Annual Actuarial Review of

The FHA Mutual Mortgage Insurance Fund

Forward Loans

Fiscal Year 2026

Submitted to:

United States Department of Housing and Urban Development

Submitted by:

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November 10, 2026

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November 10, 2026

The Honorable Joe Gormley
Performing delegable duties of the Assistant Secretary for Housing – FHA Commissioner
U.S. Department of Housing and Urban Development (HUD)
2415 Eisenhower Ave, Alexandria, VA 22314

Dear Mr. Gormley,

IT Data Consulting, LLC (ITDC) has finalized and is submitting the Fiscal Year 2026 Independent Actuarial Review of the Single-Family Forward Mortgages under the Mutual Mortgage Insurance Fund, pursuant to contract number 86615723C00002.

This report is based on data as of September 30, 2026, providing an overview of the Economic Net Worth and details regarding the Cash Flow Net Present Value (NPV) for the Mutual Mortgage Insurance (MMI) Forward Loan portfolio as of the conclusion of Fiscal Year 2026. We have included a comparison with the corresponding estimate from the end of Fiscal Year 2025, an evaluation under various scenarios, and offered detailed insights into the models employed for developing this estimate. The Appendix G tables of historical and projected loan termination rates are delivered as a separate attachment accompanying this report.

ITDC is here to answer any questions or address any comments you may have about the report and its conclusions.

Respectfully,



Benny Asnake
President and CEO
IT Data Consulting, LLC

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November 10, 2026

The Honorable Joe Gormley
Performing delegable duties of the Assistant Secretary for Housing – FHA Commissioner
U.S. Department of Housing and Urban Development (HUD)
2415 Eisenhower Ave, Alexandria, VA 22314

Dear Mr. Gormley,

I, Min Ji, am a Professor of Actuarial Science and Risk Management at Towson University. My research focuses on applying actuarial models to the risk management of insurance and financial products. I am a member of the American Academy of Actuaries (MAAA), a Fellow of the Society of Actuaries (FSA), and a Fellow of the Institute and Faculty of Actuaries (FIA). I serve on the Society of Actuaries' exam and research committees, keeping well connected to academia and the latest actuarial research in the insurance industry.

I meet the Qualification Standards for Actuaries Issuing Statements of Actuarial Opinion in the United States of the American Academy of Actuaries to render the actuarial opinion contained herein. I have reviewed the "*Annual Actuarial Review of the FHA Mutual Mortgage Insurance Fund, Forward Loans, for Fiscal Year 2026*". The purpose of my review was to determine the soundness of the methodology used, the appropriateness of the underlying assumptions applied, and the reasonableness of the resulting estimates derived in the Review.

The review was based on data and information provided by the Federal Housing Administration (FHA). I have relied on FHA for the accuracy and completeness of this data. In addition, I also relied upon the reasonableness of the assumptions used in the economic projections from the FY 2027 Mid-Session Review of the President's Economic Assumptions (PEA).

In my opinion, the Cash Flow NPV estimate provided by FHA for use in the FHA Annual Report to Congress is $32.283 billion, compared with $42.872 billion in FY 2025, representing a decrease of approximately $10.589 billion, or 24.7%. FHA's estimate falls within ITDC's moderate scenario range.

Based on its review of the underlying model changes, their financial impacts, and the range of projected outcomes, ITDC considers FHA's FY 2026 Cash Flow NPV estimate reasonable.

Respectfully,



Min Ji, Ph.D., MAAA, FSA, FIA

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Summary of Deliverables

Below, we summarize the findings associated with each of the required deliverables:

Deliverable 1: Produce a written Actuarial Study for Forward that provides actuarial central estimates of the Mutual Mortgage Insurance (MMI) Fund as of the end of Fiscal Year 2026 and assesses HUD's estimates of Economic Net Worth.

The Economic Net Worth is defined as cash available to the Fund plus the Net Present Value (NPV) of all future cash outflows and inflows that are expected to result from the mortgages currently insured by the Mutual Mortgage Insurance (MMI) Fund.

As of the end of FY 2026, ITDC's Actuarial Central Estimate (ACE) of the MMI Forward Cash Flow NPV is positive $25.571 billion.

The total capital resource as reported in the Annual Report to Congress regarding the status of the Federal Housing Administration (FHA) Mutual Mortgage Insurance Fund is a positive $146.816 billion as of the end of Fiscal Year (FY) 2026. Thus, the estimated Economic Net Worth of the MMI Forward portfolio is $172.386 billion.

Deliverable 2: Include a review of the risk characteristics of existing MMI loans including commentary on how such characteristics have changed in recent years.

A review of the risk characteristics of existing MMI Forward loans and commentary on how these risk characteristics have changed is included in Section III, Characteristics of the MMI SF Forward Books of Business, and Section I.C, FHA Policy Changes.

Deliverable 3: Apply the final Forward actuarial model to the existing portfolio to produce conditional (and cumulative) claim, prepayment, and loss-given-default rates at various levels of aggregation across loans, and for individual policy years and policy year-quarter. Cash-flow summaries should also be provided for major categories (e.g., premium revenues, claim expenses and recoveries, or net loss due to claims, with affected loan counts and balances).

Models for projecting loan terminations and loan performance are described in Appendices B and C. Cash flow summaries by major category are displayed in the table below and discussed in more detail in Section II, with a detailed analysis of the cash flow calculations in Appendix D.

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Exhibit SD-1: Projected Cash Flow Summaries ($ Million)

Cash Flow Category	Net Present Value of Cash Flow
Mortgage Insurance Annual Premium	$ 70,243
Upfront Premium Refund	(1,756)
Loss Mitigation Expense	(14,702)
Claim Expenses	(58,858)
Recoveries	30,645
Net Present Value	**$ 25,571**

Note: Components may not sum to the total due to rounding.

Deliverable 4: To promote transparency of the Studies' assessments, the Studies should identify methodological vulnerabilities that may occur in their actuarial models or in HUD's analyses of Economic Net Worth. This discussion should evaluate the scope and scale of such vulnerabilities in creating possible forecast risk and suggest possible lines of research in these areas. The Studies should assess and comment upon HUD's own models that estimate Economic Net Worth for methodological vulnerabilities and compare HUD's methodologies with those in the Studies.

The assumptions and judgments underlying the ITDC Studies' estimates are summarized in Appendices A through E of the report. Section IV provides a summary of the Net Present Value (NPV) calculations, which are based on simulated economic scenarios. We also discuss the economic conditions that could lead to materially adverse changes in the Cash Flow NPV.

The FY 2025 review, documented in Appendix F of the previous report, provided supplemental documentation and analysis of HUD's Forward models to support enhanced transparency and completeness of the actuarial review after HUD's model documentation became available. This year's Appendix F focuses on updates and modifications to the models implemented by HUD since that prior review and assesses their potential impact on the actuarial analysis.

Deliverable 5: The Studies should include historical data on changes in program terms as well as relevant loan and borrower characteristics (e.g., credit scores, loan-to-value ratios) by cohort and other sub-populations. Loan performance data (claim rates, prepayment rates, severity, and recovery rates), both historical and projected, shall be presented in the "finger-table" formats (arrayed by cohort and policy years for different loan products).

Section III, Characteristics of the MMI SF Forward Books of Business, provides historical information on changes in the MMI programs. A review of the risk characteristics of existing MMI loans and commentary on how these risk characteristics have changed are included in Section I.C, FHA Policy Changes. Historical and projected claim, prepayment, loss severity, and recovery rates in finger-table format, arrayed by cohort and policy year for each mortgage product, are provided in Appendix G as a separate spreadsheet addendum.

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Deliverable 6: The Contractor should use the President's Economic Assumptions, provided by the Office of Risk Management and Regulatory Affairs (ORMRA), for the actuarial central estimates of the Studies. However, in addition to the central single-path economic forecast, the Studies shall test alternative economic forecasts for stress-testing and sensitivity analysis to estimate ranges of reasonableness.

ITDC has conducted a comprehensive analysis based on the President's Economic Assumptions for Fiscal Year 2027 Mid-Session Review (PEA) provided by the Office of Management and Budget (OMB). Based on our assessment, the Cash Flow Net Present Value (NPV) by the conclusion of the 2026 fiscal year for cohort years 1992 to 2026 is a positive $25.571 billion.

In the table below, we estimate that the range of Cash Flow NPV based on the pessimistic downside and optimistic upside stochastic simulation scenarios is between positive $4.605 billion and positive $39.510 billion. These two values from the optimistic upside and pessimistic downside are illustrative extreme stress-test outcomes rather than forecasts and carry no probability interpretation (see Section VI.E). Our Baseline NPV of $25.571 billion stays in the middle of $33.192 billion from the moderate upside scenario and $15.784 billion from the moderate downside scenario.

Exhibit SD-2: Net Present Value of the Forward Fund under Different Economic Scenarios ($ Million)

Economic Scenario	Fiscal Year 2026 Cash Flow NPV
Baseline PEA	$ 25,571
Alternative 1 - Optimistic Upside Scenario	39,510
Alternative 2 - Moderate Upside Scenario	33,192
Alternative 3 - Moderate Downside Scenario	15,784
Alternative 4 - Pessimistic Downside Scenario	4,605

The Cash Flow NPV estimate provided by FHA to be used in the FHA Annual Report to Congress is positive $32.283 billion. Based on ITDC's actuarial central estimate utilizing the PEA and range of results from the stochastic simulation scenarios, we conclude that the FHA estimate of Cash Flow NPV is reasonable. This conclusion reflects a high-level reasonableness review of FHA's estimate against ITDC's central estimate and stress-test range; it is not a replication of FHA's model or a component-level reconciliation of the $6.712 billion difference.

Deliverable 7: To provide comparability to HUD estimates of Economic Net Worth, the Contractor shall use Federal Credit Reform Act discounting assumptions and procedures.

Section IV, MMI Fund Performance under Alternative Scenarios, and Appendix D3.1, Discount Factors, provide comparability to HUD estimates of Economic Net Worth and conform to the Federal Credit Reform Act discounting assumptions and procedures.

Deliverable 8: This Study should use stochastic or Monte Carlo simulations of future economic conditions including interest rates and house price appreciation. The objective of

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these requirements is to illustrate the sensitivity of forecasts to economic uncertainty and other forms of forecast error.

As described in Section IV, MMI Fund Performance Under Alternative Scenarios, and detailed in Appendix E: Stochastic Simulation Models, we generated different percentile economic scenarios using stochastic simulations.

Deliverable 9: Provide econometric appendices to the Study that include variable specifications and statistical output from all regressions in the Studies.

Appendix H provides variable specifications and statistical output for the loan status transition models, and Appendices D and E provide the estimation results for the loss severity, loss mitigation, outbid share, and stochastic simulation models.

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Executive Summary

The Cranston-Gonzalez National Affordable Housing Act of 1990 (NAHA) requires an independent actuarial study of the economic worth of the Federal Housing Administration (FHA) and the Department of Housing and Urban Development's (HUD's) Mutual Mortgage Insurance (MMI) Fund. On July 30, 2008, the Housing and Economic Recovery Act of 2008 (HERA) transferred the obligation for an autonomous actuarial assessment to section 12 USC 1708(a)(4).

HERA also restructured several supplementary programs under the purview of MMI. The MMI Fund has two components: forward mortgages and reverse mortgages. Reverse mortgages are insured under the Home Equity Conversion Mortgage (HECM) program and are covered in a separate report. In the remainder of this report, the term MMI refers to the Forward component of the MMI Fund only.

The primary purpose of this analysis is to provide an updated estimate of the Economic Net Worth of the current mortgage portfolio as of the end of FY 2026. Economic Net Worth is calculated by adding the available cash in the Fund to the Net Present Value (NPV) of all anticipated future cash flows from the mortgages currently insured by the MMI Fund.

ITDC has conducted a comprehensive analysis, utilizing economic forecasts from the President's Economic Assumptions for the Fiscal Year 2027 Mid-Session Review (PEA) published by OMB. Based on our assessment, the Cash Flow Net Present Value (NPV) as of the end of FY 2026 for cohort years 1992 through 2026 is a positive $25.571 billion. The pessimistic downside and optimistic upside stochastic simulation scenarios give illustrative stress-test outcomes of positive $4.605 billion and $39.510 billion, which carry no probability interpretation (see Section VI.E). The MMI Forward Fund remains in a strong financial position in FY 2026, with estimated Economic Net Worth changing from $167.697 billion in FY 2025 to approximately $172.386 billion in FY 2026, a year-over-year change of about $4.689 billion. This movement was driven by two largely offsetting factors: capital resources increased from $130.533 billion in FY 2025 to approximately $146.816 billion in FY 2026, contributing approximately $16.283 billion to Economic Net Worth, while the Cash Flow NPV decreased from $37.164 billion to approximately $25.571 billion, reducing Economic Net Worth by approximately $11.593 billion.

The decline in Cash Flow NPV was driven primarily by updated economic assumptions and emerging experience for the existing portfolio, which resulted in less favorable projected loan performance and associated future cash flows, including higher expected claim and loss mitigation costs and changes in recoveries. Model and methodology updates, measured sequentially on the FY 2025 portfolio before the data and economic update (Exhibit II-3), had offsetting effects: the revised CWCOT treatment, the updated loss severity models, and the updated termination model increased projected NPV, while the incorporation of 40-year loan extensions and the updated loss mitigation model reduced it, for a net decrease of $2.273 billion. In particular, the change in projected claims and loss mitigation expenses contributed approximately negative $14.129 billion to the NPV movement, while the change in expected recoveries and premium income (including

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premium refunds) contributed approximately positive $5.846 billion and negative $3.310 billion, respectively. Meanwhile, unamortized Insurance-in-Force increased from $1.796 trillion in FY 2025 to approximately $1.946 trillion in FY 2026, reflecting continued growth in insured exposure. As a result, because Economic Net Worth changed more slowly than Insurance-in-Force, the standalone capital ratio for the forward component of the MMI Fund changed from approximately 9.3 percent in FY 2025 to 8.9 percent in FY 2026.

This 8.9% ratio is presented for informational purposes only and should not be confused with HUD's official capital ratio for the overall MMI Fund. The statutory minimum capital requirement of 2.00% applies to the overall MMI Fund (including HECM) and not separately to the Forward portfolio.

Overall, the year-over-year movement in Economic Net Worth was driven primarily by the increase in accumulated capital resources, partially offset by a less favorable outlook for future cash flows on the insured portfolio.

A. Status of the MMI Forward Portfolio

To assess the adequacy of the current and future capital resources to meet estimated future liabilities, ITDC analyzed all Single Family (SF) Forward defaults, claims, and associated recoveries using loan-level data reported by FHA through September 30, 2026. Based on historical experience, we developed loan-level termination and cash flow models to estimate the future loan performance of the FY 1992 to FY 2026 books of business using various assumptions, including macroeconomic forecasts from the Office of Management and Budget (OMB), Moody's Analytics (Moody's), and the expected SF Forward portfolio characteristics provided by FHA.

Using the macroeconomic inputs from the PEA regarding the future trajectory of home prices, mortgage interest rates, unemployment, the 1-year Constant Maturity Treasury (CMT) rate, and the 10-year Constant Maturity Treasury (CMT) rate, ITDC projects the performance of the FY 1992 to 2026 books of SF Forward loans, and estimates the SF Forward Cash Flow Net Present Value (NPV) as of the end of FY 2026 to be positive $25.571 billion. The SF Forward portion of total capital resources, as reported in the Annual Report to Congress regarding the status of the FHA Mutual Mortgage Insurance (MMI) Fund, is positive $146.816 billion as of the end of FY 2026. Thus, the estimated Economic Net Worth of the SF Forward MMI Fund is positive $172.386 billion.

ITDC also estimates that the Cash Flow NPV based on randomly generated economic scenarios is between positive $4.605 billion and positive $39.510 billion. These two values, from the optimistic upside and pessimistic downside, are illustrative extreme stress-test outcomes rather than forecasts and carry no probability interpretation (see Section VI.E). Our Baseline PEA NPV of $25.571 billion stays in the middle of $33.192 billion from the moderate upside scenario and $15.784 billion from the moderate downside scenario.

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The Cash Flow NPV estimate provided by FHA to be used in the FHA Annual Report to Congress is a positive $32.283 billion. Based on ITDC's actuarial central estimate utilizing the baseline PEA and range of results from the stochastic simulation scenarios, we conclude that the FHA estimate of Cash Flow NPV is reasonable. This conclusion reflects a high-level reasonableness review of FHA's estimate against ITDC's central estimate and stress-test range; it is not a replication of FHA's model or a component-level reconciliation of the $6.712 billion difference.

The insurance-in-force (IIF) is reported on two bases: unamortized IIF is the original mortgage amount of all SF Forward loans remaining in the insurance portfolio as of September 30, 2026, and amortized IIF is the current scheduled Unpaid Principal Balance (UPB) of those loans. Unless otherwise noted, IIF in this Review refers to unamortized IIF. The unamortized IIF of FY 2026 originations that remain active as of the end of FY 2026 is $292.655 billion. Exhibit ES-1 provides the Actuarial Central Estimate (ACE), unamortized IIF, and amortized IIF of the SF Forward portfolio for FY 1992 through FY 2026.

Exhibit ES-1: Projected MMI Forward Performance for 2026 ($ Million)

Cohort Year	Cash Flow NPV	Unamortized Insurance-in-Force	Amortized Insurance-in-Force
1992-2026	$ 25,571	$ 1,946,181	$ 1,718,718

B. Sources of Change in the Status of the Forward Portfolio

The FY 2025 Forward Review reported that the economic net worth of the SF Forward portfolio was $167.697 billion at the conclusion of 2025, contrasting with this review, which estimates a positive value of $172.386 billion at the end of 2026. Exhibit ES-2 compares our MMI Cash Flow NPV and IIF estimate for 2026 to the estimates in the 2025 Review.

Exhibit ES-2: Estimate of Cash Flow NPV as of 2026 ($ Million)

Item	Cash Flow NPV	Capital Resources	Unamortized Insurance-In-Force (IIF)
2025	$ 37,164	$ 130,533	$ 1,795,689
2026	25,571	146,816	1,946,181
Dollar Difference	$ (11,593)	$ 16,283	$ 150,492
Percent Difference	-31.2%	12.5%	8.4%

As seen in Exhibit ES-2, the Forward portion of the MMI Fund's estimated 2026 Cash Flow NPV has decreased by $11.593 billion from the level estimated in Fiscal Year 2025, from positive $37.164 billion to positive $25.571 billion. The capital resources available to the MMI Fund have increased by 12.5 percent, from $130.533 billion to positive $146.816 billion. The unamortized IIF increased by 8.4 percent from $1.796 trillion to $1.946 trillion.

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C. Impact of Economic Forecasts

The Fund's economic net worth for 2026 will depend on the economic conditions expected to prevail over the next 40 years and, most critically, during the next 10 years. We have captured the most significant factors in the U.S. economy affecting the performance of the loans insured by the Fund using the following variables in our models:

- 30-year, 15-year, and adjustable-rate mortgage rates
- 1-year and 10-year constant maturity Treasury rates
- National and local house price indices
- National and local unemployment rates

Higher mortgage interest rates generally reduce refinancing incentives and slow prepayments, allowing FHA to collect mortgage insurance premiums for a longer period, although higher discount rates can reduce the present value of future cash flows. Higher unemployment tends to increase financial stress on borrowers, leading to greater delinquencies and defaults and, consequently, higher expected claim and loss mitigation costs. House price appreciation generally strengthens borrower equity and reduces the likelihood and severity of mortgage insurance claims; when claims do occur, higher property values also tend to increase recoveries and reduce losses to the Fund. Conversely, weaker or declining house prices can increase both default risk and loss severity.

The projected performance of FHA's current book of business, as measured by economic net worth, depends on future forecasts of these economic drivers. The baseline scenario for the primary economic drivers was developed consistently with the PEA. The PEA is published by the Office of Management and Budget in compliance with the requirements of the Federal Credit Reform Act.

Our primary source of historical data on these economic factors is Moody’s Economy.com, a leading provider of economic research and data. Moody’s has developed data from sources, including the Federal Reserve, Bureau of Labor Statistics, Bureau of the Census, Bureau of Economic Analysis, Federal Housing Finance Agency, The Conference Board, Dow Jones, National Association of Realtors, and Freddie Mac. Depending on the data series, information is provided at the national, state, county, metropolitan area, and ZIP code level. Moody’s data are combined with historical loan-level data from HUD’s Single-Family Data Warehouse (SFDW) to build out loan-level panel data and event histories (defaults, cures, claims, prepayments) for use in estimating statistical models of loan performance. The estimated loan performance models are then combined with the forecasts of economic drivers based on the PEA to produce our baseline forecast.

In addition to the mandated baseline PEA forecasts, we apply four alternative stochastic simulation scenarios of potential random deviations from the PEA baseline. It is worth noting that these

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alternative stochastic scenarios are stress-testing tools rather than forecasts. To summarize the five scenarios for which we report estimates of economic net worth:

- Baseline – Published PEA
- Alternative 1 – Optimistic Upside Scenario
- Alternative 2 – Moderate Upside Scenario
- Alternative 3 – Moderate Downside Scenario
- Alternative 4 – Pessimistic Downside Scenario

Each of these scenarios is based on combinations of selected "percentile" paths for the economic drivers that correspond to favorable or unfavorable outcomes for the prospects of the Single Family MMI Fund portfolio. Rising interest rates, rising housing values, and declining unemployment rates are favorable outcomes, because they lead to lower prepayments (increasing future premium income) and lower default, claim, and loss rates (reducing future losses). Conversely, declining interest rates, falling house prices, and rising unemployment rates are unfavorable outcomes, because they lead to higher prepayment rates (lowering future premium income) and higher default and claim rates (increasing future losses). Some elements of our more optimistic scenarios, such as higher interest rates, may not conform to the usual interpretation of favorable economic conditions, but are in fact favorable to the current economic net worth of the MMI Fund.

The combinations of selected percentile paths comprising each of the alternative scenarios described above are summarized here:

Alternative 1 – Optimistic Upside Scenario

Treasury and Mortgage Rates: 90th percentile

Unemployment Rate: 10th percentile

House Price Appreciation Rate: 90th percentile

Alternative 2 – Moderate Upside Scenario

Treasury and Mortgage Rates: 75th percentile

Unemployment Rate: 25th percentile

House Price Appreciation Rate: 75th percentile

Alternative 3 – Moderate Downside Scenario

Treasury and Mortgage Rates: 25th percentile

Unemployment Rate: 75th percentile

House Price Appreciation Rate: 25th percentile

Alternative 4 – Pessimistic Downside Scenario

Treasury and Mortgage Rates: 10th percentile

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Unemployment Rate: 90th percentile

House Price Appreciation Rate: 10th percentile

The PEA forecast developed by OMB does not cover all the economic drivers that are included in our models. Additional economic variables that must be forecast, such as Fixed Rate Mortgage (FRM) 15-Year and Adjustable-Rate Mortgage (ARM) origination rates, regional and local house price indices, and unemployment rates, are developed using the PEA and additional data from Moody's. The forecasts for all additional series are driven by the corresponding national PEA forecasts. Additional details may be found in the discussion of stochastic simulation models in Appendix E.

Exhibit ES-3 presents the actuarial central estimate of the cash flow NPV from the projections based on the PEA and four alternative scenarios. The actuarial central estimate uses the PEA for FY 2027 published by the Office of Management and Budget, in compliance with the requirements of the Federal Credit Reform Act. Four alternative scenarios represent different percentile paths of interest rates, unemployment rates, and the House Price Index (HPI) from 1,000 simulations.

Stochastic scenarios are simulated using the best-fitted GARCH model with the mean replaced by the corresponding PEA, to ensure the simulated paths will not drift far away from the PEA while having stochastic volatilities.

Exhibit ES-3: Range of Cash Flow NPV Outcomes Based on Stochastic Simulations ($ Million)

Economic Scenario	Fiscal Year 2026 Cash Flow NPV*
Baseline**	$ 25,571
Alternative 1 - Optimistic Upside Scenario***	39,510
Alternative 2 - Moderate Upside Scenario	33,192
Alternative 3 - Moderate Downside Scenario	15,784
Alternative 4 - Pessimistic Downside Scenario	4,605

**All values are expressed as of the end of the fiscal year period*
***Baseline is based on PEA*
**** Descriptions of these scenarios are found in Section IV and Appendix E*

Our baseline PEA Cash Flow NPV of $25.571 billion stays in the middle of the $15.784 billion moderate downside scenario and the $33.192 billion moderate upside scenario. The range of Cash Flow NPV based on the more extreme scenarios extends from $4.605 billion from Alternative 4 – Pessimistic Downside Scenario to $39.510 billion from Alternative 1 – Optimistic Upside Scenario. These two values from the optimistic upside and pessimistic downside are illustrative extreme stress-test outcomes rather than forecasts and carry no probability interpretation (see Section VI.E).

The 2026 Cash Flow NPV estimate provided by FHA is positive $32.283 billion. Based on ITDC's Cash Flow NPV estimate utilizing the Baseline PEA and range of results from the stochastic simulation scenarios, we conclude that the FHA estimate of Cash Flow NPV is reasonable. As noted in Section A above, this conclusion reflects a high-level reasonableness review and not a replication of FHA's model or a reconciliation of the $6.712 billion difference.

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ITDC provides this report to the FHA and policymakers for their assessment of the Economic Net Worth of the MMI Fund. Our conclusions are based on various assumptions about future conditions and events, detailed in subsequent sections of this report. These assumptions must be understood to contextualize our conclusions properly. Furthermore, our work is subject to inherent limitations, also discussed in this report.

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I. Introduction

A. Actuarial Reviews of the FHA Mutual Mortgage Insurance Fund

The National Housing Act requires an annual independent actuarial review of the Federal Housing Administration's (FHA) Mutual Mortgage Insurance (MMI) Fund.[1] ITDC was engaged by the Department of Housing and Urban Development (HUD) to conduct an independent actuarial review of the MMI Fund for 2026. This study is required by 12 USC 1708(a)(4) and must be completed in compliance with the Federal Credit Reform Act as implemented and all applicable Actuarial Standards of Practice (ASOPs) promulgated by the Actuarial Standards Board of the American Academy of Actuaries. This study analyzes the financial position of the MMI Fund for 2026 using data through September 30, 2026.

The MMI Fund is a group of accounts of the federal government that records transactions associated with the FHA's guarantee programs for single-family mortgages. Currently, the FHA insures approximately 8.4 million forward mortgages under the MMI Fund.

Per 12 USC 1711(f), FHA must ensure that the MMI Fund maintains a capital ratio of not less than 2.0 percent. This statutory requirement applies to the MMI Fund as a whole, Forward and HECM components combined; the Forward-only capital ratio reported in this Review is informational. The capital ratio is the ratio of capital to the MMI Fund's obligations on outstanding mortgages, known as Insurance in Force (IIF). Capital is defined as cash available to the Fund plus the Net Present Value (NPV) of all future cash outflows and inflows expected to result from the mortgages currently insured by the MMI Fund.

B. Forward Program Overview

i. Products

FHA mortgage insurance is available for all the most utilized mortgage products including long-term (typically 30-year) fixed rate loans, intermediate-term fixed rate loans, and adjustable-rate loans for both home purchase and the refinance of existing mortgage debt. Under the Section 203(b) program, insurance is available on one-to-four-unit homes including eligible manufactured homes and individual condominium units. The Section 203(k) program supports financing for rehabilitation costs in addition to property acquisition or refinancing needs. FHA offers a "streamline refinance" program supporting refinancing of existing FHA-insured mortgages requiring only limited borrower credit documentation and underwriting.

[1] HERA moved the requirement from the 1990 National Affordable Housing Act (NAHA) to the Federal Housing Administration operations within the National Housing Act, 12 USC 1708(a)(4).

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ii. Premiums and Claims

Premium income is collected both at the time of loan origination and annually over the life of each loan. FHA draws on this premium income to pay out mortgage insurance claims in the event of a defaulted loan termination.

iii. Delinquencies

FHA's guarantee of payment to lenders in the event of default facilitates lending to borrowers who might otherwise not be able to access mortgage credit. As an illustration, the average FHA credit score for loans insured during fiscal 2026, excluding streamline refinances, was 679, as compared with an average score of 753 on the Fannie Mae book of business as of June 30, 2026.[2] In view of these differences, it should not come as a surprise that FHA 90-day delinquency rates of 5.2% as of August 2026 exceed Fannie Mae's rate, which was 0.6% as of that date.[3]

iv. Loss Mitigation

FHA offers a wide range of loss mitigation options designed to assist FHA-insured homeowners facing financial hardship. These include forbearance programs to temporarily pause or reduce monthly payments, loan modifications adding arrearages to the principal loan balance and extending the repayment term, partial claims placing arrearages in a zero-interest subordinate lien against the collateral property, and payment supplements, which use partial claim funds to bring the mortgage current and temporarily reduce the borrower's monthly payment. If the mortgage cannot be reinstated by the aforementioned options, terminating through pre-foreclosure sales and deed-in-lieu of foreclosure are the final options in the loss mitigation program.[4] See Section I.C for discussion of recent mortgagee letters about loss mitigation.

v. Loan Terminations

An FHA loan terminates upon maturity, refinancing, or mortgage default. Default-related terminations may be resolved through foreclosure or through foreclosure alternatives, including a pre-foreclosure sale (PFS) or deed-in-lieu (DIL) of foreclosure. Following foreclosure, the property may be disposed of through Claims Without Conveyance of Title (CWCOT), under which the property is sold without being conveyed to HUD, or through conveyance to HUD for subsequent disposition as Real Estate Owned (REO). A defaulted loan may also be resolved through a note sale, under which HUD pays the insurance claim and sells the defaulted mortgage note; note sale volume has been negligible in recent years, and note sales are not modeled as a separate disposition type (see Appendix D).

[2] FHA Single Family Data Warehouse, fiscal year 2026 endorsements excluding streamline refinances; Fannie Mae 2Q 2026 financial results.
[3] FHA Single Family Loan Performance Trends August 2026 Credit Risk Report; Fannie Mae Monthly Summary, August 2026.
[4] https://www.hud.gov/helping-americans/fha-loss-mitigation.

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vi. Claims, Conveyance, and Recoveries

When an FHA-insured mortgage terminates through default, FHA may pay an insurance claim to the mortgagee and recover a portion of the claim through several disposition channels. Under CWCOT, a foreclosed property is sold without conveyance of title to HUD, allowing FHA to avoid taking possession of and subsequently disposing of the property. Alternatively, if the property is conveyed to HUD, it becomes REO and FHA may recover proceeds through the subsequent sale of the property. Recoveries may also arise from foreclosure alternatives such as PFS or DIL. The applicable disposition method affects the timing and amount of recoveries, property holding and disposition expenses, and ultimately the net claim loss incurred by the MMI Fund.

vii. Prepayments

Loan prepayment is when a borrower pays back all or part of a loan's outstanding balance before the scheduled due date. In this report, prepayment is referred to as “complete prepayment,” in which case the loan is terminated after full payment of the outstanding balance.

C. FHA Policy Changes and Recent Mortgagee Letters

Since the mid-1990s, the Federal Housing Administration (FHA) has enacted numerous policy adjustments that have had a notable impact on the financial health of the Mutual Mortgage Insurance (MMI) Fund. Essential modifications encompass revised underwriting guidelines, changes in homeownership counseling prerequisites, the adoption of automated underwriting systems, alterations to mortgage insurance premium structures, down payment assistance and closing costs, along with the introduction of programs dedicated to foreclosure avoidance and loss mitigation, and COVID-19-related changes in loss mitigation options. The following summarizes each of these significant developments.

i. Revised Underwriting Guidelines and Other Policy Issues

In 1995, the FHA implemented a series of alterations to its underwriting guidelines to remove needless obstacles to homeownership. These changes were designed to offer more flexibility in evaluating the creditworthiness of nontraditional and underserved borrowers while also providing more explicit guidance to prevent discriminatory application of underwriting requirements. While these adjustments did expand homeownership opportunities for many households, the more lenient underwriting standards also played a role in the subsequent rise in FHA claim rates for loans that originated after 1995.

In 1998, modifications were introduced to the underwriting guidelines governing adjustable-rate mortgages (ARMs) in response to the elevated loss rates that the FHA encountered with these loans. An in-depth study of ARM claim rates by the FHA revealed the necessity for credit policy changes to uphold the MMI Fund's actuarial stability. Consequently, because of these adjustments, ARM applicants were mandated to qualify based on a mortgage payment amount calculated using

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the highest potential second-year interest rate. Additionally, any temporary interest rate reduction method for ARMs could no longer be applied to establish qualifying payment ratios.

In 2008, HERA set the minimum borrower cash equity requirement to 3.5 percent for purchase loans.[5] FHA also established a minimum FICO score of 500 for loans with 90 percent or higher loan-to-value ratios (LTVs). This rule was further tightened in 2010.[6] Starting October 4, 2010, borrowers with credit scores below 500 were no longer eligible for FHA insurance, and the maximum loan-to-value ratio for borrowers with credit scores between 500 and 579 was limited to 90 percent. In 2011, FHA removed eligibility for loans on investor property.[7] In 2012, the FHA modified documentation requirements for self-employed borrowers. Starting April 1, 2012, profit-and-loss statements and balance sheets of self-employed borrowers have been required in most cases.[8] Also, for identity-of-interest transactions, the family member definition was expanded to include the extended family, including brothers, sisters, uncles, and aunts.

For manually underwritten loans assigned on or after April 21, 2014, HUD clarified a series of maximum qualifying ratios for different lowest minimum decision credit scores and acceptable compensating factors.[9] It also revised the compensating factors that must be cited to exceed FHA's standard qualifying ratios for manually underwritten loans.

In 2026, FHA has made several changes to streamline FHA Mortgagee approval and quality control by eliminating outdated, redundant, or otherwise unnecessary requirements in section I, Doing Business with FHA, and section V, Quality Control, Oversight, and Compliance of the FHA Single Family Housing Policy Handbook 4000.1.[10] The changes are not expected to have a material direct effect on projected claims, premium revenues, or Economic Net Worth.

ii. Changes to Homeownership Counseling Prerequisites

The FHA has historically promoted homebuyer counseling on the premise that educating prospective homeowners about homeownership and mortgage matters would decrease the likelihood of mortgage defaults and foster a more responsible approach to homeownership. The following provides an overview of the history of mortgagee letters about homebuyer counseling.

- In 1993, a pilot counseling program for pre-purchase and pre-foreclosure situations was announced.[11]

[5] Mortgagee Letter 2008-23, September 5, 2008: Revised Downpayment and Maximum Mortgage Requirements.
[6] Mortgagee Letter 2010-29, September 3, 2010: Minimum Credit Scores and Loan-to-Value Ratios.
[7] HUD 4155.1, Section B. Property Ownership Requirements and Restrictions. 4155.1 4.B.1.a: Occupancy Restrictions.
[8] Mortgagee Letter 2012-03, February 28, 2012: Miscellaneous Underwriting Issues.
[9] Mortgagee Letter 2014-02, January 21, 2014: Manual Underwriting.
[10] Mortgagee Letters 2026-09 and 2026-10, June 23, 2026: Eliminating Unnecessary Requirements for FHA Mortgagee Approval and Quality Control, and Updates to FHA Quality Control Requirements for Appraisal Field Reviews, respectively.
[11] Mortgagee Letter 93-28, September 20, 1993: Prepurchase and Foreclosure Prevention Counseling Demonstration.

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- In 1996, after the pilot counseling program, the upfront Mortgage Insurance Premium (MIP) was decreased by 25 basis points for first-time homebuyers who completed homeownership counseling.[12] One year later, in 1997, the upfront MIP further decreased by another 25 basis points for first-time homebuyers who completed homeownership counseling.[13] This discount was provided to recognize the expected improvement in default experience.

- In 1998, a mortgagee letter was released indicating that the homeownership counseling program would be reviewed. This was in response to homeownership counseling programs that were being used that did not meet FHA guidelines. While the counseling program required that it involve 15 to 20 hours of instruction, there were cases where homebuyers were provided with workbooks without additional interaction or instruction. The guidelines of the homeownership counseling program were reiterated in this letter.[14]

- In 2000, in conjunction with an overall reduction in upfront MIP, the homeownership counseling discount was discontinued.[15]

iii. Adoption of Automated Underwriting Systems

Beginning in 1995, automated underwriting systems (AUSs) began to increase. Theoretically, using AUSs increases the availability of mortgages and improves the efficiency and speed of mortgage processing. The following are key events in the history of AUS:

- In 1995, HUD approved the use of AUSs. Mortgagors had to request permission to use these systems and receive approval from HUD.[16]

- In 1996, criteria were established for the approval of AUSs by HUD.[17]

- In 1998, the FHA approved using Freddie Mac's Loan Prospector in underwriting FHA-insured mortgages. A specific scorecard tailored for FHA-endorsed loans was introduced. Additionally, FHA made significant alterations to its credit policies and lessened documentation prerequisites for loans assessed by the Loan Prospector. This marked the inaugural inclusion of an Automated Underwriting System (AUS) in FHA's insurance endorsement process.

[12] Mortgagee Letter 96-48, August 28, 1996: Single Family Production - Reduction in Up-Front Mortgage Insurance Premiums (UFMIP) for First-Time Homebuyers Who Receive Housing Counseling.
[13] Mortgagee Letter 97-37, August 13, 1997: Single Family Production - Further Reduction in Up-Front Mortgage Insurance Premiums (UFMIP) for First-Time Homebuyers Who Receive Housing Counseling
[14] Mortgagee Letter 98-1, January 2, 1998: Single Family Loan Production - Underwriting Adjustable Rate Mortgages, Interest Buydowns, Homeownership Counseling and Other Credit Policy Issues.
[15] Mortgagee Letter 2000-38, October 27, 2000: Single Family Loan Production - Further Reduction in Upfront Mortgage Insurance Premiums and Other Mortgage Insurance Premium Changes
[16] Mortgagee Letter 95-7, January 27, 1995: Single Family Loan Production - Revised Underwriting Guidelines and Other Policy Issues
[17] Mortgagee Letter 96-34, July 10, 1996: Single Family Loan Production - Automated Underwriting Systems.

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- In 1999, Fannie Mae's Desktop Underwriter and PMI Mortgage Services' Automated Underwriting Risk Analysis (AURA) systems received approval for underwriting FHA mortgages. Approval was followed by Countrywide Funding Corporation's Countrywide Loan-Underwriting Expert System (CLUES) and JP Morgan-Chase's Zippy shortly after that.

- Starting in May 2004, all approved AUSs applied FHA's Technology-Open-To-Approved-Lenders (TOTAL) mortgage scorecard to assess loan applications for potential automated approval for FHA insurance. Initially, over two-thirds of submitted loans typically received automated approval, eliminating the need for manual underwriting reviews. Since May 2004, HUD has mandated lenders to provide borrower credit scores.

iv. Alteration in Mortgage Insurance Premium Structures

Sufficient Mortgage Insurance Premium (MIP) plays a pivotal role in upholding the financial stability of the MMI Fund. However, the MIP rate can also influence the affordability of homes for prospective buyers. The following provides a summary of the changes in MIP since 1991.

- In 1991, FHA decided to calculate the Mortgage Insurance Premium (MIP) as a combination of an upfront MIP and an annual premium, with the latter being a percentage of the remaining outstanding mortgage balance each year.[18] This adjustment led to an overall increase in MIP, which was necessary to fulfill the new capital requirement by NAHA.

- In 1994, the upfront MIP decreased by 75 basis points to 2.25 percent.[19] This was in response to the improved financial experience of the MMI Fund.

- In 1996, the upfront MIP decreased by 25 basis points to 2.00 percent for first-time homebuyers who received mortgage counseling before purchasing their home.[20] This was implemented based on the pilot program's success, which showed that first-time homebuyers who received this counseling had better default experiences.

- In 1997, the upfront MIP was decreased by an additional 25 basis points to 1.75 percent for first-time homebuyers who received mortgage counseling before purchasing their home. The upfront MIP was 50 basis points lower than it would be for a homebuyer who did not receive counseling.[21]

[18] Mortgagee Letter 91-26, May 30, 1991: Single Family Insurance Processing for Risk Based Insurance Premiums.
[19] Mortgagee Letter 94-14, March 31, 1994: Single Family Loan Production – Reduced Upfront Mortgage Insurance Premium (UFMIP).
[20] Mortgagee Letter 96-48, August 28, 1996: Single Family Production – Reduction in Up-Front Mortgage Insurance Premiums (UFMIP) for First-Time Homebuyers Who Receive Housing Counseling.
[21] Mortgagee Letter 97-37, August 13, 1997: Single Family Production – Further Reduction in Up-Front Mortgage Insurance Premiums (UFMIP) for First-Time Homebuyers Who Receive Housing Counseling.

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- In 2000, several changes were implemented in recognition of the improved experience of the MMI Fund. First, the upfront MIP was reduced by 75 basis points to 1.50 percent. Second, the upfront MIP refund schedule was shortened to five years instead of seven. Third, a provision to cancel the annual MIP once the loan-to-value (LTV) ratio was 78 percent or less was implemented. Also, the discount in the upfront MIP for first-time homebuyers who received counseling was discontinued.[22]

- In April 2010, upfront MIP was increased by 75 basis points to 2.25 percent.[23] This premium increase was in response to the housing and economic crisis in 2008 and was the first in a series of increases over the next three years.

- In October of 2010, upfront MIP decreased, but annual MIP increased significantly.[24] Overall, this increased MIP.

- In 2011, the annual MIP was increased by 25 basis points.[25]

- In 2012, the annual MIP was increased by ten basis points.[26]

- In 2013, several changes were implemented related to the annual MIP. First, for case numbers assigned on or after June 3, 2013, the term for collection of MIPs was extended to 11 years for mortgages with an initial LTV ratio of 90 percent or less and 30 years for mortgages with an initial LTV ratio greater than 90 percent. Second, mortgages with terms of 15 years or less and an LTV ratio of 78 percent or less at the time of origination, which were exempt from MIP, would no longer be exempt. Lastly, the annual MIP was increased by 5 to 10 basis points for mortgages with terms of 15 years or less and LTV ratios of 78 percent or less at origination.[27]

- As a result of improved financial experience, in 2015, annual MIP rates were decreased by 50 basis points for loans with terms greater than 15 years.[28]

[22] Mortgagee Letter 2000-38, October 27, 2000: Single Family Loan Production – Further Reduction in Upfront Mortgage Insurance Premiums and Other Mortgage Insurance Premium Changes.
[23] Mortgagee Letter 2010-02, January 21, 2010: Increase in Upfront Premiums for FHA Mortgage Insurance.
[24] Mortgagee Letter 2010-28, September 1, 2010: Changes to FHA Mortgage Insurance Premiums.
[25] Mortgagee Letter 2011-10, February 14, 2011: Annual Mortgage Insurance Premium Changes and Guidance on Case Numbers.
[26] Mortgagee Letter 2012-04, March 6, 2012: Single Family Mortgage Insurance: Annual and Up-Front Mortgage Insurance Premium – Changes.
[27] Mortgagee Letter 2013-04, January 31, 2013: Revision of Federal Housing Administration (FHA) policies concerning cancellation of the annual Mortgage Insurance Premium (MIP) and increase to the annual MIP.
[28] Mortgagee Letter 2015-01, January 9, 2015: Reduction of Federal Housing Administration (FHA) annual Mortgage Insurance Premium (MIP) rates and Temporary Case Cancellation Authority.

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- In 2017, a decrease was proposed for annual MIP rates,[29] but this decrease was suspended later in the year.[30]

- In 2023, FHA determined that a reduction in the annual MIP rate was necessary and appropriate to execute FHA's mission and role in the mortgage market. This resulted in a 30-basis-point decrease in the annual MIP rate across most programs.[31]

v. Down Payment Assistance and Closing Costs

The origin of funds for down payments and closing costs has been a significant concern for HUD. Regulations limit the amount of assistance from sources other than the borrower or their family, and HUD has issued numerous mortgagee letters to address this matter. While aiding down payments and closing costs expand homeownership opportunities, it is worth noting that historically, mortgages with a larger share of these expenses covered by external sources have shown poorer performance. The following section summarizes the mortgagee letters addressing this issue.

- Before 1992, closing costs could not be financed as part of the loan. In 1992, the limitation on financing closing costs was removed, but mortgages were still subject to LTV ratio limits.[32] This provision was implemented to make it easier for homebuyers to meet the down payment requirements.

- In 1996, HUD allowed family members to lend the borrower 100 percent of the down payment.[33] This was also intended to make it easier for individuals and families to achieve homeownership.

- Two provisions were implemented in 1998. First, it was prohibited for the seller or any other party to pay mortgage interest for the buyer. In addition, any interest rate buydown could not result in a lower interest rate of more than 2 percent below the note rate. These changes were implemented to avoid a significant increase in the payment amount once the seller-paid mortgage interest funds were depleted or the interest rate buydown term was complete.[34]

[29] Mortgagee Letter 2017-01, January 9, 2017: Reduction of Federal Housing Administration (FHA) Annual Mortgage Insurance Premium (MIP) Rates.
[30] Mortgagee Letter 2017-07, January 20, 2017: Suspension of Mortgagee Letter 2017-01 – Reduction of Federal Housing Administration (FHA) Annual Mortgage Insurance Premium (MIP) Rates.
[31] Mortgagee Letter 2023-05, February 22, 2023: Reduction of Federal Housing Administration (FHA) Annual Mortgage Insurance Premium (MIP) Rate.
[32] Mortgagee Letter 92-39, October 16, 1992: Single Family Loan Production - Elimination of Limit on Financing Closing Costs.
[33] Mortgagee Letter 96-58, October 23, 1996: Single Family Loan Production - Secondary Financing from Family Members.
[34] Mortgagee Letter 98-1, January 2, 1998: Single Family Loan Production - Underwriting Adjustable Rate Mortgages, Interest Buydowns, Homeownership Counseling and Other Credit Policy Issues

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- In 2000, HUD guided mortgages to ensure that the source of gifts to buyers is documented, and the person giving the gift must certify that the funds did not come from someone with an interest in the transaction. This was implemented to combat a practice of sellers providing funds to family members of the buyer that would then be used for the down payment.[35]

- Section 2113 of the Housing and Economic Recovery Act of 2008 prohibited down payment contributions from a seller or any other person or entity that would financially benefit from the transaction.[36]

- In 2019, guidance by HUD was provided to clarify the rules associated with funds being provided by a governmental source for down payment assistance. The mortgagee letter requires the mortgagee to verify that the funds provided by the government agency were transferred to the Borrower before or at the time of closing and that the governmental agency was acting in its legal capacity in providing these funds. Documentation is also required by the government that the agency has the authority to provide the funds and from an attorney for the government entity verifying that the property is within the government agency's jurisdiction. There can be no direct transfer of assistance from the government agency to the mortgagee, and there can be no requirement that the loan be transferred to a specific mortgagee as a condition of receiving assistance from the government agency.[37] This guidance was subsequently suspended until further notice and ultimately rescinded.[38]

vi. Foreclosure Avoidance and Loss Mitigation Programs

The pre-foreclosure sale (PFS) program allows mortgagors to sell their homes and use the proceeds to satisfy their mortgage debt obligations even if the proceeds were less than owed. Ultimately, these programs help limit the number of defaults that turn into claims and limit the losses sustained by the MMI Fund when a claim occurs. There are also certain situations where HUD can pursue a deficiency judgment against the borrower if their PFS amount does not cover the mortgage balance, if it is consistent with state law.

