Scholar Publishing Group
International Journal of Multimedia Computing
https://doi.org/10.38007/IJMC.2026.070110
ISSN 2789-7168 Vol. 7, Issue 1:82-89

Research on Mortgage Asset Cash Flow Simulation and Risk Transmission Mechanisms across Structural Tranches Based on Loan-Level Data

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Keywords: Mortgage-backed securitization, cash flow simulation, structural layering, risk transmission mechanism, loan-level data

Abstract: With the transformation of mortgage securitization into a dynamic process of penetration analysis, loan tranche information offers a finer backing on cash flow forecasts, credit loss projections, and tiered pricing. The paper develops a simulation model based on the core axis of the model i.e. loan performance - asset pool cash flows - tiered securities profit and loss, which includes default events, prepayment events, recovery rates, and time interval allocation rules. Basic scenarios, a housing price downturn scenario, and an interest rate shock scenario are used to compare the cash flow sensitivity of different tiers. The results show that the higher tranche has strong resilience to minor default shocks, but overreacts to the nonlinear combination of continuous prepayments and credit tail risks. The mezzanine tranche bears the greatest risk transfer amplification effect, while the lowest tranche, although able to absorb the first wave of risk, quickly loses its buffering effect in extreme environments. This paper argues that the combination of loan tranche modeling, tiered trigger mechanism design, and dynamic sizing is crucial for strengthening the stability of mortgage securitization.

1. Introduction: Research Background of Mortgage Asset Securitization Driven by Loan-Level Data

The essence of mortgage-backed securitization is to pool a large number of housing loans with different terms, different interest rates, different borrower qualifications, and different collateral values into an asset pool and distribute principal and interest to investors with different risk and return levels according to the contract waterfall payment rule [1] . Traditional research generally focuses on the mean default rate, mean prepayment rate and static excess spread of the asset pool. However, with the increase in interest rate volatility, the increase in housing price differences and the large differences in borrower behavior, the average method cannot identify the real risk transfer path within the structure [2] . The construction of public disclosure system and institutional data platform has greatly promoted the research on mortgage-backed securities. Freddy Mac publicly stated that its single mortgage-level dataset contains approximately 55 million mortgage loans issued between January 1, 1999 and September 30, 2025. Based on this, it continuously publishes monthly performance reports. Meanwhile, the SEC's research on the disclosure rules for initial public offerings of RMBS mentions that under Regulation AB II, a mortgage loan needs to disclose approximately 105 asset-level fields from the basic stage, and many more fields need to be added after certain events. This indicates that cash flow simulation has reached the point where it can be transformed from the "pool-level assumption" into a triple interaction model of "borrower-loan-period" [3] . Therefore, the questions surrounding how loan-level data can improve the cash flow forecasting ability of mortgage assets, how to show the risk transmission relationship between senior, mezzanine and subprime tranches, and how to prevent risk amplification through structural design have considerable academic theoretical and practical application value [4] .

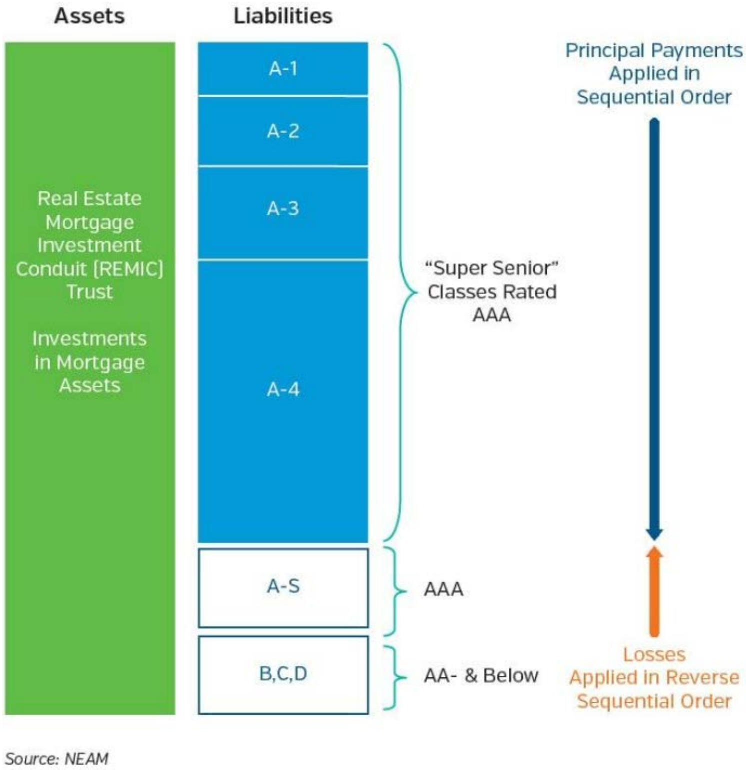

Figure 1: Loan-Level Cash Flow Simulation Framework

Figure 1 illustrates the cash flow simulation process based on loan-level data, comprising an input layer (borrower characteristics, interest rates, LTV, etc.), a state transition layer (default, prepayment, and regular repayment), and an output layer (cash flow generation and aggregation). By simulating the state changes of each individual loan on a period-by-period basis, the model establishes a mapping from micro-level behaviors to macro-level cash flows. This framework significantly enhances the accuracy of cash flow forecasting and supports multi-scenario stress testing analysis.

