Fiscal Year 2022 Independent Actuarial Review

of

Mutual Mortgage Insurance Fund Economic Net Worth from Home Equity Conversion Mortgage Insurance-In-Force

November 14, 2022

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November 14, 2022

The Honorable Julia Gordon
Assistant Secretary for Housing and Federal Housing Commissioner
U.S. Department of Housing and Urban Development (HUD)
451 Seventh Street, S.W., Room 9100
Washington, D.C. 20410

Contract: Fiscal Year 2022 Actuarial Studies of the FHA Mutual Mortgage Insurance Fund.

RMA Associates, LLC is pleased to submit this report as required by Task 1 of the engagement for Independent Actuarial Studies of The FHA Mutual Mortgage Insurance Fund on Economic Net Worth from Home Equity Conversion Mortgage Insurance-In-Force, under contract number 86615722C00009.

This report is prepared based on data as of September 30, 2022, to provide an estimate of the Economic Net Worth and the details of the Cash Flow Net Present Value (Cash Flow NPV) of the Mutual Mortgage Insurance (MMI) HECM portfolio as of the end of Fiscal Year 2022. Comparisons between this estimate and the corresponding estimate as of the end of Fiscal Year 2021, evaluation under various scenarios, and detailed information about the models used to develop the estimate are also included.

I, Roosevelt Mosley, Jr., FCAS, MAAA, CSPA, am responsible for the content and conclusions outlined in the report. I am a Fellow of the Casualty Actuarial Society and a Member of the American Academy of Actuaries. I am qualified to render the actuarial opinion contained herein under the qualification standards for actuaries issuing statements of actuarial opinion in the United States that are promulgated by the American Academy of Actuaries.

RMA remains available for any questions or comments you have regarding the report and its conclusions.

Respectfully,

Roosevelt Mosley, Jr., FCAS, MAAA, CSPA
Principal & Consulting Actuary

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Summary of Findings

RMA Associates, LLC teamed with Pinnacle Actuarial Resources, Inc, hereinto referred to as RMA, for this review. This report presents the results of RMA's independent actuarial review of the Economic Net Worth associated with Home Equity Conversion Mortgage (HECM loans or HECM) insured by the Mutual Mortgage Insurance Fund (MMI) for Fiscal Year 2022. The Economic Net Worth associated with Forward mortgages are analyzed separately and are excluded from this report. In the remainder of this report, the term MMI refers to HECM loans and excludes Forward mortgages.

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

Deliverable 1: Produce a written Actuarial Study for HECM that provides the Actuarial Central Estimate of MMI Economic Net Worth as of the end of the subject Fiscal Year and assesses the Department of Housing and Urban Development's (HUD's) estimate of Economic Net Worth.

The Economic Net Worth is defined as cash available to the MMI 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 MMI.

As of the end of Fiscal Year 2022 RMA's Actuarial Central Estimate (ACE) of the MMI HECM Cash Flow NPV is **positive $3.646 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 positive $8.929 billion as of the end of Fiscal Year 2022. Thus, the estimated Economic Net Worth of the MMI is positive $12.575 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 loans and commentary of how these risk characteristics have changed are included in Section 3.

Deliverable 3: Apply the final HECM 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 claim, with affected loan counts and balances).

Appendix G shows the interim and final claim rates, non-claim termination rates and loss severities by cohort. Each of these elements is calculated for each year of developed experience, and final projections are also included. Cash flow summaries by major category are shown in Table 1 below and discussed in more detail in Sections 2 and 4.

Table 1: Projected Cash Flow Summaries

Cash Flow Category	Net Present Value of Cash Flow
Mortgage Insurance Premium	5,950,101,577
Claim Type 1 Loss Incurred	-2,910,151,320
Claim Type 2 Loss Incurred	-11,574,135,410
Claim Type 2c Recovery	1,879,550,714
Claim Type 2p Recovery	10,555,595,455
Note Holding Expense	-255,183,386

Deliverable 4: To promote transparency of the Study's assessments, the Study should identify methodological vulnerabilities that may occur in its 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 Study 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 on which the estimates are based are summarized in Section 5. The section titled HECM Base Termination Model (Appendix B) summarizes the specifications and assumptions related to the base termination models. The HECM Cash Flow Draw Models (Appendix C) section summarizes the cash draw models for HECMs with lines of credit. Section 4 discusses the economic assumptions incorporated into the estimates. Lastly, the HECM Cash Flow Analysis (Appendix E) section of Section 5 details the assumptions associated with the cash flow projections. Section 4 also shows the sensitivity of the estimates to alternative economic scenarios.

Section 4 provides a discussion of the economic conditions that could result in material adverse changes to the Cash Flow NPV.

Appendix F provides a discussion of the HUD methodologies for estimating Economic Net Worth, a comparison of HUD modeling methodology to those used in this study, and methodological vulnerabilities of the HUD models.

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 should be presented in the "finger-table" formats (arrayed by cohort and policy years for different loan products).

Section 1 provides historical information on changes in the HECM program terms. A review of the risk characteristics of existing MMI loans and commentary of how these risk characteristics have changed are included in Section 3.

Appendix G shows the interim and final claim rates, non-claim termination rates and loss severities by cohort. Each of these elements is calculated for each year of developed experience, and final projections are also included.

Deliverable 6: The Contractor should use the President's Economic Assumptions (provided by HUD's 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 should test alternative economic forecasts for stress-testing and sensitivity analysis to estimate ranges of reasonableness.

RMA's ACE of Cash Flow NPV is based on the Economic Assumptions for the 2023 Budget provided by the Office of Management and Budget (OMB). RMA also estimated Cash Flow NPV outcomes based on economic scenarios from Moody's Analytics (Moody's). The Cash Flow NPV results based on these scenarios are shown in Table 2.

Table 2: HECM Cash Flow NPV Based on Alternative Economic Scenarios

Economic Scenario	Fiscal Year 2022 Cash Flow NPV
RMA ACE	3,645,777,629
Baseline	4,656,749,673
Alternative 0 - Upside (4th Percentile)	5,962,951,523
Alternative 1 - Upside (10th Percentile)	5,345,173,544
Alternative 2 - Downside (75th Percentile)	3,768,167,136
Alternative 3 - Downside (90th Percentile	2,910,835,831
Alternative 4 - Downside (96th Percentile)	1,498,077,324
Slower Trend Growth	4,593,059,680
Stagflation	4,550,069,945
Next-cycle Recession	4,628,694,087
Low Oil Price	4,611,311,167

The range of results based on Moody's economic scenarios is positive $1.498 billion to positive $5.963 billion.

In addition, RMA has estimated a range of outcomes based on 100 randomly generated stochastic simulations of key economic variables. Based on these simulations, the range of Cash Flow NPV estimates is negative $1.424 billion to positive $7.553 billion.

The Cash Flow NPV estimate provided by FHA to be used in the FHA's Annual Report to Congress is positive $6.172 billion. Based on RMA's ACE and range of reasonable estimates, we conclude the FHA estimate of Cash Flow NPV is reasonable.

RMA's Cash Flow NPV by cohort is shown in Table 3 for the largest negative outcome and the largest positive outcome based on the stochastic simulation results.

Table 3: Range of Reasonable Estimates - HECM Cash Flow NPV

Cohort	Largest Negative	Largest Positive	RMA ACE
2009	-231,368,967	280,293,253	20,327,974
2010	-76,735,908	226,384,673	49,954,103
2011	96,668,612	305,136,773	167,532,053
2012	107,433,586	253,154,402	146,185,333
2013	147,931,412	396,885,118	215,358,247
2014	293,273,273	817,883,833	428,917,590
2015	425,326,414	1,038,141,170	636,016,393
2016	494,787,071	1,171,156,198	731,105,183
2017	485,465,778	1,308,644,364	766,888,192
2018	-18,909,673	344,180,753	161,816,150
2019	50,567,083	154,111,493	115,664,331
2020	4,265,473	435,784,575	267,313,167
2021	-734,062,804	563,141,616	193,517,035
2022	-2,468,209,480	257,722,565	-254,818,122
Total	-1,423,568,130	7,552,620,786	3,645,777,629

Additional details for the Moody's scenarios and the stochastic simulation can be found in Section 4 and Appendix D.

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

RMA has developed estimates of Economic Net Worth using the Federal Credit Reform Act discounting assumptions.

Deliverable 8: These Studies should use stochastic or Monte Carlo simulations of future economic conditions including for interest rates and house price appreciation. The objective of these requirements is to illustrate the sensitivity of forecasts to economic uncertainty and other forms of forecast error.

As described in the results for Deliverable 6, we generated additional economic assumptions using Monte Carlo simulations and Moody's economic scenarios. These results are discussed in further detail in Section 4, and a description of the stochastic simulations is included in Appendix D.

Deliverable 9: Provide econometric appendices to the Studies that include variable specifications and statistical output from all regressions in the Studies. Individual estimation equations may not be combined for reporting.

Appendix B shows the predictive model parameters and goodness of fit measures for the Termination model. Appendix C shows the parameters and goodness of fit measures for the Cash Draw models. See the Model Parameters and Model Validation sections.

Executive Summary

FHA provides reverse mortgage insurance through the HECM program. HECM loans enable senior homeowners to access cash based on the value of their homes. The program began as a pilot program in 1989 and became permanent in 1998. Between 2003 and 2008, the number of HECM endorsements grew because of increasingly widespread product awareness, lower interest rates, higher home values, and higher FHA mortgage limits. Prior to Fiscal Year 2009, the HECM program was part of the General Insurance (GI) Fund. The FHA Modernization Act within the Housing and Economic Recovery Act of 2008 (HERA) moved all new HECM program endorsements into the MMI effective October 1, 2008.

The Cranston-Gonzalez National Affordable Housing Act (NAHA), enacted in 1990, introduced a minimum capital requirement for MMI.[1] By 1992, the capital ratio was to be at least 1.25%, and by 2000 the capital ratio was to be at least 2.0%. NAHA defines the capital ratio as the ratio of capital plus Cash Flow NPV to unamortized insurance-in-force (IIF). NAHA also implemented the requirement that an annual independent actuarial study of the MMI be completed. HERA also amended 12 USC 1708(a)-(4) to include the requirement for the annual actuarial study. Accordingly, an actuarial review must be conducted on HECM mortgages within the MMI. In this report, we analyze the HECM portion of the MMI, which is mortgages endorsed in the Fiscal Year 2009 and later.

RMA projects, as of the end of Fiscal Year 2022, the HECM Cash Flow NPV is positive $3.646 billion. The total capital resource as reported in the Annual Report to Congress Regarding the Status of the FHA Mutual Mortgage Insurance Fund is positive $8.929 billion at the end of Fiscal Year 2022. Thus, the estimated Economic Net Worth of the MMI is positive $12.575 billion.

To project the Cash Flow NPV, RMA analyzed all HECM historical terminations and associated recoveries using mortgage-level HECM performance data provided by FHA through June 30, 2022. We developed mortgage-level models using various economic and mortgage-specific factors. We then estimated the future mortgage performance of all active mortgages as of the end of Fiscal Year 2022 using various assumptions, including macroeconomic forecasts from OMB, Moody's, and HECM portfolio characteristics.

Impact of Economic and Mortgage Factors

The projected Cash Flow NPV depends on various economic and mortgage-specific factors. These include the following:

[1] Public Law 101-625, 101st Congress, November 28, 1990, Section 332.

- House Price Index (HPI): HPI reflects the relative change in housing prices from period to period. HPI rates impact the recovery FHA receives upon mortgage terminations and the rate at which borrowers will refinance or move out of their property. HPI projections are obtained from OMB, Moody's scenario projections, and stochastic simulation.

- One-year and 10-year Constant Maturity Treasury (CMT) rates, 1-year London Interbank Offered Rate (LIBOR) and Secured Overnight Financing Rate (SOFR): Interest rates impact the growth rate of mortgage balances and the amount of equity available to borrowers at origination. Interest rate projections used in the cash flow projections are from the OMB projections, Moody's scenario projections, and stochastic simulation. Beginning on May 3, 2021, the LIBOR rate was discontinued and replaced with the SOFR as an option for adjustable rate HECM loans. This will ultimately apply to both new HECM loans and existing HECM loans with adjustable rates based on LIBOR.

- Mortality Rates: Information on the date of death of borrowers and co-borrowers have either been directly obtained or derived from the U.S. Decennial Life Table for the 1990-1991, 1999-2001, and 2001-2012 populations, published by the Centers for Disease Control and Prevention (CDC) or from the Social Security Administration.

- Cash Drawdown Rates: These rates represent the speed at which borrowers access the equity in their homes over time, which impacts the growth of the mortgage balance. Predictive models have been developed to estimate borrower cash draw rates based on past HECM program experience, borrower characteristics and the economic environment.

The realized Cash Flow NPV will vary from the estimates in this analysis if the actual drivers of mortgage performance deviate from the projections based on the OMB Economic Assumptions.

Table 4 presents the Cash Flow NPV from the projections based on the OMB Economic Assumptions and ten scenarios from Moody's. Each scenario estimates the Cash Flow NPV under a specific future path of interest, unemployment and HPI. The range of Cash Flow NPV estimates based on the alternative economic scenarios is positive $1.498 billion to positive $5.963 billion.

Table 4: HECM Cash Flow NPV Based on Alternative Economic Scenarios

Economic Scenario	Fiscal Year 2022 Cash Flow NPV
RMA ACE	3,645,777,629
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Alternative 3 - Downside (90th Percentile	2,910,835,831
Alternative 4 - Downside (96th Percentile)	1,498,077,324
Slower Trend Growth	4,593,059,680
Stagflation	4,550,069,945
Next-cycle Recession	4,628,694,087
Low Oil Price	4,611,311,167

The Moody's scenario that produces the highest HECM Cash Flow NPV is the Alternative 0 – Upside (4^{th} Percentile). The Alternative 4 – Downside (96^{th} Percentile) scenario produces the lowest Cash Flow NPV.

We also randomly generated 100 stochastic simulations of key economic variables. Based on these simulations, the range of Cash Flow NPV estimates is negative $1.424 billion to positive $7.553 billion.

Distribution and Use

This report is being provided to the FHA for their use and the use of public policymakers in evaluating the Cash Flow NPV of the MMI. Permission is hereby granted for its distribution on the condition that the entire report, including the exhibits and appendices, is distributed rather than any excerpt. RMA also acknowledges that excerpts of this report will be used in preparing summary comparisons for FHA's Annual Report to Congress, and permission is granted for this purpose as well. We are available to answer any questions that may arise regarding this report.

Any third parties receiving the report, or excerpts from it, should recognize that the furnishing of this report is not a substitute for their own due diligence and should place no reliance on this report or the data and results contained herein that would result in the creation of any duty or liability by RMA to the third party.

Our conclusions are predicated on several assumptions as to future conditions and events. These assumptions, which are documented in this report, must be understood to place our conclusions in their appropriate context. In addition, our work is subject to inherent limitations, which are also discussed in this report.

Reliances and Limitations

Listed in Section 5 and Appendix A are the data sources RMA has relied on in our analysis. We have relied on the accuracy of these data sources in our calculations. If it is subsequently discovered that the underlying data or information is erroneous or incomplete, then our calculations would need to be revised accordingly.

We have relied on a significant amount of data and information without auditing or verifying the accuracy of the data. This includes economic data projected over the next 79 years from Moody's and the OMB. However, we did review as many elements of the data and information as practical for reasonableness and consistency with our knowledge of the mortgage insurance industry. It is possible the historical data used to develop our estimates may not be predictive of future default and loss experiences. We have not anticipated any extraordinary changes to the legal, social, or economic environment which might affect the number or cost of mortgage defaults beyond those contemplated in the economic scenarios described in this report. To the extent that realized experience deviates significantly from these assumptions, the actual results may differ, perhaps significantly, from estimated results.

A substantial source of uncertainty relates to the continued emergence of the COVID-19 pandemic. This uncertainty could impact the projection of Cash Flow NPV in several different ways, including distortion of historical patterns as the MMI handles claims differently and sudden changes in loan origination exposure as the peril continues to emerge. Some of these uncertainties may affect the settlement of claims that began prior to COVID-19 being declared a pandemic. At this point, it is not possible to reliably forecast these impacts. As its effects emerge, the COVID-19 pandemic may have a material impact on our Cash Flow NPV estimates.

The predictive models used in this analysis are based on a theoretical framework and certain assumptions. These models predict the termination rates, cash flow draws, and net loss based on several individual mortgage characteristics and economic variables. The parameters of the predictive models are estimated over a wide variety of mortgages that originated from 1989 through 2022. The estimations were based on the performance of these mortgages over a wide range of economic conditions and mortgage market environments. The models are combined with assumptions about future mortgage endorsements and certain key economic assumptions to produce future projections of the Cash Flow NPV. Although the models are based on mortgages from as far back as 1989, the Cash Flow NPV results presented in the report are only related to mortgages endorsed in the Fiscal Year 2009 and later, as this is when the HECM mortgages were added to the MMI.

RMA is not qualified to provide formal legal interpretation of federal legislation or FHA policies and procedures. The elements of this report that require legal interpretation should be recognized as reasonable interpretations of the available statutes, regulations, and administrative rules.

Section 1. Introduction

Scope

FHA has engaged RMA to perform an annual independent actuarial study of the MMI. 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).

The FHA Modernization Act within the HERA moved all new endorsements for FHA's HECM program from the GI Fund to the MMI starting in Fiscal Year 2009. Therefore, an actuarial review must also be conducted on the HECM portfolio within the MMI. This report provides the estimated HECM Cash Flow NPV as of September 30, 2022 using data through September 30, 2022.

The MMI is a group of accounts of the federal government which records transactions associated with the FHA's guaranty programs for single family mortgages. Currently, the FHA insures approximately 7.39 million forward mortgages and 325,250 HECMs in the MMI.

Per 12 USC 1711-(f), the FHA must ensure the MMI maintains a capital ratio of not less than 2.0%. The capital ratio is defined as the ratio of capital to MMI obligations on outstanding mortgages (IIF). Capital is defined as cash available to the MMI plus the Cash Flow NPV that is expected to result from the outstanding HECMs insured by the MMI.

The deliverables required for this study are:

1. Produce a written Actuarial Study for HECM that provides the ACEs of MMI Economic Net Worth as of the end of the subject Fiscal Year and assesses HUD's estimates of Economic Net Worth.

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

3. Apply the final actuarial HECM model to the HECM part of the MMI portfolio to produce conditional termination rates, timing of assignment, and recovery rates and amounts, by policy year and budget/endorsement year cohort, and by sub-cohort levels defined by policy initiatives and other characteristics.

4. To promote transparency of the Study's assessments, the Study shall identify methodological vulnerabilities that may occur in its actuarial models or in HUD's analyses of Economic Net Worth. This discussion shall evaluate the scope and scale of such vulnerabilities in creating possible forecast risk and suggest possible lines of research in these areas. The Study shall 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 Study.

5. The Study shall 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).

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

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

8. This Study shall use stochastic or Monte Carlo simulations of future economic conditions including for interest rates and house price appreciation. The objective of these requirements is to illustrate the sensitivity of forecasts to economic uncertainty and other forms of forecast error.

9. Provide econometric appendices to the Study that include variable specifications and statistical output from all regressions in the Study. Individual estimation equations shall not be combined for reporting.

HECM Background

FHA insures reverse mortgages through the HECM program, which enables senior homeowners to borrow against the value of their homes. Since the inception of the HECM program in 1989, FHA has insured nearly 1.3 million reverse mortgages. All the following conditions must be met to be eligible for a HECM:

1. At least one of the homeowners must be 62 years of age or older.
2. If there is an existing mortgage, the outstanding balance must be paid off with the HECM proceeds.
3. The borrower(s) must have received FHA-approved reverse mortgage counseling to learn about the program.

HECM's are available from FHA-approved lending institutions. These approved institutions provide homeowners with cash payments or lines of credit secured by the collateral property. There is no required repayment if the borrowers continue to live in the home and meet FHA guidelines on requirements for paying property taxes and homeowner's insurance premiums and for maintaining the property in a reasonable condition. A HECM terminates for reasons including death, moving out of the home, and refinancing. The existence of negative equity does not require borrowers to pay off the mortgage and does not prevent the borrowers from receiving additional cash draws, if available, based on their HECM contract.

The reverse mortgage insurance provided by FHA through the HECM program protects lenders from losses due to insufficient recovery on terminated mortgages. When a mortgage terminates and the mortgage balance exceeds the net sale price of the home, the lender can file a claim for loss up to the maximum claim amount (MCA). A lender can assign the mortgage note to FHA if the mortgage meets the eligibility requirements when the mortgage balance reaches 98% of the MCA. On assignment, the lender is reimbursed for the balance of the mortgage (up to the MCA). When note assignment occurs, FHA switches from being the insurer to the holder of the note and controls the servicing of the mortgage until termination. At mortgage termination (post-assignment), FHA attempts to recover the mortgage balance including any expenses, accrued interest, property taxes and insurance premiums.

The following are definitions of common HECM terms.

Maximum Claim Amount

The MCA is the minimum of the appraised value or purchase price of the home and the FHA mortgage limit at the time of origination. It is the maximum HECM insurance claim a lender can receive. The MCA is also used together with the Principal Limit Factor (PLF) to calculate the maximum amount of initial credit available to the borrower. The MCA is determined at origination and does not change over the life of the mortgage. However, if the home value appreciates over time, borrowers may access additional credit by refinancing. In the event of termination, the entire net sales proceeds can be used to pay off the outstanding mortgage balance, regardless of whether the size of the MCA was capped by the FHA mortgage limit at origination.

Principal Limits and Principal Limit Factors

FHA manages its insurance risk by limiting the percentage of the initial available equity that a HECM borrower can draw by use of a PLF. The PLF is similar to the loan-to-value (LTV) ratio applied to a traditional mortgage. For a HECM loan, the MCA is multiplied by the PLF, which is determined according to the HECM program features and the borrower's age and gender. The result is the maximum HECM Principal Limit (PL) available to be drawn by the applicant. The PLF increases with the borrower's age at HECM origination and decreases as the expected mortgage interest rate increases. Over the course of the mortgage, the PL increases dollar for dollar with the sum of the mortgage interest, the Mortgage Insurance Premium (MIP) and the servicing fees. Borrowers can continue to draw cash if the mortgage balance is below the current PL (except for the tenure plan, which acts as an annuity).[2]

Payment Plans

HECM borrowers access the equity available to them according to the payment plan they select. Borrowers can change their payment plan at any time during the mortgage if they have not exhausted their PL. The payment plans are:

- Tenure plan - a fixed monthly cash payment if the borrowers stay in their home.
- Term plan - a fixed monthly cash payment over a specified number of years.
- Line of credit - the ability to draw on allowable funds at any time.
- Any combination of the above.

Under the current program, the initial disbursement period limitation is applicable to all payment plans and subsequent payment plan changes that occur during the initial disbursement period.

Unpaid Principal Balance and Mortgage Costs

The Unpaid Principal Balance (UPB) is the mortgage balance and represents the amount drawn from the HECM. In general, after the initial cash draw, the mortgage balance continues to grow with additional borrower cash draws and accruals of interest, premiums, and servicing fees until the mortgage terminates.

Mortgage Terminations

When a HECM terminates, the current mortgage balance becomes due. If the net sales proceeds from the home sale exceed the mortgage balance, the borrower or the estate is entitled to the difference. If the net proceeds from the home sale are insufficient to pay off the full outstanding mortgage balance and the lender has not assigned the note, the lender can file a claim for the shortfall, up to the amount of the MCA. HECMs are non-recourse, so the property is the only collateral for the mortgage; no other assets nor the income of the borrowers can be accessed to cover any shortfall.

Assignments and Recoveries

The assignment option is a unique feature of the HECM program. When the balance of a HECM reaches 98% of the MCA and meets other assignment requirements, the lender can choose to terminate the FHA insurance by redeeming the mortgage note with FHA at face value, a transaction referred to as mortgage assignment. FHA will pay an assignment claim in the full amount of the

[2] Mortgagee Letter 97-15, April 24, 1997: Home Equity Conversion Mortgage (HECM) Insurance Program – Implementation of Final Rule and Other Information.

mortgage balance (up to the MCA) and will continue to hold the note until termination. During the note holding period, the mortgage balance will continue to grow by additional draws and unpaid taxes and insurance. Borrowers can continue to draw cash if the mortgage balance is below the current PL. The only exception is that borrowers on the tenure plan are not constrained by the PL. At mortgage termination, the borrowers or their estates are required to repay FHA the minimum of the mortgage balance and the net sales proceeds of the home. These repayments are referred to as post-assignment recoveries.

Report Structure

The remainder of this report consists of the following sections:

- **Section 2. Summary of Findings** – presents the estimated Economic Net Worth for the HECM portfolio as of the end of Fiscal Year 2022. It also provides a step-by-step analysis of changes from last year's Review.
- **Section 3. Characteristics of HECM Fund Endorsements** – presents various characteristics of HECM endorsements for Fiscal Years 2009 through 2022.
- **Section 4. Cash Flow NPV Based on Alternative Scenarios** – presents the HECM portfolio Cash Flow NPV using alternative economic scenarios.
- **Section 5. Summary of Methodology** – presents an overview of the data processing and reconciliation, base termination models, cash draw models for mortgages with a line of credit and cash flow models used to estimate the Cash Flow NPV.
- **Appendix A: Data Sources, Processing and Reconciliation** – describes the data sources used for the analysis, the data processing required to prepare the data for analysis and the data reconciliation performed.
- **Appendix B: HECM Base Termination Model** – provides a technical description of the loan performance model for the causes of loan termination.
- **Appendix C: HECM Cash Draw Models** – describes the model to project the cash draws by period for loans that have a line of credit.
- **Appendix D: Economic Scenarios** – describes the forecast of future values of economic factors that affect the performance of the MMI and presents the variation in estimated economic value based on the additional economic scenarios. We also outline the details of the stochastic simulation.
- **Appendix E: HECM Cash Flow Analysis** – provides a technical description of the cash flow model covering the various sources of cash inflows and outflows that HECMs generate.

- **Appendix F: Review of HUD Analysis of Economic Net Worth, Comparison of HUD and RMA Models, and Assessment of Vulnerabilities** – high-level review of HUD models developed to project Economic Net Worth, comparison of the models developed by HUD with the models developed by RMA, and assessment of the vulnerabilities of the models developed.
- **Appendix G: Summary of Historical and Projected Claim Rates and Loss Severities**

Section 2. Summary of Findings

This section presents the projected HECM Economic Net Worth for Fiscal Year 2022. This review covers mortgages endorsed in Fiscal Year 2009 and subsequent and are still in force as of the end of Fiscal Year 2022. Data through September 30, 2022 was used to estimate the Cash Flow NPV.

Fiscal Year 2022 Net Present Value Estimate

The Cash Flow NPV of in-force HECMs consists of discounted cash inflows and outflows. HECM cash inflows consist of MIP and recoveries. Cash outflows consist of claims and note-holding expenses. The cash flow model projects cash inflows and outflows using economic forecasts and mortgage performance projections. The Cash Flow NPV is estimated to be positive $3.646 billion as of the end of Fiscal Year 2022. This estimate is the result of the cash flow projections based on the 2023 OMB Mid-Term Review of the President's Economic Assumptions.

The total capital resource as reported in the Annual Report to Congress Regarding the Status of the FHA Mutual Mortgage Insurance Fund is positive $8.929 billion as of September 30, 2022. Thus, the ACE of the Economic Net Worth of the MMI is positive $12.575 billion.

According to Cranston-Gonzalez NAHA, IIF is defined as the "obligation on outstanding mortgages." We calculate the IIF as the total UPB of all HECMs remaining in the insurance portfolio as of September 30, 2022. Table 5 shows the Cash Flow NPV and IIF for active HECMs by cohort.

Table 5: Cash Flow NPV and IIF by Cohort

Cohort	Net Present Cash Flow of Future Cash Flows ($ Million)	Insurance-In-Force ($ Million)
2009	20	5,056
2010	50	2,385
2011	168	2,116
2012	146	1,580
2013	215	2,214
2014	429	3,989
2015	636	4,922
2016	731	4,574
2017	767	5,704
2018	162	4,352
2019	116	2,500
2020	267	4,795
2021	194	8,483
2022	-255	13,606
Total	3,646	66,276

The RMA Cash Flow NPV estimate compared to the FHA estimate by cohort is shown in Table 6.

Table 6: Comparison of Cash Flow NPV by Cohort

FHA	Cash Flow NPV		
	RMA	FHA	Difference
2009	20	-477	497
2010	50	-219	268
2011	168	-98	265
2012	146	-26	173
2013	215	29	187
2014	429	390	39
2015	636	757	-121
2016	731	1,133	-402
2017	767	1,247	-480
2018	162	623	-461
2019	116	190	-75
2020	267	736	-469
2021	194	1,091	-897
2022	-255	796	-1,051
Total	3,646	6,172	-2,526

The difference between the RMA and FHA estimate is negative \$2.526 billion, which is 3.8% of the HECM IIF. The RMA estimates of Cash Flow NPV by cohort are lower than the FHA estimates for cohorts 2015 – 2022 and are higher for the cohorts 2014 and prior.

Change in Economic Net Worth

Table 7 shows the comparison of our estimate of the Cash Flow NPV, Capital Resources available to HUD, IIF, and estimated Economic Net Worth at the end of Fiscal Year 2021 and the current estimate. The present value of future cash flows of the current book of business is estimated to be positive \$3.646 billion.

Table 7: Estimate of Cash Flow NPV as of the end of Fiscal Year 2021 (in \$ million)

Item	2021	2022	Dollar Difference	Percentage Change
Cash Flow NPV	1,102	3,646	2,544	230.8%
Capital Resources	3,418	8,929	5,511	161.2%
Economic Net Worth	4,520	12,575	8,055	178.2%
Insurance-In-Force	62,675	66,276	3,601	5.7%

As seen in Table 7, the estimated Fiscal Year 2022 Cash Flow NPV has increased by \$2.544 billion from the level estimated in Fiscal Year 2021, from positive \$1.102 billion to positive \$3.646

billion. The IIF increased from $62.675 billion to $66.276 billion. The change in the Cash Flow NPV represents the net impact of several significant factors, which are described in detail in the next section.

Sources of Change from the Fiscal Year 2021 Review to the Fiscal Year 2022 Review

Table 8 provides a summary of the decomposition of changes in the Cash Flow NPV of the MMI as of the end of Fiscal Year 2022 as compared to the Cash Flow NPV in the Fiscal Year 2021 Actuarial Review. The overall net change in the Cash Flow NPV is favorable.

Table 8: Changes in Projected Cash Flow NPV

	Change in NPV	Cash Flow NPV - 9/30/22
Baseline FY1992-FY2021		1,102,199,793
Impact of assumption change	957,065,803	2,059,265,596
Impact of model change	2,565,685,290	4,624,950,886
Impact of book change	-724,355,135	3,900,595,751
FY1992-FY2021	2,798,395,958	
FY2022	-254,818,122	3,645,777,629
Cumulative Change	2,543,577,836	

This section describes the sources of change in estimates of Cash Flow NPV between the 2021 Actuarial Review and the 2022 Actuarial Review. Separating out the specific impacts can be done only up to a certain degree of accuracy, because it depends on the order in which the decomposition is done. The interdependency among the various components of the analysis prevents us from identifying and analyzing these as purely independent effects. Given this limitation, this section presents a description of the approximate differences in the Cash Flow NPV from that presented in the Fiscal Year 2021 Actuarial Review by source of change.

Update Economic Scenario Forecast

For this decomposition step, we updated the forecasts for the purchase-only house price index (HPI), and the interest and unemployment rates from 2022 President's Economic Assumptions (PEA) forecast to the 2023 PEA forecast. In addition to the change in the projected economic forecast, we have also updated the previous projected economic forecasts for Fiscal Year 2022 with actual economic data. The net impact of these changes is an increase of $957 million in the projected Cash Flow NPV.

Update Predictive Models

In Fiscal Year 2022, we continued to refine the predictive models to better capture the termination and cash draw behavior of loans in the MMI. We re-estimated the models using updated data and revised variable specifications. For details about these model updates and refinements, refer to Appendices B, C, and E.

These model changes led to an increase in estimated economic value in the Cash Flow NPV of $2.566 billion.

Actual Performance of Fiscal Year 2021 to Fiscal Year 2022

The actual performance of the MMI for cohorts 2009 – 2021 realized during Fiscal Year 2022 affects the Cash Flow NPV of the MMI estimate of the in-force portfolio. The actual experience for this period was $724 million worse than expected.

Fiscal Year 2022 Origination Volume

The addition of the origination volume for the Fiscal Year 2022 book of business decreased the Cash Flow NPV projection by $255 million.

