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Case Study on the Knock-in Storm of Snowball Products

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Abstract: ***This case study examines the 2024 "knock-in storm" of snowball products in China's capital market. Structured as autocallable barrier options with 10%–20% annualized coupons, these products exposed investors to severe risks when the CSI 500 and CSI 1000 indices collapsed in January 2024, triggering knock-in clauses (70%–80% of initial levels) and shifting returns to index-linked losses. Causes included weak macroeconomic conditions, concentrated product maturities, clustered knock-in levels, and an asymmetric payoff structure that amplified losses. GARCH(1, 1)-t model analysis revealed underestimated tail risks in index returns. Impacts spanned investor losses, institutional hedging pressures, and market volatility. Recommendations focus on enhancing risk education, improving institutional risk management, and strengthening regulatory oversight to balance innovation and stability in derivatives markets.***

Keywords: Snowball products, Knock-in risk, GARCH model, Financial regulation.

1. Foreword

At the beginning of 2024, China's capital market experienced an extraordinary period of volatility. The "knock-in storm" of snowball products emerged as a focal point, sparking extensive attention and debate. As a complex financial derivative, snowball products have gained popularity among investors due to their unique payoff structure and relatively stable coupon rates. However, when market conditions deteriorated sharply in 2024, the inherent risks of these products were magnified exponentially. The concentrated knock-in events of numerous snowball products not only inflicted substantial losses on investors but also disrupted the stability of the financial market, highlighting the intricate and delicate relationship between financial innovation and risk management. A thorough analysis of this incident holds significant practical and theoretical value for understanding the risk transmission mechanisms in derivative markets, enhancing investor risk awareness, refining regulatory frameworks, and optimizing risk management strategies for market participants.

2. Overview of Snowball Products

2.1 Product Definition and Structural Characteristics

Snowball products are essentially exotic options known formally as "autocallable barrier options," falling within the category of over-the-counter derivatives. Their structure integrates features of barrier options with fixed coupon payments, typically issued by financial institutions such as securities firms and marketed to qualified investors. Key contractual terms of a typical snowball product include critical elements such as the knock-in price, knock-out price, tenor, and coupon rate.

Take the common snowball products linked to the CSI 500 and CSI 1000 indices as an example. During the product's validity period, if the linked index reaches or exceeds the knock-out price on the knock-out observation date, the product will be automatically redeemed, and investors will receive the agreed coupon income (the annualized coupon rate generally ranges from 10% to 20%, subject to market conditions and product design). If the index does not trigger the knock-out condition during the validity period but falls below the knock-in price on the knock-in observation date (the common knock-in level is 70%-80% of the initial price), the product structure will change, and the investor's return will be linked to the index performance. At maturity, if the index is lower than the initial price, investors will incur corresponding losses equivalent to the index's decline; if the index is higher than the initial price, investors will only obtain limited returns (generally low coupons or zero coupons). This asymmetric payoff structure makes snowball products highly attractive to investors during mild market volatility or upward trends but leads to a sharp escalation of risks during unilateral and significant market declines.

2.2 Product Revenue Logic and Risk Characteristics

In terms of revenue logic, when neither knock-in nor knock-out events are triggered, investors continuously earn coupon income, similar to fixed-income products, with relatively stable returns. This feature aligns with the preferences of investors seeking steady gains. Once a knock-out event is triggered, investors can terminate the product early to lock in coupon income, enhancing the flexibility of revenue realization. However, its risk characteristics are also highly pronounced. The most significant risk arises when the index continues to decline after a knock-in, exposing investors to substantial principal losses. Once the index falls below the knock-in level, the product's revenue structure shifts from a relatively stable coupon model to a risk-exposure model akin to direct index investment, and the coupons earned earlier often fail to offset losses from significant index declines. For example, consider a snowball product linked to the CSI 500 index with a knock-in level of 80% and a principal of ¥1 million. If the index declines by 25% (triggering the knock-in) and then further falls by 20%, the investor would incur an additional principal loss of approximately ¥160,000 after deducting pre-earned coupons (assuming a 15% annualized coupon rate and a six-month term). Additionally, snowball products carry liquidity risks: investors generally cannot redeem them early during the term, potentially leading to capital turnover difficulties if urgent cash is needed amid market volatility. Meanwhile, product pricing relies on complex financial models and market parameters, making it difficult for investors to assess the true value of the products and increasing the risk of decision-making errors due to information asymmetry.

