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Quantitative Evaluation of Tranche-Level Returns and Loss Distributions of Structured Credit Assets under Stress Scenarios

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Abstract: This paper addresses the complex evolution of tiered returns and losses in structured credit assets under the combined pressure of multiple adverse factors—namely, interest rate volatility, rising default rates, and declining recovery rates. A framework model based on the cash flow waterfall model for scenario-specific quantitative analysis is proposed. Three typical tiering methods are employed: senior, mezzanine, and subordinate. Default rate, prepayment rate, loss on default, and discount rate are used as four key determining variables. Finally, the expected return levels, extreme loss tails, and credit enhancement losses under various stress scenarios (mild, moderate, and severe stress) are simulated through cash flow allocation during the rolling period, loss absorption pattern ranking, and duration-weighted yield calculation. The conclusions are as follows: Under mild stress, the senior tier offers good defensive capabilities but suffers a significant reduction in returns; under moderate stress, the mezzanine tier exhibits the most volatile return /risk ratio. Severe pressure leads to net asset value losses for the lower tranche. Research on cross-tier risk transmission after excess spreads are exhausted, mezzanine impairments are incurred, and additional support for senior tranches is damaged results in recommendations such as tier thickness adjustment, real-time activation mechanisms, and loan pool penetration checks, which provide quantitative references for pricing, risk control, and regulatory disclosure of structured credit products.

1. Introduction

Structured credit assets can diversify risk, reset timetable and reshape returns by bundling underlying loans, receivables or credit claims and dividing them into different repayment levels according to their subordinate relationship. The layered arrangement makes the same asset package generate different credit exposures due to different legal structures and cash flow patterns. On this basis, each repayment level corresponds to its own different returns. That is, the layered returns not only depend on the average default rate of the bottom layer, but are also affected by factors such as the quality of the asset pool [1].

According to market experience, losses in tiered assets do not propagate in a linear trajectory

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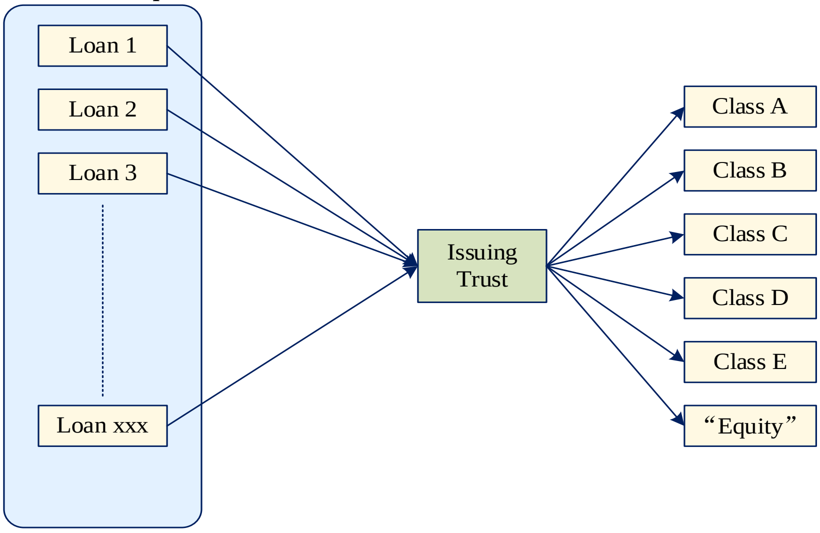
under stress. Senior tiers generally need to rely on measures such as subordinate buffers, mezzanine absorption, and liquidity support to maintain their rating levels; mezzanine tiers have both credit risk and structural redistribution risk; while subordinate tiers are very susceptible to default, recovery rate, and prepayment. If only the static average default rate is used to measure tiered returns, it will be impossible to discover the risk of loss tails, the redistribution of cash flow after triggering events , and the degree of transfer between tiers [2].