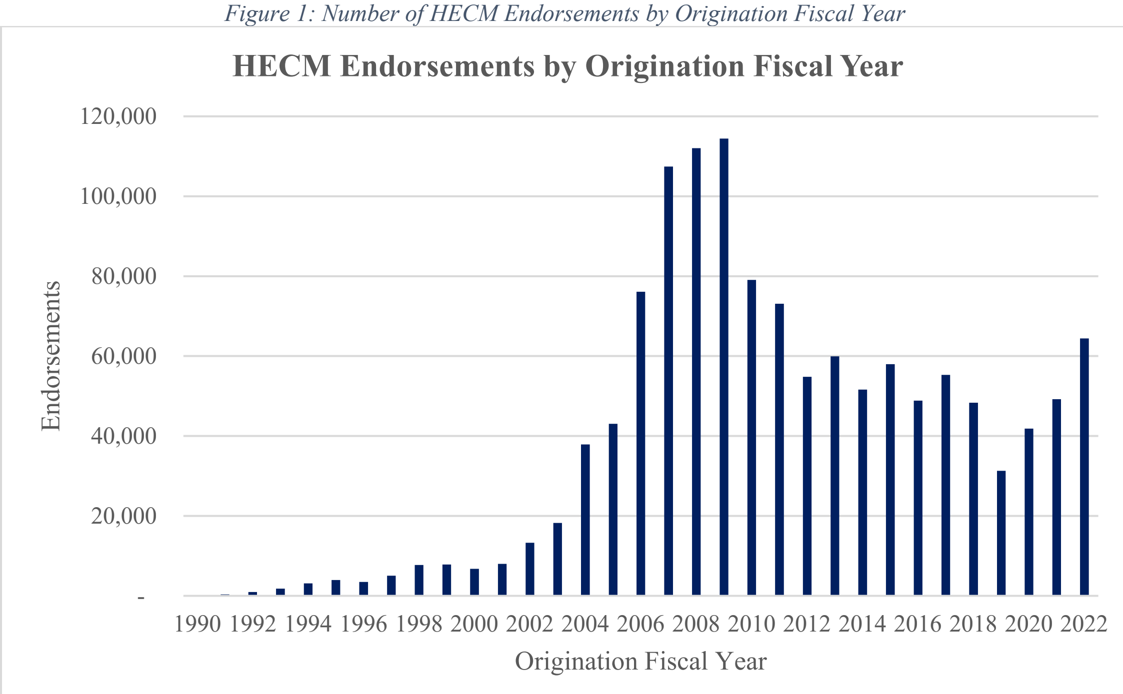
Section 3. Characteristics of HECM Fund Endorsements

This section presents the characteristics of the HECM portfolio for the HECM loans endorsed from Fiscal Year 2009 through Fiscal Year 2022. HECM loans were first included in the MMI in Fiscal Year 2009. The loans from these books of business that are still active constitute the HECM Fund portfolio as of the end of Fiscal Year 2022. A review of the characteristics of these cohorts helps define the current risk profile of the HECM Fund. Some of the characteristics of previous books are shown as well to demonstrate trends.

Volume and Share of Mortgage Originations

FHA endorsed 64,437 HECM loans in Fiscal Year 2022, with a total MCA of $24.907 billion. This is a 31.0% increase from Fiscal Year 2021 in the number of loans endorsed, and a 50.4% increase in the MCA of loans endorsed. The total number of endorsements for Fiscal Years 2009 to 2022 is 830,163. The corresponding MCA is $256.000 billion. Since the inception of the HECM program, this program has been the largest reverse mortgage product in the U.S. market, representing most reverse mortgages. Figure 1 presents the count of HECM endorsements by origination Fiscal Year.

Figure 1: Number of HECM Endorsements by Origination Fiscal Year



Loan Types

HECM borrowers receive loan proceeds by selecting from term, line of credit, and tenure payment plans. Borrowers can also choose a combination of payment plan types. Table 9 presents the distribution of HECM loans by payment plan. The majority of HECM borrowers select the line of credit option. This option has accounted for over 90% of the endorsements since Fiscal Year 2009 and has been increasing since 2017.

Table 9: Distribution of HECM Loans by Payment Type

Original Year	Term	Line of Credit	Tenure	Term Plus Line of Credit	Tenure Plus Line of Credit
2009	0.8%	91.9%	1.5%	3.8%	2.0%
2010	0.5%	94.3%	0.9%	2.8%	1.6%
2011	0.4%	94.5%	0.9%	2.8%	1.4%
2012	0.3%	94.9%	0.8%	2.6%	1.4%
2013	0.4%	95.1%	0.8%	2.4%	1.3%
2014	0.7%	93.5%	1.3%	2.9%	1.5%
2015	0.6%	94.0%	1.0%	2.8%	1.6%
2016	0.6%	93.7%	1.0%	3.0%	1.7%
2017	0.5%	93.7%	1.0%	3.0%	1.8%
2018	0.6%	94.1%	0.8%	2.8%	1.7%
2019	0.6%	94.7%	0.7%	2.5%	1.4%
2020	0.5%	95.8%	0.4%	2.2%	1.1%
2021	0.5%	96.3%	0.4%	1.9%	0.8%
2022	0.5%	96.3%	0.6%	1.7%	0.8%
Weighted Average	0.5%	94.3%	0.9%	2.8%	1.5%

Interest Rate Types

HECM borrowers can select fixed or adjustable-rate mortgages. Table 10 shows the distribution of HECM loans by interest rate type. The majority of HECM borrowers selected monthly adjustable-rate mortgages in Fiscal Year 2009. The next year, however, the percentage of fixed-rate endorsements increased sharply to 69%. This was due, in part, to the significant drop in interest rates beginning in the last half of 2008. This percentage persisted in Fiscal Years 2011 – 2013. Subsequently, the share of fixed-rate HECM loans dropped sharply. In Fiscal Year 2014, the percentage of fixed rate loans dropped to 19%, and as of the end of Fiscal Year 2020 it had dropped to less than 2% of the HECM loans originated. However, in 2021 the percentage of fixed rate loans increased to over 7% and is at 4.4% of the loans in 2022. This is due in part to the low interest rates that persisted into early 2022.

The LIBOR indexed loans were in the 30 to 40% range for Fiscal Years 2009 to 2013. In Fiscal Year 2014, the percentage of LIBOR indexed loans increased to 81%, as the fixed-rate option correspondingly declined in popularity. As of Fiscal Year 2020, this percentage had increased to over 98%. Monthly adjustable LIBOR loans were more popular in Fiscal Year 2014 and 2015; however, in Fiscal Years 2016 – 2021, the annually adjustable LIBOR loans were significantly more popular. This is due, in part, to the fact that in 2014 HUD limited the insurability of fixed interest rate mortgages under the HECM program to mortgages with the Single Disbursement Lump Sum payment option.

Beginning in 2021, the LIBOR rate was discontinued. As a result, the SOFR will replace the LIBOR as an option for an index for adjustable mortgages. As a result, the percentage of loans using the LIBOR index has decreased to 0.02%.

Table 10: Distribution of HECM Loans by Interest Rate Type

Origination Year	LIBOR Indexed		Treasury Indexed		Fixed
	Annually Adjustable	Monthly Adjustable	Annually Adjustable	Monthly Adjustable	
2009	0.02%	34.61%	0.65%	53.09%	11.63%
2010	0.01%	30.58%	0.01%	0.50%	68.90%
2011	0.01%	31.89%	0.00%	0.06%	68.03%
2012	0.00%	30.46%	0.01%	0.12%	69.41%
2013	0.00%	39.35%	0.00%	0.03%	60.63%
2014	2.40%	78.93%	0.00%	0.00%	18.67%
2015	39.97%	44.26%	0.01%	0.01%	15.75%
2016	75.42%	13.90%	0.04%	0.00%	10.64%
2017	86.13%	3.53%	0.00%	0.00%	10.34%
2018	88.44%	1.42%	0.00%	0.00%	10.14%
2019	93.74%	0.22%	0.00%	0.00%	6.04%
2020	97.98%	0.11%	0.01%	0.00%	1.91%
2021	30.19%	0.18%	3.15%	59.25%	7.23%
2022	0.02%	0.00%	0.85%	94.70%	4.43%

Product Type

Almost all loans endorsed in Fiscal Years 2009 through 2022 are “traditional” HECMs, where the borrowers had purchased their homes prior to taking out the reverse mortgage. A HECM for Purchase program was introduced in January 2009. This program allows seniors to purchase a new principal residence and obtain a reverse mortgage with a single transaction. However, these HECM for Purchase loans have been a small percentage of HECM endorsements each year as seen in Table 11. The distribution of HECMs for Purchase loans had been increasing slowly from 2009 – 2019 but has decreased since Fiscal Year 2019. In our analysis, the traditional and for-purchase HECMs are treated the same, as the volume of for-purchase HECMs is small.

Table 11: Distribution of HECM Loans by Product Type

Origination Year	Traditional HECM	HECMs for Purchase	
		First Month Cash Draw < 90% of Initial Principal Limit	First Month Cash Draw >= 90% of Initial Principal Limit
2009	99.51%	0.07%	0.42%
2010	98.25%	0.14%	1.61%
2011	97.90%	0.00%	2.07%
2012	97.04%	0.06%	2.90%
2013	96.52%	0.07%	3.41%
2014	96.46%	0.05%	3.48%
2015	95.84%	0.13%	4.03%
2016	95.16%	0.36%	4.48%
2017	95.24%	0.37%	4.39%
2018	94.59%	0.38%	5.03%
2019	92.66%	0.51%	6.83%
2020	94.10%	0.43%	5.47%
2021	95.47%	0.30%	4.22%
2022	98.03%	0.13%	1.84%

State

Among all endorsements in Fiscal Years 2014 through 2022, over half of all loans were originated in the top 10 states. California had the highest endorsement volume every year over this period, while Florida has had the second highest endorsement volume since 2015. The endorsement volume in Arizona has increased from 1.7% in Fiscal Year 2012 to 8.5% in Fiscal Year 2022 and is the third largest state. The endorsement breakdown of the top 10 states is shown in Table 12.

Table 12: Percent Distribution of HECM Loans by State

Top 10 States	Percent of Origination Year													
	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
California	13.7%	14.0%	13.5%	12.7%	14.1%	17.5%	20.3%	21.8%	23.7%	22.7%	21.1%	24.7%	26.0%	23.7%
Florida	13.2%	9.0%	6.8%	6.1%	6.5%	6.9%	8.3%	8.8%	8.7%	8.4%	8.6%	8.4%	8.2%	9.1%
Arizona	3.1%	2.1%	2.0%	1.7%	2.4%	2.9%	3.2%	3.6%	3.7%	4.0%	4.8%	5.6%	7.0%	8.5%
Colorado	1.8%	1.8%	1.9%	2.0%	2.1%	2.3%	2.4%	3.7%	5.4%	5.9%	6.0%	7.1%	7.0%	6.9%
Texas	6.6%	8.0%	9.1%	8.9%	8.6%	7.4%	7.0%	7.6%	7.6%	7.4%	7.4%	6.4%	6.0%	6.6%
Utah	1.5%	1.3%	1.4%	1.8%	2.0%	1.7%	1.7%	1.8%	1.9%	2.4%	2.8%	3.2%	4.2%	5.4%
Washington	2.8%	3.0%	2.5%	2.3%	2.3%	2.1%	2.3%	2.7%	3.2%	4.3%	4.0%	4.8%	5.7%	5.2%
Oregon	2.7%	2.3%	1.8%	1.7%	1.4%	1.4%	1.4%	1.9%	2.4%	2.6%	2.4%	2.8%	2.9%	3.2%
Nevada	0.9%	0.6%	0.6%	0.5%	0.7%	1.0%	1.4%	1.5%	1.7%	1.9%	2.3%	2.3%	2.3%	3.0%
Idaho	0.8%	0.7%	0.7%	0.6%	0.6%	0.6%	0.6%	0.7%	0.8%	1.0%	1.3%	1.8%	2.2%	2.5%
Total	47.1%	42.7%	40.2%	38.4%	40.4%	43.9%	48.6%	54.1%	59.2%	60.4%	60.6%	67.2%	71.6%	74.0%

Maximum Claim Amount

The MCA is the minimum of the FHA HECM loan limit and the appraised value (or, if a HECM for Purchase, the minimum of the purchase price and appraised value, not to exceed the HECM loan limit). It is used as the basis of the initial principal limit determination and the cap on the potential insurance claim amount. Table 13 shows the distribution of HECM endorsements by the MCA. Approximately 65% of loans endorsed in Fiscal Year 2009 had an MCA of less than or equal to $300,000, and this percentage increased to approximately 73% by Fiscal Year 2012. Since then, the percentage of endorsements less than $300,000 has decreased steadily to approximately 21% for Fiscal Year 2022.

The percentage of endorsements with an MCA between $300,000 and $417,000 decreased from 23.3% in 2009 to about 12% during Fiscal Years 2010 through 2014. In 2022, it has increased to 21.4%.

The percentage of endorsements with an MCA over $417,00 has increased steadily since 2012,

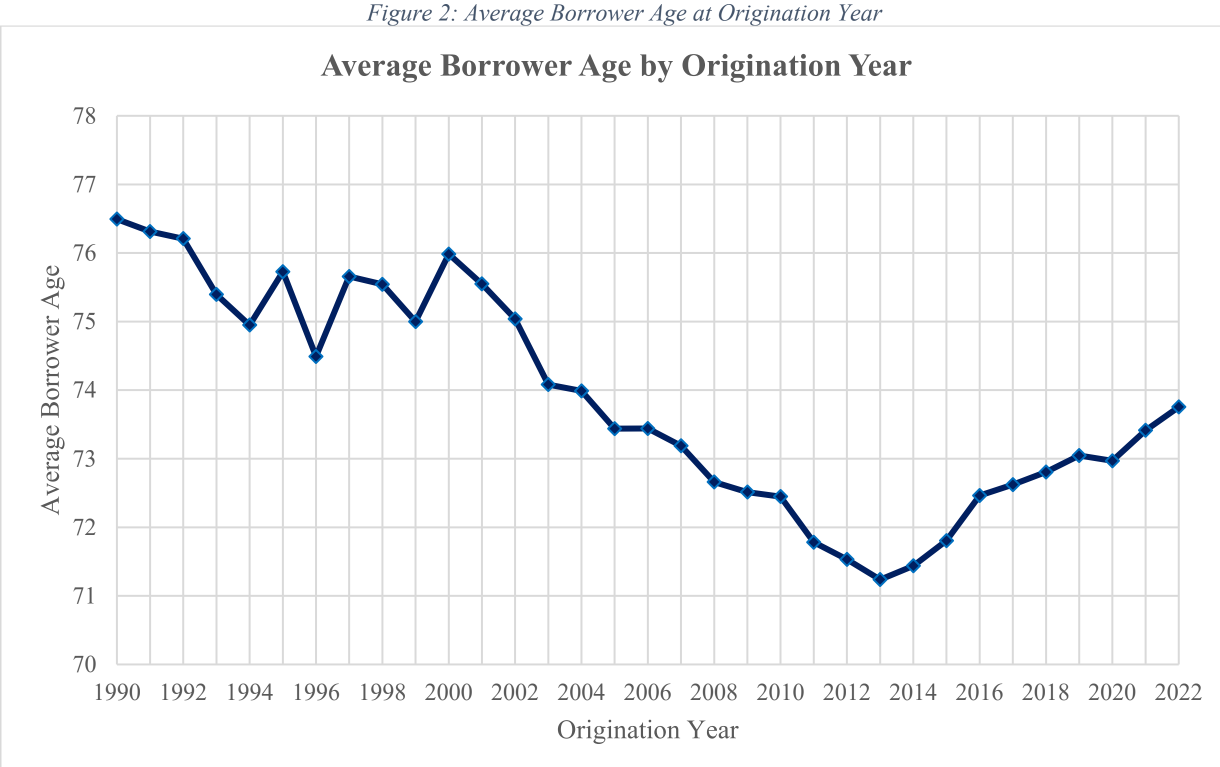
Table 13: Distribution of HECM Loans by MCA

Origination Year	< $100K	$100 to $200K	$200K to $300K	$300 to $417K	> $417K
2009	10.2%	32.4%	22.7%	23.3%	11.3%
2010	12.9%	34.3%	19.9%	12.9%	20.0%
2011	15.7%	35.9%	19.3%	12.0%	17.1%
2012	17.0%	37.0%	18.7%	11.8%	15.5%
2013	16.5%	36.4%	18.7%	12.2%	16.2%
2014	13.7%	34.3%	19.6%	13.2%	19.1%
2015	11.6%	31.7%	20.6%	14.5%	21.6%
2016	8.3%	28.6%	22.0%	16.0%	25.3%
2017	5.9%	25.3%	22.6%	17.8%	28.3%
2018	4.4%	23.2%	23.2%	19.0%	30.3%
2019	3.4%	21.9%	24.2%	19.5%	31.1%
2020	1.8%	16.2%	23.0%	20.7%	38.3%
2021	0.9%	11.5%	19.5%	21.9%	46.2%
2022	0.4%	6.0%	14.4%	21.4%	57.8%

Borrower Age Distribution

The borrower age profile of an endorsement year affects loan termination rates and the PL available to the borrower. Figure 2 shows the average borrower age at origination for Fiscal Years 1990 through 2022. The average borrower age had been declining through 2013 but has been increasing since then. Younger borrowers represent a higher financial risk exposure for FHA as they have a longer life expectancy. The PLFs, which limit the percentage of initial equity available to the borrower, were lowered for younger borrowers in September 2013, limiting their cash draws to a smaller portion of the equity in the house. This has caused the average borrower age to increase since 2013, and it is now over 73 years old in Fiscal Year 2022.

Figure 2: Average Borrower Age at Origination Year



Borrower Gender

Gender also affects termination behavior due to differences in mortality rates. HECM loan behavior indicates that single males tend to terminate their loans the quickest, followed by single females, with couples terminating the slowest. Table 14 shows the gender distribution of HECM endorsements. Single females comprised the largest gender cohort of the Fiscal Year 2010 endorsements at 42%, followed by couples at 35%, and single males at 21%. A similar pattern is observed for Fiscal Years 2011 and 2012. In Fiscal Year 2013, couples comprised 39% of HECM loans, surpassing single females to become the largest gender cohort. The single female share is currently 35% while the single male share remains the lowest at 20%. The concentration in couples rose to 41% in 2016, decreased to 38% in 2021, and has increased to just over 40% in 2022. Compared to Fiscal Year 2017, missing genders has increased to 4.4%.

Table 14: Distribution of HECM Loans by Borrower Gender

Origination Year	Male	Female	Couple	Missing
2009	21.69%	40.92%	36.75%	0.63%
2010	21.47%	41.87%	35.25%	1.41%
2011	20.86%	40.25%	37.08%	1.80%
2012	21.22%	39.16%	37.35%	2.27%
2013	21.15%	37.56%	38.96%	2.33%
2014	20.63%	38.74%	38.65%	1.99%
2015	21.86%	38.53%	38.92%	0.69%
2016	21.65%	36.82%	41.05%	0.47%
2017	20.93%	37.14%	40.93%	1.00%
2018	20.70%	36.69%	40.21%	2.39%
2019	21.16%	38.11%	38.81%	1.92%
2020	20.21%	35.29%	39.66%	4.84%
2021	20.90%	35.90%	38.61%	4.59%
2022	19.86%	35.31%	40.19%	4.42%

Cash Draw Distribution

Data show that loans which have drawn a higher percentage of the initial amount of equity available tend to have a higher likelihood of refinancing. Table 15 and Table 16 show the distribution of the cash draw in the first month as a percentage of the initial PL by age group for HECM endorsements.

Younger borrowers tend to draw a higher percentage of the initial amount of equity available than older borrowers. In Fiscal Year 2009, 78% of the 62-65 age group drew over 60% of their initial PL, compared with 54% for the greater-than-85-year-old age group. The incidence of initial draws above 60% of the PL rose sharply to nearly 80% for all age groups combined for Fiscal Years 2010 through 2013. This was mainly driven by the disproportionally high initial draws incurred by most fixed-rate HECMs during that period. In 2014, HUD limited the insurability of fixed interest rate mortgages under the HECM program to mortgages with the Single Disbursement Lump Sum payment option. Also in the same year, HUD introduced a higher MIP charge of 2.50% if the initial draw amount exceeds 60% of the available PL, as compared to the 0.50% MIP rate if the initial draw amount was less than or equal to 60% of the available PL. The overall percentage of loans with a first-month draw over 60% fell from 80% in Fiscal Year 2013 to 48% in Fiscal Year 2019. Since Fiscal Year 2019, this percentage has increased, and is at almost 70% for Fiscal Year 2022.

Although younger borrowers typically draw a higher percentage of the initial PL in the first month, the amount of cash drawn represents a smaller percentage of the MCA because the PLF is lower for younger borrowers to account for the risk implied by their longer life expectancy.

Table 15: First-Month Cash Draw as a Percentage of Initial PL (2009 – 2015)

Origination Year	Age Group	Variable Rate Loans			Fixed Rate Loans	
		0-40%	40-60%	60-100%	0-60%	60-100%
2009	62-65	11.76%	9.81%	65.03%	0.19%	13.21%
	66-70	14.14%	10.68%	62.08%	0.09%	13.01%
	71-75	18.64%	11.32%	58.67%	0.01%	11.36%
	76-85	24.66%	11.91%	53.49%	0.03%	9.92%
	86+	36.23%	10.19%	46.06%	0.03%	7.48%
	Total	18.73%	10.93%	58.72%	0.07%	11.54%
2010	62-65	7.35%	4.29%	8.39%	0.19%	79.77%
	66-70	9.07%	5.24%	9.88%	0.13%	75.68%
	71-75	13.29%	6.47%	10.96%	0.12%	69.16%
	76-85	19.95%	7.66%	13.49%	0.10%	58.80%
	86+	32.46%	8.73%	15.04%	0.17%	43.59%
	Total	13.93%	6.14%	11.04%	0.14%	68.75%
2011	62-65	8.37%	5.08%	10.09%	0.25%	76.21%
	66-70	10.60%	5.86%	9.67%	0.18%	73.70%
	71-75	15.15%	6.51%	10.25%	0.13%	67.96%
	76-85	22.49%	8.06%	11.02%	0.13%	58.31%
	86+	36.65%	7.91%	11.15%	0.07%	44.22%
	Total	15.26%	6.42%	10.30%	0.17%	67.86%
2012	62-65	8.58%	5.34%	10.78%	0.14%	75.16%
	66-70	10.83%	5.56%	9.49%	0.10%	74.03%
	71-75	14.18%	6.47%	9.54%	0.07%	69.74%
	76-85	20.69%	7.13%	10.05%	0.12%	62.00%
	86+	33.98%	7.96%	10.15%	0.24%	47.67%
	Total	14.39%	6.16%	10.03%	0.12%	69.30%
2013	62-65	8.13%	5.70%	20.97%	0.32%	64.89%
	66-70	9.69%	5.87%	20.70%	0.32%	63.42%
	71-75	13.45%	6.41%	19.40%	0.35%	60.39%
	76-85	19.35%	7.03%	19.31%	0.28%	54.03%
	86+	31.36%	7.35%	16.56%	0.38%	44.34%
	Total	13.15%	6.25%	20.01%	0.32%	60.27%
2014	62-65	12.26%	26.87%	38.16%	2.03%	20.68%
	66-70	15.15%	25.09%	39.03%	1.95%	18.79%
	71-75	18.81%	25.81%	37.34%	1.93%	16.12%
	76-85	24.68%	26.34%	34.82%	2.11%	12.06%
	86+	36.78%	27.24%	26.64%	2.48%	6.86%
	Total	18.38%	26.10%	36.85%	2.03%	16.65%
2015	62-65	12.71%	37.98%	30.65%	0.67%	17.98%
	66-70	14.58%	35.35%	31.66%	0.60%	17.80%
	71-75	18.03%	34.06%	31.82%	0.55%	15.54%
	76-85	23.60%	34.99%	29.74%	0.66%	11.01%
	86+	33.99%	36.07%	23.27%	1.10%	5.58%
	Total	18.04%	35.70%	30.50%	0.65%	15.10%

Table 16: First-Month Cash Draw as a Percentage of Initial PL (2016 – 2022)

Origination Year	Age Group	Variable Rate Loans			Fixed Rate Loans	
		0-40%	40-60%	60-100%	0-60%	60-100%
2016	62-65	16.76%	36.74%	32.68%	0.81%	13.01%
	66-70	18.02%	33.19%	35.68%	0.49%	12.62%
	71-75	19.10%	32.62%	37.22%	0.25%	10.81%
	76-85	24.21%	33.44%	35.38%	0.40%	6.57%
	86+	34.90%	34.78%	27.02%	0.66%	2.63%
	Total	20.65%	33.98%	34.73%	0.50%	10.15%
2017	62-65	17.78%	34.11%	34.77%	0.98%	12.36%
	66-70	16.75%	30.29%	40.28%	0.47%	12.21%
	71-75	19.07%	28.82%	41.42%	0.43%	10.27%
	76-85	21.88%	30.73%	40.27%	0.40%	6.71%
	86+	32.28%	33.77%	30.84%	0.41%	2.71%
	Total	19.79%	31.06%	38.81%	0.54%	9.81%
2018	62-65	18.40%	33.54%	35.88%	0.69%	11.49%
	66-70	17.14%	29.29%	40.64%	0.53%	12.40%
	71-75	19.86%	28.64%	41.09%	0.31%	10.08%
	76-85	22.04%	31.12%	39.45%	0.42%	6.97%
	86+	32.84%	33.20%	30.62%	0.33%	3.00%
	Total	20.33%	30.68%	38.84%	0.47%	9.67%
2019	62-65	17.81%	32.06%	42.89%	0.41%	6.83%
	66-70	17.19%	29.03%	46.82%	0.20%	6.76%
	71-75	19.87%	28.76%	44.73%	0.18%	6.46%
	76-85	23.93%	31.85%	39.46%	0.31%	4.45%
	86+	33.76%	33.04%	30.50%	0.64%	2.08%
	Total	20.93%	30.55%	42.48%	0.29%	5.75%
2020	62-65	16.25%	26.51%	55.21%	0.10%	1.94%
	66-70	14.23%	24.27%	58.96%	0.08%	2.47%
	71-75	15.21%	23.83%	59.22%	0.09%	1.65%
	76-85	18.86%	26.37%	53.23%	0.17%	1.38%
	86+	30.58%	29.95%	38.33%	0.37%	0.77%
	Total	17.10%	25.47%	55.53%	0.13%	1.78%
2021	62-65	12.92%	26.84%	52.52%	0.36%	7.36%
	66-70	11.13%	20.96%	59.64%	0.34%	7.93%
	71-75	10.82%	19.13%	62.10%	0.27%	7.68%
	76-85	12.57%	19.87%	61.33%	0.27%	5.96%
	86+	22.92%	23.05%	50.45%	0.22%	3.36%
	Total	12.46%	21.14%	59.17%	0.30%	6.93%
2022	62-65	13.69%	26.18%	55.00%	0.21%	4.92%
	66-70	11.37%	20.92%	62.74%	0.23%	4.74%
	71-75	6.59%	19.19%	71.30%	0.10%	2.82%
	76-85	10.64%	18.09%	67.37%	0.24%	3.67%
	86+	18.68%	19.16%	59.43%	0.40%	2.33%
	Total	10.41%	19.68%	66.11%	0.20%	3.59%

Section 4. Cash Flow NPV Based on Alternative Scenarios

The Cash Flow NPV of the MMI will vary from our estimates if the actual economic drivers of mortgage performance deviate from the baseline projections associated with the OMB Economic Assumptions. In this section, we develop additional estimates of the Cash Flow NPV based on the following approaches:

1. Moody's economic scenarios
2. Stochastic simulation of key economic variables
3. Sensitivity testing of key economic variables

We use these additional estimates of the Cash Flow NPV to develop a range of estimates. These alternative estimates are compared to the Cash Flow NPV resulting from the OMB Economic Assumptions to determine the sensitivity of the Cash Flow NPV estimate to alternative assumptions.

Each Moody's scenario produces an estimate of the Cash Flow NPV using future interest, unemployment, and HPI rates as a deterministic path. We are including 10 Moody's scenarios in the analysis. These scenarios are consistent with the scenarios used in the 2021 Actuarial Review.

The Moody's scenarios are:

- Baseline
- Alternative 0 – Upside (4th Percentile)
- Alternative 1 – Upside (10th Percentile)
- Alternative 2 – Downside (75th Percentile)
- Alternative 3 – Downside (90th Percentile)
- Alternative 4 – Downside (96th Percentile)
- Slower Trend Growth
- Stagflation
- Next-Cycle Recession
- Low Oil Price

The resulting Cash Flow NPV associated with each alternative scenario is summarized in Table 10. Below, we discuss the characteristics of each Moody's scenario.

Baseline Scenario:

In the Baseline Scenario, the HPI increases throughout the entire projection period. The rate of change declines from 7.8% to 3.1% in the fourth quarter of 2023 increases to approximately 4.0% per year by 2037, and then remains unchanged for the remainder of the projection period. The mortgage interest rate remains flat through the third quarter of 2024, increases through the third quarter of 2026, and then stabilizes at 5.6%. The unemployment rate decreases through 2022 to approximately 3.55% and then increases to 4.1% by the first quarter of 2024. The rate then decreases to 3.8% by the first quarter of 2025, and then increases to 4.1% by 2027. The rate then remains around 4% for the remainder of the projection period.

Alternative Scenario 0 – Upside (4th Percentile):

In the Alternative Scenario 0 – Upside (4th Percentile), the HPI increases throughout most of the projection period. The rate of increase decreases from 10.7% to -0.3% by 2025, and then increases to about 4.0% per year for the remainder of the projection period. The mortgage interest rate remains flat through the third quarter of 2024, increases through the third quarter of 2026, and then levels off at 5.6%. The unemployment rate is projected to decrease in the fourth quarter of 2022, remain steady through the fourth quarter of 2025, and then increase gradually until it stabilizes at approximately 3.8%.

Alternative Scenario 1 – Upside (10th Percentile):

In Alternative Scenario 1 – Upside (10th Percentile), the HPI is projected to increase most of the projection period. The rate of increases drops sharply from 9.4% per year in the fourth quarter of 2021 to -0.9% per year by the first quarter of 2025. The rate then increases to about 4.0% per year for the remainder of the projection period. The mortgage interest rate remains flat through the third quarter of 2024, increases through the third quarter of 2026, and then levels off at 5.6%. The unemployment rate is projected to decrease in the fourth quarter of 2022, remain steady through the fourth quarter of 2025, and then increase gradually until it stabilizes at approximately 3.9%.

Alternative Scenario 2 – Downside (75th Percentile):

In the Alternative Scenario 2 – Downside (75th Percentile), the HPI increases through the fourth quarter of 2022, decreases through the first quarter of 2026, and then increases for the remainder of the projection period. The rate of increase increases to approximately 4.0% by 2033. Mortgage interest rates are projected to decrease through the second quarter of 2023, then increase through third quarter of 2026, and then level off for the remainder of the projection period at approximately 5.6%. The unemployment rate is projected to increase to 6.4% by the third quarter of 2023, then decrease to 4.0% by 2024.

Alternative Scenario 3 – Downside (90th Percentile):

In the Alternative Scenario 3 – Downside (90th Percentile), the HPI increases through the fourth quarter of 2022, decreases through the first quarter of 2024, and then begins to increase. Mortgage interest rates are projected to decrease through the third quarter of 2023, then increase through the third quarter of 2026, and then level off for the remainder of the projection period at approximately

5.6%. The unemployment rate increases to 7.8% in the fourth quarter of 2023, then decreases to 4.1% by 2027.

Alternative Scenario 4 – Downside (96th Percentile):

In Alternative Scenario 4 – Downside (96th Percentile), the HPI decreases from the fourth quarter of 2023 through the second quarter of 2024, and then begins to increase. Mortgage interest rates are projected to decrease through the third quarter of 2024, then increase through first quarter of 2027, and then level off for the remainder of the projection period at approximately 5.6%. The unemployment rate spikes to 8.9% by 2024, and then decreases to 4.2% by 2032.

Slower Trend Growth:

In the Slower Trend Growth scenario, the HPI increases through the first quarter of 2024, decreases through the first quarter of 2026, and then begins to increase. Mortgage interest rates decrease through the third quarter of 2024, the increase through the second quarter of 2027 before leveling off at about 5.5%. The unemployment rate increases to 5.2% by the end of 2023, then decreases slowly to 4.1% by the end of 2028.

Stagflation:

In the Stagflation scenario, the HPI increases through the first quarter of 2023, decreases through the fourth quarter of 2025, and then begins to increase. Mortgage interest rates increase in the fourth quarter of 2022, then decrease through the second quarter of 2025. Mortgage rates then increase through the fourth quarter of 2026, and level off at 5.6%. The unemployment rate increases to 9.1% by the end of 2024, and then decreases to a long-term average of 4.1% by 2028.

Next–Cycle Recession:

In the Next-Cycle Recession scenario, the HPI increases through the first quarter of 2023, and then decreases through the fourth quarter of 2024. The HPI then increases for the remainder of the projection period. Mortgage interest rates increase in the fourth quarter of 2022, then decrease through the fourth quarter of 2023. Mortgage rates then increase through the third quarter of 2026, and level off at 5.6%. The unemployment rate increases to 6.2% by the fourth quarter of 2023. The rate then decreases to 4.1% by 2026, where it remains for the remainder of the projection period.

Low Oil Price:

In the Low Oil Price scenario, the HPI increases through the first quarter of 2023, then decreases through the first quarter of 2026. The HPI then increases for the remainder of the projection period. Mortgage interest rates are projected to decrease through the first quarter of 2024, then increase through third quarter of 2026, and then level off for the remainder of the projection period at approximately 5.5%. The unemployment rate decreases through the fourth quarter of 2022, then increases through the first quarter of 2024. The unemployment rate then decreases again through the second quarter of 2025, and then increases gradually to a long-term average of 4.1%.

Summary of Alternative Scenarios

Table 17 shows the projected Cash Flow NPV from the ten deterministic scenarios and RMA's ACE. The range of projected results is between positive $1.498 billion and positive $5.963 billion.