2.3 Development History and Scale of Snowball Products in China's Financial Market

Snowball products began to emerge in China around 2013, with low initial market awareness and limited issuance scale. As financial markets developed, investor demand for diversified investment tools grew, and financial institutions explored and innovated in derivatives business, snowball products gradually entered a phase of rapid growth. During 2018–2020, the A-share market experienced relatively stable volatility with prominent structural trends. Snowball products gained widespread favor due to their ability to generate stable returns in volatile markets, leading to a rapid expansion in issuance scale. According to Wind data, the outstanding scale of snowball products was less than ¥10 billion in early 2018 but grew to hundreds of billions by the end of 2020. From 2021 to 2023, despite changing market conditions and intensified volatility in some periods, snowball products continued to grow in scale by optimizing structural designs and expanding underlying assets (adding links to indices such as CSI 300 and ChiNext in addition to CSI 500 and CSI 1000). By the end of 2023, the estimated total outstanding scale of snowball products reached ¥300–500 billion, with those linked to CSI 500 and CSI 1000 accounting for over 80% of the total. In terms of investor structure, early participants were mainly professional institutional investors and high-net-worth clients. In recent years, with product popularization and market education, ordinary high-net-worth individual investors have gradually increased their participation, leading to a diversified investor base. Nevertheless, professional institutional investors still dominate in terms of capital scale and trading activity.

3. Panoramic Presentation of the 2024 Snowball Product Knock-inStorm

3.1 Market Environment and Trends in Early 2024

Entering 2024, China's A-share market continued its prior adjustment trend. At the macroeconomic level, the economic recovery process faced significant pressure: weak momentum in consumption and investment on the demand side, and a slowdown in export growth due to uncertainties in the global trade environment. Reduced corporate profit expectations exerted pressure on overall market valuations. In terms of market indices, from early January to mid-January, the CSI 500 and CSI 1000 indices—representing small and mid-cap stocks—led the decline, with significantly larger drops than the blue-chip-dominated CSI 300 index. Between January 1 and January 17, the CSI 500 index fell 8.6% cumulatively, while the CSI 1000 dropped 11.2%. Sustained low trading volumes eroded investor confidence, and panic began to spread. This market decline stemmed from overlapping factors, including concerns about disappointing economic data, shifts in expectations of Federal Reserve monetary policy adjustments, and the insufficient manifestation of domestic policy stimulus effects, laying the groundwork for the subsequent large-scale knock-in of snowball products.

3.2 The Outbreak Process of Concentrated Knock-in Events for Snowball Products

As the CSI 500 and CSI 1000 indices continued to decline, the first batch of snowball products triggered knock-in conditions around January 17. A WeChat chat screenshot circulated widely on social platforms on January 17, showing that an investor ("Mr. Tang") had purchased a snowball product linked to the CSI 500 index. At maturity, due to the index decline exceeding the margin ratio, both the ¥2 million principal and coupon were lost, sparking market concerns about snowball product risks. Subsequently, on January 22, market panic culminated: the CSI 500 index plummeted 4.73%, and the CSI 1000 fell 5.77%, the largest single-day decline in three years. A large number of snowball products were knocked in, with the CSI 500 futures contract 2409 and multiple CSI 1000 futures contracts hitting the daily limit-down during trading. Thereafter, the market underwent another major correction on January 31, with the CSI 1000 closing 4% lower at 4,785 points, further breaking key support levels and triggering more snowball product knock-ins. According to Guojin Securities estimates, as of January 31, the total outstanding scale of CSI 500 and CSI 1000 snowball products was less than ¥100 billion, with most knock-ins concentrated around January 22. During this period, rumors of snowball product "margin calls" proliferated, intensifying investor panic. Some investors began selling other financial assets to raise cash, further increasing market selling pressure and creating a vicious cycle.

3.3 Impacts of Snowball Product Knock-ins on Market Participants

3.3.1 Impacts on Investors

Large numbers of investors suffered severe losses, particularly those who had allocated snowball products as low-risk "fixed-income-like" assets, whose investment philosophies were shaken. Wealth shrink significantly for some high-net-worth individual investors, while institutional investors such as private equity funds and bank wealth management subsidiaries faced client redemption pressures due to falling product net values from snowball product investments. For example, in July 2024, Wanye Enterprise announced a cumulative floating loss of ¥55.593 million on snowball-type financial derivatives purchased in the first half of the year, with ¥32.637 million lost in the second quarter alone, negatively impacting corporate performance and shareholder equity. Investor confidence in financial markets was damaged, leading to more cautious investment behavior. Some investors began re-evaluating asset allocation strategies and reducing investments in complex financial derivatives.