Therefore, it is necessary to establish a comprehensive assessment system for the distribution of returns and losses at multiple levels under stress scenarios, and to take into account the quantitative relationship between loan portfolio cash flow, structured arrangements and asset valuation. The main focus is not on theoretical debates about credit risk, but on analyzing the different levels of return decline, write-down probabilities and risk transmission mechanisms through parameterized scenarios, tiered waterfalls and quantitative indicators [3].



Source: FIIG Securities

Figure 1: Schematic Diagram of the Transaction Structure and Tiered Cash Flow Allocation for Structured Credit Assets

This diagram illustrates the process by which structured credit assets are aggregated—via an Issuing Trust—from an underlying pool of loan assets, and subsequently distribute cash flows across a tiered structure to various classes of securities (Classes A–E, plus the Equity Tranche). Principal and interest recoveries from the multiple underlying loans flow collectively into the asset pool; these funds are then allocated to the respective tranches according to a waterfall mechanism based on priority, while risk is simultaneously transmitted upward, layer by layer, from the lower tranches to the higher ones.

2. Analysis of the Current Status of Research on the Layered Valuation of Structured Credit Assets

2.1 From static interest rate spread comparison to cash flow penetration calculation in tiered return assessment

Early studies have used nominal coupon, average life and rating transfer to analyze the returns of stratified assets, which are suitable for horizontal comparison under stable market conditions, but do not fully reflect the impact of default time distribution, prepayment behavior and triggering mechanism. With the increasing complexity of structured products, the focus of research has gradually shifted to monthly or quarterly cash flow estimation, unifying default, recovery, amortization, excess spread and credit enhancement loss into a single model, in order to explain the difference between the actual yield to maturity and expected loss of different tiers [4].

2.2 The stress testing method has been expanded from single-factor impact to multi-factor coupled scenarios.

The current approach is not just about increasing the single default rate or decreasing the single recovery rate, but more about using a combination of factors such as rising interest rates, falling housing prices, rising unemployment and changes in borrower behavior. To a certain extent, this is more in line with the situation where the cash flow of the loan portfolio decreases simultaneously in a stressful environment. However, this leads to problems such as difficulty in calibrating the interrelationships between model parameters, difficulty in estimating the probability of tail events, and increased dispersion of hierarchical loss distribution [5].

2.3 The study of stratified risk has shifted from exploring default rates at a single level to discovering transmission paths across multiple levels.

In recent years, research on structured credit products has paid more and more attention to the question of "how losses are passed from the subordinate to the senior tranche". Related research shows that risk transfer depends not only on the cumulative default rate at a certain moment, but also on the result of multiple factors such as cash flow priority, triggering conditions, liquidity reserves and excess spread depletion rate. That is, the total loss in the same asset portfolio of the same size will produce very different tiered return distributions under different allocation methods [7].

3. Major problems faced by stratified gain and loss distribution under stress scenarios

3.1 The heterogeneity of underlying assets leads to the cumulative deviation in the calculation of tiered returns.

Structured credit assets generally integrate assets from different regions, terms, loan amounts, coupon types, and borrower risk levels. Using pool-level mean parameters instead of individual loan parameters will result in an underestimation of the marginal losses of subprime and mezzanine loans caused by high-risk tail loans, and will not accurately describe the decrease in the return on senior reinvestment when prepayments occur in a concentrated manner [8].

3.2 Cash flow rearrangements triggered by stratification clauses are difficult to capture by static models.

Once the default rate or excess spread coverage reaches a certain level, or the value of the collateral decreases to a certain extent, structured products will typically trigger profit cut-off, accelerated repayment, and event default clauses. Static duration or simple discounting methods cannot detect the cash flow restructuring caused by this mechanism, thus causing the actual risks of the mezzanine and senior tranches to be exposed with a lag.

