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November 12, 2020

The Honorable Dana T. Wade
Assistant Secretary for Housing and Federal Housing Commissioner
U.S. Department of Housing and Urban Development
451 Seventh Street, S.W., Room 9100
Washington, D.C. 20410

Dear Commissioner Wade:

Pinnacle Actuarial Resources, Inc. (Pinnacle) has completed the final report for the Fiscal Year 2020 Independent Actuarial Review of the Mutual Mortgage Insurance Fund HECM loans. The attached report details our estimate of the Cash Flow Net Present Value for Fiscal Year 2020 using data as of September 30, 2020.

Roosevelt C. Mosley, Jr., FCAS, MAAA is responsible for the content and conclusions set forth in the report. I am a Fellow of the Casualty Actuarial Society and a member of the American Academy of Actuaries, and am qualified to render the actuarial opinion contained herein.

It has been a pleasure working with you and your team to complete this study. I am available for any questions or comments you have regarding this report and its conclusions.

Respectfully Submitted,

Roosevelt Mosley

Roosevelt C. Mosley, Jr. FCAS, MAAA, CSPA
Principal and Consulting Actuary

Fiscal Year 2020 Independent Actuarial Review of the Mutual Mortgage Insurance Fund: Economic Net Worth from Home Equity Conversion Mortgage Insurance-In-Force

Final Report Based on Data as of September 30, 2020

November 12, 2020

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Fiscal Year 2020 Independent Actuarial Review of the Mutual Mortgage Insurance Fund: Economic Net Worth from Home Equity Conversion Mortgage Insurance-In-Force

Summary of Findings

This report presents the results of Pinnacle Actuarial Resources, Inc.'s (Pinnacle's) independent actuarial review of the Economic Net Worth associated with Home Equity Conversion Mortgages (HECMs) insured by the Mutual Mortgage Insurance Fund (MMI) for Fiscal Year 2020. 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 HECMs 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 2020, Pinnacle's Actuarial Central Estimate (ACE) of the MMI HECM Cash Flow NPV is negative $329 million.

The total capital resource as reported in the Annual Report to Congress Regarding the Status of the FHA Mutual Mortgage Insurance Fund is positive $1.597 billion at the end of Fiscal Year 2020. Thus, the estimated Economic Net Worth of the MMI is positive $1.268 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 and credit subsidy cohort are shown 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	3,830,697,000
Claim Type 1 Loss Incurred	2,349,272,446
Claim Type 2 Loss Incurred	23,461,996,440
Claim Type 2c Recovery	1,350,997,973
Claim Type 2p Recovery	20,912,418,478
Note Holding Expense	612,329,359

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 Projection 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 change 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.

Pinnacle's ACE of Cash Flow NPV is based on the Economic Assumption for the 2020 Mid-Session Review from the Office of Management and Budget (OMB Economic Assumptions). Pinnacle 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 2020 Cash Flow NPV**
Pinnacle ACE	-329,484,795
Baseline	2,380,288,639
Alternative 0 – Upside (4th Percentile)	3,567,078,652
Alternative 1 – Upside (10th Percentile)	2,901,270,868
Alternative 2 – Downside (75th Percentile)	2,124,990,313
Alternative 3 – Downside (90th Percentile)	1,721,282,591
Alternative 4 – Downside (96th Percentile)	788,437,272
Slower Trend Growth	1,915,848,541
Stagflation	1,438,817,402
Next-Cycle Recession	2,150,879,681
Low Oil Price	2,261,135,045

The range of results based on Moody's economic scenarios is negative $329 million to positive $3.567 billion.

In addition, Pinnacle 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 $16.496 billion to positive $1.809 billion.

The Cash Flow NPV estimate provided by FHA to be used in the FHA's Annual Report to Congress is negative $2.089 billion. Based on Pinnacle's ACE and range of reasonable estimates, we conclude that the FHA estimate of Cash Flow NPV is reasonable.

Pinnacle's Cash Flow NPV by cohort is shown below 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

	Cash Flow NPV		
Cohort	**Largest Negative**	**Largest Positive**	**Pinnacle ACE**
2009	-2,217,630,930	-559,419,692	-738,439,394
2010	-756,063,081	-38,560,628	-171,800,692
2011	-567,139,800	42,546,483	-55,790,166
2012	-492,989,719	24,990,057	-57,465,300
2013	-978,149,134	48,546,843	-133,392,672
2014	-1,220,336,869	267,327,939	79,484,746
2015	-1,575,302,370	471,396,492	228,371,397
2016	-1,819,262,487	732,339,283	432,597,500
2017	-2,573,013,809	721,075,113	349,778,405
2018	-1,770,221,862	55,440,441	-129,899,052
2019	-725,402,425	49,313,702	-3,471,884
2020	-1,800,768,654	-6,016,774	-129,457,683
Total	-16,496,281,140	1,808,979,259	-329,484,795

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.

Pinnacle 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, additional economic assumptions were generated 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. HECMs 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 no less than 2.0%. The capital ratio is defined by NAHA as the ratio of capital plus Cash Flow NPV to unamortized insurance-in-force (IIF). NAHA also implemented the requirement that an independent actuarial study of the MMI be completed annually. 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 Fiscal Year 2009 and later.

Pinnacle projects that, as of the end of Fiscal Year 2020, the HECM Cash Flow NPV is negative $329 million. The total capital resource as reported in the Annual Report to Congress Regarding the Status of the FHA Mutual Mortgage Insurance Fund is positive $1.597 billion at the end of Fiscal Year 2020. Thus, the estimated Economic Net Worth of the MMI is positive $1.268 billion.

To project the Cash Flow NPV, Pinnacle analyzed all HECM historical terminations and associated recoveries using mortgage-level HECM performance data provided by FHA through September 30, 2020. 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 2020 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:

- 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 and 1-year London Interbank Offered

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

Rate (LIBOR): 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 in 2021, the LIBOR rate will be discontinued. As a result, a new index will be identified to replace LIBOR as an index for adjustable mortgages. HECM projections for these loans use LIBOR projections, but these projections will change in 2021. We expect that the replacement index for LIBOR loans will follow a similar projection plan.

- 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 $788 million to positive $3.567 billion.

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

Economic Scenario	Fiscal Year 2020 Cash Flow NPV
Pinnacle ACE	-329,484,795
Baseline	2,380,288,639
Alternative 0 – Upside (4th Percentile)	3,567,078,652
Alternative 1 – Upside (10th Percentile)	2,901,270,868
Alternative 2 – Downside (75th Percentile)	2,124,990,313
Alternative 3 – Downside (90th Percentile)	1,721,282,591
Alternative 4 – Downside (96th Percentile)	788,437,272
Slower Trend Growth	1,915,848,541
Stagflation	1,438,817,402
Next-Cycle Recession	2,150,879,681
Low Oil Price	2,261,135,045

The Moody's scenario that produces the highest HECM Cash Flow NPV is the Alternative 0 – Upside (4th Percentile) scenario. The Alternative 4 – Downside (96th 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 $16.496 billion to positive $1.809 billion.