3.3.2 Impacts on Financial Institutions

Securities firms, as issuers and primary dealers of snowball products, faced enormous hedging risks and liquidity management pressures. After concentrated knock-ins, brokers needed to close large long positions in the stock index futures market to hedge risks, exacerbating volatility in the futures market and causing significant basis fluctuations, which increased hedging costs and trading difficulties. Some brokers experienced reduced derivatives business revenue and greater profit pressure after the knock-in events due to earlier large-scale issuance of snowball products. Meanwhile, sales channels like banks had to invest substantial resources in customer communication and appeasement due to investor complaints and redemption pressures, affecting their reputation and business stability.

3.3.3 Impacts on Financial Markets

In the short term, snowball product knock-ins triggered the spread of market panic, a surge in sell orders, and exacerbated the overall decline in the A-share market, particularly impacting constituent stocks ofthe CSI 500 and CSI 1000 indices and the stock index futures market. Liquidity in the futures market tightened, with some contracts hitting limit-downs, significantly increasing market volatility and sharply reducing risk appetite. In the medium to long term, the incident prompted regulators to strengthen oversight of financial derivatives markets, pushed financial institutions to improve risk management systems, and encouraged more rational investment behavior among market participants—all conducive to the long-term healthy development of the market. However, short-term market confidence recovery will take time.

4. Quantitative Analysis of Market Risks for Snowball Products

4.1 Model Selection

As the mainstream method for measuring financial market risks, Value at Risk (VaR) quantifies the maximum potential loss of a financial asset or portfolio within a specified time horizon at a given confidence level. The CSI 500 Index, the primary underlying asset triggering the concentrated knock-in events of snowball products, serves as a critical proxy for analyzing risk fluctuations and trends during this incident. By simulating and predicting the CSI 500 Index, insights into market trends can be derived, contributing to the sustained and healthy development of China's stock market. Therefore, this study employs a GARCH model to forecast the VaR of the index and uses the likelihood ratio test to evaluate the validity trend of the prediction results. This approach aids investors in better understanding the logic and underlying causes of the storm.

4.2 Literature Review

Zheng Wentong (1997) [1] was the first to introduce the concept and applications of VaR to China, emphasizing its importance for risk management in China's financial markets. Fan Ying (2000) [2], through calculating the value at risk of the Shenzhen Composite Index, demonstrated the feasibility of applying the VaR method to analyze investment risks in China's stock market. Xu Wei and Huang Yanlong (2008) [3] derived volatility equations using GARCH model fitting and calculated VaR through one-step-ahead forecasting. Yan Zhiyong (2011) [4] applied the GARCH model to estimate the value at risk in the gold market. Zhou Aimin and Chen Yuan (2013) [5] argued that the GARCH-t distribution model can effectively reflect market risks in China's small and medium-sized board. Xue Shiqi (2019) [6] incorporated jump factors into the GARCH model, using the GARCH-Jump model to more reasonably characterize jumps in financial markets and calculate VaR with residuals following jump distributions. Wang Pengwu (2020) [7] applied asymmetric GARCH models under normal and t-distributions to study stock market volatility, finding that the t-distribution yields better model estimation results than the normal distribution. Xiang Fangfang (2022) [8] proposed that multivariate GARCH models can characterize the dynamic volatility of portfolio returns and provide more effective risk information.

4.3.1 The GARCH Model

The GARCH model is developed on the basis of the ARCH model. The essence of the ARCH model lies in fitting the current heteroscedasticity function value using a q-order moving average of the squared residual series. However, the moving average model exhibits q-order truncation of autocorrelation coefficients, making this model suitable only for short-term autocorrelation coefficients of heteroscedasticity functions in practical applications. Its variance equation is as follows:

$$\sigma^2{}_t = \alpha_0 + \alpha_1\mu^2{}_{t-1} + \cdots + \alpha_p\mu^2{}_{t-p} \tag{1}$$

In practical applications, since the heteroscedasticity functions of some residual series exhibit long-term autocorrelation, using the ARCH model would result in a very high order of moving averages. This not only increases the difficulty of parameter estimation but may also affect the model's fitting performance. Therefore, the GARCH(p,q) model incorporates the p-order autoregressive nature of the heteroscedasticity function, enabling effective fitting of heteroscedasticity functions with long-term memory. Its variance equation is as follows:

$$\sigma^2{}_t = \alpha_0 + \sum \alpha_q\mu^2{}_{t-q} + \sum \beta_p\sigma^2{}_{t-p} \tag{2}$$

4.3.2 VaR Definition

Value at Risk (VaR) refers to the maximum potential loss of a financial asset or portfolio value within a specified time horizon at a given confidence level. It is expressed by the formula:

$$Porb(\Delta p > VaR) = 1 - \alpha \tag{3}$$

In Equation (3), $1\text{-}\alpha$ represents the confidence level, Δp denotes the loss of the portfolio during the holding period, and VaR is the value at risk under the confidence level. This means that the potential loss suffered by the financial asset holder during the holding period is less than or equal to VaR.