3.3 The loss distribution exhibits a significant tail amplification characteristic.

The tiered architecture causes significant profit fluctuations in the second tier even with minor setbacks. Moreover, once credit protection is exhausted, losses are quickly transferred to the middle tier and eventually to the priority tier. Therefore, the mean- standard deviation model cannot characterize tail losses, write-down probabilities, and profit and loss distribution skewness. A series of variables such as scenario quantiles, extreme loss percentages, and support coverage must be added to measure these factors [9].

3.4 Valuation and risk assessment methods were not effectively aligned.

In actual market operations, IRR, nominal interest rate spread and expected loss are often assigned to the investment department, risk control department and audit department for independent calculation. This results in different levels having a large tail loss risk even when the income performance is still good, or credit enhancement has been greatly damaged before the book impairment has occurred, thus reducing the speed of risk warning [10].

4. Stratified quantitative assessment based on stress scenarios

4.1 Evaluation Framework and Sample Setting

To enable the quantitative assessment of layered gains and losses, the following unified modeling framework is introduced, featuring the cash flow expression for a single asset:

$$CF_{i,t} = P_{i,t} + I_{i,t} - L_{i,t} + R_{i,t} \tag{1}$$

where P_(i,t) represents principal repayment, I_(i,t) represents interest income, L_(i,t) represents default loss, and R_(i,t) represents the recovery amount. The aggregate cash flow function for the asset pool is:

$$CF_t^{pool} = \sum_{i=1}^{N} CF_{i,t} \tag{2}$$

The aggregate result of all loan cash flows serves as the basis for hierarchical allocation. Tiered Cash Flow Waterfall Distribution Model:

$$CF_t^{(k)} = \min\left(CF_t^{pool} - \sum_{j<k} CF_t^{(j)}, Obligation_t^{(k)}\right) \tag{3}$$

In this case, k is the layering sequence (A -> B -> C) that reflects the priority-subordinate allocation mechanism. The loss transmission function is layered as:

$$Loss^{(k)} = \alpha_k \cdot Loss^{pool} + \beta_k \cdot Stress_t \tag{4}$$

Here， α_k is the loss absorption weight.， β_k represents the pressure amplification effect.

To enhance the feasibility of this study, a structured credit asset pool with a base size of RMB 10 billion is defined. The underlying assets consist of a mix of credit and mortgage loans with varying maturities, an average interest rate of 6.10%, a base annualized default rate of 2.80%, a prepayment rate of 8.50%, and a default recovery rate of 58.00%. The equity structure comprises a senior tranche A of RMB 8 billion, a mezzanine tranche B of RMB 1.5 billion, and a subordinated tranche C of RMB 500 million. Additional interest spreads and reserves jointly bear the responsibility for the first tier of credit protection. The basic scenario and sensitivity parameters for the three stress scenarios are described below [11].

As shown in Table 1, the default rate and discount rate both increase under greater stress, while the prepayment rate and recovery rate decrease significantly. It implies that the portfolio does not only incur larger credit risk losses but also faces the double constraint of long-term recovery of cash flows and more significant valuation discounts. The overall three-year rate of default between baseline and severe stress is 8.1-29.4 percent. It means that credit enhancement protection of structured products will soon be used up, which will negatively impact the performance of mezzanine and subordinate tranches [12].

Table 1. Core Parameter Settings for Asset Pools under Different Scenarios

Scene	Annualized default rate	Prepayment rate	Recovery rate	discount rate	Cumulative default rate (3 years)
Baseline Scenario	2.80%	8.50%	58%	5.00%	8.10%
Mild stress	4.50%	7.20%	52%	5.80%	12.70%
moderate pressure	7.20%	6.00%	45%	6.60%	19.80%
Severe stress	11.00%	4.80%	36%	7.50%	29.40%

4.2 Gains and losses at different levels in various scenarios

The cash flow waterfall principle stipulates that the service fees and taxes are paid first, and then interest and principal payments are made in accordance with the categories A, B, and C. In case of default category C credit limit will be used first and then category B and finally category A. Depending on the specified scenarios, the expected yield to maturity, expected loss rate, and extreme loss quantile values of each level are calculated as it is presented in Table 2.