Table 17: Cash Flow NPV Summaries from Alternative Scenarios

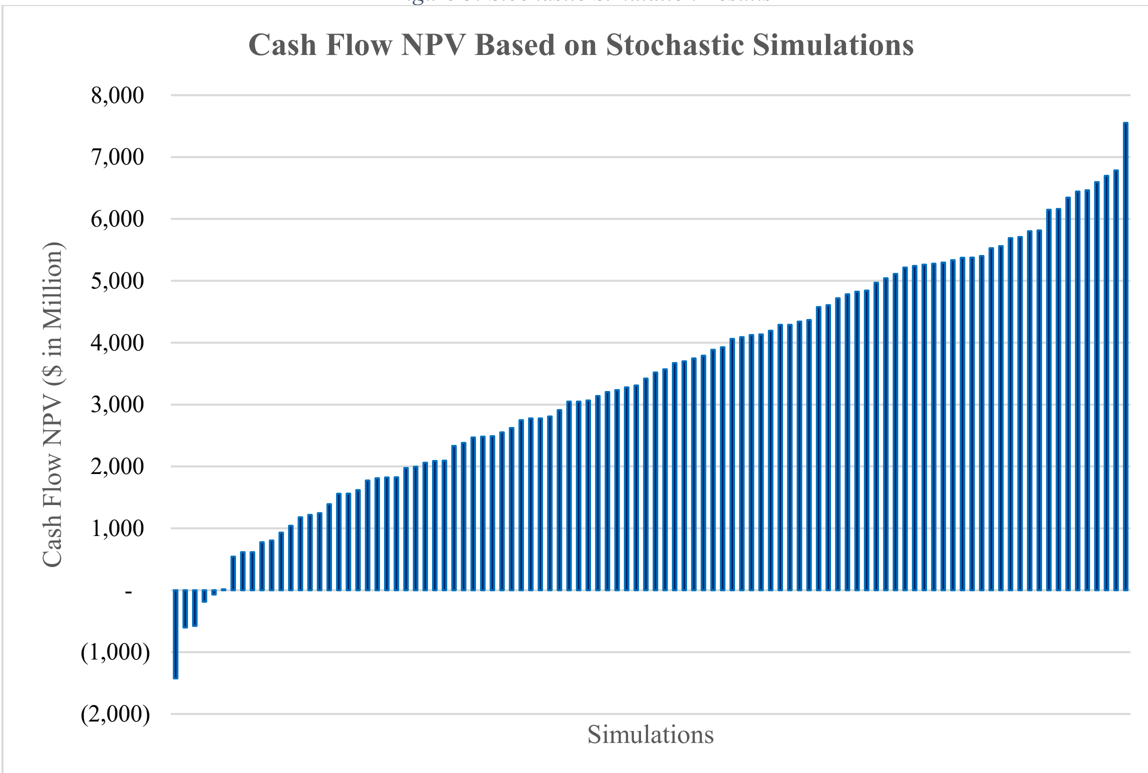
Cohort	RMA ACE	Baseline	Alternative 0 -Upside (4th Percentile)	Alternative 1 -Upside (10th Percentile)	Alternative 2 -Downside (75th Percentile)	Alternative 3 -Downside (90th Percentile)	Alternative 4 -Downside (96th Percentile)	Slower-Trend Growth	Stagflation	Next-Cycle Recession	Low Oil Price
2009	20,327,974	2,596,432	95,400,841	60,113,206	-41,222,644	-93,346,814	-170,082,961	-20,567,929	-17,635,792	-5,103,135	-9,738,159
2010	49,954,103	40,522,226	100,507,217	78,453,606	23,046,057	3,382,147	-34,101,746	34,505,638	42,312,398	45,118,133	49,127,021
2011	167,532,053	175,585,218	205,729,011	195,512,303	147,848,975	127,945,883	104,849,428	166,107,781	169,913,607	172,566,308	168,594,422
2012	146,185,333	149,619,099	178,262,259	155,461,220	123,073,630	114,366,459	84,963,157	136,419,667	141,425,868	145,687,942	146,079,855
2013	215,358,247	224,792,334	271,405,184	255,997,354	183,802,662	169,009,425	128,280,208	198,979,913	213,878,458	229,010,737	220,726,462
2014	428,917,590	496,065,650	578,290,183	552,076,134	439,887,471	388,037,708	289,130,081	480,193,969	499,392,063	487,207,693	495,542,006
2015	636,016,393	709,304,273	835,719,690	771,561,534	652,632,377	581,776,622	463,651,767	713,112,098	716,381,919	741,224,419	703,455,886
2016	731,105,183	896,014,506	995,551,945	939,612,013	818,949,261	753,291,071	586,960,984	880,620,973	894,668,200	876,341,672	904,124,592
2017	766,888,192	955,524,262	1,054,475,741	1,002,361,942	836,418,645	786,745,766	609,925,553	936,110,425	978,435,151	958,885,138	943,497,553
2018	161,816,150	237,062,761	280,111,415	251,019,316	202,167,175	157,052,946	80,455,354	227,590,219	240,764,548	241,110,972	231,631,218
2019	115,664,331	141,978,502	140,610,189	145,159,167	140,566,620	123,056,286	108,387,149	143,091,331	143,329,688	138,442,476	144,390,867
2020	267,313,167	382,967,480	395,110,967	401,036,455	343,358,188	297,243,566	240,126,159	375,514,540	390,091,592	389,479,256	374,987,756
2021	193,517,035	372,903,614	506,869,750	437,324,753	279,948,667	135,366,032	-44,643,617	381,926,708	369,259,469	382,050,832	370,662,939
2022	-254,818,122	-128,186,684	324,907,131	99,484,541	-382,309,948	-633,091,266	-949,824,192	-60,545,653	-232,147,224	-173,328,356	-131,771,251
Total	3,645,777,629	4,656,749,673	5,962,951,523	5,345,173,544	3,768,167,136	2,910,835,831	1,498,077,324	4,593,059,680	4,550,069,945	4,628,694,087	4,611,311,167

Stochastic Simulation

The stochastic simulation approach provides information about the probability distribution of the HECM Cash Flow NPV with respect to different possible future economic conditions and the corresponding terminations, cash flow draws, and loss rates. The simulation provides the Cash Flow NPV associated with each one of the 100 possible future economic paths. The distribution of Cash Flow NPV based on these scenarios allows us to gain insights into the sensitivity of the MMI's Cash Flow NPV to different economic conditions.

Figure 3 below shows the range of Cash Flow NPV resulting from the 100 simulated scenarios.

Figure 3: Stochastic Simulation Results



Based on the stochastic simulation results, the range of Cash Flow NPV estimates is negative $1.424 billion to positive $7.553 billion. The range of Cash Flow NPV estimates may not include all conceivable outcomes. For example, it would not include extreme events where the contribution of such events to an expected value is not reliably estimable.

The Cash Flow NPV estimate provided by FHA to be used in the FHA's Annual Report to Congress is positive $6.172 billion. Based on RMA's ACE and range of estimates, we conclude the FHA estimate of Cash Flow NPV is reasonable.

Sensitivity Tests of Economic Variables

The scenario analyses described above were conducted to estimate the distribution of the Cash Flow NPV of the MMI with different possible combinations of economic variable movements in the future. It is also useful to understand the marginal impact of a change in each single economic factor on the Cash Flow NPV. Below, we show the sensitivity of the Cash Flow NPV with respect to the change of a single economic factor at a time. This sensitivity test is conducted for the House Price Appreciation (HPA) and interest rates.

The marginal impact is measured by the change in Cash Flow NPV based on the OMB Economic Assumption scenario result. These simulations change each of these variables one at a time from the Baseline scenario. The changes are parallel shifts in the path of each variable in the OMB

Economic Assumption scenario, where all three interest rates are shifted together and at the same magnitudes but are kept from going negative.

Figure 4 reports the sensitivity of the Cash Flow NPV with respect to changes in the HPA rate forecast. Specifically, we applied a parallel shift to the annualized HPA rates from the Baseline scenario up and down by 20, 50, 100 and 200 basis points. The sensitivity to shifts in the annualized HPA rates from the Baseline scenario has a positive slope. A negative 100 basis points parallel shift in HPA rate will decrease Cash Flow NPV by $2.870 billion, and a positive 100 basis points parallel shift in HPA will increase Cash Flow NPV by $2.567 billion. Figure 5 shows the change in Cash Flow NPV as a percentage of the IIF. The change as a percentage of IIF across all basis point ranges from -8.5% to +6.6%.

Figure 4 also reports the sensitivity of the Cash Flow NPV with respect to changes in interest rates. Specifically, we applied a parallel shift to the annualized CMT and mortgage rates from the Baseline scenario up and down by 20, 50, 100 and 200 basis points. The sensitivity to shifts in the interest rates from the Baseline scenario has an upward slope. A negative 100 basis points parallel shift in interest rates will increase Cash Flow NPV by $531 million, and a positive 100 basis points parallel shift in HPA rates will decrease Cash Flow NPV by $632 million. Figure 5 shows the change in Cash Flow NPV as a percentage of the IIF. The change as a percentage of IIF ranges from -1.8% to +1.1%**.**

Figure 4: HECM Sensitivity Analysis – Change in Cash Flow NPV

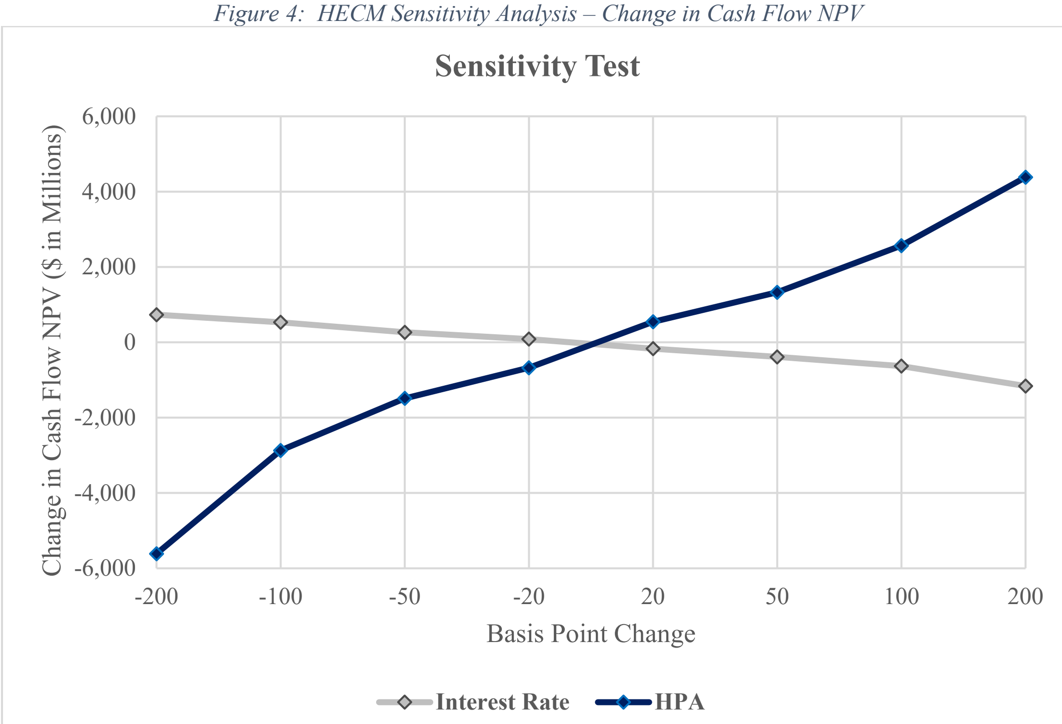
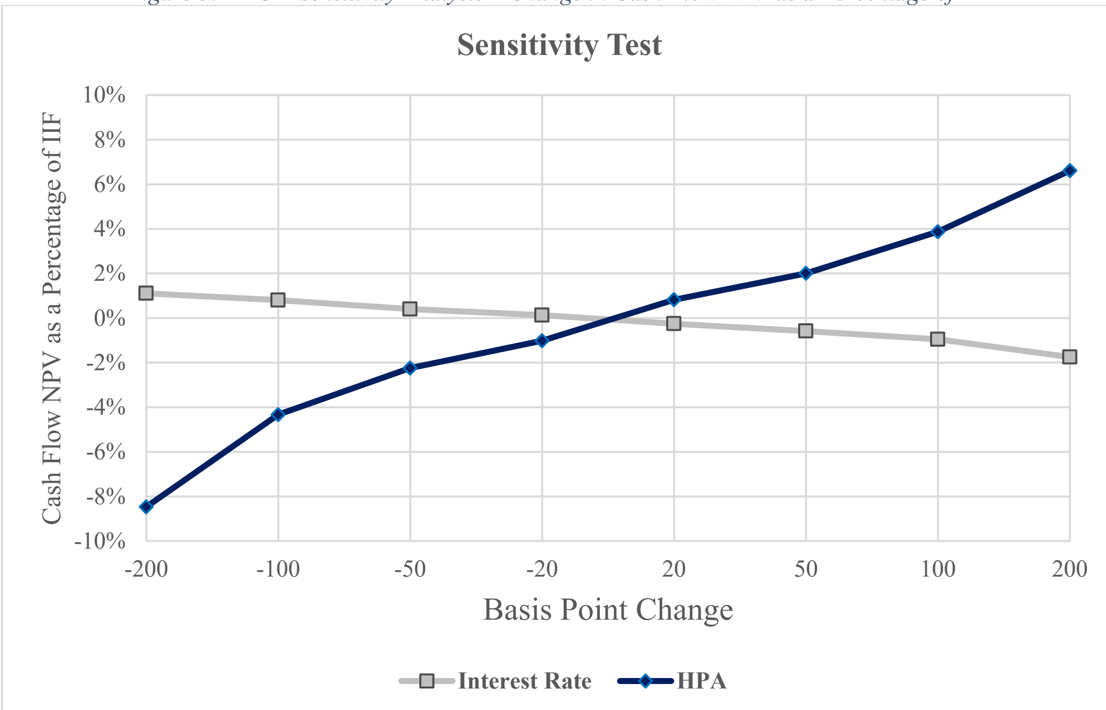


Figure 5: HECM Sensitivity Analysis – Change in Cash Flow NPV as a Percentage of IIF



Section 5. Summary of Methodology

This section describes the analytical approach implemented in this analysis.

Data Sources (Appendix A)

In our analysis, we have relied on data from FHA, Summit-Milliman (S-M), Moody's, and OMB.

From FHA and S-M, we have received the following data tables:

1. hermit_case_detail: case-level data for mortgages
2. hermit_claim_detail: data for electronically processed claims
3. hermit_transactions_balance: balance transactions data
4. hermit_transactions_setaside: set aside transactions data
5. hermit_transactions_growth: growth transactions data
6. hermit_payment_plan: payment plan information
7. hermit_lender_detail: supporting lender information
8. sams_case_record: union of sams_monthly_record and sams_archive_record
9. hecm_claim_detail: data for paper claims
10. assigned_f12_transactions: historical F12 transaction records for HECM cases that were assigned prior to October 3, 2012
11. idb_1_and_coborr: Integrated Database (IDB) idb_1_and_coborr is a composite of five Single Family legacy systems
12. Consolidated Balance Transfer Files
13. Tmod_cd_full: consolidated mortgage-level dataset with information on all cases endorsed to date. The dataset contains variables on mortgage characteristics, borrower characteristics, current mortgage status, and current unpaid principal balance.

From Moody's, we have received the following data elements:

1. Historical Economic Data
2. Baseline Economic Scenario Projections
3. Alternative Economic Scenario Projections

From OMB, we have received the Economic Assumptions for the 2023 Budget.

The economic data that is included in the analysis is shown below:

1. HPI
2. CMT rates
3. LIBOR

Data Processing – Mortgage-Level Modeling

Starting with the raw data, RMA processed the data to create datasets for developing the mortgage-level transition, loss severity and cash draw models. The steps below describe the data processing that occurred to prepare the data was used for this analysis.

1. Pre-Processing: fields from supplemental tables are added to main HECM case file
2. HECM Quarterly: several calculated fields and flags are added to the dataset
3. Transaction Processing: quarterly historical transactions are then processed
4. Claim Processing: historical claim amounts are calculated based on claim transactions
5. UPB: historical quarterly UPB is calculated for each mortgage
6. MIP Processing: initial and subsequent MIP inflows are summarized by case number and period from the Consolidated Balance Transfer Files
7. Cash Draw Processing: incremental and cumulative cash draws are calculated by case number and period
8. Taxes and Insurance Processing: incremental and cumulative taxes and insurance are calculated by case number and period
9. Line of Credit Processing: incremental and cumulative line of credit draws are calculated by case number and period
10. Table Joins: tables generated in steps 3 through 9 are joined to the main table created in step 2

Data Reconciliation

To reconcile the data processed by RMA with the data provided by FHA, RMA compared summaries of key data elements with the summaries provided by FHA. The summaries for the IIF, number of active assignments and the number of claims to date are shown in the following tables. Most of the data processed matches the FHA data totals with 1%. The exceptions are the number of claims to date for the 2009 and 2010 cohorts. RMA has made HUD aware of these discrepancies and HUD is investigating the differences.

The reconciliation tables 18 through 20 were based on data as of September 30, 2022.

Table 18: Data Reconciliation for Number of Active Loans

Credit Subsidy Cohort	Federal Housing Administration	Independent Actuary	Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
2009	42,328	42,328	0	0.0
2010	31,555	31,555	0	0.0
2011	31,003	31,003	0	0.0
2012	24,574	24,574	0	0.0
2013	28,501	28,501	0	0.0
2014	22,075	22,075	0	0.0
2015	26,468	26,468	0	0.0
2016	23,709	23,709	0	0.0
2017	29,020	29,020	0	0.0
2018	25,295	25,295	0	0.0
2019	16,785	16,785	0	0.0
2020	26,582	26,582	0	0.0
2021	40,510	40,510	0	0.0
2022	63,404	63,404	0	0.0
Total	431,809	431,809	0	0.0

Note: Count of case numbers where status in ("IIF", "CT2a")

Table 19: Data Reconciliation for Number of Active Assignments

Credit Subsidy Cohort	Federal Housing Administration	Independent Actuary	Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
2009	21,804	21,804	0	0.0
2010	22,772	22,772	0	0.0
2011	22,333	22,333	0	0.0
2012	18,110	18,110	0	0.0
2013	18,608	18,608	0	0.0
2014	1,539	1,539	0	0.0
2015	730	730	0	0.0
2016	421	421	0	0.0
2017	229	229	0	0.0
2018	13	13	0	0.0
2019	-	0	0	0.0
2020	-	0	0	0.0
2021	-	0	0	0.0
2022	-	0	0	0.0
Total	106,559	106,559	0	0.0

Table 20: Data Reconciliation for Number of Claims to Date

Credit Subsidy Cohort	Federal Housing Administration	Independent Actuary	Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
2009	57,422	55,154	-2,268	-3.9
2010	46,596	45,818	-778	-1.7
2011	39,986	39,923	-63	-0.2
2012	29,567	29,574	7	0.0
2013	28,198	28,203	5	0.0
2014	3,737	3,737	0	0.0
2015	2,168	2,168	0	0.0
2016	1,103	1,104	1	0.1
2017	592	591	-1	-0.2
2018	90	90	0	0.0
2019	5	5	0	0.0
2020	1	-	-1	-100.0
2021	1	1	0	0.0
2022	-	-	0	0.0
Total	209,466	206,368	-3,098	-1.5

Note: Count of case numbers where clm_typ in (21, 22, 23, 24)

HECM Base Termination Model (Appendix B)

RMA developed predictive models to estimate future HECM terminations. No repayment of principal is required on a HECM while the mortgage is active. Termination of a HECM typically occurs due to death of the borrower, the borrower moving out, or voluntary termination via refinance or payoff. The termination model estimates the probabilities of the three mutually exclusive HECM termination events denoted as mortality, mobility, and refinance. The modeling approach is as follows:

1. If there is a borrower, we develop two binomial models to determine refinance (“refi” model) or non-mortality termination (“other” model). These models are combined into a single competing hazards probability draw for simulation purposes.
2. If no borrowers are alive going into the period, run-off probabilities are used to determine if the loan terminates. No cash draws or refinances are allowed if there are no borrowers remaining on the loan. If a termination is simulated, then the loan follows the non-mortality termination path described in Step 4.
3. If the loan results in a non-mortality termination, there are two possible paths:
   a. If the loan is assigned, the “CT2c” model determines the probability the loan ends in conveyance of the property (a CT2c termination) or in repayment of the loan (a CT2p termination).

b. If the loan is not assigned, the “CT1” incident model determines if the loan results in a Claim Type 1 (a CT1 termination) or no claim (a NClm termination). If it is a CT1, a CT1 sales model determines the sales price of the home relative to UPB which is used in the calculation of the CT1 loss amount.

4. If the loan does not terminate, then we determine if it becomes assigned and/or if any of the borrowers die.

The models incorporate four main categories of explanatory variables:

- Fixed initial borrower characteristics, such as borrower age at origination and gender.
- Fixed initial mortgage characteristics, such as mortgage interest rate, and origination year and quarter.
- Dynamic variables based on mortgage/borrower characteristics, such as mortgage age and borrower and co-borrower ages.
- Dynamic variables derived by combining mortgage characteristics with external macroeconomic data, such as interest rates, HPI, the amount of additional equity available to the borrower through refinancing and the updated ratio of UPB to home value.

HECM Cash Flow Draw Models (Appendix C)

Over 90% of HECMs have a line of credit associated with them. To estimate the present value of future cash flows on the existing portfolio of HECMs, we need to estimate the future cash draws associated with the line of credit. As these cash draws are not certain, we have developed predictive models to forecast cash draws. We have incorporated the following modeling approach:

1. A binomial model is developed to estimate the likelihood of a cash draw occurring in a period.
2. If a cash draw is simulated, then the next step determines whether it is a full draw of all funds available through the LOC. There are two separate logistic models built for this: 1) A model built only on data from cohorts 2014 and subsequent for the first 8 quarters (“FD8” model), and 2) a model built on all data for quarters 9+ (“FD9+” model). The reason for the split is to account for the first twelve-month disbursement period on the funds available for distribution from the LOC.
3. A Generalized Linear Model (GLM) is then developed to estimate the amount of the cash draw for the period if the cash draw is not a full draw.

Using the historical HECM data, for each quarter we develop indicators of whether a net positive unscheduled cash draw was taken from the line of credit during that quarter, and the amount of the cash draw. We then develop models to predict the amount of future cash draws based on a series of explanatory variables.

HECM Cash Flow Analysis (Appendix E)

HECM termination rates are projected for all future policy years for each active mortgage. The variables used in the projection are derived from mortgage characteristics and economic forecasts. Moody's August 2022 forecasts of interest rates and HPI are combined with the mortgage-level data to simulate the projected economic paths and create the necessary forecasted variables. MSA-level forecasts of HPI apply to mortgages in metropolitan areas; otherwise, mortgages use the state-level HPI forecasts. Moody's house price forecasts are generated simultaneously with various macroeconomic variables.

For each mortgage during future policy years, the derived mortgage variables serve as independent variables to the multinomial logistic termination models described in the <u>HECM Base Termination Model</u> section (Appendix B). The termination projections by claim type are then calculated to generate the probability of mortgage termination in a policy quarter by different modes of termination given that it survives to the end of the prior policy quarter. The HECM cash flow model uses these forecasted termination rates to project the cash flows associated with different termination events. Based on the specific characteristics of the mortgage, the probability of each termination is calculated. Then, a random number between 0 and 1 is generated, and based on this random draw a mortgage transition is determined. The projection process continues for each mortgage until the mortgage ends by termination or claim.

<u>Cash Flow Components</u>

There are four major components of HECM cash flows:

1. MIP
2. Claims
3. Note holding expenses
4. Recoveries on notes in inventory (after assignment)

Premiums consist of upfront and annual MIPs, which are inflows to the HECM program. Recoveries are the property recovery amount received by FHA at the time of note termination after assignment, which is the minimum of the mortgage balance and the predicted net sales proceeds at termination. The recovery amount for refinance termination is always the mortgage balance. Claim Type 1 payments are cash outflows paid to the lender when the net proceeds of a property sale are insufficient to cover the balance of the mortgage. Claim Type 2 payments result from assignment of mortgages to HUD and note holding payments are additional outflows.

Net Future Cash Flows

The Cash Flow NPV for the HECM book of business is computed by summing the individual components as they occur over time:

$Net\ Cash\ Flow_t = Annual\ Premiums_t + Recoveries_t - Claim\ Type\ 1_t - Claim\ Type\ 2_t - Note\ Holding\ Expenses_t$

Discount Factors

The discount factors applied were provided by FHA and reflect the most recent U.S. Treasury yield curve, which captures the Federal government's cost of borrowing in raising funds. These factors reflect the capital market's expectation of the consolidated interest risk of U.S. Treasury securities. RMA has relied on FHA for the discount factors and has not performed an independent analysis of the appropriateness of the discount factors. Our simulations aggregate each future quarter's cash flows, which are treated as being received at the end of the quarter.

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Appendix A: Data Sources, Processing and Reconciliation

Data Sources

In our analysis, we have relied on data from FHA, S-M, Moody's, and OMB.
From FHA and S-M, we have received the following data tables.

1. hermit_case_detail: case level data for mortgages
2. hermit_claim_detail: data for electronically processed claims
3. hermit_transactions_balance: balance transactions data
4. hermit_transactions_setaside: set aside transactions data
5. hermit_transactions_growth: growth transactions data
6. hermit_payment_plan: payment plan information
7. hermit_lender_detail: supporting lender information
8. sams_case_record: union of sams_monthly_record and sams_archive_record
9. hecm_claim_detail: data for paper claims
10. assigned_f12_transactions: historical F12 transaction records for HECM cases that were assigned prior to October 3, 2012
11. idb_1_and_coborr: Integrated Database (IDB) idb_1_and_coborr is a composite of five Single Family legacy systems
12. Consolidated Balance Transfer Files
13. Tmod_cd_full: consolidated mortgage-level dataset with information on all cases endorsed to date. The dataset contains variables on mortgage characteristics, borrower characteristics, current mortgage status, and current unpaid principal balance.

From Moody's, we have received the following data elements:

1. Historical Economic Data
2. Baseline Economic Scenario Projections
3. Alternative Economic Scenario Projections

From OMB, we have received the Economic Assumptions for the 2023 Budget.
The economic data that is included in the analysis is shown below:

1. HPI
2. CMT rates
3. LIBOR

Data Processing – Mortgage-Level Modeling

Starting with the raw data, RMA processed the data to create datasets for developing the mortgage-level transition, loss severity, and cash draw models. The steps below describe the data processing that occurred to prepare the data that was used for this analysis.

1. Pre-Processing: fields from supplemental tables were added to main HECM case file

2. HECM Quarterly: several calculated fields and flags are added to the dataset
3. Transaction Processing: quarterly historical transactions are then processed
4. Claim Processing: historical claim amounts are calculated based on claim transactions
5. UPB: historical quarterly UPB is calculated for each mortgage
6. MIP Processing: initial and subsequent MIP inflows are summarized by case number and period from the Consolidated Balance Transfer Files
7. Cash Draw Processing: incremental and cumulative cash draws are calculated by case number and period
8. Taxes and Insurance Processing: incremental and cumulative taxes and insurance are calculated by case number and period
9. Line of Credit Processing: incremental and cumulative line of credit draws are calculated by case number and period
10. Table Joins: tables generated in steps 3 through 9 are joined to the main table created in step 2

Data Reconciliation

To reconcile the data processed by RMA with the data provided by FHA, RMA compared summaries of key data elements with the summaries provided by FHA. The summaries for the IIF, number of active assignments and the number of claims to date are shown in the following tables. Most of the data processed by RMA matches the FHA data totals within 1%. The exceptions are the number of claims to date for the 2009 and 2010 cohorts. RMA has made HUD aware of these discrepancies and HUD is investigating the differences.

The reconciliation tables 21 through 23 were based on data as of September 30, 2022.

Table 21: Data Reconciliation for Number of Active Loans

Credit Subsidy Cohort	Federal Housing Administration	Independent Actuary	Difference (Actuary -FHA)	Percent Difference (Actuary - FHA) / FHA
2009	42,328	42,328	0	0.0
2010	31,555	31,555	0	0.0
2011	31,003	31,003	0	0.0
2012	24,574	24,574	0	0.0
2013	28,501	28,501	0	0.0
2014	22,075	22,075	0	0.0
2015	26,468	26,468	0	0.0
2016	23,709	23,709	0	0.0
2017	29,020	29,020	0	0.0
2018	25,295	25,295	0	0.0
2019	16,785	16,785	0	0.0
2020	26,582	26,582	0	0.0
2021	40,510	40,510	0	0.0
2022	63,404	63,404	0	0.0
Total	431,809	431,809	0	0.0

Note: Count of case numbers where status in ("IIF", "CT2a")

Table 22: Data Reconciliation for Number of Active Assignments

Credit Subsidy Cohort	Federal Housing Administration	Independent Actuary	Difference (Actuary -FHA)	Percent Difference (Actuary - FHA) / FHA
2009	21,804	21,804	0	0.0
2010	22,772	22,772	0	0.0
2011	22,333	22,333	0	0.0
2012	18,110	18,110	0	0.0
2013	18,608	18,608	0	0.0
2014	1,539	1,539	0	0.0
2015	730	730	0	0.0
2016	421	421	0	0.0
2017	229	229	0	0.0
2018	13	13	0	0.0
2019	-	0	0	0.0
2020	-	0	0	0.0
2021	-	0	0	0.0
2022	-	0	0	0.0
Total	106,559	106,559	0	0.0

Table 23: Data Reconciliation for Number of Claims to Date

Credit Subsidy Cohort	Federal Housing Administration	Independent Actuary	Difference (Actuary -FHA)	Percent Difference (Actuary - FHA) / FHA
2009	57,422	55,154	-2,268	-3.9
2010	46,596	45,818	-778	-1.7
2011	39,986	39,923	-63	-0.2
2012	29,567	29,574	7	0.0
2013	28,198	28,203	5	0.0
2014	3,737	3,737	0	0.0
2015	2,168	2,168	0	0.0
2016	1,103	1,104	1	0.1
2017	592	591	-1	-0.2
2018	90	90	0	0.0
2019	5	5	0	0.0
2020	1	-	-1	-100.0
2021	1	1	0	0.0
2022	-	-	0	0.0
Total	209,466	206,368	-3,098	-1.5

Note: Count of case numbers where clm_typ in (21, 22, 23, 24)

Appendix B: HECM Base Termination Model

HECM mortgages terminate due to borrower mortality (death), the borrower(s) refinancing the mortgage, or other reasons including the borrower(s) moving out of their home (mobility). A series of binomial logistic models are specified and estimated to capture the mortgage termination behavior.

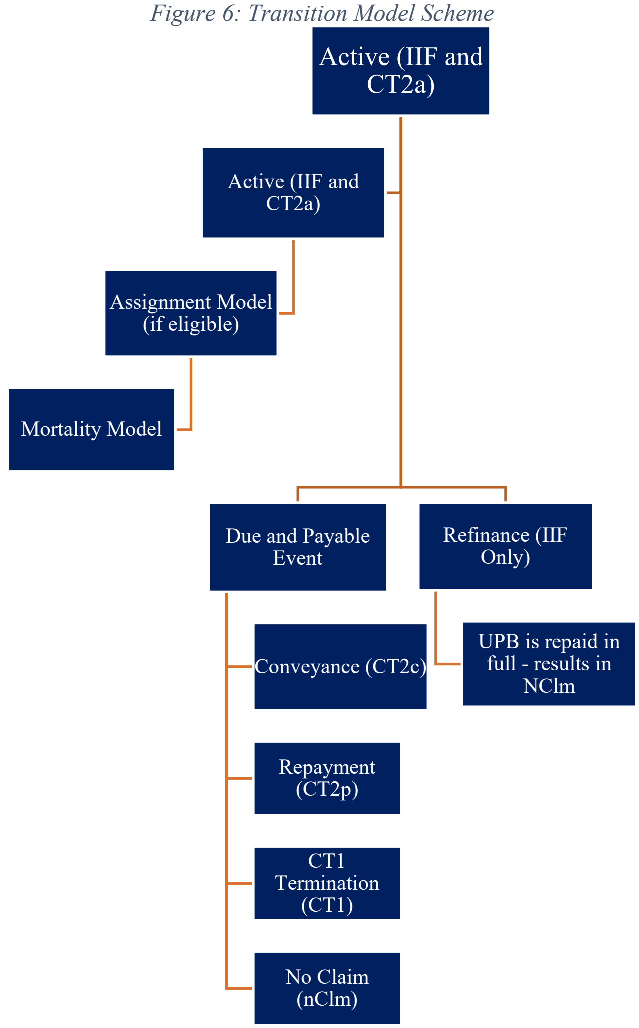
The available FHA historical HECM termination data was used to develop the base termination model. This data includes mortgages that were endorsed under the GI Fund between Fiscal Years 1990 and 2008, and mortgages endorsed under the MMI from Fiscal Year 2009 through June 30, 2022. Only mortgages endorsed under the MMI, however, are used in the calculation of the Cash Flow NPV in this analysis.

Model Specification

To model the possible transitions, we first specify two binomial models and a mortality run-off model. The binomial models determine the probability of a due and payable event other than mortality and the probability of refinance.

Figure 6 shows the modeling scheme for this structure:

Figure 6: Transition Model Scheme



To model the possible transitions shown above, we incorporate the following approach.

1. If there are borrower(s) alive on the loan going into the period, we develop two binomial models to determine refinance ("refi" model) or non-mortality termination ("othr" model). These models are combined into a single competing hazards probability draw for simulation purposes. If neither a refinance nor a due and payable event is simulated the loan continues.
2. If the loan is not assigned and the UPB has reached 98% of the MCA on the loan, we simulate if the loan is assigned. If assignment is simulated the loan moves to "CT2a" status indicating the loan has been assigned but has not yet terminated and a CT2 loss occurs. If the loan is not assigned in the simulation, it continues as "IIF" indicating that the loan is still insured and in-force.

3. At the end of each simulated period, we determine if any of the remaining borrowers die based on probabilities derived from mortality tables. If no borrowers remain at the end of the period, the model follows item 4 below in the next period.
4. If no borrowers are alive going into the period, we calculate run-off probabilities that determine if the loan terminates. No cash draws or refinances are allowed if the there are no borrowers. If a termination is simulated the loan follows the due and payable termination path described in item 5.
5. If the loan ends up in a due and payable termination, there are two possible paths:
    a. If the loan is assigned, the "CT2c" model determines the probability the loan ends in conveyance of the property (a CT2c termination) or in repayment of the loan (a CT2p termination)
    b. If the loan is not assigned, the "CT1" incident model determines if the loan results in a Claim Type 1 (CT1 termination) or no claim (NClm termination). If it is a CT1, a CT1 sales model determines the sales price of the home relative to UPB which is used in the calculation of the CT1 loss amount.

Explanatory Variables

The following explanatory variables are used in the transition models for assigned and unassigned claims. A general description of the variables is provided below, and more specific detail is included in the Model Parameters section.