4.4 Quantitative Analysis

4.4.1 Sample Selection and Descriptive Statistics

This study selects 3,452 daily closing prices ofthe CSI 500 Index from January 4, 2010, to March 20, 2024, as the time-series sample data for empirical analysis, with the daily logarithmic return series as the research object. The formula for calculating daily logarithmic returns is: $R(t)=lnp_t-lnp_{t-1}$. A total of 3,451 return data points are obtained, of which the first 2,941 data points are used to establish the GARCH model within the sample, and the remaining 510 data points are used as out-of-sample data for VaR forecasting and testing. The data are sourced from the Tushare database.

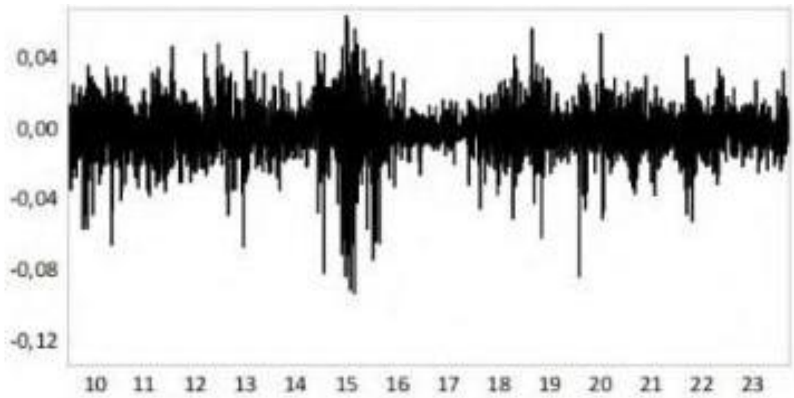

Figure 1: Time Series Chart of Daily Logarithmic Returns of the CSI 500 Index

Table 1: Descriptive Statistics of Daily Logarithmic Returns of the CSI 500 Index

Series	Mean value	Maximum value	Minimum Value	Standard deviation	Kurtosis	Skewness	Jarque - Bera test Statistic	Jarque - Bera test P-value
Daily Logarithmic Return	0.0000	0.0650	--0.0915	0.0139	7.8586	-0.6268	3620.3860	0.0000

As shown in Figure 1, the daily logarithmic returns of the CSI 500 Index fluctuate around 0 as the central value, with most data ranging between -0.4 and 0.4, indicating the presence of volatility clustering in this time series.

From Table 1, the logarithmic return series of the CSI 500 Index has a mean of approximately 0, a standard deviation of approximately 0.0139, and a skewness of -0.6268, indicating that the series exhibits left-skewed distribution characteristics. On one hand, the kurtosis of the series is 7.8586, far greater than 3, suggesting that the peak of its probability density curve is relatively sharp. Compared with the normal distribution, its peak is steeper, indicating that the probability density curve of the return series has the characteristic of "leptokurtic and fat-tailed." On the other hand, the Jarque-Bera test statistic is 3620.3860, far greater than 0, and its corresponding P-value is approximately 0, which also indicates that the series does not satisfy the normal distribution assumption.

Meanwhile, the QQ plot of the daily logarithmic returns of the CSI 500 Index (see Figure 2) shows obvious asymmetry in the return series, exhibiting distinct "fat-tailed" characteristics. Therefore, it can be further concluded that the daily logarithmic return series of the CSI 500 Index does not follow a normal distribution.

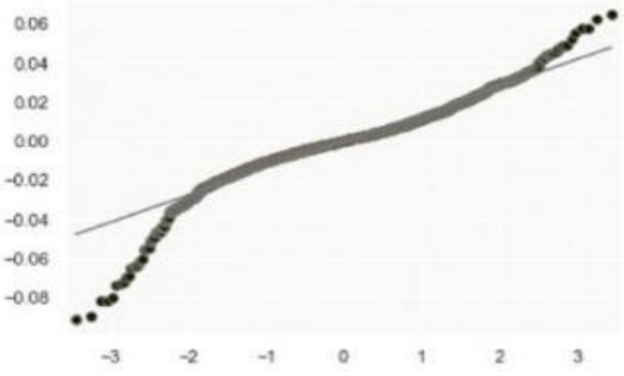

Figure 2: QQ Plot of Daily Logarithmic Returns of the CSI 500 Index

4.4.2 Stationarity, Autocorrelation, and ARCH Effect Tests

1) Stationarity Test. This study uses the ADF (Augmented Dickey-Fuller) test to conduct a unit root test on the daily logarithmic return series of the CSI 500 Index. The test results are shown in Table 2.