Distribution and Use

This report is being provided to the Federal Housing Administration (FHA) for their use and the use of makers of public policy 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. Pinnacle 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 Pinnacle to the third party.

Our conclusions are predicated on a number of assumptions as to future conditions and events. These assumptions, which are documented in this report, must be understood in order 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 Pinnacle 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, 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 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 that the historical data used to develop our estimates may not be predictive of future default and loss experience. 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 emergence of the COVID-19 pandemic in 2020. 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. The COVID-19 pandemic may have a material impact on our Cash Flow NPV estimates as its effects emerge.

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 a number of individual mortgage characteristics and economic variables. The parameters of the predictive models are estimated over a wide variety of mortgages that originated since 1989 and their performance under the range of economic conditions and mortgage market environments experienced. 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 Fiscal Year 2009 and later, as this is when the HECM mortgages were added to the MMI.

Pinnacle 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 Pinnacle 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, 2020 using data through September 30, 2020.

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 7.96 million forward mortgages and 434,938 HECMs in the MMI.

Per 12 USC 1711-(f), the FHA must ensure that 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 actuarial central estimates (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 Federal Credit Reform Act discounting assumptions and procedures.

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 over 1.1 million reverse mortgages. 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 and
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 as long as 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 it 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 is greater than 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 conceptually to the loan-to-value (LTV) ratio applied to a traditional mortgage. For a HECM, 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 grows at a rate equal to the sum of the mortgage interest, the Mortgage Insurance Premium (MIP) and the servicing fees. Borrowers can continue to draw cash as long as 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 course of the mortgage as long as they have not exhausted

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

their PL. The payment plans are:

- Tenure plan: a fixed monthly cash payment as long as 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; and
- 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 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 as long as 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 2020. It also provides a step-by-step analysis of changes from last year's Review.

- **Section 3. Characteristics of MMI HECMs** – presents various characteristics of HECM endorsements for Fiscal Years 2009 through 2020.

- **Section 4. HECM 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** – provides a description of 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: Cash Flow Draw Projection Models** – provides a description of 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 Pinnacle 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 Pinnacle, and assessment of the vulnerabilities of the models developed.

- **Appendix G: Summary of Historical and Projected Claim Rates, Non-Claim Termination Rates and Loss Severities**

Section 2. Summary of Findings

This section presents the projected HECM Economic Net Worth for Fiscal Year 2020. This review covers mortgages that were endorsed in Fiscal Year 2009 and subsequent and are still in force as of the end of Fiscal Year 2020. Data through September 30, 2020 was used to estimate the Cash Flow NPV.

Fiscal Year 2020 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 negative $329 million as of the end of Fiscal Year 2020. This estimate is the result of the cash flow projections based on the 2021 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 $1.597 billion as of September 30, 2020. Thus, the Actuarial Central Estimate (ACE) of the Economic Net Worth of the MMI is positive $1.268 billion.

According to Cranston-Gonzalez National Affordable Housing Act (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, 2020. 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 ($ Millions)	Insurance-In-Force ($ Millions)
2009	-738	7,873
2010	-172	3,083
2011	-56	2,861
2012	-57	2,221
2013	-133	3,711
2014	79	5,242
2015	228	6,402
2016	433	6,235
2017	350	8,041
2018	-130	6,333
2019	-3	3,893
2020	-129	6,750
Total	-329	62,645

The Pinnacle Cash Flow NPV estimate compared to the FHA estimate by cohort is shown below.

Table 6: Comparison of Cash Flow NPV by Cohort

	Cash Flow NPV		
Cohort	**Pinnacle**	**FHA**	**Difference**
2009	-738	-2,243	1,504
2010	-172	-717	545
2011	-56	-484	428
2012	-57	-321	263
2013	-133	-401	267
2014	79	-97	176
2015	228	229	-1
2016	433	723	-291
2017	350	767	-417
2018	-130	302	-431
2019	-3	115	-119
2020	-129	37	-166
Total	-329	-2,089	1,760

The difference between the Pinnacle and FHA estimate is $1.760 billion, which is 2.8% of the HECM IIF. The Pinnacle estimates of Cash Flow NPV by cohort are lower (more negative) than the FHA estimates for cohort 2015 and later, and are higher (less negative) 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 2019 and the current estimate. The present value of future cash flows of the current book of business is estimated to be negative $329 million.

Table 7: Estimate of Cash Flow NPV as of the end of Fiscal Year 2020 ($ in millions)

Item	**2019**	**2020**	**Dollar Difference**	**Percent Change**
Cash Flow NPV	-11,228	-329	10,899	97.1%
Capital Resources	1,694	1,597	-97	-5.7%
Economic Net Worth	-9,534	1,268	10,802	113.3%
Insurance-In-Force	64,212	62,645	-1,567	-2.4%

As seen in Table 7, the estimated Fiscal Year 2020 Cash Flow NPV has increased by $10.90 billion from the level estimated in Fiscal Year 2019, from -$11.23 billion to -$329 million. The unamortized IIF decreased from $64.21 billion to $62.65 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 2019 Review to the Fiscal Year 2020 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 2020 as compared to the Cash Flow NPV in the Fiscal Year 2019 Actuarial Review. The overall net change in the Cash Flow NPV is favorable.

Table 8: Changes in Projected Cash Flow NPV ($ in Millions)

	Change in NPV	Cash Flow NPV - 9/30/19
Baseline FY2009-FY2019		-11,228,067,911
Impact of assumption change	2,588,383,609	-8,639,684,302
Impact of model change	8,349,623,690	-290,060,612
Impact of book change	90,033,500	-200,027,112
FY2009-FY2019	11,028,040,799	
FY2020	-129,457,683	-329,484,795
Cumulative Change	10,898,583,116	

This section describes the sources of change in estimates of Cash Flow NPV between the 2020 Actuarial Review and the 2019 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 2019 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 2020 President's Economic Assumptions (PEA) forecast to the 2021 PEA forecast. In addition to the change in the projected economic forecast, we have also updated the previous projected economic forecasts for the fourth quarter of 2019 through the third quarter of 2020 with actual economic data. The net impact of these changes is an increase of $2.588 billion in the projected Cash Flow NPV.

Update Predictive Models

In Fiscal Year 2020, 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. In addition to the re-estimation of the model parameters, we have also incorporated an adjustment for appraisal inflation. Based on research by FHA, historical HECM appraisal information captured in the database was determined to be inflated based on independent appraisal information. This issue has been addressed by incorporating additional appraisal requirements to ensure that property values are not inflated, and thus the property values used in the HECM simulation incorporate this adjustment. See the HECM Base Termination Model appendix (Appendix B) and HECM Cash Flow Draw Models appendix (Appendix C).

These model changes led to a increase in estimated economic value in the Cash Flow NPV of $8.350 billion.

