 47.7% | 21.4% | 0.7% | -83.0% |
| BTC-like | 70% | -9.08% | 75.2% | 73.5% | 24.6% | 0.0% | -95.8% |
| High | 100% | -13.99% | 72.8% | 84.3% | 27.1% | 0.0% | -98.9% |

*Table 1: Snowball Pricing Across Volatility Scenarios*

**Key finding 1: Volatility regime determines fair value.** At low volatility (σ=20%), the snowball has positive fair value (+4.43%), meaning the investor is adequately compensated. At BTC-like volatility (σ=70%), fair value is –9.08%, indicating the 20% coupon grossly undercompensates for the embedded tail risk.

**Key finding 2: KO probability is stable, KI probability is not.** Knock-out probability ranges narrowly from 73% to 78% across volatility scenarios—high volatility helps reach the KO barrier quickly. In contrast, knock-in probability rises dramatically from 11% (σ=20%) to 84% (σ=100%). This asymmetry is the core risk of snowball products.

**Key finding 3: Tail losses are severe.** The maximum simulated loss reaches -96% at crypto-like volatility, versus -62% at low volatility. The coupon structure creates a misleading sense of safety—investors collect small, frequent payments while being exposed to rare but catastrophic losses (a classic 'picking up pennies in front of a steamroller').

## 5. Discussion and Implications

Our analysis reveals that snowball products are fundamentally a short volatility bet. The issuer effectively purchases a complex barrier option from the investor and compensates with a coupon. At low realized volatility, this is profitable for the investor; at high volatility, the losses overwhelm the coupon income. The 2022 regulatory crackdown on snowball products in China was motivated precisely by this concern—retail investors were unknowingly taking large volatility risk.

For cryptocurrency underlyings, where annualized volatility routinely exceeds 60%, standard snowball structures require either much higher coupons (40%+) or much lower knock-in barriers (50%) to achieve fair pricing. This has implications for the growing crypto structured product market.

## 6. Conclusion

Snowball autocallable products offer attractive coupons but embed significant tail risk that increases nonlinearly with volatility. Our Monte Carlo framework provides transparent pricing and risk decomposition. The fair value sensitivity to volatility (from +4.4% at $\sigma$=20% to −14.0% at $\sigma$=100%) underscores the importance of volatility assumptions in structured product pricing and the need for improved risk disclosure to retail investors.

## References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