Table 2: Unit Root Test for the Daily Logarithmic Return Series of the CSI 500 Index

Series	T-statistic	Critical values at each level of significance 1%	5%	10%	P-value
Earnings yield	-57.402162	-3.960700	-3.411108	-3.127378	0.000000

Table 2 presents the critical values of the t-statistic at the 1%, 5%, and 10% significance levels as -3.960700, -3.411108, and -3.127378, respectively. All these critical values are greater than the calculated t-statistic of -57.402162, and the corresponding p-value is 0. This indicates that the return series is stationary.

2) Autocorrelation Test. As shown in Table 3, the probability values associated with the Q-statistics for the first 5 lags of the index's daily logarithmic return series are all greater than 0.05, indicating no autocorrelation when the lag order is within the first 5 lags. Starting from the 6th lag, the probability values of the Q-statistics are less than 0.05, and at the 6th lag, the absolute values of both AC (autocorrelation) and PAC (partial autocorrelation) exceed 0.05, suggesting autocorrelation exists at the 6th lag. When using ordinary least squares (OLS) for modeling analysis, this study primarily accounts for the factor of 6th-order lag correlation.

Table 3: Autocorrelation Test for the Daily Logarithmic Return Series of the CSI 500 Index

Hysteresis order	AC	PAC	Q-stat	Prob
1	0.023	0.023	1.765	0.184
2	-0.030	-0.031	4.932	0.085
3	0.012	0.014	5.449	0. 142
4	0.021	0.019	6.955	0.138
5	0.003	0.003	6.984	0.222
6	-0.062	-0.061	20.400	0.002
7	0.040	0.043	25.867	0.001
8	0.036	0.030	30.347	0.000
9	0.024	0.026	32.285	0.000
10	-0.015	-0.013	33.024	0.000

3) ARCH Effect Test. Table 4 presents the ARCH effect test for the daily logarithmic return series of the CSI 500 Index. The output shows that the probability value (P-value)

associated with the observed R^2 is 0, indicating the presence of ARCH effects at the 5% significance level. Therefore, a GARCH model can be established for the daily logarithmic return series.

Table 4: ARCH Effect Test for the Daily Logarithmic Return Series of the CSI 500 Index

ARCH-LM test			
F-Statistic	124.0729	*Prob.F*(1,3448)	0.0000
R^2	119.8328	*Prob. Chi-Square*(1)	0.0000

4.4.3 Empirical Testing

Next, the daily logarithmic returns of the CSI 500 Index are simulated using GARCH(1, 1), GARCH(1,2), GARCH(2, 1), and GARCH(2,2) models. According to the simulation results, GARCH(1,2), GARCH(2, 1), and GARCH(2,2) models all exhibit cases where the p-values of some estimated coefficients are greater than 0.05. This indicates that some coefficients of these three models are not significant at the 5% significance level. Therefore, this study selects the GARCH(1, 1) model, in which all estimated coefficients are significant at the 5% significance level. The regression results are shown in Table 5.

Table 5: Estimation Results of the GARCH(1, 1) Model

Mean value equation				
Variable	*Coeficient*	*Std.Error*	*Z-Statistic*	*Prob.*
rt-6	-0.043456	0.019186	-2.265062	0.023503
Variance equation				
Constant term	0.000001	0.000000	4.566183	0.000000
ARCH term	0.066087	0.004093	16.14563	0.000000
GARCH term	0.930074	0.003780	246.0203	0.000000

It can be seen that the sum of the coefficients of the ARCH term and GARCH term in the variance equation of the GARCH(1, 1) regression model is close to 1, indicating that the shock to the conditional variance is persistent. In summary, the GARCH(1, 1) model has a better fitting effect compared to other models. The equations of this model are as follows:

$$r_t = -0.043456 r_{t-6} + \mu_t$$

$$\sigma^2{}_t = 0.000001 + 0.066087\mu^2{}_{t-1} + 0.930074\sigma^2{}_{t-1}$$

Next, the ARCH-LM test is conducted on the GARCH(1, 1) model, and the results are shown in Table 6. The results indicate that no ARCH effect remains in the established model, confirming the model's validity.