Actual Performance of Fiscal Year 2019 to Fiscal Year 2020

The actual performance of the MMI for cohorts 2009 – 2019 realized during Fiscal Year 2020 affects the Cash Flow NPV of the MMI estimate of the in-force portfolio. The actual experience for this period was $90 million better than expected.

Fiscal Year 2020 Origination Volume

The addition of the origination volume for the Fiscal Year 2020 book of business decreased the Cash Flow NPV projection by $129 million.

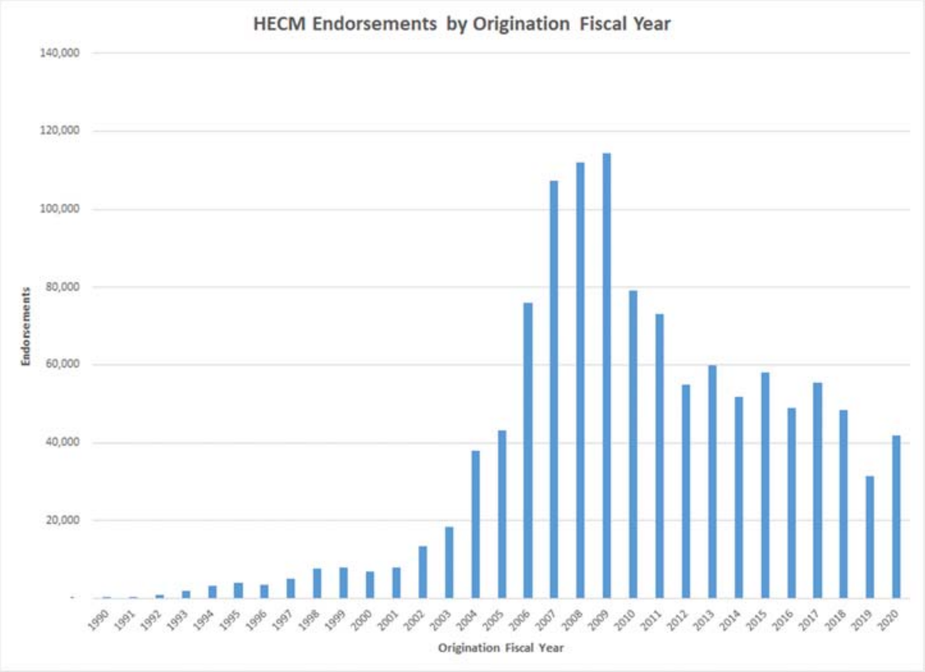
Section 3. Characteristics of HECM Fund Endorsements

This section presents the characteristics of the HECM portfolio for the HECM loans endorsed from Fiscal Year 2009 through Fiscal Year 2020. 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 2020. 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 41,819 HECM loans in Fiscal Year 2020, with a total MCA of $16.282 billion. This is a 33.7% increase from Fiscal Year 2019 in the number of loans endorsed, and a 49.9% increase in the MCA of loans endorsed. The total number of endorsements for Fiscal Years 2009 to 2020 was 716,516. The corresponding MCA was $202.539 billion. Since the inception of the HECM program, this program has been the largest reverse mortgage product in the U.S. market, representing the vast majority of 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

Origination Year	Term	Line of Credit	Tenure	Term Plus Line of Credit	Tenure Plus Line of Credit
2009	0.8%	91.8%	1.5%	3.8%	2.1%
2010	0.5%	94.3%	0.9%	2.8%	1.6%
2011	0.4%	94.5%	0.9%	2.8%	1.5%
2012	0.3%	94.8%	0.8%	2.6%	1.4%
2013	0.4%	95.0%	0.9%	2.4%	1.3%
2014	0.7%	93.4%	1.4%	2.9%	1.6%
2015	0.6%	93.8%	1.1%	2.8%	1.7%
2016	0.7%	93.5%	1.1%	3.0%	1.7%
2017	0.6%	93.5%	1.1%	3.0%	1.9%
2018	0.7%	94.0%	0.9%	2.8%	1.7%
2019	0.7%	94.6%	0.9%	2.4%	1.4%
2020	0.6%	95.7%	0.5%	2.1%	1.1%

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. Subsequent to this, 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 has dropped to less than 2% of the HECM loans originated.

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 has increased to over 98%. Monthly adjustable LIBOR loans were more popular in Fiscal Year 2014 and 2015; however, in Fiscal Years 2016 – 2020, 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 will be discontinued. As a result, a new index will be identified to replace LIBOR as an index for adjustable mortgages. HECM projections for these loans use LIBOR projections, but these projections will change in 2021. We expect that the replacement index for LIBOR loans will follow a similar projection plan.

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%	0.02%	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	93.73%	0.22%	0.01%	0.00%	6.05%
2020	98.36%	0.10%	0.11%	0.03%	1.40%

Product Type

Almost all the loans endorsed in Fiscal Years 2009 through 2020 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 decreased in 2020. 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 HECMs	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%	0.04%	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	93.89%	0.43%	5.68%

State

Among all endorsements in Fiscal Years 2014 through 2020, over half were originated in the top 10 states as measured by loan counts. 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 Texas increased from Fiscal Year 2009 to Fiscal Year 2011, and has decreased since then. The endorsement volume in Colorado has increased from 1.8% in Fiscal Year 2009 to 7.1% in Fiscal Year 2020, and now is the third largest state. The endorsement breakdown of the top 10 states is shown in Table 12.

Table 12: Distribution of HECM Loans by State

State	Origination Year											
	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
California	13.7%	14.0%	13.5%	12.7%	14.1%	17.5%	20.3%	21.8%	23.7%	22.7%	21.1%	24.1%
Florida	13.2%	9.0%	6.8%	6.1%	6.5%	6.9%	8.3%	8.8%	8.7%	8.4%	8.6%	8.3%
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%
Texas	6.6%	8.0%	9.1%	8.9%	8.6%	7.4%	7.0%	7.6%	7.6%	7.4%	7.4%	6.5%
Arizona	3.1%	2.1%	2.0%	1.8%	2.4%	2.9%	3.2%	3.6%	3.7%	4.0%	4.8%	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%	4.5%
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%
New York	5.3%	5.9%	5.9%	7.2%	6.4%	5.9%	5.7%	4.8%	4.2%	3.8%	4.0%	3.0%
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%
North Carolina	1.8%	2.0%	2.6%	2.8%	3.1%	2.6%	2.4%	2.5%	2.3%	2.5%	2.5%	2.4%

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 as 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 43% for Fiscal Year 2020.

The percentage of endorsements with an MCA greater than $300,000 and less than or equal to $417,000 dropped from 23.3% in 2009 and had been around 12% - 13% percent for Fiscal Years 2010 through 2014, but has since risen to 20.5% in 2020. The percentage of endorsements with an MCA greater than $417,000 has increased consistently since 2012, and now is at 36.5%.