- **Min_age**: the youngest age amongst the borrower and co-borrowers. This variable is incorporated as a piecewise variate and a grouped categorical variable.
- **Refi_var**: refinance incentive - the ratio of the expected gain in principal limit from refinancing to the expected transaction cost. This variable is calculated as (MCA_t x PLF - ($init\_MIP_t$ + $orig\_fee_t$) - $curr\_prncpl\_lmt\_pinn_i$)/($init\_MIP_t$ + $orig\_fee_t$). This variable is incorporated as a piecewise variate.
- **Periodnbr**: the number of quarters since the inception of the mortgage. This variable is incorporated as a piecewise variate and a grouped categorical variable.
- **LTV**: ratio of the unpaid principal balance (UPB) to the current principal limit. This variable is incorporated as a piecewise variate.
- **Mob**: home equity ratio - the current indexed property value minus UPB minus the unused principal limit divided by the current indexed property value. This variable is incorporated as a piecewise variate.

- **Delta1yr4q**: change in the one-year CMT rate over the past four quarters. This variable is incorporated as a grouped categorical variable.
- **Delta1yrinit**: change in the one-year CMT rate since loan origination. This variable is incorporated as a grouped categorical variable.
- **Loantyp**: type of HECM loan. Possible values are: 01 – Term, 02 - Line of Credit (LOC), 03 - Tenure; 04 - Term and LOC, 05 - Tenure and LOC, and 06 = Lump Sum. This variable is incorporated as a grouped categorical variable.
- **Gender**: gender of the borrower and co-borrower. Possible values are 1 - Borrower is male and co-borrower information is not available, 2 - borrower is female and the co-borrower information is not available, and 3 - there are two borrowers. This variable is incorporated as a grouped categorical variable.
- **MCA**: maximum claim amount. This variable is incorporated as a piecewise variate.
- **Season**: the quarter of the year. Possible values are 1 – January through March, 2 – April through June, 3 – July through September, and 4 – October through December. This variable is incorporated as a grouped categorical variable.
- **Origfy**: original Fiscal Year. This variable is incorporated as a grouped categorical variable.
- **UPBRatio**: the ratio of the UPB to the current property value. This variable is included as a piecewise variate.
- **Propval**: the indexed property value divided by 10,000. This variable is included as a piecewise variate.
- **Appraisal inflation**: predicted appraisal inflation, which is the percentage by which the original appraisal value reported to HUD is inflated. The appraisal inflation is provided by FHA and Summit-Milliman and is based on additional appraisal information obtained from VEROS. RMA has relied on this appraisal inflation value without independent validation.

For variables that are incorporated as a piecewise variate, further information is provided on how these variates are specified in the Model Parameters section.

Model Parameters[3]

Likelihood of Refinance

The model parameters for the likelihood of refinance are shown in Table 24.

Table 24: Model Parameters – Likelihood of Refinance

Parameter	ClassVal0	Description	Description Detail	DF	Estimate	StdErr	ProbChiSq
Intercept				1	-7.4491	0.4262	<.0001
vminage_refi_pw2		Variate piecewise min_age	median(0,min_age-64,71-64)	1	0.0582	0.0024	<.0001
vminage_refi_pw3		Variate piecewise min_age	median(0,min_age-71,87-71)	1	0.0492	0.0011	<.0001
vminage_refi_pw4		Variate piecewise min_age	median(0,min_age-87,90-87)	1	0.0354	0.0109	0.0012
vminage_refi_pw5		Variate piecewise min_age	max(0,min_age-90)	1	-0.0460	0.0106	<.0001
vrefi_refi_pw1		Variate piecewise refi_var[1]	min(refi_var,-3)	1	0.4306	0.1020	<.0001
vrefi_refi_pw2		Variate piecewise refi_var[1]	median(0,refi_var+3,4+3)	1	0.0479	0.0110	<.0001
vperiodnbr_REFI_pw1		Variate piecewise period number	min(7,period_number)	1	0.3066	0.0042	<.0001
vperiodnbr_REFI_pw2		Variate piecewise period number	median(0,period_number-7,19-7)	1	-0.0587	0.0013	<.0001
vperiodnbr_REFI_pw3		Variate piecewise period number	median(0,period_number-19,30-19)	1	-0.0620	0.0022	<.0001
vperiodnbr_REFI_pw4		Variate piecewise period number	median(0,period_number-30,38-30)	1	-0.0532	0.0041	<.0001
vperiodnbr_REFI_pw5		Variate piecewise period number	median(0,period_number-38,65-38)	1	-0.0393	0.0021	<.0001
mSeason	L01	Categorical Season	mod(period,100) = 1	1	-0.2825	0.0120	<.0001
mSeason	L02	Categorical Season	mod(period,100) = 2	1	-0.4277	0.0120	<.0001
mSeason	L03	Categorical Season	mod(period,100) = 3	1	-0.1598	0.0121	<.0001
mloantyp_REFI	L01_01	Categorical Loan Type	loan_typ ="01"	1	0.3130	0.0524	<.0001
mloantyp_REFI	L02_05	Categorical Loan Type	loan_typ ="05"	1	0.3106	0.0328	<.0001
vltv_REFI_pw3		Variate piecewise Loan to Value[2]	median(0,LTV-7,60-7)	1	0.0211	0.0007	<.0001
vltv_REFI_pw4		Variate piecewise Loan to Value[2]	median(0,LTV-60,86-60)	1	0.0198	0.0009	<.0001
vltv_REFI_pw5		Variate piecewise Loan to Value[2]	median(0,LTV-86,94-86)	1	0.0428	0.0028	<.0001
vltv_REFI_pw6		Variate piecewise Loan to Value[2]	median(0,LTV-94,99.5-94)	1	0.0181	0.0033	<.0001
vltv_REFI_pw7		Variate piecewise Loan to Value[2]	median(0,LTV-99.5,116-99.5)	1	-0.2175	0.0104	<.0001
vmob_REFI_pw1		Variate piecewise Mobility	median(0,mobility_2,10)	1	0.0772	0.0057	<.0001
vmob_REFI_pw2		Variate piecewise Mobility	median(0,mobility_2-10,28-10)	1	0.0561	0.0022	<.0001
vmob_REFI_pw3		Variate piecewise Mobility	median(0,mobility_2-28,50-28)	1	0.1118	0.0008	<.0001

[3] For categorical variables, only non-base levels are listed.

Parameter	ClassVal0	Description	Description Detail	DF	Estimate	StdErr	ProbChiSq
mDeltaTy1Init_REFI	L02_3.0	Categorical Change in 1 Year Treasury Rate Initial	Delta_T1Y_Init_p>3	1	-0.2947	0.0120	<.0001
MGender	L01_M	Categorical Gender	(gender = 1 and borr_alive = 1) or (gender = 3 and coborr_gender_1=1 and coborr_1_alive=1)	1	0.0333	0.0092	0.0003
mAlive	L02_2	Categorical Number Alive	else	1	-0.0433	0.0088	<.0001
vdelta_T1Y_4Q_pw1		Variate piecewise Change in 1 Year Treasury Rate 4Q	min(delta_T1Y_4Q,.271)	1	7.1243	0.1003	<.0001
vdelta_T1Y_4Q_pw2		Variate piecewise Change in 1 Year Treasury Rate 4Q	median(0,delta_T1Y_4Q-.271,.44-.271)	1	-10.6505	0.1156	<.0001
vdelta_T1Y_4Q_pw3		Variate piecewise Change in 1 Year Treasury Rate 4Q	median(0,delta_T1Y_4Q-.44,2-.44)	1	0.0910	0.0111	<.0001
vdelta_T1Y_4Q_pw4		Variate piecewise Change in 1 Year Treasury Rate 4Q	median(0,delta_T1Y_4Q-2,2.57-2)	1	0.8616	0.0275	<.0001
vMCA_REFI_pw1		Variate piecewise max_clm_amt	median(0,max_clm_amt/1000,312)	1	0.0043	0.0001	<.0001
vMCA_REFI_pw2		Variate piecewise max_clm_amt	median(0,(max_clm_amt-312000)/1000,495-312)	1	0.0005	0.0001	<.0001
vMCA_REFI_pw3		Variate piecewise max_clm_amt	median(0,(max_clm_amt-495000)/1000,700-495)	1	-0.0041	0.0001	<.0001
vp_appr_infl_REFI_pw1		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1--.1,-.06--.1)	1	-106.7391	6.9744	<.0001
vp_appr_infl_REFI_pw4		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1--.01,.2--.01)	1	-6.0875	0.0889	<.0001
vp_appr_infl_REFI_pw5		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.2,.3-.2)	1	3.8437	0.3189	<.0001

Likelihood of Non-Mortality Termination

The model parameters for the likelihood of non-mortality termination are shown in Table 25.

Table 25: Model Parameters – Likelihood of Non-Mortality Termination

Parameter	ClassVal0	Description	Description Detail	DF	Estimate	StdErr	ProbChiSq
Intercept				1	-5.8955	0.1461	<.0001
vminage_othr_pw1		Variate piecewise Minimum Age	median(0,min_age-72,79-72)	1	0.1225	0.0047	<.0001
vminage_othr_pw2		Variate piecewise Minimum Age	median(0,min_age-79,91-79)	1	0.0945	0.0023	<.0001
vminage_othr_pw3		Variate piecewise Minimum Age	max(0,min_age-91)	1	0.0586	0.0056	<.0001
vmob_othr_pw1		Variate piecewise Mobility	median(0,mobility_2-0,30-0)	1	0.0266	0.0010	<.0001
vmob_othr_pw2		Variate piecewise Mobility	max(0,mobility_2-30)	1	0.0357	0.0005	<.0001
vmob_othr_pw0 * vmob_othr_pw0		Interacted Mobility	min(0,mobility_2)	1	0.0000	0.0000	<.0001
vminage_othr_pw1* vmob_othr_pw0		Interacted piecewise Minimum Age and Mobility	median(0,min_age-72,79-72) and min(0,mobility_2)	1	0.0032	0.0002	<.0001
vminage_othr_pw2 * vmob_othr_pw0		Interacted piecewise Minimum Age and Mobility	median(0,min_age-79,91-79) and min(0,mobility_2)	1	-0.0012	0.0001	<.0001
vminage_othr_pw3 * vmob_othr_pw1		Interacted piecewise Minimum Age and Mobility	median(0,min_age-72,79-72) and median(0,mobility_2-0,30-0)	1	-0.0017	0.0002	<.0001

Parameter	ClassVal0	Description	Description Detail	DF	Estimate	StdErr	ProbChiSq
vminage_othr_pw2 * vmob_othr_pw1		Interacted piecewise Minimum Age and Mobility	median(0,min_age-79,91-79) and median(0,mobility_2-0,30-0)	1	-0.0007	0.0001	<.0001
levelvminage_othr_pw3 * vmob_othr_pw1		Interacted piecewise Minimum Age and Mobility	max(0,min_age-91) and median(0,mobility_2-0,30-0)	1	-0.0010	0.0003	0.0001
vminage_othr_pw1 * vmob_othr_pw2		Interacted piecewise Minimum Age and Mobility	median(0,min_age-72,79-72) and max(0,mobility_2-30)	1	-0.0018	0.0001	<.0001
vminage_othr_pw2 * vmob_othr_pw2		Interacted piecewise Minimum Age and Mobility	median(0,min_age-79,91-79) and max(0,mobility_2-30)	1	-0.0012	0.0001	<.0001
vltv_othr_pw1		Variate piecewise Loan to Value	min(6.5,LTV)	1	-0.0875	0.0060	<.0001
vltv_othr_pw2		Variate piecewise Loan to Value	median(0,LTV-6.5,88-6.5)	1	-0.0057	0.0002	<.0001
vltv_othr_pw3		Variate piecewise Loan to Value	median(0,LTV-88,96.5 -88)	1	-0.0365	0.0014	<.0001
vltv_othr_pw4		Variate piecewise Loan to Value	median(0,LTV-96.5,102-96.5)	1	0.1777	0.0027	<.0001
vltv_othr_pw5		Variate piecewise Loan to Value	max(0,LTV-102)	1	0.0545	0.0018	<.0001
min_age65	L02__62	Categorical Minimum Age	Min_age=62	1	-0.3289	0.0681	<.0001
min_age65	L03__63	Categorical Minimum Age	Min_age=63	1	-0.3102	0.0363	<.0001
min_age65	L04__64	Categorical Minimum Age	Min_age=64	1	-0.2622	0.0286	<.0001
min_age65	L05__65	Categorical Minimum Age	Min_age=65	1	-0.2000	0.0245	<.0001
min_age65	L05__72	Categorical Minimum Age	65 < min_age <= 72	1	-0.0654	0.0118	<.0001
mloantyp	L01_01	Categorical Loan Type	loan_typ in ("01","03","04","05","06")	1	-0.0179	0.0088	<.0001
mSeason_othr	L02	Categorical Season	mod(period,100) = 2	1	0.1356	0.0061	<.0001
mSeason_othr	L03	Categorical Season	mod(period,100) = 3	1	0.0784	0.0064	<.0001
mOrigFY	L01_2001	Categorical Origination Fiscal Year	Orig_FY = 2001	1	0.3142	0.0476	<.0001
mOrigFY	L02_2002	Categorical Origination Fiscal Year	Orig_FY = 2002	1	0.2105	0.0363	<.0001
mOrigFY	L03_2003	Categorical Origination Fiscal Year	Orig_FY = 2003	1	0.3288	0.0312	<.0001
mOrigFY	L04_2004	Categorical Origination Fiscal Year	Orig_FY = 2004	1	0.2312	0.0202	<.0001
mOrigFY	L05_2005	Categorical Origination Fiscal Year	Orig_FY = 2005	1	0.1341	0.0174	<.0001
mOrigFY	L06_2006	Categorical Origination Fiscal Year	Orig_FY = 2006	1	0.1461	0.0116	<.0001
mOrigFY	L07_2007	Categorical Origination Fiscal Year	Orig_FY = 2007	1	-0.0257	0.0106	0.0152
mOrigFY	L08_2008	Categorical Origination Fiscal Year	Orig_FY = 2008	1	-0.0658	0.0105	<.0001
mOrigFY	L09_2009	Categorical Origination Fiscal Year	Orig_FY = 2009	1	0.0147	0.0103	0.1506
mOrigFY	L10_2010	Categorical Origination Fiscal Year	Orig_FY = 2010	1	0.0040	0.0108	0.7093
mperiod_num_othr	L01_02	Categorical Period Number	period_number = 2	1	-0.9674	0.0251	<.0001
mperiod_num_othr	L02_03	Categorical Period Number	period_number = 3	1	-0.4994	0.0207	<.0001
mperiod_num_othr	L03_04	Categorical Period Number	period_number = 4	1	-0.2401	0.0189	<.0001

Parameter	ClassVal0	Description	Description Detail	DF	Estimate	StdErr	ProbChiSq
mperiod_num_othr	L04_05	Categorical Period Number	period_number = 5	1	-0.0895	0.0180	<.0001
vperiodnbr_othr_pw1		Variate piecewise Period Number	median(0,period_number-6,20-6)	1	0.0188	0.0008	<.0001
vperiodnbr_othr_pw2		Variate piecewise Period Number	median(0,period_number-20,44-20)	1	0.0042	0.0004	<.0001
vperiodnbr_othr_pw3		Variate piecewise Period Number	max(0,period_number-44)	1	-0.0177	0.0008	<.0001
p_appr_infl_1		Variate Appraisal Inflation			-3.7577	0.5924	<.0001
vp_appr_infl_othr_pw1		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1--.1,-.04--.1)	1	6.2785	2.2149	0.0046
vp_appr_infl_othr_pw2		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1--.04,.05--.04)	1	3.7020	0.6167	<.0001
vp_appr_infl_othr_pw3		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.05,.2-.05)	1	3.2438	0.6010	<.0001
vp_appr_infl_othr_pw4		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.2,.3-.2)	1	2.7828	0.5779	<.0001
vp_appr_infl_othr_pw5		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.3,.4-.3)	1	4.4469	0.9915	<.0001

CT2c Claim

The model parameters for the likelihood that an assigned loan ends with a CT2c at termination are in Table 26.

Table 26: Model Parameters – Likelihood of CT2c

Parameter	ClassVal0	Description	Description Detail	DF	Estimate	StdErr	ProbChiSq
Intercept				1	-10.5134	0.4741	<.0001
vUPBRatio_CT2C_pw1		Variate piecewise UPB Ratio[1]	median(0,.85,UPB_Ratio)	1	6.1508	0.1362	<.0001
vUPBRatio_CT2C_pw2		Variate piecewise UPB Ratio[1]	if UPB_Ratio<=.85 then 0; else min(UPB_Ratio,1.5)-.85;	1	5.2618	0.191	<.0001
mMinage	L01_Miss	Categorical Minimum Age	min_age=.	1	1.3027	0.0411	<.0001
vminage_CT2C_pw1		Variate piecewise Minimum Age	median(0,min_age-62,95-62)	1	0.067	0.00373	<.0001
vminage_CT2C_pw2		Variate piecewise Minimum Age	max(0,min_age-95)	1	-0.0566	0.0312	0.0702
v_appr_infl_CT2C_pw1		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1--.1,-.04--.1)	1	29.6057	7.9582	0.0002
v_appr_infl_CT2C_pw2		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1--.04,.05--.04)	1	15.1319	1.0526	<.0001
v_appr_infl_CT2C_pw3		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.05,.2-.05)	1	4.3058	0.3673	<.0001
v_appr_infl_CT2C_pw4		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.2,.3-.2)	1	2.9261	0.8168	0.0003

UPB_Ratio[1] = C_UPB_Build_Amt_i/Property_Value_Curr

CT2c Sales Price Model

The model parameters for the CT2c sales price model as a percentage of the UPB are shown in Table 27. This model includes an offset term of the natural log of the UPB.

Table 27: Model Parameters – CT2c Sales Price Model

Parameter	Description	Description Detail	DF	Estimate	StdErr	Pr > ChiSq
Intercept			1	2.3270	0.1359	<.0001
vperiodnbr_CT2c_pw1	Variate piecewise Period Number	min(43,period_number)	1	-0.0032	0.0009	0.0002
vpropval_ct2c_pw1	Variate piecewise Property Value[1]	min(8,vpropval)	1	-0.3457	0.0102	<.0001
vpropval_ct2c_pw2	Variate piecewise Property Value[1]	median(0,vpropval-8,10-8)	1	0.2516	0.0168	<.0001
vpropval_ct2c_pw3	Variate piecewise Property Value[1]	median(0,vpropval-10,15-10)	1	0.0225	0.0049	<.0001
vpropval_ct2c_pw4	Variate piecewise Property Value[1]	median(0,vpropval-15,30-15)	1	0.0094	0.0012	<.0001
vpropval_ct2c_pw5	Variate piecewise Property Value[1]	median(0,vpropval-30,60-30)	1	-0.0017	0.0008	0.0271
vpropval_ct2c_pw6	Variate piecewise Property Value[1]	max(0,vpropval-60)	1	-0.0039	0.0001	<.0001
v_appr_infl_CT2S_pw1	Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1--.1,-.03--.1)	1	-4.7835	1.7547	0.0064
v_appr_infl_CT2S_pw2	Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1--.03,.06--.03)	1	-2.1674	0.3037	<.0001
v_appr_infl_CT2S_pw3	Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.06,.2-.06)	1	-0.7870	0.1404	0.0001
v_appr_infl_CT2S_pw4	Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.2,.3-.2)	1	-0.9233	0.3252	0.0045
vminage_CT2c_pw1	Variate piecewise Minimum Age	median(0,min_age-62,95-62)	1	-0.0007	0.0009	0.3893
vminage_CT2c_pw2	Variate piecewise Minimum Age	max(0,min_age-95)	1	-0.0147	0.0072	0.0409
Scale			0	7.4744	0	

vpropval[1]= property_value_curr/10,000

CT1 Claim Model

The model parameters for the likelihood of a CT1 claim given the loan has terminated in due and payable status and is not assigned are shown in Table 28.

Table 28: Model Parameters – Likelihood of CT1 Claim

Parameter	ClassVal0	Description	Description Detail	DF	Estimate	StdErr	ProbChiSq
Intercept				1	-14.6600	0.6681	<.0001
vUPBRatio_MRA_pw1		Variate piecewise UPB Ratio[1]	median(0,.2,UPB_Ratio)	1	-6.5943	0.4922	<.0001
vUPBRatio_MRA_pw2		Variate piecewise UPB Ratio[1]	median(0,UPB_Ratio-.2,.35-.2)	1	-7.1070	0.4902	<.0001
vUPBRatio_MRA_pw3		Variate piecewise UPB Ratio[1]	median(0,UPB_Ratio-.35,.6-.35)	1	10.5381	0.1643	<.0001
vUPBRatio_MRA_pw4		Variate piecewise UPB Ratio[1]	median(0,UPB_Ratio-.6,.95-.6)	1	10.5252	0.0687	<.0001
vUPBRatio_MRA_pw5		Variate piecewise UPB Ratio[1]	max(0,UPB_Ratio-.95)	1	5.4198	0.1874	<.0001
mMinage	L01_Miss	Categorical Minimum Age	min_age=.	1	1.0832	0.0123	<.0001
vminage_MRA_pw1		Variate piecewise Minimum Age	median(0,min_age-62,67-62)	1	0.2860	0.0615	<.0001
vperiodnbr_mra_pw1		Variate piecewise period number	median(0,period_number-1,6-1)	1	0.6591	0.1075	<.0001

Parameter	ClassVal0	Description	Description Detail	DF	Estimate	StdErr	ProbChiSq
vperiodnbr_mra_pw2		Variate piecewise period number	median(0,period_number-6,9-6)	1	0.5881	0.0335	<.0001
vperiodnbr_mra_pw3		Variate piecewise period number	median(0,period_number-9,22-9)	1	0.1378	0.0025	<.0001
vperiodnbr_mra_pw4		Variate piecewise period number	median(0,period_number-22,40-22)	1	0.0321	0.0012	<.0001
vperiodnbr_mra_pw5		Variate piecewise period number	max(0,period_number-40)	1	-0.0040	0.0014	0.0035
vp_appr_infl_mra_pw1		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1--.1,-.04--.1)	1	32.2611	5.3487	<.0001
vp_appr_infl_mra_pw2		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1--.04,.05--.04)	1	20.7260	0.5622	<.0001
vp_appr_infl_mra_pw3		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.05,.2-.05)	1	5.5952	0.1448	<.0001
vp_appr_infl_mra_pw4		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.2,.4-.2)	1	5.6694	0.2034	<.0001

UPB_Ratio[1] = C_UPB_Build_Amt_i/Property_Value_Curr

CT1 Sales Price Model

The model parameters for the CT1 sales price model are shown in Table 29. This model includes an offset term of the natural log of the UPB.

Table 29: Model Parameters – CT1 Sales Price Model

Parameter	Description	Description Detail	DF	Estimate	StdErr	Pr > ChiSq
Intercept			1	-0.4164	0.0957	0.001
vperiodnbr_CT1_pw1	Variate piecewise Period Number	if period_number <=8 then period_number; else if 8<period_number<=40 then period_number-8; else 40-8;	1	-0.0030	0.0002	0.0046
vperiodnbr_CT1_pw2	Variate piecewise Period Number	if period_number <=40 then period_number; else if 40<period_number<=58 then period_number-40; else 58-40;	1	-0.0004	0.0001	0.0012
vpropval_pw1	Variate piecewise Property Value[1]	min(8,vpropval)	1	0.0191	0.0033	<.0001
vpropval_pw2	Variate piecewise Property Value[1]	median(0,vpropval-8,12-8)	1	0.0410	0.0021	<.0001
vpropval_pw3	Variate piecewise Property Value[1]	median(0,vpropval-12,15-12)	1	0.0275	0.0021	<.0001
vpropval_pw4	Variate piecewise Property Value[1]	median(0,vpropval-15,30-15)	1	0.0096	0.0003	<.0001
vpropval_pw6	Variate piecewise Property Value[1]	max(0,vpropval-50)	1	-0.0025	0.0003	<.0001
vUPB_CT1_Ratio_pw3	Variate piecewise UPB Ratio[2]	median(0,UPB_Ratio-47.8,59-47.8)	1	0.0097	0.0011	<.0001

Parameter	Description	Description Detail	DF	Estimate	StdErr	Pr > ChiSq
vUPB_CT1_Ratio_pw4	Variate piecewise UPB Ratio2	median(0,UPB_Ratio-59,65.5-59)	1	0.0113	0.0013	<.0001
vUPB_CT1_Ratio_pw5	Variate piecewise UPB Ratio2	median(0,UPB_Ratio-65.5,88-65.5)	1	0.0022	0.0002	<.0001
vUPB_CT1_Ratio_pw6	Variate piecewise UPB Ratio2	median(0,UPB_Ratio-88,121-88)	1	-0.0015	0.0002	<.0001
vminage_CT1_pw1	Variate piecewise Minimum Age	median(0,min_age-70,78-70)	1	0.0024	0.0008	0.0022
vminage_CT1_pw2	Variate piecewise Minimum Age	median(0,min_age-78,91-78)	1	0.0092	0.0005	<.0001
vminage_CT1_pw3	Variate piecewise Minimum Age	max(0,min_age-91)	1	-0.0074	0.0025	0.0029
vp_appr_infl_CT1_pw1	Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1--.1,-.03--.1)	1	-9.3245	1.3765	<.0001
vp_appr_infl_CT1_pw2	Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1--.03,.05--.03)	1	-0.7016	0.1613	<.0001
vp_appr_infl_CT1_pw3	Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.05,.2-.05)	1	-1.1313	0.0382	<.0001
vp_appr_infl_CT1_pw4	Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.2,.3-.2)	1	-1.0642	0.0825	<.0001
vp_appr_infl_CT1_pw5	Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.3,.4-.3)	1	-1.3955	0.1346	<.0001
Scale			0	5.4106	0	

vpropval1= property_value_curr/10,000
UPB_Ratio2 = C_UPB_Build_Amt_i/Property_Value_Curr * 100

Model Validation

Model validation was accomplished by applying the models developed using the training set to the validation dataset. The application of this model to the validation data produces the predicted target variable for each model. The actual target variable is then compared to the predicted target variable to ensure the model fits the transition and sales price processes without over-fitting the actual data.

Specifically, we calculate the predicted probability of each transition for the logistic model and the expected sales price for each sales price model.

Decile charts are then created for each final model. All records are sorted, or ranked, by the predicted value. Ten equal sized decile groups are created with 10% of the records in each group. The sum of the actual result and the sum of the predicted result within each decile is calculated. The actual and predicted numbers are then compared for consistency. The objective of a model is to have a significant spread in predicted values while maintaining a close relationship between the resulting actual and predicted values.

The validation charts for the claim termination models are shown in Figures 7 through 12.