Over the years, FHA has issued many mortgagee letters related to foreclosure and loss mitigation:

- In 1996, a mortgagee letter was released to provide information on the loss mitigation procedures, including unique forbearance plans, mortgage modifications, PFSs, deeds instead of foreclosure, and partial claims. The primary objective was to keep the

[35] Mortgagee Letter 2000-28, August 7, 2000: Gift Documentation, Mortgage Forms and other Credit Policy and Appraisal Issues.
[36] https://www.congress.gov/110/plaws/publ289/PLAW-110publ289.pdf
[37] Mortgagee Letter 2019-06, April 18, 2019: Downpayment Assistance and Operating in a Governmental Capacity.
[38] Mortgagee Letter 2019-12, August 13, 2019: Rescission of Mortgagee Letters 2019-06, Downpayment Assistance And Operating in a Governmental Capacity; 2019-07, Extension of the Effective Date of Mortgagee Letter 2019-06, Downpayment Assistance and Operating in a Governmental Capacity; and 2019-10, Suspension of the Effective Date of Mortgagee Letter 2019-06, Downpayment Assistance and Operating in a Governmental Capacity.

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homeowner in the home, and if that was not possible, then the objective was the disposition of the property without full foreclosure.[39]

- In 2008, due to the increase in defaults resulting from the housing crisis, FHA released a mortgagee letter reminding mortgagees of PFS as an option and consolidated the provisions of the PFS program into one place. This letter also updated the provisions of the PFS to address the mortgage crisis better.[40]

- In 2010, FHA released a mortgagee letter announcing enhancements to the FHA refinance program to allow responsible borrowers an opportunity to stay in their homes. This could occur if the lender agreed to write off at least 10 percent of the principal balance and if the remaining loan provisions were met.[41]

- In 2011, FHA issued guidance requiring a trial payment program before completing a permanent loan modification or partial claim. During the trial payment period, the borrower must complete three months of payments at the amount that will continue under the modification.[42]

- In 2012, FHA revised the Loss Mitigation Home Retention Options to reduce the claims against the MMI Fund and help more borrowers stay in their homes. These revisions included eliminating the maximum back-end debt-to-income ratio, the restriction on the principal, interest, taxes, and insurance that can be included in the claim, and the requirement that the existing mortgage be no more than 12 months past due.[43]

- In 2013, FHA established updated PFSs and Deed in Lieu (DIL) requirements. These changes included using the Deficit Income Test (DIT) – a test to determine if expenses exceed income and whether a hardship exists – and eliminating the financial hardship/deficit income PFS requirement for service members who have received a Permanent Change of Station order.[44] In 2013, additional modifications were made to the FHA Loss Mitigation Home Retention Options. These changes included defining continuous income that can be considered in the transaction, allowing for arrearages to be included in partial claims, and allowing for modifications for mortgagors in bankruptcy.[45]

- In 2014, the updated PFS guideline required a minimum marketing period of 15 calendar days for all PFS transactions. It also clarified that non-arms-length transactions are

[39] Mortgagee Letter 96-61, November 12, 1996: FHA Loss Mitigation Procedures - Special Instructions.
[40] Mortgagee Letter 2008-43, December 24, 2008: Pre-Foreclosure Sale (PFS) Program - Utilizing the PFS Loss Mitigation Option to Assist Families Facing Foreclosure.
[41] Mortgagee Letter 2010-23, August 6, 2010: FHA Refinance of Borrowers in Negative Equity Positions.
[42] Mortgagee Letter 2011-28, August 15, 2011: Trial Payment Plan for Loan Modifications and Partial Claims under Federal Housing Administration's Loss Mitigation Program.
[43] Mortgagee Letter 2012-22, November 16, 2012: Revisions to FHA's Loss Mitigation Home Retention Options.
[44] Mortgagee Letter 2013-23, July 9, 2013: Updated Pre-Foreclosure Sale (PFS) and Deed in Lieu (DIL) of Foreclosure Requirements.
[45] Mortgagee Letter 2013-32, September 20, 2013: Update to FHA's Loss Mitigation Home Retention Options

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permitted only if necessary to comply with state law.[46] Also, in 2014, FHA issued a mortgagee letter to increase the use of Claims Without Conveyance of Title (CWCOT) procedures. This letter also established that the Commissioner's Adjusted Fair Market Value must be used for all foreclosure sales and PFS efforts.[47]

- In 2018, FHA issued a mortgagee letter implementing unique loss mitigation processes for Hurricanes Irma, Harvey, and Maria victims and the California Wildfires. These procedures were implemented to help homeowners stay home and reduce losses to FHA.[48] Later, in 2018, FHA issued a mortgagee letter in response to continued elevated default rates and lower utilization of loss mitigation options in Puerto Rico and the U.S. Virgin Islands. This mortgagee letter expanded loss mitigation assistance to borrowers in default.[49]

- In 2019, HUD incorporated additional changes to streamline and revise Loss Mitigation Procedures for Presidentially Declared Major Disaster Areas (PDMDAs).[50]

vii. COVID-19 and Changes in Loss Mitigation Options

The COVID-19 pandemic and policy response significantly impacted borrower behavior. Starting on March 18, 2020, a 60-day foreclosure moratorium was implemented for properties secured by FHA-insured mortgages, covering both the initiation of foreclosures and those already in progress.[51] Subsequently, this moratorium was extended several times. The moratorium on new and in-process foreclosures expired on July 31, 2021, while the moratorium on foreclosure-related evictions was extended through September 30, 2021.[52] During this period, the first legal action deadlines and reasonable diligence times were extended by 90 days from the moratorium's expiration. On February 7, 2022, it was further clarified that these deadlines would be extended

[46] Mortgagee Letter 2014-15, July 10, 2014: Updated Requirements for Pre-Foreclosure Sales (PFS) and Deeds in Lieu (DIL) of Foreclosure.
[47] Mortgagee Letter 2014-24, November 26, 2014: Increasing Use of FHA's Claims Without Conveyance of Title (CWCOT) Procedures
[48] Mortgagee Letter 2018-01, February 22, 2018: Loss Mitigation for borrowers with FHA-insured mortgages whose property and/or place of employment is located in Presidentially-Declared Major Disaster Areas, adversely affected by Hurricanes Harvey, Irma, Maria, certain California wildfires that occurred in October 2017 (FEMA-DR4344) or certain California Wildfires, Flooding, Mudflows, and Debris Flows that occurred in December 2017 (FEMA-DR-4353).
[49] Mortgagee Letter 2018-05, August 15, 2018: Updated Loss Mitigation for mortgagees servicing mortgage loans for borrowers with FHA-insured mortgages whose property and/or place of employment is located in the Presidentially-Declared Major Disaster Areas (PDMDAs) of Puerto Rico Hurricane Maria DR-4339 or Virgin Islands Hurricane Maria DR-4340 and Disaster Foreclosure Moratorium for certain FHA-insured mortgages secured by properties located in areas of Puerto Rico and the U.S. Virgin Islands that the U.S. Department of Homeland Security's Federal Emergency Management Agency (FEMA) has declared to be eligible for Individual Assistance (Affected Counties) as a result of Hurricane Maria (Puerto Rico Hurricane Maria DR-4339 and Virgin Islands Hurricane Maria DR-4340).
[50] Mortgagee Letter 2019-14, August 29, 2019: Updates to FHA's Loss Mitigation Options for Borrowers in Presidentially-Declared Major Disaster Areas (PDMDAs)
[51] Mortgagee Letter 2020-04, March 18, 2020: Foreclosure and Eviction Moratorium in connection with the Presidentially Declared COVID-19 National Emergency.
[52] Mortgagee Letter 2021-19 / FHA INFO 21-62, July 30, 2021: Extension of Foreclosure-Related Eviction Moratorium in Connection with the Presidentially Declared COVID-19 National Emergency.

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180 days from the end of the borrower's COVID-19 forbearance or the expiration of the foreclosure moratorium.[53]

Multiple FHA mortgagee letters issued during the pandemic period included provisions for loan forbearance, partial claims, loan modifications including 40-year term extensions, and incentive payments to servicers for completing COVID-19 Recovery options. On July 23, 2021, HUD set forth a range of COVID-19 Recovery Loss Mitigation Options, encompassing the COVID-19 Standalone Partial Claim, a zero-interest subordinate lien to cover arrearages, and the COVID-19 Recovery Modification, a 360-month loan modification.[54] On April 18, 2022, HUD introduced a 40-year loan modification as one of the COVID-19 recovery loss mitigation choices.[55] Effective April 30, 2023, the Federal Housing Administration (FHA) continued expanding its COVID-19 loss mitigation options by making it available to all eligible borrowers, regardless of the cause of their delinquency.[56]

Under Mortgagee Letter ("ML") 2025-12, "Tightening and Expediting Implementation of the New Permanent Loss Mitigation Options", effective October 1, 2025, COVID-19 Recovery Loss Mitigation Options were extended through and expired on September 30, 2025. After that sunset date, eligible borrowers may avail themselves of loss mitigation options under a "loss mitigation waterfall" implemented sequentially via the following steps:

[53] Mortgagee Letter 2022-02, February 7, 2022: Technical Update to the Extension of the Deadlines for the First Legal Action and Reasonable Diligence Time Frame.
[54] Mortgagee Letter 2021-18, July 29, 2021: COVID-19 Recovery Loss Mitigation Options.
[55] Mortgagee Letter 2022-07, April 18, 2022, Update to the COVID-19 Recovery Loss Mitigation Options.
[56] Mortgagee Letter 2023-03, April 30, 2023, Expansion of the COVID-19 Recovery Loss Mitigation Options.

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Exhibit I-1: Loss Mitigation Waterfall

Step	Criterion	Yes	No
1	Is the Borrower no more than 120 Days in Default and able to repay arrearages over a set period of no more than 24 months?	Review for a Repayment Plan	Proceed to Step 2
2	Does the Borrower require a period of reduced or suspended payments before they can resume payments?	Review for a Forbearance	Proceed to Step 3
3	Does the Borrower attest they can resume making their current Mortgage Payments?	Review for a Standalone Partial Claim	Proceed to Step 4
4	Can a Standalone Loan Modification achieve the target payment?	Review for a Standalone Loan Modification	Proceed to Step 5
5	Can a Combination Loan Modification and Partial Claim achieve the target payment?	Review for a Combination Loan Modification and Partial Claim	Proceed to Step 6
6	Does the Borrower qualify for a Payment Supplement?	Review for a Payment Supplement	Return to Step 5, if required, or proceed to Step 7
7	Does the Borrower meet the requirements to participate in a Home Disposition Option?	Review for a PFS	Proceed to Step 8
8	If an approved PFS marketing period is unsuccessful, review for a DIL of Foreclosure.	DIL of Foreclosure	Foreclosure

Borrowers must complete three successive timely monthly payments under a Trial Payment Plan (TPP) to remain eligible for any of the above waterfall loss mitigation options and are only permitted a single loss mitigation option per 24-month period.

ML 2025-21, "Updates to Mortgagee Letter 2025-12, Tightening and Expediting Implementation of the New Permanent Loss Mitigation Options," incorporates minor changes to facilitate implementation of servicing and loss mitigation announced in the above referenced ML 2025-12.57

ML 2026-08 introduces vital updates to FHA Single Family loss mitigation requirements. To prevent borrowers from deliberately failing to accept a TPP repeatedly, a third failure to accept a TPP Agreement will automatically count as a TPP failure. The ML also limits borrower requests for multiple re-reviews for loss mitigation that prevent the mortgagee from initiating foreclosure.

[57] Mortgagee Letter 2025-21, September 24, 2025: Updates to Mortgagee Letter 2025-12, *Tightening and Expediting Implementation of the New Permanent Loss Mitigation Options*.

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Overall, MLs 2025-12, 2025-21, and 2026-08 tighten and refine FHA's loss mitigation framework. These changes are expected to reduce the frequency and potentially the cost of loss mitigation and subsequent redefaults, thereby having a generally favorable impact on Economic Net Worth, although tighter access to assistance could partially offset these savings through higher foreclosure-related claims.

viii. LIBOR to SOFR Transition

Mortgagee Letter 2023-09 requires indexation of adjustable-rate loans to the Secured Overnight Financing Rate (SOFR) in place of the London Interbank Offered Rate (LIBOR), which has been discontinued. This change affects the way interest rates are calculated for ARMs, affecting both new originations and existing mortgages. FHA has implemented provisions to ensure a smooth transition for existing and new adjustable-rate mortgages (ARMs) that were previously indexed to LIBOR.

D. Current and Future Market Environment

i. Interest Rates

Average 30-year fixed-rate mortgage rates declined to a historic low of 2.65% in January 2021 before rising sharply in 2022 and reaching a peak of 7.76% in November 2023, amid the Federal Reserve's monetary tightening to combat inflation. As illustrated in Exhibit I-2, mortgage rates generally declined from their 2023 peak, reaching approximately 6.5% by mid-May 2026. However, this downward trend reversed in recent months, with rates rising above 7% in late September 2026 and reaching 7.40% by mid-October. Mortgage rates remain substantially elevated compared with pre-2022 levels, continuing to constrain housing affordability, home purchase demand, and refinancing activity. Looking ahead, mortgage rates are expected to remain sensitive to inflation expectations, long-term Treasury yields, and broader economic conditions, creating continued uncertainty for the housing market.

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Exhibit I-2: 30-Year Fixed Rate Mortgage Interest Rates

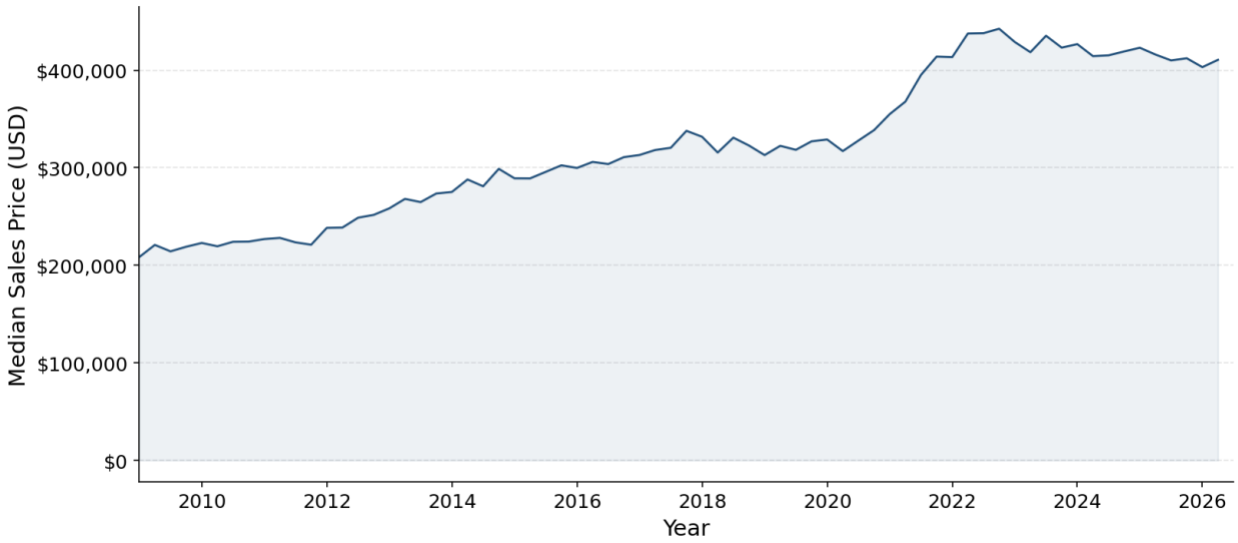


ii. House Price

As illustrated in Exhibit I-3, the median sales price of houses sold in the United States increased substantially from just over $200,000 in 2009 to more than twice that level by 2022, reaching a peak of approximately $442,000 in the fourth quarter of 2022. Since then, the median sales price exhibited a generally declining trend from early 2023, falling to $403,200 in the first quarter of 2026 before edging up to $410,700 in the second quarter of 2026. Despite this decline, home prices remain substantially above pre-pandemic levels, reflecting significant appreciation over the past decade. Looking ahead, elevated mortgage rates and affordability constraints may continue to weigh on housing demand, while limited housing supply could provide support for home prices.

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Exhibit I-3: Median Sales Price of Houses Sold for the United States[58]



iii. Mortgage Credit

Per the New York Federal Reserve Household Debt and Credit Report for Q2 2026, mortgage balances shown on consumer credit reports declined by $74 billion during the second quarter of 2026, totaling $13.1 trillion at the end of June. Origination volume was $505 billion in the second quarter. Transition into early delinquency rose slightly, while the transition into serious delinquency, defined as 90 days or more past due, remained mostly unchanged. Approximately 55,000 consumers had new foreclosure notations in credit reports, a slight improvement from the prior quarter.

Based on their National Delinquency Survey, the Mortgage Bankers Association (MBA) reported that the national delinquency rate (including loans at least one payment past due, but excluding loans in the process of foreclosure) was 4.37% as of June 30, 2026. This figure represents a 7 basis-point decrease from the prior quarter and is 44 basis points above the corresponding figure as of June 30, 2025.

In August 2026, FHA reported a serious delinquency rate, comprising loans with at least three payments past due or in foreclosure or bankruptcy, of 6.42%, an increase over the 4.44% figure one year before.

E. Structure of this Report

The remainder of this report is divided into the following sections:

[58] U.S. Census Bureau and U.S. Department of Housing and Urban Development, Median Sales Price of Houses Sold for the United States [MSPUS], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/MSPUS, October 20, 2026.

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Section II. Summary of Findings: Presents the economic net worth and insurance-in-force of the Forward portfolio as of the end of FY 2026.

Section III. Characteristics of the MMI SF Forward Books of Business: Presents various characteristics of the SF Forward portfolio for FYs 1992 through 2026.

Section IV. MMI Fund Performance under Alternative Scenarios: Presents the SF Forward portfolio economic net worth under alternative economic scenarios and sensitivity tests.

Section V. List of Methodological Appendices: Provides a summary of the models utilized in the analysis.

Section VI. Qualifications and Limitations: Describes the main assumptions and the limitations of the data and models relevant to the results presented in this Review.

Appendix A. Data Reconciliation: This section provides the data sources, processing, and reconciliation tables used for this model.

Appendix B. Econometric Analysis of Mortgage Status Transitions and Terminations: Provides a technical description of our econometric models of default, claim, and prepayment for individual mortgage product types along with a description of the explanatory variables used in the models.

Appendix C. Loan Performance Projections: Describes the loan status transition framework as it relates to the estimated probability models, how those models are applied in forecasting, and the application of the forecasted probabilities to the actuarial calculations that summarize future loan performance.

Appendix D. Loss Severity and Cash Flow Analysis: Provides a technical description of the loss severity methodology and cash flow model.

Appendix E. Stochastic Simulation Models: Discusses the estimation and application of stochastic simulation models that are used to generate alternative forecasts for sensitivity analysis of our baseline estimates of economic net worth for the Single-Family portfolio.

Appendix F. Comparison of HUD and ITDC Models and Assessment of Vulnerabilities: As part of the statutory actuarial review process, this report presents the results of the review of HUD's Forward models.

Appendix G. Tables of Historical and Projected Rates of Loan Termination and Loss Severity: Provides finger tables of conditional and cumulative claim and prepayment rates and of loss severity and recovery rates by endorsement cohort year and policy year for each mortgage product. These are provided in spreadsheet files as a separate addendum to the report.

Appendix H. Logistic Model Estimation Results: Provides tables of estimated coefficients for each of the loan status transition probability models, including explanatory variable names and descriptions. These are provided in spreadsheet files as a separate addendum to the report.

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II. Summary of Findings

This section presents the projected economic net worth and insurance-in-force of the FY 2026 SF Forward MMI portfolios endorsed in FY 1992 or later. In addition to the capital resources as of the end of the fiscal year, the economic net worth of the SF Forward MMI portfolio depends on the discounted net present value of the future cash flows from the surviving portfolio of loans existing at the start of the valuation forecast (the end of the fiscal year under review). A fiscal year's economic net worth calculation does not include the effect of endorsements in future fiscal years. According to NAHA, the economic net worth of the Fund is defined as the "cash available to the Fund, plus the net present value of all future cash inflows and outflows expected to result from the outstanding mortgages in the Fund." We estimated the current economic net worth for the Forward portfolio as the sum of the amount of capital resources and the net present value of all expected future cash flows of the active Forward loans as of the end of FY 2026.

A. The FY 2026 Actuarial Review

The 2026 Review estimates the economic net worth of the SF Forward portfolio as of the end of FY 2026 (September 30, 2026). The objectives of our analysis include:

- Analysis of historical loan performance using data provided by FHA, developing econometric models, estimating their parameters, and generating future performance based on economic forecasts in the PEA. The economic net worth of the Fund is determined by comparing estimates from the models with the Fund's capital resources.
- Evaluation of the historical experience of the Fund, including loan termination experience due to claims and prepayments and losses associated with claims.
- Projection of future loan termination rates and their corresponding cash flows of the existing Fund portfolio.
- Estimation of the present economic net worth and insurance-in-force of the Fund.

This Review is carried out by examining historical loan performance data supplied by FHA, creating econometric models with the estimation of their parameters, and generating economic scenarios consistent with the PEA. Econometric models are employed to forecast the Fund's future cash flows, and their present value is compared to the Fund's financial resources to determine the economic worth of the Fund.

Estimation of the loan status transition models utilized loan-level data on the Fund's historical loan performance from the early 1990s through the end of FY 2026. The performance of FHA loans through the 2007-2010 mortgage crisis, the period of recovery and declining interest rates that followed the crisis, and the recent COVID-19 emergency have all provided real-world "stress tests" upon which to train our econometric models and develop forecasts of future performance. Further discussion and in-depth descriptions of the individual models, their underlying

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assumptions, and comprehensive econometric outputs are provided in a series of appendices to the report. Three data scopes are used in this Review: the valuation portfolio of loans active as of September 30, 2026; the loan-level history extracted from FY 1975 onward, used to link streamline refinances to their original fully underwritten mortgages; and the FY 1992 through FY 2026 cohorts, with loan status transitions observed through the fourth quarter of FY 2026, used to estimate the transition, loss severity and loss mitigation models (Appendix B1.5).

B. Economic Net Worth

The Economic Net Worth is calculated as the sum of available cash in the Fund and the Cash Flow NPV of all anticipated future cash inflows and outflows related to the mortgages currently insured by the MMI Fund. For the 2026 Review, we determined the Cash Flow NPV of the MMI Fund using data through September 30, 2026. This estimation involved an analysis of historical loan performance based on data from FHA, the creation of predictive models for loan transitions and losses, and the utilization of these model outcomes in conjunction with economic projections from OMB and Moody's to forecast the future cash flows of the MMI Fund. The NPV of these cash flows, combined with the MMI Fund's capital resources, constitutes the economic net worth of the MMI Fund.

Capital resources represent the Fund's net assets that can be converted into cash to fulfill the Fund's obligations, such as the payment of claims as they become due. These resources are determined by subtracting total liabilities from total assets and are documented in the year-end financial statements of the Fund.

Exhibit II-1 presents the components of the economic net worth for Fiscal Year 2026. The estimated Economic Net Worth is $172.386 billion. The total economic net worth consists of the following components:

Exhibit II-1: Estimated Economic Net Worth of the Forward Portfolio in the MMI Fund at the End of FY 2026 ($ Million)

Item	End of FY 2026
Total Capital Resources*	$ 146,816
+ NPV of Future Cash Flows on Outstanding Business	25,571
Economic Net Worth	$ 172,386
Insurance-In-Force (Unamortized)	1,946,181

*Source: FHA Financial Statements for 2026. Economic Net Worth is computed from unrounded components; the rounded components shown sum to $172,387 million.

Total Capital Resources equals assets less liabilities on the Fund’s balance sheet. The total capital resources are $146.816 billion at the end of FY 2026. Data through September 2026 was used for the total capital resources.

Net Present Value of Future Cash Flows on Outstanding Business consists of discounted cash inflows and outflows. Forward cash inflows consist of premiums and recoveries. Cash

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outflows consist of claims, loss mitigation, and premium refund expenses. The cash flow model projects quarterly cash inflows and outflows using economic forecasts and loan performance projections. ITDC projects the Actuarial Central Estimate (ACE) of the MMI Forward Cash Flow NPV to be *positive* $25.571 billion as of the end of FY 2026.

C. Changes in the Economic Net Worth

As illustrated in Exhibit II-2, the projected Cash Flow NPV of the MMI Fund for FY 2026 decreased by $11.593 billion compared to the Fiscal Year 2025 estimate, shifting from positive $37.164 billion to a positive $25.571 billion. The capital resources available to the MMI Fund have grown, marking a 12.5 percent increase from a positive $130.533 billion to a positive $146.816 billion. Unamortized IIF increased 8.4 percent, from $1,796 billion to $1,946 billion. Exhibit II-2 compares our estimate of the MMI's Cash Flow NPV and IIF as of the end of Fiscal Year 2026 to the Cash Flow NPV estimate in the 2025 Review.

Exhibit II-2: Cash Flow NPV, Insurance-In-Force, and Capital Resources for FY 2026 ($ Million)

Item	Cash Flow NPV	Capital Resources	Unamortized Insurance-In-Force
2025	$ 37,164	$ 130,533	$ 1,795,689
2026	25,571	146,816	1,946,181
Dollar Difference	$ (11,593)	$ 16,283	$ 150,492
Percent Difference	-31.2%	12.5%	8.4%

This change can be attributed to the changes in our models and the PEA baseline assumptions. To quantify the source of change in NPV, we identify key factors that affect the NPV and discuss the total change using the following sources of change

Exhibit II-3: Decomposition of Changes in NPV from 2025 to 2026 ($ Million)

Decomposition Steps	Change in NPV	NPV
FY 2025 NPV in FY 2025 Actuarial Report		$ 37,164
- Update Model – 40-year Extensions	(1,393)	35,771
- Update Model – CWCOT Methodology	713	36,484
- Update Model – Termination Model	147	36,631
- Update Model – Loss Severity Models	1,693	38,324
- Update Model – Loss Mitigation Model	(3,433)	34,891
- Update Data – FY 2026 Data for Cohorts 1992-2025	(9,354)	25,537
- Update Data – New Originations in FY 2026	34	25,571
FY 2026 Estimate of NPV		$ 25,571

- In 2026, we incorporated loan extensions beyond the standard 30-year term directly into the baseline cash flow projections, extending the total forecasting horizon to 40 years from each loan's origination (a 40-year loan modification, by contrast, re-amortizes the loan over 40 years from the modification date; see Appendix D4), and explicitly modeled CWCOT

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outbids and their impact. On FY 2025 data, the loan extensions decreased NPV by $1.393 billion and the CWCOT methodology resulted in a $713 million increase, a net decrease of $680 million.

- We updated our termination, loss severity, and loss mitigation models with additional data. These changes decreased NPV on FY 2025 data by $1.593 billion.

- We then updated the economic assumptions based on the FY 2027 Mid-Session Review of the President's Economic Assumptions (PEA). When incorporating the updated PEA assumptions along with amortization and loan terminations for cohorts 1992 through 2025, we observe a decrease in the NPV of $9.354 billion.

- Finally, we measure the NPV impact due to the $296 billion new endorsement volume during Fiscal Year 2026. Based on modeling projections, cohort 2026 is expected to have a net positive impact on the NPV, increasing the NPV by $34 million.

- The overall decrease in the baseline NPV from the FY 2025 Review to this year's review is $11.593 billion, which is the sum of negative $680 million, negative $1.593 billion, negative $9.354 billion, and positive $34 million.

Exhibit II-3a presents the $11.593 billion decrease by cash flow component, comparing the components of the FY 2025 Review's Cash Flow NPV with those of this review. Higher projected claim and loss mitigation expenses reduced the Cash Flow NPV by $14.129 billion, higher expected recoveries increased it by $5.846 billion, and premium income net of upfront premium refunds decreased it by $3.310 billion. Please note that these changes are the net effect of multiple factors, including economic condition changes, performance of existing loans during the year, as well as new book of business in FY 2026.

Exhibit II-3a: Change in Cash Flow NPV by Component from 2025 to 2026 ($ Million)

Cash Flow Category	FY 2025	FY 2026	Change
Mortgage Insurance Annual Premium	$ 72,846	$ 70,243	$ (2,603)
Upfront Premium Refund	(1,050)	(1,756)	(706)
Loss Mitigation Expense	(12,317)	(14,702)	(2,385)
Claim Expenses	(47,114)	(58,858)	(11,744)
Recoveries	24,799	30,645	5,846
Cash Flow NPV	$ 37,164	$ 25,571	$ (11,593)

Note: FY 2025 values are as published in the FY 2025 Review. Components may not sum to the totals due to rounding. Exhibit II-3 separates the FY 2026 cohort ($34 million) from the data and economic update for the FY 1992 to FY 2025 cohorts ($9.354 billion decrease); Exhibit II-3a does not isolate realized FY 2026 cash flows or the pre-2026 portfolio.

The Fund's present value of future cash flows is aggregated from separate estimates of the present value of future cash flows from each book of business and for each of the six mortgage product

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types. Exhibit II-4 shows the present values of future cash flows for each of the six mortgage product types from FY 1992 through FY 2026 books of business estimated to have survived to the end of FY 2026. From Exhibit II-4, the total present value of these future cash flows is a positive $25.571 billion.

The housing and economic downturn of 2008 led to elevated claim rates for mortgages that originated during Fiscal Years 2005 to 2010. Due to the upfront MIP having already been collected and being part of the current capital resources, and considering their substantial origination volume, the Fiscal Year 2008 to 2012 cohorts are expected to incur negative Cash Flow NPVs, although their combined magnitude is smaller than that of either the Fiscal Year 2024 or the Fiscal Year 2025 cohort. Nevertheless, with the conclusion of the housing recession, property values hit a low point and subsequently began to rise. Consequently, mortgages originating in Fiscal Years 2013 through 2022 exhibit positive Cash Flow NPVs. This positive trend is further bolstered by the collection of MIPs over the mortgage's entire duration. Additionally, the historically low mortgage interest rates on loans originated in 2020, 2021, and the initial quarter of 2022 reduced the refinance incentives, resulting in extended MIP collection periods in the simulation. In contrast, the higher-rate Fiscal Year 2023 cohort exhibits a negative Cash Flow NPV, and the most recently originated Fiscal Year 2024 and 2025 cohorts exhibit negative Cash Flow NPVs of $1.8 billion and $1.5 billion, respectively, as elevated delinquency and projected losses on these books outweigh their remaining premium collection. The newest Fiscal Year 2026 cohort is positive at $34 million.

Also, a significant increase in new originations influenced the 2020 and 2021 Cash Flow NPV. There was a significant increase in refinance activity during this period. While this resulted in a decrease in Cash Flow NPV for older cohorts, it also increased Cash Flow NPV for the 2020–2022 cohorts as the older loans refinanced into newer cohorts.

Interest rates had remained historically low during the first half of Fiscal Year 2022, which tended to increase the NPV on loans originated during that time due to the reduced likelihood of refinancing. As interest rates started to rise in the latter part of Fiscal Year 2022, the refinance probability for these loans was expected to decline. With the resulting interest rate increase, the refinance rate remained relatively stable for mortgages originated in Fiscal Year 2022. The rising interest rates and subsequent mortgage rates throughout Fiscal Years 2022-2026 have reduced the projected level of prepayment rates for loans originating prior to 2023, due to the widely noted “lock-in” effect.

Exhibit II-4: Present Value of Future Cash Flows by Origination Fiscal Year & Mortgage Type as of the End of FY 2026 ($ Million)

Fiscal Year	FRM 30	FRM 15	ARM	SR 30	SR 15	SR ARM	Total
1992	$ 0	$ 0	$ 0	$ 0	$ 0	$ 0	$ 0
1993	0	0	0	0	0	0	0
1994	0	0	0	0	0	0	0

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Fiscal Year	FRM 30	FRM 15	ARM	SR 30	SR 15	SR ARM	Total
1995	0	0	0	0	0	0	0
1996	(1)	0	0	0	0	0	(1)
1997	(1)	0	(1)	0	0	0	(1)
1998	(2)	0	0	0	0	0	(2)
1999	(4)	0	0	0	0	0	(4)
2000	(5)	0	0	0	0	0	(5)
2001	(12)	0	0	(1)	0	0	(13)
2002	(8)	0	(1)	(1)	0	0	(10)
2003	(19)	0	(1)	(3)	0	0	(23)
2004	(19)	0	(2)	(4)	0	(1)	(25)
2005	(21)	0	(2)	(2)	0	0	(26)
2006	(13)	0	(1)	(1)	0	0	(15)
2007	(42)	0	0	(1)	0	0	(43)
2008	(151)	0	(1)	(3)	0	0	(156)
2009	(174)	0	(1)	(16)	0	(1)	(192)
2010	(207)	0	(6)	(8)	0	(1)	(223)
2011	(101)	0	(5)	(4)	0	(1)	(110)
2012	(126)	(1)	(1)	(3)	0	0	(132)
2013	232	0	1	76	0	0	309
2014	586	0	4	41	0	1	632
2015	963	0	3	151	0	1	1,118
2016	1,521	0	1	155	0	0	1,678
2017	1,767	1	1	156	1	0	1,926
2018	1,472	1	0	53	0	0	1,526
2019	1,669	1	1	81	0	0	1,752
2020	4,554	2	0	1,024	1	0	5,582
2021	8,076	7	0	2,711	5	0	10,799
2022	4,452	7	2	623	2	0	5,086
2023	(606)	1	(2)	0	0	0	(608)
2024	(1,774)	0	(7)	(6)	0	0	(1,787)
2025	(1,461)	0	(13)	(20)	0	0	(1,494)
2026	(20)	(1)	46	10	0	0	34
Total	$ 20,524	$ 20	$ 14	$ 5,005	$ 10	$ (3)	$ 25,571

D. Current Insurance-In-Force

Both the unamortized and the amortized IIF are presented in this Review. From 1992 to 2026, the total Unamortized IIF was $1,946 billion, and the total Amortized IIF was $1,719 billion. Unamortized IIF is the original mortgage amount of all active endorsements. The amortized IIF reflects the current outstanding loan balance of all active endorsements. Exhibit II-5 shows the

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total volume of new mortgage endorsements for each book of business, the unamortized IIF, and the amortized IIF as of the end of FY 2026.

Exhibit II-5: Endorsements and Insurance-in-Force as of the End of FY 2026 ($ Million)[59]

Fiscal Year	Mortgage Endorsement	Unamortized Insurance-in-Force	Amortized Insurance-in-Force
1992	$ 43,576	$ 51	$ 24
1993	71,778	97	48
1994	83,560	165	83
1995	40,664	127	73
1996	64,448	261	148
1997	67,012	713	217
1998	93,274	1,375	455
1999	111,837	1,993	758
2000	84,866	1,238	601
2001	121,639	2,370	1,173
2002	131,416	3,686	1,838
2003	115,971	5,764	2,854
2004	107,621	7,358	3,891
2005	57,975	5,517	3,135
2006	51,733	4,756	2,966
2007	56,516	5,023	3,370
2008	171,806	12,961	8,937
2009	330,385	27,532	18,039
2010	297,502	31,405	20,570
2011	217,642	25,095	16,528
2012	213,272	33,989	21,707
2013	240,115	51,242	33,717
2014	135,216	18,031	13,019
2015	213,121	35,574	26,594
2016	245,405	53,951	41,496
2017	250,954	62,508	49,675
2018	209,049	50,883	42,476
2019	214,621	54,162	46,741
2020	310,321	128,570	110,426
2021	342,823	241,414	210,516
2022	255,504	210,871	191,315
2023	208,728	160,162	151,150
2024	231,525	173,886	167,653
2025	274,755	240,799	235,854
2026	296,222	292,655	290,673

[59] Source: SFDW.IDB_1.

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Fiscal Year	Mortgage Endorsement	Unamortized Insurance-in-Force	Amortized Insurance-in-Force
Total	$ 5,962,854	$ 1,946,181	$ 1,718,718

Note: For loans whose term was extended by a modification, amortized IIF reflects the outstanding balance on the modified terms (new principal, interest rate and maturity). Amortized IIF is the scheduled amortized balance; it does not reflect missed payments on delinquent loans or borrower curtailments.

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III. Characteristics of the MMI SF Forward Books of Business

In this section, we examined the characteristics of the loan portfolio insured by the MMI Fund for 2026. Our analysis is divided into three key areas:

- Evaluation of loan volume and composition, considering different loan types.
- A comparison between new purchase loans and refinances.
- An examination of the distribution of loans based on various loan characteristics.

Furthermore, we conducted a comprehensive assessment of the FY 2026 cohort and compared it to prior cohorts to assess its potential impact on the future performance of the MMI Fund.

A. Volume and Share of Mortgage Originations

FHA endorsed $296.222 billion in single-family forward mortgages in Fiscal Year 2026, bringing the MMI Fund's total unamortized IIF to $1.946 trillion. Exhibit III-1 shows the FHA's count and volume of originations by fiscal year and mortgage product type.

As shown in the exhibit below, the count of new purchase loans followed a fluctuating trend, declining notably from Fiscal Year 2002 to Fiscal Year 2007, surging significantly through Fiscal Year 2010, and eventually stabilizing at levels akin to those in Fiscal Years 2000–2002. This oscillation resulted from the aggressive marketing strategies by Government Sponsored Enterprises (GSEs) and non-conforming lenders during the subprime era and their financial constraints when the housing market collapsed. Furthermore, the diminished capital strength of private mortgage insurance firms contributed to the increase in FHA's loan volume post-crash. With private mortgage insurance companies grappling with severe capital limitations, GSEs could not acquire or guarantee loans with less than a 20 percent down payment. Consequently, FHA assumed the primary role as the source of high Loan-to-Value (LTV) loans post-Fiscal Year 2008.

The trends in new purchase loan volumes exhibit a similar pattern. However, in the post-housing crisis, the volumes significantly surpassed those of the early 2000s. This surge was prompted by heightened loan size limits influenced by the GSEs, rendering more loans eligible for FHA insurance.

Changes in FHA origination volume affect the size and composition of the MMI Fund's insured exposure and, consequently, its future premium income and claim obligations. Higher endorsement volume generally increases expected future mortgage insurance premiums, but it also increases the Fund's exposure to future defaults and claims. Therefore, the ultimate impact of new originations on Economic Net Worth depends not only on volume, but also on the credit quality, product mix, and expected performance of the newly insured loans.

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Exhibit III-1: Total Count and Volume of FHA-Insured Originations[60]

Fiscal Year	Count of Originations						Volume of Originations ($ Million)					
	FRM 30	FRM 15	ARM	FRM 30 SR	FRM 15 SR	ARM SR	FRM 30	FRM 15	ARM	FRM 30 SR	FRM 15 SR	ARM SR
1992	402,237	20,932	83,170	77,892	20,340	7,878	$ 28,046	$ 1,114	$ 7,065	$ 5,528	$ 1,185	$ 639
1993	452,157	27,270	98,187	280,491	90,685	17,228	33,217	1,529	8,908	21,248	5,371	1,506
1994	479,179	27,276	157,267	300,292	117,921	25,149	36,397	1,521	14,799	22,125	6,565	2,154
1995	341,404	10,159	121,075	21,849	8,097	3,920	26,162	549	11,442	1,728	429	354
1996	485,169	13,724	173,545	58,465	18,259	11,366	39,338	812	17,076	5,055	1,028	1,139
1997	462,202	11,828	225,273	29,079	8,388	15,468	38,522	744	22,812	2,760	481	1,692
1998	676,262	15,355	80,967	187,078	21,476	15,772	61,348	1,054	8,509	19,201	1,402	1,760
1999	858,805	16,456	51,898	165,938	27,325	10,443	84,702	1,228	6,342	16,618	1,766	1,180
2000	710,754	7,637	63,929	18,797	2,648	3,371	73,641	579	8,045	2,065	163	374
2001	785,502	13,398	19,173	230,058	11,992	8,132	87,446	1,200	2,654	28,278	984	1,075
2002	746,734	17,066	54,213	238,151	30,468	31,922	86,561	1,622	7,911	28,782	2,308	4,231
2003	483,786	15,134	28,512	356,612	46,284	27,725	58,889	1,552	4,408	43,646	3,618	3,857
2004	547,285	14,709	56,306	200,256	39,462	34,405	66,924	1,474	8,714	23,129	2,796	4,583
2005	329,810	7,494	34,097	81,435	12,939	12,578	40,084	731	5,255	9,376	815	1,715
2006	349,171	6,858	9,292	29,787	3,933	865	45,574	702	1,476	3,602	249	128
2007	370,494	6,634	4,329	19,792	843	252	52,070	692	754	2,895	63	42
2008	935,015	21,964	10,871	59,878	2,537	1,318	155,961	2,760	2,434	10,149	242	260
2009	1,439,817	51,856	10,253	315,231	9,978	4,186	254,750	7,207	2,612	63,634	1,235	947
2010	1,342,770	77,114	34,159	191,578	8,450	12,842	234,999	10,808	8,407	39,161	1,080	3,047
2011	900,567	80,420	35,459	156,885	7,883	15,459	157,328	12,270	9,120	33,655	1,356	3,913
2012	812,220	86,034	12,213	251,332	14,552	8,149	139,505	13,601	3,179	52,333	2,516	2,138
2013	778,838	48,517	5,648	490,461	17,714	3,667	139,939	7,400	1,666	87,867	2,306	938
2014	631,750	24,852	14,712	105,170	5,264	4,604	111,509	3,393	4,006	14,890	498	922
2015	847,270	26,796	9,353	225,915	3,489	3,407	158,695	3,552	2,767	46,744	397	966
2016	1,014,559	26,269	4,189	207,172	5,395	463	199,123	3,295	1,351	40,894	604	138
2017	1,053,874	24,711	3,749	155,980	8,071	48	214,953	3,197	1,010	30,879	903	12
2018	940,820	17,526	3,745	49,197	3,255	57	195,635	2,357	1,000	9,741	302	14
2019	914,816	14,292	3,384	56,180	1,727	26	197,041	1,930	934	14,554	155	7
2020	1,000,990	9,826	344	319,166	2,823	1	230,205	1,359	113	78,227	417	0
2021	1,018,184	10,849	174	397,176	6,476	5	249,496	1,462	64	90,955	845	1
2022	887,760	8,253	1,166	83,310	1,698	7	235,753	1,143	383	18,012	211	2
2023	727,149	3,379	641	1,124	25	0	207,592	546	236	352	2	0
2024	747,794	3,687	1,486	13,947	18	0	225,276	673	636	4,937	3	0
2025	810,973	6,187	6,121	53,093	98	18	252,418	1,141	2,386	18,780	22	8
2026	777,412	6,343	42,629	108,298	245	241	241,881	1,212	15,093	37,870	58	108

Exhibit III-2 displays FHA's origination volume and market share in home purchase mortgages from calendar year 2000 through calendar year 2025.

[60] Source: SFDW.IDB_1.

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Exhibit III-2: FHA's Market Share in the Single-Family Forward Mortgage Market[61]

Calendar Year	FHA Market Shares (Percent)			Origination Volume ($ Billion)					
				Purchase		Refinance		All	
	Purchase	Refinance	All	FHA	Market	FHA	Market	FHA	Market
2000	9.90	3.20	8.60	$ 89	$ 897	$ 7	$ 220	$ 96	$ 1,117
2001	10.20	5.80	8.20	97	951	49	841	146	1,792
2002	8.50	3.20	5.40	90	1,056	49	1,526	139	2,582
2003	6.40	2.60	3.70	78	1,221	77	2,970	155	4,191
2004	4.40	2.00	3.20	58	1,314	29	1,415	87	2,729
2005	2.60	1.10	1.90	40	1,512	16	1,514	56	3,026
2006	2.70	1.30	2.00	38	1,399	17	1,326	55	2,725
2007	3.90	2.90	3.40	44	1,140	33	1,166	77	2,306
2008	19.50	12.90	16.10	143	731	100	777	243	1,508
2009	28.10	12.80	17.90	187	664	171	1,331	358	1,995
2010	27.40	8.60	14.90	165	602	103	1,203	268	1,805
2011	25.32	6.46	13.09	128	505	60	931	188	1,436
2012	21.28	7.38	11.38	125	587	108	1,456	233	2,044
2013	15.94	7.84	11.07	117	734	87	1,111	204	1,845
2014	13.83	5.62	10.56	105	760	28	503	133	1,263
2015	16.74	10.60	13.90	151	903	82	776	233	1,679
2016	16.39	8.09	12.35	173	1,053	81	1,000	253	2,053
2017	14.95	9.64	13.09	171	1,143	59	616	230	1,759
2018	12.86	9.10	11.81	155	1,209	42	467	198	1,676
2019	13.66	7.58	10.88	167	1,225	78	1,029	245	2,254
2020	12.83	4.35	7.41	190	1,482	114	2,625	304	4,107
2021	10.85	4.83	7.35	202	1,863	124	2,575	326	4,438
2022	10.78	7.54	9.81	174	1,619	52	687	226	2,306
2023	14.22	15.69	14.44	176	1,239	34	218	210	1,457
2024	14.33	14.94	14.45	192	1,338	52	348	244	1,686
2025	15.12	9.72	13.29	205	1,356	67	694	272	2,050

FHA's market share declined to a low of 1.9 percent in 2005. However, this trend reversed over the next several years, and by calendar year 2009, FHA's market share had risen to 17.9 percent. Capital limitations encumbered private mortgage insurers and non-conforming lenders, effectively establishing FHA as the sole viable avenue for high Loan-to-Value (LTV) loans. Subsequently, the market share experienced a decline from 2018 through 2021, when it fell to 7.35 percent. It has since increased to 14.45 percent in 2024 before dropping to 13.29 percent as of the end of Calendar Year 2025.

[61] https://www.hud.gov/sites/default/files/Housing/documents/FHA-SF-Market-Share-2025Q4.pdf

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B. Originations by Location

FHA insures loans in all regions of the U.S., but about half of FHA's total dollar volume is concentrated in only ten states. Exhibit III-3 shows the percentage of FHA's total dollar volume originating in these ten states from FY 2021 through FY 2026. The states are ordered based on the dollar volume endorsed during FY 2026 to highlight the most recent changes.

Exhibit III-3: Percentage of Origination Volume by the Top 10 States[62]

State	2021	2022	2023	2024	2025	2026
TX	9.6	9.1	10.9	11.6	11.4	11.1
CA	12.4	11.3	10.5	10.7	10.8	11.0
FL	9.1	9.1	10.5	11.3	10.4	9.5
GA	4.2	4.5	5.1	4.9	4.8	4.7
AZ	3.2	3.1	3.7	3.9	4.0	3.8
NC	2.4	2.6	3.1	3.4	3.4	3.5
OH	2.5	2.8	2.7	2.6	2.7	2.9
TN	2.0	2.2	2.6	2.8	2.8	2.9
VA	3.3	3.1	2.7	2.6	2.7	2.8
NJ	4.0	3.8	3.0	2.7	2.7	2.7

For the year 2026, the top three states of origination are TX, CA, and FL. Texas remains the state with the highest percentage of origination volume, a position it has held since 2023, with California a close second. Florida maintains the final spot in the top three.