Table 6: GARCH(1, 1)Model ARCH-LM Test

ARCH-LM test			
F-statistic	0.3476	*Prob.F*(1,2729)	0.5554
R^2	0.3480	*Prob. Chi-Square*(1)	0.5553

4.4.4 VaR Risk Measurement Based on GARCH Model

Based on the GARCH(1, 1) model, VaR values for the 510 out-of-sample data points are predicted under different distribution assumptions and confidence levels. Given that return series typically exhibit leptokurtic and fat-tailed characteristics, this study considers not only the normal distribution assumption but also the t-distribution assumption (used to characterize tail features) when calculating VaR. As shown in Table 7, the GARCH(1, 1) model yields similar MAE (Mean Absolute Error) and RMSE (Root Mean Squared Error) values under the normal distribution and t-distribution assumptions. Comparatively, the normal distribution-based GARCH(1, 1) model has smaller MAE and RMSE values, indicating more accurate out-of-sample predictions.

Table 7: Out-of-Sample Forecasting Results of the GARCH(1, 1) Model

Model	Distribution	MAE	RMSE
GARCH(1,1)	Normal distribution	0.008168	0.010889
	t distribution	0.008169	0.010889

Next, the VaR values of the GARCH(1, 1) model under the normal distribution and t-distribution assumptions are calculated and compared at confidence levels of 90%, 95%, and 99%, respectively. The likelihood ratio (LR) test method proposed by Kupeic in 1995 is used to backtest the VaR, with the calculation formula for the LR value as follows:

$$LR = -2\ln((1-\alpha)^{T-n}\alpha_n) + 2\ln((1-n/T)_{T-n}(n/T)_n)$$

Among them, (1-α) represents the confidence level, T is the sample size, and n is the number of failure days, i.e., the number of days when the actual loss exceeds the VaR estimate. Under the null hypothesis, the LR statistic follows a χ^2 distribution with 1 degree of freedom. At the 0.1 significance level, if the LR value is greater than 2.71, the null hypothesis is rejected, meaning that the VaR failure rate of the model is not 10% at the 90% confidence interval. Similarly, at the 0.05 significance level, the null hypothesis is rejected if the LR value exceeds 3.84; at the 0.01 significance level, rejection occurs when the LR value exceeds 6.63. The VaR calculation and test results are shown in Table 8.

The test results show that although the number of failure days under the GARCH(1, 1)-t distribution model at the 99% confidence level is 0, which underestimates the risk of return losses for the CSI 500 Index, the model passes both the failure day count and LR test at the 90% confidence level, and also passes the LR test at the 95% confidence level. In contrast, the GARCH(1, 1)-normal distribution model fails all tests at the 90%, 95%, and 99% confidence levels. This indicates that the GARCH(1, 1)-t distribution model better captures the risk characteristics of the CSI 500 Index compared to the GARCH(1, 1)-normal distribution model.

Table 8: Calculation and Testing of VaR under the GARCH(1, 1) Model

Model	Confidence interval	VaR mean	Number of days of failure	Failure rate	LR test statistic
GARCH(1,1) Normal distribution	90%	-0.0143	88	17.25%	25.0761
	95%	-0.0183	41	8.04%	8.4425
	99%	-0.0260	17	3.33%	17.4176
GARCH(1,1) *t* distribution	90%	-0.0167	57 (Pass)	11.18%	0.7585 (Pass)
	95%	-0.0229	23	4.51%	0.2664 (Pass)
	99%	-0.0385	0	0	0

Note: "Pass" means that the VaR value passes the likelihood ratio test method proposed by Kupiec.

Based on the above analysis, when giving priority to the GARCH(1, 1)-t distribution model, the risk of the CSI 500 Index is underestimated. Consequently, the risks corresponding to snowball products based on the CSI 500 Index may also be underestimated, which could be a reason for the market's misassessment of snowball product risks.