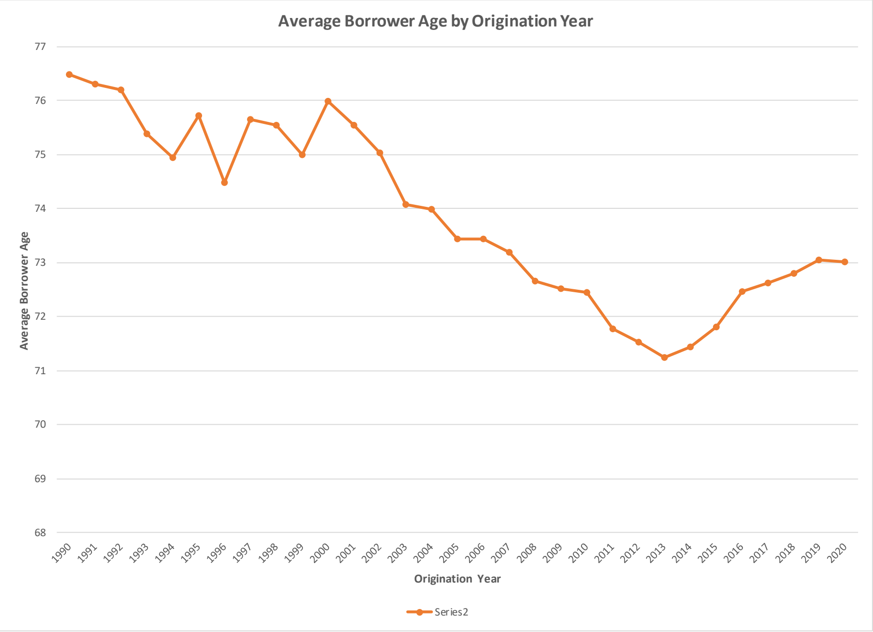
Table 13: Distribution of HECM Loans by MCA

Origination Year	Less Than $100K	$100K to $200K	$200K to $300K	$300K to $417K	Greater Than $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%	21.8%	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	2.1%	17.3%	23.7%	20.5%	36.5%

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 2020. 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 just over 73 years old in Fiscal Year 2020.

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 36% while single males remains the lowest at 20%. The concentration in couples rose to 41% in 2016, decreased to 39% in 2019, but has increased in 2020 to 40%. Compared to Fiscal Year 2019, missing genders has increased by almost three percentage points in 2020 to 4.8%.

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%	41.86%	35.25%	1.41%
2011	20.86%	40.25%	37.07%	1.80%
2012	21.21%	39.16%	37.35%	2.28%
2013	21.14%	37.56%	38.95%	2.34%
2014	20.63%	38.73%	38.65%	1.99%
2015	21.86%	38.52%	38.91%	0.71%
2016	21.64%	36.81%	41.04%	0.51%
2017	20.93%	37.13%	40.91%	1.03%
2018	20.69%	36.68%	40.18%	2.45%
2019	21.13%	38.10%	38.78%	1.99%
2020	19.91%	35.56%	39.77%	4.76%

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 shows 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. In Fiscal Year 2020, however, this percentage increased to 56%.

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 – 2014)

Origination Year	Age Group	Variable Rate Loans			Fixed Rate Loans	
		0-40%	40-60%	60-100%	0-60%	60-100%
2009	62-65	11.77%	9.81%	65.02%	0.19%	13.21%
	66-70	14.15%	10.68%	62.08%	0.09%	13.01%
	71-75	18.63%	11.32%	58.67%	0.01%	11.36%
	76-85	24.67%	11.90%	53.48%	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%	9.89%	0.13%	75.68%
	71-75	13.30%	6.47%	10.95%	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%	0.26%	76.21%
	66-70	10.60%	5.86%	9.67%	0.17%	73.70%
	71-75	15.15%	6.51%	10.25%	0.13%	67.96%
	76-85	22.49%	8.05%	11.01%	0.13%	58.32%
	86+	36.65%	7.91%	11.15%	0.07%	44.22%
	Total	15.26%	6.42%	10.29%	0.17%	67.86%
2012	62-65	8.58%	5.35%	10.78%	0.14%	75.16%
	66-70	10.83%	5.56%	9.49%	0.10%	74.02%
	71-75	14.18%	6.47%	9.54%	0.07%	69.74%
	76-85	20.68%	7.13%	10.05%	0.13%	62.00%
	86+	33.99%	7.97%	10.15%	0.24%	47.65%
	Total	14.39%	6.16%	10.03%	0.12%	69.29%
2013	62-65	8.13%	5.70%	20.96%	0.32%	64.89%
	66-70	9.68%	5.87%	20.70%	0.32%	63.43%
	71-75	13.43%	6.43%	19.40%	0.35%	60.40%
	76-85	19.34%	7.04%	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%	2.04%	20.67%
	66-70	15.15%	25.09%	39.03%	1.95%	18.79%
	71-75	18.81%	25.80%	37.35%	1.94%	16.11%
	76-85	24.69%	26.35%	34.79%	2.11%	12.06%
	86+	36.77%	27.33%	26.56%	2.51%	6.83%
	Total	18.38%	26.11%	36.84%	2.04%	16.64%

Table 16: First-Month Cash Draw as a Percentage of Initial PL (2015 – 2020)

Origination Year	Age Group	Variable Rate Loans			Fixed Rate Loans	
		0-40%	40-60%	60-100%	0-60%	60-100%
2015	62-65	12.71%	38.00%	30.64%	0.67%	17.98%
	66-70	14.57%	35.34%	31.69%	0.60%	17.80%
	71-75	18.03%	34.07%	31.81%	0.55%	15.54%
	76-85	23.60%	35.00%	29.73%	0.66%	11.01%
	86+	33.99%	36.04%	23.29%	1.10%	5.58%
	Total	18.04%	35.71%	30.50%	0.65%	15.10%
2016	62-65	16.76%	36.76%	32.66%	0.81%	13.01%
	66-70	18.02%	33.15%	35.73%	0.49%	12.62%
	71-75	19.11%	32.63%	37.19%	0.25%	10.81%
	76-85	24.21%	33.40%	35.41%	0.40%	6.57%
	86+	34.90%	34.78%	27.02%	0.66%	2.63%
	Total	20.65%	33.96%	34.74%	0.50%	10.15%
2017	62-65	17.78%	34.13%	34.75%	0.98%	12.36%
	66-70	16.75%	30.27%	40.29%	0.47%	12.21%
	71-75	19.07%	28.85%	41.38%	0.43%	10.27%
	76-85	21.88%	30.74%	40.26%	0.40%	6.71%
	86+	32.28%	33.79%	30.81%	0.41%	2.71%
	Total	19.78%	31.07%	38.80%	0.54%	9.81%
2018	62-65	18.39%	33.56%	35.87%	0.69%	11.49%
	66-70	17.12%	29.31%	40.63%	0.53%	12.40%
	71-75	19.86%	28.64%	41.09%	0.31%	10.08%
	76-85	22.05%	31.11%	39.46%	0.42%	6.97%
	86+	32.82%	33.21%	30.63%	0.33%	3.00%
	Total	20.32%	30.69%	38.84%	0.47%	9.67%
2019	62-65	17.86%	32.03%	42.84%	0.41%	6.85%
	66-70	17.27%	28.91%	46.85%	0.20%	6.76%
	71-75	19.98%	28.62%	44.76%	0.18%	6.46%
	76-85	24.00%	31.83%	39.41%	0.31%	4.45%
	86+	33.93%	32.91%	30.45%	0.64%	2.08%
	Total	21.02%	30.47%	42.47%	0.29%	5.75%
2020	62-65	16.68%	26.88%	54.89%	0.08%	1.47%
	66-70	14.79%	24.63%	58.63%	0.09%	1.85%
	71-75	15.39%	24.92%	58.57%	0.07%	1.04%
	76-85	19.35%	27.36%	52.12%	0.16%	1.01%
	86+	32.05%	30.56%	36.62%	0.41%	0.36%
	Total	17.62%	26.21%	54.78%	0.12%	1.26%