The geographic distribution of FHA originations remained generally stable in FY 2026 compared with FY 2025 and recent years, with no significant shift in the concentration of insured volume across major states. Accordingly, the FY 2026 geographic mix is not expected, by itself, to materially change the projected risk profile or Economic Net Worth of the MMI Fund. Geographic composition nevertheless remains relevant to actuarial performance because local house price appreciation, unemployment, and other economic conditions affect borrower defaults, claim incidence, and property recoveries. Greater concentration in areas experiencing weaker housing or labor market conditions could therefore increase expected claim costs and reduce Economic Net Worth, while geographic diversification limits the Fund's exposure to adverse conditions in any single market.

C. Originations by Mortgage Type

Exhibit III-4 illustrates that the fully underwritten 30-year fixed-rate mortgage (FRM) has consistently constituted most of FHA's single-family business, averaging 78.2 percent over FYs 1992-2026. The proportion of total mortgages represented by 30-year FRMs began to evolve in the early 1990s when the FHA introduced insurance for adjustable-rate mortgages (ARMs) and

[62] Source: SFDW.IDB_1.

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streamline-refinancing mortgages (SRs). Over the following years, ARM and SR mortgages gradually claimed a more significant portion of annual loan originations, causing a decrease in the fully underwritten 30-year FRM share. FYs 1993, 1994, and 2003 marked the periods with the lowest shares of fully underwritten 30-year FRMs. This proportion has exceeded 90 percent each year from FY 2018 through 2025 except for 2020-2021. In 2026, the proportion fell to 81.7 percent as the share of 30-year SRs grew to 12.8 percent.

The ARM share of the portfolio, including SR ARMs, has declined substantially since reaching 9.9 percent in 2000, remaining less than 1 percent from 2016 until 2026, when it grew to 5.1 percent. Liquidity injected into the financial system in the context of the 2000-2001 recession and the 2008-2009 financial crisis, combined with declining inflationary expectations and a narrowing of spreads between mortgage interest rates and long-term Treasury yields, brought long-term primary mortgage rates to historic lows, incentivizing borrowers to shift from ARM to FRM products. FRM-30 mortgage rates have risen sharply since 2022, as noted earlier, but this increase has been accompanied by a simultaneous increase in ARM rates, explaining the continuation of market share trends from the prior low mortgage interest rate period.[63]

Meanwhile, 15-year FRMs grew from 1.2 percent in Fiscal Year 2007 to 6.4 percent in Fiscal Year 2012 but have generally declined since then, currently standing at 0.4 percent in Fiscal Year 2026. The 15-year SR continues to represent a negligible product type in the MMI Fund.

Overall, the mortgage-type composition changed more noticeably in FY 2026 than in recent years, primarily driven by the consistently high mortgage interest rates. The shifts may affect projected loan performance because streamline refinances and ARMs have different prepayment and default patterns from fully underwritten fixed-rate mortgages, with ARM performance also sensitive to future interest-rate movements and potential payment changes. Accordingly, the changing product mix may affect the timing of premium collections and expected claims and is incorporated into the estimated Economic Net Worth through the product-specific loan performance models.

Exhibit III-4: Percentage of Origination Volume by Mortgage Type[64]

	Fully Underwritten Mortgages			Streamline Refinancing		
Fiscal Year	30-Year FRMs	15-Year FRMs	ARMs	30-Year SRs	15-Year SRs	ARM SRs
1992	64.4%	2.6%	16.2%	12.7%	2.7%	1.5%
1993	46.3%	2.1%	12.4%	29.6%	7.5%	2.1%
1994	43.6%	1.8%	17.7%	26.5%	7.9%	2.6%
1995	64.3%	1.3%	28.1%	4.2%	1.1%	0.9%
1996	61.0%	1.3%	26.5%	7.8%	1.6%	1.8%
1997	57.5%	1.1%	34.0%	4.1%	0.7%	2.5%
1998	65.8%	1.1%	9.1%	20.6%	1.5%	1.9%

[63] Justiniano, Alejandro; Primiceri, Giorgio E.; Tambalotti, Andrea, "The Mortgage Rate Conundrum", The Journal of Political Economy, 2022-01, Vol.130 (1), p.121-156

[64] Source: SFDW.IDB_1.

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Fiscal Year	Fully Underwritten Mortgages			Streamline Refinancing		
	30-Year FRMs	15-Year FRMs	ARMs	30-Year SRs	15-Year SRs	ARM SRs
1999	75.7%	1.1%	5.7%	14.9%	1.6%	1.1%
2000	86.8%	0.7%	9.5%	2.4%	0.2%	0.4%
2001	71.9%	1.0%	2.2%	23.2%	0.8%	0.9%
2002	65.9%	1.2%	6.0%	21.9%	1.8%	3.2%
2003	50.8%	1.3%	3.8%	37.6%	3.1%	3.3%
2004	62.2%	1.4%	8.1%	21.5%	2.6%	4.3%
2005	69.1%	1.3%	9.1%	16.2%	1.4%	3.0%
2006	88.1%	1.4%	2.9%	7.0%	0.5%	0.2%
2007	92.1%	1.2%	1.3%	5.1%	0.1%	0.1%
2008	90.8%	1.6%	1.4%	5.9%	0.1%	0.2%
2009	77.1%	2.2%	0.8%	19.3%	0.4%	0.3%
2010	79.0%	3.6%	2.8%	13.2%	0.4%	1.0%
2011	72.3%	5.6%	4.2%	15.5%	0.6%	1.8%
2012	65.4%	6.4%	1.5%	24.5%	1.2%	1.0%
2013	58.3%	3.1%	0.7%	36.6%	1.0%	0.4%
2014	82.5%	2.5%	3.0%	11.0%	0.4%	0.7%
2015	74.5%	1.7%	1.3%	21.9%	0.2%	0.5%
2016	81.1%	1.3%	0.6%	16.7%	0.2%	0.1%
2017	85.7%	1.3%	0.4%	12.3%	0.4%	0.0%
2018	93.6%	1.1%	0.5%	4.7%	0.1%	0.0%
2019	91.8%	0.9%	0.4%	6.8%	0.1%	0.0%
2020	74.2%	0.4%	0.0%	25.2%	0.1%	0.0%
2021	72.8%	0.4%	0.0%	26.5%	0.2%	0.0%
2022	92.3%	0.4%	0.2%	7.0%	0.1%	0.0%
2023	99.5%	0.3%	0.1%	0.2%	0.0%	0.0%
2024	97.3%	0.3%	0.3%	2.1%	0.0%	0.0%
2025	91.9%	0.4%	0.9%	6.8%	0.0%	0.0%
2026	81.7%	0.4%	5.1%	12.8%	0.0%	0.0%
Total	78.2%	1.6%	3.2%	15.6%	0.7%	0.7%

D. Initial Loan-to-Value Ratio Distributions

Based on studies of mortgage behavior, a borrower's equity position in the mortgaged house is one of the most critical drivers of default behavior. The larger the equity position a borrower has, the greater the incentive to avoid default. The original LTV is the complement of the borrower's equity at origination. Exhibit III-5 shows the distribution of mortgage originations by original LTV categories.

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Exhibit III-5: Percentage of Origination Volume by Original LTV Category[65]

Fiscal Year	Unknown LTV	<=80%	>80% <=90%	>90% <=95%	>95% <97%	>=97%
1992	14.0%	4.4%	13.2%	24.6%	32.7%	11.1%
1993	31.2%	3.7%	10.7%	18.0%	20.9%	15.5%
1994	30.5%	3.6%	9.7%	17.2%	21.4%	17.6%
1995	5.3%	3.0%	10.3%	23.4%	32.3%	25.7%
1996	8.6%	3.0%	10.7%	23.6%	31.2%	22.8%
1997	5.6%	3.4%	11.4%	24.8%	32.5%	22.4%
1998	16.3%	3.8%	12.0%	22.8%	27.5%	17.5%
1999	10.1%	3.8%	9.8%	11.6%	26.0%	38.8%
2000	4.1%	2.6%	6.8%	7.2%	31.2%	48.1%
2001	17.6%	4.0%	9.9%	9.4%	22.4%	36.7%
2002	11.4%	4.9%	11.2%	10.1%	23.8%	38.7%
2003	9.2%	6.3%	12.8%	11.9%	23.4%	36.3%
2004	12.9%	6.6%	11.7%	10.3%	22.5%	36.0%
2005	15.1%	6.4%	10.7%	9.1%	22.2%	36.5%
2006	15.2%	7.1%	10.7%	14.3%	19.9%	32.8%
2007	14.3%	7.4%	11.7%	21.2%	18.2%	27.2%
2008	21.9%	6.2%	12.2%	24.0%	14.1%	21.6%
2009	9.7%	5.0%	13.3%	18.8%	35.7%	17.4%
2010	0.1%	4.8%	14.5%	12.6%	58.8%	9.1%
2011	0.1%	4.9%	14.8%	14.1%	59.9%	6.3%
2012	0.0%	5.5%	13.4%	20.0%	57.2%	3.8%
2013	0.0%	5.7%	16.1%	27.2%	48.6%	2.3%
2014	0.0%	6.1%	14.1%	12.9%	65.0%	1.8%
2015	0.1%	6.1%	14.8%	12.9%	63.8%	2.2%
2016	0.0%	6.9%	16.1%	11.1%	64.1%	1.7%
2017	0.0%	7.9%	17.2%	10.1%	63.7%	1.2%
2018	0.0%	7.8%	16.8%	8.1%	66.2%	1.1%
2019	0.0%	7.6%	17.5%	7.8%	65.5%	1.7%
2020	0.1%	10.5%	12.1%	12.3%	62.7%	2.4%
2021	0.0%	12.5%	11.2%	14.5%	60.8%	0.9%
2022	0.0%	20.7%	7.5%	10.8%	60.8%	0.2%
2023	0.0%	18.9%	7.1%	9.7%	64.1%	0.2%
2024	0.0%	17.7%	7.1%	9.7%	64.3%	1.0%
2025	0.0%	17.7%	7.5%	9.3%	62.8%	2.7%
2026	0.1%	16.8%	8.2%	9.5%	61.8%	3.7%

The distribution among original LTV categories had undergone significant shifts after FY 1998. During the period spanning from FY 2000 to FY 2006, over a third of loans insured had LTVs equal to or greater than 97 percent. However, this concentration in the highest-risk category

[65] Source: SFDW.IDB_1.

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gradually waned over the following years. In 2008, MMI imposed a 96.5 percent limit on the original LTV, with no additional allowances for financing closing costs. Loans with LTV greater than or equal to 97 percent have remained low for each FY since 2017. Since 2014, over 60 percent of mortgages have had LTV ratios falling between 95 percent and 97 percent.

In FY 2022, over 20 percent of mortgages had an initial LTV of 80 percent or lower, possibly related to refinance incentives in a historically low mortgage rate environment. Such loans remained above 17 percent of the total through FY 2025 and were 16.8 percent in FY 2026. The distribution of mortgage LTVs remained consistent from 2023 through 2026.

The original LTV concentration of individual business books affects the predictive models in two ways. First, it serves as the starting position for updating the current LTV. Holding everything else constant, loans with higher original LTVs will experience a higher current LTV in future years. Second, the original LTV is also included in the models to capture potential behavioral differences among borrowers who self-select into different original LTV categories. For SR loans, we use the original LTV of the prior fully underwritten mortgage, updated for the local house price appreciation and amortization, as a proxy for this variable.

E. Borrower Credit History Distributions

Since May 2004, all lenders originating loans for FHA insurance have been required to report borrower credit scores directly to HUD if any credit scores were ordered as part of the underwriting process. All loans going through the FHA TOTAL scorecard have credit scores obtained electronically by the affiliated automated underwriting systems. This provides a reliable source of credit score data. There are no exceptions to this requirement, so the credit scores collected through this channel are comprehensive and unbiased. These loans have become the primary source of credit score information. Credit scores pre-2004 were derived by UNICON or obtained from Fannie Mae as discussed below.

Exhibit III-6 shows the distributions of fully underwritten FHA mortgage loans by borrower credit score categories and origination years. The distribution among credit score categories remained stable for the FY 2005 through FY 2008 books. For loans originating after FY 2008, the credit score distribution significantly improved over the previous years. FY 2011 witnessed the highest percentage (62.5%) of originations with credit scores above 680. Loans with credit scores below 600 have remained less than 10 percent since 2009, currently standing at 6.0 percent. Since 2023, loans with credit scores 640 or above have accounted for over 75 percent of the origination volume. As of 2025 and 2026, the highest proportion of credit scores falls between 640 and 679, followed by >720, and finally between 680 and 719.

Accordingly, the FY 2026 credit score mix does not indicate a material change in expected credit risk relative to the FY 2025 book. Credit score nevertheless remains an important predictor of mortgage performance, as lower-credit-score borrowers generally have a higher likelihood of

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delinquency, default, and claim; therefore, a material shift toward lower credit scores would be expected to increase projected claim costs and reduce Economic Net Worth, all else equal.

Exhibit III-6: Percentage of Origination Volume by Credit Score among Fully Underwritten Loans[66]

Fiscal Year	Missing	300-499	500-599	600-639	640-679	680-719	>720
1992	98.4%	0.0%	0.5%	0.3%	0.3%	0.2%	0.2%
1993	98.2%	0.0%	0.6%	0.4%	0.3%	0.2%	0.3%
1994	97.9%	0.0%	0.7%	0.5%	0.4%	0.2%	0.3%
1995	97.4%	0.0%	0.9%	0.6%	0.4%	0.3%	0.3%
1996	97.4%	0.0%	0.8%	0.6%	0.5%	0.3%	0.4%
1997	97.3%	0.0%	0.8%	0.6%	0.5%	0.4%	0.4%
1998	97.2%	0.1%	0.9%	0.6%	0.5%	0.4%	0.4%
1999	96.8%	0.1%	1.0%	0.7%	0.6%	0.4%	0.4%
2000	82.1%	0.1%	4.4%	3.8%	3.7%	2.9%	3.0%
2001	76.9%	0.2%	5.4%	5.0%	4.8%	3.7%	4.1%
2002	68.7%	0.2%	7.5%	6.9%	6.5%	4.7%	5.5%
2003	63.9%	0.3%	8.8%	8.2%	7.6%	5.3%	6.0%
2004	44.4%	0.4%	14.0%	13.6%	12.0%	7.6%	8.1%
2005	6.5%	0.9%	26.1%	24.3%	20.0%	11.3%	10.9%
2006	5.0%	0.9%	25.4%	24.5%	20.7%	11.5%	12.0%
2007	4.4%	1.5%	31.2%	25.1%	18.9%	9.5%	9.3%
2008	2.5%	0.8%	21.0%	24.2%	22.7%	13.6%	15.1%
2009	1.5%	0.0%	6.2%	18.0%	24.8%	20.6%	28.8%
2010	1.6%	0.0%	1.0%	12.4%	25.0%	23.1%	36.9%
2011	1.5%	0.0%	0.5%	8.4%	27.1%	24.0%	38.5%
2012	1.1%	0.0%	0.6%	8.2%	30.7%	24.8%	34.6%
2013	1.1%	0.0%	0.5%	6.5%	36.4%	27.7%	27.9%
2014	0.7%	0.0%	1.0%	11.3%	41.5%	27.6%	17.8%
2015	0.8%	0.0%	1.7%	14.5%	37.8%	27.3%	17.8%
2016	0.8%	0.0%	1.9%	15.5%	36.4%	27.1%	18.4%
2017	0.7%	0.0%	2.7%	17.6%	36.1%	25.7%	17.1%
2018	0.6%	0.0%	4.3%	20.9%	36.8%	23.2%	14.1%
2019	0.5%	0.0%	5.2%	22.5%	37.6%	21.6%	12.5%
2020	0.6%	0.0%	3.4%	18.7%	39.1%	23.6%	14.5%
2021	0.8%	0.0%	2.0%	18.6%	42.3%	23.1%	13.3%
2022	0.7%	0.0%	4.5%	23.2%	40.4%	20.3%	10.8%
2023	0.6%	0.0%	4.7%	19.5%	36.3%	23.3%	15.6%
2024	0.7%	0.0%	4.8%	17.0%	31.2%	23.9%	22.4%
2025	0.8%	0.0%	5.7%	17.1%	28.4%	23.1%	25.0%
2026	0.9%	0.0%	6.0%	17.7%	28.0%	22.4%	25.0%

Note: Excludes streamline refinance loans.

[66] Source: SFDW.IDB_1.

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F. Initial Relative Loan Size Distributions

The relative loan size variable is computed for each loan as loan origination amount divided by the average FHA loan size in the same location in the same year for the same product. Empirical results show that this variable is significant in prepayment-related terminations.

FHA experience indicates that larger loans tend to perform better than smaller ones in the same geographical area, all else being equal. Larger loans incur claims at a lower probability; in those cases where a claim occurs, loss severity tends to be lower. Before the increase in FHA's loan limits in FY 2008, houses securing larger FHA loans tended to fall into the average house price range within their surrounding areas. Since this market is relatively liquid and there are a relatively large number of similar-quality homes in the area, the house price volatility of these houses tends to be relatively low compared to the house price volatility of low- and high-priced houses. With the increased FHA loan size limit, FHA started endorsing higher-priced houses after FY 2008.

Exhibit III-7 displays the percentage of new fully underwritten mortgage originations within each relative loan size category, controlling for credit subsidy cohort and property state. The distribution remained reasonably stable over time, with the most substantial share of 75 percent, 100 percent, and 125 percent of area loan size categories. Nevertheless, since Fiscal Year 2000, there has been a continuous increase in the variance among loan size categories.

The proportion in the highest loan size category (above 150 percent of average loan size) had risen from 11.0% in Fiscal Year 2000 to 26.5% in Fiscal Year 2007 but decreased to 13.2% in 2020. As of 2026, the proportion in the highest loan size category is 13.7%.

The share in the lowest loan size category (less than or equal to 50% of average loan size) peaked at 12.3% in 2011, dropping to 9.2% in 2026.

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Exhibit III-7: Percentage of Origination Count by Relative Loan Size [67]

Cohort Year	<=50% of Loan Size	75% of Loan Size	100% of Loan Size	125% of Loan Size	150% of Loan Size	>150% of Loan Size
1992	5.5%	20.3%	28.2%	23.2%	12.7%	10.0%
1993	4.9%	19.7%	29.1%	25.1%	12.0%	9.1%
1994	5.6%	20.3%	28.6%	23.4%	11.6%	10.4%
1995	6.0%	20.3%	27.5%	21.6%	12.6%	11.9%
1996	5.9%	19.8%	27.9%	21.6%	14.0%	10.7%
1997	5.8%	19.9%	27.9%	21.0%	14.6%	10.8%
1998	5.3%	19.2%	28.9%	21.8%	15.0%	9.8%
1999	5.6%	20.3%	28.0%	21.9%	13.7%	10.5%
2000	6.4%	20.7%	26.1%	22.6%	13.2%	11.0%
2001	6.0%	20.4%	25.9%	24.8%	12.7%	10.2%
2002	6.3%	20.7%	25.8%	24.4%	12.4%	10.5%
2003	5.9%	20.1%	26.4%	25.0%	12.4%	10.3%
2004	6.4%	20.1%	24.7%	23.5%	13.7%	11.6%
2005	6.0%	18.2%	23.1%	23.1%	15.5%	14.0%
2006	4.1%	15.0%	20.8%	22.4%	16.8%	20.9%
2007	3.5%	13.5%	18.4%	21.1%	17.1%	26.5%
2008	7.6%	18.4%	23.7%	19.6%	12.5%	18.2%
2009	9.8%	20.6%	24.0%	17.3%	11.4%	16.9%
2010	11.5%	22.5%	23.3%	15.8%	10.5%	16.3%
2011	12.3%	22.0%	22.6%	15.1%	10.5%	17.5%
2012	12.2%	22.4%	23.1%	15.4%	10.3%	16.5%
2013	10.9%	22.9%	23.9%	15.7%	10.5%	16.0%
2014	10.9%	21.4%	23.7%	16.3%	10.1%	17.6%
2015	11.4%	21.5%	22.8%	16.4%	11.3%	16.5%
2016	11.4%	21.6%	23.5%	16.5%	12.2%	14.8%
2017	11.2%	20.8%	23.0%	17.4%	12.4%	15.2%
2018	11.2%	20.4%	22.9%	17.9%	12.4%	15.3%
2019	11.0%	20.9%	22.5%	18.7%	12.4%	14.5%
2020	9.0%	20.5%	24.2%	20.2%	12.9%	13.2%
2021	9.3%	20.9%	23.6%	19.5%	12.8%	13.8%
2022	9.9%	20.2%	20.7%	18.4%	13.7%	17.0%
2023	11.1%	19.4%	21.0%	19.0%	13.7%	15.7%
2024	10.5%	19.1%	22.7%	19.9%	13.1%	14.6%
2025	9.7%	19.6%	23.7%	20.0%	12.6%	14.2%
2026	9.2%	20.5%	24.5%	19.9%	12.2%	13.7%

[67] Source: SFDW.IDB_1.

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G. Initial Contract Interest Rate

Exhibit III-8 presents the average mortgage contract rate by type since FY 1992. Before FY 2020, the average contract rates in FY 2013 were the lowest in this entire period. Rates had risen since FY 2013 but declined substantially in FY 2020 and FY 2021 in the context of pandemic-era stimulus. Interest rates for 30-year SRs in FY 2021, averaging 2.88 percent, contributed significantly to a surge in refinance activity in FY 2020 and FY 2021.

Interest rates increased rapidly in FY 2022 in response to factors including anti-inflationary action by the Federal Reserve Board of Governors. From 2023 through 2026, the average interest rate consistently remained above 5.5 percent for 30-year fixed-rate products, often reaching over 6 percent.

In general, an FRM with a lower initial contract rate tends to prepay at a slower speed. As interest rates continue to rise or remain steady, the prepayment rates of the recent originations are likely to remain low. The longer duration of these loans is reflected in our econometric models, so that additional insurance premium income is forecasted, thereby increasing the economic net worth of recent books with historically low contract rates. We note that there will be some level of prepayments associated with employment change and residential mobility, regardless of the level of interest rates.[68] Our econometric models fall under the general description of logit models that include both baseline and systematic components that determine conditional transition rates, so that projected transition rates will never reach either 0 or 1.

Also, a mortgage with a contract rate lower than the market rate tends to experience a lower probability of default because the borrower is incentivized to keep the below-market rate mortgage longer, even when experiencing some negative equity. This tendency is captured in our econometric models through the inclusion of variables measuring the length of time the default option may be in-the-money and not exercised, which we refer to as "credit burnout." The recent low-interest-rate books are projected to experience fewer default episodes and claim terminations as mortgage rates rise, contributing to improving the portfolio economic net worth.

Exhibit III-8: Average Contract Interest Rate by Loan Type (Percent)[69]

Fiscal Year	30-Year FRMs	15-Year FRMs	ARMs	30-Year SRs	15-Year SRs	ARM SRs
1992	8.5%	8.2%	6.4%	8.8%	8.2%	6.5%
1993	7.7%	7.4%	5.8%	8.1%	7.6%	6.2%
1994	7.7%	7.2%	6.3%	7.8%	7.5%	6.2%
1995	8.3%	8.0%	7.1%	8.4%	8.2%	7.1%
1996	7.9%	7.6%	6.5%	8.0%	7.7%	6.8%

[68] Non-streamlined refinance (NSR) prepayment propensity attributable to housing turnover would be captured primarily in the segment of the "relative spread" variable measuring refinance incentive spline value less than zero (i.e. mortgage note rate less than market rate) and in seasonal indicator variables included in transition model specifications.
[69] Source: SFDW.IDB_1.

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Fiscal Year	30-Year FRMs	15-Year FRMs	ARMs	30-Year SRs	15-Year SRs	ARM SRs
1997	7.9%	7.7%	6.5%	8.2%	7.9%	6.8%
1998	7.3%	7.1%	6.1%	7.5%	7.1%	6.5%
1999	7.4%	7.1%	6.2%	7.2%	7.0%	6.0%
2000	8.3%	8.1%	7.0%	8.2%	7.9%	6.4%
2001	7.4%	7.0%	6.0%	7.3%	6.7%	5.9%
2002	7.0%	6.4%	5.3%	6.8%	6.3%	5.3%
2003	6.1%	5.5%	4.4%	6.0%	5.5%	4.4%
2004	6.1%	5.5%	4.4%	5.9%	5.5%	4.3%
2005	5.9%	5.6%	4.8%	5.9%	5.7%	4.7%
2006	6.3%	6.1%	5.4%	6.1%	6.0%	5.0%
2007	6.5%	6.4%	5.6%	6.4%	6.2%	5.6%
2008	6.3%	5.9%	5.4%	6.1%	5.6%	5.3%
2009	5.6%	5.1%	5.0%	5.3%	4.8%	4.5%
2010	5.1%	4.6%	4.0%	5.1%	4.7%	4.3%
2011	4.6%	4.2%	3.5%	4.6%	4.2%	3.7%
2012	4.0%	3.5%	3.1%	4.0%	3.5%	3.4%
2013	3.6%	3.2%	2.8%	3.7%	3.4%	2.9%
2014	4.3%	3.7%	3.3%	4.5%	3.9%	3.4%
2015	4.0%	3.5%	3.3%	4.0%	3.7%	3.4%
2016	3.9%	3.4%	3.2%	3.9%	3.5%	3.4%
2017	4.0%	3.5%	3.2%	3.7%	3.6%	3.0%
2018	4.5%	3.9%	3.5%	4.1%	4.0%	3.5%
2019	4.7%	4.1%	4.0%	4.2%	4.4%	4.0%
2020	3.6%	3.5%	3.5%	3.5%	3.4%	3.5%
2021	3.0%	2.7%	2.6%	2.9%	2.8%	2.3%
2022	4.1%	3.2%	3.1%	3.1%	3.0%	2.5%
2023	6.2%	5.5%	4.9%	5.7%	3.9%	N/A
2024	6.6%	6.0%	5.4%	6.4%	5.5%	N/A
2025	6.2%	5.7%	5.2%	6.2%	5.8%	5.4%
2026	6.0%	5.7%	4.7%	6.0%	5.7%	5.0%

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IV. MMI Fund Performance under Alternative Scenarios

The Fund's Single-Family Forward economic net worth for FY 2026 depends on the economic conditions expected to prevail over the next 40 years and, most critically, during the next 10 years.

We have captured the most significant factors in the U.S. economy affecting the performance of the loans insured by the Fund using the following variables in our models:

- 30-year, 15-year, and adjustable-rate mortgage rates
- 1-year and 10-year constant maturity Treasury rates
- National and local house price indices
- National and local unemployment rates

The projected performance of FHA's current book of business, as measured by economic net worth, depends on future forecasts of these economic drivers. The baseline scenario for the primary economic drivers was developed consistently with the PEA. The PEA is published by the Office of Management and Budget in compliance with the requirements of the Federal Credit Reform Act.

A. FHFA House Price Indices

House price appreciation increases borrowers' home equity, reducing both the likelihood of mortgage default and the loss severity when a claim occurs, and therefore is positively associated with Economic Net Worth. The actuarial central estimates are based on the PEA for the quarterly future performance of the FHFA Purchase Only (PO) seasonally adjusted HPI for the period FY 2027 FQ1 to FY 2037 FQ1 and 3% annualized HPA thereafter.

FHFA publishes both purchase-only (PO) and all-transactions (AT) versions of their HPIs. Some prior reviews have expressed the view that the HPI PO version is necessarily more accurate than the HPI AT version due to the reliance of the latter on appraisal valuations in addition to observed sale prices. We use the national FHFA Purchase Only (PO) seasonally adjusted HPI and have applied the AT version of the FHFA HPIs in model estimation for deriving local and state HPI, due to the significantly broader regional coverage provided by the AT version of the HPI, including more than 300 additional Metropolitan Statistical Area (MSA) level HPIs.

Calhoun (1991) first noted the benefits of having appraisal-based HPIs during periods when sales transactions are limited or in locations where they are non-existent. Calhoun (1991) also examined the potential for greater sample-selection bias when only sales transaction data are used. Simply stated, mortgage borrowers may be willing to refinance at appraised values well below their reservation prices for selling, so that relying solely on sales prices draws from the higher end of the house price distribution at any point in time. In our view, geographic aggregation bias far

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outweighs concerns about appraisal bias, particularly given the overall consistency between AT and PO versions of the HPI at the same level of geography. Later research by Calhoun, C.A.; Michelle Harter; and Mathew R. VanderGoot (1999) and Leventis (2006) indicates that the actual evidence for systematic appraisal bias is mixed or inconclusive. On the other hand, geographic bias is large, immediate, and certain if the HPI PO version must be applied at the state level when no MSA-level HPI is available. Therefore, we opted for broader geographic coverage at the MSA level.

Nevertheless, we were required to use the PEA for the national FHFA PO HPI in developing our baseline forecast of portfolio economic net worth. To meet this requirement, we applied the following two-step procedure to obtain regional (MSA/State) HPI forecasts from the PEA national forecasts: (1) compute the period-by-period (FYFQ) differentials between the FHFA AT national forecast HPI appreciation rates and the corresponding appreciation rates for each regional HPI from the same FHFA AT forecast; and then (2) apply these differential appreciation rates to the PEA national PO HPI forecast to obtain regional HPI forecasts consistent with the PEA national PO forecast. So as the PEA PO national forecast varies period-by-period, our regional HPIs (the newly created PEA MSA/State PO forecast) vary in a consistent manner, and enable us to retain the broader geographic coverage of the AT version of the FHFA HPIs (over 300 individual MSAs).

To be clear, we are not applying Moody's FHFA AT forecasts in place of the mandated PEA national HPI PO forecast. Changes in the local forecasts will still represent the pattern of house price appreciation for the PEA national forecast, plus regional differentials in appreciation rates based on observed historical patterns. Moody's AT and PO version national forecasts are quite consistent in terms of projected appreciation rates at both the national and regional levels, and Moody's baseline national forecasts are quite similar to the PEA. As described in Appendix E, alternative scenarios for sensitivity analysis based on our stochastic simulation models use a similar approach to go from the simulated national PO version HPI forecasts to the corresponding simulated regional forecasts. The same procedure for developing regional forecasts from PEA national HPI forecasts was applied for both Single Family Forward and HECM Fund performance.

B. Interest Rates

Mortgage interest rates govern borrower prepayment and default behavior and the payment adjustments on adjustable-rate mortgages, thereby influencing the duration of FHA insurance, future premium collections, and ultimately Economic Net Worth. Mortgagee Letter (ML) 2023-09 required that the Secured Overnight Financing Rate (SOFR) replace LIBOR for both new and existing adjustable-rate mortgages (ARMs) indexed to LIBOR to phase out LIBOR.

The Alternative Reference Rates Committee (ARRC) noted that regardless of what rate was chosen as a LIBOR alternative, there would need to be an adjustment for the difference between LIBOR and the fallback rate. Market participants preferred the 'historical mean/median approach,' which is based on the 5-year historical median difference between USD LIBOR and SOFR for the spread

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adjustment, and the ARRC recommended this static spread adjustment for cash products. Exhibit IV-1 shows historical recommended long-term spread adjustments used to facilitate the conversion of LIBOR-indexed loans, based on historical 5-year median spreads between USD LIBOR and compounded averages of SOFR:

Exhibit IV-1: Historical Median Difference between USD LIBOR and SOFR

LIBOR tenor being replaced	Spread applied to SOFR-based rate (bps)
1-week USD LIBOR	3.839
1-month USD LIBOR	11.448
2-month USD LIBOR	18.456
3-month USD LIBOR	26.161
6-month USD LIBOR	42.826
1-year USD LIBOR	71.513

Source: Bloomberg, as reproduced by ARRC[70]

The interest rate inputs to the cash flow model are the PEA one-year and ten-year Treasury rates and the PEA 30-year mortgage rate. The 15-year mortgage rate is the PEA 30-year rate plus Moody's baseline spread between the 15-year and 30-year rates, and the ARM mortgage rate is Moody's baseline ARM rate. These rates enter the models through the refinance incentive and the slope of the yield curve.

The residual impact of LIBOR transition is expected to decrease as legacy LIBOR-indexed loans continue to terminate and are replaced by SOFR-indexed originations. Benchmark transition risk is no longer considered a material source of model vulnerability. Uncertainties in SOFR projections are incorporated by alternative stochastic scenarios of future SOFRs that are simulated using the best-fitted GARCH models calibrated to the historical data.

C. Unemployment Rates

Household unemployment directly impacts borrowers' ability to make mortgage payments and is positively associated with mortgage default. However, due to the lack of household-level data, researchers have initially used aggregate unemployment rates as proxies for studying mortgage defaults, and only weak correlations were found (e.g., Deng, Quigley, and Van Order, 2000). More recent studies show that stronger relationships can be found when county- or household-level unemployment measures were adopted (e.g., Gyourko and Tracy, 2014; Gerardi, Herkenhoff, Ohanian, and Willen, 2018). Therefore, we include regional unemployment rates for model

[70] Alternative Reference Rates Committee (ARRC). 2021. *Summary of the ARRC's Fallback Recommendations*. Federal Reserve Bank of New York, October 6, 2021. https://www.newyorkfed.org/medialibrary/Microsites/arrc/files/2021/spread-adjustments-narrative-oct-6-2021, retrievable on September 1, 2026

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estimation and forecasting. However, for unemployment forecasting, the FY 2027 Mid-Session Review of the PEA national unemployment rates was required for the actuarial central estimate.

Similar to the process we used for regional HPI forecasts, regional unemployment rate forecasts incorporate a geographic dispersion factor calculated from Moody's forecast of national and regional state- and MSA-level unemployment forecasts. The dispersions are then applied to the PEA national unemployment to obtain the forecasts for regional unemployment rates. The unemployment rate is countercyclical in nature. It tends to rise during economic downturns and fall during economic expansion periods. We simulate alternative unemployment scenarios based on a fitted GARCH model with the conditional mean replaced by baseline unemployment rates. A detailed discussion of historical unemployment rates and stochastic simulation can be found in Appendix E.

D. Stochastic Scenarios

Our additional source of historical data for economic factors is Moody's Economy.com. Moody's has developed data from original sources, including the Federal Reserve, Bureau of Labor Statistics, Bureau of the Census, Bureau of Economic Analysis, Federal Housing Finance Agency, The Conference Board, Dow Jones, National Association of Realtors, and Freddie Mac. Depending on the data series, information is provided at the national, state, county, metropolitan area, and ZIP code level. Moody's data are combined with historical loan-level data from HUD's Single-Family Data Warehouse (SFDW) to build out loan-level panel data and event histories (defaults, cures, claims, prepayments) for use in estimating statistical models of loan performance. The estimated loan performance models are then combined with the forecasts of economic drivers based on the PEA to produce our baseline forecast.

In addition to the mandated baseline PEA forecasts, we apply four alternative stochastic scenarios based on Monte Carlo simulation of potential random deviations from the PEA baseline. Four scenarios for which we report estimates of economic net worth are:

- Optimistic Upside Scenario in Simulation: the path that is most favorable of the five selected paths to the SF Forward MMI Fund.
- Moderate Upside Scenario in Simulation: the path that is moderately favorable to the SF Forward MMI Fund.
- Moderate Downside Scenario in Simulation: the path that is moderately unfavorable to the SF Forward MMI Fund.
- Pessimistic Downside Scenario in Simulation: the path that is most unfavorable of the five selected paths to the SF Forward MMI Fund.

Each of the simulated scenarios is based on combinations of selected "percentile" paths for the economic drivers that correspond to favorable or unfavorable outcomes for the prospects of the Single-Family Forward MMI Fund portfolio. Rising interest rates, rising housing values, and declining unemployment rates are favorable outcomes, because they lead to lower prepayments

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(increasing future premium income) and lower default, claim, and loss rates (reducing future losses). Conversely, declining interest rates, falling house prices, and rising unemployment rates are unfavorable outcomes, because they lead to higher prepayment rates (lowering future premium income) and higher default and claim rates (increasing future losses). Some elements of our more optimistic scenarios, such as higher interest rates, may not conform to the usual interpretation of favorable economic conditions, but are in fact favorable to the current economic net worth of the MMI Fund.

The combinations of selected percentile paths comprising each of the alternative scenarios described above are summarized here:

Alternative 1 – Optimistic Upside Scenario

Treasury and Mortgage Rates: 90th percentile

Unemployment Rate: 10th percentile

House Price Appreciation Rate: 90th percentile

Alternative 2 – Moderate Upside Scenario

Treasury and Mortgage Rates: 75th percentile

Unemployment Rate: 25th percentile

House Price Appreciation Rate: 75th percentile

Alternative 3 – Moderate Downside Scenario

Treasury and Mortgage Rates: 25th percentile

Unemployment Rate: 75th percentile

House Price Appreciation Rate: 25th percentile

Alternative 4 – Pessimistic Downside Scenario

Treasury and Mortgage Rates: 10th percentile

Unemployment Rate: 90th percentile

House Price Appreciation Rate: 10th percentile

The percentile paths are simulated using Autoregressive Moving Average (ARMA) - Generalized Autoregressive Conditional Heteroskedasticity (GARCH) modeling. ARMA (p, q)-GARCH (1,1) models are used, where the orders p, q are selected based on goodness-of-fit, stationarity, and forecast stability tests. The stochastic paths are simulated around the PEA baseline forecast. The PEA forecast developed by the White House Council of Economic Advisers, Treasury, and OMB does not cover all the economic drivers that are included in our models. Additional economic variables that must be forecasted, such as FRM 15-Year and ARM origination rates, regional and local house price indices, and local unemployment rates, are developed using the PEA and

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additional forecast data from Moody's. Additional details may be found in the discussion of stochastic simulation models in Appendix E.

E. NPV Values

The summary of the estimated Cash Flow NPV resulting from the Baseline PEA is $25.571 billion. This projection constitutes the baseline against which the projections from the alternative scenarios are compared. Each scenario is shown in Exhibit IV-2. The projected results extend from positive $4.605 billion to positive $39.510 billion; the two endpoints are illustrative extreme stress-test outcomes rather than a probability range (see Section VI.E).

Exhibit IV-2: Range of Cash Flow NPV Outcomes Based on Stochastic Simulations ($ Million)

Economic Scenario	Fiscal Year 2026 Cash Flow NPV
Baseline PEA	$ 25,571
Alternative 1 - Optimistic Upside Scenario	39,510
Alternative 2 - Moderate Upside Scenario	33,192
Alternative 3 - Moderate Downside Scenario	15,784
Alternative 4 - Pessimistic Downside Scenario	4,605

Exhibit IV-3 presents a breakdown of the Cash Flow NPV by Cohort for the baseline PEA scenario along with the four simulated alternative scenarios.

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Exhibit IV-3: Cash Flow NPV Summaries from Alternative Scenarios by Cohort ($ Million)

Cohort Year	Baseline PEA	Alternative 1 - Optimistic Upside	Alternative 2 - Moderate Upside	Alternative 3 - Moderate Downside	Alternative 4 - Pessimistic Downside
1992	$ 0	$ 0	$ 0	$ 0	$ 0
1993	0	0	0	0	0
1994	0	0	0	0	0
1995	0	0	0	0	0
1996	(1)	(1)	(1)	(1)	(1)
1997	(1)	(1)	(1)	(1)	(2)
1998	(2)	(2)	(2)	(2)	(2)
1999	(4)	(4)	(4)	(4)	(4)
2000	(5)	(5)	(5)	(6)	(6)
2001	(13)	(12)	(13)	(14)	(14)
2002	(10)	(9)	(10)	(11)	(12)
2003	(23)	(22)	(23)	(25)	(26)
2004	(25)	(23)	(24)	(26)	(27)
2005	(26)	(24)	(25)	(26)	(28)
2006	(15)	(14)	(15)	(16)	(17)
2007	(43)	(42)	(42)	(45)	(48)
2008	(156)	(149)	(152)	(161)	(170)
2009	(192)	(186)	(189)	(196)	(203)
2010	(223)	(219)	(221)	(226)	(231)
2011	(110)	(108)	(109)	(111)	(113)
2012	(132)	(131)	(131)	(133)	(135)
2013	309	323	316	300	290
2014	632	651	641	616	598
2015	1,118	1,158	1,137	1,088	1,054
2016	1,678	1,742	1,709	1,630	1,578
2017	1,926	2,011	1,968	1,858	1,777
2018	1,526	1,618	1,573	1,435	1,316
2019	1,752	1,877	1,817	1,627	1,466
2020	5,582	5,934	5,751	5,321	5,050
2021	10,799	11,570	11,171	10,259	9,735
2022	5,086	6,234	5,707	4,097	2,747
2023	(608)	1,275	445	(1,911)	(3,513)
2024	(1,787)	523	(535)	(3,136)	(4,890)
2025	(1,494)	1,654	235	(3,462)	(5,698)
2026	34	3,892	2,223	(2,934)	(5,864)
Total	$ 25,571	$ 39,510	$ 33,192	$ 15,784	$ 4,605

The 2026 Cash Flow NPV estimate provided by FHA is positive $32.283 billion. Based on ITDC's Cash Flow NPV estimate utilizing the Baseline PEA and the range of results from the stochastic simulation scenarios, we conclude that the FHA estimate of Cash Flow NPV is reasonable. This conclusion reflects a high-level reasonableness review of FHA's estimate against ITDC's central estimate and stress-test range; it is not a replication of FHA's model or a component-level reconciliation of the $6.712 billion difference.

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F. Sensitivity Tests for Economic Variables and Important Assumptions

The stochastic scenario test results revealed that important economic assumptions, such as interest rates, drive the NPV. Exhibit IV-4 illustrates NPV changes from baseline to increases and decreases in home price appreciation, interest rates (including Treasury and mortgage interest rates), loss severity, loss mitigation rates, and unemployment rates. For interest rates, loss severity, loss mitigation, and unemployment, each forecast value is increased or decreased by 10 percent. For HPA, which can be zero or negative, the shock is instead a parallel shift of 0.25 percentage points per year to forecast house price growth.

Exhibit IV-4: NPV Sensitivity to Home Price Appreciation, Interest Rates, Loss Severity, Loss Mitigation, and Unemployment

Description	NPV (% Change from the Baseline NPV)	
	Decrease	Increase
Interest Rates (±10%)	$ 18,856 (-26.3%)	$ 31,473 (23.1%)
Loss Severity Rates (±10%)	28,392 (11.0%)	22,749 (-11.0%)
Loss Mitigation Rates (±10%)	27,041 (5.7%)	24,100 (-5.7%)
House Price Appreciation (±0.25 pp per year)	24,421 (-4.5%)	26,607 (4.1%)
Unemployment Rates (±10%)	25,666 (0.4%)	25,471 (-0.4%)

The direction and magnitude of NPV impacts to shocks of these key model inputs are broadly consistent with economic intuition. Raising mortgage interest rates reduces refinance incentives relative to the baseline and contributes to a slowdown in prepayment speeds, extending the period over which MIP can be collected. Because Treasury rates are incorporated into transition models as a measure of curve slope, simultaneous increases in 10-year and 1-year rates will not significantly affect model-predicted transition outcomes.

Exhibit IV-4a decomposes the interest rate sensitivity by cash flow component. Most of the effect operates through prepayments. A 10 percent decrease in interest rates speeds prepayment, which reduces annual premium income by $6.3 billion and increases upfront premium refunds by $1.1 billion; claims net of recoveries change by only $0.2 billion, and loss mitigation expense falls by $0.9 billion as fewer loans remain exposed to default. A 10 percent increase works in the opposite direction, raising annual premium income by $5.2 billion. Discount factors are the prescribed single effective rates and do not change under either shock.

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Exhibit IV-4a: Change in Cash Flow NPV by Component under the Interest Rate Sensitivity Tests ($ Million)

Cash Flow Category	Interest Rates Down 10%	Interest Rates Up 10%
Mortgage Insurance Annual Premium	$ (6,299)	$ 5,234
Upfront Premium Refund	(1,123)	506
Loss Mitigation Expense	946	(829)
Claim Expenses	(634)	2,138
Recoveries	396	(1,147)
Change in Cash Flow NPV	$ (6,715)	$ 5,903

Note: Change from the baseline Cash Flow NPV of $25,571 million. Components may not sum to the totals due to rounding.

Loss severity rates impact the NPV as these rates feed directly into realized loss from a claim. As loss severity rates increase, we anticipate a reduction in the NPV through a reduction in the amount recovered. Conversely, as loss severity rates decrease, we anticipate an increase in the recovery amount, increasing cash flow NPV.

Exhibit IV-4 shows that all else being equal, a 10% increase in loss mitigation rates results in a 5.7% decrease in NPV and vice versa. Loss mitigation rates are the third most sensitive of the tested five factors. Note that the purpose of the sensitivity test is to help investigate how sensitive the NPV is to changes in the estimated loss mitigation rates, all else being equal, rather than study whether loss mitigation improves or impairs the MMI Fund. Loss mitigation options help keep borrowers from losing their homes, which is expected to slow future claim speeds. Whether the benefits of delaying or avoiding a claim outweigh the underlying cost of loss mitigation tools is not addressed in sensitivity tests.

Faster home price appreciation contributes to rising property values and declining LTV ratios, reducing borrower propensity to default and, consequently, claim rates. At the same time, lower LTV ratios may facilitate refinancing, resulting in faster prepayments and a reduction in future MIP collections, which partially offsets the NPV benefits associated with lower claim rates. Conversely, lower HPA increases claim rates as property values grow more slowly and LTV ratios remain higher; however, the resulting adverse impact on NPV is partially mitigated by slower prepayment speeds and the associated continuation of MIP collections.

Of the economic drivers for NPV, the model is least sensitive to changes to the unemployment rate. We anticipate that a higher unemployment rate would increase mortgage delinquencies and defaults, as job losses reduce borrowers' income, particularly affecting borrowers who often have less financial flexibility. As such, when the unemployment rate increases, the NPV decreases, and when the unemployment rate decreases, the NPV increases.

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V. List of Methodological Appendices

This section describes the analytical approach implemented in this review. Detailed descriptions of the component models are provided in Appendices A through H. The following briefly summarizes how we process the data and develop component models in the appendices.

Data Reconciliation (Appendix A)

This appendix provides the data sources, processing, and reconciliation tables used for this model. Loan-level panel data are extracted from HUD databases, supplemented by UNICON and Fannie Mae credit score data. A variety of derived variables are incorporated, for example, estimates of current loan-to-value ratio utilizing original property value, amortization, and estimated regional home price appreciation. Macroeconomic time series data are merged into the estimation data to ensure the corresponding risk factors are appropriately integrated.

Econometric Analysis of Mortgage Status Transitions and Terminations (Appendix B)

This appendix provides a technical description of our econometric models of quarterly default, claim, and prepayment for individual mortgage product types. We also provide a description of the explanatory variables used in the models.

A competing risk logistic regression, or logit model approach, is used to estimate the probability of loan transition events. We test the significance of parameters to achieve a parsimonious model that provides goodness-of-fit.

The multinomial logit approach has several benefits. First, logit models eliminate the likelihood of a negative probability for any estimated event. Second, the multinomial approach ensures the event probabilities sum to 100 percent. Third, it captures the zero-sum nature of the different termination events, whereby the increased probability of one risk decreases the probabilities of the other risks.

The transition models adopt four main categories of explanatory variables:

- Fixed initial loan characteristics, e.g., credit score, original loan size, loan purpose, spread relative to market mortgage rates at origination, and debt-to-income ratio.
- Dynamic variables based entirely on loan history, e.g., mortgage age, burnout, and default duration.
- Dynamic variables incorporating macroeconomic data separately or in conjunction with loan characteristics such as fixed-rate refinance incentive, local/national home price appreciation, current loan-to-value ratio, unemployment, and Treasury curve slope.