Figure 7: Model Validation – Likelihood of Refinance

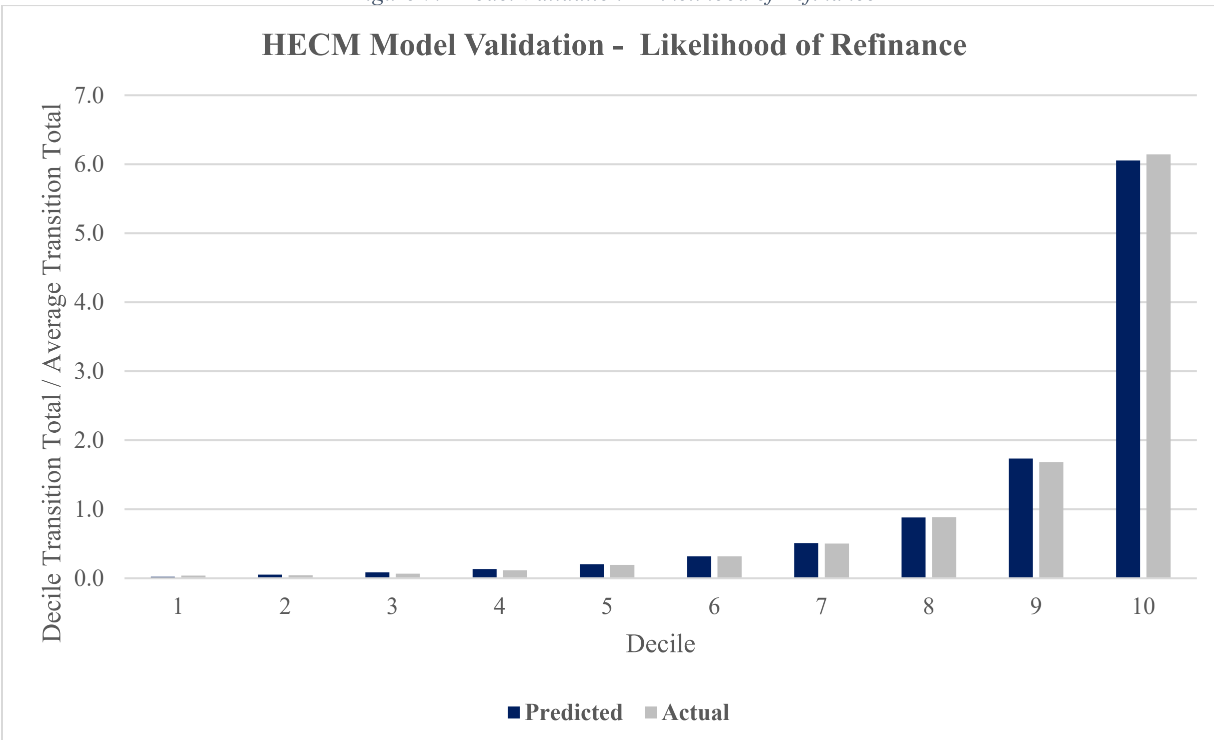


Figure 8: Model Validation - Likelihood of Non-Mortality Termination

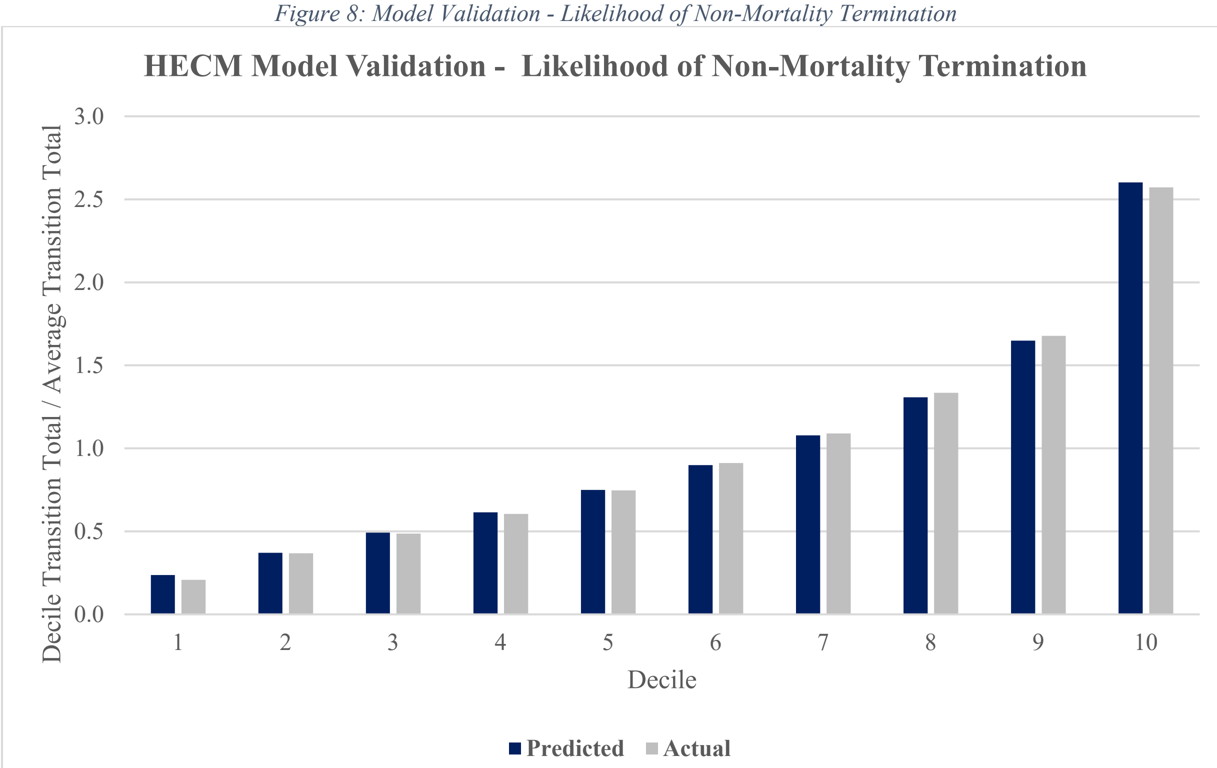


Figure 9: Model Validation - Likelihood of CT2c Claim

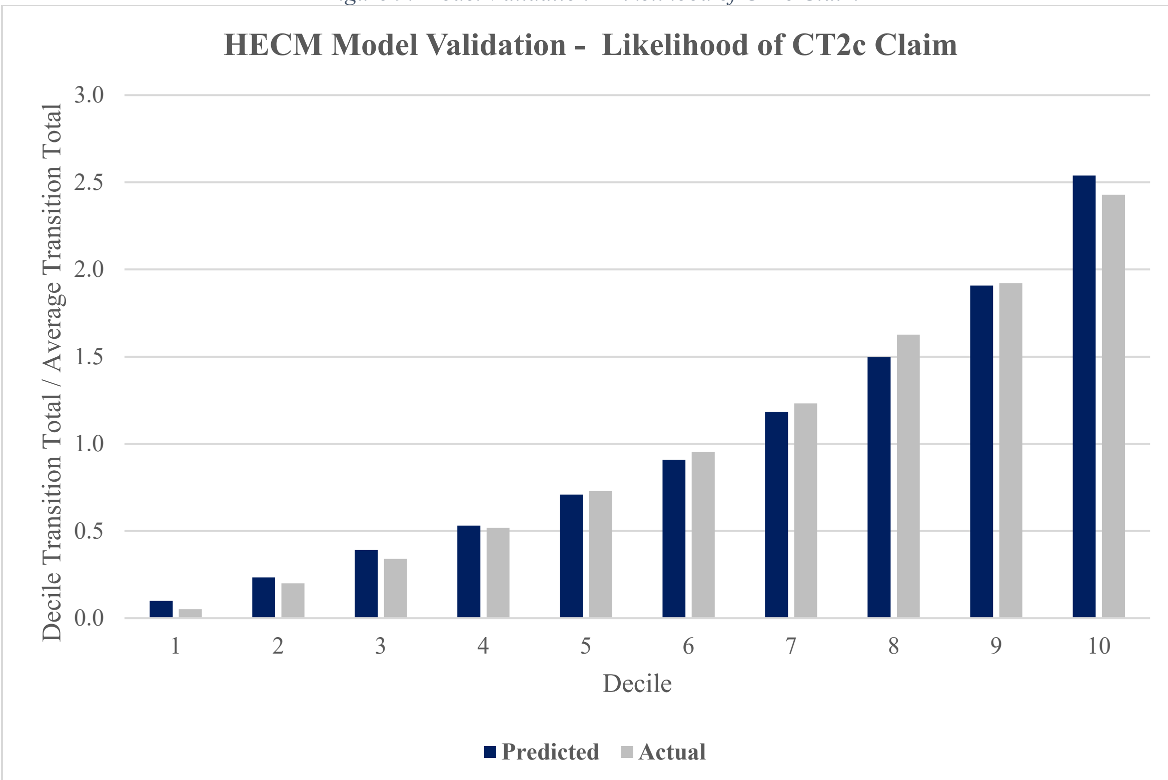


Figure 10: Model Validation – CT2c Sales Amount Model

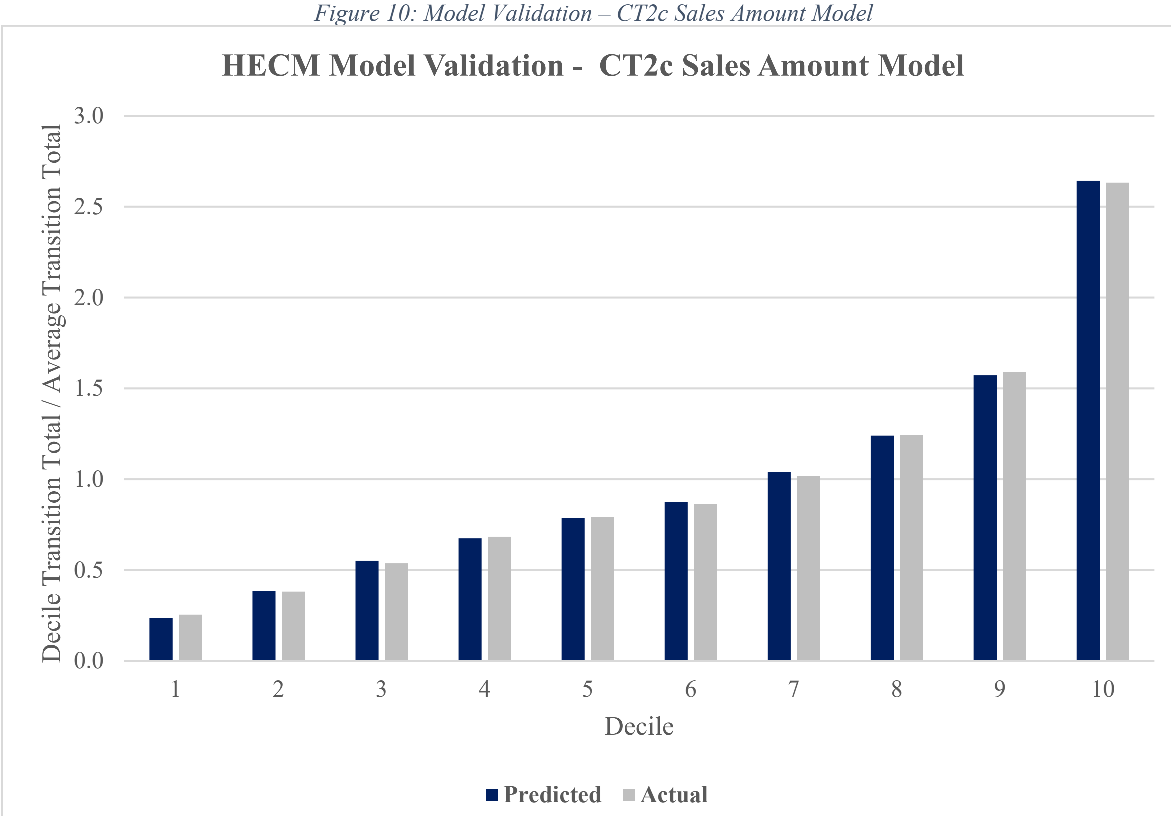


Figure 11: Model Validation – Likelihood of CT1 Claim

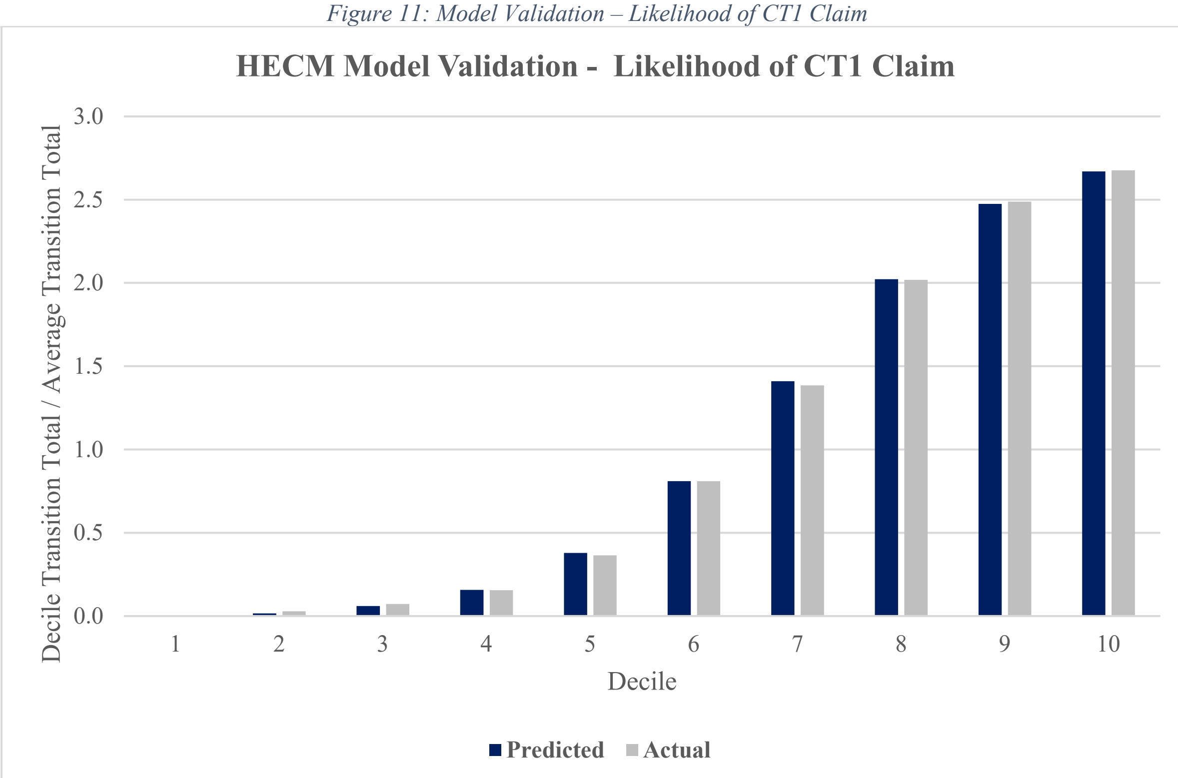
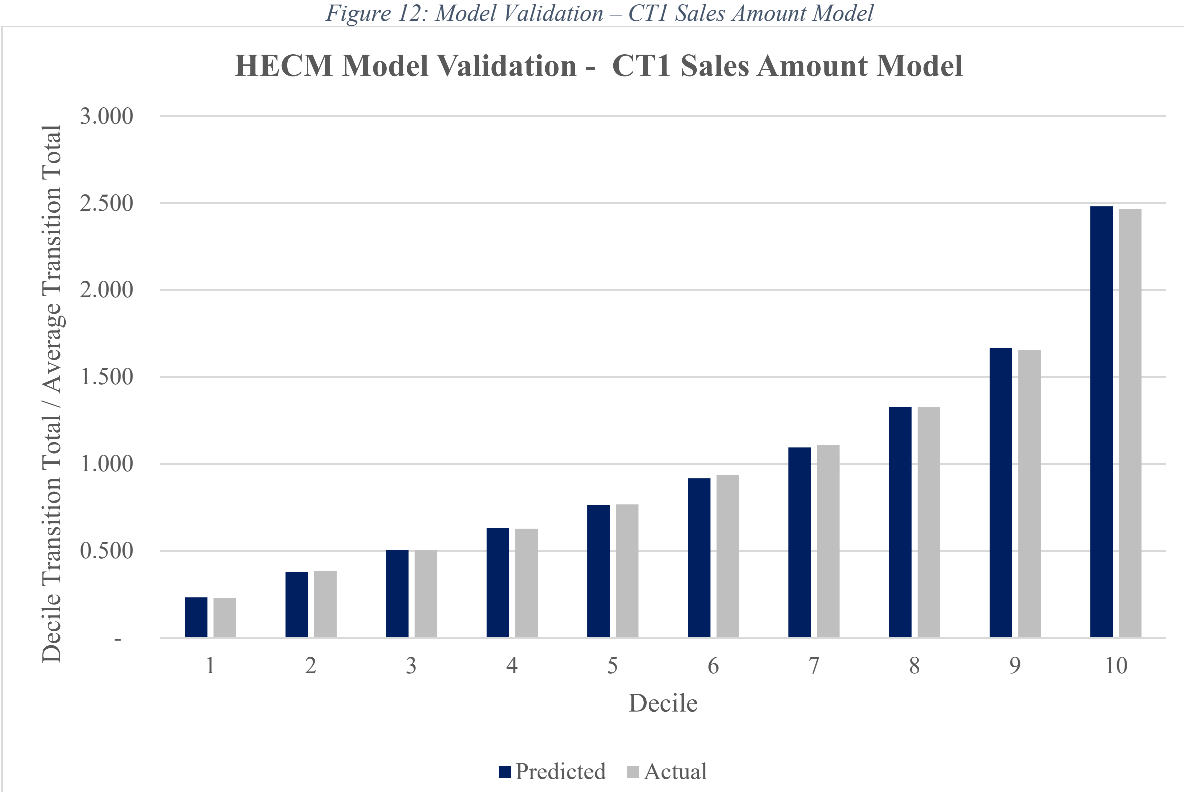


Figure 12: Model Validation – CT1 Sales Amount Model



Appendix C: HECM Cash Draw Models

Over 90% of HECM loans have a line of credit associated with them. To estimate the Cash Flow NPV on the existing portfolio of HECM mortgages, we need to estimate the future unscheduled cash draws associated with mortgages with a line of credit.

Model Specification

As these cash draws are not certain, we have developed predictive models to forecast cash draws. We have incorporated the following approach:

1. A binomial model is developed to estimate the likelihood of a cash draw occurring in a period.
2. If a cash draw is simulated, then the next step determines whether it is a full draw of all funds available through the Line of Credit (LOC). There are two separate logistic models built for this: 1) A model built only on data from cohorts 2014 and subsequent for the first 8 quarters ("FD8" model), and 2) a model built on all data for quarters 9 and subsequent ("FD9+" model). The reason for the split is to account for the first twelve-month disbursement period on the funds available for distribution from the LOC.
3. A Generalized Linear Model (GLM) is then developed to estimate the amount of the cash draw for the period if the cash draw is not a full draw.

Using the historical HECM data, for each quarter, we developed indicators of whether a net positive unscheduled cash draw was taken from the line of credit during that quarter and the amount of the cash draw. We used this data to develop the binomial logistic models described above to estimate the likelihood of an unscheduled cash draw occurring during the quarter based on a series of explanatory variables, and to estimate the likelihood that this cash draw is a full draw. The explanatory variables used in the model are similar to those used for the termination models. These variables are described in Appendix B. Additionally, we include the amount remaining on the line of credit (LOCRemain) as an explanatory variable in the Cash Draw likelihood models.

For the estimated cash draw amount, we developed a model using the incremental line of credit cash draw from the historical HECM data. This incremental cash draw was used as the target variable, and we estimated the predicted amount of the cash draw based on a series of explanatory variables. The explanatory variables used in the model are the same as those for the termination models described in Appendix B and the Cash Draw likelihood models described above.

Models are also developed to project cash draws for taxes and insurance defaults. When a loan assigned to HUD goes into default due to unpaid property taxes or insurance premiums, rather than letting the property default, HUD advances the tax or insurance payment. This amount is then added to the UPB. To project future tax and insurance default payments, RMA has developed a model to predict the frequency of tax and insurance defaults and has also developed a model to estimate the amount of the tax or insurance payment for those that have defaulted.

Explanatory Variables

The following explanatory variables are used in the cash draw projection models. A general description of the variable is provided below, and more specific detail is included in the Model Parameters section.

- **Min age**: the youngest age amongst the borrower and co-borrowers. This variable is incorporated as a piecewise variate and a grouped categorical variable.
- **Season**: the quarter of the year. Possible values are 1 – January through March, 2 – April through June, 3 – July through September, and 4 – October through December. This variable is incorporated as a grouped categorical variable.
- **Alive**: Number of borrowers and co-borrowers that are alive. Possible values are 1 – alive and 0 – not alive. This variable is incorporated as a categorical variable.
- **Gender**: gender of the borrower and co-borrower. Possible values are 1 - borrower is male and co-borrower information is not available, 2 - borrower is female and the co-borrower information is not available, and 3 - there are two borrowers. This variable is incorporated as a grouped categorical variable.
- **Delta1yrinit**: change in the one-year CMT rate since loan origination. This variable is incorporated as a grouped categorical variable.
- **Loantyp**: type of HECM loan. Possible values are: 01 – Term, 02 - LOC, 03 - Tenure; 04 - Term and LOC, 05 - Tenure and LOC, and 06 = Lump Sum. This variable is incorporated as a grouped categorical variable.
- **Loccap**: capped line of credit. If the loan is within its first year of origination, was originated after 2014 and has an LTV of greater than or equal to 60%, then the capped line of credit is 0, otherwise the capped line of credit is equal to the available line of credit. This variable is incorporated as a piecewise variate.
- **LocRemain**: line of credit remaining. This is calculated as a line of credit available divided the total line of credit x 100. This variable is incorporated as a piecewise variate.
- **Periodnbr**: the number of quarters since the inception of the mortgage. This variable is incorporated as a piecewise variate and a grouped categorical variable.
- **LTV**: ratio of the unpaid principal balance (UPB) to the current principal limit. This variable is incorporated as a piecewise variate and a grouped categorical variable.

- **TICnt**: the number of previous tax and insurance defaults. This variable is calculated as the count of prior periods where i_TI_Debit_Amt is greater than $100. This variable is incorporated as a grouped categorical variable.
- **Appraisal inflation**: predicted appraisal inflation, which is the percentage by which the original appraisal value reported to HUD is inflated. The appraisal inflation is provided by FHA and Summit-Milliman and is based on additional appraisal information obtained from VEROS. RMA has relied on this appraisal inflation value without independent validation.

For variables that are incorporated as a piecewise variate, further information is provided on how these variates are specified in the Model Parameters section.

Model Parameters[4]

Likelihood of Cash Draw

The model parameters for the likelihood of a cash draw are shown in Table 30.

Table 30: Model Parameters – Likelihood of Cash Draw

Parameter	ClassVal0	Description	Description Detail	DF	Estimate	StdErr	ProbChiSq
Intercept				1	-2.6922	0.0174	<.0001
mMinage_cdf	L01_62	Categorical Minimum Age	min_age=62	1	0.1820	0.0140	<.0001
mMinage_cdf	L02_63	Categorical Minimum Age	min_age=63	1	0.1509	0.0084	<.0001
mMinage_cdf	L03_64	Categorical Minimum Age	min_age=64	1	0.0966	0.0070	<.0001
mMinage_cdf	L04_65	Categorical Minimum Age	min_age=65	1	0.0334	0.0063	<.0001
mMinage_cdf	L05_93	Categorical Minimum Age	88<min_age<=93	1	-0.0302	0.0047	<.0001
mMinage_cdf	L06_99	Categorical Minimum Age	min_age>93	1	0.0403	0.0089	<.0001
mSeason_CDF	A01	Categorical Season	period <201300 and mod(period,100) = 1	1	-0.0861	0.0045	<.0001
mSeason_CDF	A02	Categorical Season	period <201300 and mod(period,100) = 2	1	-0.0188	0.0044	<.0001
mSeason_CDF	A03	Categorical Season	period <201300 and mod(period,100) = 3	1	0.0392	0.0044	<.0001
mSeason_CDF	A04	Categorical Season	period <201300 and mod(period,100) = 4	1	0.0681	0.0043	<.0001
mSeason_CDF	B01	Categorical Season	period >=201300 and mod(period,100) = 1	1	-0.1419	0.0035	<.0001
mSeason_CDF	B02	Categorical Season	period >=201300 and mod(period,100) = 2	1	-0.1462	0.0035	<.0001
mSeason_CDF	B03	Categorical Season	period >=201300 and mod(period,100) = 3	1	-0.0753	0.0036	<.0001
mAlive	L02_2	Categorical Alive	Else	1	-0.2246	0.0021	<.0001
MGender	L01_M	Categorical Gender	(gender = 1 and borr_alive = 1) or (gender = 3 and coborr_gender_1=1 and coborr_1_alive=1)	1	-0.0421	0.0022	<.0001
mDeltaTy1Init	L01_2.0	Categorical Change in 1 year Treasury from Initial	Delta_T1Y_Init_p>2	1	0.0752	0.0028	<.0001

[4] For categorical variables, only non-base levels are listed.

Parameter	ClassVal0	Description	Description Detail	DF	Estimate	StdErr	ProbChiSq
mloantyp	L01_01	Categorical Loan Type	loan_typ in ('01", "03", "04", "05", "06")	1	-0.4259	0.0043	<.0001
vLOCCap_CDF_pw1		Variate piecewise Line of Credit[1]	min(4500,loc_capped_i)	1	0.0010	6.39E-06	<.0001
vLOCCap_CDF_pw1 * vLOCCap_CDF_pw1		Interacted Line of Credit	min(4500,loc_capped_i)	1	-1.41E-07	1.29E-09	<.0001
vLOCCap_CDF_pw2		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-4500,12500-4500)	1	6.E-05	7.56E-07	<.0001
vLOCCap_CDF_pw3		Variate piecewise Line of Credit[1]	max(0,loc_capped_i-12500)	1	1.72E-06	2.25E-08	<.0001
vLOCRemain_CDF_pw2		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-.45,1.4-.45)	1	1.0983	0.0118	<.0001
vLOCRemain_CDF_pw3		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-1.4,3.4-1.4)	1	-0.0210	0.00534	<.0001
vLOCRemain_CDF_pw4		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-3.4,15.5-3.4)	1	-0.0139	0.0006	<.0001
vLOCRemain_CDF_pw5		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-15.1,40.5-15.5)	1	-0.0150	0.0002	<.0001
vLOCRemain_CDF_pw6		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-40.5,77-40.5)	1	-0.0178	0.0001	<.0001
vLOCRemain_CDF_pw7		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-77,93.4-77)	1	-0.0257	0.0003	<.0001
vLOCRemain_CDF_pw8		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-93.4,99-93.4)	1	-0.1107	0.0016	<.0001
vLOCRemain_CDF_pw9		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-99,99.9-99)	1	-0.4645	0.0135	<.0001
vLOCRemain_CDF_pw10		Variate piecewise Line of Credit Remaining[2]	max(0,loc_remaining-99.9)	1	0.9670	0.0963	<.0001
mperiod_num_CDF	L01_02	Categorical Period Number	period_number = 2	1	0.6415	0.0058	<.0001
mperiod_num_CDF	L02_03	Categorical Period Number	period_number = 3	1	0.3457	0.0058	<.0001
mperiod_num_CDF	L03_04	Categorical Period Number	period_number = 4	1	0.2439	0.0058	<.0001
mperiod_num_CDF	L04_05	Categorical Period Number	period_number = 5	1	0.6017	0.0050	<.0001
vPeriodNbr_CDF_pw1		Variate piecewise Period Number	median(0,period_number-5,24-5)	1	-0.0488	0.0002	<.0001
vPeriodNbr_CDF_pw2		Variate piecewise Period Number	median(0,period_number-24,40-24)	1	-0.0175	0.0003	<.0001
vPeriodNbr_CDF_pw3		Variate piecewise Period Number	median(0,period_number-40,52-40)	1	-0.0422	0.0008	<.0001
vPeriodNbr_CDF_pw4		Variate piecewise Period Number	max(0,period_number-52)	1	-0.0293	0.0014	<.0001
vLTV_CDF_pw1		Variate piecewise Loan to Value	median(0,LTV-20,20)	1	0.0262	0.0006	<.0001
vLTV_CDF_pw2		Variate piecewise Loan to Value	median(0,LTV-20,80-20)	1	-0.0033	9.6E-5	<.0001
vLTV_CDF_pw3		Variate piecewise Loan to Value	median(0,period_number-80,95.5-80)	1	-0.0264	0.0003	<.0001
vLTV_CDF_pw4		Variate piecewise Loan to Value	median(0,LTV-95.5,98-95.5)	1	-0.0679	0.0024	<.0001
mLTV_CDF	0	Categorical Loan to Value	LTV <99.5	1	-0.2488	0.0071	<.0001
vp_appr_infl_CDF_pw2		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1--.04,.05--.04)	1	2.3695	0.0657	<.0001
vp_appr_infl_CDF_pw3		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.05,.2-.05)	1	0.3529	0.0256	<.0001
vp_appr_infl_CDF_pw4		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.2,.3-.2)	1	-1.2505	0.0584	<.0001

Likelihood of Full Cash Draw

The model parameters for the likelihood of a full cash draw in the first eight quarters are shown in Table 31.

Table 31: Model Parameters – Likelihood of Full Cash Draw (Quarters 1 through 8)

Parameter	ClassVal0	Description	Description Detail	DF	Estimate	StdErr	ProbChiSq
Intercept				1	-1.8313	0.1621	<.0001

Parameter	ClassVal0	Description	Description Detail	DF	Estimate	StdErr	ProbChiSq
mperiod_num_cd100	L01_02	Categorical Period Number	period_number = 2	1	-0.7331	0.1444	<.0001
mperiod_num_cd100	L02_03	Categorical Period Number	period_number = 3	1	-0.7121	0.1374	<.0001
mperiod_num_cd100	L03_04	Categorical Period Number	period_number = 4	1	0.8398	0.0588	<.0001
mperiod_num_cd100	L04_05	Categorical Period Number	period_number = 5	1	0.7393	0.1096	<.0001
mperiod_num_cd100	L05_06	Categorical Period Number	period_number = 6	1	0.1466	0.0297	<.0001
vLOCCap_cd100_pw1		Variate piecewise Line of Credit[1]	min(3500,loc_capped_i)	1	-0.0004	1.9E-5	<.0001
vLOCCap_cd100_pw2		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-3500,10000-3500)	1	-8.E-05	7.69E-06	<.0001
vLOCCap_cd100_pw3		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-10000,20000-10000)	1	-7.E-05	3.91E-06	<.0001
vLOCCap_cd100_pw4		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-20000,100000-20000)	1	-2.E-05	5.16E-07	<.0001
vLOCCap_cd100_pw6		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-165000,300000-165000)	1	-7.92E-06	1.75E-06	<.0001
vltv_cd100_pw1		Variate piecewise Loan to Value	min(55,LTV)	1	-0.0200	0.0032	<.0001
vltv_cd100_pw2		Variate piecewise Loan to Value	median(0,LTV-55,60-55)	1	0.6533	0.0195	<.0001
vltv_cd100_pw3		Variate piecewise Loan to Value	median(0,LTV-60,64-60)	1	-0.5960	0.0192	<.0001
vltv_cd100_pw4		Variate piecewise Loan to Value	median(0,LTV-64,95-64)	1	0.0578	0.0028	<.0001
vltv_cd100_pw5		Variate piecewise Loan to Value	max(0,LTV-95)	1	0.1711	0.0148	<.0001
vminage_cd100_pw1		Variate piecewise Minimum Age	median(0,min_age-62,78-62)	1	0.0069	0.0016	<.0001
vminage_cd100_pw2		Variate piecewise Minimum Age	max(0,min_age-78)	1	0.0406	0.0048	<.0001
mSeason	L01	Categorical Season	mod(period,100) = 1	1	0.0502	0.0251	0.0459
mSeason	L02	Categorical Season	mod(period,100) = 2	1	0.0853	0.025	0.0006
mSeason	L03	Categorical Season	mod(period,100) = 3	1	0.0734	0.0256	0.0041
MGender	L01_M	Categorical Gender	(gender = 1 and borr_alive = 1) or (gender = 3 and coborr_gender_1=1 and coborr_1_alive=1)	1	0.1902	0.0191	<.0001
mAlive	L02_2	Categorical Alive	Else	1	0.1764	0.0192	<.0001
mloantyp	L01_01	Categorical Loan Type	loan_typ in ('01", "03", "04", "05", "06")	1	0.8583	0.0813	<.0001
vltv_cd100_pw2 * mperiod_num5_cd100	L01_5	Interacted Loan to Value and Period Number	median(0,LTV-55,60-55) and period_number = 5	1	0.0966	0.0228	<.0001
vltv_cd100_pw2 * mperiod_num5_cd100	Z02_AO	Interacted Loan to Value and Period Number	median(0,LTV-55,60-55) and period_number <> 5	1	0.0000		
vltv_cd100_pw3 * mperiod_num5_cd100	L01_5	Interacted Loan to Value and Period Number	median(0,LTV-60,64-60) and period_number = 5	1	0.2239	0.023	<.0001
vltv_cd100_pw3 * mperiod_num5_cd100	Z02_AO	Interacted Loan to Value and Period Number	median(0,LTV-60,64-60) and period_number <> 5	1	0.0000		
vltv_cd100_pw4 * mperiod_num5_cd100	L01_5	Interacted Loan to Value and Period Number	median(0,LTV-64,95-64) and period_number = 5	1	-0.0264	0.0034	<.0001
vltv_cd100_pw4 * mperiod_num5_cd100	Z02_AO	Interacted Loan to Value and Period Number	median(0,LTV-64,95-64) and period_number <> 5	1	0.0000		

Parameter	ClassVal0	Description	Description Detail	DF	Estimate	StdErr	ProbChiSq
vltv_cd100_pw5 * mperiod_num5_cd100	L01_5	Interacted Loan to Value and Period Number	max(0,LTV-95) and period_number = 5	1	-0.2905	0.0169	<.0001
vltv_cd100_pw5 * mperiod_num5_cd100	Z02_AO	Interacted Loan to Value and Period Number	max(0,LTV-95) and period_number <> 5	1	0.0000		
vp_appr_infl_CD100_pw2		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.03,.16-.03)	1	-1.8510	0.2635	<.0001
vp_appr_infl_CD100_pw3		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.16,.25-.16)	1	5.3697	0.9566	<.0001

The model parameters for the likelihood of a full cash draw in the ninth and subsequent quarters are shown in Table 32.

Table 32: Model Parameters – Likelihood of Full Cash Draw (Quarters 9+)

Parameter	ClassVal0	Description	Description Detail	DF	Estimate	StdErr	ProbChiSq
Intercept				1	-0.6413	0.2882	0.026
vLOCCap_cd1009_pw0		Variate piecewise Line of Credit[1]	min(1000,loc_capped_i)	1	-0.0011	2.37E-05	<.0001
vLOCCap_cd1009_pw1		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-1000,3500-1000)	1	-0.0004	1.01E-05	<.0001
vLOCCap_cd1009_pw2		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-3500,10000-3500)	1	-0.0001	4.4E-06	<.0001
vLOCCap_cd1009_pw3		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-10000,20000-10000)	1	-6.79E-05	2.81E-06	<.0001
vLOCCap_cd1009_pw4		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-20000,100000-20000)	1	-1.39E-05	5.5E-07	<.0001
vLOCCap_cd1009_pw5		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-100000,185000-100000)	1	-2.59E-06	8.97E-07	0.0039
vLOCCap_cd1009_pw6		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-185000,300000-185000)	1	-4.22E-06	1.34E-06	0.0016
vltv_cd1009_pw2		Variate piecewise Loan to Value	median(0,LTV-60,95-60)	1	0.0100	0.0009	<.0001
vltv_cd1009_pw3		Variate piecewise Loan to Value	max(0,LTV-95)	1	-0.0511	0.0041	<.0001
vminage_cd1009_pw1		Variate piecewise Minimum Age	median(0,min_age-62,78-62)	1	0.0084	0.0015	<.0001
vminage_cd1009_pw2		Variate piecewise Minimum Age	max(0,min_age-78)	1	0.0316	0.0015	<.0001
vperiodnbr_CD1009_pw1		Variate piecewise Period Number	median(0,period_number -9,25-9)	1	-0.0455	0.0011	<.0001
vperiodnbr_CD1009_pw2		Variate piecewise Period Number	max(0,period_number-25)	1	-0.0247	0.0010	<.0001
mSeason	L01	Categorical Season	mod(period,100) = 1	1	0.0781	0.0148	<.0001
mSeason	L02	Categorical Season	mod(period,100) = 2	1	0.1262	0.0147	<.0001
mSeason	L03	Categorical Season	mod(period,100) = 3	1	0.1753	0.0146	<.0001

Parameter	ClassVal0	Description	Description Detail	DF	Estimate	StdErr	ProbChiSq
MGender	L01_M	Categorical Gender	(gender = 1 and borr_alive = 1) or (gender = 3 and coborr_gender_1=1 and coborr_1_alive=1)	1	0.0408	0.0118	0.0005
mAlive	L02_2	Categorical Alive	Else	1	0.1526	0.0116	<.0001
mloantyp	L01_01	Categorical Loan Type	loan_typ in ('01", "03", "04", "05", "06")	1	0.5929	0.0260	<.0001
v_appr_infl_CD1009_pw1		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1--.1,-.04--.1)	1	12.9331	4.8392	0.0075
v_appr_infl_CD1009_pw2		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1--.04,.05--.04)	1	-5.8627	0.3566	<.0001
v_appr_infl_CD1009_pw3		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.05,.2-.05)	1	-2.0067	0.1329	<.0001
v_appr_infl_CD1009_pw4		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.2,.3-.2)	1	2.3918	0.2979	<.0001

Cash Draw Amount Model

The model parameters for the cash draw amount are shown in Table 33.

Table 33: Model Parameters – Cash Draw Amount

Parameter	Level1	Description	Description Detail	DF	Estimate	StdErr	ProbChiSq
Intercept				1	6.5937	0.0172	<.0001
vLOCCap_cds_pw1		Variate piecewise Line of Credit[1]	min(1,loc_capped_i)	1	-0.0639	0.0088	0.0017
vLOCCap_cds_pw3		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-3.5,10-3.5)	1	-0.0259	0.0009	<.0001
vLOCCap_cds_pw4		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-10,15-10)	1	-0.0207	0.0012	<.0001
vLOCCap_cds_pw5		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-15,30-15)	1	-0.0164	0.0003	<.0001
vLOCCap_cds_pw6		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-30,125-30)	1	-0.0048	0.0000	<.0001
vLOCCap_cds_pw7		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-125,200-125)	1	-0.0011	0.0001	<.0001
vLOCCap_cds_pw8		Variate piecewise Line of Credit[1]	max(0,loc_capped_i-200)	1	-0.0007	0.0001	<.0001
vminage_cds_pw1		Variate piecewise Min Age	median(0,min_age-62,67-62)	1	-0.0092	0.0013	<.0001
vminage_cds_pw2		Variate piecewise Min Age	median(0,min_age-67,75-67)	1	-0.0077	0.0004	<.0001
vminage_cds_pw3		Variate piecewise Min Age	median(0,min_age-75,85-75)	1	0.0074	0.0003	<.0001
vminage_cds_pw4		Variate piecewise Min Age	max(0,min_age-85)	1	0.0256	0.0006	<.0001
vperiodnbr_cds_pw1		Variate piecewise Period Number	median(0,period_number-5,10-5)	1	-0.0755	0.0007	<.0001
vperiodnbr_cds_pw2		Variate piecewise Period Number	median(0,period_number-10,20-10)	1	-0.0248	0.0003	<.0001
vperiodnbr_cds_pw3		Variate piecewise Period Number	median(0,period_number-20,54-20)	1	-0.0092	0.0002	<.0001
vperiodnbr_cds_pw4		Variate piecewise Period Number	max(0,period_number-54)	1	-0.0098	0.0015	<.0001

Parameter	Level1	Description	Description Detail	DF	Estimate	StdErr	ProbChiSq
vltv_cds_pw1		Variate piecewise Loan to Value	min(20,LTV)	1	-0.0111	0.0006	<.0001
vltv_cds_pw2		Variate piecewise Loan to Value	median(0,LTV-20,60-20)	1	0.0114	0.0001	<.0001
vltv_cds_pw3		Variate piecewise Loan to Value	max(0,LTV-60)	1	0.0053	0.0001	<.0001
mltv_cds	L01_60	Categorical Loan to Value	LTV=60 and orig_fy>2014 and period_number=5 and loan_typ="02"	1	0.5244	0.0136	<.0001
mSeason	L01	Categorical Season	mod(period,100) = 1	1	0.0013	0.0025	0.615
mSeason	L02	Categorical Season	mod(period,100) = 2	1	0.0249	0.0025	<.0001
mSeason	L03	Categorical Season	mod(period,100) = 3	1	0.0369	0.0025	<.0001
MGender	L01_M	Categorical Gender	(gender = 1 and borr_alive = 1) or (gender = 3 and coborr_gender_1=1 and coborr_1_alive=1)	1	0.0370	0.0020	<.0001
mAlive	L02_2	Categorical Alive	Else	1	0.0573	0.0019	<.0001
mloantyp	L01_01	Categorical Loan Type	loan_typ in ('01", "03", "04", "05", "06")	1	-0.0993	0.0042	<.0001
vLOCRemain_cds_pw1		Variate piecewise Line of Credit Remaining[2]	min(6.4,loc_remaining)	1	-0.0177	0.0015	<.0001
vLOCRemain_cds_pw2		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-6.4,14.6-6.4)	1	-0.0248	0.0009	<.0001
vLOCRemain_cds_pw3		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-14.6,29-14.6)	1	-0.0125	0.0004	<.0001
vLOCRemain_cds_pw4		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-29,53.5-29)	1	-0.0082	0.0002	<.0001
vLOCRemain_cds_pw5		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-53.5,85.5-53.5)	1	-0.0058	0.0001	<.0001
vLOCRemain_cds_pw6		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-85.5,88.5-85.5)	1	-0.0142	0.0021	<.0001
vLOCRemain_cds_pw7		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-88.5,96.25-88.5)	1	-0.0118	0.0012	<.0001
vLOCRemain_cds_pw8		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-96.25,97.5-96.25)	1	0.0892	0.0091	<.0001
vLOCRemain_cds_pw9		Variate piecewise Line of Credit Remaining[2]	max(0,loc_remaining-97.5)	1	0.1989	0.0040	<.0001
vp_appr_infl_cds_pw2		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1--.04,.05--.04)	1	-0.6917	0.0592	<.0001
vp_appr_infl_cds_pw3		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.05,.2-.05)	1	-0.2452	0.0227	<.0001
vp_appr_infl_cds_pw4		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.2,.3-.2)	1	0.4516	0.0533	<.0001
Scale				0	0.8699	0.0000	

Variate Line of Credit1: if (period_number<=4 and orig_fy>=2014 and LTV>=60) then loc_capped_i=0;
else loc_capped_i = loc_avail_i / 1000;
LOC_remaining2 = (Loc_avail_i/loc_total_i)*100;

Tax and Insurance Default Frequency Model

The model parameters for the tax and insurance default frequency model are shown in Table 34.