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 2019 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 17. Below, we discuss the characteristics of each Moody's scenario.

Baseline Scenario

In the Baseline scenario, the HPI is flat through the third quarter of 2021, and then increases over the remainder of the projection period. The rate of increase is about 5% per year through 2030, and then decreases to about 3% per year for the remainder of the projection period. The mortgage interest rate decreases to about 3% through the second quarter of 2021 and then increases for the remainder of the projection period. The mortgage rate levels off at approximately 5.5% by 2026. The unemployment rate is projected to decrease through 2023 to approximately 4.5%, and then remain steady at that level for the remainder of the projection period. Under this scenario, it is projected that it will take approximately three years for unemployment to fully return to more stable levels, and it is projected to stabilize at a level higher than pre-COVID-19 unemployment levels.

Alternative Scenario 0 – Upside (4th Percentile)

In the Alternative Scenario 0 – Upside (4th Percentile), the HPI is projected to increase throughout the entire projection period. The rate of increase is about 5% per year through 2030, and then decreases to about 3% per year for the remainder of the projection period. The mortgage interest rate increases for the entire projection period, leveling off at approximately 5.5% by 2026. The unemployment rate is projected to decrease through 2023 to approximately 3.6%, and then increase gradually until it stabilizes in the range of 4.5% - 4.8%. Under this scenario, unemployment recovers to better than pre-COVID-19 levels over the next three years.

Alternative Scenario 1 – Upside (10th Percentile)

In the Alternative Scenario 1 – Upside (10th Percentile), the HPI is projected to increase throughout the entire projection period. The rate of increase gradually increases from 1.5% per year in the third quarter of 2021 to 5% per year by the fourth quarter of 2022. The rate remains at 5% per year through 2030, and then decreases to about 3% per year for the remainder of the projection period. The mortgage interest rate increases for the entire projection period, leveling off at approximately 5.5% by 2026. The unemployment rate is projected to decrease through 2023 to approximately 3.8%, and then increase gradually until it stabilizes in the range of 4.5% - 4.8%. Under this scenario, unemployment recovers to pre-COVID-19 levels over the next three years.

Alternative Scenario 2 – Downside (75th Percentile)

In the Alternative Scenario 2 – Downside (75th Percentile), the HPI decreases through the second quarter of 2021, and then increases throughout the remainder of the projection period. Mortgage interest rates are projected to decrease through the second quarter of 2021, and then increase through 2027. Mortgage rates level off for the remainder of the projection period at approximately 5.5%. The unemployment rate is projected to decrease slowly to 4.8% by 2026. Under this scenario, the recovery in the unemployment rate occurs over a longer period, and is projected to stabilize at a level higher than pre-COVID-19 unemployment levels.

Alternative Scenario 3 – Downside (90th Percentile)

In the Alternative Scenario 3 – Downside (90th Percentile), the HPI decreases through the second quarter of 2021, and then begins to increase. Mortgage interest rates drop significantly through the second quarter of 2021, and then begin to increase until they reach the long-term average of about 5.6%. The unemployment rate decreases to 10.4% in the third quarter of 2020, then increases to 12% in 2021. The unemployment rate then begins to decrease to 5% by the end of 2025. Under this scenario, the recovery in the unemployment rate occurs over a longer period, and is projected to stabilize at a level higher than pre-COVID-19 unemployment levels.

Alternative Scenario 4 – Downside (96th Percentile)

In the Alternative Scenario 4 – Downside (96th Percentile), the HPI decreases through the third quarter of 2021, and then begins to increase. Mortgage interest rates drop through the second quarter of 2021, and then begin to slowly increase until they reach the long-term average of 5.5% in 2029. The unemployment rate spikes to 13% by 2022, and then decreases to 5% by 2030. Under this scenario, the recovery in the unemployment rate occurs over a longer period, and is projected to stabilize at a level higher than pre-COVID-19 unemployment levels.

Slower Trend Growth

In the Slower Trend Growth scenario, the HPI increases more slowly than in the Baseline scenario. Mortgage interest rates decrease to 2.7% by the second quarter of 2021, and then settle at a long-term average of 5.2%. The unemployment rate is stable at 10.3% and then begins to decrease to 5.1% by 2026. Under this scenario, the recovery in the unemployment rate occurs over a longer period, and is projected to stabilize at a level higher than pre-COVID-19 unemployment levels.

Stagflation

In the Stagflation scenario, the HPI decreases through the end of 2021, and then begins to increase. Mortgage interest rates increase to 3.5% by the end of 2020, and then drop through the third quarter of 2021. Mortgage interest rates then begin to increase to the long-term average of 5.5%. Unemployment rates decrease to 10% by the end of 2020, and then increase to 11.5% by the end of 2021. Unemployment rates then decrease to a long-term average of 5.1% by 2025.

Next-Cycle Recession

In the Next-Cycle Recession scenario, the HPI increases through the third quarter of 2022, and then decreases significantly through the fourth quarter of 2023. The HPI then increases for the remainder of the projection period. The mortgage interest rates increase through the third quarter of 2022, and then decrease through the third quarter of 2023. The rates then settle in at a long-term average of about 5.5%. The unemployment rate is equal to the Baseline assumptions through the second quarter of 2022, and then increases to 8% through the third quarter of 2023. The rate then decreases to 4.8% by 2028, where it remains for the remainder of the projection period.

Low Oil Price

In the Low Oil Price scenario, the HPI increases throughout the entire projection period, similar to the Baseline scenario. Mortgage interest rates decrease to 2.6% by the second quarter of 2021, and then increase to 5.8% by 2027. The mortgage rate then decreases gradually through the remainder of the projection period. Unemployment rates decrease through the fourth quarter of 2023, and then increase gradually to a long-term average of 4.8% - 5.0%.

Summary of Alternative Scenarios

Table 17 shows the projected Cash Flow NPV from the ten deterministic scenarios and Pinnacle's ACE. The range of projected results is between negative $329 million and positive $3.567 billion.