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- Indicator variables capture the impacts of loss mitigation policy responses to the COVID-19 pandemic.

Transition models are estimated for each of the following six products: FRM-30 non-streamlined refinance (NSR); FRM-15 NSR; ARM NSR; FRM-30 streamlined refinance (SR); FRM-15 SR; and ARM SR. For loans that are "current" as of the beginning of a quarterly period (i.e., less than 90 days delinquent), binomial logistic models are estimated for four transitions: to default, to SR prepayment, to NSR prepayment, and a return to current status within the quarter following an intervening default. For "defaulted" loans that are 90 days or more delinquent, binomial models are estimated for four transitions: to claim, to prepayment, to cure through loan modification, and to self-cure. This yields eight transition models for each of the six products, or 48 models in total.

A separate binomial logit transition model is estimated for each combination of product and transition event. For forecasting purposes, these logit regression models are reconfigured as multinomial logit competing hazard models following the approach suggested in Begg and Gray (1984).

Loan Performance Projections (Appendix C)

This appendix describes the loan status transition framework as it relates to the estimated probability models, how those models are applied in forecasting, and the application of the forecasted probabilities to the actuarial calculations that summarize future loan performance. Forty-year projections are developed utilizing regression models and coefficients described in Appendix B together with macroeconomic risk factor values for housing prices, long-term mortgage rates, unemployment, and Treasury interest rates from the PEA forecast, supplemented by data from Moody's Data Buffet.

Loss Severity Model and Cash Flow Analysis (Appendix D)

This appendix provides a technical description of our econometric model of FHA mortgage loss severity rates, loss mitigation modeling, and cash flow analysis.

Stochastic Simulation Models (Appendix E)

This appendix discusses the estimation and application of stochastic simulation models used to generate alternative forecasts for analysis of our baseline estimates of economic net worth for the Single-Family Forward portfolio.

Comparison of HUD and ITDC Models and Assessment of Vulnerabilities (Appendix F)

As part of the statutory actuarial review process, this report presents the results of the review of HUD's Forward models. This review includes analysis necessary to support enhanced transparency and completeness of the actuarial review.

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Tables of Historical and Projected Rates of Loan Termination and Loss Severity (Appendix G)

These tables, generated as output from processes outlined in Appendix C and Appendix D, are provided in a separate addendum to the main report.

Logistic Model Estimation Results (Appendix H)

This appendix provides tables for the 48 estimated econometric models, including variable descriptions, explanatory variable functional forms (dummy, linear, spline, etc.), piece-wise linear spline knot specifications, estimated coefficients, and t-statistics for each status transition model for each of the six mortgage product types. Sample counts, likelihood values, and model chi-square statistics are also presented. These tables are provided as a separate addendum to the main report.

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VI. Qualifications and Limitations

The actuarial models used in this review are based on a theoretical framework and certain assumptions. This framework relates the default, claim, loss, and prepayment rates to several individual loan characteristics and certain critical macroeconomic variables. The models are estimated utilizing econometric regression techniques based on data from actual historical experience regarding the performance of FHA-insured mortgage loans. The parameters of the econometric models are estimated across a wide variety of loans originating starting in fiscal 1992 and their performance under the range of economic conditions and mortgage market environments experienced over the past 35 years. The estimated models are used together with assumptions about future loan performance and certain key economic assumptions to produce future projections of the performance of the Fund.

The financial estimates presented in this Review require projections of events up to 40 years into the future.[71] These projections depend on the validity and robustness of the underlying models and the assumptions about future economic environments and loan characteristics. These include projections of future outcomes for key economic inputs to the models based on economic forecasts provided as components of the FY 2027 Mid-Session Review of the PEA, as well as the forecasts from Moody's Data Buffet. We did not develop these assumptions and have not assessed their likelihood. If the realized experience deviates from these or other assumptions, the actual results may differ, perhaps significantly, from current projections. The projections do not otherwise rely on models or forecasts developed by third parties.

A. Fundamental Data Limitations

The quality of any model built on historical data is constrained by the scope, availability, and accuracy of the data. Key variables determining market behavior may not be observed, or they may be observed with error. Moreover, the theoretical specification of a model may not adequately capture the economic phenomena when there were material changes in market structure, regulatory policy, or technological advancement.

The econometric analysis in this Review uses data extracted from FHA's Single-Family Data Warehouse (SFDW). The volume and composition of the existing portfolio are based on FHA data

[71] The review explicitly incorporates extended term ("ET") modifications where the term to maturity is extended to 40 years. A 40-year modification propensity is applied to loans curing through modification in every future period, including periods after FY 2026. Cash flows for each loan are projected through the 160th quarter after origination, that is, 40 years from origination; the projection therefore ends in FY 2066 for the FY 2026 cohort and earlier for older cohorts. The same horizon applies to loans whose term is extended by a modification: a loan originated in FY 2010 and modified onto a 40-year term in FY 2026 is projected through FY 2050, not to its modified maturity in FY 2066. The cash flows omitted beyond that point fall after the original amortization schedule, when no annual MIP is collected, and are small after discounting. ITDC estimates the omitted net cost at roughly $50 million, about 0.2 percent of the baseline Cash Flow NPV, by applying the model's policy-year-40 claim, loss severity, and loss mitigation rates to the balance surviving at that point over a linear runoff; treating the policy-year-40 discounted net cost as a perpetuity at each cohort's single effective rate gives an upper bound of about $200 million (0.8 percent).

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as of September 30, 2026. Records for the most recent months are the most likely to be revised as late transactions, such as claims, loss mitigation actions, and changes in default status, are reported. As a result, FY 2026 Q4 experience may be less settled than that of earlier quarters. While we have reviewed the integrity and consistency of these data and believe them to be reasonable, we have not audited them for accuracy. The information in this Review may not correspond exactly with other published analyses that rely on FHA data compiled at different dates or obtained from other data sources.

The data tables extracted from the SFDW for model estimation and forecasting included the following:

idb_1 - Integrated Database (IDB): idb_1 is a composite of 5 Single Family Forward legacy systems providing case-level data. idb_1 contains informational data for 255 of the most frequently used attributes. The data is refreshed monthly with the most current month's data. IDB is not a historical data mart and cannot provide a case-level month-to-month audit trail.

idb_2 - Single Family Forward legacy system providing case-level data. idb_2 contains informational data for approximately 250 of the less frequently used attributes. The data is refreshed monthly with the most current month's data.

decision_fico_score - The structure contains the Loan Underwriting Decision FICO Score that represents a composite of FICO scores generated from loan-applicant credit reports. It is refreshed monthly on the same schedule as IDB. Data values exist for cases endorsed starting in 2003.

default - The Default Data Mart provides case-level information on cases that are 30-, 60-, or 90-days delinquent. This data mart was enhanced during a November 2006 refresh, adding many new columns that reflect the change in reporting by the servicing lenders. The tables, default_episodes, sfdw_default_history, and sfdw_default_current_detail are refreshed monthly, typically on the 9th working day of the month.

sfdw_default_history - This table contains case-level historical data, reported by the lender, which reflects everything that happens during a default episode, whether it is a loss mitigation engagement, a first legal action to foreclose, the start of the pre-foreclosure sale process, etc. The data in this table is refreshed on the 9th working day of each month and may contain multiple records for a case and is provided by the SFDMS/F42D.

default_episode - This table provides case-level default data. An episode is either one complete cycle of a case going into default then coming out of default or a case which is in active default status. This table may contain multiple records for a case and is refreshed on the 9th working day of each month.

sfdw_default_current_detail - This table contains case-level default data reflecting the last occurrence of default for a case. This table is refreshed on the 9th working day of each month and contains only one record for each case.

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loss_mitigation - Case-level information provided weekly for the three Loss Mitigation Retention claim types: Special Forbearance, Mortgage Modification, and Partial Claim.

loan_modification - This structure contains case-level data for incentivized and non-incentivized loan modifications. The data are refreshed weekly.

lossmit_costs - Derived table based on the loss_mitigation table and idb_1. Used to obtain mitigation claim amounts.

claims_601_case_data - This table contains data to support the accelerated claims disposition programs.

sams_case_record - This is a Union between sams_monthly_record and sams_archive_record and is refreshed the 1st week of each month. It is used to determine the status of conveyances, the capital/income expense amounts, the sales and real estate owned (REO) expenses, and sales proceeds to FHA.

fannie_fico_pre2004 - A derived database used to provide supplemental credit data. Not a component of the SFDW but based on research conducted by HUD and other parties and provided to ITDC for use in this study.

unicon_fico - A derived database used to provide supplemental credit data. Not a component of the SFDW but based on research conducted by HUD and other parties and provided to ITDC for use in this study.

Economic series used by the models but not provided in the PEA, such as local house price indices and unemployment rates, are supplemented with data from Moody's Data Buffet. Consequently, the results also depend on the accuracy of those data, which we have reviewed for reasonableness but not audited.

B. Model Sensitivity to Economic Projections

Three critical economic variables used in making these projections are future house prices, interest rates, and unemployment rates. We conducted a sensitivity analysis to examine how the Fund's economic net worth may change with these macroeconomic factors to gain insight into the possible magnitude of the impacts. Specifically, we investigated the changes in economic net worth by applying the four alternative combinations of percentile paths outlined previously. The benchmark for these sensitivity tests is the deterministic base case, using the FY 2027 Mid-Session Review of the President's Economic Assumptions.

Mortgage interest rates have been at historically low levels since FY 2012 and reached their lowest values as recently as FY 2021. Rates have since risen rapidly in response to anti-inflationary actions by the Federal Reserve, roughly doubling over two years. The mandated PEA assumptions

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applied as the baseline scenario in our analysis stipulate that mortgage rates will generally decline over the next 10 years.

To allow for variation around this likelihood, our analysis applies four alternative scenarios for mortgage interest rates, Treasury rates, unemployment rates, and housing prices to examine the potential impact on portfolio performance. Alternative scenarios that lead to even higher interest rates than the PEA will only further reduce prepayment speeds on outstanding loans; a substantial decline in interest rates would be required to precipitate a refinance boom among current borrowers with historically low-rate mortgages associated with the widely noted "lock-in" effect, incentivizing homeowners to remain in their homes rather than incurring costs associated with higher current mortgage rates.

C. Changing Market Landscape and Policy Regimes

The mortgage market, broader economic environment, and housing policy landscape continue to evolve over time. Changes in interest rates, house price dynamics, borrower characteristics, mortgage products, servicing practices, and other market conditions may alter borrower behavior and loan performance in ways that differ from historical experience. Because the actuarial models are estimated using historical loan performance, relationships observed in prior periods may not fully represent default, prepayment, claim, and recovery behavior under future market conditions. Such changes may cause actual future cash flows to differ from modeled expectations and may result in either higher or lower Economic Net Worth than estimated.

Changes in FHA policies and servicing requirements may similarly affect future loan performance and fund cash flows. Changes to loss mitigation eligibility, available loss mitigation options, servicing requirements, foreclosure processes, or other program policies can affect the frequency and timing of defaults, claims, recoveries, and loss mitigation expenditures. In particular, recent changes to FHA's loss mitigation framework may alter borrower transitions following delinquency relative to experience observed under the COVID-era policy regime. Because historical experience reflects different policy regimes, the estimated relationships embedded in the models may not fully capture borrower and servicer behavior under newly implemented policies until sufficient post-implementation experience becomes available. The resulting policy uncertainty may therefore affect projected claim and loss mitigation costs and, consequently, the estimated Economic Net Worth of the MMI Fund.

D. Model Uncertainty

The Economic Net Worth estimate is subject to model uncertainty because the actuarial projection models necessarily provide simplified representations of complex borrower behavior, mortgage performance, and fund cash flows. Although the models incorporate key loan characteristics, economic variables, and historical performance relationships, actual default, prepayment, claim, recovery, and loss mitigation behavior may be influenced by factors or interactions that are not fully captured by the model specifications. In addition, model parameters are estimated from

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historical experience and are therefore subject to estimation uncertainty, particularly for loan segments or economic conditions with relatively limited historical observations.

Model uncertainty may affect Economic Net Worth through both the projected incidence and timing of future cash flows. For example, differences between modeled and actual default or prepayment behavior can affect projected claim payments and the duration of future mortgage insurance premium collections, while differences in modeled claim severity, recoveries, or loss mitigation outcomes can affect the expected cost associated with distressed loans. Because these components interact over the projection horizon, model uncertainty may result in either higher or lower Economic Net Worth than the point estimate presented in this Review. The alternative economic scenarios and sensitivity analyses presented in this Review provide additional information regarding the potential effect of changes in key economic variables and modeling assumptions, but they do not capture all possible sources of model uncertainty. Moreover, simplified model assumptions could also affect Economic Net Worth. For instance, the Cash Flow NPV excludes repayments of subordinate notes on partial claims and payment supplements that FHA is projected to pay after September 30, 2026. Repayments of notes already outstanding are reflected in capital resources at HUD's carrying value. Based on the Review's projections, ITDC estimates a potential upside to the Cash Flow NPV of approximately $2.0 billion to $3.2 billion from repayments of future partial claims (Section D2.3).

E. Other Limitations and Disclosures

Subsequent events. The estimates reflect data as of September 30, 2026, and the economic assumptions and FHA policies in effect when the analysis was prepared. Events after that date, including changes in economic conditions, new mortgagee letters or other policy changes, and revisions to FHA data, are not reflected in the estimates.

Interpretation of scenarios. The alternative economic scenarios and stochastic scenarios presented in Section IV show how the Cash Flow NPV responds to economic paths that depart from the PEA baseline. They are stress-testing tools in addition to the central single-path economic forecasts for sensitivity analysis and assessment of reasonableness. However, since no probability is provided for the prescribed PEA baseline itself, the range of results produced based on these scenarios should not be directly interpreted as a probability distribution or confidence interval for the Cash Flow NPV or the Economic Net Worth.

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Acknowledgement

ITDC acknowledges the authors and organizations responsible for the referenced reports, namely the 2022, 2016, and 2010 Actuarial Reviews, which have been instrumental in informing and enhancing our analysis. ITDC also confirms that acknowledgements do not imply that HUD personnel endorsed the contractor's assumptions, methods, or conclusions.

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Appendix A. Data Reconciliation

A1. Data Sources

In our analysis, we have relied on data from FHA, Moody's, and the OMB.

From FHA, we have received the following data:

1. Claims_601_Case_Data: used for the cash entry from note sales.
2. IDB: core case data; this table is derived based on fields from IDB_1, IDB_2, IDB_3 and the Decision_FICO_Score (one file each for 1975 – 2026)
3. Lossmit_Costs: derived table based on the Loss Mitigation table and IDB_1, used to obtain mitigation claim amounts.
4. Sams_case_record: used to determine the status of the conveyances, the capital income/expense amounts, the sales and REO expenses, and sales proceeds to FHA, where applicable
5. SFDW_Default_History: used to create period information related to default histories.
6. Fannie_FICO_pre2004: used for supplemental credit data.
7. Current_Status: table displaying the current status of each loan.

From OMB, we have received the Economic Assumptions for the PEA. The economic data that is included in the analysis is shown below:

8. HPI
9. Mortgage rates
10. Treasury rates
11. Unemployment rates

The following historical series are obtained from Moody's Economy.com

12. FHFA house price indices
13. BLS household unemployment rates
14. FHLMC mortgage rates
15. Census median home prices
16. Treasury yields

A2. Data Processing – Mortgage Level Modeling

Starting with the raw data, ITDC developed datasets for the mortgage-level transition and loss severity models. The first step in preparing the data for analysis was the processing of the economic data. Historical economic data were imported by quarter, additional data elements were derived, and data were joined to the FHA mortgage data.

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Once the economic data was prepared, core data processing occurred. We used mortgage-level data to reconstruct quarterly mortgage-event histories by relating mortgage origination information to other data reflecting events that occurred over the history of the mortgage. In the process of creating quarterly event histories, each mortgage contributed an observed transition for every quarter from origination up to and including the period of mortgage termination, or until the end of FY 2026, if the mortgage remained active.

A3. Data Reconciliation

Data reconciliation is a very important step to ensure the accuracy of the model and the estimation results. To reconcile the data processed with the data provided by FHA, we compared summaries of key data elements with the summaries provided by FHA. The summaries for the number of active mortgages, IIF, number of 90-day delinquencies, and the number of claims to date are shown in the following tables, Exhibits A-1 through A-4. Most of the data processed matches the FHA data totals, with differences concentrated in the FY 2026 cohort for active loans and IIF (Exhibits A-1 and A-2) and in the 90-day delinquency counts (Exhibit A-3). The reconciliation tables are based on data as of September 2026.

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Exhibit A-1: Data Reconciliation for Number of Active Loans[72]

Credit Subsidy Cohort	Federal Housing Administration (Data as of September 2026)	Independent Actuary	Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
1992	790	790	0	0.00%
1993	1,426	1,426	0	0.00%
1994	2,391	2,391	0	0.00%
1995	1,881	1,881	0	0.00%
1996	3,722	3,722	0	0.00%
1997	10,155	10,155	0	0.00%
1998	18,315	18,315	0	0.00%
1999	25,446	25,446	0	0.00%
2000	16,081	16,081	0	0.00%
2001	27,363	27,363	0	0.00%
2002	39,310	39,310	0	0.00%
2003	54,426	54,426	0	0.00%
2004	69,214	69,214	0	0.00%
2005	50,832	50,832	0	0.00%
2006	41,652	41,652	0	0.00%
2007	40,883	40,883	0	0.00%
2008	91,915	91,915	0	0.00%
2009	180,557	180,557	0	0.00%
2010	213,552	213,552	0	0.00%
2011	167,583	167,583	0	0.00%
2012	220,857	220,857	0	0.00%
2013	321,673	321,673	0	0.00%
2014	133,634	133,634	0	0.00%
2015	226,321	226,321	0	0.00%
2016	319,881	319,881	0	0.00%
2017	352,750	352,750	0	0.00%
2018	283,334	283,334	0	0.00%
2019	285,505	285,505	0	0.00%
2020	585,143	585,143	0	0.00%
2021	1,002,057	1,002,057	0	0.00%
2022	795,596	795,596	0	0.00%
2023	561,181	561,181	0	0.00%
2024	581,823	581,823	0	0.00%
2025	770,422	770,422	0	0.00%
2026	904,264	923,234	18,970	2.10%
Total	8,401,935	8,420,905	18,970	0.23%

[72] Source: SFDW.IDB_1.

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Exhibit A-2: Data Reconciliation for Insurance in Force ($ Million)

Credit Subsidy Cohort	Federal Housing Administration (Data as of September 2026)	Independent Actuary	Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
1992	$ 51	$ 51	$ 0	0.00%
1993	97	97	-	0.00%
1994	165	165	-	0.00%
1995	127	127	-	0.00%
1996	261	261	-	0.00%
1997	713	713	-	0.00%
1998	1,375	1,375	-	0.00%
1999	1,993	1,993	-	0.00%
2000	1,238	1,238	-	0.00%
2001	2,370	2,370	-	0.00%
2002	3,686	3,686	-	0.00%
2003	5,764	5,764	-	0.00%
2004	7,358	7,358	-	0.00%
2005	5,517	5,517	-	0.00%
2006	4,756	4,756	-	0.00%
2007	5,023	5,023	-	0.00%
2008	12,961	12,961	-	0.00%
2009	27,532	27,532	-	0.00%
2010	31,405	31,405	-	0.00%
2011	25,095	25,095	-	0.00%
2012	33,989	33,989	-	0.00%
2013	51,242	51,242	-	0.00%
2014	18,031	18,031	-	0.00%
2015	35,574	35,574	-	0.00%
2016	53,951	53,951	-	0.00%
2017	62,508	62,508	-	0.00%
2018	50,883	50,883	-	0.00%
2019	54,162	54,162	-	0.00%
2020	128,570	128,570	-	0.00%
2021	241,414	241,414	-	0.00%
2022	210,871	210,871	-	0.00%
2023	160,162	160,162	-	0.00%
2024	173,886	173,886	-	0.00%
2025	240,799	240,799	-	0.00%
2026	286,780	292,655	5,875	2.05%
Total	$ 1,940,306	$ 1,946,181	$ 5,875	0.30%

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Exhibit A-3: Data Reconciliation for Number of 90 Day Delinquencies

Credit Subsidy Cohort	Federal Housing Administration (Data as of September 2026)	Independent Actuary	Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
1992	76	77	1	1.32%
1993	121	124	3	2.48%
1994	198	203	5	2.53%
1995	196	201	5	2.55%
1996	363	373	10	2.75%
1997	617	645	28	4.54%
1998	885	919	34	3.84%
1999	1,371	1,401	30	2.19%
2000	1,030	1,062	32	3.11%
2001	1,490	1,554	64	4.30%
2002	1,934	2,010	76	3.93%
2003	2,402	2,482	80	3.33%
2004	3,442	3,540	98	2.85%
2005	2,859	2,977	118	4.13%
2006	2,526	2,623	97	3.84%
2007	2,964	3,062	98	3.31%
2008	6,799	7,022	223	3.28%
2009	9,283	9,605	322	3.47%
2010	8,807	9,107	300	3.41%
2011	6,110	6,290	180	2.95%
2012	6,549	6,729	180	2.75%
2013	7,836	8,052	216	2.76%
2014	6,555	6,730	175	2.67%
2015	11,531	11,768	237	2.06%
2016	16,495	16,875	380	2.30%
2017	21,024	21,415	391	1.86%
2018	23,725	24,205	480	2.02%
2019	27,348	27,871	523	1.91%
2020	38,632	39,347	715	1.85%
2021	64,092	65,199	1,107	1.73%
2022	75,906	77,540	1,634	2.15%
2023	60,854	62,268	1,414	2.32%
2024	52,158	53,270	1,112	2.13%
2025	44,964	45,560	596	1.33%
2026	11,273	11,385	112	0.99%
Total	522,415	533,491	11,076	2.12%

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Exhibit A-4: Data Reconciliation for Number of Claims to Date[73]

Credit Subsidy Cohort	Federal Housing Administration (Data as of September 2026)	Independent Actuary	Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
1992	36,809	36,809	0	0.00%
1993	52,350	52,350	0	0.00%
1994	66,024	66,024	0	0.00%
1995	44,763	44,763	0	0.00%
1996	63,639	63,639	0	0.00%
1997	60,094	60,094	0	0.00%
1998	67,845	67,845	0	0.00%
1999	84,734	84,734	0	0.00%
2000	71,706	71,706	0	0.00%
2001	85,977	85,977	0	0.00%
2002	91,321	91,321	0	0.00%
2003	92,129	92,129	0	0.00%
2004	117,185	117,185	0	0.00%
2005	93,294	93,294	0	0.00%
2006	95,692	95,692	0	0.00%
2007	108,052	108,052	0	0.00%
2008	227,764	227,764	0	0.00%
2009	231,107	231,107	0	0.00%
2010	119,503	119,503	0	0.00%
2011	49,861	49,861	0	0.00%
2012	31,715	31,715	0	0.00%
2013	30,156	30,156	0	0.00%
2014	18,176	18,176	0	0.00%
2015	18,983	18,983	0	0.00%
2016	17,794	17,794	0	0.00%
2017	14,898	14,898	0	0.00%
2018	11,065	11,065	0	0.00%
2019	7,502	7,502	0	0.00%
2020	5,404	5,404	0	0.00%
2021	6,739	6,739	0	0.00%
2022	9,623	9,623	0	0.00%
2023	7,122	7,122	0	0.00%
2024	3,194	3,194	0	0.00%
2025	779	779	0	0.00%
2026	10	10	0	0.00%
Total	2,043,009	2,043,009	0	0.00%

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Appendix B. Econometric Analysis of Mortgage Status Transitions and Terminations

B1. Model Specification and Estimation

B1.1. Specification of FHA Mortgage Status Transition and Termination Models

Actuarial Reviews before the FY 2010 analysis applied a competing risk framework based on multinomial logit models for quarterly conditional probabilities of prepayment and claim terminations. The general approach was based on the multinomial logit models reported by Calhoun and Deng (2002), initially developed for application to the Office of Federal Housing Enterprise Oversight (OFHEO) and Federal Housing Finance Agency (FHFA) risk-based capital adequacy tests for Fannie Mae and Freddie Mac. The multinomial model recognized the competing-risks nature of prepayment and claim terminations.

Starting in FY 2010, the modeling utilized FHA historical data on new 90-day default episodes on outstanding mortgages beginning with FY 1990 Q1 originations. The date at which a loan is first reported to be 90 or more days in arrears is used to define the start of a 90-day default episode, which continues until the default episode ends in a cure (i.e., becoming current once again) or the loan terminates through claim or prepayment. Under this approach, loans that start a quarter in 90 days or more delinquent are deemed to be in default status at the beginning of that quarter. Similarly, active loans not in a 90-day default episode at the beginning of the quarter are classified as current. Thus, a new default event (NDE) marking the entry into 90-day default status occurs during the quarter preceding the quarter the loan is first assigned to default status (i.e., begins the quarter in default status). Claims, prepayments, and streamlined refinancings comprise terminal events occurring within a quarter that result in the removal of the loan from the outstanding book of business at the start of the next quarter.

We have used the data on 90-day default episodes to develop and apply a greatly expanded status transition approach that extends the analysis to an eight-transition equation framework. This includes modeling transitions from current-to-default to default to current while accounting for the prior occurrence of any default or cure events. Indicators of prior default and prior mod-cure are included as additional explanatory variables in the transition models to further control for the initial conditions of each loan, but without having to expand the number of equations to be estimated. At the same time, it expands the state-space used in performing the actuarial calculations to better reflect differences in behavior associated with path dependence.

Exhibit B-1 summarizes the loan status transitions we modeled for the FY 2026 review. As described above, we track loans with and without prior default episodes and with and without prior self- or mod-cures as separate loan status categories to introduce path dependence into the analysis.

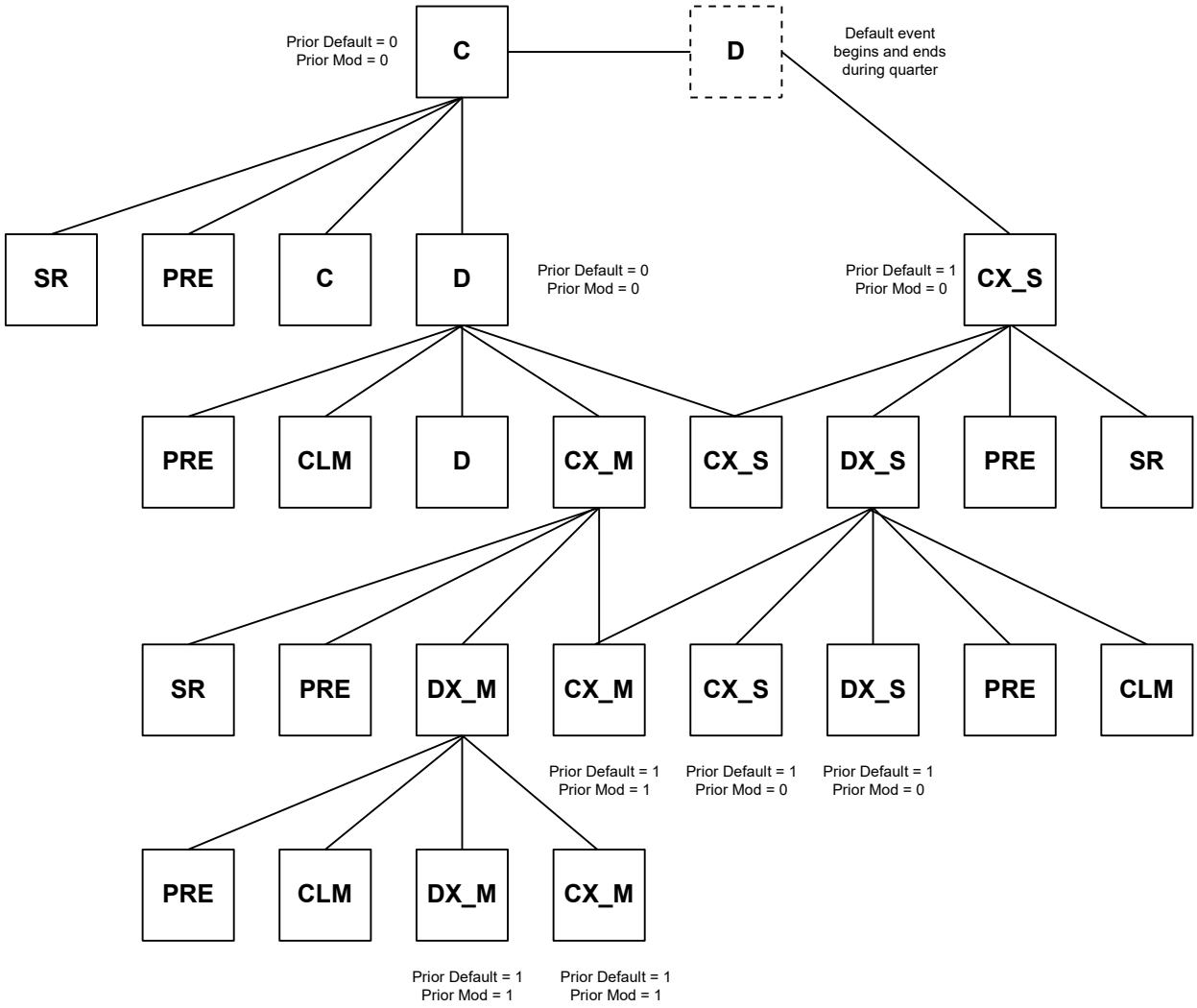
[73] Source: SFDW.IDB_1.

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We also account for duration dependence in transition rates by controlling for the duration of default for loans in default status and the duration of cure for loans in self-cure or mod-cure status.

Exhibit B-1 illustrates how the statuses emerge as loan proceeds period-by-period (row-by-row in the figure). However, it is not intended to show all possible transitions that could occur each time for readability purposes. For example, the figure shows the transition from C to D in rows 1 and 2, and then all possible transitions from D to D, D to CX_S, D to CX_M, D to CLM, and D to PRE in rows 2 and 3, but to preserve clarity does not subsequently repeat transitions from status D in rows 3 and 4. We do not repeat those transitions in the figure once we show the statuses to which any given status may lead.

Exhibit B-1: Loan Status Transitions Framework



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Next, we will discuss the interpretation of each loan status and the associated transitions represented in Exhibit B-1.

Initial Status Current C: Current with No Prior Default or Prior Mod

Loans originating in current status (C) can continue in current status (C), transition to default status (D), or terminate as a claim (CLM) or prepayment (PRE). In addition, we allow for the possibility that an initially current loan starts a 90-day default status during the quarter but self-cures to become current again before the start of the next quarter. These loans are considered to have transitioned to a new status, CX_S, defined as a loan with a prior default that has self-cured. We model these transitions as a distinct competing risk for loans initially in status C. Note that this is a by-product of using 90-day default to track non-performance. A monthly model would include separate transitions from C to D and D to CX_S. This highlights the critical distinction between a new default "event" (NDE) that starts a 90-day default episode and a current-to-default "transition," which corresponds to the change in status at the start of one quarter versus the status occupied at the start of the next quarter.

Initial Status D: Default with No Prior Default or Prior Mod

Loans initially in default status D, having no default or prior mod, return to cured status along two possible paths, depending on whether they self-cure (CX_S) or cure with a loan modification (CX_M). In addition, these loans may remain in default status (D) or terminate in a claim (CLM) or prepayment (PRE). Termination as a streamline refinance (SR) from default status (D) is not allowed under FHA guidelines.

Initial Status CX_S: Current with Prior Default and No Prior Mod-Cure

Loans that have self-cured (CX_S) may remain in that status, transition back to default as loans now having both a prior default and self-cure (DX_S), or terminate as prepayment (PRE) or streamline refinance (SR). We note that current loans with a prior default may be allowed to streamline refinance if there has been sufficient time since the default. We control statistical modeling for the length of time since the preceding default was cured. As discussed above, this status is somewhat unique in that it may be reached directly from current status C and default statuses D and DX_S. Once reached, the status is distinguished by having had a prior default episode.

Initial Status CX_M: Current with Prior Default and Prior Mod-Cure

Current loans that have had one or more prior defaults and at least one mod-cure (CX_M) may remain in that status, transition back to default (DX_M), or terminate as prepayment (PRE) or streamline refinance (SR). It is important to emphasize that our prior default and mod indicators

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correspond to "one or more prior defaults" and "one or more prior mods." Thus, CX_M does not necessarily describe the most recent cure type for loans with multiple cures status. Conversely, self-cure status (CX_S) only applies when all prior defaults are self-cured, and there has been no prior mod-cure.

Initial Status DX_S: Default with Prior Default and No Prior Mod-Cure

Loans in default having one or more prior defaults that all self-cured (DX_S) may remain in that status, cured again by either self-cure (CX_S) or mod-cure (CX_M), or terminate as prepayment (PRE) or claim (CLM). As noted above, for loans in status DX_S, we know that all prior cures were self-cures.

Graphic Illustrations of the Timeline of Status Transitions

Exhibit B-2 is provided to further illuminate how the default episode data contributes to identifying observed default and cure transitions for modeling loan performance through a series of examples.

Example 1 corresponds to the occurrence of a new default event (NDE) for a loan initially in current status C and the subsequent transition of the defaulted (D) loan to claim (CLM).

Example 2 shows a current loan with no prior default or loan mod (status C) transitioning to default (D), remaining in default status for one complete quarter, and then transitioning back to current status (CX_M) after a loan modification.

Example 3 starts with a previously defaulted and self-cured loan spending four quarters in current status (CX_S), defaulting again, and remaining in default status DX_S for one quarter before terminating in prepayment (PRE).

Example 4 has a recently mod-cured loan in current status (CX_M) defaulting again and remaining in default status DX_M until the historical sample ends. This results in the censoring of that default episode, so we do not yet know how long the episode will continue or the ultimate status of the loan.

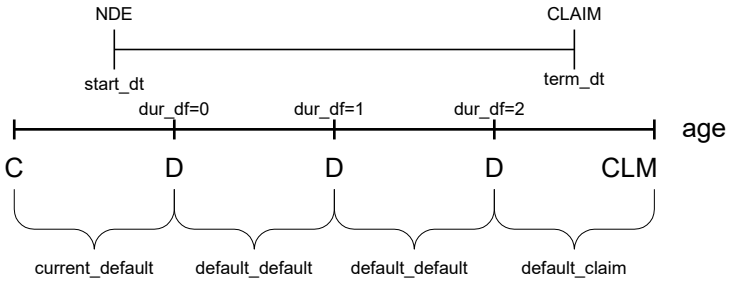
Example 5 includes the case of a current loan with no prior default or prior mod (C) entering 90-day default status (NDE) but quickly self-curing to return to current status (CX_S) by the end of the same quarter.

These examples are intended to illustrate the observational scheme used to define the loan status transition framework in Exhibit B-1 and do not exhaust all the possible loan transitions one might observe or the varying timing of these transitions. They highlight the distinction between transitions associated with period-to-period changes in loan status and loan termination, either through prepayment or claim, which ends the sequence of transitions for an individual loan.

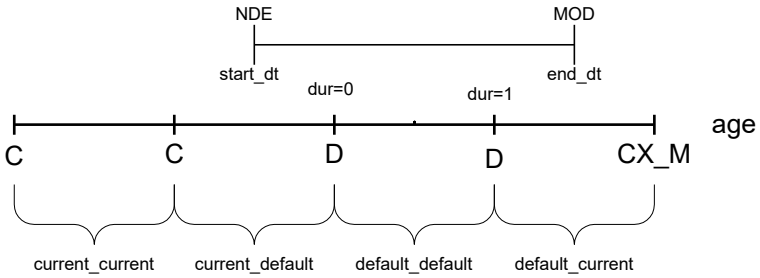
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Exhibit B-2: Examples of Loan Transition Types

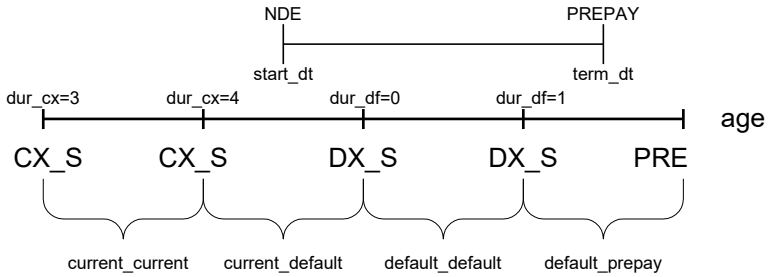
Example 1 : C to D / D to CLM



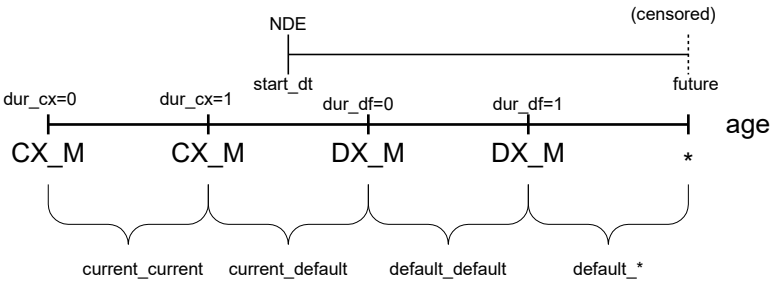
Example 2 : C to D / D to CX_M



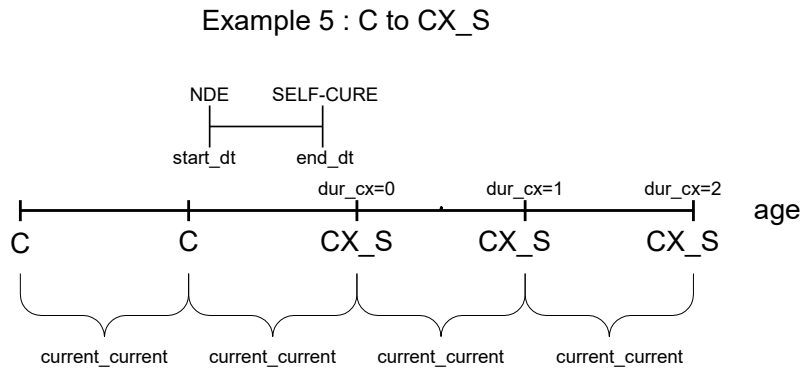
Example 3: CX_S to DX_S / DX_S to PRE



Example 4: CX_M to DX_M / DX_M to Censored



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B1.2. Specification of Multinomial Logit Models

The status transition framework results in two sets of competing risks: one for loans in current status and one for loans in default status. For loans current at the start of the quarter, the competing risks are prepayment through Non-Streamlined Refinance (NSR) or Streamlined Refinance (SR), transition to default status, or remaining current (either without any modification or modified and remaining current within the same quarter). The competing risks for loans in default status at the start of the quarter are claim, prepayment, or transition to current status through self-cure, modification, or continuing in the default state. This gives rise to 10 possible transitions and their corresponding probabilities (i.e., 5 transitions each for transitions from current and default) requiring estimation for 8 independent binomial logits (i.e., 4 binomial logits each for transitions from current and default). Therefore, across the six loan products, there are 48 logit models.

The starting point for specification of the loan performance models is multinomial logit models of quarterly conditional probabilities for transitions from current to prepayment (streamlined or non-streamlined refinance), default, or remaining current, and for transitions from default to claim, prepayment, back to current (self-cured or modified cure), or continuing in the default state. The corresponding mathematical expressions for the conditional probabilities for loans starting in current status in quarter t and transitioning to prepay, default, or remaining current in the subsequent quarter $t + 1$ are given by:

$$\boldsymbol{B}_{\boldsymbol{DEF}}^{\boldsymbol{CUR}} = \left(\boldsymbol{\beta}_{\boldsymbol{0}}^{\boldsymbol{CUR_DEF}}, \boldsymbol{\beta}_{\boldsymbol{1}}^{\boldsymbol{CUR_DEF}}, \ldots, \boldsymbol{\beta}_{\boldsymbol{k}}^{\boldsymbol{CUR_DEF}}\right); \; \boldsymbol{X} = (\boldsymbol{1}_{\boldsymbol{n}}, \boldsymbol{X}_{\boldsymbol{1}}, \ldots, \boldsymbol{X}_{\boldsymbol{k}})^{\boldsymbol{T}}$$

Where $\boldsymbol{X}_{\boldsymbol{i}} = (\boldsymbol{X}_{\boldsymbol{i1}}, \boldsymbol{X}_{\boldsymbol{i2}}, \ldots, \boldsymbol{X}_{\boldsymbol{in}})^{\boldsymbol{T}}$, n : number of observations; X = Extended design matrix of explanatory variables.

$$\boldsymbol{B} = \left\{\boldsymbol{B}_{\boldsymbol{DEF}}^{\boldsymbol{CUR}}, \boldsymbol{B}_{\boldsymbol{PRE_NSR}}^{\boldsymbol{CUR}}, \boldsymbol{B}_{\boldsymbol{PRE_SR}}^{\boldsymbol{CUR}}, \boldsymbol{B}_{\boldsymbol{CUR_X}}^{\boldsymbol{CUR}}\right\}$$

Here, the transition *CUR_CUR* is the baseline category.

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In general, $\boldsymbol{B_j^i} = \left(\boldsymbol{\beta_0^{i_j}}, \boldsymbol{\beta_1^{i_j}}, \ldots, \boldsymbol{\beta_k^{i_j}}\right)$where *i_j* in the superscript denotes the transition from state *i* to state *j*.

Here, *i* is *CUR* and $\boldsymbol{j} \in \{DEF, PRE_NSR, PRE_SR, CUR_X\}$

It is to be noted that *CLM, CUR_S, and CUR_M* will be discussed later in the section when all transitions from the default state will be dealt with. Also, the vector *X* is different for loans transitioning from the current state and the default state.

$$\boldsymbol{\pi_{DEF}^{CUR}(t \mid X) = \frac{exp(B_{DEF}^{CUR} X)}{1 + \sum_{\forall B} exp(BX)}} \quad (1a)$$

$$\boldsymbol{\pi_{CUR_X}^{CUR}(t \mid X) = \frac{exp(B_{CUR_X}^{CUR} X)}{1 + \sum_{\forall B} exp(BX)}} \quad (1b)$$

$$\boldsymbol{\pi_{PRE_NSR}^{CUR}(t \mid X) = \frac{exp(B_{PRE_NSR}^{CUR} X)}{1 + \sum_{\forall B} exp(BX)}} \quad (1c)$$

$$\boldsymbol{\pi_{PRE_SR}^{CUR}(t \mid X) = \frac{exp(B_{PRE_SR}^{CUR} X)}{1 + \sum_{\forall B} exp(BX)}} \quad (1d)$$

Note: The probability of the baseline category has not been calculated, as it is just one minus the rest of the probabilities. This has been followed for both types of loans that started from current and default states as the initial state.

The corresponding equations for loans started in default status in quarter *t* and transitioning to claim, prepay, current with self-cure, current with mod-cure, or remaining in default, respectively, in the subsequent quarter *t* + 1 are given by:

Here $\boldsymbol{B} = \left\{\boldsymbol{B_{PRE}^{DEF}}, \boldsymbol{B_{CUR_S}^{DEF}}, \boldsymbol{B_{CUR_M}^{DEF}}, \boldsymbol{B_{CLM}^{DEF}}\right\}$, and *DEF_DEF* is the baseline category.

$$\boldsymbol{\pi_{PRE}^{DEF}(t \mid X) = \frac{exp(B_{PRE}^{DEF} X)}{1 + \sum_{\forall B} exp(BX)}} \quad (2a)$$

$$\boldsymbol{\pi_{CUR_S}^{DEF}(t \mid X) = \frac{exp(B_{CUR_S}^{DEF} X)}{1 + \sum_{\forall B} exp(BX)}} \quad (2b)$$

$$\boldsymbol{\pi_{CUR_M}^{DEF}(t \mid X) = \frac{exp(B_{CUR_M}^{DEF} X)}{1 + \sum_{\forall B} exp(BX)}} \quad (2c)$$

$$\boldsymbol{\pi_{CLM}^{DEF}(t \mid X) = \frac{exp(B_{CLM}^{DEF} X)}{1 + \sum_{\forall B} exp(BX)}} \quad (2d)$$

The coefficient vectors $\boldsymbol{B_j^i}$ are the unknown parameters to be estimated for the multinomial logit model for initial status *i* indicating current (CUR) or default (DEF) and ending status *j* indicating prepayment (PRE_NSR or PRE_SR), default (DEF), or current (CUR) when *i* is current, and *j* is prepayment (PRE), current (CUR_S or CUR_M), or claim (CLM) when *i* is default. It is important to note that *j* is not CUR when *i* is CUR and j is not DEF when *i* is DEF, because CUR_CUR and

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DEF_DEF are baseline categories for transitions starting from CUR and DEF, respectively. We denote by *X* the vector of explanatory variables for the conditional probability of transitioning from starting status CUR and DEF. Some components of *X* are constant over the life of the loan and therefore do not vary with time. The "dynamic" or time-varying explanatory components (variables) of *X* include mortgage age, the duration of the default episode for loans in default status, and the duration of cure for current loans with a prior default. They also include an array of time-varying economic factors that predict default, prepay, cure, and claim, which will be described in detail below.

As illustrated in Exhibit B-1, for the FY 2026 review actuarial projections, we ultimately stratify initial current status (CUR) by whether the loan has had a prior default or prior mod (or both). As discussed further below, the econometric equations (1a) - (1d) and (3.1a) - (3.2d) for loans in current statuses (C, CX_S, CX_M) presented above were jointly estimated using pooled samples of loans with and without prior default episodes and prior loan modifications, and the explanatory variables in *X* include indicators (dummy variables) for prior events.

B1.3. Computation of Multinomial Logit Probabilities from Binomial Logit Parameters

As in prior-year reviews, we apply an approach first proposed by Begg and Gray (1984), in which we estimate separate independent binomial logit models for each possible transition type and then recombine the estimates to derive multinomial logit probabilities. Begg and Gray (1984) applied Bayes' Law for conditional probabilities to demonstrate that the values of parameters *B* estimated from separate independent binomial logit (BNL) models are parametrically equivalent to those for the corresponding multinomial logit (MNL). Here we have 4 BNL models for loans in current status at the start of quarter *t*; the pairs in each of the 4 BNLs are (CUR_DEF, CUR_CUR), (CUR_PRE_NSR, CUR_CUR), (CUR_PRE_SR, CUR_CUR), and (CUR_CUR_X, CUR_CUR). Here, *C* in the equations below is equivalent to *B* in MNL.