Table 2. Benefit and loss indicators of each structural layer under different scenarios

Hierarchy	Scene	Expected yield to maturity	Expected loss rate	95% quantile loss	Average lifespan (years)	Reduce probability
Priority A	benchmark	4.10%	0.20%	0.80%	2.6	0.50%
Priority A	Mild stress	3.75%	0.55%	1.60%	2.9	1.80%
Priority A	moderate pressure	3.12%	1.40%	3.90%	3.2	6.50%
Priority A	Severe stress	1.85%	4.80%	9.50%	3.8	18.20%
B mezzanine	benchmark	7.20%	1.90%	5.60%	3.5	6.00%
B mezzanine	Mild stress	6.10%	4.50%	11.80%	3.8	18.50%
B mezzanine	moderate pressure	3.95%	9.80%	22.60%	4.1	39.00%
B mezzanine	Severe stress	-0.80%	21.70%	41.40%	4.6	68.50%
C secondary	benchmark	12.80%	5.50%	14.20%	4.4	15.00%
C secondary	Mild stress	8.30%	11.60%	27.80%	4.7	33.00%
C secondary	moderate pressure	2.10%	24.50%	46.90%	5	61.00%
C secondary	Severe stress	-12.60%	48.80%	72.30%	5.4	89.50%

Table 2 indicates a strong stratification asymmetry. In the baseline scenario, stock A is a low return with a loss rate of merely 0.20% and has all the usual features of a defensive asset. Although stock C has a large nominal return, it is already prone to impairment with greater probability. When there is mild stress, the return of stock A was reduced by 0.35 percentage points whereas stocks B and C were reduced by 1.10 and 4.50 percentage points respectively showing that the subordinated and mezzanine tranches were the first ones to be impacted by stress. With a moderate stress scenario, the estimated loss rate of stock B attained 9.80 percent which is close to the limit where returns can no longer offset losses. In a severe stress situation, the yields to maturity of stocks B and C were negative, which means that the excess spread and the subordinated buffer were used up, and the mezzanine tranche became the primary channel of risks[13].

Grade A has a 9.50% tail loss in extreme situations (95th percentile loss). In spite of its reasonably decent floor protection layer, the tail loss may explode once it defaults and the recovery rate decreases. The higher average lifetime means that there is a longer period of cash flow recovery and a greater valuation discount which in turn causes the overall decrease in the total return on the senior tranche during the period of stress.

4.3 Identification of Cross-Level Risk Transmission Paths

As shown in the cash flow waterfall diagram, risk is not concurrently transmitted but instead flows in a series as follows: excess spread depletion, subordinated write-down, mezzanine erosion and weakening senior support. The analysis of this operation was done through computing some of its indicators based on different situations, including credit protection coverage ratio, risk transfer ratio and net cash flow coverage ratio; these are indicated in Table 3.

Table 3. Indicators of cross-level risk transmission under stress scenarios

scene	Category A Credit Support Multiplier	Category B Credit Support Multiplier	Excess spread depletion month	Loss proportion transferred from C to B	The proportion of losses transferred from B to A
benchmark	5.8	1.9	Not exhausted	18%	0%
Mild stress	4.2	1.3	28th month	36%	2%
moderate pressure	2.6	0.8	17th month	57%	11%
Severe stress	1.4	0.3	9th month	74%	29%

Table 3 shows that as the stress level increases, the credit support multiples of Tier A and Tier B continuously decrease, reflecting the trend of rapid decay of the safety cushion corresponding to each unit of potential loss. Under relatively low stress, the excess spread is exhausted in the 28th month, and the loss is mainly caused by the transfer from Tier C to Tier B. After medium-scale stress, the proportion of losses transferred from Tier C to Tier B rises to 57%, and the transfer from Tier B to Tier A reaches 11%, indicating that the risk is no longer limited to the subprime and mezzanine tranches, but is eroding the safety barrier of the senior tranche. Under large-scale stress, the excess spread is exhausted in the 9th month, the credit support multiple of Tier A drops to 1.4, and the proportion of losses transferred from Tier B to Tier A reaches 29%. In terms of its structure, the buffering effect is no longer an isolated loss but an amplifier of the effect.