Table 17: Cash Flow NPV Summaries from Alternative Scenarios

Cohort	Pinnacle 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	-738,439,394	-442,858,356	-225,277,903	-346,609,905	-489,553,365	-584,021,976	-741,975,211	-500,931,970	-665,384,156	-526,194,530	-464,641,716
2010	-171,800,692	-58,443,139	35,712,222	-23,947,698	-91,297,921	-136,809,749	-213,977,913	-95,050,266	-154,265,473	-105,579,165	-69,911,324
2011	-55,790,166	35,779,045	101,980,614	51,273,767	7,297,699	-30,026,949	-92,323,677	-7,487,314	-50,081,204	-4,626,724	12,959,031
2012	-57,465,300	12,799,458	95,583,221	49,586,325	6,210,399	-12,232,423	-72,576,298	-4,723,530	-36,170,903	3,062,896	19,218,800
2013	-133,392,672	42,759,505	171,700,760	108,409,064	26,328,864	-18,122,521	-106,980,173	16,345,311	-50,088,736	15,287,662	37,516,728
2014	79,484,746	310,494,180	414,349,579	362,453,624	298,221,880	269,256,880	188,343,517	263,394,489	241,327,848	295,095,004	310,163,346
2015	228,371,397	536,160,316	643,074,709	582,768,521	524,940,420	475,253,376	403,865,371	489,848,499	475,723,141	531,924,006	522,616,030
2016	432,597,500	817,634,382	928,518,629	870,092,666	797,291,592	768,489,100	661,108,213	746,586,829	751,466,225	828,524,031	795,338,052
2017	349,778,405	862,414,163	1,013,187,252	927,261,644	799,240,179	756,792,265	618,185,463	786,649,535	730,460,013	837,335,995	848,616,991
2018	-129,899,052	110,683,311	172,309,660	138,535,476	97,370,353	82,462,256	18,890,102	83,876,159	57,782,852	105,738,602	99,603,690
2019	-3,471,884	73,222,567	84,319,825	76,925,582	73,519,990	77,291,368	76,366,463	69,533,086	80,659,717	81,612,058	73,501,772
2020	-129,457,683	79,643,207	131,620,084	104,521,802	75,420,223	72,950,964	49,511,415	67,807,713	57,388,078	88,699,846	76,153,645
Total	-329,484,795	2,380,288,639	3,567,078,652	2,901,270,868	2,124,990,313	1,721,282,591	788,437,272	1,915,848,541	1,438,817,402	2,150,879,681	2,261,135,045

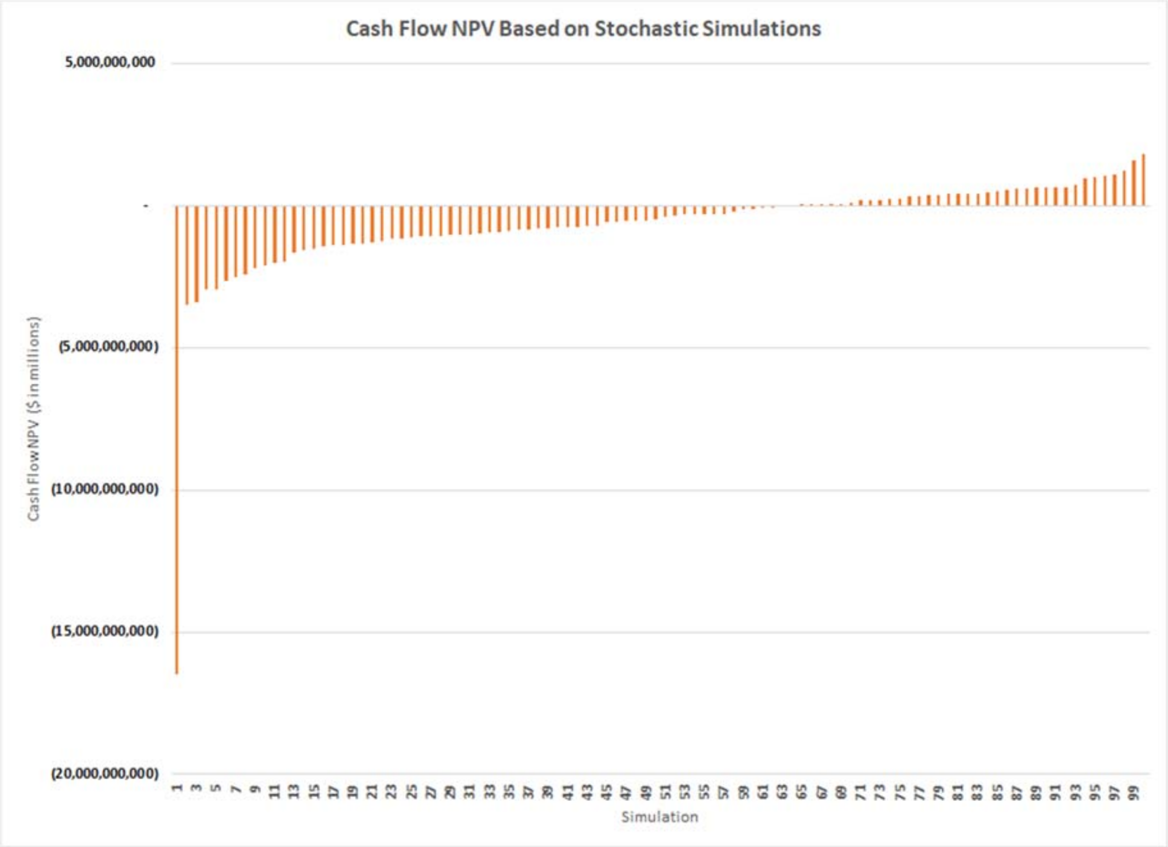
The Pinnacle ACE is based on the PEA, which were developed in 2019 prior to the impacts of COVID-19 on the economy. The Moody's projections incorporate the effects of COVID-19. This has the effect of assuming an immediate economic recovery for the PEA, whereas the Moody's scenarios project an economic recovery over a longer period. As a result, the NPV projection based on the PEA is significantly different than the Moody's Baseline projection.

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 $16.496 billion to positive $1.809 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 negative $2.089 billion. Based on Pinnacle's ACE estimate and range estimates, we conclude that 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 $3.092 billion, and a positive 100 basis points parallel shift in HPA will increase Cash Flow NPV by $2.726 billion. Figure 5 shows the change in Cash Flow NPV as a percentage of the IIF. The change as a percentage of IIF ranges from -10.2% to +7.9%.

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 a negative slope. A negative 100 basis points parallel shift in interest rates will increase Cash Flow NPV by $475 million, and a positive 100 basis points parallel shift in HPA rates will decrease Cash Flow NPV by $283 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 -0.7% to +1.5%.