Table 34: Model Parameters – Tax and Insurance Default Frequency Model

Parameter	ClassVal0	Description	Description Detail	DF	Estimate	StdErr	ProbChiSq
Intercept				1	-4.6674	0.0119	<.0001
mSeason	L01	Categorical Season	mod(period,100) = 1	1	-0.0734	0.0048	<.0001

Parameter	ClassVal0	Description	Description Detail	DF	Estimate	StdErr	ProbChiSq
mSeason	L02	Categorical Season	mod(period,100) = 2	1	0.0271	0.0047	<.0001
mSeason	L03	Categorical Season	mod(period,100) = 3	1	0.0909	0.0047	<.0001
mTICnt	L01	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 1	1	2.1707	0.0048	<.0001
mTICnt	L02	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 2	1	2.8149	0.0056	<.0001
mTICnt	L03	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 3	1	3.0682	0.0065	<.0001
mTICnt	L04	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 4	1	3.2248	0.0074	<.0001
mTICnt	L05	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 5	1	3.3499	0.0085	<.0001
mTICnt	L06	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 6	1	3.4729	0.0098	<.0001
mTICnt	L07	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 7	1	3.5719	0.0112	<.0001
mTICnt	L08	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 8	1	3.6467	0.0129	<.0001
mTICnt	L09	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 9	1	3.7319	0.0150	<.0001
mTICnt	L10	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 10	1	3.8218	0.0173	<.0001
mTICnt	L11	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 11	1	3.9183	0.0202	<.0001
mTICnt	L12	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 12	1	3.9626	0.0234	<.0001
mTICnt	L13	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 13	1	4.0584	0.0272	<.0001
mTICnt	L14	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 14	1	4.1368	0.0320	<.0001
mTICnt	L15	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 15	1	4.1373	0.0372	<.0001
mTICnt	L16	Categorical Count of Tax and Ins Default[1]	Else	1	4.4048	0.0238	<.0001
vperiodnbr_TIDF_pw1		Variate piecewise Period Number	median(0,period_number -7,29-7)	1	-0.0219	0.0003	<.0001
vperiodnbr_TIDF_pw2		Variate piecewise Period Number	median(0,period_number -29,54-29)	1	-0.0278	0.0003	<.0001
vperiodnbr_TIDF_pw3		Variate piecewise Period Number	median(0,period_number -54,67-54)	1	-0.0110	0.0019	<.0001
vp_appr_infl_TID_pw2		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1--.04,.05--.04)	1	3.5149	0.1477	<.0001
vp_appr_infl_TID_pw3		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.05,.2-.05)	1	0.5260	0.0430	<.0001
vp_appr_infl_TID_pw4		Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.2,.3-.2)	1	1.2544	0.0759	<.0001

Tax and Insurance Default Amount Model

The model parameters for the tax and insurance default amount model are shown in Table 35.

Table 35: Model Parameters – Tax and Insurance Default Amount Model

Parameter	Description	Description Detail	DF	Estimate	StdErr	ProbChiSq
Intercept			1	0.6251	0.1310	<.0001
vperiodnbr_TIDS	Period Number	mod(period,100) = 1	1	-0.0106	0.0016	<.0001
vProperty_Value_TIDS	Categorical Season	mod(period,100) = 2	1	0.0003	0.0000	<.0001
vp_appr_infl_tids_pw2	Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1--.04,.05--.04)	1	8.5879	1.5628	<.0001
vp_appr_infl_tids_pw3	Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.05,.2-.05)	1	3.6235	0.4990	<.0001

Parameter	Description	Description Detail	DF	Estimate	StdErr	ProbChiSq
vp_appr_infl_tids_pw4	Variate piecewise Appraisal Inflation	median(0,p_appr_infl_1-.2,.4-.2)	1	-2.9249	0.6956	<.0001
Scale			0	0.6789	0.0000	

Model Validation

Model validation was accomplished by applying the models developed using the training set to the validation dataset. The application of this model to the validation data produces the probability of a cash draw or a predicted cash draw amount. The actual target variable is then compared to the predicted target variable to ensure the model fits the cash draw process without over-fitting the actual data.

Specifically, we calculate the predicted probability of the cash draw or the predicted amount for the cash draw amount models. The actual result is 1.0 if the cash draw was taken and 0.0 if it was not, or an actual cash draw amount for the cash draw amount model. The probability of a cash draw or the predicted amount of the cash draw for each record in the validation dataset is derived from the model parameters.

Decile charts are then created for each final cash draw likelihood or average draw amount. All records are sorted, or ranked, by the predicted value. Ten equal sized decile groups are created with 10% of the records in each group. The sum of the actual result and the sum of the predicted result within each decile is calculated. The actual and predicted numbers are then compared for consistency. The objective of a model is to have a significant spread in predicted values while maintaining a close relationship between the resulting actual and predicted values.

The validation charts for the cash draw models are shown in Figures 13 through 16.

Figure 13: Model Validation - Likelihood of Cash Draw

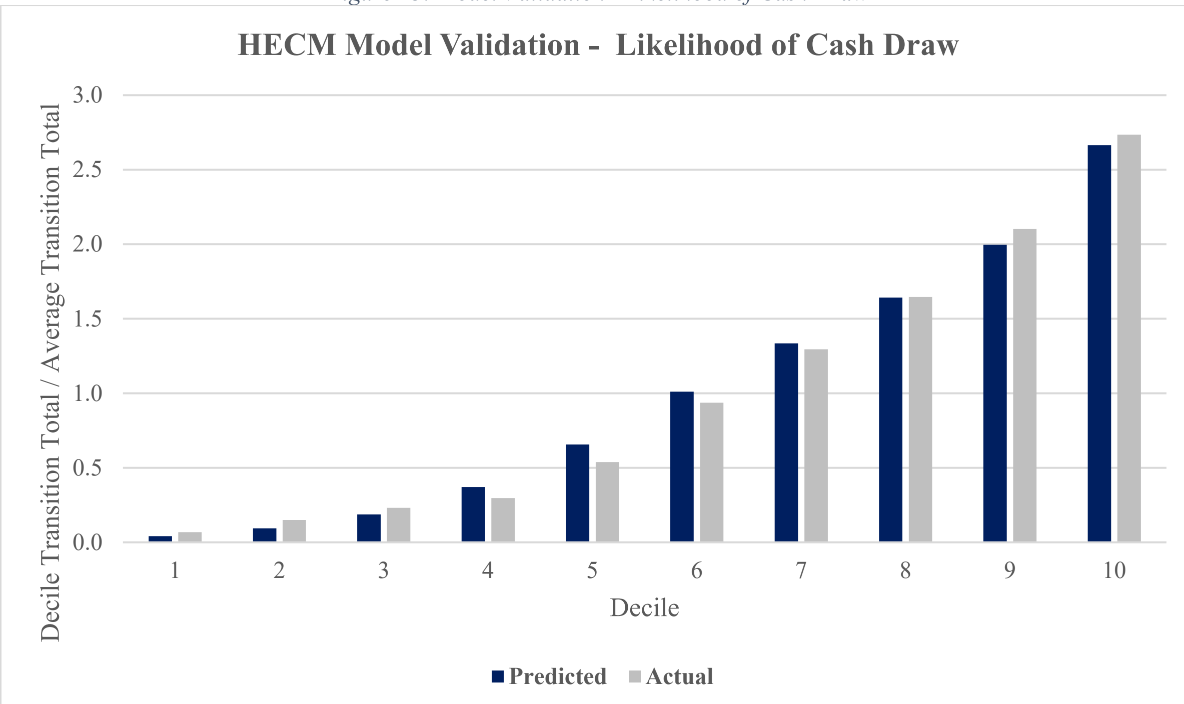


Figure 14: Model Validation - Likelihood of Full Cash Draw (Quarters 1 through 8)

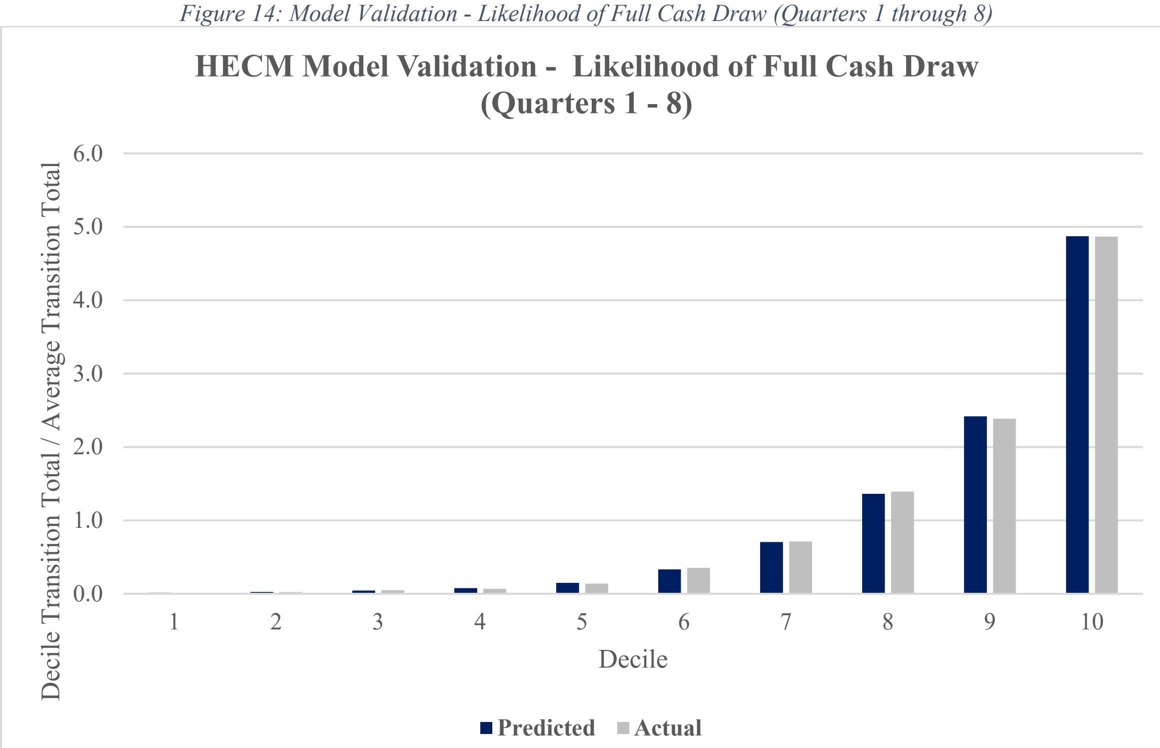


Figure 15: Model Validation - Likelihood of Full Cash Draw (Quarters 9+)

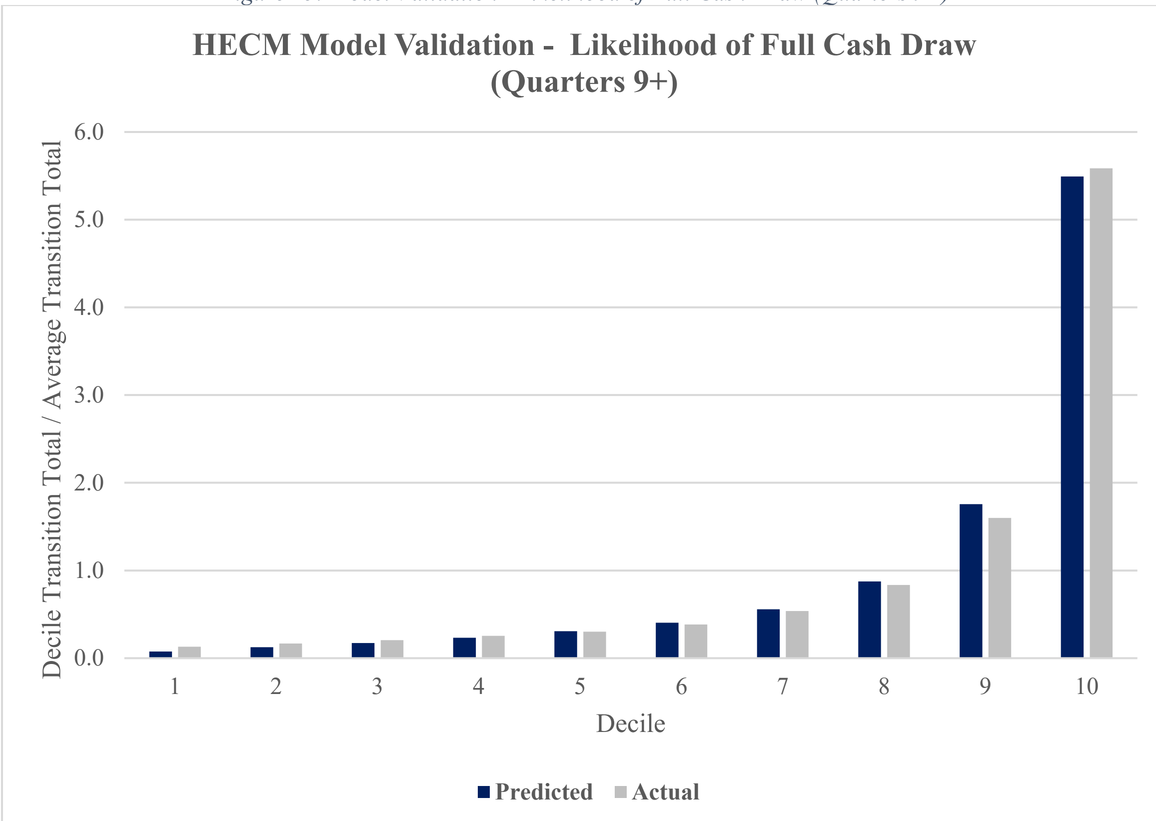
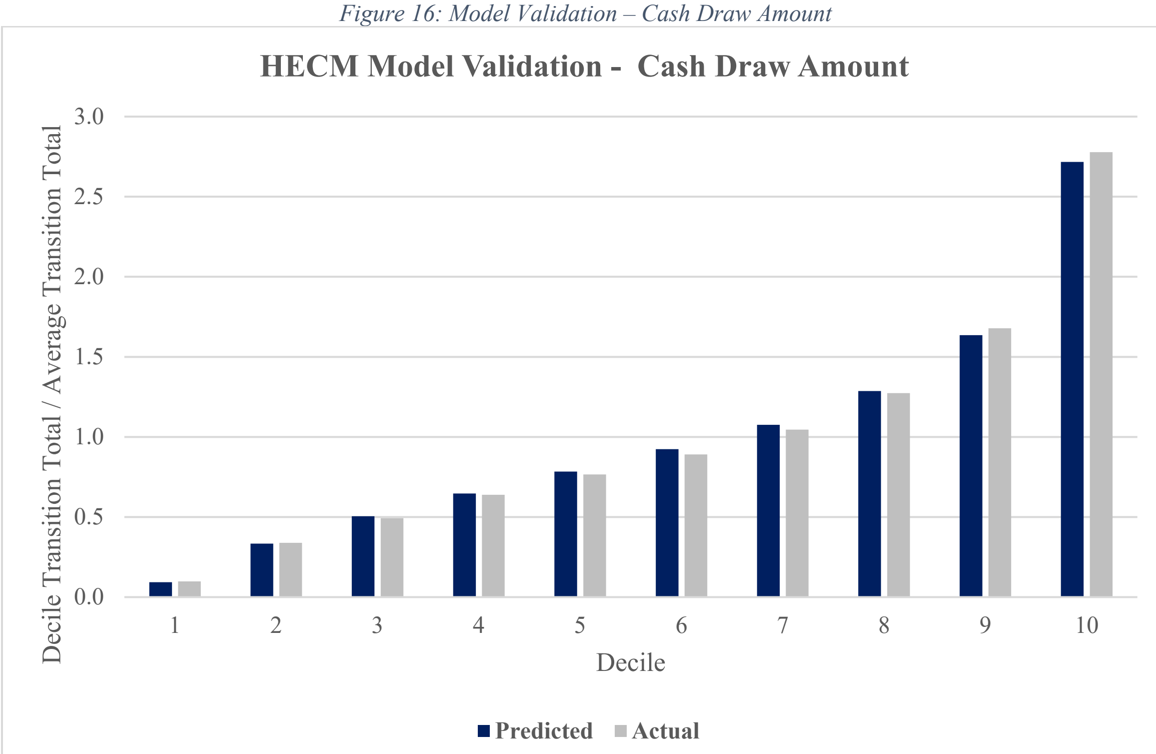


Figure 16: Model Validation – Cash Draw Amount



The validation chart for the tax and insurance default model is shown in Figures 17 and 18.

Figure 17: Model Validation – Tax and Insurance Default Likelihood Model

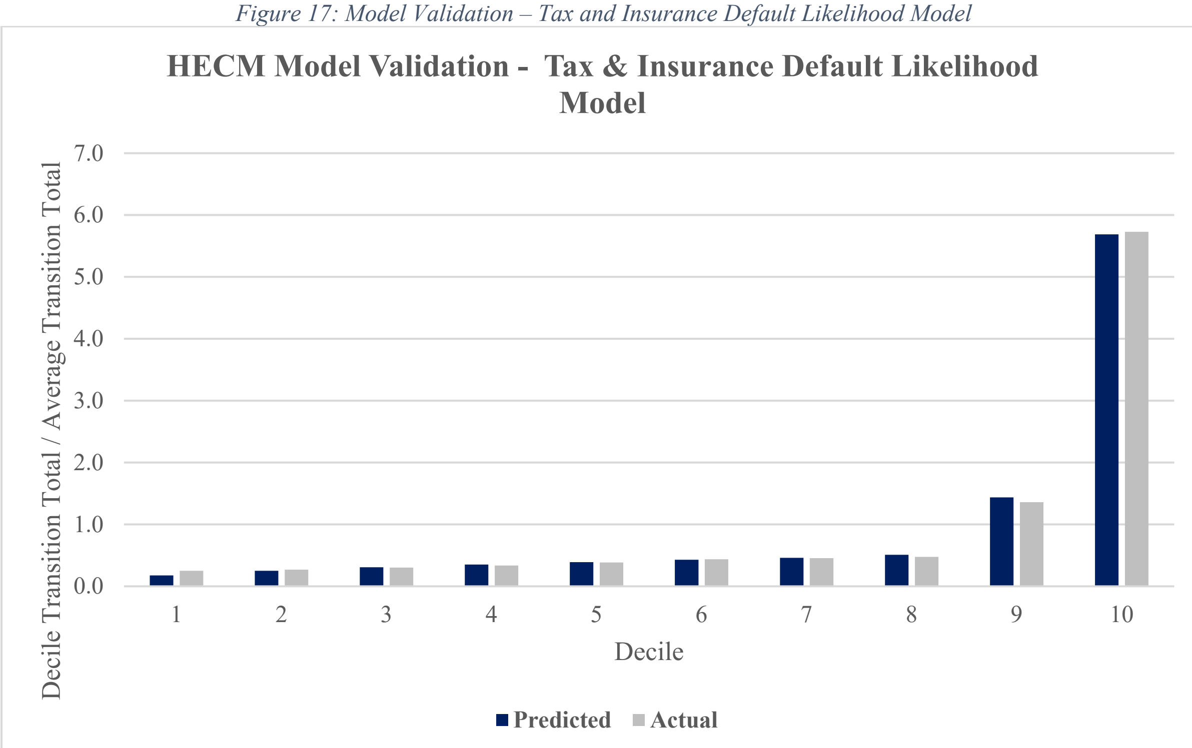
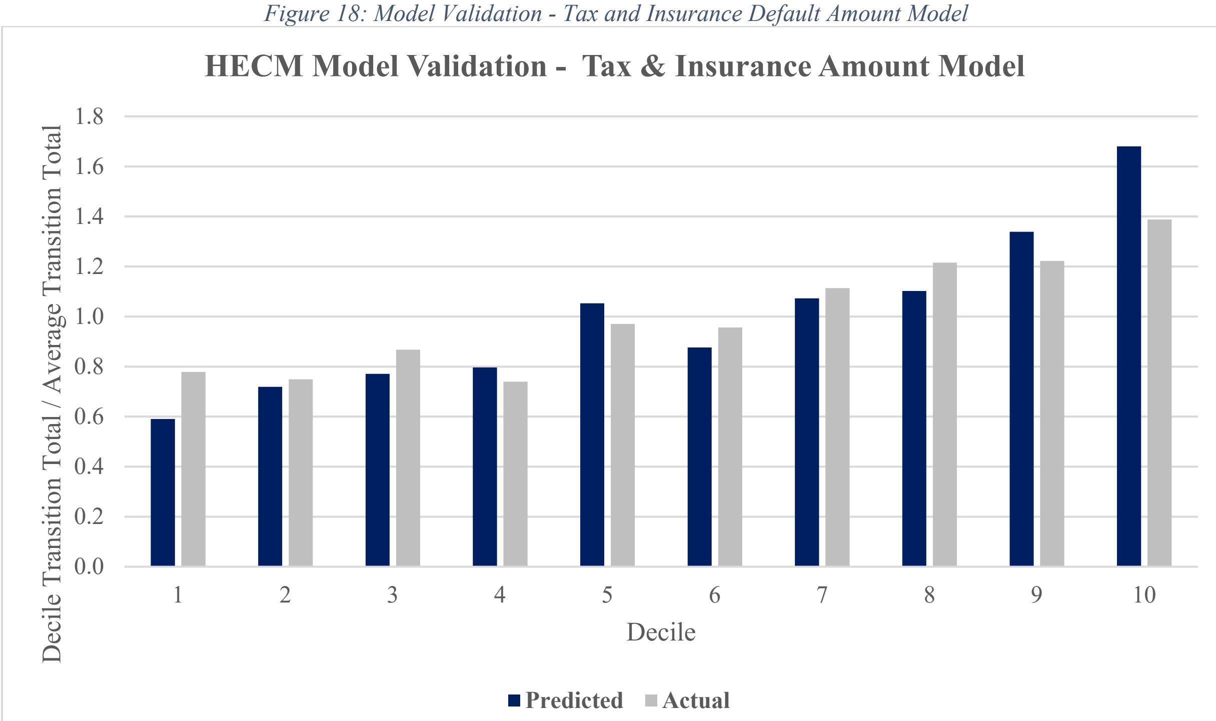


Figure 18: Model Validation - Tax and Insurance Default Amount Model



Appendix D: Economic Scenarios

To measure the possible variation in MMI's Cash Flow NPV on the existing portfolio, we developed a baseline projection using OMB Economic Assumptions and projections for ten additional deterministic economic scenarios from Moody's. For this analysis, we used the Moody's October 2022 forecast of the U.S. economy. For purposes of our analysis, the components of Moody's forecast include:

- HPI at the MSA, state, regional and national levels
- One-year CMT rate
- Three-year CMT rate
- Five-year CMT rate
- 10-year CMT rate
- 30-year CMT rate
- Commitment rate on 30-year fixed-rate mortgages
- Unemployment rates at the MSA, state, regional and national levels
- GDP

Alternative Scenarios

To assess the effect of alternative economic scenarios on the Cash Flow NPV, ten alternative scenarios from Moody's were used. The ten Moody's scenarios are:

- Baseline
- Alternative 0 – Upside (4th Percentile)
- Alternative 1 – Upside (10th Percentile)
- Alternative 2 – Downside (75th Percentile)
- Alternative 3 – Downside (90th Percentile)
- Alternative 4 – Downside (96th Percentile)
- Slower Trend Growth
- Stagflation
- Next-Cycle Recession
- Low Oil Price

The Moody's projections provide a range of better-than-expected economic assumptions and worse than expected economic assumptions. This range of assumptions produces a range of Cash Flow NPV projections.

Graphical Depiction of the Scenarios

Figure 19 shows the future movements of the HPI under the baseline and the alternative economic scenarios. In the Baseline scenario, the HPI increases throughout the entire projection period. The rate of decreases from 9.1% to about 0.0% in the second quarter of 2023, and then increases to about 4.0% per year by 2028 and remains at this level for the remainder of the projection period.

Figure 19: Paths of the Future National House Price Index in Different Scenarios

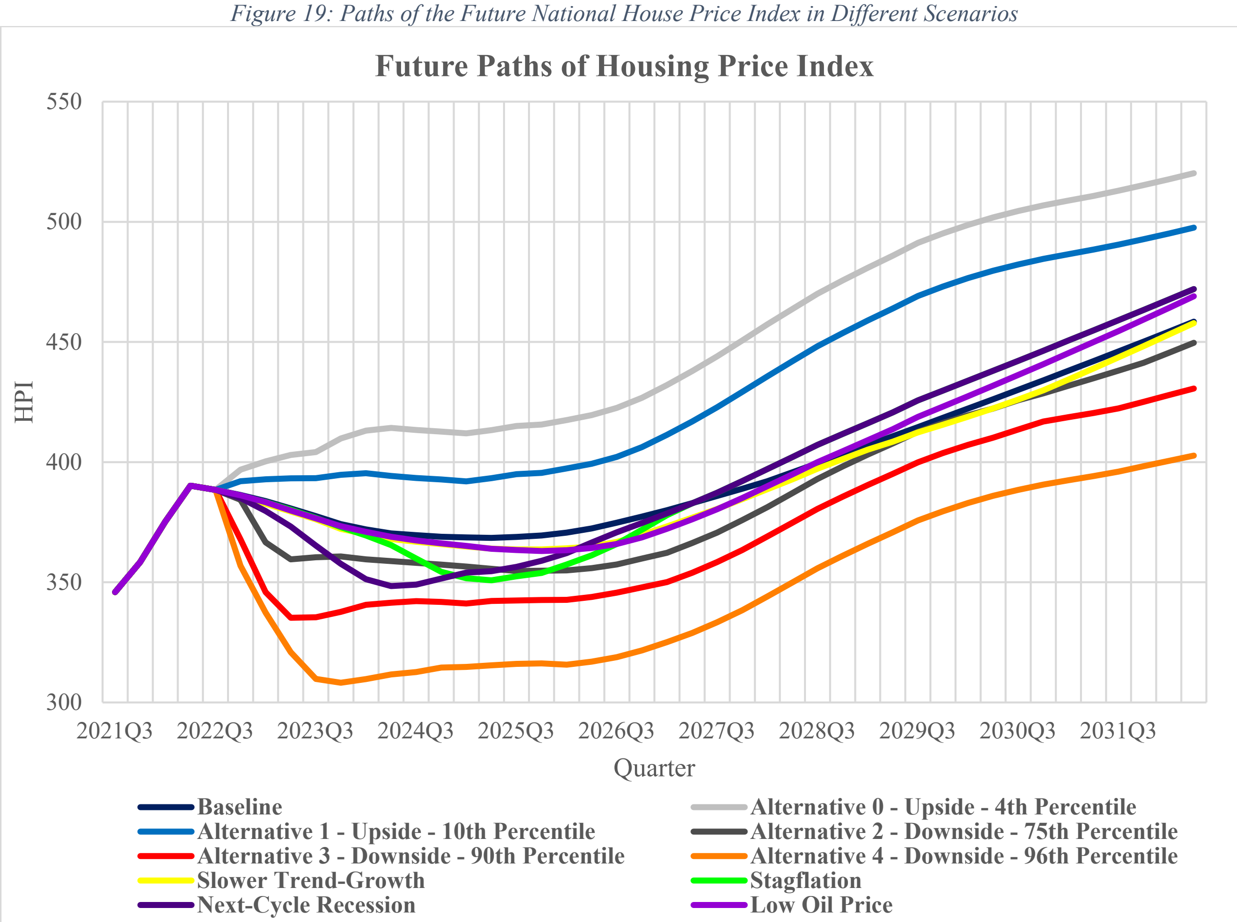


Figure 20 shows the forecasted mortgage rate of 30-year fixed-rate mortgages for the ten Moody's scenarios. For the Moody's Baseline Scenario, the mortgage interest rate remains flat through the second quarter of 2024, increases through the second quarter of 2026, and then levels off at 5.6%.

Figure 20: Paths of the Future Mortgage Rate

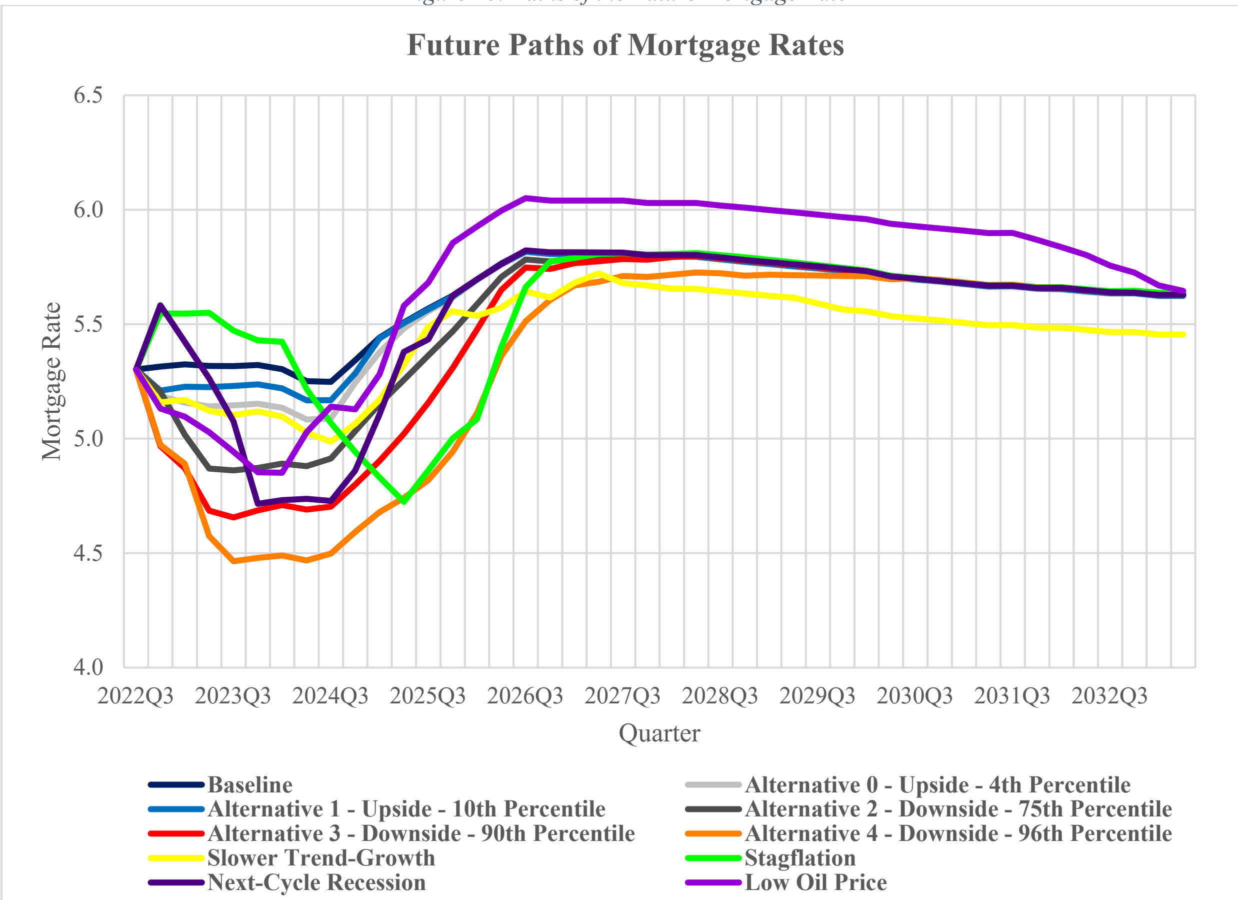
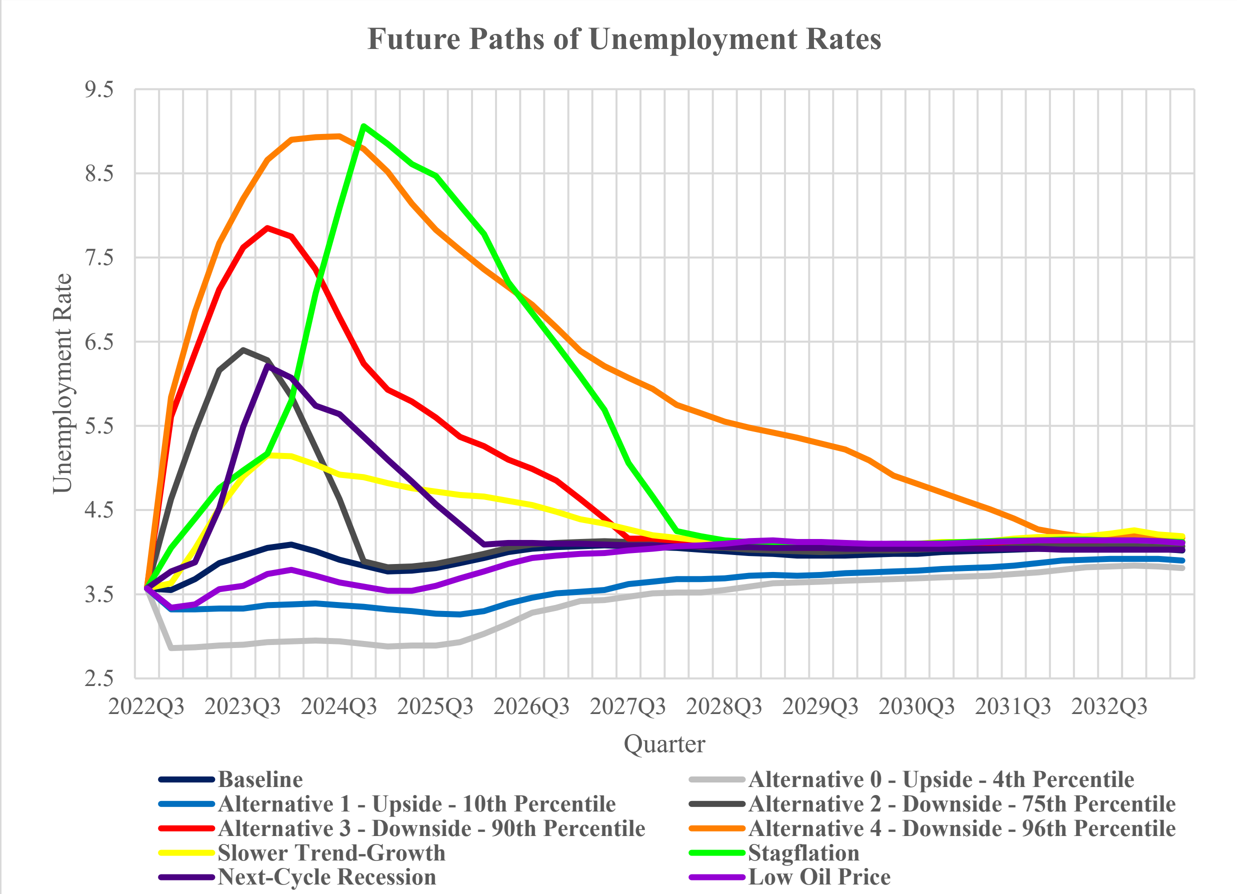


Figure 21 shows the forecasted unemployment rate under alternative economic scenarios. Under the Moody’s Baseline forecast, the unemployment rate is projected to decrease through 2022 to approximately 3.5%, and then increases to 4.1% at the end of 2026. The rate then remains steady at that level for the remainder of the projection period.