2. Analysis of the Current Status of Research on Mortgage Asset Cash Flow Driven by Loan-Level Data

2.1 Shift from pool-level averaging assumption to loan-level heterogeneity characterization

Current research has reached a consensus: the probability of default, the probability of prepayment and the loss rate are not variables that are evenly distributed in the asset pool, but are affected by factors such as the borrower's credit rating, loan amount ratio, debt repayment capacity ratio, regional housing price change trend and remaining term, interest rate refinancing incentives, etc. Loan-level modeling focuses on estimating the probability of each borrower's status change in each period, and at the same time conducts a dual assessment of "normal-overdue-default handling-recovery" and "holding-partial prepayment-full prepayment", so that the cash flow simulation is closer to the actual contract performance [5] .

2.2 Extending from Static Layered Return Calculation to Dynamic Waterfall Rule Simulation

From the perspective of structural stratification, the research focus has also evolved from the original description of static credit support multiples and loss absorption order to dynamic waterfall cash flow simulation. In addition to the nominal sequential repayment relationship, the senior, intermediate, and junior tranches are also affected by excess spread protection, triggering conditions, allocation clauses, liquidation procedures, and recovery period. Therefore, the same default rate shock will produce drastically different intra-tier profit and loss situations at different times and under different interest rate conditions [6] .

2.3 Deepening from Single Credit Risk Assessment to Multi-Factor Linkage Identification

Recent studies have placed more emphasis on the structural connections between interest rate shocks, falling housing prices, regional concentration, and different service provider behaviors. Especially after the rapid rise in mortgage rates, reduced prepayments will lead to longer risk exposure time; at the same time, falling housing prices will also increase the size of losses, and the combination of the two will make mezzanine tranches face greater duration-credit dual pressure. It can be seen that the value of loan-level information is far more than just improving the accuracy of individual default probability estimates, but also supporting the discovery of the mutual influence of cross-risk indicators [7] .

Table 1. Basic characteristics grouping and corresponding risk performance of the loan-grade sample pool

Grouping Dimensions	Sample features	Loan ratio	Annualized default rate	Annualized prepayment rate	Average loss rate
FICO<680	Borrowers with weak credit	18.0%	4.8%	9.6%	33.5%
FICO≥740	High-credit borrowers	36.0%	0.8%	15.1%	16.3%
LTV>85%	High leverage loans	22.0%	4.2%	8.4%	31.8%
LTV≤70%	Low leverage loans	29.0%	0.9%	14.8%	15.5%

Table 1 shows that loan-level data can clearly reflect the risk differences between asset pools. Although loans with a credit score below 680 account for only 18.0% of the total, the annualized default rate reached 4.8%, which is about 6 times that of the high-credit group. At the same time, its average loss rate is also relatively high, that is, high-risk loans are more likely to default and have poor repayment and recovery capabilities after default [8] . In addition, from the perspective of leverage, the default rate and loss rate of loans with an LTV greater than 85% are much higher than those of the low-leverage group, but the prepayment rate is lower, indicating that the risk exposure of leveraged assets is higher. During economic recession, there will be a greater probability of default and a more difficult cash flow problem to recover, which becomes an important source of risk transmission in the tiered structure .

3. Problems in the Study of Loan-Level Cash Flow Simulation and Structural Stratification

If a single prepayment ratio or a single default rate is used to replace the entire loan portfolio, it is easy to hide the influence of factors such as refinancing motivation, borrower refinancing, regional housing price differences and loan age. Especially for asset portfolios containing a large number of high LTV and low FICO repeated samples, the mean parameter will systematically underestimate tail loss. In the case of a large number of high LTV and low FICO repeated samples in the asset pool, the mean parameter will systematically underestimate tail loss. The cash flow allocation mechanism of mortgage-backed securitization is not simply "first senior and then subordinate", but also includes excess spread accounts, loan-by-loan coverage tests, principal diversion after triggering, cumulative loss threshold and liquidation repurchase clauses [9] . Such an institutional arrangement will cause a small change in a single loan to be transformed into a leap in the return of a certain tier through triggering events. Many models regard prepayment as an exogenous variable independent of default, but in fact, a decrease in interest rates will increase prepayment caused by refinancing motivation, and an increase in interest rates will extend the average life of assets, thereby increasing the credit risk exposure period. Therefore, if the relationship between interest rates and credit performance is not considered, the risk exposure of the mezzanine tier will be underestimated. Loan-level information generally has the advantages of rich fields and long time series, but it is also accompanied by problems such as missing items, field transformation, extended recovery period after default, and inconsistencies in multiple source descriptions. Public information can help us to conduct research with transparency, but it will also bring greater challenges to our sample preprocessing, state definition and structure mapping [10] .