Hence,

For Binomial Model 1, we have

$$\boldsymbol{\Pi}_{\boldsymbol{DEF}}^{\boldsymbol{CUR}}(\boldsymbol{t} \mid \boldsymbol{X}) = \frac{\boldsymbol{exp}(\boldsymbol{C}_{\boldsymbol{DEF}}^{\boldsymbol{CUR}}\boldsymbol{X})}{\mathbf{1} + \boldsymbol{exp}(\boldsymbol{C}_{\boldsymbol{DEF}}^{\boldsymbol{CUR}}\boldsymbol{X})} \qquad (3.1a)$$

$$\boldsymbol{\Pi}_{\boldsymbol{CUR}}^{\boldsymbol{CUR}}(\boldsymbol{t} \mid \boldsymbol{X}) = \frac{\mathbf{1}}{\mathbf{1} + \boldsymbol{exp}(\boldsymbol{C}_{\boldsymbol{DEF}}^{\boldsymbol{CUR}}\boldsymbol{X})} \qquad (3.2a)$$

The $\boldsymbol{C}_{\boldsymbol{DEF}}^{\boldsymbol{CUR}}$ computed from this binomial model will be substituted for $\boldsymbol{B}_{\boldsymbol{DEF}}^{\boldsymbol{CUR}}$ in the multinomial logit model in (1a)

For Binomial Model 2, we have

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$$\boldsymbol{\Pi}^{\boldsymbol{CUR}}_{\boldsymbol{CUR_X}}(\boldsymbol{t} \mid \boldsymbol{X}) = \frac{\boldsymbol{exp}(\boldsymbol{C}^{\boldsymbol{CUR}}_{\boldsymbol{CUR_X}}\boldsymbol{X})}{\mathbf{1} + \boldsymbol{exp}(\boldsymbol{C}^{\boldsymbol{CUR}}_{\boldsymbol{CUR_X}}\boldsymbol{X})} \quad (3.1b)$$

$$\boldsymbol{\Pi}^{\boldsymbol{CUR}}_{\boldsymbol{CUR}}(\boldsymbol{t} \mid \boldsymbol{X}) = \frac{\mathbf{1}}{\mathbf{1} + \boldsymbol{exp}(\boldsymbol{C}^{\boldsymbol{CUR}}_{\boldsymbol{CUR_X}}\boldsymbol{X})} \quad (3.2b)$$

The $\boldsymbol{C}^{\boldsymbol{CUR}}_{\boldsymbol{CUR_X}}$ computed from this binomial model will be substituted for $\boldsymbol{B}^{\boldsymbol{CUR}}_{\boldsymbol{CUR_X}}$ in the multinomial logit model in (1b)

For Binomial Model 3, we have

$$\boldsymbol{\Pi}^{\boldsymbol{CUR}}_{\boldsymbol{PRE_NSR}}(\boldsymbol{t} \mid \boldsymbol{X}) = \frac{\boldsymbol{exp}(\boldsymbol{C}^{\boldsymbol{CUR}}_{\boldsymbol{PRE_NSR}}\boldsymbol{X})}{\mathbf{1} + \boldsymbol{exp}(\boldsymbol{C}^{\boldsymbol{CUR}}_{\boldsymbol{PRE_NSR}}\boldsymbol{X})} \quad (3.1c)$$

$$\boldsymbol{\Pi}^{\boldsymbol{CUR}}_{\boldsymbol{CUR}}(\boldsymbol{t} \mid \boldsymbol{X}) = \frac{\mathbf{1}}{\mathbf{1} + \boldsymbol{exp}(\boldsymbol{C}^{\boldsymbol{CUR}}_{\boldsymbol{PRE_NSR}}\boldsymbol{X})} \quad (3.2c)$$

The $\boldsymbol{C}^{\boldsymbol{CUR}}_{\boldsymbol{PRE_NSR}}$ computed from this binomial model will be substituted for $\boldsymbol{B}^{\boldsymbol{CUR}}_{\boldsymbol{PRE_NSR}}$ in the multinomial logit model in (1c)

For Binomial Model 4, we have

$$\boldsymbol{\Pi}^{\boldsymbol{CUR}}_{\boldsymbol{PRE_SR}}(\boldsymbol{t} \mid \boldsymbol{X}) = \frac{\boldsymbol{exp}(\boldsymbol{C}^{\boldsymbol{CUR}}_{\boldsymbol{PRE_SR}}\boldsymbol{X})}{\mathbf{1} + \boldsymbol{exp}(\boldsymbol{C}^{\boldsymbol{CUR}}_{\boldsymbol{PRE_SR}}\boldsymbol{X})} \quad (3.1d)$$

$$\boldsymbol{\Pi}^{\boldsymbol{CUR}}_{\boldsymbol{CUR}}(\boldsymbol{t} \mid \boldsymbol{X}) = \frac{\mathbf{1}}{\mathbf{1} + \boldsymbol{exp}(\boldsymbol{C}^{\boldsymbol{CUR}}_{\boldsymbol{PRE_SR}}\boldsymbol{X})} \quad (3.2d)$$

The $\boldsymbol{C}^{\boldsymbol{CUR}}_{\boldsymbol{PRE_SR}}$ computed from this binomial model will be substituted for $\boldsymbol{B}^{\boldsymbol{CUR}}_{\boldsymbol{PRE_SR}}$ in the multinomial logit model in (1d)

We used an uppercase $\boldsymbol{\Pi}$ to indicate the binomial logit probability and distinguish it from the lower-case π used above to denote the multinomial logit probabilities. Here, again, we have 4 BNL models for loans in default status at the start of quarter *t*; the pair in each of the 4 BNLs is (DEF_PRE, DEF_DEF), (DEF_CUR_S, DEF_DEF), (DEF_CUR_M, DEF_DEF), and (DEF_CLM, DEF_DEF). The corresponding binomial probabilities for transitions from default status to claim, prepayment, current (self-cure or modified cure), or remaining in default status are given by:

For Binomial Model 5, we have

$$\boldsymbol{\Pi}^{\boldsymbol{DEF}}_{\boldsymbol{PRE}}(\boldsymbol{t} \mid \boldsymbol{X}) = \frac{\boldsymbol{exp}(\boldsymbol{C}^{\boldsymbol{DEF}}_{\boldsymbol{PRE}}\boldsymbol{X})}{\mathbf{1} + \boldsymbol{exp}(\boldsymbol{C}^{\boldsymbol{DEF}}_{\boldsymbol{PRE}}\boldsymbol{X})} \quad (4.1a)$$

$$\boldsymbol{\Pi}^{\boldsymbol{DEF}}_{\boldsymbol{DEF}}(\boldsymbol{t} \mid \boldsymbol{X}) = \frac{\mathbf{1}}{\mathbf{1} + \boldsymbol{exp}(\boldsymbol{C}^{\boldsymbol{DEF}}_{\boldsymbol{PRE}}\boldsymbol{X})} \quad (4.2a)$$

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The $\boldsymbol{C_{PRE}^{DEF}}$ computed from this binomial model will be substituted for $\boldsymbol{B_{PRE}^{DEF}}$ in the multinomial logit model in (2a)

For Binomial Model 6, we have

$$\boldsymbol{\Pi_{CUR_S}^{DEF}(t \mid X) = \frac{exp(C_{CUR_S}^{DEF} X)}{1 + exp(C_{CUR_S}^{DEF} X)}} \quad (4.1b)$$

$$\boldsymbol{\Pi_{DEF}^{DEF}(t \mid X) = \frac{1}{1 + exp(C_{CUR_S}^{DEF} X)}} \quad (4.2b)$$

The $\boldsymbol{C_{CUR_S}^{DEF}}$ computed from this binomial model will be substituted for $\boldsymbol{B_{CUR_S}^{DEF}}$ in the multinomial logit model in (2b)

For Binomial Model 7, we have

$$\boldsymbol{\Pi_{CUR_M}^{DEF}(t \mid X) = \frac{exp(C_{CUR_M}^{DEF} X)}{1 + exp(C_{CUR_M}^{DEF} X)}} \quad (4.1c)$$

$$\boldsymbol{\Pi_{DEF}^{DEF}(t \mid X) = \frac{1}{1 + exp(C_{CUR_M}^{DEF} X)}} \quad (4.2c)$$

The $\boldsymbol{C_{CUR_M}^{DEF}}$ computed from this binomial model will be substituted for $\boldsymbol{B_{CUR_M}^{DEF}}$ in the multinomial logit model in (2c)

For Binomial Model 8, we have

$$\boldsymbol{\Pi_{CLM}^{DEF}(t \mid X) = \frac{exp(C_{CLM}^{DEF} X)}{1 + exp(C_{CLM}^{DEF} X)}} \quad (4.1d)$$

$$\boldsymbol{\Pi_{DEF}^{DEF}(t \mid X) = \frac{1}{1 + exp(C_{CLM}^{DEF} X)}} \quad (4.2d)$$

The $\boldsymbol{C_{CLM}^{DEF}}$ computed from this binomial model will be substituted for $\boldsymbol{B_{CLM}^{DEF}}$ in the multinomial logit model in (2d)

This way, the estimation of the binomial logit (BNL) probabilities in (3.1a)-(3.2d) and (4.1a)-(4.2d) produces estimates of the parameters of each of the elements of set *C* that can be substituted directly into equations (1a)-(1d) and (2a)-(2d) to derive the corresponding multinomial logit (MNL) probabilities.

B1.4. Loan Transition and Event Data

We used loan-level data to construct quarterly loan event histories by combining mortgage origination information with contemporaneous values of time-dependent factors. In the process of creating quarterly event histories, each loan contributed an additional observed "transition" for every quarter from origination up to and including the period of mortgage termination, or until the last time of the historical data sample. The term "transition" is used here to refer to any situation

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in which a loan remains active and the loan status is observed at the start of the next quarter, or in which terminal claim or prepayment events are observed in the current quarter.

The FHA single-family data warehouse (SFDW) records each loan for which insurance was endorsed and includes additional data fields updating the timing of changes in the status of the loan. The historical data used in model estimation for this Actuarial Review are from an extract from FHA's database as of September 30, 2026.

B1.5. Data Samples

A full 100-percent sample of loan-level data from the FHA single-family data warehouse was extracted for the FY 2026 analysis. This produced a very large sample of approximately 42 million single-family loans originating between the first quarter of FY 1975 and the fourth quarter of FY 2026. While our analysis of economic net worth will ultimately focus on those loans originated since FY 1992 that continue as active MMI Fund exposures, we include data as far back as FY 1975 to support the process of linking FHA streamline refinance (SR) loans to information associated with the original fully underwritten mortgage to the same borrower. Model estimation is based on data samples from the more recent FY 1992 through FY 2026 cohorts comprising those that impact the current economic net worth of the MMI Fund. Approximately 35 million loans have been endorsed for insurance during those years. For estimation, these data were used to generate quarterly loan-level event histories extending to the age at which the loan would mature based on the original term of the loan product or the end of the historical sample period. Forecasting the future performance of loans still active at the end of FY 2026 extends to 40 years after each loan's origination (through FY 2066 for the FY 2026 cohort) to explicitly incorporate extended term modifications where the term to maturity is extended to 40 years.

Estimation and forecasting were undertaken separately for each of the following six FHA mortgage product types:

Product 1	FRM30	Fixed-rate 30-year fully underwritten purchase and refinance
Product 2	FRM15	Fixed-rate 15-year fully underwritten purchase and refinance
Product 3	ARM	Adjustable-rate fully underwritten purchase and refinance
Product 4	FRM30 SR	Fixed-rate 30-year streamlined refinance
Product 5	FRM15 SR	Fixed-rate 15-year streamlined refinance
Product 6	ARM SR	Adjustable-rate streamlined refinance

B1.5.1. Random Sampling for Estimation and Validation

The following random sampling rates were applied to the panel data for each product to produce the data for estimation and validation:

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Product 1	FRM30	10 percent
Product 2	FRM15	100 percent
Product 3	ARM	100 percent
Product 4	FRM30_SR	100 percent
Product 5	FRM15_SR	100 percent
Product 6	ARM_SR	100 percent

The samples for each product were then evenly split by case number into estimation samples (50%) and validation samples (50%) to ensure there are no overlapping loan records in estimation and validation panel data samples.

The above sampling rates were motivated by fully utilizing historical data to the extent feasible, while recognizing that incorporation of the full Product 1 population was not necessary to achieve sufficient classification accuracy as per AUC scores and cross-validation performance as discussed below.

Proportional sampling (i.e., proportionate stratification) was utilized for Product 1 to ensure sample representation of loans using alternative credit scores in proportion to the population. In general, FHA loan data include significant numbers of loans across all product types to support random sampling. There are two main channels through which alternatives to random sampling affected prior year reviews: (1) the use of alternative sources of credit score data for FHA loans with missing credit scores (primarily before 2004); and (2) over-sampling of default events and under-sampling of more prevalent non-default events.

The use of alternative sources of credit score data from the 1990s and early 2000s from a study conducted by UNICON Corporation raised issues of bias that could result from over-sampling of defaulted loans. Further oversampling of these loans to increase the share of loans having usable credit scores further magnified the potential bias issue. However, research by Manski and Lerman (1977) and others indicates that the impact of stratified sampling bias in logit models is limited to estimates of the intercept terms. In a stratified sample, it is possible to control stratification impacts on coefficient estimates by including an indicator (0/1 dummy) for these loans (i.e., an indicator for the source of credit score).

Regarding over-sampling of quarterly default versus non-default events, we have not implemented that approach as we found that all samples contained sufficient representation of transition events to achieve acceptable AUC scores and cross-validation results.

B1.5.2. Random Sampling for Forecasting

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Smaller samples are applied when forecasting the larger product types due to the significant expansion of the state-space when tracking prior default and prior mod status and the durations of default episodes and duration of cures. At the forecasting stage, sample size sufficiency is reduced as the parameters are estimated and fixed, and the main concern becomes representative coverage and weighting of all loan types and explanatory variables. Having multiple duplicates of more-or-less identical loans does not improve the accuracy of the forecasted performance of those loans to the extent that additional data improves the estimation of model parameters. Forecasting samples are therefore developed using stratified samples designed to ensure representativeness by cohort, LTV, and FICO.

B1.5.3. Sample Periods for Transition Model Estimation

We used loans originated from FY 1992 through FY 2026 to estimate the status transition models. This covers the loan cohorts for which complete data were available on new 90-day default episodes. Loans whose amortization began in FY 2006 Q2 through FY 2007 Q3 were excluded from the estimation of the current-to-default transition and of all transitions from default status, due to data issues associated with changes in FHA's default episode tracking system during that period.

B2. Explanatory Variables

Four main categories of explanatory variables were employed:

1. Fixed initial loan characteristics including mortgage product type, purpose of loan (home purchase or refinance), amortization term, origination year and quarter, original loan-to-value (LTV) ratio, original loan amount, original mortgage interest rate, mortgage rate spread to market at origination, and relative house price level by geographic location (MSA, state, Census division).

2. Fixed initial borrower characteristics including borrower credit score, source of down payment assistance, and first-time buyer indicator.

3. Dynamic variables based entirely on loan information, including mortgage age, duration of default, duration of cure, whether a loan has had a prior default episode, whether a loan has had a prior loan modification, season of the year, and scheduled amortization of the loan balance.

4. Dynamic variables derived by combining loan information with external economic data including interest rates and house price indexes to compute refinance incentives, current LTV, the relative spread of the coupon rate to market, the slope of the yield curve, and changes in household unemployment rates. A dynamic model explaining mortgage

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decisions incorporating house price, inflation, and interest rate risk can be found in Campbell and Cocco (2015).

In some cases, the two types of dynamic variables are combined, as in the case of adjustable-rate mortgage (ARM) loans, where external data on changes in one-year Treasury yields are used to update the original coupon rates and payment amounts by standard FHA loan contract features. This in turn affects the amortization schedules of the loans.

Goodness-of-fit and statistical significance metrics included in Appendix H demonstrate that specifications for all 48 models sufficiently explain variation in transition behavior across products and default status, a conclusion supported by the validation testing reported in Appendix BSection B6.

B2.1. Fixed Initial Loan Characteristics

B2.1.1. Mortgage Product Types

As described above, separate statistical models were estimated for the following six FHA mortgage product types:

Product 1	FRM30	Fixed-rate 30-year fully underwritten purchase and refinance
Product 2	FRM15	Fixed-rate 15-year fully underwritten purchase and refinance
Product 3	ARM	Adjustable-rate fully underwritten purchase and refinance
Product 4	FRM30_SR	Fixed-rate 30-year streamlined refinance
Product 5	FRM15_SR	Fixed-rate 15-year streamlined refinance
Product 6	ARM_SR	Adjustable-rate streamlined refinance

B2.1.2. Loan-to-Value Ratio at Origination

Initial loan-to-value (LTV) is recorded in FHA's data warehouse for fully underwritten mortgages and SR loans with required appraisals. If available, these values are used directly. For SR loans without required appraisals, we attempt to apply the original LTV from the original fully underwritten mortgage (FUWM) to the same borrower. The FUWM is identified through a complicated matching process.

B2.1.3. Relative Loan Size

Relative loan size is computed as the size of a borrower's loan relative to the average loan for the same product within the same geographic location. Relative loan size is an indicator of a borrower's position in the local income and house price distributions and historically has been associated with higher FHA claim rates at both the lower and upper range of values.

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B2.1.4. Relative House Price

The relative house price variable was computed by comparing the original purchase price of the house underlying a particular mortgage with the Census median house value in the same period and location. We used Census median house price data at the county and Metropolitan Statistical Area (MSA) level obtained from Moody's.

B2.1.5. Spread at Origination

Spread-at-origination (SATO) is the relative difference between the original coupon rate and the average mortgage offer rate at the time of origination. It is an indicator of the relative credit qualifications of the individual borrower, as higher values of SATO are associated with higher lending rates to less creditworthy borrowers. Alternatively, lower values of SATO may indicate the willingness and ability of a borrower to pay more at closing to obtain a lower rate, thereby reducing their monthly payment burden and improving their ability to make continued payments on the mortgage and avoid default.

B2.1.6. Property Type

The majority of mortgages in the FHA single-family portfolio are single-unit properties, but other owner-occupied property types are also eligible for financing, including 2-unit (duplex) properties and 1-4-unit rental properties. We include dummy variables to control for these two property types and differences in their loan performance relative to that for 1-unit properties. We also include an indicator of whether a property is a condominium unit.

B2.1.7. Judicial Foreclosure State Indicators

The duration of default and foreclosure is likely to be longer for loans originating in states providing borrowers with a right to judicial foreclosure proceedings. We include an indicator of judicial foreclosure taking the value 1 for loans originated in judicial foreclosure states and 0 otherwise. We find that this variable has a negative impact on default-to-claim probabilities for all products except ARM SR, where it is omitted from the specification. This suggests borrowers are slower to transition from default to claim, as expected, in states providing for the longer judicial foreclosure process.

B2.1.8. Deficiency Judgment State Indicators

We expect that lenders having the option to seek personal deficiency judgments against borrowers following foreclosure will discourage borrowers from defaulting. Some states that allow deficiency judgments on consumer and business loans may prohibit them in the case of residential foreclosures on mortgages that were secured by residential properties. Signs on current-to-default and default-to-claim transitions are mostly, although not always, negative.

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B2.2. Fixed Initial Borrower Characteristics

B2.2.1. First-Time Buyer

An indicator for first-time buyers is included to distinguish these buyers from more experienced and seasoned buyers. The FHA single-family was originally developed to support first-time buyers with lower down payments. The program has evolved over the years to include a broader cross-section of borrowers, particularly during the mortgage crisis years of 2007-2010, as emergency provisions were implemented to expand the availability of FHA-insured loans following the implosion of the subprime market and withdrawal of several private mortgage insurance providers.

B2.2.2. Source of Down Payment Assistance

As documented in the FY 2006 and FY 2007 Reviews, the FHA single-family program experienced a significant increase in the use of down payment assistance from relatives, non-profit organizations, and government programs. Loans to borrowers utilizing down payment assistance from non-profit organizations have been observed to generate significantly higher claim rates. Although this particular form of down payment assistance is now prohibited, it is still necessary to control its impact on historical loan performance. Following the approach first applied in the FY 2006 Review, we have included a series of indicators to control the use of different types of down payment assistance by FHA borrowers. Through the process of linking streamlined refinance loans with the original fully underwritten FHA mortgages to the same borrowers, we have developed a parallel indicator of down payment assistance received on the prior fully underwritten mortgages to apply when estimating the transition models for streamlined refinance loans. Thus, a streamline refinance loan originated in FY 2010, FY 2011, and the next few years may be issued to a borrower that was a prior recipient of down payment assistance, and the type of prior down payment assistance is controlled for in the loan status transition estimates for these loans. For this reason, some of the negative impacts of the earlier loans may carry over and impact the economic net worth of outstanding streamline refinance loans.

B2.2.3. Borrower Credit Scores

Our primary source of credit scores on FHA single-family mortgages is those collected by FHA since 2004 and available from the SFDW. We supplement these data with additional credit score information collected through internal studies conducted for HUD that retrospectively obtained scores for FHA loan applications. The studies were conducted by UNICON Corporation and Fannie Mae. The UNICON study included credit scores collected for a sample of FHA applications from FY 1992, FY 1994, and FY 1996, and subsequently extended to loan applications during FY 1997 through FY 2004. This set of credit score data is useful because these loans have existed for many years and provide valuable historical delinquency, claim, and prepayment performance information. The Fannie Mae data provides additional credit score coverage for the loans originated from FY 2000 to FY 2004. There is surprisingly little overlap between the two sources, resulting in substantial credit score coverage during these years. Together, the two data sources

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provide credit score information on hundreds of thousands of loans during a period in which none was collected by FHA. There are some limitations to the data. First, the data does not provide credit score data on all FHA loans originated during those years, so missing data remains an issue. Second, the data were initially collected for policy research purposes and were not randomly selected from all FHA loan applications. For example, there was an over-sampling of early-default loans among applications from FY 1997 through FY 2004. As a standalone dataset, these loans are a stratified sample. This does not translate directly to our analysis, as our loan samples are randomly selected based on all endorsed FHA loans. However, use of the data does imply that scores are not assigned to all FHA loans, and those that are assigned are not randomly selected. We address these issues by controlling for the source of credit score data among our three sources (FHA, UNICON, Fannie Mae) and whether credit score remains missing, as discussed under Section B1.5.1. Random Sampling for Estimation and Validation. These three sets of FICO data represent the most reliable sources of borrower credit history information available for historical FHA-endorsed loans before FY 2005, when FHA credit scores became available for almost all loans.

Through the process of linking streamlined refinance loans to the original fully underwritten FHA mortgages to the same borrowers, we developed a parallel set of FICO score indicators for streamlined refinance loans and included these as explanatory variables when estimating the transition probability models for these products.

B2.2.4. Debt-to-Income (DTI) Ratio

The ratio of mortgage debt to income is a standard underwriting measure (front-end ratio) of borrower credit capacity and ability that is reported for individual borrowers in the SFDW. DTI ratio is a static measure collected during the loan application process.

B3. Dynamic Variables Based on Loan Information

B3.1. Mortgage Age

Mortgage age is an important predictor of mortgage performance. Conditional default, cure, claim, and prepayment rates tend to be non-linear over age even when many other factors are controlled statistically.[74] A flexible and efficient way to represent these non-linearities is through the application of piecewise linear spline functions. These represent the age function as a sequence of linear segments with different slopes but connecting exactly at a sequence of specified age values. This concept is illustrated for a 6-segment age function in Exhibit B-3.

[74] Except for age, there are several other loan characteristics and borrower behaviors presenting non-linear influence on mortgage status transitions (Sadhwani, Giesecke, and Sirignano, 2021). We apply the same piece-wise linear spline method wherever appropriate.

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Exhibit B-3: Example of a 6-Segment Mortgage Age Function

$$\text{age1} = \begin{Bmatrix} \text{AGE} & \text{if AGE} \leq \text{k}_1 \\ \boldsymbol{k_1} & \text{if AGE} > \text{k}_1 \end{Bmatrix}$$

$$\text{age2} = \begin{Bmatrix} \boldsymbol{0} & \text{if AGE} \leq \text{k}_1 \\ \text{AGE-k}_1 & \text{if k}_1 < \text{AGE} \leq \text{k}_2 \\ \boldsymbol{k_2 - k_1} & \text{if AGE} > \text{k}_2 \end{Bmatrix}$$

$$\text{age3} = \begin{Bmatrix} \boldsymbol{0} & \text{if AGE} \leq \text{k}_2 \\ \text{AGE-k}_2 & \text{if k}_2 < \text{AGE} \leq \text{k}_3 \\ \boldsymbol{k_3 - k_2} & \text{if AGE} > \text{k}_3 \end{Bmatrix}$$

$$\text{age4} = \begin{Bmatrix} \boldsymbol{0} & \text{if AGE} \leq \text{k}_3 \\ \text{AGE-k}_3 & \text{if k}_3 < \text{AGE} \leq \text{k}_4 \\ \boldsymbol{k_4 - k_3} & \text{if AGE} > \text{k}_4 \end{Bmatrix}$$

$$\text{age5} = \begin{Bmatrix} \boldsymbol{0} & \text{if AGE} \leq \text{k}_4 \\ \text{AGE-k}_4 & \text{if k}_4 < \text{AGE} \leq \text{k}_5 \\ \boldsymbol{k_5 - k_4} & \text{if AGE} > \text{k}_5 \end{Bmatrix}$$

$$\text{age6} = \begin{Bmatrix} \boldsymbol{0} & \text{if AGE} \leq \text{k}_5 \\ \text{AGE-k}_5 & \text{if AGE} > \text{k}_5 \end{Bmatrix}$$

Coefficient estimates corresponding to the slopes of the line segments between each knot point and for the slope of the last line segment were estimated for each product and transition type combination. The resulting overall AGE function for the 6-age segment example described above is given by:

$$\text{Age Function} = \boldsymbol{\beta_1} \cdot \text{age1} + \boldsymbol{\beta_2} \cdot \text{age2} + \boldsymbol{\beta_3} \cdot \text{age3} + \boldsymbol{\beta_4} \cdot \text{age4} + \boldsymbol{\beta_5} \cdot \text{age5} + \boldsymbol{\beta_6} \cdot \text{age6}$$

Age functions with fewer or greater numbers of segments are developed similarly. The number of segments and the selection of the knot points were determined by testing alternative specifications and assessing the reasonableness of the resulting functions. For some products and transition types, age functions were reduced to simple linear functions or were omitted altogether due to the instability or statistical non-significance of the estimated parameters. For example, mod-cure and self-cure transition probabilities are not as closely related to mortgage age as other events, such as current-to-default or current-to-prepayment transitions.

B3.2. Prior Loan Default Indicator

A loan that experiences a 90-day default episode and later returns to its current status is then classified as having had a prior default episode. Once this occurs and the dummy (0/1) variable

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for prior default is set to 1, it remains at this value for the remainder of the loan life. This enables us to distinguish these loans from those that have never entered the 90-day default status, a strong predictor of subsequent default, and a negative factor for the likelihood of prepayment.

B3.3. Prior Loan Modification Indicator

Loan modifications are identified from the default episodes data, and once the modified loan has returned to current status (cured), it is categorized as having had a prior loan modification. Once this occurs and the dummy (0/1) for the prior loan mod is set to 1, it remains at this value for the remainder of the loan life.

B3.4. Duration of Default Episode

The duration of a default episode is 0 at the start of the first full quarter following the date of entry into 90-day default status and then increments by one for each additional quarter spent in default status. For model estimation, the number of quarters in default is entered as a series of dummy variables for values from 0 to 5, where 5 represents 5 or more quarters. This variable applies only to loans in default status and is reset to zero at the start of any new default episode.

B3.5. Duration of Cure Episode

Each time a defaulted loan returns to current status, we track the number of quarters since the default episode ended. The values include 0 at the initial return to current and then increment by 1 quarter as long as the loan remains current. For model estimation, the number of quarters current is entered as a series of dummy variables for values from 0 to 5, where 5 represents 5 or more quarters. This variable only applies to current loans with a prior default, and current loans with no prior default are assigned 0 values for this variable.

B3.6. Seasonality Indicator

The season of an event observation quarter is defined as the season of the year corresponding to the calendar quarter identified as Winter (January, February, March), Spring (April, May, June), Summer (July, August, September), and Fall (October, November, December). Historically, borrowers are least likely to default or have a non-SR prepayment during the Winter months. Not surprisingly, prepayments to SR follow a less consistent pattern as these are undertaken primarily in response to favorable interest rate conditions and exclude prepayments for purposes of residential mobility.

B3.7. Time-Period Indicators for Policy Changes

Loss Mitigation FY 2021 FQ3 to FY 2025 FQ4 – Period of extended COVID loss mitigation procedures extended through and expiring on September 30, 2025, per Mortgagee Letter 2025-12. This variable captures the prolonged impact of loss mitigation policy changes in response to the COVID pandemic on loan status transitions and associated loss mitigation costs. We control for

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these effects for the forecasting period, following the implementation of the new loss mitigation waterfall effective October 1, 2025.

B4. Dynamic Variables Incorporating External Economic Data

B4.1. FHFA House Price Indices

Consistent with the PEA, historical house price indices (HPIs) produced and published by FHFA were applied in loan status transition model estimation. We opt for broader geographic coverage at the MSA level. The HPI PO version is applied at the state level when no MSA-level HPI is available, and the national level is applied if the state level is not available.

B4.2. Current Loan-to-Value (CLTV) Ratio

The current loan-to-value (CLTV) is computed as the ratio of the outstanding loan balance to the current property value. Current property values are derived by updating the original purchase price or appraised value of the collateral property using local-area house price indices (HPIs) from FHFA. Metro-level HPIs are used if available; otherwise, a state-level HPI is applied. This is a dynamic variable that is updated based on changes in the HPI and amortization of the loan balance. For SR loans with no appraisals with identified original FUWMs, we utilize the original property value and loan balance of the FUWM to derive the current LTV.

B4.3. House Price Volatility

House price volatility parameter estimates are a byproduct of the estimation of the FHFA weighted-repeat-sales HPIs. FHFA publishes the estimated volatility parameters at the state level and has provided FHA with MSA-level volatility parameter estimates for application to the FY 2025 review. The volatility parameters can be used to derive the expected dispersion of individual house price appreciation around the market average represented by HPI. Higher dispersion makes it more likely that an individual housing value may be too low to enable a borrower to qualify for refinancing. This will reduce the probability of prepayment and increase the probability of default for borrowers subject to higher and higher levels of volatility. Since the dispersion of individual housing values increases over time, so does the probability of negative equity. While these estimates are developed over time as parameters of the house price diffusion process, we apply them as cross-sectional indicators of relative market volatility in the borrower's location.

B4.4. House Price Appreciation

The FHFA HPIs are used to compute short-term rates of local and national house price appreciation as proxies for borrower expectations regarding future house price changes. These measures provide alternative indicators of market conditions that may impact the likelihood of prepayment, default, or cure in different directions. For example, borrowers whose personal or loan factors may increase their chances of default may have greater opportunities to sell their property and avoid default through prepayment if local markets are appreciating. Conversely, borrowers in declining

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markets may be less mobile in the face of strong national appreciation, thus reducing the likelihood of prepayment and increasing the risk of default. The local house and national house price appreciation (HPA) measures are computed as the ratio of the region-specific HPI one-year ahead to the value of the same HPI one-year prior:

$$\boldsymbol{HPA = \frac{HPI(t+1)}{HPI(t)} - 1}$$

B4.5. Refinance Incentive

The financial incentive of a borrower to refinance is measured using a variable for the relative spread between the current mortgage contract interest rate and the current market mortgage rate:

$$\boldsymbol{MP(t) = \left\{\frac{C(t) - R(t)}{C(t)}\right\}}$$

Where *C(t)* is the current note rate on the mortgage and *R(t)* is the current market average fixed-rate mortgage rate. This variable approximates the call option value of the mortgage given by the difference between the present value of the "anticipated" future stream of mortgage payments discounted at the current market rate of interest, *R(t)*, and the present value of the mortgage evaluated at the current note rate, *C(t)*. Additional details are given in Deng, Quigley, and Van Order (2000) and Calhoun and Deng (2002).

The relative mortgage premium values for ARMs and FRMs are derived in the same manner, except that the current coupon is always equal to the coupon at origination for FRMs, whereas ARM coupon rates are updated over the life of the mortgage as described next.

B4.6. Unemployment Rate Change

Unemployment impacts are captured by including changes in household unemployment rates at the metropolitan area level, or at the state level for non-metro area loans. Unemployment rates are a stock variable showing the size of the pool of unemployed during a point in time. By looking at changes in unemployment rates, we can better capture the likelihood that a borrower is at greater or lesser risk of entering unemployment. The unemployment rate change is computed as the difference between the rates observed one period prior and three periods prior:

$$\boldsymbol{delta_ue = ue_rate(t-1) - ue_rate(t-3)}$$

B4.7. Refinance Burnout

Refinance burnout is the tendency for borrowers who have missed refinance opportunities in the past to have lower conditional probabilities of prepayment going forward. A burnout factor is included to identify borrowers who have foregone recent opportunities to refinance. The burnout factor is quantified as the moving average number of basis points the borrower was in the money, for all quarters during which the borrower was in the money, during the preceding 8 quarters. The

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refinance burnout factor is included to account for individual differences in propensity to prepay, often characterized as unobserved heterogeneity. Empirical evidence now suggests that borrowers who refinance now tend to do so at much lower thresholds than in the past.

B4.8. Credit Burnout

Credit burnout exists when borrowers with negative equity do not default as expected and then have lower-than-average default rates going forward. As with refinance burnout, this may be interpreted as the impact of unobserved heterogeneity among borrowers but may also be attributed to unmeasured differences in borrower equity at the loan level. Credit burnout is quantified as the cumulative number of quarters the loan has been in a negative equity position as indicated by values of current LTV greater than 100 percent.

B4.9. ARM Coupon Rate Dynamics

To estimate the current financial value of the prepayment option for ARM loans, and to compute amortization rates that vary over time, we needed to track the path of the coupon rate over the active life of individual ARM loans. The coupon rate resets periodically to a new level that depends on the underlying index, plus a fixed margin, subject to periodic and lifetime caps and floors that specify the maximum and minimum amounts by which the coupon can change on each adjustment date and over the life of the loan. Accordingly, the ARM coupon rate at time *t* was computed as follows:

$$\begin{aligned} \boldsymbol{C(t) = \max\{\min[\mathrm{Index}(t-S) + Margin,}& \\ \boldsymbol{C(t-1) + A(t)\cdot Period_UpCap, C(0) + Life_UpCap], C(t-1) - A(t)}& \\ \boldsymbol{\cdot Period_DownCap(t), \max(C(0) - Life_DownCap, Life_Min)\}}& \end{aligned}$$

where C(t) is the ARM coupon rate at time t, Index(t) is the underlying rate index value at time *t*, *S* is the "look-back" period, and *Margin* is the amount added to *Index(t – S)* to obtain the "fully indexed" coupon rate. The periodic adjustment caps are given by *Period_UpCap* and *Period_DownCap*, and are multiplied by a dummy variable *A(t)* which equals zero except during scheduled adjustment periods. Maximum lifetime adjustments are determined by *Life_UpCap* and *Life_DownCap*, and *Life_Min* is the overall minimum lifetime rate level. Any initial discounts in ARM coupon rates are reflected in the original interest rate represented by C(0) in the equation above.

B4.10. ARM Payment Shock

The relative change in the monthly payment on ARM loans since origination is an approximation to the call option value of prepayment. We calculate this as follows:

$$\boldsymbol{arm_pmt_shock(t) = 100\, x\, \frac{PMT(t) - PMT(0)}{PMT(0)}}$$

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The ARM payment shock measure is expected to have a positive impact on current-to-prepay, current-to-default, and default-to-claim transitions for non-SR ARM loans since it represents both the value of the prepayment option and is a direct measure of the payment burden of ARM loans if interest rates increase significantly after origination, although these impacts will be delayed and negated somewhat given the annual and lifetime caps on ARM coupon rate increases.

B4.11. Yield Curve Slope

Expectations about future interest rates and differences in short-term and long-term borrowing rates associated with the slope of the Treasury yield curve influence the choice between ARM and FRM loans and the timing of refinancing. We use the ratio of the ten-year Constant Maturity Treasury (CMT) yield to the one-year CMT yield to measure the slope of the Treasury yield curve.

B4.12. Current Exposure-Period FRM Offer Rate

A variable measuring the market average FRM mortgage rate during each period is included to distinguish particularly high-rate or low-rate market environments.

B5. Prior Loan Information for Streamline Refinance Mortgages

We apply a method first developed in the FY 2010 Review that links streamlined refinance mortgages to the original fully underwritten FHA loans previously issued to the same borrower. Many FHA borrowers received multiple streamlined refinances over time, so the process of linking any given streamlined refinance mortgage to their original ancestor loan often requires establishing prior linkages through a sequence of FHA SR loans. We can identify the original fully underwritten FHA mortgage (FUWM) for about 95 percent of all streamlined refinance mortgages endorsed for FHA insurance since FY 1993.

Here we provide a brief explanation of the SR matching process. Each SR loan record includes a current FHA case number (case_nbr) and a prior FHA case number for the preceding FHA loan to the same borrower (old_case_nbr). If we assign the old_case_nbr of the subject SR loan to a new variable, call it match_case_nbr, and then assign the actual case numbers of all other loans to the same variable, we can sort by date and match_case_nbr; any matching loans should appear together in chronological order in the data. This requires matching the SR with old_case_nbr = match_case_nbr against all loans for all product types within a state since the subject SR may have been streamlined refinanced from any one of the 6 product types. Matching within a state is sufficient since the borrower and the property location must be the same for all potential matches.

Once the first match is obtained, we create a new combined match group/match sequence code to uniquely identify matched loans. We can then repeat the entire process for the newly matched prior SR loan using its old_case_nbr. Some borrowers undertake more than a dozen SRs, so we repeat the process again and again until we match with the original FUWM. Along the way, we create a two-digit refi-type sequence number that identifies the two product types involved in each match. This also enables us to later distinguish SR from non-SR prepayment terminations for the last SR

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in the sequence. If the sorting-matching process fails to identify the original FUWM, we attempt a direct match of old_case_nbr for any unmatched SR loan to the case_nbr values of unmatched non-SR loans to obtain a few additional matches. The entire process yields match rates in the range of 92 to 98 percent of SR loans depending on the vintages and state locations of the SR loan.

The main benefit of linking SR mortgages with the original FUWM is that it enables us to use underwriting characteristics and other information from that original FUWM in predicting the behavior of later SR loans to the same borrowers. For example, the process of updating current LTVs usually begins at loan origination and proceeds period-by-period over the life of the loan. In the case of the streamline refinance mortgage, we can obtain the original LTV and property values of the FUWM and update from that point forward, as if the current streamline refinance was a continuation of the original mortgage (for this purpose only, not for amortization and other dynamic processes specific to the current loan). We only apply this process to streamline refinance mortgages without required appraisals. In those cases where appraisals were required, we used the information from that appraisal to compute the current LTV for the streamline mortgage. We are also able to assign indicators of original LTV, relative house price, and down payment assistance type to current streamline mortgages based on the original fully underwritten mortgage and to include these variables in the models for streamlined mortgage products. Finally, we develop indicators of the prior product type to include as an additional explanatory variable in the status transition models for SR loans.

B6. Transition Model Validation and Backtesting

Model validation is required to comply with Actuarial Standards of Practice 23 (Data Quality) and 56 (Modeling). ASOP 23 applies when an actuary is selecting, using, or relying on data provided by others, all of which are relevant to our review of MMI Fund performance. ASOP 56 guides designing, developing, selecting, modifying, and using models when performing actuarial services. We employ models that are descended from those originally developed by members of our team and applied in the 2004 to 2016 actuarial reviews. As such, the models we use are the culmination of a multi-year process of model design, development, and application that we feel contributes meaningfully to the current validation process. This ongoing process has also provided us with considerable past experience with the data required for estimation and forecasting the performance of FHA single-family mortgages. Nevertheless, we are not simply relying on prior models and experience. We have undertaken an expansive and fresh look at data and model development to support the FY 2026 review.

The primary data source for our analysis is the FHA Single-Family Data Warehouse (SFDW). We consider that the SFDW is compliant with ASOP 23 regarding the appropriateness, availability of current information, internal consistency of the data, and comprehensive coverage of current and past FHA mortgages. The data are well documented by the SFDW Metadata workbook that ITDC requested from HUD to better understand the available data. The SFDW is an appropriate and

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sufficient source of FHA loan data, including detailed information on over 60 million single-family mortgages.

ASOP 23 instructs us to consider known data limitations. Historically, data limitations specifically impacting loan performance model development efforts include: (1) missing borrower credit scores; (2) missing detail on default episodes; and (3) missing underwriting information on FHA streamline refinance (SR) originations. The first two issues have faded over time as FHA improved its credit scoring and default tracking systems. Nevertheless, we still rely on mortgage data for loans originated as many as 30 years ago, so these issues must still be addressed in modeling.

The first issue of missing credit score information has been addressed in our modeling using additional data from HUD research studies that provide credit score information before 2004, when FHA began collecting credit score information on every loan. The second issue of default episode tracking has been addressed at HUD with three major improvements to default data collection in 1990, 1996, and 2006, such that each 90-day default episode is now tracked. The third issue regarding limited or missing underwriting data for SRs is simply a feature of these loans that makes them attractive to existing FHA borrowers. We have developed a partial solution to the problem through a process of matching SR loans back to the original fully underwritten loan to the same FHA borrowers. That process is complicated by the fact that some borrowers undertake more than 10 successive streamline refinance originations. The matching process provides the benefit of adding some information on the original fully underwritten FHA mortgage that can be used in modeling the performance of the latest SR mortgage, such as their original LTV and property value, which can be used to extrapolate forward to obtain an estimate of the LTV at origination of the latest SR loan.

To avoid data attrition from missing values for LTV, current LTV, DTI, and credit score, we retain as many observations as possible by treating missing values as a categorical factor (reference group) in the variables.[75]

The primary ASOP 56 requirement for model output validation is that the model output reasonably represents that which is being modeled, which in our case are loan status transition probabilities and loan insurance cash flows.[76] The validation should include testing the model output against observed historical results and evaluating whether the model output applied to hold-out data is reasonably consistent with model output developed without using the hold-out data. ASOP 56 also raises the issue of potential model over-fitting, defined as a situation where the model fits the data used to develop the model so closely that prediction accuracy materially decreases when the model is applied to different data. For example, over-fitting may occur when an excessively flexible function form is applied to a relatively small number of data points, such that the model explains those data almost perfectly, while failing to conform to other data from the same process. The

[75] The proportions of missing values for these variables are too large to perform any meaningful value imputation.
[76] Cash flow model backtesting and validation are discussed in Appendix D.

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voluminous data available from the SFDW mitigates the risk of over-fitting, even for models with large numbers of explanatory variables.

The AUC for each transition model, for both the estimation dataset and a holdout sample, shown in the table below indicates that the transition models generate consistent performance in holdout samples. Moreover, 45 out of 48 transition models provide acceptable discrimination power (i.e., AUC>0.7) in identifying underlying transition events.

Exhibit B-4: AUC, Transition Model Estimation Holdout Samples

Product	Transition	Estimation AUC	Validation AUC
1	current_currentX	0.8372	0.8369
1	current_default	0.7893	0.7895
1	current_prepay_nsr	0.7568	0.7565
1	current_prepay_sr	0.8819	0.8815
1	default_claim	0.7463	0.7460
1	default_cure_m	0.7866	0.7855
1	default_cure_s	0.7674	0.7654
1	default_prepay	0.7649	0.7644
2	current_currentX	0.8650	0.8591
2	current_default	0.8306	0.8319
2	current_prepay_nsr	0.6587	0.6591
2	current_prepay_sr	0.8898	0.8892
2	default_claim	0.7715	0.7759
2	default_cure_m	0.8255	0.8267
2	default_cure_s	0.8235	0.8212
2	default_prepay	0.7124	0.7107
3	current_currentX	0.8136	0.8121
3	current_default	0.7721	0.7725
3	current_prepay_nsr	0.7442	0.7447
3	current_prepay_sr	0.8012	0.8005
3	default_claim	0.7498	0.7513
3	default_cure_m	0.8051	0.8008
3	default_cure_s	0.8005	0.7973
3	default_prepay	0.7490	0.7467
4	current_currentX	0.8322	0.8329
4	current_default	0.7985	0.7985
4	current_prepay_nsr	0.7248	0.7250
4	current_prepay_sr	0.8751	0.8753
4	default_claim	0.7328	0.7336
4	default_cure_m	0.7905	0.7904
4	default_cure_s	0.7803	0.7815
4	default_prepay	0.7724	0.7724
5	current_currentX	0.8127	0.8160

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Product	Transition	Estimation AUC	Validation AUC
5	current_default	0.7927	0.7870
5	current_prepay_nsr	0.6683	0.6672
5	current_prepay_sr	0.8886	0.8871
5	default_claim	0.7685	0.7601
5	default_cure_m	0.8358	0.8414
5	default_cure_s	0.8519	0.8540
5	default_prepay	0.6821	0.6818
6	current_currentX	0.8085	0.8119
6	current_default	0.7435	0.7426
6	current_prepay_nsr	0.7304	0.7305
6	current_prepay_sr	0.7893	0.7902
6	default_claim	0.7299	0.7307
6	default_cure_m	0.7793	0.7748
6	default_cure_s	0.7941	0.7861
6	default_prepay	0.7801	0.7794

Relatedly, it may be asked whether our transition model outputs, which are estimated loan status transition probability functions, can reasonably represent observed average loan status transition frequencies. We will demonstrate this using a series of comparisons based on whether fitted loan status transition probabilities estimated using one sample are accurate in predicting observed loan status transition rates in a hold-out sample from the same data, but where the latter were not used in estimation.

We include the results of our comparisons for each loan status transition type comprising the dependent variables in our logit estimation models. We compared fitted and observed transition rates stratified across explanatory factors similar to those used in our transition models, including: original LTV, credit score, current LTV, relative spread (refinance incentive), mortgage age, season of year, prior default, prior mod, duration of cure for loans initially in current status, and duration of default for loans initially in default status.

The model fits indicated by these comparisons appear quite good, with little deviation of the average fitted rates from the average observed rates of transition in most comparisons, confirming the effectiveness of transition model regression specifications and that model outputs reasonably represent what was being modeled as required by ASOP 56.

Note: The validation back testing charts for all 48 transition rate models are submitted in a separate supplemental file alongside this report: FY2026_Q4_Appendix_B_Supplemental_Backtesting.

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Appendix C. Loan Performance Projections

C1. General Approach to Loan Termination Projections

C1.1. Loan Status Transitions Modeled

Econometric models are estimated for the following transitions:

current_default	90-day default event from current status
current_prepay_nsr	Prepayment termination non-SR
current_prepay_sr	Prepayment termination as SR
current_currentX	Default and self-cure within the same quarter
default_current_s	Self-cure from default status
default_current_m	Mod-cure from default status
default_prepay	Prepayment termination from default status (non-SR)
default_claim	Claim termination

There are two additional "transitions" corresponding to current loans that remain in current status and loans in default episodes that remain in default status. We list these for completeness but note that no estimation is undertaken since these probabilities are derived as the complement to the other probabilities for the same initial status.

current_current	Not estimated. Derived as a complement of other current_* probabilities.
default_default	Not estimated. Derived as a complement of other default_* probabilities.

A loan is either active in current or default status or terminated as a prepayment or claim. These are the outcomes that primarily determine future cash flows and the economic net worth of the MMI Fund. In addition, certain transitions between default and current status may have additional cash flow implications associated with partial claims, which occur when defaults are cured via loan modification, or mod-cures, and FHA reimburses lenders for any losses. These contrast with self-cures, where there are no cash flow implications for the MMI Fund when the loan again becomes current.

We also distinguish two types of prepayment events from the current status: prepayments via SR (streamline refinance) and other non-SR prepayments. While the occurrence of these events has similar cash flow implications for the current portfolio (termination of insurance premiums and

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elimination of future risk of claim), they respond differently to economic factors and vary in their timing, warranting treatment as separate competing risks. We note that prepayments via SR from default status are prohibited under HUD regulations for SR originations.