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

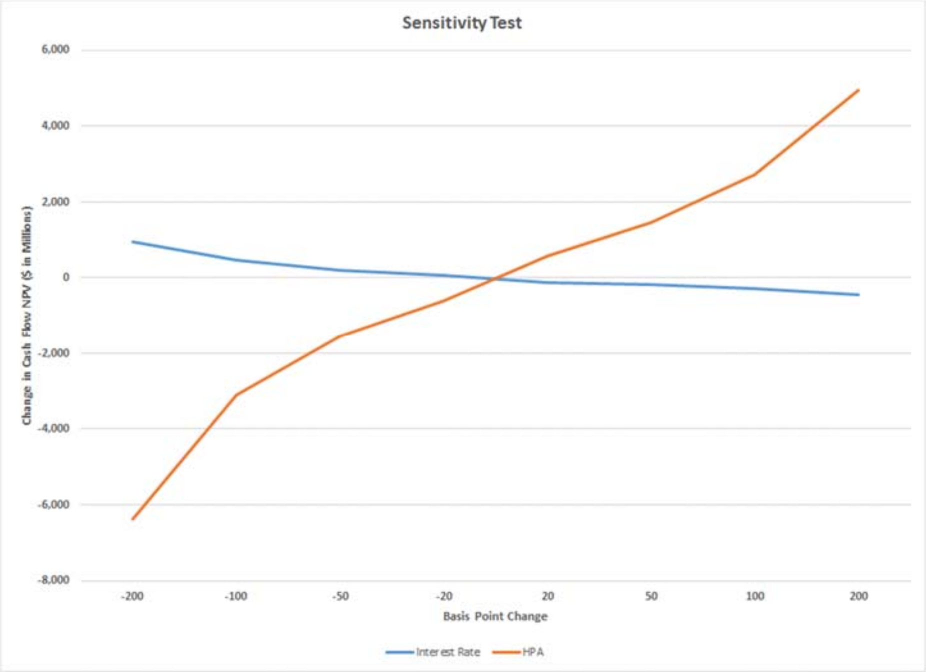
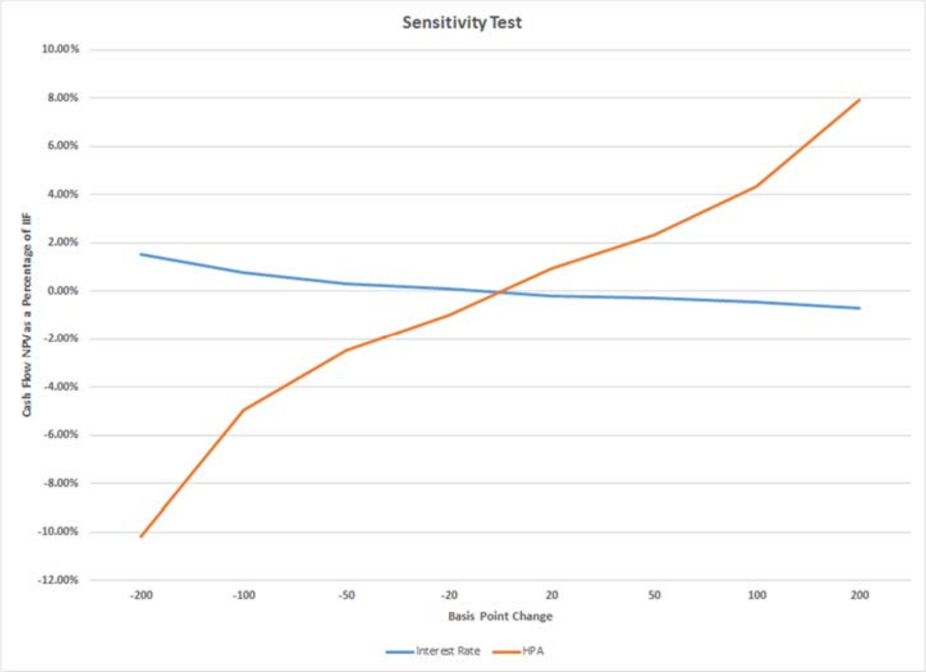


Figure 5: HECM Sensitivity Analysis – Change in Cash Flow NPV as a Percentage of IIF



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: setaside 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 2021 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, Pinnacle 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.

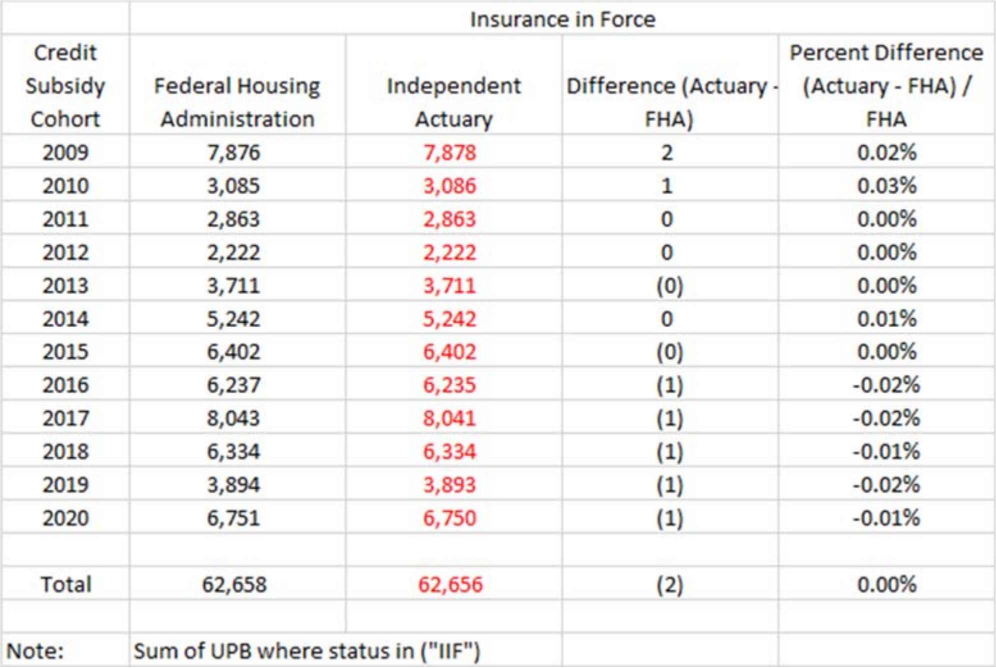
1. Pre-Processing: fields from supplemental tables are added to main HECM case file
2. HECM Quarterly: a number of calculated fields and flags are added to the dataset
3. Transaction Processing: quarterly historical transactions are then processed
4. Claim Processing: historical claim amounts are calculated based on claims 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 – 9 are joined to the main table created in step 2

Data Reconciliation

To reconcile the data processed by Pinnacle with the data provided by FHA, Pinnacle 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. The data processed matches the FHA data totals with 1%.