5. Analysis of the Causes of the Snowball Product Knock-in Incident

5.1 Macroeconomic and Market Environment Factors

Downgraded Economic Growth Expectations and Corporate Profit Pressures: In early 2024, the domestic and international macroeconomic landscape was complex and severe. Global economic growth slowed, and trade protectionism rose, impacting China's export industries and shrinking external demand markets. During domestic economic restructuring, traditional industries faced pressure to transform and upgrade, while emerging industries had not yet formed sufficient growth momentum, putting significant downward pressure on economic growth. Against this backdrop, corporate profit expectations were generally downgraded, and the earnings growth rate of listed companies slowed or even declined, leading to a downward shift in the overall market valuation center. Take the manufacturing industry as an example: PMI data continued to fluctuate near the expansion-contraction threshold, with reduced corporate orders, inventory backlogs, and compressed profit margins. This unfavorable situation in macroeconomics and micro-level corporate profits left the A-share market lacking upward momentum, eroded investor confidence, and increased market downside risks, creating macroenvironmental conditions for snowball product knock-ins.

Sustained Market Declines and Spread of Panic Sentiment: Since 2022, the A-share market has undergone a prolonged adjustment, with the market overall in a bear market cycle. The market continued to decline in early 2024, and consecutive falling trends caused investor panic to accumulate continuously. In the absence of effective positive stimuli, panic gradually dominated market trading behavior, as investors rushed to sell stocks and other financial assets, creating a stampede effect that accelerated market declines. The CSI 500 and CSI 1000 indices, as the main underlying assets of snowball products, bore the brunt of the market panic selling, with declines far exceeding the market average, triggering knock-in clauses for a large number of snowball products and leading to the full-scale outbreak of the snowball product knock-in incident.

5.2 Product Structure and Design Factors

Concentrated Maturities and Knock-in Level Distribution: During 2022–2023, snowball product issuance reached a peak, with a large number of products maturing in early 2024. Meanwhile, due to relatively optimistic market expectations for small and mid-cap stocks, the knock-in levels set for previously issued snowball products were concentrated within a specific range (e.g., 70%–80% of the initial levels of the CSI 500 and CSI 1000 indices). When the market fell rapidly, a large number of products triggered knock-ins at similar times and levels, leading to concentrated risk exposure in the short term and impacting market stability. According to Cinda Securities' calculations, the concentrated knock-in ranges for snowball products linked to the CSI 500 and CSI 1000 are below 4,800 points and 5,200 points, respectively. Within these ranges, an average decline of 100 points triggers knock-ins for approximately CNY 10 billion of CSI 500-linked snowball products and CNY 13 billion of CSI 1000-linked products. The characteristics of concentrated maturities and knock-in level distribution intensified the magnitude of risk shocks.

Asymmetric Return Structure and Risk Amplification Mechanism: The unique asymmetric return structure of snowball products amplifies risks during market declines. When no knock-in occurs, investors receive relatively stable coupon returns, but after a knock-in, investors face losses directly linked to the index decline, with prior coupons often unable to offset losses from significant index drops. This return structure causes losses to increase rapidly once a knock-in is triggered, altering investor psychology and potentially triggering panic selling of other assets, further exacerbating market volatility. For example, an investor who purchases a CNY 1 million snowball product with a 15% annual coupon and an 80% knock-in level would, after a 20% index decline triggering the knock-in, suffer an additional loss of approximately CNY 100,000 in principal (after deducting a six-month coupon of CNY 75,000) if the index falls by another 10%. This loss magnitude far exceeds the loss ratio of ordinary stock investments, creating a dual impact on investor psychology and capital strength.

5.3 Investor Behavior and Market Participant Factors

Inadequate Risk Awareness and Irrational Investment: Some investors lack a deep understanding of the complex structures and risk characteristics of snowball products, leading to cognitive biases during investment. They mistakenly equate snowball products with fixed-income products and overlook their potential risks. Against the backdrop of relatively stable market performance and consistent high coupon payments from snowball products, investor risk appetite increased, prompting blind follow-the-crowd investing—some even used leveraged funds to purchase such products, further amplifying investment risks. When market trends reversed and knock-in risks materialized, investors, unprepared psychologically and financially, panicked, exacerbating market volatility. For example, in some investor communication groups, certain investors bought large quantities of snowball products on others' recommendations without understanding the risks. After knock-ins occurred, they exhibited anxiety and panic, frantically seeking coping strategies and even resorting to extreme selling behaviors.

Flaws in Financial Institutions' Sales and Risk Management: During snowball product sales, some financial institutions engaged in misleading practices, failing to fully disclose product risks to investors. They excessively emphasized product return features while neglecting strict adherence to investor suitability management principles. In risk management, some institutions underestimated market risks and failed to effectively diversify risks or implement effective hedging strategies during product creation and hedging. When issuing snowball products, some brokerages did not conduct sufficient stress tests for extreme market conditions. As a result, when markets plunged and volatility spiked, they could not adjust hedging strategies in a timely manner, leading to sharply increased hedging costs and significant risk exposures. For instance, during the rapid market decline in early 2024, some brokerages failed to liquidate their long positions in stock index futures promptly, causing expanded hedging losses that impacted their operational performance and market reputation.