Note that we have also included a transition referred to as current-to-currentX. These are transitions associated with 90-day default episodes that start and cure in the same quarter. The loan is identified in the SFDW as having entered 90-day default status during the quarter but does not remain in default status until the start of the next quarter. In this case, the loan would be considered to have had a prior default and a self-cure, both of which would be censored when tracking quarter-to-quarter status transitions. The primary motivation for tracking these transitions is the importance of prior default experience for predicting future behavior, although there is no recorded change in loan status; by tracking them, we can more completely account for path dependence in default behavior.

Once the logit probability models have been estimated on historical data, the forecast programs rebuild the data used in estimation and extend the data into the future periods for each loan, generating new values of the explanatory variables based on the forecasted values of the same economic factors used in estimation (FHFA house price indices, BLS household unemployment rates, FHLMC mortgage rates, Census median home prices, Treasury rates, and yields). The historical series are obtained from Moody's Economy.com. The baseline scenario utilized is the PEA. We also apply four alternative scenarios based on stochastic simulation models to illustrate the sensitivity of the model to other possible outcomes. The stochastic model development is described in Appendix E.

The logit probabilities are estimated controlling for age, duration of default for loans in default status, duration of cure for previously defaulted loans in current status, and indicators of prior default and prior mod. This level of detail in the estimation makes it possible to develop the forecasted probabilities required to project the survivorship of loans or their claim or prepayment termination. The survivorship calculations are probabilistic, so it is necessary to track the shares of the portfolio stratified by age, duration of default, duration of cure, and prior default and prior mod. Before those survivorship calculations can occur, we must forecast future probabilities in a form that enables us to recover this detail along with all the other explanatory variables for each loan at each age and possible duration over the forecast period. The following section introduces the approach.

C2. Economic Scenarios

We use the baseline assumption plus four alternative stochastic simulation scenarios. The following four alternative scenarios for which we report economic net worth estimates are:

- Optimistic Upside Scenario in Simulation: the path that is most favorable of the five selected paths to the MMI Fund.

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- Moderate Upside Scenario in Simulation: the path that is moderately favorable to the MMI Fund.
- Moderate Downside Scenario in Simulation: the path that is moderately unfavorable to the MMI Fund.
- Pessimistic Downside Scenario in Simulation: the path that is most unfavorable of the five selected paths to the MMI Fund.

C3. Future Default / Cure Probabilities by Duration and Prior Default and Prior Mod Status

When projecting data and loan performance into the future, we generate probabilities that can be applied to all possible future loan situations defined in terms of initial loan status (current or default), prior default, prior modification, duration of default, duration of cure, and occurrence of claim or prepayment. This requires that we compute probabilities across all relevant durations of default or cure and simultaneously account for prior default and prior mod status.

To illustrate, consider the probabilities for current-to-default transitions covering the three possible scenarios: (1) no prior default or prior mod; (2) prior default and self-cure; and (3) prior default and prior mod. We will label these probabilities as follows:

(1) prob_current_default_N (corresponds to prior_default=0 and prior_mod=0)
(2) prob_current_default_S (corresponds to prior_default=1 and prior_mod=0)
(3) prob_current_default_M (corresponds to prior_default=1 and prior_mod=1)

The estimation program automatically saves the fitted parameters of each transition model to a separate file and recalls these when generating forecasts. The estimated parameters are used to recompute the linear "regression" function component of the non-linear logit probabilities of the form X*b, where X is the matrix of explanatory variables, and b is the coefficient vector. We note that the regression functions X*b_N, X*b_S, and X*b_M for each of the probabilities above will differ only in the values of prior_default and prior_mod, as all other variables of X will be identical at a given age and duration of default for a particular loan. This implies that the regression function X*b_S for prob_current_default_S can be computed from X*b_M by simply subtracting the coefficient for prior_mod, thus implicitly changing prior_mod=1 to prior_mod=0. Similar calculations can be applied to all other transition types as well.

In practice, this is achieved by the following steps:

(1) add additional records at each future age corresponding to each possible duration 0, 1, …, D and set prior_default=1 and prior_mod=1 for all these future loan records;

(2) compute X*b_M and prob_current_default_M at each duration 0, 1, …, D ;

(3) compute X*b_S by subtracting the coefficient for prior_mod=1 from X*b_M and use to compute prob_current_default_S at each duration 0, 1, …, D;

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(4) compute X*b_N by subtracting the coefficient for prior_default=1 from X*b_S and use to compute prob_current_default_N at each duration 0, 1, …, D .

This results in new data columns for each of the three probabilities at each future age and hypothetical duration. The duration-specific synthetic loan records created for each future age of the loan simultaneously utilize identical forecasted values for all explanatory variables other than the relevant duration value. The updated forecast data are then saved for input into subsequent survivor programs that will select and apply the loan-status and duration-specific probabilities to the appropriate survivor totals to evolve the portfolio further into future periods.

C4. Actuarial Projections

C4.1. Further Stratification of Transition Probabilities to Compute Survivorship

Given these basic events, the timing and duration of changes in loan status depend on the path that each loan takes on its way to prepayment or claim. Much of this path dependence can be captured by tracking the duration of default for defaulted loans, whether a loan has a prior default, whether a defaulted loan cures through a loan modification or self-cures, the duration of cure for cured loans, and whether a defaulted or cured loan has a prior modification.

The more detailed and specific transition probabilities that are needed for the actuarial calculations for each event type described above are listed below, where duration of default takes values 0,1,…, D; duration of cure takes values 0, 1, 2, …, C; “N” refers to having had no prior default or prior modification; “S” refers to having a prior default that was self-cured, but no prior modification; “M” refers to having had a prior default that mod-cured; lower-case “s” refers to self-cure transitions; and lower-case “m” refers to mod-cure transitions.

Loan transitions from current status are duration-dependent only if there was a prior default that has self-cured (S) or mod-cured (M). Duration of cure is indicated by 0, 1, 2, …, C. The values of C and D are set to the same maximum value. During data construction and estimation, observed durations higher than C or D are given the maximum value, so the maximum duration represents duration ≥ C or D quarters. At present, values of C=D=5 quarters have been applied, in part because observed transition rates seem to level off by that point, and because the data become thinner so estimating beyond that point is both materially unimportant and unreliable.

C4.2. Survivorship Probabilities

<u>current-to-default</u>

pr_cur_def_N	no duration dependence, no prior default, no prior mod
pr_cur0_def_S	duration cure 0, prior default, no prior mod
pr_cur0_def_M	duration cure 0, prior default, prior mod
pr_cur1_def_S	duration cure 1, prior default, no prior mod

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pr_cur1_def_M duration cure 1, prior default, prior mod

⋮

pr_curC_def_S duration cure C, prior default, no prior mod

pr_curC_def_M duration cure C, prior default, prior mod

current-to-prepay (non-SR)

pr_cur_pre_nsr_N

pr_cur0_pre_nsr_S

pr_cur0_pre_nsr_M

pr_cur1_pre_nsr_S

pr_cur1_pre_nsr_M

⋮

pr_curC_pre_nsr_S

pr_curC_pre_nsr_M

current-to-prepay (SR)

pr_cur_pre_sr_N

pr_cur0_pre_sr_S

pr_cur0_pre_sr_M

pr_cur1_pre_sr_S

pr_cur1_pre_sr_M

⋮

pr_curC_pre_sr_S

pr_curC_pre_sr_M

current-to-currentX

pr_cur_curX_N

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pr_cur0_curX_S

pr_cur0_curX_M

pr_cur1_curX_S

pr_cur1_curX_M

⋮

pr_curC_curX_S

pr_curC_curX_M

default-to-current

pr_def0_cur_s_N	duration default 0, no prior default, no prior modification, self-cure
pr_def0_cur_s_S	duration default 0, prior default, no prior modification, self-cure
pr_def0_cur_s_M	duration default 0, prior default, prior modification, self-cure
pr_def1_cur_s_N	duration default 1, no prior default, no prior modification, self-cure
pr_def1_cur_s_S	duration default 1, prior default, no prior modification, self-cure
pr_def1_cur_s_M	duration default 1, prior default and prior modification, self-cure
⋮	
pr_defD_cur_s_N	duration default D, no prior default, no prior modification, self-cure
pr_defD_cur_s_S	duration default D, prior default, no prior modification, self-cure
pr_defD_cur_s_M	duration default D, prior default, prior modification, self-cure

pr_def0_cur_m_N	duration default 0, no prior default, no prior modification, mod-cure
pr_def0_cur_m_S	duration default 0, prior default (self-cure), no prior modification, mod-cure
pr_def0_cur_m_M	duration default 0, prior default and prior modification, mod-cure
pr_def1_cur_m_N	duration default 1, no prior default, no prior modification, mod-cure
pr_def1_cur_m_S	duration default 1, prior default (self-cure), no prior modification, mod-cure
pr_def1_cur_m_M	duration default 1, prior default and prior modification, mod-cure
⋮	

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pr_defD_cur_m_N	duration default D, no prior default, no prior modification, mod-cure
pr_defD_cur_m_S	duration default D, prior default (self-cure), no prior modification, mod-cure
pr_defD_cur_m_M	duration default D, prior default and prior modification, mod-cure

default-to-prepay

pr_def0_pre_N

pr_def0_pre_S

pr_def0_pre_M

pr_def1_pre_N

pr_def1_pre_S

pr_def1_pre_M

⋮

pr_defD_pre_N

pr_defD_pre_S

pr_defD_pre_M

default-to-claim

pr_def0_clm_N

pr_def0_clm_S

pr_def0_clm_M

pr_def1_clm_N

pr_def1_clm_S

pr_def1_clm_M

⋮

pr_defD_clm_N

pr_defD_clm_S

pr_defD_clm_M

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The future probabilities correspond to estimated transition probabilities to be applied to loans in specific loan statuses with the corresponding initial conditions regarding age, duration, and path dependence. To clarify, note that N, S, and M refer to the path dependence of a loan and, along with duration, comprise "initial conditions" for the next transition. Conversely, the lower-case s and m distinguish types of cure events. Thus, a loan in default may have either N, S, or M to define its prior history and still undertake either a self-cure or mod-cure to end a default episode.

There is no further updating of N, S, and M once a loan has had both a prior default and prior mod and is labeled an M-type transition, and a loan may go directly from N-type to M-type since a prior mod implies a prior default. S describes loans that have only had one or more self-cures and have never been modified, while M describes loans that have had at least one modification and may have had one or more prior self-cures as well. Loan modification implies third-party intervention that changes the terms of the mortgage (and potentially debt forgiven), whereas self-cure is basically "catching up" on delinquent payments. Accounting for S and M is about controlling for path dependence to improve estimation and not about the cash flow impacts of partial claims arising from loan modifications. The latter is accounted for by distinguishing between self-cure (s) and mod-cure (m) events, and both self-cures (s) and mod-cures (m) may occur to defaulted loans in any initial N, S, or M status and duration of default.

The survivor programs include the further development of the forecasted probabilities just described as a first step. The next step is to apply those probabilities to evolve loans forward from the final historical period during which actual loan statuses and durations are observed for the last time, to probabilistically allocate them to the potential future statuses and durations in the subsequent periods.

We expand the categories of loans to be projected to include initial status, duration, prior default, and mod history according to the same mnemonics used above for the probabilities. For example, default3_S would measure total loans in a current default episode of duration 3 that have a prior default that self-cured and would be multiplied by probability pr_def3_def_S to obtain default4_S, the corresponding total for duration 4. Of course, the updating is proportional based on the probability, and some of the loans in default3_S would proceed to current status (with probability pr_def3_cur_s_S for self-cure and probability pr_def3_cur_m_S for mod-cure), to claim (with probability pr_def3_clm_S), or to prepay (with probability pr_def3_pre_S). For loans transitioning back to current status, the loan categories to be incremented are current0_S or current0_M, for self-cure or mod-cure, respectively.

To summarize, the final outputs of the survivorship calculations for each period are updated values of the percentage of survivors with current and default statuses delineated by duration of default, or duration of cure, and the path dependence indicators S and M reflecting whether the loan had a prior default and self-cure (S) or a prior default and a modification (M). These include the following:

current0 – current status never defaulted

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current0_S to current5_S	– current status with prior default and self-cure by duration of cure
current0_M to current5_M	– current status with prior default and mod-cure by duration of cure
default0	– default status with no prior self-cure or mod-cure
default0_S to default5_S	– default status with prior default and self-cure by duration of default
default0_M to default5_M	– default status with prior default and mod-cure by duration of default

We note that the status current0_M provides an estimate of the share of surviving loans that have recently returned to current status after receiving a loan modification. In this case, the status current0_M volume reflects the timing and incidence of mod-cures to which an estimate of modification partial claim severity may be applied to estimate the timing and magnitude of these partial claim expenses.

For example, we know loans in this status are recently cured because the duration of cure is 0, corresponding to the first quarter in a cured state. We know the loan was previously modified, as denoted by the M component of the status code. And we assume that the majority of loans receiving a loan modification only receive a single modification over the entire life of the loan, so that the timing of the mod cure coincides with entry to this status. Finally, we know that any loan spends only one quarter in this status since, in the next quarter, duration increases and they are promoted to status current1_M, so current0_M is specific to the quarter in which it is reported.

The outputs of the survivorship programs retain the additional detail on original loan characteristics such as case_nbr, product, LTV, credit score, original loan amount, DPA type, and geographic location that may be needed for linking to other SFDW information related to the cash flow analysis (upfront- and annual-premia, partial claim loss amounts, full claim loss amounts, etc.).

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Appendix D. Loss Severity and Cash Flow Analysis

D1. Introduction

The calculation of the economic net worth of the Fund involves the estimation of the present value of future cash flows generated by the existing portfolio into the future. The analysis requires the projection of future prepayment and claims incidents, and severity and cash flow items associated with each type of outcome. This Appendix describes the components of these cash flow calculations.

The evaluation of the Fund's economic net worth at a point in time (e.g., FY 2026) requires the addition of the current value of net assets and the expected present value of future cash flows. The latter comprises future revenue and expenses. The actuarial model uses projections from econometric models as discussed in Appendices B-E.

We estimated econometric models for conditional transition probabilities for individual loans depending on the loan type, origination year, age, interest rate, loan purpose, initial and current LTV ratio, credit score, refinancing incentive, relative loan size, loan term, and refinance and credit burnouts, and other characteristics. The models also used data on serious delinquency status and default history. Using detailed loan-level characteristics, we estimated the various transition probabilities (Appendix C) and then generated respective cash flows for individual loans.

We estimated an econometric model of loss severity rates (Appendix D). The loss rate model distinguishes between pre-foreclosure sales, conveyance, and third-party sales (i.e., claims without conveyance of title (CWCOT))[77]. Based on the mortgage termination rates projected by the econometric models, individual components of cash flows are projected into the future. These cash flows are discounted to the present time based on the MMI Single Effective Rate discount factors provided by FHA. The relevant cash flow components are itemized in Exhibit D-1.

Exhibit D-1: Cash Flow Components

Cash Flow Component	Inflow	Outflow
Mortgage Insurance Annual Premium	X	
Upfront Premium Refund		X
Loss Mitigation Expense		X
Claim Expenses		X
Recoveries	X	

These components were projected quarterly for individual loans and then aggregated according to the product type and cohort year for reporting purposes. Below, we discuss the derivation of each of these cash flows.

[77] For notation convenience, we use third-party sales (TPS) throughout this appendix.

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The following definitions and background information clarify our discussion of the cash flow components:

Insurance-in-Force (IIF): the nominal value of the unamortized original mortgage loan balances of the surviving mortgages insured by FHA. This is distinct from the conventional notion of amortized insurance-in-force, which includes only the current outstanding balances on surviving loans.

Conditional Claim Rate (CCR): the number of loans that become claims during a period divided by the number of surviving loans in force at the beginning of that period.

Conditional Prepayment Rate (CPR): the number of loans being completely prepaid during a period divided by the number of surviving loans in force at the beginning of that period.

Policy Year: measures the number of fiscal years since origination. The year in which the mortgage originated is assigned as fiscal policy year one.

Termination Year: the fiscal year in which a mortgage terminates through a claim, prepayment, or other reasons.

Unpaid Principal Balance (UPB) Factor: the principal balance outstanding at a given time divided by the original mortgage amount. The UPB factor is calculated based only on amortization, given the original or modified maturity, the type of mortgage, and the mortgage contract rate. For FRMs, the UPB factor for each quarter in the future can be directly computed using the initial contract rate and the amortization term. If a loan is modified into a new 30-year or 40-year term, the UPB factor after modification is recalculated based on the revised amortization term. The annual premium is the exception: it is calculated on the UPB factor of the original amortization schedule (see D2.1.3). For ARMs, the UPB factor changes depending on the interest rate of the loan, which is updated according to the contractual rate adjustment rule. In our model, the contract interest rates of ARM loans are updated by using changes in the 1-year Treasury rate as an approximation for changes in the underlying index, subject to limits implied by FHA annual and lifetime rate adjustment caps.

D2. Cash Flow Components

D2.1. Premiums

D2.1.1. Premium Structure

The primary source of revenue for the Fund is insurance premiums. If the Fund's mortgage insurance is priced to meet the expected liabilities, the insurance premiums collected and interest earned on them will cover all costs associated with mortgage loans insured by the Fund, under a normal economic environment. The insurance premium has been structured in different ways during different periods.

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For loans originated before September 1, 1983, the mortgage premium was collected monthly at an annualized rate of 0.50 percent of the outstanding principal balance for the period. To align this change with fiscal quarters, we assumed that this annual premium policy was in effect through September 30, 1983.

Between September 1, 1983, and June 30, 1991, the mortgage premium was charged only upon loan origination and was based on a percentage of the original mortgage amount at the time of origination. This amount was 3.80 percent for 30-year mortgages and 2.40 percent for 15-year mortgages.

Effective July 1, 1991, the National Affordable Housing Act specified a new premium structure. This structure specified an upfront premium of 3.80 percent for all product types except for 15-year non-streamline refinance loans (for which the upfront premium was set at 2.00 percent) and an annual renewal premium of 0.50 percent per year on the outstanding balance. The annual premium would cease at different policy years depending on the initial LTV of the loan.

- On October 1, 1992, the upfront premium for 30-year mortgages was reduced from 3.80 percent to 3.00 percent. The annual premium for 30-year mortgages was extended for a longer time, while for 15-year mortgages it was lowered to 0.25 percent for a shorter time or completely waived if the initial LTV ratio was less than 90 percent.

- As of April 17, 1994, FHA lowered the upfront premium rate on 30-year mortgages from 3.00 percent to 2.25 percent. To align this change with fiscal quarters, we started applying this policy change on April 1, 1994.

- Starting from October 1, 1996, FHA lowered the upfront premium rate on 30-year mortgages for first-time homebuyers who receive homeowner counseling from 2.25 percent to 2.00 percent. This rate was further reduced to 1.75 percent for mortgages executed on or after September 22, 1997. This favorable treatment for borrowers with homeownership counseling was terminated shortly thereafter.

- Effective January 1, 2001, FHA lowered the upfront premium rate for all mortgages to 1.50 percent. The annual premium would stop as soon as the current LTV ratio of the loan was below 78 percent according to the home price as of the loan origination date. The annual premium was required to be paid for a minimum of five years for 30-year mortgages.

- Effective October 1, 2008, FHA charged an upfront premium rate of 1.75 percent for purchase money mortgages and full-credit qualifying refinances; and 1.50 percent for all types of streamline refinance loans. A varying annual premium, remitted monthly, was charged based on the initial loan-to-value ratio and maturity of the mortgage.

- Effective April 1, 2010, FHA changed the upfront premium to 2.25 percent for all mortgages executed after April 1, 2010.

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- Effective October 4, 2010, FHA lowered the upfront premium of all mortgages to 1.0 percent. The annual premium for loans with 30-year terms was increased to 0.85 percent for LTV ratios up to 95 percent and 0.90 percent for LTV ratios greater than 95 percent. For loans with 15-year terms, an annual premium of 0.25 percent was set for LTV ratios greater than 90 percent. To align this change with fiscal quarters, we started applying this policy change on October 1, 2010.

- Effective April 18, 2011, the annual premium for loans with 30-year terms was increased to 1.10 percent for LTV ratios up to 95 percent and 1.15 percent for LTV ratios greater than 95 percent. For loans with 15-year terms, the annual premiums were increased to 0.25 percent for LTV ratios up to 90 percent and to 0.50 percent for LTV ratios greater than 90 percent. To align this change with fiscal quarters, we started applying this policy change on April 1, 2011.

- Effective April 9, 2012, FHA increased the upfront premium of all mortgages to 1.75 percent. The annual premium for loans with 30-year terms was increased to 1.20 percent for LTV ratios up to 95 percent, and 1.25 percent for LTV ratios greater than 95 percent. For loans with 15-year terms, the annual premiums were increased to 0.35 percent for LTV ratios up to 90 percent, and 0.60 percent for LTV ratios greater than 90 percent. To align this change with fiscal quarters, we started applying this policy change on April 1, 2012.

- Effective June 11, 2012, the annual premium for loans with 30-year terms and base loan amounts above $625,500 was increased to 1.45 percent for LTV ratios up to 95 percent, and 1.50 percent for LTV ratios greater than 95 percent. For loans with 15-year terms and a base loan amount above $625,500, the annual premium was increased to 0.60 percent for LTV ratios up to 90 percent, and to 0.85 percent for LTV ratios greater than 90 percent. Also, effective June 11, 2012, for all single-family forward streamline refinance loans which are refinancing existing FHA loans that were endorsed on or before May 31, 2009, the upfront premium decreased to 0.01 percent of the base loan amount, and the annual premium was set at 0.55 percent, regardless of the base loan amount. To align this change with fiscal quarters, we started applying this policy change on July 1, 2012.

- Effective April 1, 2013, the annual premium for loans with 30-year terms and base loan amounts below $625,500 was increased to 1.30 percent for LTV ratios up to 95 percent, and 1.35 percent for LTV ratios greater than 95 percent. The annual premium for loans with 30-year terms and base loan amounts above $625,500 was increased to 1.50 percent for LTV ratios up to 95 percent, and 1.55 percent for LTV ratios greater than 95 percent. For loans with 15-year terms and base loan amounts below $625,500, the annual premium was increased to 0.45 percent for LTV ratios up to 90 percent, and 0.70 percent for LTV ratios greater than 90 percent. For loans with 15-year terms and base loan amounts above $625,500, the annual premium was increased to 0.70 percent for LTV ratios up to 90 percent, and to 0.95 percent for LTV ratios greater than 90 percent. This increase was

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effective for all forward mortgages except single-family forward streamline refinance transactions that refinance existing FHA loans that were endorsed on or before May 31, 2009.

- Effective June 3, 2013, the annual premium rates for loans with an LTV of less than or equal to 78 percent and with terms of up to 15 years were 0.45 percent. The new payment period for annual premiums for loans with case numbers assigned on or after June 3, 2013, and with an LTV up to 90 percent was 11 years, and the annual premium applied for the full mortgage term for LTVs greater than 90 percent. To align this change with fiscal quarters, we started applying these policy changes on July 1, 2013.
- Effective January 26, 2015, the annual premium rates for loans with a term greater than 15 years have been reduced by 50 basis points. To align this change with fiscal quarters, we started applying these policy changes effective January 1, 2015.
- Effective March 20, 2023, under Mortgagee Letter 2023-05, the annual premium rate was reduced by 30 basis points for all mortgages except streamline refinance and simple refinance mortgages on previous FHA-endorsed mortgages on or before May 31, 2009, along with Hawaiian Home Lands (HHL).
- Effective January 1, 2024, the threshold for one-unit loans in high-cost areas was increased from $1,089,300 to $1,149,825 pursuant to Mortgagee Letter 2023-21.
- Effective January 1, 2026, the limits for one-unit loans in high-cost areas were changed to $1,249,125 per Mortgagee Letter 2025-23.

D2.1.2. Upfront Premium

The upfront premium is assumed to be fully paid at the mortgage origination date, and the amount is calculated as follows:

*Upfront Premium Payment = Origination Loan Amount * Upfront Insurance Premium Rate*

In practice, FHA allows a premium finance program for those qualified for mortgage insurance, so that the upfront premium does not add to the borrower's equity burden at the beginning of the contract. Instead, the borrower can add it to the original loan balance, in essence paying the upfront premium on the same schedule as their principal balance. The annual premium is charged based on the unpaid principal balance excluding the financed upfront premium. Almost all borrowers finance their upfront premiums in this fashion. However, the LTV, including financed upfront premiums, cannot exceed 96.5 percent.

D2.1.3. Annual Premium

The annual premium is calculated as follows:

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*Quarterly Payment of Annual Premium = UPB (excluding any upfront premiums) * Annual Insurance Premium Rate / 4*

The premium is collected monthly. For each quarter, the model applies the formula to the original-schedule balance after that quarter's scheduled payments, for loans still insured at the end of the quarter, and discounts the result from the middle of the quarter. In addition, the termination rate will have an impact on future premium flows. A loan that prepays or goes to claim pays no premium for the quarter in which it terminates or thereafter. The annual premium is not assessed on the amount of the financed upfront premium. The UPB used for the annual premium follows the amortization schedule established at origination, without regard to agreements to recast the mortgage (24 CFR 203.261). For a loan whose term has been extended by a modification, the annual premium and the 78 percent LTV cancellation test are based on the original-schedule balance, and no annual premium is collected after the original maturity date. This LTV cancellation test applies only to loans governed by this rule and not applied to loans governed by other terms.

D2.2. Losses Associated with Claims

The Fund's largest expense component comes in the form of payments arising from claims. FHA pays the claim to the lender after a lender files a claim. Traditionally, in most cases, FHA takes possession of the foreclosed property and sells the property to partially recover the loss. This type of claim is called a conveyance.

Based on this practice, claim cash flows can be decomposed into two components:

- Cash outflow of the claim payment at the claim date, including expenses incurred, and
- Cash inflow of any net proceeds received from selling the conveyed property at the property disposition date.

For tractability, we simplify this two-step cash flow into one lump-sum amount. We also separately estimate losses from pre-foreclosure sales, wherein the property is sold before the completion of a foreclosure and the property is not conveyed to HUD, and losses from third-party sales. The claim loss payment estimated in our model at time t is

$$\boldsymbol{ClaimLoss_t = UPB_t * LossRate_t}$$

For this review, we applied a dynamic simulation approach that tracks loan transitions to default, claim, and prepayment that reflect the probabilities of the various transitions (see Appendix C). The $\boldsymbol{UPB_t}$ is the amount of the unpaid balance of the loan at the beginning of time t for loans that terminate at time t with a claim.

The loss rate is usually referred to as the loss-given-default (LGD) or "severity" in the banking industry. It measures the amount of principal not recovered from property sale and expenses incurred in property acquisition, holding, and sales. This amount is divided by the unpaid principal balance at the time of claim. The portfolio-level loss rate is predicted as the weighted average loss

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rates among conveyance, pre-foreclosure sales, and the implemented policy of third-party sales, where the weights reflect the probability that a claim is associated with the individual types of claims. Note that since FY 2018, Single Family Forward note sales have been negligible. This disposition type is therefore excluded from disposition modeling. However, this disposition type may be modeled in future studies based on potential future policy changes that trigger new Single Family Forward note sales. The loss rate formulation is as follows:

$$\begin{aligned} \boldsymbol{LossRate_t} = & (\boldsymbol{Probability\ of\ PFS} \times \boldsymbol{LossRate_{PFS}}) \\ & + (\boldsymbol{Probability\ of\ REO} \times \boldsymbol{LossRate_{REO}}) \\ & + (\boldsymbol{Probability\ of\ TPS} \times \boldsymbol{LossRate_{TPS}}) \end{aligned}$$

To model the probabilities of Pre-Foreclosure Sale (PFS), Third Party Sale (TPS), and Real Estate Owned (REO) dispositions, a multinomial logistic regression model was deployed to estimate the likelihood that a property would undergo a PFS transaction or a TPS transaction for loan claim k using explanatory variables $\boldsymbol{X}$ defined in Exhibit D-4.

$$\boldsymbol{P(PFS)} = \frac{\boldsymbol{e^{\beta_{PFS} X_k}}}{\boldsymbol{1 + e^{\beta_{PFS} X_k} + e^{\beta_{TPS} X_k}}}$$

$$\boldsymbol{P(TPS)} = \frac{\boldsymbol{e^{\beta_{TPS} X_k}}}{\boldsymbol{1 + e^{\beta_{PFS} X_k} + e^{\beta_{TPS} X_k}}}$$

The probability of conveyance was calculated by taking the difference between 1 minus the probability of a pre-foreclosure sale and the probability of third-party sales.

$$\boldsymbol{P(REO)} = \boldsymbol{1 - P(PFS) - P(TPS)}$$

Following the estimation of the disposition probabilities, we calculate the loss rates of each of the dispositions. Generalized least-squares regression was deployed to estimate the PFS, TPS, and REO loss rate dispositions, respectively, with the explanatory variables listed in Exhibits D-5 through D-7 and historical loss rate data from the SFDW as the dependent variable.

A share of CWCOT or TPS foreclosure auctions ends in an outbid, in which a third party's bid covers the outstanding debt. In this case, no claim is filed with HUD, and FHA incurs no loss. Since the claim and loss severity models are estimated on positive claims, outbids are only reflected through the outbid share embedded in historical TPS experience. The share of outbids, measured in dollars, has varied significantly: it fell from about 16 percent of TPS auctions in FY 2014 to about 9 percent in FY 2019–2020 and then rose to between 20 and 28 percent in FY 2022–2025.

Beginning in FY 2026, the cash flow model treats outbids explicitly. A dollar-weighted logistic regression, estimated on TPS auctions from FY 2014 onward, relates the probability that an auction ends in an outbid to current loan-to-value and local house price appreciation, with state fixed

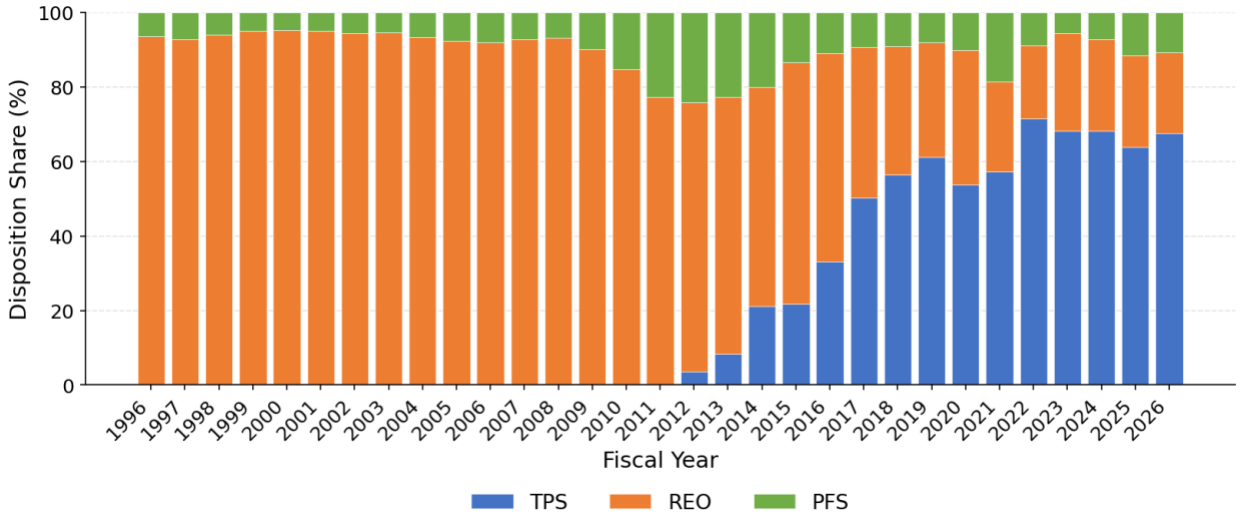
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effects and a post-FY 2022 policy indicator included in estimation. For each cohort and quarter, projected TPS claims are grossed up to the auction volume they imply using a baseline outbid share, and that volume is divided again at the forecast outbid share. Outbids carry no claim and no loss; the remaining claims take their severity from the existing TPS loss rate model. REO and PFS projections and the timing of terminations are unchanged. Exhibit D-7a presents the estimated parameters.

The historical loan disposition shares (excluding note sales) from fiscal year 1996 to 2026 are displayed in Exhibit D-2. As illustrated in Exhibit D-2, REO made up most of HUD's recovery on claimed assets from experience years 1997 through 2012. However, since 2012, TPS has quickly overtaken REO as the most utilized disposition method. Examining this historical trend in loss severity disposition, we determined that data including experience years from 2012 to 2026 is more in line with the current state of claim recoveries and hence used for the estimation of the disposition-type model.

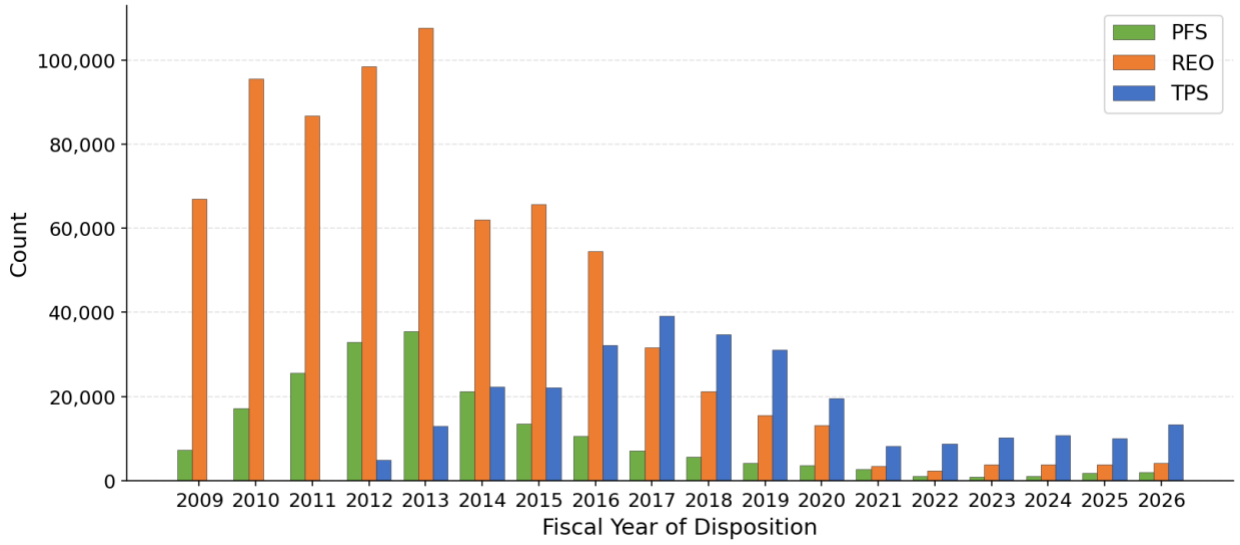
It is also important to note that the historical claim counts are significantly less in recent years than the period before 2015, as displayed in Exhibit D-3. As a result, the REO disposition remains dominant in the estimation sample in terms of counts, which can distort the forecasting power of the model. To better reflect the recent trends of claim disposition in forecasting, we adopted a weighting approach so that each experience period has the same importance level in model estimation. Specifically, instead of imposing equal weights on each observation, we assign the same total weights to each experience quarter and then equally allocate the weights to each observation within the quarter.

Exhibit D-2: Disposition Type Share by Disposition Year



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Exhibit D-3: Disposition Type Counts by Disposition Year



The estimation of the loss severity rate models utilized loan-level data from the FHA single-family data warehouse from experience years 1997 to 2026. The full history of data is available for conveyance and pre-foreclosure claims, while there were no TPS claims before 2012. As a result, the TPS loss rate model is estimated on experience years 2012 to 2026. The estimation panel also applies product-level origination cohort windows: the 15-year products begin with loans endorsed in FY 2007, and ARM streamline refinance loans end with the 2016 cohort. Due to the COVID loss mitigation policy, we also find that the loss counts since 2019 for all three claim types were much smaller than those in previous experience years. The historical loss severity rates for REO disposition before and after 2012 can be different due to the fact that loans disposed through REO after 2012 tend to be those loans that could not or would not be disposed through TPS or note sale. Nevertheless, including data before 2012 can help the GLM model learn the loan differences before and after 2012 and better capture the determinants of REO severity as well as its trend. Therefore, it is appropriate to incorporate as much data as possible for REO severity estimation. Our validation results reported in Exhibit D-13 provide strong evidence that the estimated model based on the selected data period effectively identified the distinctions between REO loss severity levels before and after 2012.

The final sample used for estimation included 77,257 loans claimed over the timeframe, drawn from the stratified forecasting sample described in Section B1.5.2, which is sampled within each origination year to represent that year's credit score and LTV mix.[78] Both the loss severity disposition model and loss severity rate models went through comprehensive collinearity tests and

[78] In a TPS outbid, the winning third-party bid at the foreclosure auction is sufficient to satisfy the outstanding indebtedness, so no claim is filed with HUD. Because no claim is filed, outbid terminations do not appear in the loss severity estimation sample; their incidence is instead reflected in the forecast through the outbid-share adjustment described in this section.

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a variable selection process through the Lasso procedure. The following tables include the estimated parameters for the models, including the coefficients, Chi-square, and t-statistics confirming the sufficiency of the model specification.

Exhibit D-4: Loss Severity Disposition Model Parameters

Description	Parameter	Loss Severity Type	Estimate	Wald Chi-Square	Pr > ChiSq
	Intercept	PFS	-0.1737	0.0979	0.7544
	Intercept	TPS	-6.8802	285.7848	<0.0001
Log Loan Age	Agelog	PFS	-1.0624	492.2456	<0.0001
	Agelog	TPS	0.7536	368.3082	<0.0001
ARM Payment Shock	arm_pmt_shock	PFS	0.0206	179.4517	<0.0001
	arm_pmt_shock	TPS	0.0134	145.6339	<0.0001
Loan Beginning Amortization Date	beg_amort_dt	PFS	-0.0001	51.7204	<0.0001
	beg_amort_dt	TPS	0.0002	237.6505	<0.0001
Loan-level Mortgage Interest Rate	Coupon	PFS	-0.1910	82.0982	<0.0001
	Coupon	TPS	-0.1058	48.3636	<0.0001
Current Number of Consecutive Quarters Loan Underwater	credit_burnout	PFS	0.0363	414.6771	<0.0001
	credit_burnout	TPS	-0.0082	35.7676	<0.0001
Credit Score	credit_score_FHA	PFS	0.1756	22.8634	<0.0001
	credit_score_FHA	TPS	0.1375	24.1149	<0.0001
Deficiency Judgment State Indicator	Deficiency	PFS	0.1412	10.3094	0.0013
	Deficiency	TPS	0.2009	37.2196	<0.0001
Front-End DTI	dti_front_end	PFS	0.0028	6.2112	0.0127
	dti_front_end	TPS	0.0017	3.6106	0.0574
Quarterly Primary Market FRM 30 Mortgage Interest Rate	ey_rate	PFS	0.1507	41.6289	<0.0001
	ey_rate	TPS	0.3339	488.3033	<0.0001
Local Home Price Appreciation Since Origination	hpa_local	PFS	2.8586	37.9880	<0.0001
	hpa_local	TPS	4.5011	111.5534	<0.0001
Squared Local Home Price Appreciation	hpa_local_sq	PFS	0.5434	0.1757	0.6751
	hpa_local_sq	TPS	-5.7944	23.3234	<0.0001
National Home Price Appreciation	hpa_usa	PFS	3.0659	65.2040	<0.0001
	hpa_usa	TPS	5.6028	357.8006	<0.0001
Indicator, Credit Score >= 620	ind_credit_score_ge_620	PFS	-0.3037	79.8766	<0.0001
	ind_credit_score_ge_620	TPS	0.0315	1.5800	0.2088
Indicator, Loan Size 100-160% of State Average	ind_loansize_100_160	PFS	0.0011	0.0012	0.9723
	ind_loansize_100_160	TPS	0.0395	1.9242	0.1654
Indicator, Judicial Foreclosure State	Judicial	PFS	-0.2143	42.5321	<0.0001
	Judicial	TPS	0.1455	37.7666	<0.0001

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Description	Parameter	Loss Severity Type	Estimate	Wald Chi-Square	Pr > ChiSq
Ratio of Original Loan Amount to State Average	Loansize	PFS	0.0101	573.3499	<0.0001
	Loansize	TPS	-0.0002	0.4403	0.5070
Original Loan Term Recoded to 180 or 360	Loanterm	PFS	0.0069	172.1414	<0.0001
	Loanterm	TPS	0.0000	0.0052	0.9422
Change in Unemployment Rate, t-3 to t-1	ue_delta	PFS	-0.0313	9.5965	0.0019
	ue_delta	TPS	0.0921	134.8284	<0.0001
Square Root of Change in Unemployment Rate	ue_relative_sqrt	PFS	1.2199	87.4236	<0.0001
	ue_relative_sqrt	TPS	-2.1829	466.7473	<0.0001
Model Fit Statistics					
Chi-Square Statistic			15771.4508		
Adjusted R-Square			0.3301		

Exhibit D-5: Loss Rate Given Conveyance (REO) Model Parameters

Description	Parameter	Estimate	t Value	Pr > |t|
Intercept	Intercept	-0.9227	-14.3855	<0.0001
Indicator, Missing Credit Score	credit_score_MISSING	-0.0571	-19.4370	<0.0001
Deficiency Judgment State Indicator	Deficiency	0.0506	15.7073	<0.0001
Local Home Price Appreciation Since Origination	hpa_local	-0.7760	-67.4334	<0.0001
Indicator, Judicial Foreclosure State	Judicial	0.0978	37.3585	<0.0001
Living Units Equals 2	liv_units_2	0.2313	22.5246	<0.0001
Original Loan Term Recoded to 180 or 360	Loanterm	-0.0013	-25.7434	<0.0001
Indicator, Current LTV <= 80	ind_ltvcurrent_le_80	-0.0642	-18.5903	<0.0001
Indicator, Current LTV <= 90	ind_ltvcurrent_le_90	-0.0606	-16.9522	<0.0001
Indicator: Loan Size 100-160% of State Average	ind_loansize_100_160	-0.0306	-10.0012	<0.0001
Cube root of Loan Size	Loansizecubrt	-0.1603	-48.4955	<0.0001
Cube Root of HPI Market Volume	hpi_mkt_vol_cubrt	2.1995	21.3182	<0.0001
Indicator: Credit Score >= 620	ind_credit_score_ge_620	-0.0427	-12.7684	<0.0001
Log Loan Age	Agelog	0.1843	80.6175	<0.0001
Log Current Loan-to-Value Ratio	log_ltv_current	0.3052	31.1615	<0.0001
Indicator, Product 3 (ARM)	ind_product_3	-0.0673	-24.8642	<0.0001
Model Fit Statistics				
R-Square		0.4168		

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Exhibit D-6: Loss Rate Given PFS Model Parameters

Description	Parameter	Estimate	t Value	Pr > |t|
Intercept	Intercept	-2.0985	-24.5512	<0.0001
Log Loan Age	Agelog	0.1328	40.9552	<0.0001
Loan-level Mortgage Interest Rate	Coupon	-0.0072	-5.9231	<0.0001
Judicial Foreclosure State	Judicial	0.0304	7.8445	<0.0001
Living Units Equals 2 Indicator	liv_units_2	0.1706	10.5981	<0.0001
Indicator, Current LTV <= 90	ind_ltvcurrent_le_90	-0.0517	-10.0307	<0.0001
Cube Root of Loan Size	Loansizecubrt	-0.0711	-17.8543	<0.0001
Cube-Root of HPI Market Volume	hpi_mkt_vol_cubrt	2.1376	14.0362	<0.0001
Indicator, Credit Score >= 620	ind_credit_score_ge_620	-0.0423	-9.5073	<0.0001
Indicator, Missing Credit Score	credit_score_MISSING	-0.0399	-7.3646	<0.0001
Indicator, Down Payment Assistance from a Relative	dpa_relative	-0.0289	-4.4408	<0.0001
Indicator, Default Duration <= 5	ind_dur_df_le_5	0.0408	7.2301	<0.0001
Local Home Price Appreciation Since Origination	hpa_local	-0.1880	-11.7906	<0.0001
Log Current Loan-to-Value Ratio	log_ltv_current	0.3740	30.4881	<0.0001
Indicator, Product 3 (ARM)	ind_product_3	-0.0590	-9.4305	<0.0001
Indicator, Loan Size 100-160% of State Average	ind_loansize_100_160	-0.0221	-5.8182	<0.0001
Model Fit Statistics				
R-Square		0.3705		

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Exhibit D-7: Loss Rate Given TPS Model Parameters

Description	Parameter	Estimate	t Value	Pr > |t|
Intercept	Intercept	-0.5118	-3.9155	<0.0001
Local Home Price Appreciation Since Origination	hpa_local	-0.6971	-13.1404	<0.0001
Indicator, Judicial Foreclosure State	Judicial	0.1507	21.2395	<0.0001
Living Units Equals 2	liv_units_2	0.1924	6.2791	<0.0001
Cube-Root of Loan Size	Loansizecubrt	-0.1306	-20.9165	<0.0001
Cube-Root of HPI Market Volume	hpi_mkt_vol_cubrt	2.7580	9.5739	<0.0001
Indicator, Credit Score >= 620	ind_credit_score_ge_620	-0.0639	-8.7366	<0.0001
Indicator, 20 < Loan Age <= 32	ind_loanage_20_32	-0.0692	-7.6722	<0.0001
Indicator, Loan Age <= 20	ind_loanage_le_20	-0.1565	-16.3322	<0.0001
Log Current Loan-to-Value Ratio	log_ltv_current	0.1599	13.4119	<0.0001
Indicator, Current LTV <= 90	ind_ltvcurrent_le_90	-0.1136	-11.2758	<0.0001
Model Fit Statistics				
R-Square		0.2273		

Exhibit D-7a: TPS Outbid Share Model Parameters

Description	Parameter	Estimate	z Value	Pr > |z|
Intercept (anchored)	Intercept	-1.1957	–	–
Current LTV Spline, LTV <= 50	ltvc1	-0.0041	-0.70	0.4867
Current LTV Spline, 50 < LTV <= 100	ltvc2	-0.0426	-14.79	<0.0001
Local Home Price Appreciation	hpa_local	1.1552	2.65	0.0080
Indicator, Post-FY 2022 Policy Regime	post_2022	0.3516	4.37	<0.0001
State Fixed Effects (estimation only)	state_fe	Included		
Model Fit Statistics				
Auctions (FY 2014–2026)		10,188		
McFadden Pseudo R-Square		0.1796		

The multivariate logistic regression model predicting loss disposition types demonstrated fair data fitting with an adjusted R-Square of 0.3301. The GLM model for REO loss rates also provides satisfactory explanatory power with an R-squared of 0.4168. For PFS and TPS loss rates, fewer significant variables were identified, and the fitted GLM models have R-squared values of 0.3705

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and 0.2273, respectively. However, this is reasonable, given that the sample sizes of PFS and TPS are significantly smaller than those of REO. Overall, loss recovery rates can be affected by many subjective factors that are difficult to capture by quantitative models. Importantly, all the loss severity rate models provide reasonable predictive power, as demonstrated in model validation, which is shown in Section D3.3. Similarly, the fitted TPS outbid share model has a McFadden Pseudo R-Square of 0.1796, which can be improved when more data are observed.