Figure 21: Paths of Future National Unemployment Rate



Stochastic Simulation

This section describes the stochastic models fitted to generate the economic variables simulations used in the projection of Cash Flow NPV.

The economic variables modeled herein as stochastic for computing expected present values include:

- Three-month CMT rates
- Six-month CMT rates
- 10-year CMT rates
- 1-year CMT rates
- 30-year CMT rates
- 30-year FRM rates
- FHFA National Purchase Only House Price Index (HPI-PO)
- Unemployment Rates
- Gross Domestic Product (GDP)

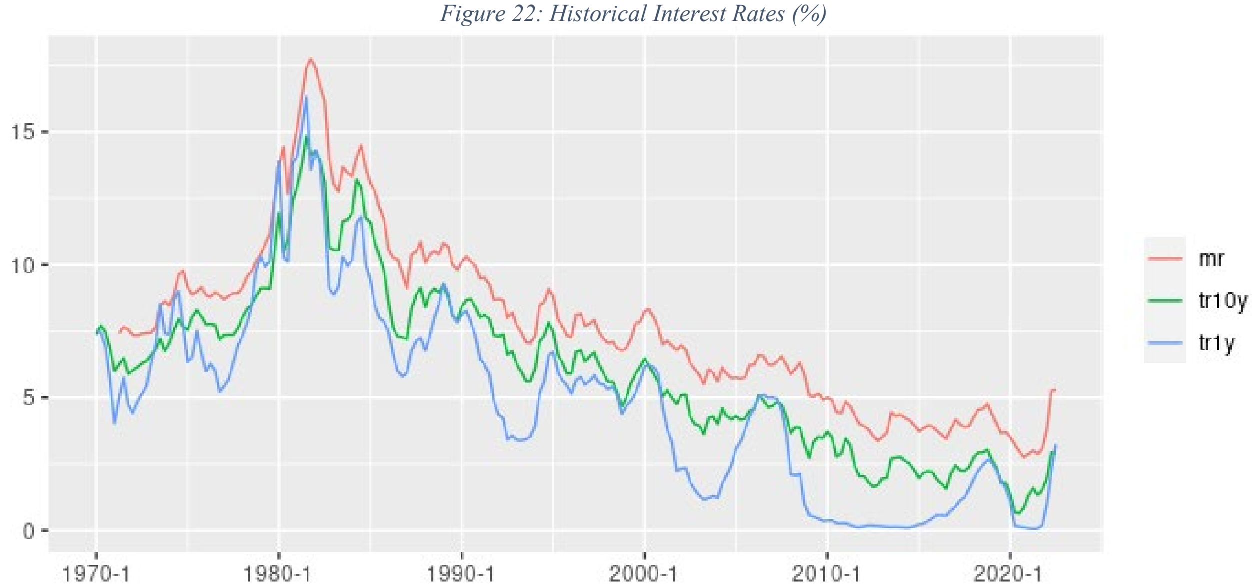
- Small Business Normalized Optimism Index (NOI)
- Consumer Confidence Index (CCI)
- London Interbank Offered Rates (LIBOR)
- Secured Overnight Financing Rates (SOFR)

Historical Data

A. Interest Rates

Figures 22 and 23 show historical interest rates since 1971. These graphs illustrate the variability of interest rates over time and the consistent spread between rates. Shown are the one-year CMT rate (tr1y), 10-year CMT rate (tr10y) and the 30-year FRM rate (mr). High inflation rates caused by the global oil crisis in the late 1970's was the major factor for the historically high level in early 1980's. The Federal Reserve shifted its monetary policy from managing interest rates to managing the money supply to influence interest rates after this period. The one-year CMT rate was around 5% in calendar year 1971 and increased steadily to its peak of 16.31% in the third quarter of calendar year 1981. After that, it followed a decreasing trend and reached a low of 0.10% in second quarter of calendar year 2014. Since then, rates had started a slow upward trend until recently where there is a sharp downward trend reaching a historic low of 0.06% in the second quarter of 2021, a result of the COVID-19 pandemic before turning up since that time. We see the beginning of the Federal Reserve tightening in the most recent quarter where the one-year rate has increased to 3.2%.

Figure 22: Historical Interest Rates (%)



Multiple short-term rates were included in these simulations, including three-, six- and 12-month CMT rates, SOFR, and LIBOR. Figure 23 illustrates the close relationship between these rates with the most volatility in LIBOR.

Figure 23: Historical Shorter-Term Interest Rates (%)

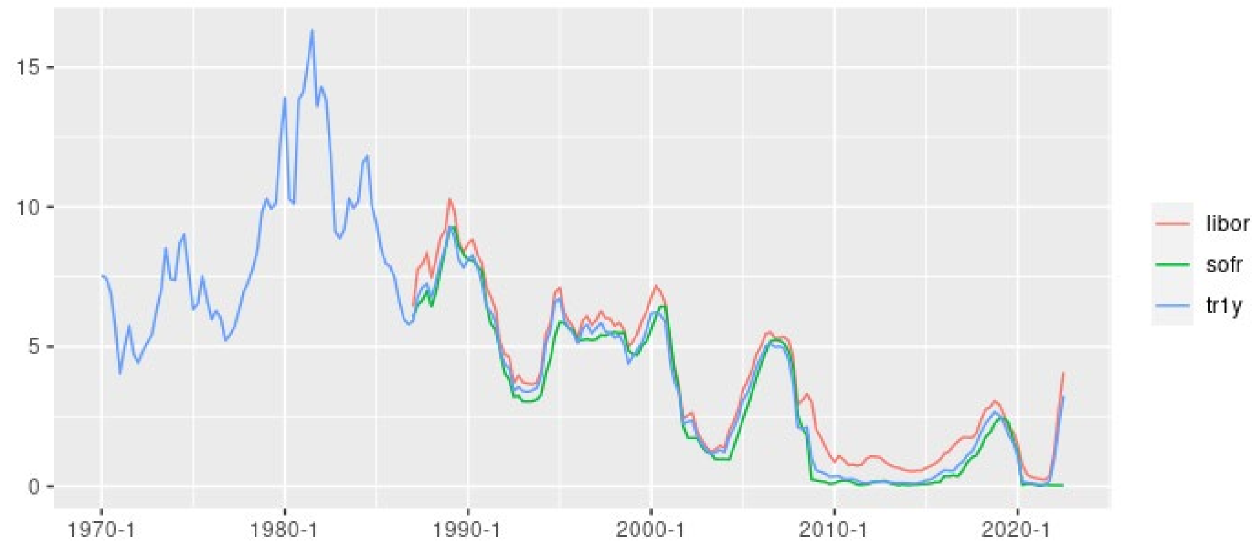
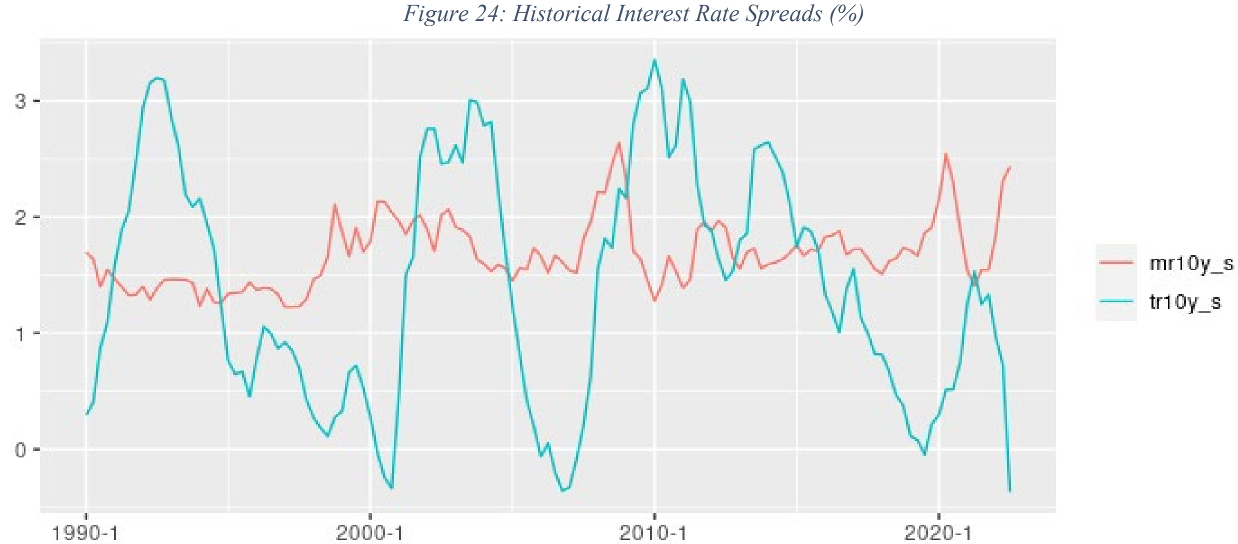


Figure 24 shows historical interest rate spreads, including the spread between 10-year and one-year CMT rates (tr10y_s) and the spread between the 30-year FRM rate and the 10-year CMT rate (mr10y_s). Both spreads are primarily positive with long cycles. Lower, negative spreads typically correspond with economic downturns, such as the downturn that occurred during the late 1970's through the early 1980's. Also note, the spread of the mortgage rate over the 10-year CMT rate is always positive, reflecting the premium for credit risk.

Both spreads turn sharply in the last four quarters.

Figure 24: Historical Interest Rate Spreads (%)



B. House Price Appreciation Rates

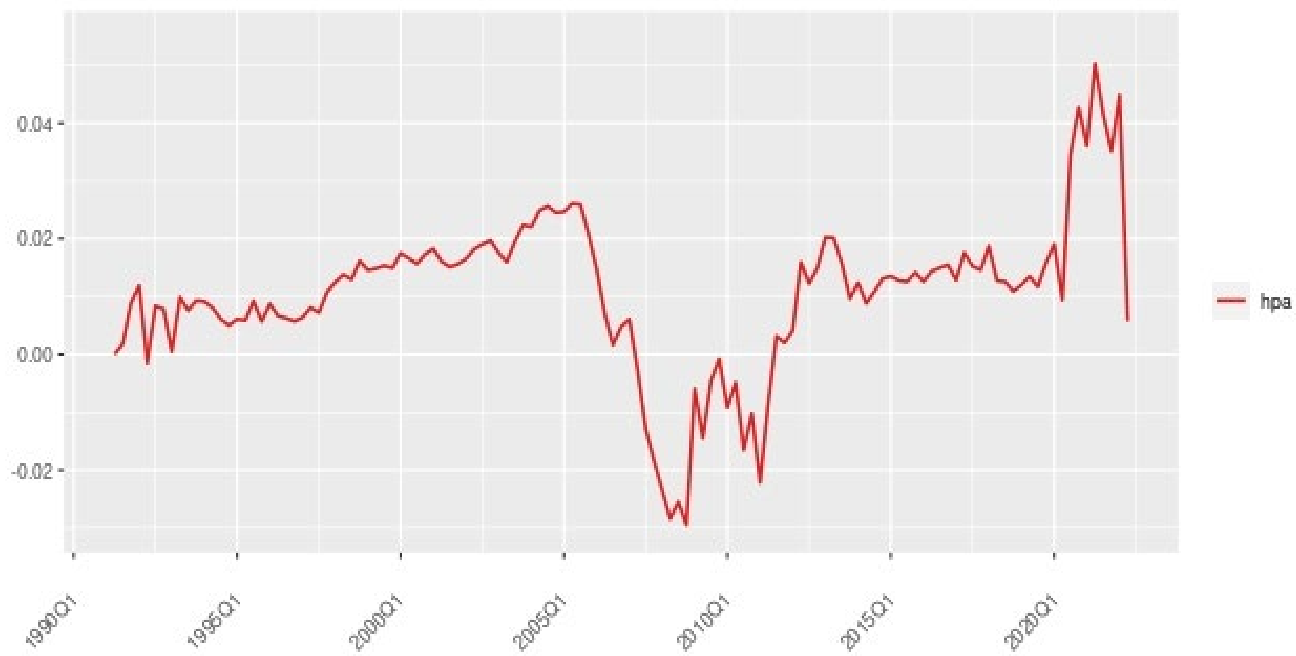
The national house price appreciation rate (HPA) is derived from the FHFA repeat sales house price indexes (HPIs) of purchase-only (PO) transactions. The PO HPI provides a reliable measure of housing market conditions since it is based on repeat sales at market prices and does not use any appraised values.

The HPA series being modeled is defined as:

$$HPA_t = \ln(\frac{HPI_t}{HPI_{t-1}}) \qquad (1)$$

Figure 25 shows the national quarterly HPA from the first quarter of calendar year 1991 to the third quarter of calendar year 2022. The long-term average quarterly HPA is approximately 1.08% (4.41% annual rate).

Figure 25: Historical National HPI and Quarterly HPA



The HPI increased steadily before 2004, and the quarterly appreciation rate was around 1.14%. Then house prices rose sharply starting in 2004. The average quarterly home-price appreciation rate was 1.88% during the subprime mortgage expansion period from 2004 to 2006 and reached its peak of 2.59% in 2005 Q2. After 2006, the average growth rate of house prices became negative until 2011, when appreciation returns to a positive value. The appreciation rate generally increased until approximately the end of 2012, when it decreased slightly before increasing at a gradual rate until approximately 2018. Following a slight dip in 2018, there was a period of almost eight quarters with a steady appreciation rate of about 1%. This period was followed by historic home appreciation not seen since the sub-prime bubble. Low inventory, low interest rates, prohibitively high construction costs, and more remote work options were all contributing factors to this recent home appreciation. In the latest quarter, increases in interest rates, increasing inventory and affordability challenges have led to a significant slowdown in HPA. Table 36 below shows the quarterly HPA by selected time periods.

Table 36: Average Quarterly HPA by Time Span

Period	Average Quarterly HPA
1991 – 2003	1.13%
2004 – 2006	1.84%
2007 – 2010	-1.25%
2011 – 2019	1.13%
2020 – 2022Q3	3.28%

C. Confidence Indices

The Small Business NOI and CCI are confidence indices based on surveys conducted throughout the year by The Conference Board. These indexes are designed to provide a relative measure of how optimistic or pessimistic consumers and small business are regarding their expected financial situation. Both indices are based around 100 points where indicators above 100 signal relative optimism for the future of the economy, values below 100, relative pessimism. Figure 26 and Figure 27 show historical CCI and NOI, with noted sharp drops in confidence associated to the 2008 mortgage crisis and the beginning of the COVID-19 shutdowns. Since the second quarter of 2020 during the COVID-19 shutdown, the CCI has improved to a level of modest optimism as of the third quarter of 2022. During the same period the NOI has bounced up and down with the most recent quarter staying firmly in negative territory.

Figure 26: Consumer Confidence Index

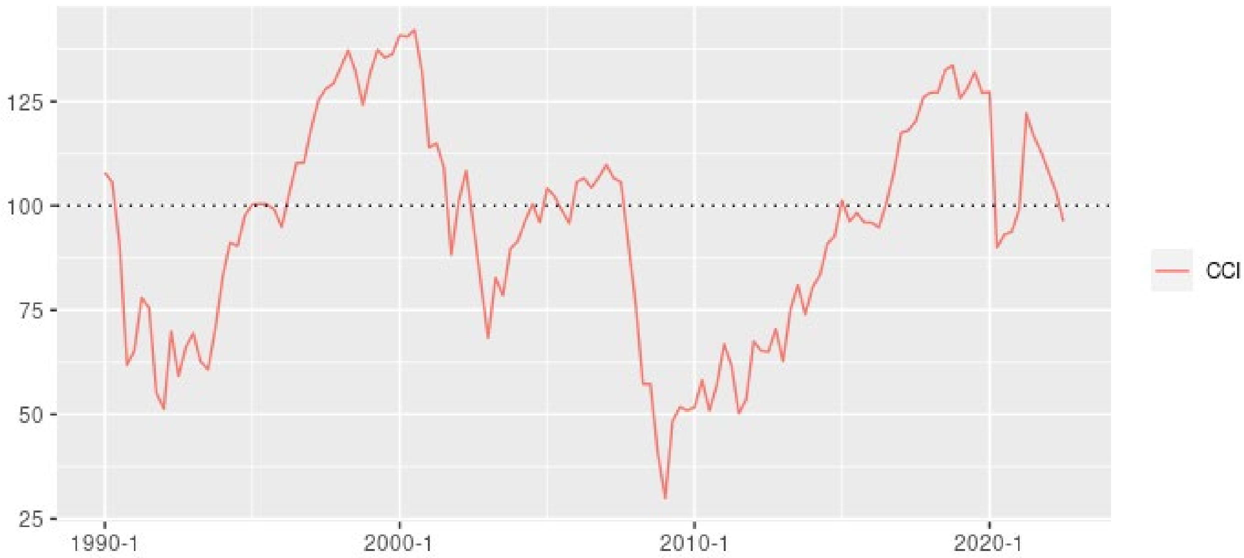
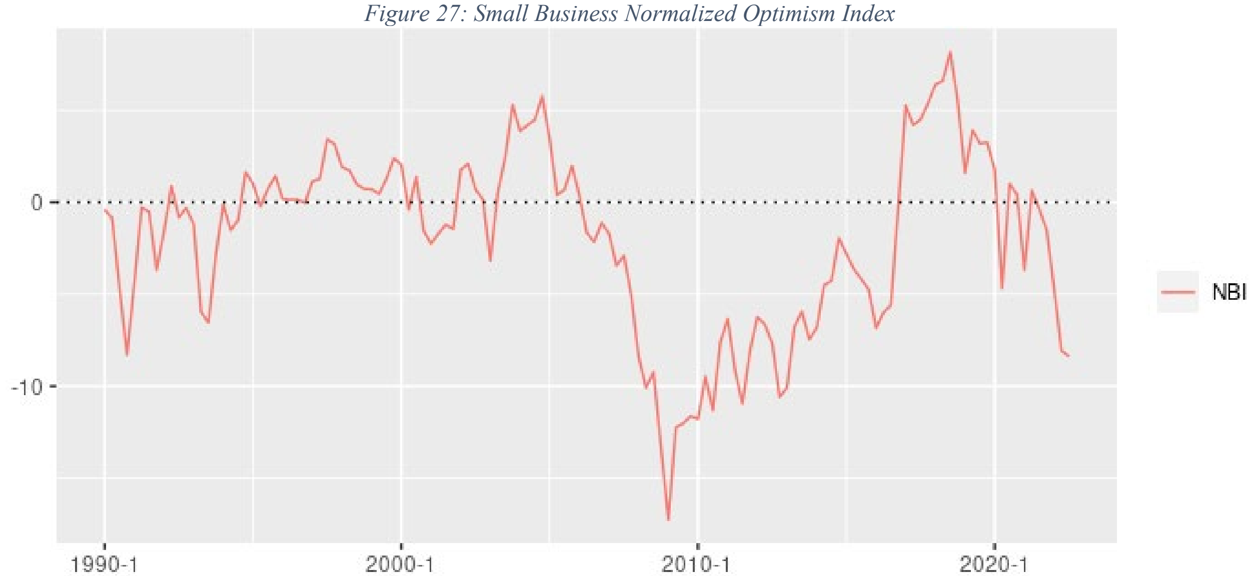


Figure 27: Small Business Normalized Optimism Index

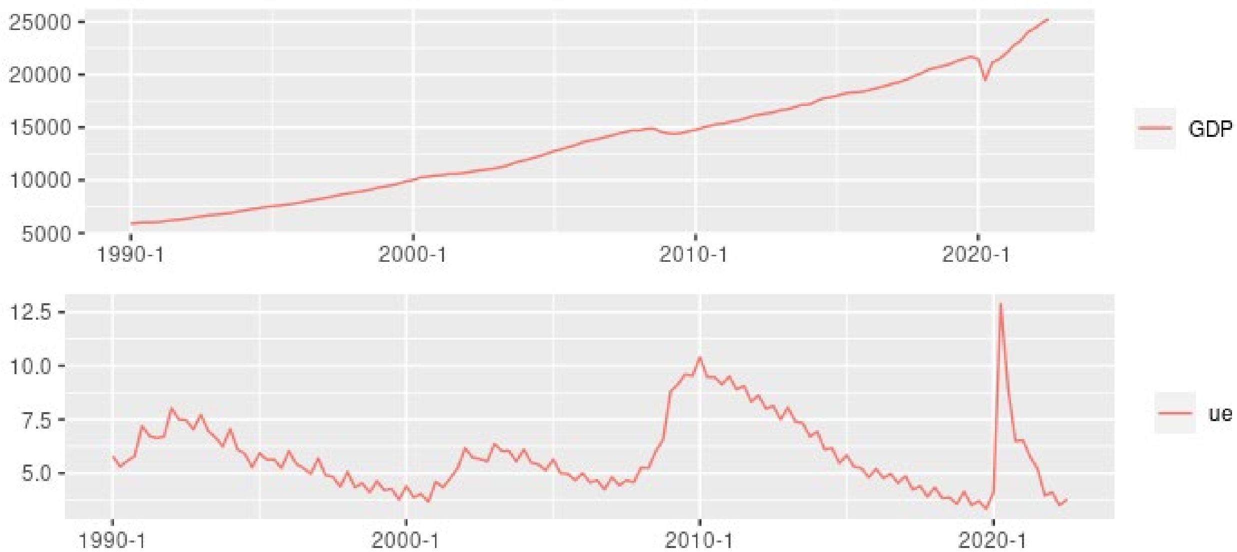


Modeling Method

In financial econometrics and management understanding, predicting the dependence in the co-movements of these series is important when simulating a set of economic factors. This is illustrated in Figure 22, where interest rates track closely.

Long periods of high unemployment will lead to lower GDP. In Figure 28, we can see two obvious examples of this following the mortgage crisis in 2008 and again with the recent COVID-19 pandemic. The most recent quarters illustrate how lockdown restrictions lessened, unemployment dropped, and GDP again begins to increase.

Figure 28: Unemployment vs. GDP



Volatilities will also move together across these series. High levels of economic instability and uncertainty will lead to volatility in these measures, affecting all economic indicators. A modeling method that accounts for these factors will lead to models that are more relevant.

Recognizing and accounting for these features through a multivariate model should lead to more accurate empirical models than working with separate univariate models.

For these reasons a multivariate General Auto Regressive Conditional Heteroscedasticity (GARCH) modeling approach was chosen.

Univariate GARCH models are typically specified as GARCH(*p,q)* where *p* is the auto regressive (AR) component of ${\sigma_t}^2$, and q is the auto regressive component of the error term. Multivariate GARCH models are defined similarly to a standard GARCH model, where the univariate term is replaced with a vector of terms. Mezrich (1995) and Shephard (1996) provide a more detailed explanation of these models.

There are several implementations of multivariate GARCH models. One such implementation, Dynamic Conditional Correlation (DCC) estimators, have the flexibility of univariate GARCH but avoid the complexity of conventional multivariate GARCH algorithms. Engle and Sheppard (2000) detail descriptions and examples of using a DCC models for time series analysis.

The 'rmgarch' package implemented with the Cran-R project was specifically used for this modeling effort, developed by Ghalanos (2019), and based off the methods described by Engle (2000).

Data Transformation

The algorithms required to calculate maximum likelihood estimates in these families of models are prone to non-convergence. Variable scale, stationarity of the variables, and covariance within the variable vector set are often the underlying issue when dealing with non-convergence in these complex matrix calculations. Data transformation was performed on these variables to provide a more robust and consistent estimate.

Dickey-Fuller stationarity tests were performed on all variables. GDP and HPA test as non-stationary. As a result, first difference transformations were applied to all variables to provide stationarity. Further scaling was required for index variables (*Ind*) using a log transformation:

$$Ind_{trans} = \ln(Ind + \sqrt{Ind^2 + 1}) \qquad (1)$$

Table 37 below provides a description of each variable transformation.

Model Specifications

Each variable is provided a univariate type specification, in a standard (p,q) format where p,q for the ARMA (mean) specification describes the number of autoregressive and moving average lags to include in the model, and (p,q) for the GARCH specification correspond to the autoregressive components and heteroskedastic components (auto regressive component of error term) respectively. See Table 37 for each variable specification.

Table 37: Model Variable Transformations and Specifications

Variable	Variable Transformation	ARMA(p,q)	GARCH(p,q)	Distribution
SOFR	First difference	(0,1)	(1,1)	Normal
LIBOR	First difference	(0,1)	(1,1)	Normal
3-MONTH	First difference	(0,1)	(1,1)	Normal
6-MONTH	First difference	(0,1)	(1,1)	Normal
1-YEAR	First difference	(1,0)	(1,1)	Normal
10-YEAR	First difference	(1,0)	(1,1)	Normal
30-YEAR	First difference	(1,0)	(1,1)	Normal
30-YEAR FRM	First difference	(1,0)	(1,1)	Normal
UNEMPLOYMENT	First difference	(0,0)	(1,1)	Normal
GDP	First difference, log function transformation	(1,1)	(1,1)	Skewed generalized error
HPI	First difference, log function transformation	(1,1)	(1,0)	Normal
NOI	First difference	(0,0)	(0,1)	Normal
CCI	First difference	(0,0)	(0,1)	Normal

When fitting a DCC model, the dynamic correlation is fitted with an autoregressive parameter that is applied across all variables. This was set with a (p,q) value of (1,1), describing the correlation across all variables as one autoregressive and one moving average period. These parameters are then used in calculating the correlation matrix.

Table 38 provides all parameter estimates, where “mu” is the mean, “ar” represent the auto regressive and “ma” represent the moving average of the mean model.

Parameters “omega”, “alpha” and “beta” are the mean, autoregressive, and heteroskedastic parameters of the variance model.

Parameters “skew” and “shape” are estimates to account for specified skewed distributions (GDP and HPI).

Table 38: Parameter Estimates

Variable	Estimate
TR1YR.MU	0.0239
TR1YR.MA1	0.7271
TR1YR.OMEGA	0.0005
TR1YR.ALPHA1	0.3113
TR1YR.BETA1	0.6877
TR3M.MU	-0.3182
TR3M.AR1	0.8823
TR3M.OMEGA	0.0011
TR3M.ALPHA1	0.2095
TR3M.BETA1	0.7895
TR6M.MU	-0.4814
TR6M.AR1	0.9854
TR6M.OMEGA	0.0009
TR6M.ALPHA1	0.5172
TR6M.BETA1	0.4818
TR10YR.MU	0.0242
TR10YR.AR1	0.7296
TR10YR.OMEGA	0.0004
TR10YR.ALPHA1	0.3124
TR10YR.BETA1	0.6866
TR30YR.MU	-0.3056
TR30YR.AR1	0.8069
TR30YR.OMEGA	0.0012
TR30YR.ALPHA1	0.2192
TR30YR.BETA1	0.7798

Variable	Estimate
MR.MU	-0.4773
MR.AR1	0.9850
MR.OMEGA	0.0010
MR.ALPHA1	0.5304
MR.BETA1	0.4686
UE.OMEGA	1.7921
UE.ALPHA1	0.9782
UE.BETA1	0.0445
GDP.MU	0.1865
GDP.AR1	0.4311
GDP.MA1	2.0152
GDP.OMEGA	0.9865
GDP.ALPHA1	0.0709
GDP.BETA1	0.3218
GDP.SKEW	0.1940
GDP.SHAPE	3.1386
HPI.MU	0.9766
HPI.AR1	0.0530
HPI.OMEGA1	0.4205
HPI.ALPHA1	0.1515
NOI.MU	0.0059
NOI.AR1	0.0000
NOI.OMEGA	0.9990
NOI.ALPHA1	5.5226
NOI.BETA1	0.0583

Variable	Estimate
CCI.MU	0.2006
CCI.AR1	0.0083
CCI.OMEGA	0.0764
CCI.ALPHA1	0.8998
CCI.BETA1	0.7695
LIBOR.MU	0.4515
LIBOR.AR1	1.0713
LIBOR.OMEGA	0.5064

Variable	Estimate
LIBOR.ALPHA1	0.8105
LIBOR.BETA1	0.5077
SOFR.MU	0.0055
SOFR.AR1	0.0393
SOFR.OMEGA	0.7433
SOFR.ALPHA1	0.1324
SOFR.BETA1	0.7117

COVID-19 Pandemic Considerations

The impact from the COVID-19 pandemic is noticeable and dramatic when analyzing these economic indicators. Dramatic, historic, and rapid changes to these economic measures provided additional challenges when fitting these models and produced simulated results that were skewed and assumed to misrepresent historical data.

Because of the historic nature of this event, and its impact on the economy, it is unknown what the long-term impacts of this pandemic will have on the economy. Numerous research articles have been produced to estimate or predict these long-term impacts (Chudik, 2020; Malliet, 2020).

Based on this and an analysis of historical data, a randomized impact of the pandemic was applied.

As a result, two models were estimated, one basing estimates on pre-pandemic variables, and the second including the pandemic data. A continued impact of eighteen months to five years (six to 20 quarters) was applied randomly as a diminishing linear weight. The two model simulations were then combined using this weighting factor, where COVID-19 simulations were given the most weight, and then we slowly decreased the COVID-19 impacts to the simulations over the randomized period until the COVID-19 simulations were given no weight.

Simulation Generation

Model fit was performed through an iterative process, varying parameter specifications for both ARMA and GARCH model components.

Distributions were determined using standard distribution fitting techniques, including QQ-plots and Kolmogorov-Smirnov tests.

Further parameter selection and distribution adjustments were made based on comparative analysis of simulations to historical series, providing the most reasonable estimates and simulations possible.

One hundred simulations were generated for each of the economic variables. These variables were fully transformed back to the common form and scale as the original un-transformed versions.