4. Cash Flow Comparison Based on Scenario Simulation

4.1 Loan-level cash flow simulation framework and scenario setting

In loan-level cash flow modeling, the following core calculation model is introduced , which is the expression for the cash flow of a single loan in period t.

$$\mathrm{CF}_{i,t} = \mathrm{P}_{i,t} + \mathrm{I}_{i,t} - \mathrm{L}_{i,t} + \mathrm{R}_{i,t} \tag{1}$$

Where: $\mathrm{P}_{i,t}$represents principal recovery, $\mathrm{I}_{i,t}$represents interest income, $\mathrm{L}_{i,t}$represents default loss, $\mathrm{R}_{i,t}$and represents the amount recovered.

Default probability model

$$\mathrm{PD}_{i,t} = f(\mathrm{FICO}_i, \mathrm{LTV}_i, \mathrm{DTI}_i, \mathrm{HPI}_t, r_t) \tag{2}$$

This indicates that the probability of default is determined by the borrower's creditworthiness, leverage ratio, income ratio, housing price index, and interest rate. (Prepayment probability model)

$$\mathrm{PP}_{i,t} = g(r_t - r_i, \mathrm{Age}_i, \mathrm{Incentive}_t) \tag{3}$$

This reflects the driving effect of interest rate spreads and refinancing motives on prepayment.

To avoid overly abstract descriptions, the field construction for the simulated database containing 10,000 mortgage loans adopted a public loan-level disclosure framework, including parameters such as FICO, initial LTV, debt-to-income ratio, coupon rate, regional housing price index sensitivity, and loan duration. Stepping monthly, the probability of default , the probability of prepayment, and default settlement losses were simultaneously estimated for each loan. Finally, a waterfall method was used to map the principal, interest, default losses, and recovered cash flows to the A-class senior tier, M1 mezzanine tier, M2 secondary tier, and B-class equity tier.

Three scenarios are set up: the baseline scenario maintains a slow rise in housing prices and a low unemployment rate; stress scenario I see a cumulative 12% decline in housing prices and a 60% increase in the default rate for high LTV groups; stress scenario II builds upon stress scenario I by adding a 150 basis point increase in market interest rates, reducing prepayment rates. The risk transmission path is analyzed using the weighted average maturity, cumulative loss rate, and principal and interest coverage ratio for each tranche .

Table 2. Cash Flow and Loss Absorption Results for Each Structural Tier under Different Scenarios

gear	Credit support thickness	Baseline scenario cumulative loss rate	Stress Scenario 1 Cumulative Loss Rate	Stress Scenario 2 Cumulative Loss Rate	Basic Scenario WAL (Year)	Stress Scenario 2 WAL (Year)
A Advanced Level	20%	0.00%	0.15%	0.62%	4.1	6.3
M1 mezzanine	12%	0.38%	3.94%	8.27%	5.2	7.4
M2 Sub-class	6%	2.46%	11.83%	19.65%	5.8	7.9
B-Tier Benefits	0%	7.92%	32.44%	46.71%	6.4	8.1

Table 2 shows that under the baseline scenario, the high-tier tranche generally does not incur actual default losses, demonstrating the initial protective effect of tiered credit enhancement. Nevertheless, if the rate of houses goes down and the interest rate increases, the total loss rate of the high-tier tranche is 0.62 percent. Even though this percentage is small, it shows that the losses previously located in the subprime and equity tranches are starting to shift upward, which is an additional indication of the characteristic of mezzanine tranches as risk amplifiers. The cumulative loss in stress scenario one on M1 tranche is near 4 percent, and in stress scenario two it is 8.27 percent and the weighted average lifespan increases to 7.4 years. It therefore bears not only the burden of the effects of increasing credit losses but also the burden of extended maturities because of fewer prepayments. Consequently, the mezzanine tranche is a hub layer of transmission of risk. The subprime and equity tranches also have a part in absorbing the first wave of losses and their risk rates increase very fast in unfavorable conditions. This implies that as soon as the bottom layer of the protection vanishes, the entire resilience of the product structure will be greatly compromised and the safety margin of the high-tier tranche will be diminished.