This indicates that mezzanine layers are an important node of risk transmission and can offer security to priority tiers under normal conditions. Nevertheless, once the risks they hold reach a particular level, priority tiers move out of the state of protection to direct exposure. Hence, it is more efficient to watch mezzanine returns and write-down limits than just monitoring priority ratings to identify trends of systemic deterioration at an earlier stage.

5. Research Topic Optimization Strategies

5.1 Establish a loan-level, transparent data governance mechanism

The tiered assessment input indicators should be based on the pool means to loan-level features such as a minimum of the borrower credit score, loan-to-value, remaining term, geographic area, interest rate repricing structure, and presence of delinquency. The default, recovery and prepayment pathways should be updated on a monthly basis. It will only be when the underlying information has been comprehensively infiltrated that the real susceptibility of the subprime and mezzanine tranches will be truly exposed.

5.2 Dynamic stress testing using layered trigger clause linkage

The static stress test is to be converted into a rolling dynamic test, which should take into account factors like default rate, recovery rate, interest rate, unemployment shock, and housing price changes as well as structural trigger clauses should be included in the research. For the three important critical levels of excess spread coverage ratio, cumulative default rate, and cash flow coverage ratio, warning ranges should be set to assess the marginal changes in yields and write-down levels that would result from their activation.

5.3 Optimize capital structure depth and credit enhancement allocation

As shown in Tables 2 and 3, the mezzanine is a key link in risk transmission. Therefore, the design of the capital structure should not solely aim to expand the senior tranche. When designing the product, factors such as the thickness of the mezzanine, the proportion of the subordinated tranche, the size of the reserve account, and the liquidity support method should be taken into account so that the risk can be effectively fixed in the lower tranche under mild to moderate pressure, avoiding the rapid depletion of the senior tranche.

5.4 Constructing an integrated evaluation index system for gains and losses

Should be constructed, with expected yield to maturity, expected loss rate, 95th percentile loss, write-down probability, and average lifespan as the main components. At the investment company level, this matrix can be used to identify whether there is a mismatch problem between different layers, where "the interest rate spread appears large in form but the tail loss is large in substance." From a regulatory perspective, it is also conducive to strengthening the standardization and consistency of risk disclosure requirements for different types of structured products.

5.5 Strengthen the application of stress scenario results in investment and regulation

Investment decisions should not only consider ratings and coupon rates, but also include tail losses under heavy and moderate stress, changes in support multiples, and transmission rates in portfolio limits. Regulators should encourage the use of a standardized template to publicly disclose the stress test results of asset pools, especially information on the timing of excess spread depletion, the likelihood of write-downs in each tier , and the sensitivity of important triggering conditions, in order to improve the market's pricing capabilities.

6. Conclusion

The returns of structured credit products are not solely determined by the quality of their underlying assets; they are also influenced by cash flow cascades, credit enhancement measures , triggering conditions, and stress scenarios. A tiered quantitative evaluation system based on stress levels reveals significant differences in the degree of yield compression, tail loss exposure, and risk transmission between different tiers. Mild stress primarily manifests as yield losses, while moderate stress leads to instability within the tiers. In extreme events, excess spreads and subordinate buffers are rapidly depleted, causing risk to propagate upwards layer by layer.

Research has found that relying solely on average default rates or static ratings is insufficient to accurately determine the vulnerability of tiered products. The effectiveness of valuation and risk management could be enhanced only through integration of loan level data with dynamic triggering mechanisms and cross-tier loss transmission signals into an effective structure. In the future, to issue structured securitised products, select portfolios, and make regulatory disclosures, it will be important to enhance the transparency of data management and dynamic stress testing more to obtain a holistic balance between the profit calculation, loss reporting, and risk signal delivery.

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