Interest Rate Simulations

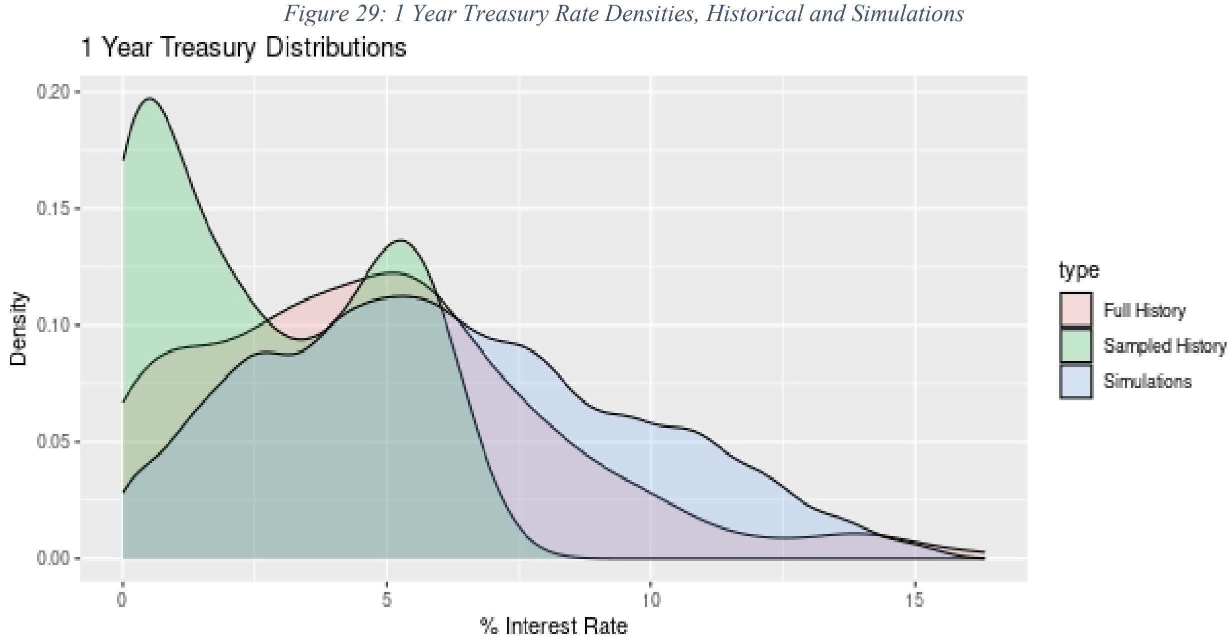
Table 39 shows the summary statistics of the historical one-year Treasury rates for two different periods as well as the simulated series. We can see that in the last 50 or more years, interest rates have had a much broader range as compared to the last 25 years.

Table 39: Statistics for the 1-Year Treasury Rates

Statistics	Since 1953	Since 1991	Simulations
95-PERCENTILE	10.28%	6.08%	13.08%
90-PERCENTILE	8.88%	5.66%	11.80%
50-PERCENTILE	4.44%	2.25%	7.07%
25-PERCENTILE	2.17%	0.46%	4.66%
10-PERCENTILE	0.35%	0.14%	2.81%
5-PERCENTILE	0.15%	0.12%	1.76%
MEAN	4.64%	2.69%	7.17%
MAX	16.31%	6.71%	16.40%
MIN	0.06%	0.06%	0.01%
VARIANCE	10.95%	4.74%	11.28%

Figure 29 shows density distributions, comparing the distribution of the historical CMT rates, historic sample used for simulations, and the distributions of all the simulations.

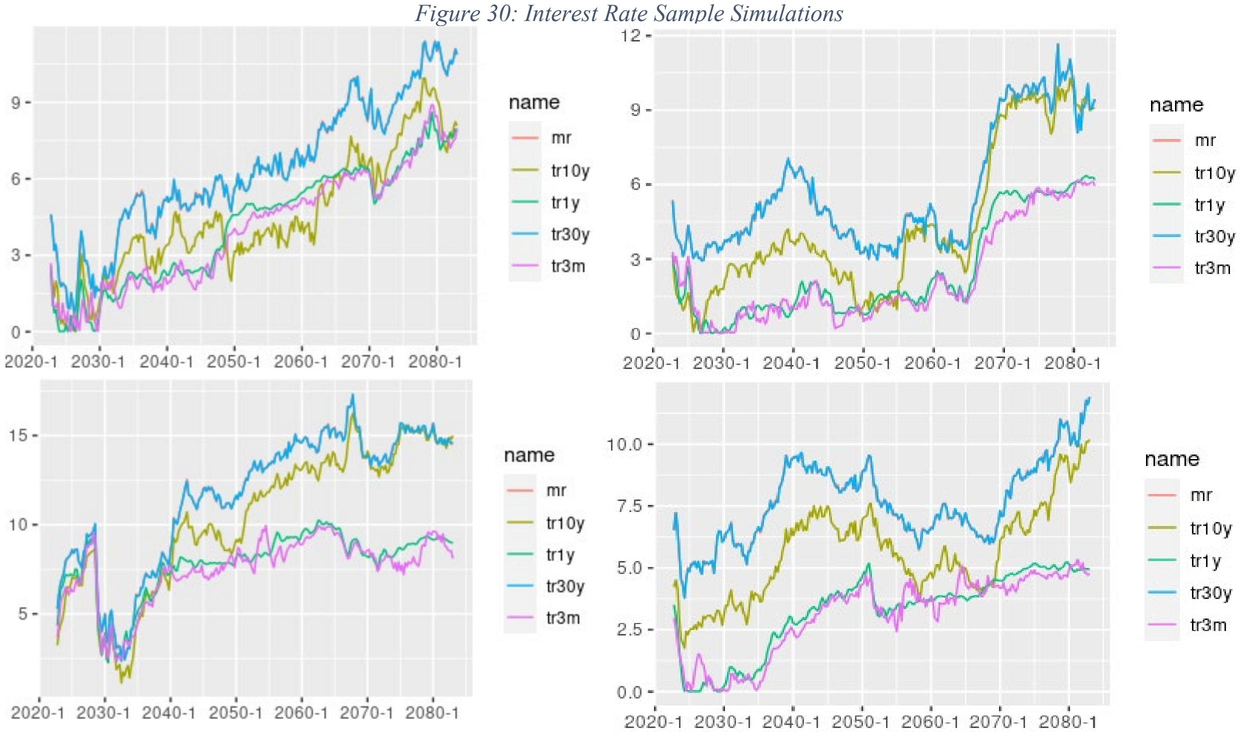
Figure 29: 1 Year Treasury Rate Densities, Historical and Simulations



To avoid negative interest rates, a lower bound of 0.01 percent was applied to all the simulated future interest rates.

Figure 30 graphs four of the one-hundred simulations, illustrating the co-movements and correlations between these variables and how the multivariate modeling method accounts for these interdependencies.

Figure 30: Interest Rate Sample Simulations



<u>House Price Appreciation Rate (HPA)</u>

A. National HPA

The national HPA is calculated by first estimating and simulating HPI. From the HPI simulation, these simulations are then transformed using formula (1) to simulate HPA. Table 40 provides comparison of simulated HPI average trends and the historical sample trends.

The analysis shows a significant spread between the series when comparing the largest and smallest quarter over quarter changes, but when simulated quarterly changes are averaged across all series, they are very close to the historical quarterly changes used in model fitting.

Table 40: HPI Simulation Statistics

	Simulated Series			Historical
	Max QoQ	Min QoQ	Mean QoQ	QoQ
HPI	7.7%	-7.7%	0.5%	1.1%

B. Geographic Dispersion

The MSA-level HPA forecasts were based on Moody's forecast of local and the national HPA forecasts. Specifically, at each time *t*, there is a dispersion ratio of HPAs between the i^{th} MSA or State level and the national forecast:

$$Disp_{i,t}^{Base} = HPA_{i,t}^{Base} / HPA_{national,t}^{Base} \quad (6)$$

This dispersion forecast under Moody's base case was preserved for all local house price forecasts under individual future economic paths. That is, for economic path j, the HPA of the i^{th} MSA at time *t* was computed as:

$$HPA_{i,t}^{j} = HPA_{national,t}^{j} * Disp_{i,t}^{Base} \quad (7)$$

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.[5]

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 of the Fund.

<u>Unemployment Rate</u>

A. National Unemployment Rate

Table 41 provides statistics comparing series samples of unemployment rates to the simulated series.

[5] The dispersion of each MSA remains constant among all alternative Moody's forecast scenarios.

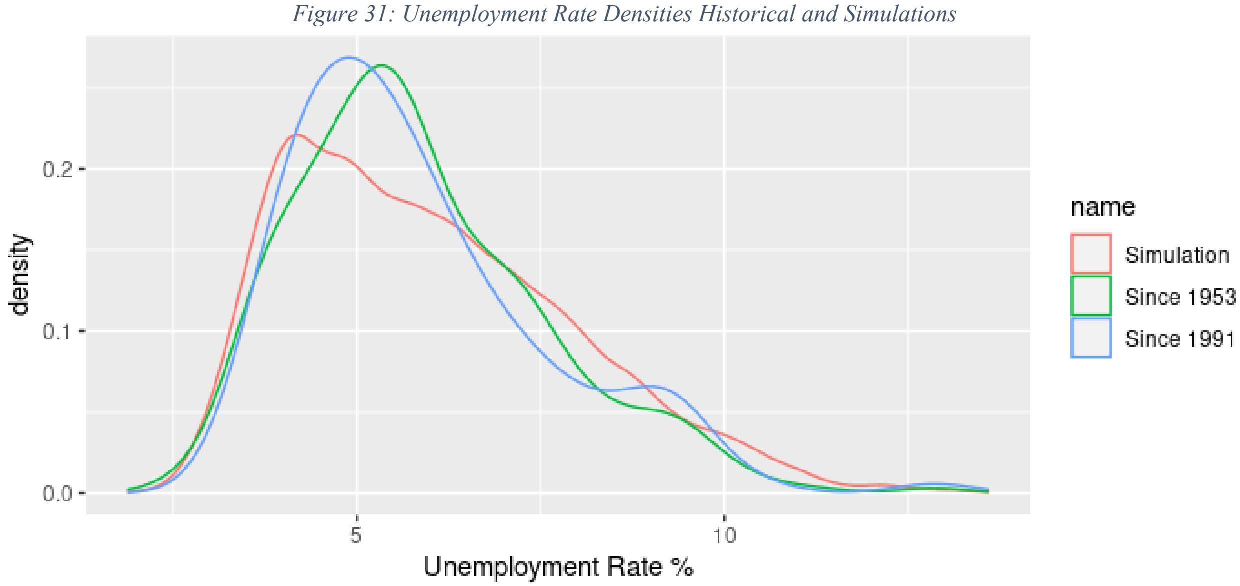
Table 41: Unemployment Historical and Simulation Statistics

Statistics	Since 1953	Since 1991	Simulations
95-Percentile	9.13%	9.37%	9.68%
90-Percentile	8.18%	8.70%	8.75%
50-Percentile	5.57%	5.43%	5.69%
25-Percentile	4.65%	4.57%	4.41%
10-Percentile	3.83%	4.01%	3.74%
5-Percentile	3.60%	3.77%	3.42%
Mean	5.85%	5.86%	5.99%
Max	12.87%	12.87%	13.58%
Min	2.57%	3.33%	1.89%
Variance	2.89%	3.10%	3.82%

Based on historical statistics, the national unemployment rate limits were set at 20% maximum and a 2% minimum.

Figure 31 is a density plot comparison of the historical series and simulated sets.

Figure 31: Unemployment Rate Densities Historical and Simulations



B. Geographic Dispersion

Following the same logic that we applied to the MSA-level HPA forecasts, we first obtained the dispersion of unemployment rates between the i^{th} MSA or State level and the national level from Moody's July base-case forecast at each time *t*:

$$Disp_{i,t}^{Base} = ue_{i,t}^{Base} / ue_{national,t}^{Base} \quad (9)$$

This dispersion forecast was preserved for all local unemployment rate forecasts under each individual future economic path. That is, for economic path j, the unemployment rate of the i^{th} MSA at time t was computed as:

$$ue_{i,t}^{j} = ue_{national,t}^{j} * Disp_{i,t}^{Base} \tag{10}$$

For the simulation, we capped the unemployment rate at the local level at 30% with a floor at 1%.

Gross Domestic Product

Table 42 provides statistics comparing the historical GDP series trend to simulated trends. The analysis shows a small spread between the series when comparing the largest and smallest quarter over quarter changes, and when simulated quarterly changes are averaged across all series, they are very close to the historical GDP quarterly change used in model fitting.

Table 42: GDP Simulation Statistics

	Simulated Series			Historical
	Max QoQ	**Min QoQ**	**Mean QoQ**	**QoQ**
GDP	11.0%	-23.6%	0.5%	1.1%

Small Business Normalized Optimism Index / Consumer Confidence Index

The Small Business NOI and CCI are based on a 100-point scale, where values under 100 represent less confidence in the economy, values over 100 indicate an increase in confidence. Table 43 provides comparisons of range and means for both indices and the corresponding simulate data showing that the simulations provide reasonable ranges compared to historical data.

Table 43: Confidence Indices Statistics

	Historical NOI	Simulated NOI	Historical CCI	Simulated CCI
MAX	108.18	173.42	142.12	200.00
MIN	82.74	20.00	29.87	10.00
MEAN	98.06	91.63	95.16	111.13

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Appendix E: HECM Cash Flow Analysis

This appendix describes the calculation of the Cash Flow NPV. Future cash flow calculations are based on forecasted variables, such as HPI and interest rates, in addition to individual mortgage characteristics and borrower behavior assumptions. HECM cash flows are discounted according to the latest discount factors published by OMB.

General Approach to Mortgage Termination Projections

HECM termination rates are projected for all future policy years for each active mortgage. The variables used in the projection are derived from mortgage characteristics and economic forecasts. Moody's October 2022 forecasts of interest rates and HPI are combined with the mortgage-level data to simulate the projected economic paths and create the necessary forecasted variables. MSA-level forecasts of HPI apply to mortgages in metropolitan areas; otherwise, mortgages use the state-level HPI forecasts. Moody's house price forecasts are generated simultaneously with various macroeconomic variables.

For each mortgage during future policy years, the derived mortgage variables serve as independent variables to the multinomial logistic termination models described in Appendix B. The termination projections by claim type are then calculated to generate the probability of mortgage termination in a policy quarter by different modes of termination given that it survives to the end of the prior policy quarter. The HECM cash flow model uses these forecasted termination rates to project the cash flows associated with different termination events. Based on the specific characteristics of the mortgage, the probability of each termination is calculated. Then, a random number between 0 and 1 is generated, and based on this random draw a mortgage transition is determined. The projection process continues for each mortgage until the mortgage ends by termination or claim.

Cash Flow Components

There are four major components of HECM cash flows:

1. MIP
2. Claims
3. Note holding expenses
4. Recoveries on notes in inventory (after assignment)

Premiums consist of upfront and annual MIPs, which are inflows to the HECM program. Recoveries are the property recovery amount received by FHA at the time of note termination after assignment, which is the minimum of the mortgage balance and the predicted net sales proceeds at termination. The recovery amount for refinance termination is always the mortgage balance. Claim Type 1 (CT1) payments are cash outflows paid to the lender when the net proceeds of a property sale are insufficient to cover the balance of the mortgage. Claim Type 2 (CT2) payments result from assignment of mortgages to HUD and note holding payments are additional outflows. Table 44 summarizes the HECM inflows and outflows.

Table 44: HECM Cash Flows

Cash Inflows	Cash Outflows
Upfront MIP	Claim Type 1 Payments
Annual MIP	Claim Type 2 Payments
Recoveries	Note Holding Expenses

Mortgage Balance

The UPB is a key input to the cash flow calculations. In general, the UPB at a given time t is calculated as follows:

$$UPB_t = UPB_{t-1} + Cash\ Draw_t + Accruals_t$$

The UPB for each period t consists of the previous mortgage balance plus any new borrower cash draws and accruals. The accruals include interest, annual MIP, and servicing fees. Future draws for borrowers with a line of credit are estimated based on a model of historical cash flow draws as described in Appendix D. Otherwise, mortgages with a tenure plan use the cash draws associated with the tenure of the mortgage.

Tax & Insurance Defaults

In ML 2011-01, FHA announced that a HECM with tax and insurance (T&I) delinquencies is considered due and payable, and therefore subject to foreclosure if the borrower does not comply with the repayment plan.[6] Through impacts on termination speeds and recovery rates, this ruling was intended to positively impact the economic value of the HECM program by providing an intervention that could reduce potential losses.

There were several major policy changes in Fiscal Year 2015 that may affect the T&I default experience. In ML 2015-09, FHA introduced the requirement and calculation of Life Expectancy Set-Aside (LESA), which is used for the payment of property taxes and hazard and flood insurance premiums. The LESA guidelines became effective on April 27, 2015. With this set-aside, HECM's with LESA will have fewer funds available for withdrawal, but there will be no T&I default before the life expectancy of the borrowers. Since this program has only five years of history and there is no origination data showing information related to LESA, we assume no effect of this LESA guideline due to limited information about mortgages impacted by this guideline. Once more

[6] Mortgagee Letter 2011-01, January 3, 2011 – "Home Equity Conversion Mortgage Property Charge Loss Mitigation."

origination data with LESAs become available, the potential performance impact of this policy will be re-evaluated.

For HECMs before assignment, FHA provided additional guidance on due and payable policies and the timing requirements in ML 2015-10[7] and ML 2015-11.[8] For HECMs after assignment, FHA currently does not foreclose on assigned mortgages that are in T&I default. To secure and maintain FHA's position on the lien of an assigned mortgage, FHA advances T&I payments on behalf of the borrower. FHA first advances funds from the borrower's available HECM funds. If no funds are available, FHA advances the tax payment and adds the payment amount to the UPB. These policies affect all existing books and future books.

For unassigned mortgages, if a mortgage goes to into default, the lender may provide a separate mortgage to the borrower to cover the T&I. If this occurs, once a mortgage becomes eligible for assignment, it will not be able to be assigned until the separate mortgage is satisfied.

For assigned mortgages, the T&I payments are treated as note holding expenses, a component of cash outflows, and added to the UPB. The projected T&I payments are projected separately as described in Appendix C.

MIP

Upfront and annual MIP, along with recoveries, are the sources of FHA revenue from the HECM program. Borrowers typically finance the upfront MIP when taking out a HECM mortgage. Similarly, the recurring annual MIP is added to the balance of the mortgage. The upfront MIP is paid to FHA at the time of mortgage closing. It is equal to a stated percentage of the MCA. Typically, the upfront MIP is financed by the HECM lender. The upfront MIP is paid in full to FHA at the mortgage closing and is a positive cash flow. The annual MIP is calculated as a percentage of the current mortgage balance. Before a mortgage is assigned, the annual MIP is assumed to be advanced by the lender, paid to FHA, and added to the accruing mortgage balance.

Claims

Claims made by lenders consist of CT1 and CT2.

[7] Mortgagee Letter 2015-10, April 23, 2015 – "Home Equity Conversion Mortgage (HECM) Due and Payable Policies."
[8] Mortgagee Letter 2015-11, April 23, 2015 – "Loss Mitigation Guidance for Home Equity Conversion Mortgages (HECMs) in Default due to Unpaid Property Charges."

CT1 enters the HECM cash flows as payments to the lender when a property is sold and the net proceeds from the sale are not sufficient to cover the balance of the mortgage at termination. The CT1 payment for a mortgage that terminates without assignment is expressed as:

Claim Type 1 Payment = maximum (0, UPB - Net Property Sales Price)

The net sales price of the property is:

Net Property Sales Price = Estimated Property Sales Price × (1 – sales expenses % – other expenses %)

The estimated property sale price is developed using models that incorporate the Maintenance Risk Adjustment (MRA). The MRA factors vary by period number and are determined such that the expected CT1 claim severity rate after applying the MRA to the projected home appraisal value is equal to the observed CT1 claim severity rate. The development of the MRA is incorporated in the CT1 and CT2 sales price models described in Appendix B.

Sales expenses are those required to conduct the actual sale, and other expenses are those incurred to manage the property until the sale. Sales and other expenses are estimated to be 24.7% of the sales price for REO claims based on home sale data provided by FHA. This is based on data related to the sale of over 9,000 FHA owned properties. The sales and other expenses include repair costs, taxes, M&O (Other), and sales expenses.

Lenders can assign a mortgage to FHA when the UPB reaches 98% of the MCA. A CT2 occurs when FHA acquires the note resulting in a cash outflow (the acquisition cost) which is the mortgage balance (up to the MCA). The ultimate net losses from CT2 depends on two components: the note holding expenses after assignment and recoveries from assigned notes.

FHA imposes a set of requirements that, if any of them are not met, makes the HECM ineligible for assignment even when UPB reaches 98% of the MCA. We project the probability of assignment based on historical data by the number of quarters the mortgage has been eligible for assignment as follows:

Table 45: Probability of Mortgage Assignment

Number of Quarters Since Eligible for Assignment	Probability of Assignment
1	15%
2	30%
3	15%
4	9%
5	5%
6	3%
7 – 8	2%
9+	1%

This results in approximately a 40% probability that the mortgage is assigned within the first two years it becomes eligible, and a small probability it is assigned after the first two years of eligibility.

Note Holding Expenses After Assignment

The note holding cash outflows include the additional cash draws by the borrower and property taxes FHA paid for those borrowers who default on their T&I payments during their assignment period.

Additional cash draws by the borrowers can occur under the contract after FHA takes ownership of the note only if the total cash drawn by the borrower has not reached the maximum PL upon the assignment date.

Recoveries from Assigned Mortgages

At note termination for an assigned mortgage, the HECM is due and payable to FHA. The timing of mortgage terminations after assignment (when UPB reaches 98% of MCA) is projected with the termination model described in Appendix B. The amount of recovery of assigned mortgages at termination, can be expressed as:

$$\textbf{Recovery Amount} = \begin{cases} \boldsymbol{minimum\ (UPB, Net\ Property\ Sales\ Price)} & if\ terminated\ with\ \mathrm{death}\ or\ \mathrm{move}\ out \\ \boldsymbol{UPB} & if\ terminated\ with\ refinance \end{cases}$$

where the net sales price of the property is:

Net Property Sales Price = *Estimated Property Sales Price × (1 – sales expenses % – other expenses %)*

Net Future Cash Flows

The Cash Flow NPV for the HECM book of business is computed by summing the individual components as they occur over time:

$$\boldsymbol{Net\ Cash\ Flow_t} = Annual\ Premiums_t + Recoveries_t - Claim\ Type\ 1_t - Claim\ Type\ 2_t - Note\ Holding\ Expenses_t$$

Discount Factors

The discount factors applied were provided by FHA and reflect the most recent U.S. Treasury yield curve, which captures the Federal government's cost of capital in raising funds. These factors reflect the capital market's expectation of the consolidated interest risk of U.S. Treasury securities. RMA has relied on FHA for the discount factors and has not performed an independent analysis of the appropriateness of the discount factors. Our simulations aggregate each future quarter's cash flows, which are treated as being received at the end of the quarter.

Appendix F: Review of HUD Analysis of Economic Net Worth, Comparison of HUD and RMA Models, and Assessment of Vulnerabilities

Appendix F presents a high-level review of HUD models developed to project Economic Net Worth, compares the models developed by HUD with the models developed by RMA, and assesses the vulnerabilities of the models developed as well as developing potential areas of future research to address these vulnerabilities.

Deliverable 5 of the Actuarial Report states:

> ***To promote transparency of the Studies' assessments, the Studies should identify methodological vulnerabilities that may occur in its 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 shall 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.***

There are several different aspects of forecast risk that can arise in the projection of Economic Net Worth, including:

- Process risk - actual results varying from projected results due to variability in the mortgage insurance process
- Parameter risk - uncertainty related to the parameters selected for a given model
- Specification risk - uncertainty related to the type of model that is selected for a forecast

The following discussion comments on these various types of forecast risk.

HECM Budget Model Commentary

Summit-Milliman (S-M) has developed a series of models consisting of their HECM Model Schema.

Model Schema

The HECM Budget Model Schema consists of six different modules:

- Volume Demand
- Home Price Projection
- Unpaid Principal Balance Projection
- Claim & Recovery
- Termination
- Insurance Cash Flow

The Volume Demand Module is used to forecast FHA's endorsement volumes for future cohorts. This model only applies to the budget formulation and not the Liability of Loan Guarantee (LLG) calculation. The Home Price Projection Module is used to forecast property values and is used to estimate the home price at claim or termination of a HECM. The Unpaid Principal Balance Projection Module estimates the future unpaid loan balance for each loan.

The Claim & Recovery Module includes multiple components to address both the probability of a particular claim type as well as the value recovered. S-M identify two types of claims: Claim Type 1 (CT1) or a shortfall claim where a HECM terminates prior to assignment and the proceeds of the property sale are insufficient to cover the unpaid principal balance (UPB); and Claim Type 2 (CT2) where FHA purchased the loan from the lender due to the UPB reaching 98% of the maximum claim amount (MCA). They utilize use a logistic regression model to estimate the probability of CT1 versus a Non-Claim Termination (NClm). A separate logistic regression model estimates the probability of CT2 Conveyance (CT2c) versus a Payoff Termination. The recovery estimation models are used to estimate sales price at claim or termination. The CT1 and CT2c sales price model is developed using linear regression. The CT1 and CT2c sales expense assumption is developed based on historical expenses as a percentage of the home sales price.

The Termination Module consists of logistic models for separate termination types as part of the multinomial logistic model. Probabilities are estimated for each type (mortality termination, refinance termination and other termination – which is a combination of mobility terminations, and tax and insurance default terminations [T&I]). Mortality tables were used to determine mortality terminations separately by gender and age with a time lag between death and termination of the loan regardless of claim type applied based on a study of the data. This is a reasonable approach given the data available. S-M estimates the probabilities for refinance terminations and other terminations through a competing risks framework, utilizing binomial logistic regressions to estimate the probability of each loan terminating as a particular type each year. This is a reasonable approach given the data available.

Finally, the sixth module is the Insurance Cash Flow Module. Here, claim, premium, cash draw, and recovery inflows and outflows are projected and weighed using the different termination probabilities generated in the previously described models to produce the expected cash flows. This analysis is completed at the individual loan level. Once the projected cash flows are determined, they are discounted to present value to arrive at the final Cash Flow NPV estimates for the portfolio.

S-M uses an 80% training and 20% validation split of the data for model development. Also, S-M tested actual versus expected results from their models and evaluated C-Statistics, which is reasonable. S-M also reviewed the Gini statistic for some of the models.

S-M identified limitations of the HUD data which in some cases make it difficult to determine with certainty how a HECM terminates. As a result, S-M grouped several causes of termination together. This could be a source of vulnerability in this analysis. However, due to these data limitations, S-M applied a variety of techniques, such as identifying variable interactions, using industry mortality tables, and classifying data into various groups of termination types to maximize the value of the data available.

There have been several policy changes made to the HECM program in recent years, but it is not clear if or how well they are reflected in the HUD data. This is both a possible source of vulnerability and an area for future research. S-M employs methodologies to assess and help ensure data quality, including model testing/validation, and input/assumption consistency and sensitivity testing. These approaches are reasonable. Also, S-M HECM code directly pulls the Moody's and President's Economic Assumption inputs from the forward model development. This improves consistency and efficiency of the process, while reducing risk of error.

From the prior analysis, S-M implemented several model changes.

- S-M updated the Future Cash Draw Econometric Assumption to include the disbursement type.
- S-M made several updates to the splines based on a review of updated data.

Finally, S-M evaluated potential impacts on the HECM model results due to COVID-19. Initially, interim adjustments were made for potential borrower behavior changes including increased mortality rates, increased T&I defaults, and increased cash draws. These changes had very small effects on the models themselves. In addition, as recent data has emerged, S-M noted that they did not actually see changes in portfolio composition or borrower behavior. Also, they felt that any changes to mortality rates are too uncertain at this point to adjust. Therefore, no changes were made to the HECM models due to potential COVID-19 impacts. This is reasonable based on the information available.

Following are additional potential sources of vulnerabilities and future research.

- Sensitivity tests performed on Home Price Appraisal (HPA) and interest rate factors assumed independence of the factors. To the extent that these factors are not independent, this will affect the resulting Cash Flow NPV sensitivity.
- A potential area for future research is testing the two-year lookback for variables that use that period in a similar manner to what was done for Return on Properties.
- S-M selected the 2006 cohort due to volume and seasoning of data for performing back-testing of their model results. While this is not unreasonable, this could be a potential source of vulnerability if the results would change significantly by using different cohort years for back-testing. S-M also noted that most results within one coefficient of variation of the model's point estimate for recent years on several variables. S-M provided some rationale for variables outside these deviations.

- From 2017 through 2021 the maximum mortgage limit for HECMs increased at a relatively consistent rate, but the January 2022 increase was roughly triple the amount of the previous years (Table 46), both in raw dollars and in percent increase year over year. While this increase may be captured by changes in interest rates and increase in home values, it is also a potential source of vulnerability if it fundamentally changes the market that the models encompass. A potential area of future research is identifying the effect of these increases on the properties included.

Table 46: HECM loans changes from 2016 to 2022

Effective Date	Maximum Mortgage Limit	Dollar Increase Year over Year	Percent Increase Year over Year
December 2016	$636,150		
January 2018	$679,650	$43,500	6.84%
January 2019	$726,525	$46,875	6.90%
January 2020	$765,600	$39,075	5.38%
January 2021	$822,375	$56,775	7.42%
January 2022	$970,800	$148,425	18.05%

- Recovery rates for v2024 display a large increase from v2023 (Table 47). Both models rely on the most recent two years of data to capture trends, but this leaves the model susceptible to single year spikes potentially creating volatility in future models. A potential area of future research is identifying the effect of these trends and considerations regarding possible weighting of values over time to minimize volatility.

Table 47: Asset Return Comparison

Field	Return on Assets - v2023 01APR2019 – 31MAR2021	Return on Assets - v2024 01JAN2020–31DEC2021
MMI UPB	$32,727,941,292	$33,657,258,255
MMI Recovery Rate	75.69%	84.74%
GISRI UPB	$9,754,934,407	$10,083,774,043
GISRI Recovery Rate	69.17%	79.89%

RMA HECM Budget Model Commentary

The following illustrates some of the similarities and differences in methodologies for the HECM model development between the RMA analysis and the analysis performed by S-M.

Similar to the RMA forward model approach, mortgage-level transition (frequency) and loss severity models were developed for HECM. The models were developed on mortgage level data, as was done by S-M. The RMA models were built using a training/validation approach, similar to S-M's methodology. To validate the performance of the models, RMA compared the actual to predicted results: the predicted probability of each transition for the logistic models and the expected sales price for each sales price model. Deciles were used for this purpose. This same validation approach was used for the Cash Draw models.

The primary vulnerability in the models is the same general vulnerability in developing predictive models: the extent to which historical patterns between target and projections are indeed predictive. RMA has endeavored to address this potential vulnerability through a training and validation construct. We split the data into training and validation sets, similar to the approach that S-M used, which allowed us to build the model on the training set and then determine how well it generalizes to a different dataset with the validation.

Model Schema

The flow of the models used to determine the disposition of a HECM (the Termination Models) is as follows. There are many similarities to the HECM Budget Model Schema defined for the S-M analysis.

- Binomial logistic models were constructed to determine the probability of refinance or non-mortality termination ("other") for a living borrower. If neither event happens, the loan continues.
- If the loan is not assigned and UPB is greater than or equal to 98%, RMA simulates assignment based on assignment likelihoods. If the loan is assigned, then a CT2a status is applied and a CT2 loss occurs.

- If the loan does not terminate and is not assigned, then RMA determines if any borrowers die based on mortality tables.
- If mortality occurs, then run-off probabilities are used to determine if the loan terminates.
- If there is a non-mortality termination, there are two possible paths:
    - Assigned loans use a CT2c model to determine the probability the loan ends up in conveyance (CT2c termination) or repayment (CT2p termination).
    - Non-assigned loans use a CT1 model to determine if the loan is a CT1 termination or no claim (NClm termination).
- Also, RMA has developed CT1 and CT2c sales price models to estimate the sale price of the home and ultimately the potential loss to HUD.

The Cash Flow Draw Projection Models are used to estimate the future unscheduled cash draws associated with mortgages with a line of credit. This model is a binomial model to estimate likelihood of cash draw occurring in a period. If the model determines a cash draw occurs, then two separate logistic models are used to determine if the cash draw is a full draw. A GLM is then used to estimate the amount of the cash draw if it is not a full draw. S-M incorporates cash draws in their calculation but does not develop models for cash draws. RMA also develops a T&I default model which S-M also incorporates into the other termination model.

Finally, the Cash Flow Analysis is completed. Based on specific characteristics of the mortgage, the probability of each termination is calculated. The derived mortgage variables are independent variables to the multinomial logistic termination models in the Base Termination Model. A random number is generated and used in comparison to the model probabilities to determine the projected mortgage transition. This projection process continues for each mortgage until the mortgage ends by termination or claim.

The Net Cash Flow is defined as

$$\text{Net Cash Flow}_t = \text{Annual Premiums}_t + \text{Recoveries}_t - \text{Claim Type } 1_t - \text{Claim Type } 2_t - \text{Note Holding Expenses}_t$$

Annual Premiums are defined to include both Upfront MIP and Annual MIP. Note Holding Expenses include post-assignment cash draws and payments made by FHA borrowers who default on their T&I payments during their assignment period.

This is consistent with the HUD formula which is

Net Cash Flow = Upfront Premium + Annual Premium - CT1 - CT2 - Post-assignment Cash Draws + Recovery - Post-Conveyance Expense

To bring the cash flows to present value, RMA used discount factors provided by FHA.

Cash Flow projections were generated for the OMB Economic Assumptions, 10 Moody's scenarios and 100 randomly generated stochastic simulations of key economic variables. The projections were used to develop a range of reasonable Cash Flow NPV projections. S-M and RMA utilized Moody's data on a state and MSA levels, when possible, to provide for a greater reflection of differences in home prices, etc. across the country.

Simulation

RMA ultimately utilized 100 economic scenarios generated by stochastic simulation to determine the range of cash flow NPV estimates. The HUD process used 10,000 simulations of key target variables using a Monte Carlo approach. This represents a key difference in the development of the range of results.

RMA used ARMA and GARCH models to simulate various interest rates, HPA, unemployment rates, and GDP. Akaike Information Criterion (AIC) and/or Pearson's Goodness-of-Fit test were used to determine best fitting time series models to include in the simulation.

Appendix G: Summary of Historical and Projected Claim Rates and Loss Severities

The following incremental annual summaries are shown by cohort for Claim Type 1 and Claim Type 2 in the below attached pdf file.

1. **Claim Rate**: number of claims divided by the number of originations for the cohort
2. **Loss Severity**: net loss paid divided by the MCA for the cohort

HECM Triangle Report - 2022Q4.pdf