D2.3. Loss Mitigation Expenses

HUD initiated a loss mitigation program in 1996 to provide opportunities for borrowers in financial difficulties to retain homeownership. Loss mitigation also reduces foreclosure costs. In the standard process, mortgage servicers provide default counseling for borrowers who are behind on their payments and offer appropriate loss mitigation options to prevent borrowers from losing their homes. In 2009, FHA started the Home Affordable Modification Program (HAMP) as a new loss mitigation option, and the program represented increasing percentages of loss mitigation assistance through the years. In 2016, Loan Modification as a standalone option was eliminated and combined into HAMP.

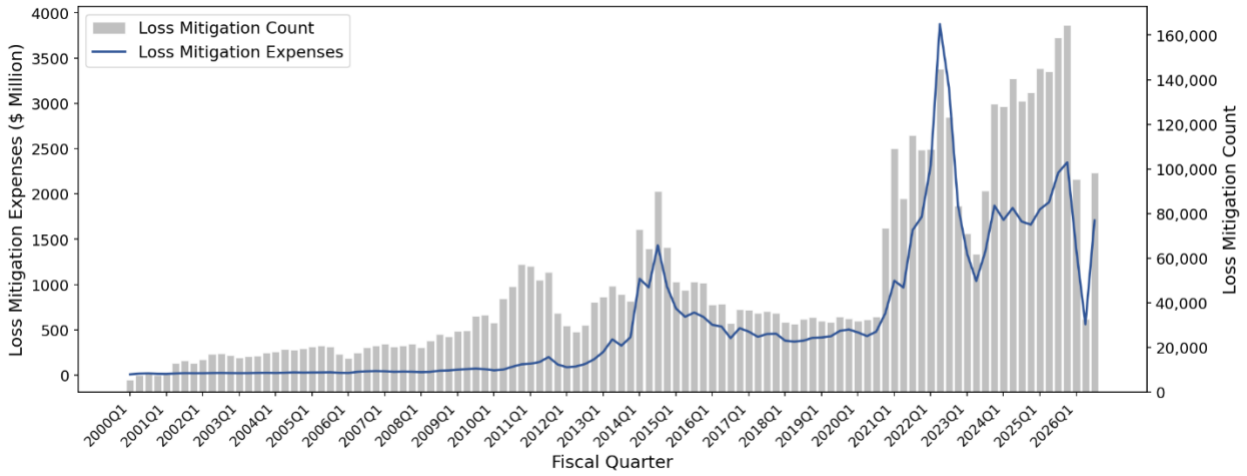
The loss mitigation program includes Forbearance and HAMP, which has Loan Modification and Partial Claim options. A Special Forbearance is a written repayment agreement between the mortgagee, acting on behalf of FHA, and the borrower that contains a plan to reinstate a loan.

Loan Modification modifies the contractual terms of the mortgage permanently, such as lowering the interest rate or increasing the loan term. Under the partial claim option, a mortgagee will advance funds on behalf of a mortgagor in an amount necessary to reinstate a delinquent loan. The borrowers are required to sign a promissory note and a subordinated mortgage payable to FHA for the amount advanced. Loss mitigation payments made by FHA may include administrative fees and costs of title searches, recording fees, subordinated mortgage note amounts associated with partial claims and the payment supplement program, and costs associated with preforeclosure sales.

Exhibit D-8 shows the historical loss mitigation expenses by fiscal quarter, setting aside preforeclosure sales and third-party sales, which are captured separately under the loss severity model discussion.

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Exhibit D-8: Loss Mitigation Expenses[79]



The expected value of loss mitigation is as follows:

$$\boldsymbol{Loss\ Mitigation\ Expected\ Value} = (\boldsymbol{P}(\boldsymbol{Loss\ Mitigation}) \times (\boldsymbol{Loss\ Mitigation\ Expense}))$$

This model estimates total costs associated with loss mitigation. These costs are incorporated into future FHA cash flows that are discounted as part of the net present value (NPV) calculation. The loss mitigation expense is FHA's gross payment when made, including partial claims and payment supplements. Repayments of the related subordinate notes, on existing or future partial claims, are not projected.

The model uses a comprehensive dataset drawn from FHA's single-family data warehouse. This dataset includes a wide range of loans that have undergone various forms of loss mitigation, offering a strong empirical base for analysis.

We use a Generalized Linear Model (GLM) for loss mitigation rate estimation with LASSO variable selection, tailored to the specific characteristics of the data—namely, that the target variable (loss mitigation expense as a percentage of UPB) will be continuous, strictly positive, and right-skewed. The model uses a gamma distribution for the response variable to model cost data where the variance increases with the mean. A log link function is used to relate the linear predictor (a weighted sum of the independent variables) to the expected value of the loss mitigation expense rate. This ensures that the model's predictions remain positive and are interpretable in multiplicative terms.

The estimation of loss mitigation expenses utilized loan-level data of historical mitigations from the FHA single-family data warehouse from 1997 to 2026. The sample used for estimation included 64,256 loans with associated loss mitigation over the timeframe, drawn from the same stratified forecasting sample (Section B1.5.2). The following table includes the model parameters

[79] Source: SFDW.IDB_1.

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for the loss mitigation expense estimates, including the coefficients, standard errors, and Chi-square statistics.

Exhibit D-9: Loss Mitigation Expense Model Parameters

Description	Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	Intercept	-1.4497	0.1301	124.20	<0.0001
Loan-level Mortgage Interest Rate	Coupon	-0.1623	0.0112	210.79	<0.0001
Indicator, COVID Loss Mitigation Period	covid_lossmit	0.7360	0.0370	396.57	<0.0001
Front-End DTI	dti_front_end	0.0078	0.0012	44.68	<0.0001
Indicator, Front-End DTI Missing	dti_front_end_MISSING	0.1629	0.0371	19.29	<0.0001
Refinance Burnout Measure on Moving Average of Amount Prepayment Option in the Money	in_money	0.0013	0.0001	157.60	<0.0001
Indicator, Judicial Foreclosure State	Judicial	0.0694	0.0172	16.19	<0.0001
Original Property Value	orig_value	0.0000	0.0000	133.04	<0.0001
Relative Difference Between Coupon Rate and Market Refinance Rate	Relspread	0.0017	0.0004	18.91	<0.0001
Change in Unemployment Rate, t-3 to t-1	ue_delta	0.0439	0.0070	38.84	<0.0001
Yield Curve Slope Ratio (Treasury 10 Year Rate to Treasury 1 Year Rate)	Ycslope	0.0186	0.0017	123.79	<0.0001
Indicator, Fiscal Period 2012 through 2021 Q2	fy_2012_2021Q2	0.3433	0.0377	82.83	<0.0001
Relative Unemployment Rate	ue_relative	-0.7559	0.0382	390.84	<0.0001
Cube Root of Loan Size	Loansizecubrt	-0.2146	0.0199	116.01	<0.0001
Indicator, ML 2025-12 Policy Regime	ml_2025_12	0.7971	0.0620	165.08	<0.0001

As previously discussed, all COVID-19 Recovery Loss Mitigation Options were extended through and expired on September 30, 2025, and the new "loss mitigation waterfall" was effective October 1, 2025. The limited FY 2026 data under the new loss mitigation waterfall in Exhibit D-8 indicates that the loss mitigation expenses overall decrease from the levels during the COVID-19 policy regime, imposing a positive effect on the NPV of the MMI Fund. This is consistent with the expectation that the new waterfall is generally returning to more restrictive and conservative standards, which are similar to the pre-COVID ones in the following three ways.

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First, ML 2025-12 requires mortgagees to obtain certification and documents necessary from borrowers to demonstrate specific financial hardship, similar to the pre-COVID period. In contrast, during the COVID-19 pandemic, no documentation was required to prove the hardship beyond the borrower's assertion of hardship under the CARES Act, and some streamlined modification options, such as COVID-19 Advance Loan Modification (ALM), were automatically offered to eligible borrowers and did not require borrower contact (ML 2021-15).

Second, ML 2025-12 limits one permanent loss mitigation option every 24 months versus 18 months, representing a return to the same pre-pandemic standard under the FHA-HAMP options (ML 2012-22).

Third, to reduce the increased redefaults under the COVID-19 loss mitigation options, FHA returns to its practice under HAMP of requiring servicers to impose Trial Payment Plans (TPPs) before borrowers could execute any retention options for its permanent waterfall (FHA Annual Report to Congress FY 2024).

With the reinforcement of the prudent risk management approach FHA observed before the COVID-19 pandemic, the new waterfall represents a shift from broad and repeated borrower assistance under the COVID-19 loss mitigation regime toward a more selective and sequential loss-minimization approach. However, this change is expected to reduce loss-mitigation expenditures primarily through lower utilization and reduced repeated assistance rather than necessarily through materially lower costs per completed intervention. Although the new waterfall differs from the pre-COVID HAMP regime in certain respects, including the availability of payment supplements and 40-year loan modifications, both regimes rely substantially on structured loss mitigation options involving loan modifications, Partial Claims, or combinations of these mechanisms as shown in Exhibit I-1. Therefore, the pre-COVID HAMP experience remains relevant for estimating conditional loss mitigation expense rates under the new waterfall. This assumption is also heuristically supported by the historical percentage loss mitigation experience rates across different policy regimes presented in Exhibit D-16.

Given the limited emerging experience under the new waterfall, we adopt a blended approach for the FY 2026 forecast. Specifically, we assign equal weights (i.e., 50% each) to the estimated effects associated with the fy_2012_2021Q2 indicator and the new waterfall indicator, respectively, for the projected loss mitigation expense rate per incidence. The ml_2025_12 coefficient reported in Exhibit D-9 (0.7971) is the fitted, pre-blend estimate; the 50 percent weight is applied at scoring. The new waterfall indicator captures the overall effect brought by a series of new-waterfall-related policy revisions since ML 2025-12, including ML 2026-08. This approach recognizes the relevance of the historical HAMP policy effect while incorporating emerging experience under the new waterfall, without relying exclusively on either policy regime. Given the uncertainty brought by the new loss mitigation waterfall, sensitivity tests on loss mitigation rates are performed in Section IV.F to assess the magnitude of potential effects. It is also important to point out that this assumption should be re-examined when more credible loss mitigation data under the new policy regime is available.

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Cash flow scope for partial claim and payment supplement repayments. Partial claims and payment supplements are secured by zero-interest subordinate notes payable to HUD. A note falls due when the first mortgage is paid off (other than by a Streamline Refinance, to which HUD subordinates the note), the property is sold or transferred, the mortgage is assumed or matures, or, if the note provides, FHA insurance terminates (Handbook 4000.1, Section III.A.2, as updated by ML 2025-12). Since the loss_mitigation data used for estimation record loss mitigation payments only, no repayment is netted against this expense, and the model does not project repayments on future partial claims and payment supplements. However, repayments of existing notes, on partial claims and payment supplements paid through September 30, 2026, are considered as loan receivable by HUD, net of an allowance for subsidy (HUD Agency Financial Report, Fiscal Year 2025, pp. 65, 69, and 96). Therefore, they have been reflected in capital resources at HUD's carrying value.

Excluding repayments of future notes values loss mitigation on a gross cash basis, consistent with the FY 2025 Review, and is a conservative approach. Partial claims account for about 98 percent of paid loss mitigation dollars (SFDW loss_mitigation table), or about $14.4 billion of the estimated $14.702 billion loss mitigation expense. If each note were repaid in full when its loan prepays, and nothing were repaid when the loan goes to claim, the present value of projected repayments on future partial claims would be approximately $7.8 billion. Furthermore, three additional factors must be weighed in. The first judgmental factor, 0.40 to 0.60, reflects that fewer loans with partial claims reach prepayment than average, because they redefault more often. FHA reports one-year redefault rates after loss mitigation approaching 60 percent for recent actions (Annual Report to Congress Regarding the Financial Status of the FHA Mutual Mortgage Insurance Fund, Fiscal Year 2025, Exhibit O-10, p. 14). The second factor, 0.85, reflects that HUD subordinates the note to a Streamline Refinance rather than collecting it. The third factor reflects the estimated collection ratio of partial claims due. HUD's Office of Inspector General estimated that HUD collected 77 to 81 percent of the partial claims that became due in FY 2015 (Audit Report 2016-KC-0001), and a 2026 audit found that the servicing and collection weaknesses persist (Audit Report 2026-KC-0005). Together, these factors give an indication of approximately $2.0 billion to $3.2 billion in repayments on future partial claims.

D2.4. Refunded Premiums

FHA first introduced the upfront premium refund program in 1983. It specified that FHA would refund a portion of the upfront premium when a household prepaid its mortgage. The upfront premium was "earned" over the life of the loan. Upon prepayment, an approximation of the unearned upfront premium is returned to the borrower. Therefore, the amount of the refund depends on the time from origination to when the mortgage is prepaid. For modeling purposes, the refund payments are calculated as follows:

*Refund Payments = Original UPB * Upfront Premium Rate * Refund Rate*

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For this review, we applied a dynamic simulation approach that tracks loan transitions to default, claim, and prepayment that reflect the probabilities of the various transitions (see Appendix C). Refund payments for each quarter are calculated based on the number of loans repaid in that quarter. In the past, borrowers always received the upfront premium refund when they prepaid their mortgages before the maturity of the mortgage contract. In 2000, FHA changed its policy so that borrowers would obtain refunds only if they prepaid within the first five years of their mortgage contracts. The most recent policy change at the end of 2004 eliminated refunds for early prepayments of any mortgages endorsed after that date, except for those borrowers who refinanced into a new FHA loan within 3 years following the original endorsement date.

D3. Economic Net Worth

Once all the above future cash flow components are estimated, their present value can be computed by discounting them at an appropriate rate. The economic net worth is the sum of the present value of future net cash flows plus the current capital resources.

D3.1. Discount Factors

The discount factors applied in computing the present value of cash flows are the OMB Single Effective Rates (SER). Pursuant to Federal Credit Reform Act (FCRA) guidelines, the net present value of HUD's forward portfolio is determined utilizing the cohort-specific single effective rate. Because this rate is a statutory parameter fixed by law, it is treated as a deterministic baseline constraint within the model, distinct from empirical actuarial variables subject to statistical variance or estimation risk. Our simulations aggregate each future year's cash flows, which are treated as being received at the end of the year. The single effective rates applied for discounting are listed in Exhibit D-10.

Exhibit D-10: OMB Single Effective Rate

Cohort Year	Single Effective Rate
1992	7.36%
1993	6.68%
1994	6.86%
1995	7.22%
1996	6.80%
1997	6.59%
1998	5.93%
1999	5.93%
2000	6.20%
2001	6.12%
2002	5.48%
2003	4.76%
2004	3.71%
2005	2.33%

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Cohort Year	Single Effective Rate
2006	4.55%
2007	4.61%
2008	4.88%
2009	4.47%
2010	1.67%
2011	3.72%
2012	2.04%
2013	2.41%
2014	2.98%
2015	2.30%
2016	2.43%
2017	2.65%
2018	2.81%
2019	2.68%
2020	1.40%
2021	1.42%
2022	2.36%
2023	4.07%
2024	4.58%
2025	4.86%
2026	3.70%

D3.2. Calculating Economic Net Worth

The economic net worth of the Fund as of the end of FY 2026 was calculated first by determining the present value of the future cash flows for all surviving loans as of September 30, 2026. This figure was then added to the capital resources of the Fund, estimated as of the same date.

D3.3. Cash Flow Model Validation and Backtesting

D3.3.1. Premium Income

We evaluate premium income forecasting performance by comparing the predicted quarterly premium and refinance repayments with realized outcomes on a rolling basis from FY 2020 Q1 to FY 2026 Q2. The backtesting data are the model's stratified loan sample, weighted to represent all active loans at the beginning of each quarter. The backtest applies the final FY 2026 models at every test date and the models were not re-estimated as of each date.

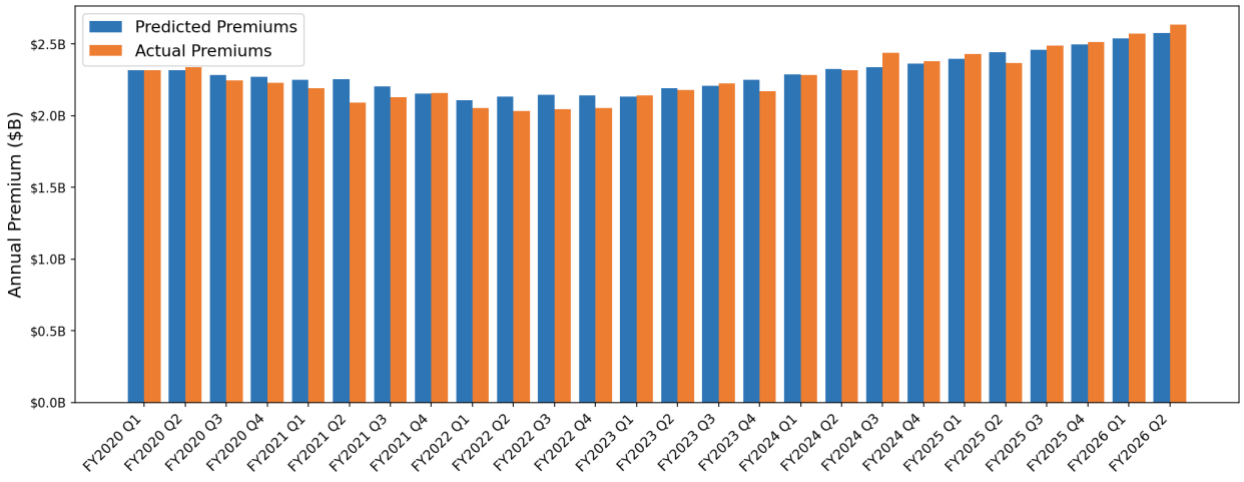
Each quarter, we “walk forward” the loans considered in the survivorship calculation by one quarter, removing conditional termination, to derive projected quarterly premium income and refinance premium outflow for each quarter through FY 2026 Q2. This is achieved by applying

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the transition model for each loan, considering dynamically updating loan, borrower, and property characteristics. Premium income projections are then derived by applying the appropriate premium formulas to the surviving loans, aggregated by product type, origination period, LTV, credit score, and age. As in the forecast, annual MIP is calculated on the original amortization schedule after the quarter's scheduled payments, for loans still insured at the end of the quarter (Section D2.1.3), and loans that prepay or go to claim during a quarter pay no premium for that quarter.

Exhibit D-11 presents the annual premium income backtesting results. Over the 26 quarters, actual premiums collected totaled $59.01 billion. Predicted premiums were 0.94 percent above actuals at $59.57 billion (percentages are computed from unrounded amounts). In terms of Mean Absolute Percentage Error, the average difference is 2.2 percent.

Exhibit D-11: Annual Premium Income Predicted versus Actual



D3.3.2. Loss Severity

Both the loss selection model and loss severity rate models were tested on the validation data set. The training data set represents 80% of available data, and conversely, the validation data set represents the remaining 20%. Exhibit D-12 presents the predicted loss severity by disposition type, with each cell weighted by the population weight used in model estimation. The classification decision thresholds of the logistic regression were determined based on the GHOST (Generalized Threshold Shifting) procedure, which is particularly useful for imbalanced data. The overall accuracy of the prediction was 63.47%, which confirms the effectiveness of the model. The model achieves a sensitivity of 56.89% for REO, correctly identifying more than half of REO claims. The recall for PFS is 23.05%, which implies that the model is relatively biased toward REO and TPS. This is largely due to the imbalanced proportion of PFS in the sample. The recall for TPS is 79.96%, indicating that most TPS claims, the predominant disposition since 2012, are correctly identified. On the other hand, the model achieves a precision of 51.94% for PFS, 56.78% for REO,

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and 68.68% for TPS, indicating that a relatively high portion of the model predictions are accurate for each type.

Exhibit D-12: Actual and Predicted Loss Severity by Type

Loss Severity Type	Final Prediction Type			
Percent Row Pct Col Pct	PFS	REO	TPS	Total
PFS	3.47 23.05 51.94	6.09 40.46 17.67	5.49 36.49 9.33	15.05
REO	1.88 5.47 28.16	19.57 56.89 56.78	12.95 37.65 22.00	34.40
TPS	1.33 2.63 19.89	8.80 17.41 25.55	40.43 79.96 68.68	50.56
Total	6.68	34.46	58.87	100.00

The following three graphs compare the actual and predicted loss severity rates for REO, PFS, and TPS by fiscal year, respectively. These graphs indicate that the three loss rate models provide reasonable forecasts of the observed loss rates for each type. The count-weighted mean absolute errors for REO, PFS, and TPS on the validation data are 0.0378, 0.0333, and 0.0532, respectively. They are 6.74%, 8.08%, and 9.79% of their respective mean loss severity rates, indicating small model prediction errors for both REO and PFS. The prediction error is slightly higher but acceptable for TPS, largely attributed to a lack of sufficient data. Additionally, Exhibits D-13 to D-15 show that the model performance is superior in periods with large data observations, and the prediction error generally increases in those periods with less data, further confirming that data availability can reduce the overall prediction errors.

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Exhibit D-13: Actual and Predicted REO Loss Severity Rates by Fiscal Year

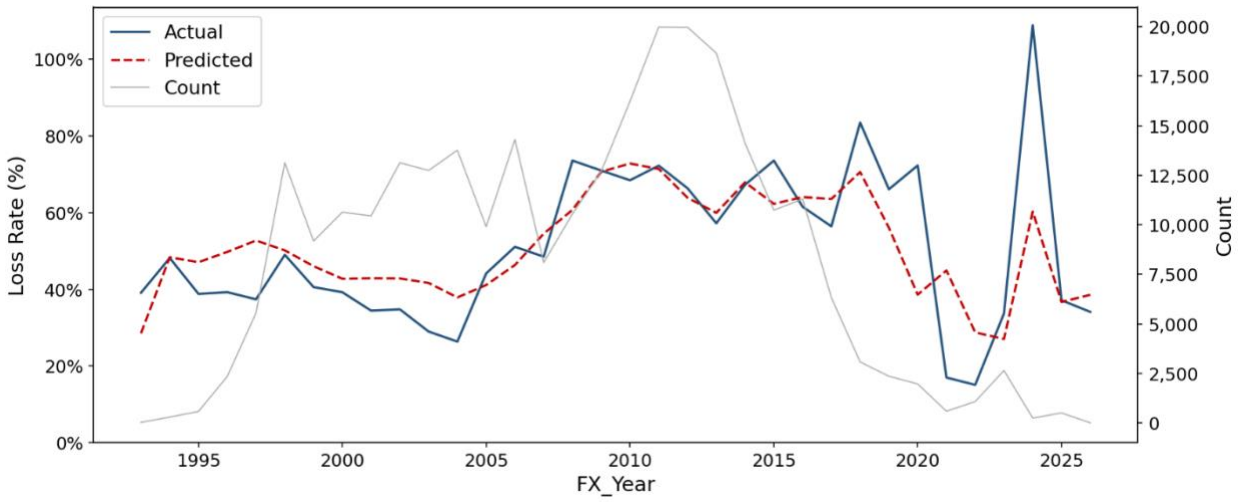


Exhibit D-14: Actual and Predicted PFS Loss Severity Rates by Fiscal Year

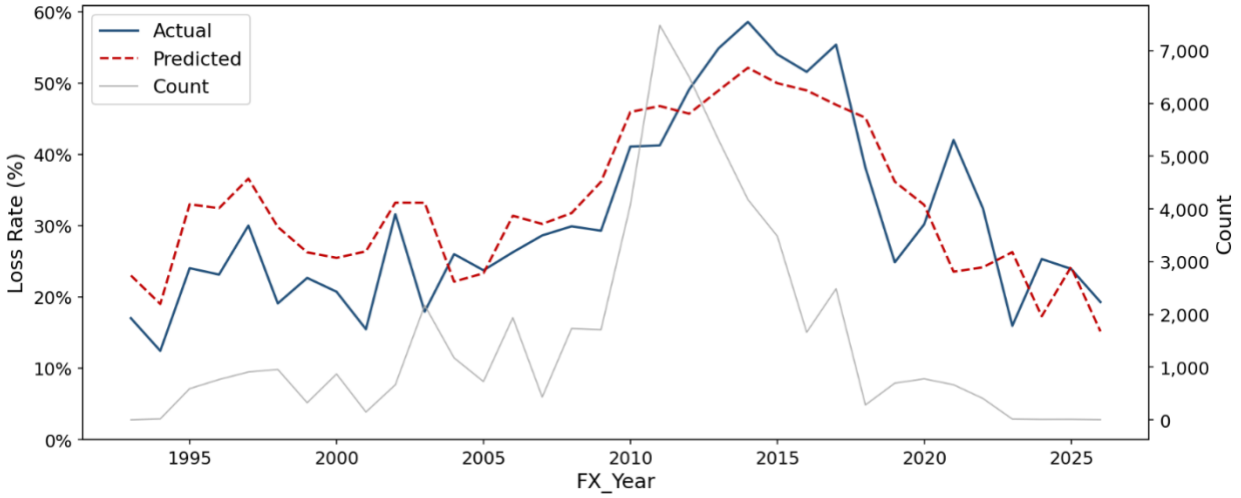
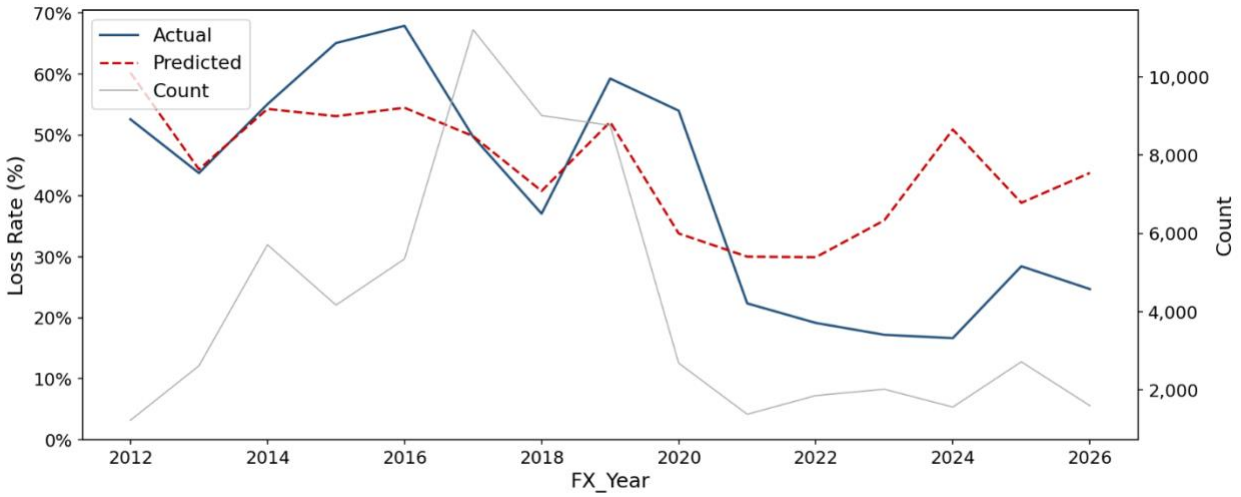


Exhibit D-15: Actual and Predicted TPS Loss Severity Rates by Fiscal Year



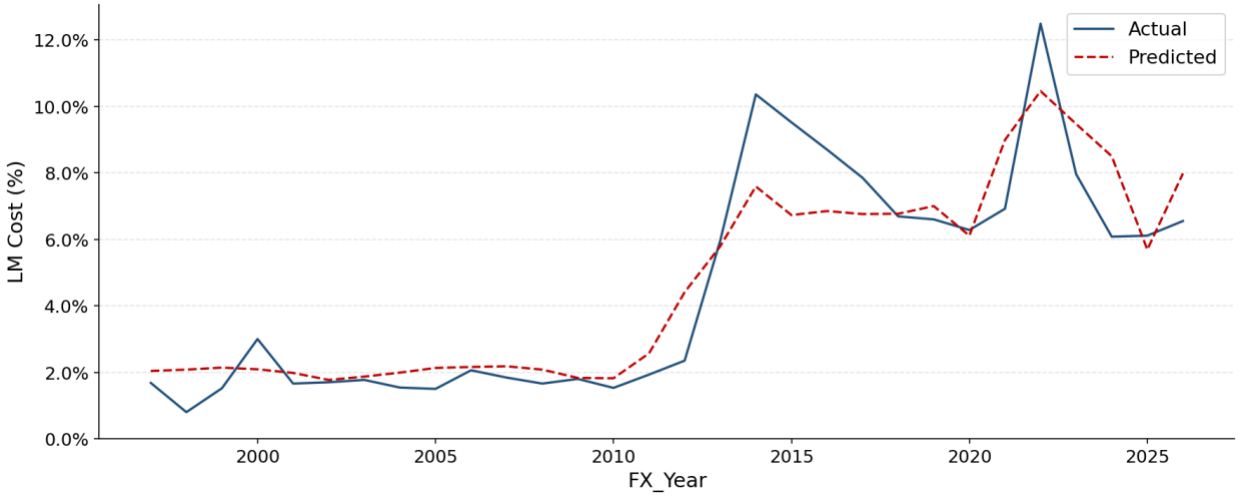
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D3.3.3. Loss Mitigation

The loss mitigation expense samples were equally split into an estimation sample and a holdout sample. The loss mitigation model was applied to generate predictions for the holdout sample, which were compared to the actual loss mitigation expense rates.

Exhibit D-16 compares the estimated and actual percentage loss mitigation expenses by fiscal year for the validation dataset. The count-weighted mean absolute error of the loss mitigation model on the validation dataset is 0.0042, which is 8.44% of the mean loss mitigation rate, indicating a small model error. Overall, the loss mitigation model effectively captured loss mitigation policy regime changes and properly predicted the loss mitigation expenses across years.

Exhibit D-16: Estimated and Actual Percentage Loss Mitigation Expenses by Fiscal Year



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D4. Extension of Cash Flows Up to 40 Years

In this review, we incorporate loan extensions beyond the standard 30-year term directly into the baseline cash flow projections, extending the total forecasting horizon to 40 years. This replaces last year's exploratory treatment, in which the effect of extended loans was measured only as a separate experiment outside the baseline. The implemented methodology captures two channels:

- **Loans already extended beyond 30 years.** We identify the stock of currently active loans whose modified maturity extends past 30 years, using the modified maturity date recorded in the loan modification data. Their cash flows are projected up to 40 years from origination, the end of the projection horizon, using our existing transition, claim, and loss mitigation models.

- **Future modification-driven extensions.** We also project extensions arising from future loss mitigation activity, applying a 40-year modification propensity of 10 percent to the flow of loans cured through modification. The 10 percent is the observed share of modification cures that received a 40-year term from recent history, which ranged between 9 and 11 percent FY 2024 – FY 2026. Because the permanent loss mitigation waterfall is dominated by partial claims, only a modest share of modified-cure loans ultimately receive a 40-year re-amortization. The split between partial claims and loan modifications depends on prevailing and projected mortgage interest rates; the recent higher-rate experience used to project the split may not hold throughout the forecast horizon.

Annual MIP is calculated on the amortization schedule established at origination, without regard to agreements to recast the mortgage, and is collected only over that schedule (24 CFR 203.261). The model follows this rule: for an extended loan, annual MIP and its duration rule (Section D2.1.3) are based on the loan's original-schedule balance, and no annual MIP is collected after the original maturity date. Claims, recoveries, and loss mitigation are projected on the extended balance and over the extended term. An extension therefore adds no premium income, while claim and loss mitigation exposure continues on a higher balance for up to ten additional years.

We measure the effect of extensions against a counterfactual run of the same model and inputs, in which loans already extended are projected on their original maturity and no future modification extends a loan to 40 years. On this review's FY 2026 baseline (FY 2026 data, models, and economic assumptions), incorporating extensions reduces the Cash Flow NPV by $1.355 billion[80] or 5.0 percent from $26.926 billion to $25.571 billion (Exhibit D-17). The reduction falls in every cohort group, for different reasons:

- **Cohorts 1996–2012:** NPV falls by $380 million, enlarging the group's net loss from $602 million to $982 million (63 percent). Most of these loans have reached automatic MIP cancellation and pay almost no annual premium with or without an extension. Without an

[80] This figure differs from the $1.393 billion change shown in Exhibit II-3, which measures the impact of the 40-year extension change in the FY 2025 review, based on the FY 2025 portfolio and data.

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extension they would pay off at their original maturity; if extended, they remain insured, adding $302 million in claims and $233 million in loss mitigation, partly offset by $156 million in recoveries.

- **Cohorts 2013–2025:** NPV falls by $967 million, primarily driven by a $890 million reduction in annual premium income. Most of these loans pay MIP for the full mortgage term, with premium payments determined by their original amortization schedules. Consequently, extending the loan terms does not generate any additional premium income. Furthermore, the extended loans tend to have higher current LTVs and are more likely to default, reducing the number of loans that continue making the scheduled premium payments. Lower claims ($300 million) are largely offset by lower recoveries ($185 million) and higher loss mitigation ($201 million).

- **Cohort 2026:** The $8 million decrease in NPV, from $42 million without extensions to $34 million with extensions, is driven primarily by an $11 million increase in claims and a $3 million increase in loss mitigation, partially offset by $6 million in additional recoveries. Unlike the earlier cohort groups, the 2026 cohort shows little change in annual premium income or premium refunds. This indicates that the impact of loan extensions for this cohort is mostly attributable to changes in projected claims and loss mitigation cash flows rather than changes in premium collections.

Exhibit D-17: Effect of Loan Extensions on Cash Flow NPV by Cohort Group ($ Million)

Credit Subsidy Cohort	NPV Without Extensions	NPV With Extensions	Change	Annual Premiums	Premium Refunds	Claims	Recoveries	Loss Mitigation
1992–1995	$ 0	$ (1)	$ (1)	$ 0	$ 0	$ (1)	$ 0	$ 0
1996–2012	(602)	(982)	(380)	(1)	0	(302)	156	(233)
2013–2025	27,486	26,519	(967)	(890)	8	300	(185)	(201)
2026	42	34	(8)	0	0	(11)	6	(3)
Total	$ 26,926	$ 25,571	$ (1,355)	$ (891)	$ 8	$ (14)	$ (22)	$ (437)

Note: Component columns show the change in each component's contribution to NPV (positive increases NPV). Components may not sum to the change because of rounding. “With extensions” is the FY 2026 baseline; “without extensions” is the counterfactual described in the text.

For extended loans, we apply our existing modification-state transition and claim rate models rather than separately re-estimating transition probabilities for extended-maturity loans.

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Appendix E. Stochastic Simulation Models

This Appendix describes the stochastic models used to generate economic variables used in the Monte Carlo simulations of the FHA Single-Family Forward Mortgages Actuarial Review 2026. Based on the best-fitted stochastic model, we use the Monte Carlo simulation technique to simulate 1,000 paths of future economic variables and obtain the 1st, 10th, 25th, 50th, 75th, 90th, and 99th percentiles of the simulated paths.

This year's review updates the simulation models used to obtain percentile paths. Each quarterly point of a percentile path is the percentile value across all simulation paths at that quarter, used as the percentile reference path. Whichever real simulated path is closest to the percentile reference path is identified as the obtained percentile path. This method uses the real simulated trajectory and represents the overall percentile profile among all the simulated paths. At the same time, in our Monte Carlo simulation, the simulated paths are centered on the baseline economic assumptions; that is, the 50th percentile of the simulated path is close to the baseline PEA and is replaced by the PEA baseline assumption.

The estimated simulation models are identical for the Single-Family Forward Mortgages and HECM with respect to Treasury rates, SOFRs, and national and regional HPIs. Additional forecast models for 30-year mortgage rates and unemployment rates are applied to Single-Family Forward mortgages.

The simulated scenarios of the U.S. economy used as the components of the forecast include:

- 1-year CMT rate,
- 10-year CMT rate,
- 1-month Secured Overnight Financing Rate (SOFR),
- 30-year fixed mortgage rate,
- Unemployment rate, and
- FHFA national Purchase Only house price appreciation rate (HPI-PO).

The stochastic models are calibrated to historical data and are chosen based on the Augmented Dickey–Fuller (ADF) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test for stationarity in time series; Ljung-Box (LB) for autocorrelation in residuals after model fitting; likelihood, AIC, and BIC values for parameter selection; and a one-step rollover forecast test. Model adequacy is further evaluated using the weighted ARCH-LM test for remaining conditional heteroskedasticity, the Nyblom tests for parameter stability, sign-bias tests for asymmetric shock effects, and the Pearson goodness-of-fit test for the assumed residual distribution.

At the same time, since all status transition probabilities are estimated and projected using a series of historically observed and projected interest rates with different maturity terms, the stochastic interest rate models are internally consistent in model calibration and forecasting. This approach is appropriate for the Actuarial Review as we are computing the present value of projected future cash flows for liability valuation.

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In addition, the methodology to identify percentile paths in the FY 2026 Actuarial Review is changed to improve the representation of percentile paths in the variation of economic variables in early years of forecast, except the HPA percentile paths identification. The new percentile paths identification method equally weights the dispersions in simulated paths in early simulation years and the dispersions in long horizon. This new method is in line with the demonstration of optimistic and pessimistic scenarios.

E1. Historical Data

E1.1. Interest Rates

With the high inflation rate caused by the global oil crisis in the late 1970s, interest rates rose to a historically high level in the early 1980s. Then the Federal Reserve shifted its monetary policy from managing interest rates to managing the money supply, at least until inflation, and consequently interest rates, receded. Exhibit E-1 shows historical 1-year and 10-year CMT rates from 1970 Q1 to 2026 Q2. The one-year Treasury rate (CMT1) fluctuated around 6% in the early 1970s and increased steadily to its peak of 16.31% in CY 1981 Q3. After that, it followed a decreasing trend and reached a then-record low of around 1.2% in 2004. From then on, rates started a slow upward trend until the 2007 financial crisis, and then started a sharp downward trend, reaching a historic low of 0.06% in CY 2021 Q2. Inflation turned up dramatically because of the COVID-19 pandemic. Monetary policy initiatives aimed to overturn the post-pandemic inflation, and we saw the Federal Reserve tightening with the one-year rate increasing to 5.39% in 2023 Q3 and then turning down. The one-year CMT rate is 3.88% in 2025 Q3, and 3.80% in 2026 Q2.

The ten-year Treasury rate (CMT10) generally followed a similar long-run pattern, though with less volatility. It rose from around 7% in the early 1970s to a peak of nearly 15% in 1981 and then declined steadily over the next four decades. The 10-year CMT fell below 1% in 2020 before rising alongside the post-pandemic recovery. As inflation accelerated in the post-pandemic period, long-term rates moved upward again, reaching about 4.45% in 2024 Q2 before easing slightly. The ten-year CMT rate is 4.29% in 2025 Q3 and 4.20% in 2026 Q2.

Also shown in Exhibit E-1 is the 1-year SOFR curve. Historical SOFR data date back to 2006 Q1. The SOFRs reflect Treasury-backed short-term funding costs and are closely tied to Federal Reserve policy, showing a similar cyclical pattern to the 1-year CMT but with a smaller term premium. In the mid-2000s, 1-year SOFR peaked near 5.4%, fell to near 0.1% during the zero-interest-rate era, and then climbed to around 2.5%–2.7% during the 2018–2019 tightening cycle. Pandemic relief drove SOFR to record lows of 0.04–0.11% in 2020–2021 before it surged alongside policy rates, reaching 5.38% in 2023 Q3. It declined to 3.81% in 2025 Q3 and stayed at 3.81% in 2026 Q2, maintaining a tight alignment with the 1-year CMT.

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Exhibit E-1: Historical Interest Rate

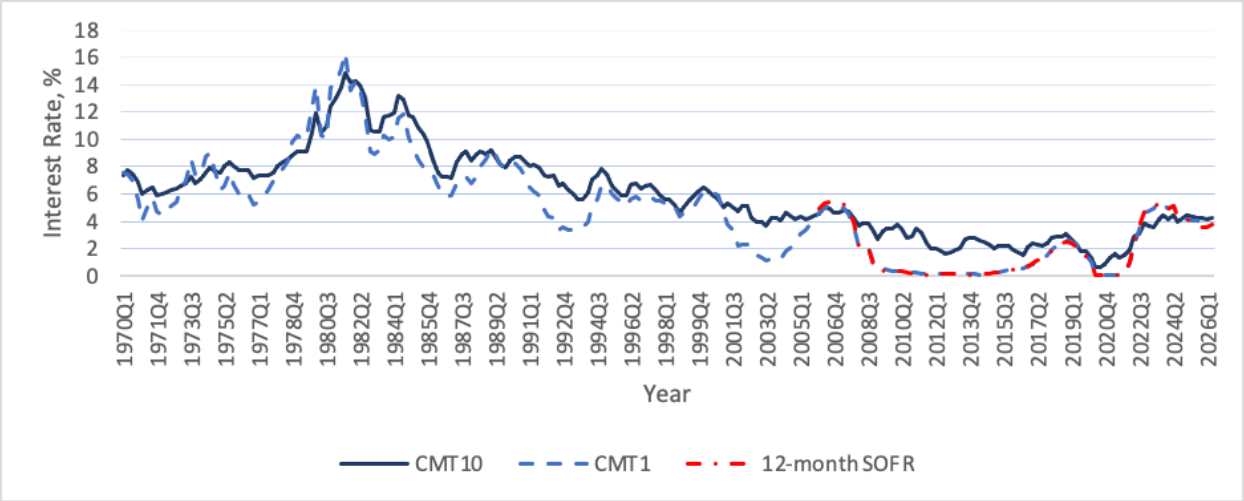


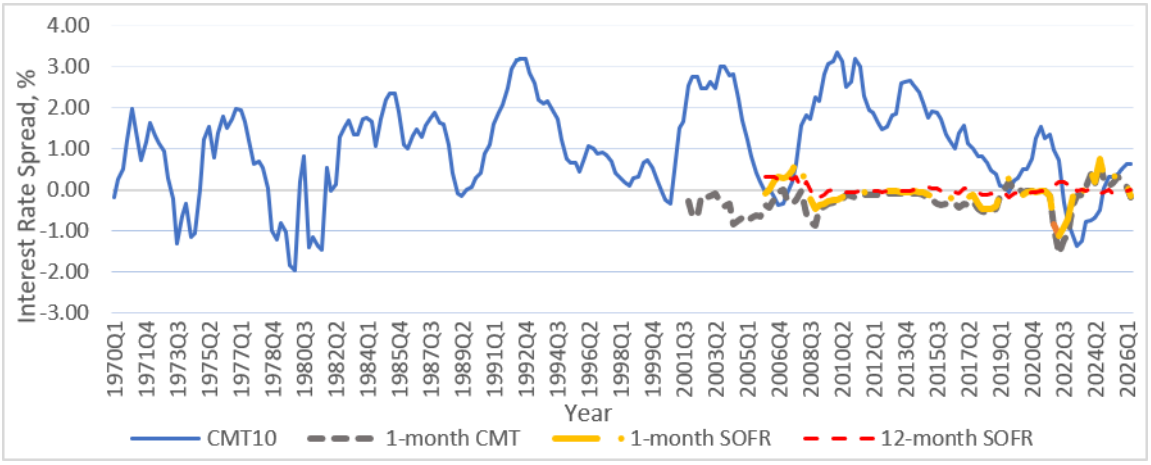
Exhibit E-2 shows historical interest rate spreads for the 10-year CMT, 1-month CMT, and SOFR tenors (1-year and 1-month). The spread between the 10-year and 1-year Treasury rates appears to have cycles above and below zero and high volatility. Historically, the spread has turned negative (yield curve inversion) before recessions, for example, in the late 1970s, early 1980s, 2000, 2006–2007, and again in 2022–2023. The most recent inversion saw the spread reach –1.35% in 2023 Q2. The spread normalized to a positive 0.38% in 2025 Q3 and 0.54% in 2026 Q2, suggesting some easing in monetary policy and reduced recession concerns.

The spread between the 1-month CMT rate and 1-year CMT rate is typically negative (–0.1 to –1.5) having liquidity premium price incorporated. Episodes when the spread narrowed toward zero or briefly turned positive during the late 1970s–early 1980s, mid-2000s, and 2022–2023 correspond to aggressive Federal Reserve rate hikes. During easing cycles and crisis periods, including the early 1990s, post-2008, and pandemic years, the spread widened.

SOFRs are tied to secured funding markets and policy expectations, and their spread over the 1-year CMT rate fluctuates around zero with much smaller variation than Treasury spreads at comparable maturities. The ARMA-GARCH models are identified for the 1-year CMT rate and interest rate spreads.

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Exhibit E-2: Historical Interest Rate Spread (%) with the 1-Year CMT



E1.2. House Price Appreciation Rates

The national house price appreciation rate (HPA) is derived from the FHFA repeat sales seasonally adjusted purchase-only (PO) house price indices (HPIs). The PO HPI is used for national HPA simulation as it provides a reliable measure of housing market conditions since it is based on repeat sales at market prices and does not use any appraised values. The All Transaction (AT) version of HPI is used for deriving geographic dispersion factors as it retains significantly broader regional coverage. At the national level, the AT HPI is very close to the PO HPI.
The HPA at time $\boldsymbol{t}$ is defined as:

$$\boldsymbol{HPA_t = \frac{HPI_t}{HPI_{t-1}} - 1}$$

Exhibit E-3 shows the quarterly national HPI and annualized HPA from CY 1995 Q1 to CY 2026 Q2. The long-term average quarterly HPA is around 1.085% (4.41% annual rate). The HPI increased steadily before 2004 with an annual appreciation rate of about 4.64%. Then house prices rose sharply starting in 2004. The house price appreciation rate was around 10% annually during the subprime mortgage expansion period from 2004 to 2005 and reached its peak at an annual rate of 11.2% in the second quarter of CY 2005. The house price appreciation slowed down in 2006. The downturn started in the second quarter of 2007, and the average growth rate of house prices became negative in 2011. Since then, house price appreciation has stabilized for 10 years. During the COVID-19 pandemic period from 2020 to 2022, house prices increased at a much higher appreciation rate due to economic stimulus policies and then slowed down after the pandemic was over. The house appreciation rate started upward in the third quarter of 2020 and reached 19.45% in the second quarter of 2021. House appreciation reversed after the second quarter of 2022, dropping to an average annual rate of 6.20% in 2023, 4.60% in 2024, and continued to drop to an

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average annual rate of 1.95% in 2025 and 1.05% in 2026 Q2. Exhibit E-4 shows the average annual HPA for selected historical time periods.