6. Strategies and Measures to Address the Snowball Product Knock-in Incident

6.1 Investor-Side Response Strategies

Strengthen Risk Education and Investor Protection: Financial regulatory authorities and institutions should jointly carry out investor risk education campaigns. Through online and offline channels—such as investor seminars, risk warning articles, and financial literacy videos (financial knowledge popularization videos)—they should educate investors about the characteristics of financial derivatives like snowball products and their associated risks, enhancing investors' risk awareness and

identification capabilities. Improve investor protection mechanisms, strengthen the handling of investor complaints, and severely investigate and punish misleading sales practices by financial institutions that infringe on investor rights to safeguard legitimate investor interests. For example, institutions such as the China Securities Inter-Institutional Quotation System Co., Ltd. have published a series of articles on their official websites and social media platforms analyzing the risks of snowball products, detailing their structures, return-risk profiles, and investment considerations to help investors better understand the products.

Optimize Portfolio and Diversify Risks: Investors should adopt sound investment philosophies, reasonably allocate assets based on their risk tolerance, investment objectives, and time horizons, and avoid over-concentration in single products or asset classes. When investing in snowball products, treat them as part of a broader portfolio, combining them with other assets such as stocks, bonds, and funds to reduce overall portfolio risk. Meanwhile, strictly control the scale of snowball product investments to prevent portfolio risk from spiraling out of control due to overexposure to a single product. For instance, a high-net-worth investor might allocate 10% of their investable assets to snowball products, with the remainder spread across equity funds, bond funds, and cash-like assets, thereby reducing the impact of single-product volatility through diversification.

6.2 Risk Management Measures for Financial Institutions

Improve Risk Assessment and Hedging Systems: Financial institutions should enhance risk assessments for snowball products by establishing scientific and reasonable risk assessment models that quantify risks by incorporating multiple factors such as market volatility, product structures, and investor characteristics. Optimize hedging strategies and expand hedging tools: in addition to traditional stock index futures, rationally use derivatives like options and swaps to improve hedging efficiency and effectiveness. Strengthen market risk monitoring and early warning systems, track market trends in real time, and adjust risk exposures promptly. For example, a major brokerage firm invested heavily in developing a snowball product risk assessment system that uses big data and AI technologies to monitor and warn of market risks in real time. When risk indicators reach pre-set thresholds, the system automatically prompts risk management teams to adjust hedging strategies, effectively reducing risk losses from knock-ins.

Standardize Sales Practices and Enhance Investor Suitability Management: Financial institutions must strictly regulate the sales of snowball products, ensuring sales personnel possess professional knowledge and qualifications, fully disclosing product risks to investors during sales, and prohibiting false propaganda or misleading tactics. Strengthen investor suitability management by classifying and evaluating investors based on factors such as risk tolerance, investment experience, and asset size, and matching appropriate products to suitable investors. Establish investor follow-up mechanisms to regularly review investors' understanding of products and changes in their risk tolerance, adjusting investment advice accordingly. For example, a bank conducts comprehensive risk assessments for investors before selling snowball products, categorizing them into conservative, stable, balanced, growth-oriented, and aggressive types. Snowball products are only recommended to stable-type and above investors, with regular post-sales follow-ups to ensure investors fully understand and can bear the products' risks.

6.3 Regulatory Measures and Enhanced Market Oversight

Strengthen Regulation of Financial Derivatives Markets: Regulatory authorities should promptly introduce relevant policies and regulations to improve the regulatory framework for financial derivatives markets. Clarify regulatory requirements for all stages of over-the-counter (OTC) derivatives like snowball products, including issuance, trading, and risk management, to standardize market participants' behaviors. Tighten the review of financial institutions' business qualifications, raise market entry barriers, and ensure institutions engaged in derivatives businesses have adequate risk management capabilities and professional standards. For example, in February 2024, the China Securities Regulatory Commission (CSRC) issued guidelines on strengthening oversight of OTC derivatives markets, setting specific regulatory requirements for product design, risk control, and investor protection in snowball products and other OTC derivatives to provide a policy framework for standardized market development.

Enhance Market Risk Monitoring and Early Warning Mechanisms: Regulatory authorities should establish and improve risk monitoring and early warning mechanisms for financial derivatives markets, leveraging technologies like big data and cloud computing to monitor and analyze market transaction data in real time.

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