4.2 Identification of the mechanism of risk transmission between structural levels

Risk contagion is not a unidirectional process, however, it spreads via various channels of transmission: disruption of loan behavior reduces the net cash flow in the pool which triggers a default and redistribution of profits and losses between the tiers. In turn, high-leverage with low-credit customers are more prone to default when housing prices are decreasing, which initiates the first wave of credit depletion. On the other hand, rising interest rates reduce the willingness to repay, causing higher-risk loans to remain in the pool for longer periods, resulting in increased future credit loss discounting. Simultaneously, once the accumulated losses exceed the coverage test threshold, the profits originally intended for the subprime tier will be used to protect the higher-level subprime tiers, squeezing the cash flow of the intermediate tiers.

After the asset pool cash flow is incorporated into the structural stratification, it is allocated as follows:

$$CF_t^{(k)} = \min\left(CF_t^{pool} - \sum_{j<k} CF_t^{(j)}, Obligation_t^{(k)}\right) \quad (4)$$

Where represents kthe hierarchical order (A→M→B).

Table 3 Shock transmission elasticity of risk factors

Risk shock variables	A Advanced Level	M1 mezzanine	M2 Sub-class	B-Tier Benefits
The probability of default has increased by 10%.	0.08	0.46	0.71	0.93
Prepayment rate decreased by 10%.	0.05	0.31	0.44	0.52
Recovery rate decreased by 10%.	0.11	0.39	0.58	0.76
The housing price index fell by 5%.	0.14	0.57	0.82	1.05

Table 3 shows the transmission elasticity, indicating the percentage change in cumulative loss rates across different tiers when each risk factor changes by one unit. The table reveals that a decrease in the housing price index results in the greatest pressure across all tiers, particularly for M2 and B tiers, with elasticities of 0.82 and 1.05 respectively. This means that even collateral depreciation alone can lead to increased default rates and loan losses, exhibiting a "double whammy" effect. Increased default rates have the greatest impact on equity tranches, but also a relatively high elasticity coefficient for mezzanine tranches, indicating that equity tranches cannot completely isolate themselves from the risks above. In contrast, a decrease in prepayment ratios has little impact on senior tranches, but significantly increases the loss elasticity of mezzanine and subprime tranches. It shows that slow repayment is an active occurrence and does not remain neutral, as it extends the time of high-risk exposure, thus increasing the credit risk.

5. Collaborative Improvement of Loan-Level Penetration Modeling and Hierarchical Structure

The fundamental solution to enhance the performance of cash flow simulation is to ensure that default and prepayment as well as recovery rates are incorporated into the same loan grade transition model. To estimate the migration probabilities individually by various ages of the loans, credit ratings, and LTV bands, and subsequently introduce the changes in interest rates and housing prices at the scenario level may greatly enhance the uniformity of pool-level cash flow predictions. Mezzanine tranches are structurally valuable buffer regions of risk escalation. Their association with accumulated loss limits, excess spread accounts and the rules of principal conversion should be reinforced. The risk of rapid spread to higher tranches can be mitigated during periods of concentrated initial losses by setting installment trigger limits with dynamic credit support supplementary clauses. Credit risk is not an isolated phenomenon; a stress test system based on the combination of housing prices, interest rates, unemployment rates, and down payment behavior must be developed. In the event of refinancing closure, reducing housing prices and rising unemployment, the time and credit exposure resonance effect of each tranche in the same period should be analyzed. To properly assess high tranches, it is not enough to just monitor the fixed level of credit support but, in the worst-case scenario, how fast the credit support has been used up. The available loan-level information in the open domain is more transparent, though the uniform standards in processing of data, labeling, caliber checking and validating backtest are required to be defined during conducting and using them. Multi-sample rolling backtesting with a variety of different regional combinations and aging categories might decrease model overfitting and increase the reasonableness of the outcomes.

6. Conclusion

The general accessibility of loan-level information has made a breakthrough in the study of mortgage-backed securities, allowing to closely monitor the micro-level behavior biases and changes in the structural transmission of risks. In comparison with the analyses that are based entirely on the mean parameters of pools, the loan-level cash flow simulations are able to better illustrate the delinquencies and prepayments, and demonstrate the manner in which losses are continuously transferred to the equity, subordinate, and mezzanine tranches. The simulations indicate that the mezzanine tranche is the most important in terms of risk transmission as it acts as an amplifier and also a buffer. The cumulative impact of lower housing values and reduced prepayments results into increased risk penetration. The future studies and product creation must enhance the loan tranche level management of data, form joint stress scenarios, and create dynamic additional collateral measures to improve the resilience of mortgage-backed securities to complex market shocks and their underlying rationale.

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