Exhibit E-3: Historical National HPI and Annualized HPA

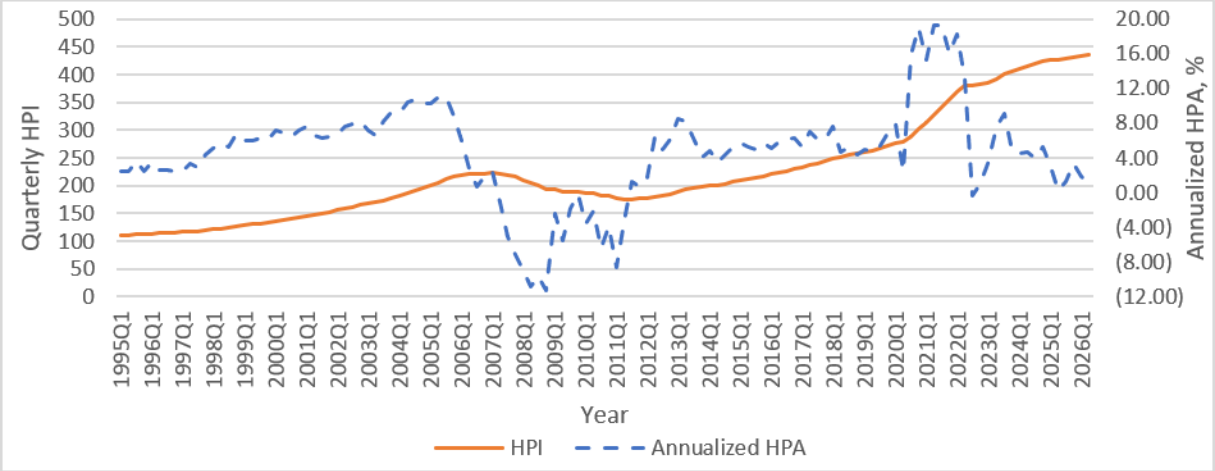


Exhibit E-4: Average Annual HPA by Time Span

Period	Average Annual HPA
1991 – 1997	2.65%
1997 – 2001	6.24%
2002 – 2006	8.95%
2007 – 2011	-3.18%
2012 – 2020 Q2	5.53%
2020 Q3 – 2022 Q2	17.02%
2022 Q3 – 2025 Q1	4.26%
2025 Q2 – 2026 Q2	1.59%

E1.3. Unemployment Rates

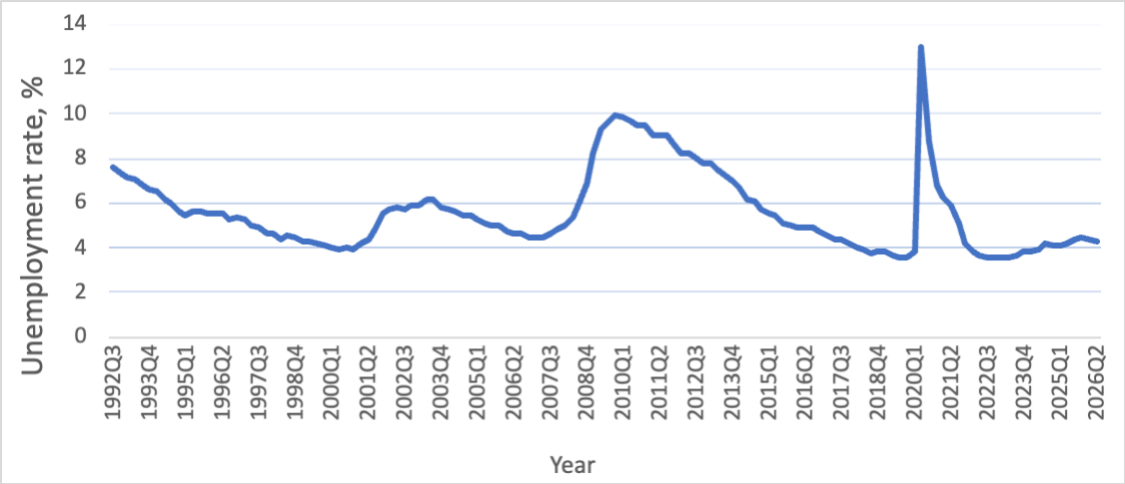
Unemployment rates typically increase during economic downturns and decrease during economic growth periods. Government policies also significantly impact employment. Exhibit E-5 displays historical national unemployment rates since CY 1992 Q3.

A period of robust job creation in the late 1990s brought unemployment steadily down, reaching historically low levels below 4% by 2000 Q4, fueled by the technology boom. The dot-com crash and 9/11 shock pushed unemployment above 6% by 2003, and it fell to the mid-4% range by 2006–2007. The global financial crisis drove it sharply higher, peaking at nearly 10% in 2009–2010. Economic recovery brought a long, steady economic expansion and reduced unemployment to 3.6% by late 2019. The pandemic triggered an unprecedented spike to 13% in 2020 Q2, as enforced

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lockdowns led to widespread business closures and disruptions. Aggressive fiscal and monetary policy, for example, the Coronavirus Aid, Relief, and Economic Security Act (CARES Act), provided the largest economic stimulus in U.S. history and brought the unemployment rate back below 4% by early 2022, and it stayed below 4% until 2024 Q1. Since 2024 Q1, unemployment has drifted up only slightly. Overall, structural resilience in the U.S. labor market, along with policy interventions, has consistently brought unemployment back toward a long-run average of 4 to 5%.

Exhibit E-5: Historical National Unemployment Rates



E2. Stochastic Models and the Simulated Scenarios

Economic variables, either monetary policy-driven or credit conditions driven, exhibit high jumps in volatility around regime shifts. Stochastic models need to account for heteroskedastic volatilities in these economic indicators caused by high economic instability and uncertainty. For these reasons, an Autoregressive Moving Average (ARMA) - Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is chosen for each economic variable.

ARMA-GARCH models combine two types of time series models: Autoregressive Moving Average (ARMA) models for the mean and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models for the variance. This approach is used when dealing with time series data that exhibits both autocorrelation (dependence of a value on its past values) and volatility clustering (periods of high volatility followed by periods of low volatility).

Stationarity is very important in forecasting. It enables the use of simpler and more accurate models to provide a solid foundation for forecasting future values. Non-stationary data, on the other hand, can lead to misleading results and inaccurate predictions because its statistical properties change over time, making it difficult to identify true trends and patterns. Therefore, ADF and KPSS tests for stationarity were performed on all variables before specifying GARCH candidate models for the velocities.

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Ljung-Box (LB) tests are performed on the residuals of candidate models to identify the presence of autocorrelation (serial correlation) in the residuals of a fitted model. It assesses the overall autocorrelation up to a specified lag, rather than individual lags, to identify the best model.

Weighted ARCH-LM test results are reviewed for any remaining ARCH effect present in the standardized residuals. A non-significant result suggests that the volatility model adequately captures conditional heteroskedasticity.

The Nyblom stability test is used to evaluate whether the estimated model parameters remain stable over time. It provides both joint and individual parameter stability tests. In addition, sign-bias tests examine whether the model adequately captures asymmetric volatility responses to positive and negative shocks. Both individual and joint tests are reported. The Pearson goodness-of-fit test is reported to show whether the assumed innovation distribution (e.g., normal, Student-t, or skewed Student-t) provides an adequate fit to the standardized residuals.

The following is the detailed description of the chosen univariate ARMA-GARCH model for each economic variable:

E2.1. 1-Year Treasury Rate

Several Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are tested using historical 1-year CMT rates from CY 1970 Q1 to CY 2026 Q2. Expanding the sample introduces additional historical volatility regimes and worsens parameter instability, while substantially shortening the sample reduces estimation reliability and leaves residual autocorrelation. The selected sample provides the best balance among residual adequacy, sample relevance, and parameter stability, although it does not eliminate the near-integrated volatility behavior.

An ARMA(3,5)–sGARCH(1,1) model with Student-(t) innovations was selected to generate stochastic deviations around the externally specified baseline PEA interest-rate. The specification adequately captures the serial dependence and conditional heteroskedasticity in the selected estimation sample. The weighted Ljung–Box tests indicate no remaining autocorrelation in either the standardized residuals or the squared standardized residuals. The ARCH-LM, sign-bias, and adjusted Pearson goodness-of-fit tests are also satisfactory. The estimated Student-(t) shape parameter indicates heavy-tailed innovations, allowing the simulations to reflect historically plausible extreme movements. In addition, the model is used to produce stochastic deviations around the prescribed baseline rather than determine the long-run central interest-rate forecast independently.

Let $r_{1,t}$ be the one-year Treasury rate at time t. The stochastic process takes the following form:

$$\Delta r_{1,t} = \sum_{i=1}^{3} a_{1,i} \Delta r_{1,t-i} + \sum_{i=1}^{5} b_{1,i} e_{1,t-i} + \varepsilon_t$$

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where $\varepsilon_t = \sigma_t z_t$. $z_t = \sqrt{\frac{v-2}{v}} T_v$, where T_v follows a Student's t-distribution with degrees of freedom $v > 2$, and variance ${\sigma_t}^2$ follows a GARCH (1, 1) model,

$$ {\sigma_t}^2 = \omega + \alpha {\varepsilon_{t-1}}^2 + \beta {\sigma_{t-1}}^2, $$

with the usual stationary constraints $\omega > 0, \alpha \geq 0, \beta > 0$ and $\alpha + \beta < 1$.

The estimated results are presented in Exhibit E-6.

Exhibit E-6: Estimation Results for 1-Year Rate Model

Parameter	Estimate	Std. Error	t value	Pr(>|t|)
$a_{1,1}$	0.79938	0.165516	4.82962	0.000001
$a_{1,2}$	0.568118	0.178981	3.17419	0.001503
$a_{1,3}$	-0.504418	0.126456	-3.98887	0.000066
$b_{1,1}$	-0.2625	0.17087	-1.53626	0.124475
$b_{1,2}$	-0.92163	0.144767	-6.36628	0
$b_{1,3}$	0.416372	0.115433	3.60705	0.00031
$b_{1,4}$	0.270862	0.086144	3.14431	0.001665
$b_{1,5}$	-0.233424	0.076092	-3.06766	0.002157
ω	0.000443	0.000493	0.89908	0.36861
α	0.324362	0.063609	5.09931	0
β	0.674638	0.045561	14.80739	0
v	5.392487	1.180447	4.56817	0.000005

The estimated GARCH persistence ($\alpha + \beta$ =0.999) indicates that volatility shocks decay extremely slowly. Consequently, shocks occurring early in a simulation can materially affect dispersion throughout the long forecast horizon. The ARCH and GARCH coefficients are sensitive to historical interest-rate regimes. The long-term tail paths should therefore be interpreted as stress-oriented scenarios rather than precise probability forecasts.

The model based on these parameters is used to simulate the one-year Treasury rates for the forecast period starting in FY 2027 Q1. When conducting simulation, the conditional mean is replaced by the PEA baseline forecast to ensure stochastic deviations around the PEA interest-rate baseline forecast. We applied the same procedure for the conditional mean in the simulations for all the other economic variables.

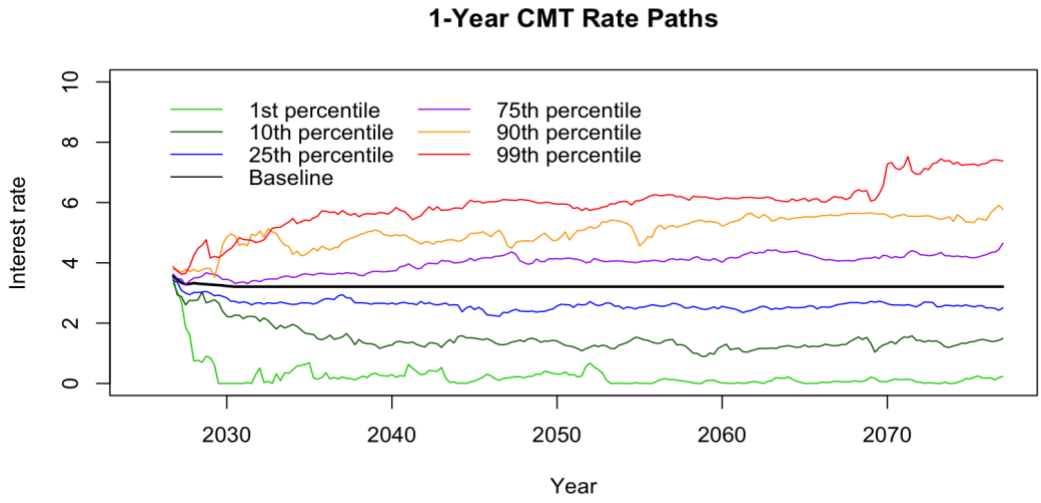
1,000 paths of the future 40 years[81] of 1-year Treasury rates are simulated. The 1st, 10th, 25th, 75th, 90th, and 99th percentile paths are displayed. The 50th percentile path is close to the baseline forecast and is replaced by the PEA baseline assumption. The resulting forecasts for the one-year Treasury

[81] The number of projection years is 40 in the 2026 Actuarial Review.

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rates are shown in the following chart for the baseline PEA and the four alternative stochastic percentile paths.

Exhibit E-7: Simulated 1-Year CMT Rate Percentile Paths



E2.2. 10-Year Treasury Rate

The 10-year Treasury rate is modeled by adding a stochastic spread term to the simulated 1-year Treasury rate. We estimate the dynamics of the spread between the 10-year Treasury rate and the 1-year Treasury rate from historical data.

An AR(2)–sGARCH(1,1) model with normally distributed innovations was selected to model the spread between the 1-year and 10-year CMT rates. Both autoregressive coefficients and the ARCH and GARCH parameters are statistically significant under robust standard errors. The estimated volatility persistence indicates persistent but mean-reverting volatility. The weighted Ljung–Box and ARCH-LM tests indicate no remaining residual autocorrelation or ARCH effects. The joint Nyblom test supports overall parameter stability, while the sign-bias tests show no significant asymmetric volatility response. The adjusted Pearson tests also support the normal distribution, although some p-values are moderately close to 5%. Overall, the model provides an adequate and relatively stable framework for simulating the spread, but tail projections should still be interpreted cautiously because normal innovations may understate unusually large interest-rate movements.

Let $s_{10,t}$ be the spread between the 10-year and one-year Treasury rates at time t. Mathematically, the model for $s_{10,t}$ is as follows.

$$s_{10,t} = a_{10,0} + \sum_{i=1}^{2} a_{10,i} s_{10,t-i} + \varepsilon_t$$

where ε_t is a normal innovation with mean 0 and variance ${\sigma_t}^2$ following a GARCH (1, 1) model,

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$$\sigma_t{}^2 = \omega + \alpha\varepsilon_{t-1}{}^2 + \beta\sigma_{t-1}{}^2$$

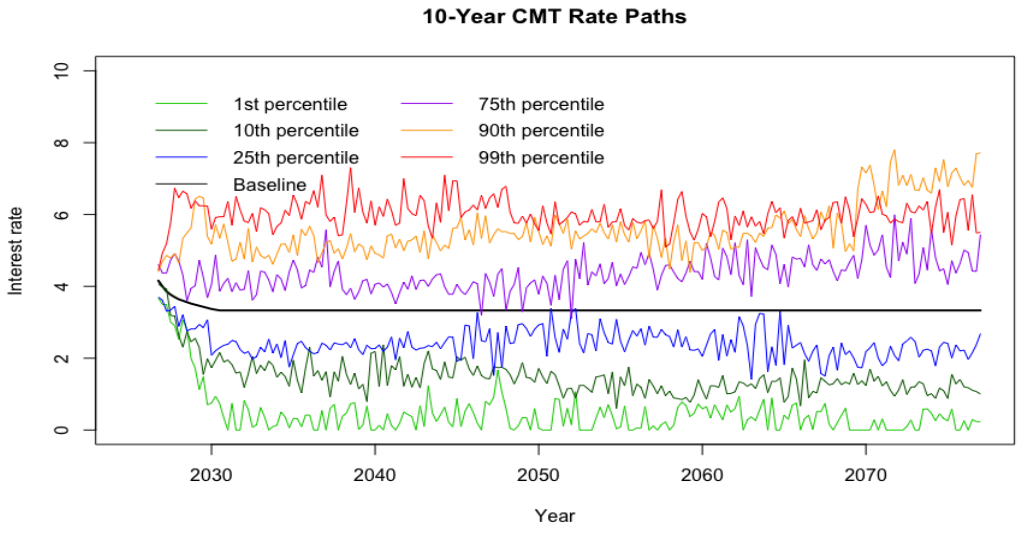
The model is estimated based on historical spread data from CY 1970 Q1 to CY 2026 Q2. Parameters are shown in the following Exhibit E-8.

Exhibit E-8: Estimation Results for 10-Year Rate Spread Model

	Estimate	Std. Error	t value	Pr(>|t|)
$a_{10,0}$	0.70686	0.240827	2.9351	0.003
$a_{10,1}$	1.367596	0.072851	18.7724	0
$a_{10,2}$	-0.443214	0.070722	-6.267	0
ω	0.009369	0.005032	1.8619	0.06
α	0.235739	0.077634	3.0365	0.002
β	0.723516	0.074791	9.6738	0

We used the estimated parameters to simulate the spread between the 10-year and 1-year Treasury rates with the conditional mean equal to the PEA baseline forecast, such that the 1,000 simulated paths are centered on the baseline estimation. The simulated spread percentile paths are added to the corresponding 1-year CMT percentile paths. Percentile paths are obtained therein. The 1st, 10th, 25th, 75th, 90th, and 99th percentile paths, together with the PEA baseline assumption for the ten-year Treasury rates, are shown in the following chart.

Exhibit E-9: Simulated 10-Year CMT Rate Percentile Paths



E2.3. 1-Month SOFR

The first order of difference is taken to ensure stationarity in time series. An AR(1)–sGARCH(1,1) model with Student-(t) innovations was selected to model quarterly changes in the spread between the one-month SOFR and one-year rate. The AR coefficient is marginally significant (p = 0.054)

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under robust standard errors, and the model passes the residual Ljung–Box, squared-residual Ljung–Box, ARCH-LM, sign-bias, adjusted Pearson goodness-of-fit, and joint Nyblom stability tests. The Student-(t) distribution appropriately captures the heavy-tailed movements observed in the spread.

Let $\Delta s_{s1,t}$ be the first-order difference of the spread between the 1-Month SOFR and 1-year CMT rates at time t and $r_{1,t}$ 1-year CMT rate at time t, the best-fitted model for the 1-Month SOFR spread rate is an AR(1)-GARCH (1,1) model with Student's t-distribution innovations:

$$\Delta s_{s1,t} = a_{s1,1}\Delta s_{s1,t-1} + \varepsilon_{s1,t}$$

where $\varepsilon_{s1,t} = \sigma_t z_t$ and innovations $z_t = \sqrt{\frac{v-2}{v}}T_v$, where T_v follows a Student's t-distribution and variance ${\sigma_t}^2$ follows a GARCH (1, 1) model,

$${\sigma_t}^2 = \omega + \alpha{\varepsilon_{s1,t-1}}^2 + \beta{\sigma_{t-1}}^2$$

Moody's historical 1-Month SOFR data date back to 2006 Q1. The best-fitted GARCH model is chosen based on the Ljung-Box test on standardized residuals, the Ljung-Box test on standardized squared residuals, the AIC, BIC, and likelihood values. The estimated parameters are shown in Exhibit E-10.

Exhibit E-10: Estimation Results for the 1-Month SOFR Spread Model

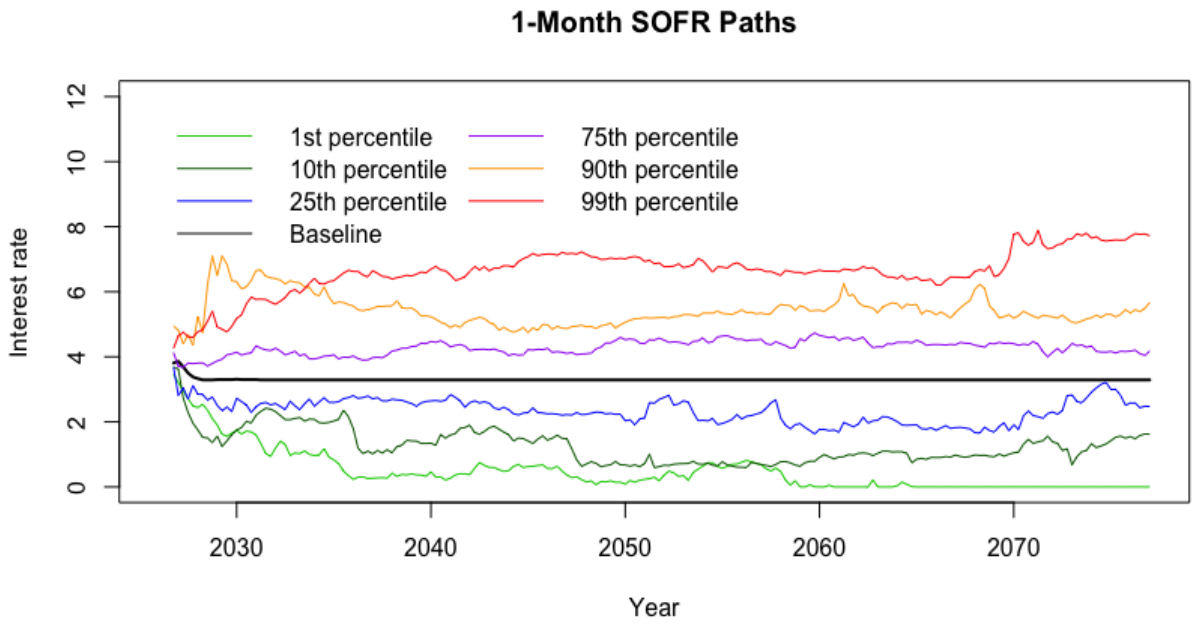
	Estimate	Std. Error	t value	Pr(>|t|)
$a_{s1,1}$	0.22274	0.11570	1.92508	0.05422
ω	0.00060	0.00066	0.91101	0.36229
α	0.41478	0.15039	2.75797	0.00582
β	0.58422	0.12263	4.76406	0.00000
v	3.73749	0.88602	4.21830	0.00003

The AR(1) coefficient has a p-value of 0.05422, showing marginal significance, while removing this term would leave autocorrelation in the residuals. Therefore, AR(1)-GARCH (1,1) is chosen. The estimated volatility persistence is very high, implying that volatility shocks dissipate extremely slowly. Because the estimation sample contains fewer than 100 observations, long-term forecasts and extreme percentile paths should be interpreted cautiously.

We used the estimated parameters to simulate the 1-Month SOFR spread rate with the conditional mean equal to the baseline spread. The simulated spread percentile paths are added to the simulated 1-year CMT percentile paths. The 1-Month SOFR percentile paths are obtained therein, as shown in the following chart.

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Exhibit E-11: Simulated 1-Month SOFR Percentile Paths



E2.4. 30-Year Fixed Rate Mortgage (FRM)

Based on the ADF and KPSS tests for stationarity, a GARCH model is used to model the spread between the fixed 30-year mortgage rate and the 1-year CMT rate. The best-fitted GARCH model is chosen based on the Ljung-Box test on standardized residuals, the Ljung-Box test on standardized squared residuals, the AIC, BIC, and likelihood values. Let $\boldsymbol{s_{m,t}}$ be the spread between the 30-year mortgage rate and 1-year CMT rate. The spread is modeled by ARMA (2, 2)-sGARCH (1,1). Mathematically put,

$$s_{m,t} = a_{m,0} + \sum_{i=1}^{2} a_{m,i} s_{m,t-i} + \sum_{i=1}^{2} b_{m,i} e_{m,t-i} + \varepsilon_{m,t}$$

where $\varepsilon_{m,t}$ is a skewed t-distributed innovation with variance ${\sigma_t}^2$ following a GARCH (1, 1) model,

$${\sigma_t}^2 = \omega + \alpha {\varepsilon_{t-1}}^2 + \beta {\sigma_{t-1}}^2$$

Using historical fixed 30-year mortgage rates from 1971 Q2 to 2026 Q2 from Moody's, the estimated results are presented in Exhibit E-12. The weighted Ljung–Box and ARCH-LM tests indicate no remaining residual autocorrelation or ARCH effects, while the sign-bias and adjusted Pearson tests support the volatility and distributional specifications. The estimated skewness and heavy tails allow the model to capture asymmetric and extreme spread movements.

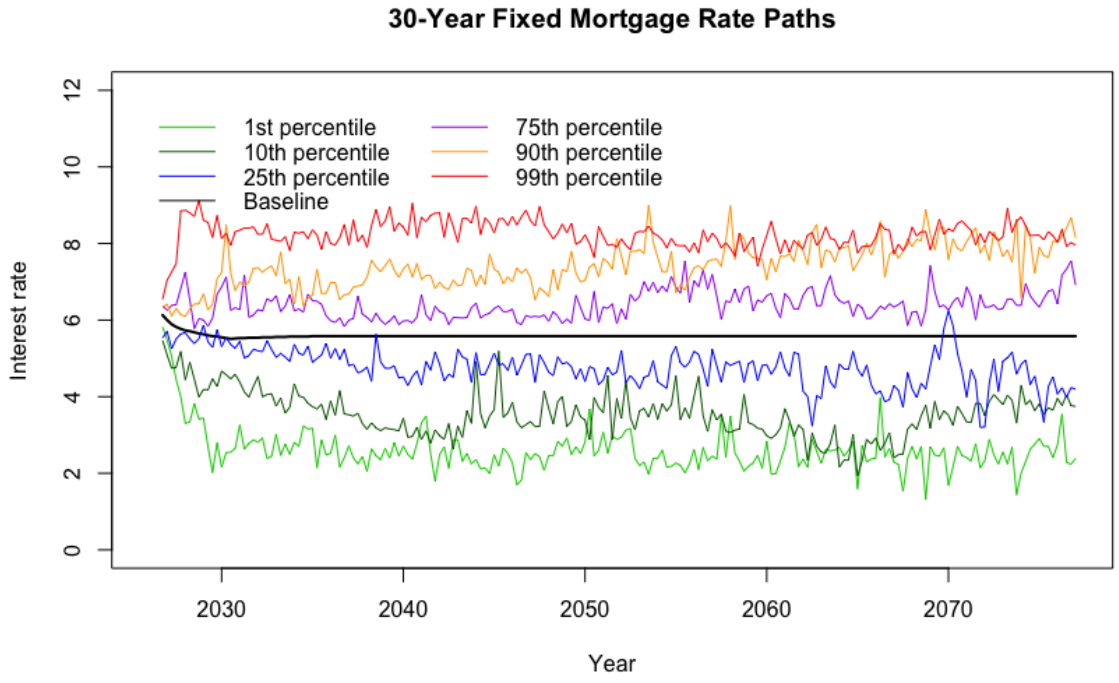
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Exhibit E-12: Estimation Results for 30-Year Mortgage Rate Model

Parameter	Estimate	Std. Error	t value	Pr(>|t|)
$a_{m,0}$	2.723066	0.181753	14.9822	0
$a_{m,1}$	1.789615	0.046393	38.5753	0
$a_{m,2}$	-0.818167	0.0456	-17.9421	0
$b_{m,1}$	-0.56586	0.059536	-9.5044	0
$b_{m,2}$	-0.114936	0.074422	-1.5444	0.1225
ω	0.009138	0.005454	1.6754	0.0939
α	0.256888	0.123296	2.0835	0.0372
β	0.716522	0.098934	7.2424	0
Skew	1.288265	0.122887	10.4833	0
Shape	4.707181	1.330716	3.5373	0.0004

We used the estimated parameters to simulate a 30-year mortgage rate spread with the conditional mean equal to the baseline spread. The simulated spread percentile paths are added to the simulated 1-year CMT percentile paths. The 30-year mortgage rate percentile paths are obtained therein, as shown in the following chart.

Exhibit E-13: Simulated 30-Year Fixed Mortgage Rate Percentile Paths



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E2.5. Unemployment Rate (UE)

E2.5.1. National Unemployment Rate

The COVID-19 pandemic disproportionately impacted service-based industries where work was typically in-person. The high unemployment rate was unprecedented in its speed and scale, leading to 13% in 2020 Q2, the highest rate since the Great Depression. In the model estimation, this one-time jump in the unemployment rate was treated as an outlier and smoothed out using the moving average of the data.

Based on the ADF and KPSS tests for stationarity, the first order of difference is taken to ensure a stationary time series for use. An ARMA(1,1)–sGARCH(1,1) model with Student-(t) innovations was selected for changes in the unemployment rate. The AR and MA coefficients are statistically significant, and the model adequately captures both serial dependence and conditional heteroskedasticity. The residual Ljung–Box, ARCH-LM, sign-bias, adjusted Pearson goodness-of-fit, and joint Nyblom stability tests are satisfactory. The estimated Student-(t) shape parameter indicates heavy-tailed shocks, appropriately allowing for occasional sharp changes in unemployment. The symmetric Student-(t) specification is preferred over the skewed alternative because it has better information criteria and the estimated skewness is not materially different from symmetry.

Let Δue_t be the first order of difference of the unemployment rates. The best-fitted model to $\Delta ue_t$is

$$\Delta ue_t = a_{u,1}\Delta ue_{t-1} + b_{u,1}e_{ue,t-1} + \varepsilon_{ue,t},$$

and $\varepsilon_{ue,t}$ is a Student t-distributed innovation with variance ${\sigma_t}^2$ following a GARCH (1, 1) model,

$${\sigma_t}^2 = \omega + \alpha{\varepsilon_{ue,t-1}}^2 + \beta{\sigma_{t-1}}^2,$$

Using the historical data from 1970 Q1 to 2026 Q2, we estimate the model and have the results as shown in Exhibit E-14. The unemployment percentile paths are obtained as shown in the following chart.

Exhibit E-14: Estimation Results for the National UE Rate Model

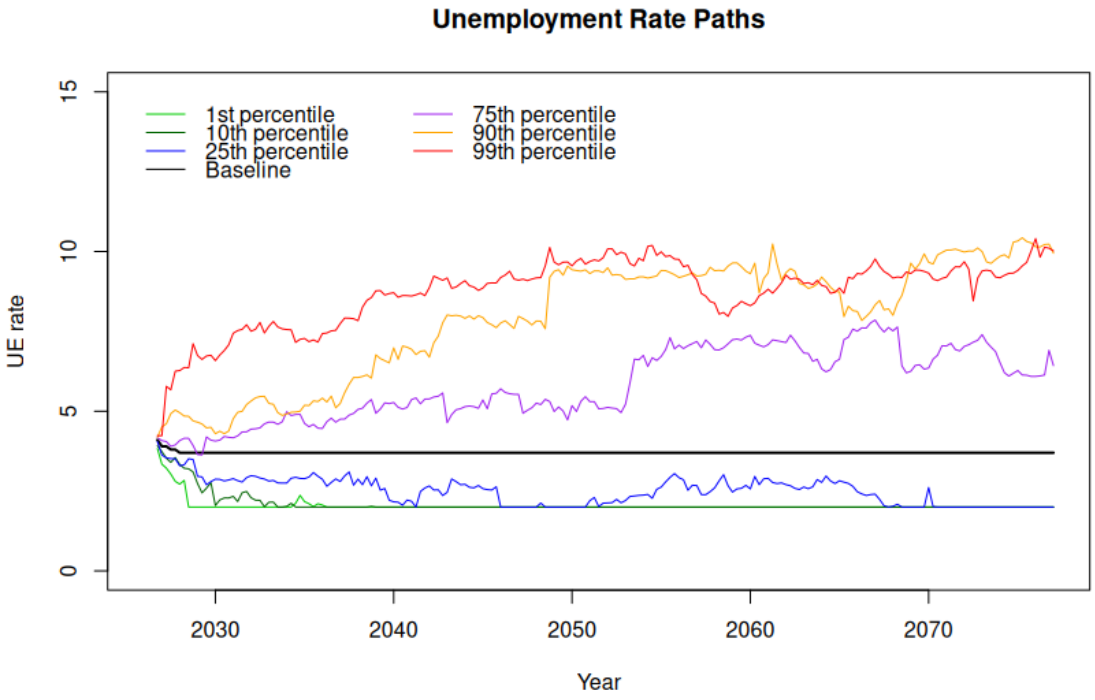
	Estimate	Std. Error	t value	Pr(>|t|)
$a_{u,1}$	0.98214	0.00323	303.66120	0.00000
$b_{u,1}$	0.29865	0.07749	3.85420	0.00012
ω	0.03111	0.01674	1.85880	0.06306
α	0.58278	0.36509	1.59620	0.11043
β	0.22671	0.10657	2.12740	0.03339
shape	2.76729	0.55906	4.94990	0.00000

We used the estimated parameters to simulate unemployment rates with the conditional mean equal to the baseline unemployment rates. A maximum of 20% and a minimum of 2%, based on

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historical statistics, are enforced to cap the simulated paths. The simulated percentile paths are obtained therein, as shown in the following chart.

Exhibit E-15: Simulated Quarterly Unemployment Rate Percentile Paths



E2.5.2. Geographic Dispersion

Regional unemployment rate forecasts incorporate a geographic dispersion factor calculated from Moody's forecast of national and regional state- and MSA-level unemployment forecasts. Specifically, at each time t, the dispersion of unemployment rates between the i^{th} region and the national forecast is calculated as follows:

$$Disp_{i,t}^{Base} = (UE_Moodys_{i,t}^{Base} - UE_Moodys_{national,t}^{Base})$$

This dispersion forecast under Moody's baseline estimates was preserved for all local unemployment forecasts under individual future economic paths. That is, for each economic path, j, the unemployment of the ith region at time t was computed as:

$$UE_{i,t}^{j} = (UE_{national,t}^{j} + DISP_{i,t}^{Base})$$

This approach retains the relationship between national and regional unemployment rates captured in the Moody's baseline forecast while preserving consistency with the national-level stochastic simulations.

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E2.6. House Price Appreciation Rates

E2.6.1. National HPA

Several GARCH models are fitted to the historical house appreciation rates, and its first order of difference and one-year rollover forecast tests are conducted to evaluate the models. An AR(2)–sGARCH(1,1) model with skewed Student-(t) innovations and variance targeting was selected to model the house-price appreciation rate. Both autoregressive coefficients and the ARCH and GARCH parameters are statistically significant under robust standard errors. The estimated GARCH persistence indicates persistent but mean-reverting volatility. The weighted Ljung–Box, ARCH-LM, Nyblom stability, sign-bias, and adjusted Pearson goodness-of-fit tests are all satisfactory. The skewed, heavy-tailed innovation distribution also captures asymmetric and extreme HPA movements.

Let HPA_t denote quarterly house price appreciation rate. The selected AR(2)–sGARCH(1,1) model with skewed Student-(t) innovations and variance targeting model is

$$HPA_t = a_{h,1}HPA_{t-1} + a_{h,2}HPA_{t-2} + \varepsilon_{h,t}$$

where $\varepsilon_{h,t}$ is a skewed t-distributed innovation with variance ${\sigma_t}^2$ modelled by a GARCH (1, 1) model,

$${\sigma_t}^2 = \omega + \alpha {\varepsilon_{h,t-1}}^2 + \beta {\sigma_{t-1}}^2,$$

where ω is equal to targeted historical variance multiplied by $1 - \alpha - \beta$.

The GARCH (1,1) model with skewed t-distributed innovations performs much better than the one with normal innovations in this model. Using the historical data from 1991 Q1 to 2026 Q2, we estimate the model and have the results as shown in Exhibit E-16.

Exhibit E-16: Estimation Results for the National HPA Model

	Estimate	Std. Error	t value	Pr(>|t|)
$a_{h,1}$	0.81737	0.07496	10.90400	0.00000
$a_{h,2}$	0.18200	0.07758	2.34600	0.01897
α	0.39891	0.07912	5.04200	0.00000
β	0.55638	0.08828	6.30240	0.00000
skew	0.83704	0.08294	10.09180	0.00000
shape	4.44409	1.10345	4.02740	0.00006
ω	0.01871	-	-	-

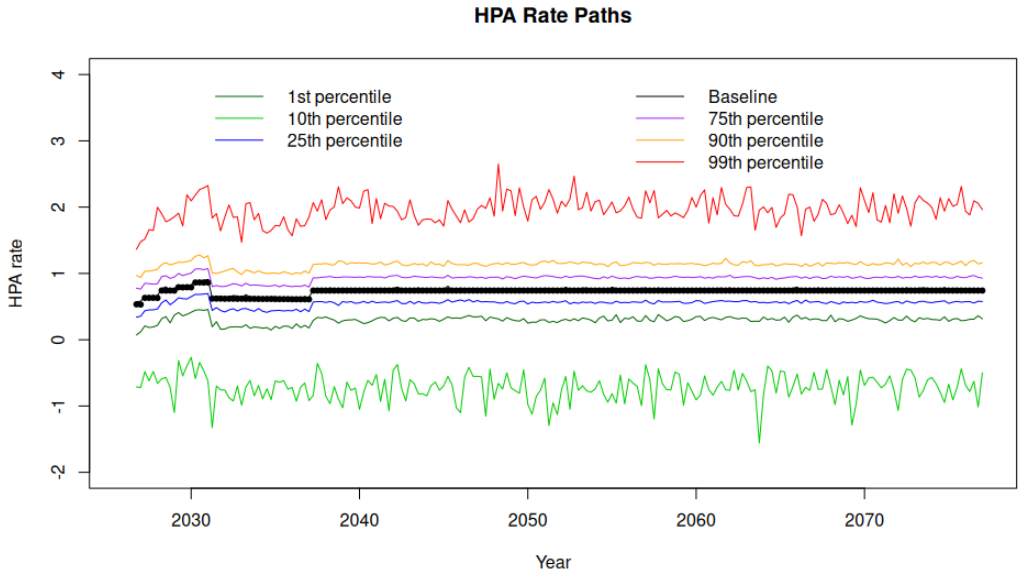
Variance targeting was applied by setting the GARCH intercept so that the model-implied unconditional variance equaled the historical variance of the mean-adjusted HPA series, assuming that the historical sample variance is a reasonable estimate of future long-run variance. It may be inappropriate if the sample contains major structural breaks or if future HPA volatility is expected to differ materially from historical volatility. This variance targeting reduces the number of freely estimated variance parameters and avoids the near-unit volatility persistence produced by the

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unrestricted specification. The resulting model retained statistically significant ARCH and GARCH effects, passed the parameter-stability and residual diagnostic tests, and produced more credible mean-reverting volatility for long-term simulation.

Due to the high volatility of house price appreciation (HPA) rates, the selected simulated percentile paths may cross one another. Under the original approach, each percentile path is identified as the simulated path closest to the corresponding quantile path, where the quantile path is constructed from the specified percentile of simulated HPA rates at each quarter. Because the selected paths are individual simulated trajectories, their relative rankings may change over time, resulting in crossings. To eliminate these crossings, the HPA percentile paths are instead constructed using the corresponding percentile of simulated HPA rates independently at each quarter, as illustrated in the following chart.

Exhibit E-17: Simulated Quarterly HPA Rate Percentile Paths



E2.6.2. Geographic Dispersion

The MSA-level HPA forecasts were based on Moody's forecast for local and national HPA levels. Specifically, at each time t, there is a dispersion of HPAs between the $\boldsymbol{i}$th MSA and the national forecast:

$$Disp_{i,t}^{Base} = (HPA_{i,t}^{Base} - HPA_{national,t}^{Base})$$

This dispersion forecast under Moody's baseline estimates was preserved for all local house price forecasts under individual future economic paths. That is, for each economic path, j, the HPA of the$i$th MSA at time t was computed as:

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$$HPA_{i,t}^{j} = (HPA_{national,t}^{j} + DISP_{i,t}^{Base})$$

This approach retains the relative current housing market cycle among different geographic locations, and it allows us to capture the geographical concentration of FHA's current endorsement portfolio. This approach is also consistent with Moody's logic in creating local market HPA forecasts relative to the national HPA forecast under alternative economic scenario forecasts. We understand this approach is equivalent to assuming perfect correlation of dispersions among different locations across simulated national HPA paths, which creates systematic house price decreases during economic downturns and vice versa during booms. Due to Jensen's Inequality, this tends to generate a more conservative estimate of claim losses.

E3. COVID-19 Pandemic Consideration

The impact of the COVID-19 pandemic is noticeable and dramatic when analyzing these economic indicators, causing higher volatility in these economic variables. Abrupt changes in the recent historical data of these economic measures present additional challenges when fitting stochastic models. Because of the historic nature of this event and the changing economic environment before and after the pandemic, it is difficult to ascertain which impacts might be attributed solely to the pandemic, and whether these changes will persist in the future or revert to pre-pandemic conditions. Rather than apply different models including and excluding the pandemic period to interpret COVID-19 impacts, we use customized GARCH models for the individual economic variables to capture the high volatility in the COVID-19 period and subsequent economic changes in the data and to develop the simulated diversions from the PEA baseline assumptions.

With 2026 economic data, the best-fitted GARCH models have similar structures to the corresponding models used in the 2023, 2024, and 2025 Actuarial Reviews, with slightly changed parameters based on model validation test results. This provides evidence that GARCH models can capture the volatilities in various economic variables, including the impact of COVID-19. Therefore, we continue to use this approach for the FY 2026 review.

Appendix F. Comparison of HUD and ITDC Models and Assessment of Vulnerabilities

F1. Scope and Relationship to the FY 2025 Assessment

The FY 2025 Appendix F provided a high-level comparison of the HUD/Summit-Milliman-IFE (S-M-I) and ITDC modeling frameworks and identified methodological considerations affecting loan transitions, loss mitigation, claim disposition, loss severity, and long-horizon cash-flow projections. That assessment remains the reference for the underlying model structures. The FY 2026 review therefore focuses on material updates implemented in HUD's Forward Budget Model from version 2027.0 to version 2028.0 and assesses the principal advantages and vulnerabilities associated with those changes.

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The most substantive FY 2026 changes relate to a new Near-Term Claims module and refinements to loss severity and recovery modeling. HUD also refreshed the Stage 1 and Stage 2 loan performance models using more recent experience and updated selected model specifications. Because the latter largely represents routine model maintenance rather than a new modeling framework, it is discussed after the two more substantive methodological changes.

F2. Near-Term Claims Module

The Near-Term Claims module is the most significant new structural feature in v2028. HUD developed the module in response to the transition from the COVID-era loss mitigation regime to the new post-COVID waterfall. Under the COVID loss mitigation regime, some borrowers received repeated home-retention assistance despite recurring payment difficulty. Under the new waterfall, borrowers generally must complete a Trial Payment Plan (TPP) before receiving a home-retention option and are subject to restrictions on repeated assistance. HUD therefore identified a subset of borrowers with repeated and recent loss mitigation activity and limited remaining payment-relief capacity whose near-term claim risk may not be fully captured by the broader Stage 2 model.

Conceptually, separate treatment for this population is reasonable. Historical Stage 2 relationships reflect experience across multiple policy regimes and may not fully capture the behavior of borrowers affected by a significant change in loss mitigation policy. The new module allows the model to recognize elevated risk for borrowers who have repeatedly required assistance and may have fewer remaining options to cure future delinquencies.

In the meantime, the module relies on judgment-based static assumptions regarding borrower identification, remaining payment-relief capacity, ultimate claim incidence, and claim timing. Because direct experience under the new policy regime remains limited, historical experience from earlier periods is used to inform these assumptions. Differences in economic conditions, servicing practices, borrower characteristics, and available loss mitigation options may limit the comparability of those historical benchmarks. In addition, assumptions used to estimate available payment relief may become less representative as mortgage rates and policy provisions change.

Accordingly, the module should be monitored as post-policy experience develops. Validation could focus on whether borrowers identified by the module exhibit materially higher claim risk than other seriously delinquent borrowers, whether projected claim timing is consistent with emerging experience, and whether the results remain stable under reasonable alternative assumptions. The module might also be reviewed for potential overlap with risks already captured in the Stage 2 model so that the additional adjustment does not inadvertently duplicate effects reflected elsewhere in the projection framework.

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F3. Loss Severity and Recovery Model Updates

HUD made several refinements to the loss severity and recovery framework. These include updates to the statistical specification of selected severity equations, additional consideration of borrower and property characteristics, revisions to the estimation of certain disposition-related expenses, and limits on unusually high projected recoveries. The loss severity models and related assumptions were also refreshed using more recent experience.

The recovery limits are particularly relevant to the FY 2025 actuarial assessment. The prior review noted that allowing projected recoveries to materially exceed corresponding claim and acquisition amounts could generate unusually favorable loss-severity outcomes and recommended further evaluation of the treatment of such recoveries. The v2028 approach reduces excessive recovery outcomes and therefore improves the stability and interpretability of projected loss severity. This represents a reasonable response to potential model limitations identified in the prior review. Other v2028 refinements generally increase the granularity of the severity framework by allowing additional borrower, property, and disposition characteristics to affect projected outcomes. Greater granularity can improve predictive accuracy when the relationships are stable and supported by sufficient data.

F4. Stage 1/Stage 2 Re-estimation and Recent Experience

The overall Stage 1 and Stage 2 loan transition framework remains substantially consistent with the model reviewed in FY 2025. The principal v2028 changes involve re-estimation using an additional year of loan performance experience, review of continuous-variable transformations and spline specifications, removal or revision of selected variables whose relationships were no longer stable or statistically supported, and alignment of the treatment of certain claim dispositions across model components.

Refreshing the models with more recent experience is an appropriate part of ongoing model maintenance. The ITDC model performed similar procedures to improve responsiveness to changes in portfolio performance. The recent data includes higher delinquency and claim-related experience than some earlier periods, and incorporating this information appropriately affects projected future performance. At the same time, the material sensitivity of long-term projections to a recent year of experience highlights a continuing modeling tradeoff: a model estimated over a long history may be slow to recognize structural change, while greater reliance on recent observations may cause projections to respond to conditions that are temporary rather than persistent.

The central validation task is therefore whether the resulting parameter changes are stable and improve predictive performance. It is important to continue to evaluate coefficient stability, discrimination and calibration, and actual-to-expected results by relevant loan cohorts and risk characteristics under both models. Comparisons across alternative estimation periods can also help

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determine whether changes in projected claims reflect persistent shifts in borrower behavior or sensitivity to the particular experience period used for estimation.

F5. Overall Assessment

Overall, the v2028 updates are directionally reasonable and address several issues relevant to the evolving FHA portfolio and policy environment. The Near-Term Claims module provides a mechanism for recognizing a potentially high-risk borrower population that may not be fully represented by historical Stage 2 relationships. The loss severity and recovery refinements mitigate excessive recovery outcomes and introduce additional information into the projection of claim losses. Stage 1 and Stage 2 refresh appropriately incorporate more recent loan performance experience.

Some potential uncertainties arise from the increased reliance on assumptions and recent experience in areas where the future policy and economic environment may differ from the historical data used for calibration. These risks do not necessarily indicate deficiencies in the model, but they increase the importance of monitoring, sensitivity testing, and component-level validation. As additional experience becomes available, assumptions introduced to address the transition from the COVID-era environment could be revisited and, where appropriate, replaced or recalibrated using emerging post-policy experience.

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Appendix G. Tables of Historical and Projected Rates of Loan Termination and Loss Severity

Note: The relevant tables are provided separately as accompanying attachments.

In the finger tables, a blank cell indicates that no value is reported for that cohort and policy year (the cohort has no loans of that product type, or no forecast) and is distinct from a cell with a value of zero.

The termination finger tables classify mortgage types by the ARM indicator and include the full origination population, consistent with Exhibits III-1, III-4, and III-8, so that Year 1 of each table equals the Exhibit III-1 origination count. Loans whose insurance terminated for reasons other than claim, prepayment, or maturity are counted in Year 1 and leave the survivor count in the year they terminate, and the CUM_OTHER_TERM_COUNT sheet reports cumulative maturities and other terminations. Survivors in year k therefore equal Year 1 less cumulative claims, prepayments, and other terminations through year k−1, and the product tables sum to the All-Products table.

Note: Historical values in the termination finger tables differ slightly from those in the FY 2025 Review tables for two reasons: the tables now include loans that terminated for other reasons, as described above, and the SFDW data received for FY 2026 Q4 restate earlier periods. Within this package the tables reconcile to Exhibits III-1, A-1, and A-4.

Appendix H. Logistic Model Estimation Results

Note: The detailed results are provided separately as accompanying attachments.

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