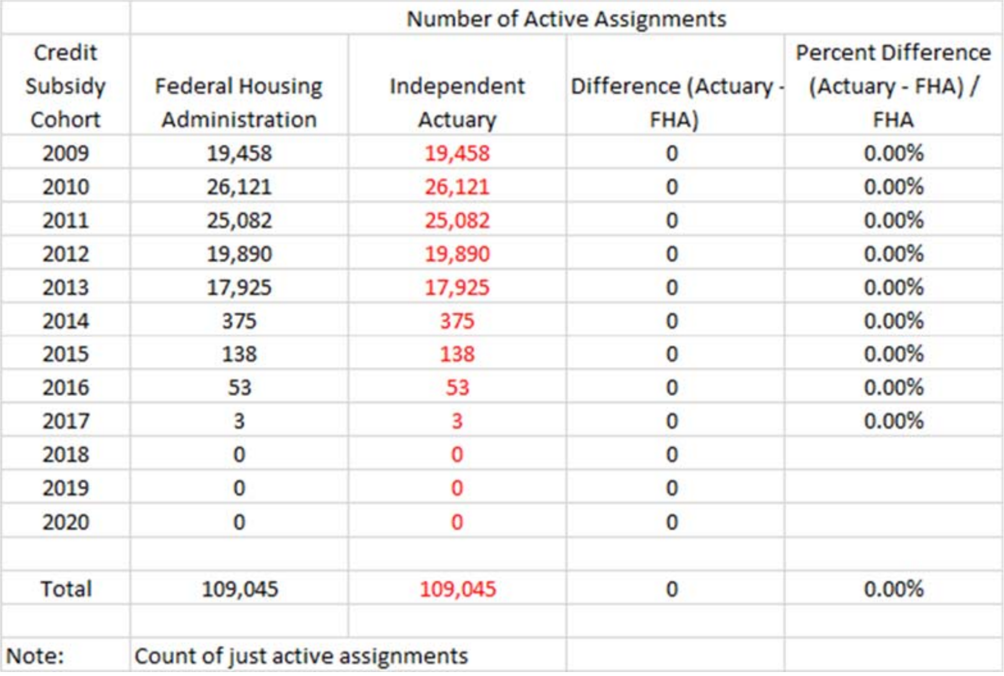
The reconciliation tables were based on data as of September 30, 2020.

Table 18: Data Validation – Insurance in Force



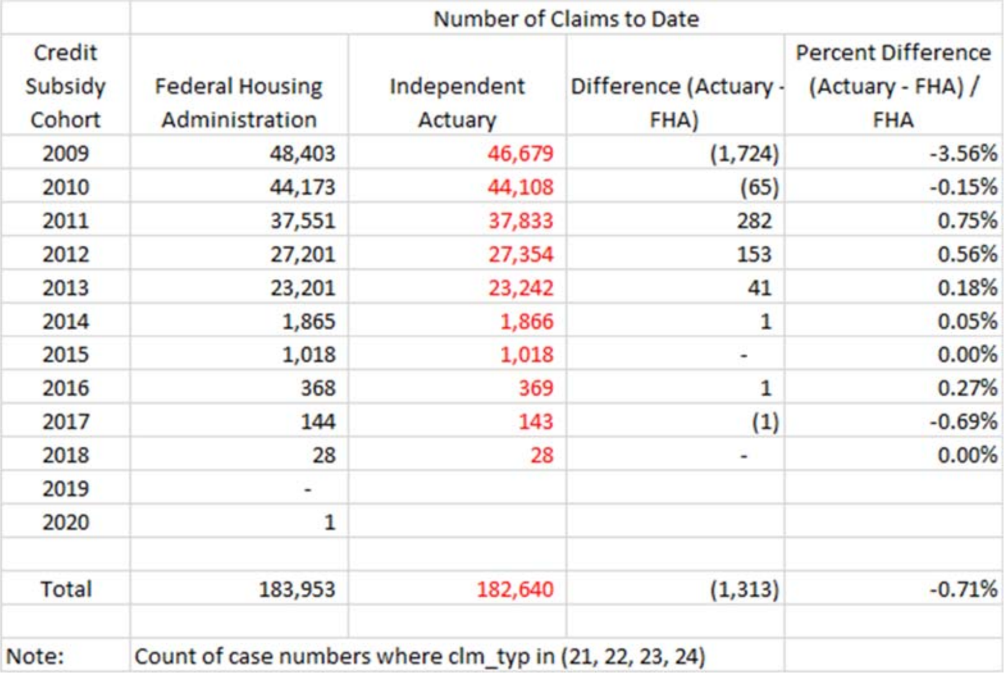
	Insurance in Force			
Credit Subsidy Cohort	Federal Housing Administration	Independent Actuary	Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
2009	7,876	7,878	2	0.02%
2010	3,085	3,086	1	0.03%
2011	2,863	2,863	0	0.00%
2012	2,222	2,222	0	0.00%
2013	3,711	3,711	(0)	0.00%
2014	5,242	5,242	0	0.01%
2015	6,402	6,402	(0)	0.00%
2016	6,237	6,235	(1)	-0.02%
2017	8,043	8,041	(1)	-0.02%
2018	6,334	6,334	(1)	-0.01%
2019	3,894	3,893	(1)	-0.02%
2020	6,751	6,750	(1)	-0.01%
Total	62,658	62,656	(2)	0.00%
Note:	Sum of UPB where status in ("IIF")			

Table 19: Data Reconciliation - Number of Active Assignments



	Number of Active Assignments			
Credit Subsidy Cohort	Federal Housing Administration	Independent Actuary	Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
2009	19,458	19,458	0	0.00%
2010	26,121	26,121	0	0.00%
2011	25,082	25,082	0	0.00%
2012	19,890	19,890	0	0.00%
2013	17,925	17,925	0	0.00%
2014	375	375	0	0.00%
2015	138	138	0	0.00%
2016	53	53	0	0.00%
2017	3	3	0	0.00%
2018	0	0	0	
2019	0	0	0	
2020	0	0	0	
Total	109,045	109,045	0	0.00%
Note:	Count of just active assignments			

Table 20: Data Reconciliation – Number of Claims to Date



	Number of Claims to Date			
Credit Subsidy Cohort	Federal Housing Administration	Independent Actuary	Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
2009	48,403	46,679	(1,724)	-3.56%
2010	44,173	44,108	(65)	-0.15%
2011	37,551	37,833	282	0.75%
2012	27,201	27,354	153	0.56%
2013	23,201	23,242	41	0.18%
2014	1,865	1,866	1	0.05%
2015	1,018	1,018	-	0.00%
2016	368	369	1	0.27%
2017	144	143	(1)	-0.69%
2018	28	28	-	0.00%
2019	-			
2020	1			
Total	183,953	182,640	(1,313)	-0.71%
Note:	Count of case numbers where clm_typ in (21, 22, 23, 24)			

HECM Base Termination Model (Appendix B)

Pinnacle 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 or not a net positive unscheduled cash draw was taken from the line of credit during that quarter, and also 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 2020 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 HECM Base Termination Model 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.

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 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:

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

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. Pinnacle 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.

List of Appendices

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: setaside 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 2021 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, Pinnacle 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.

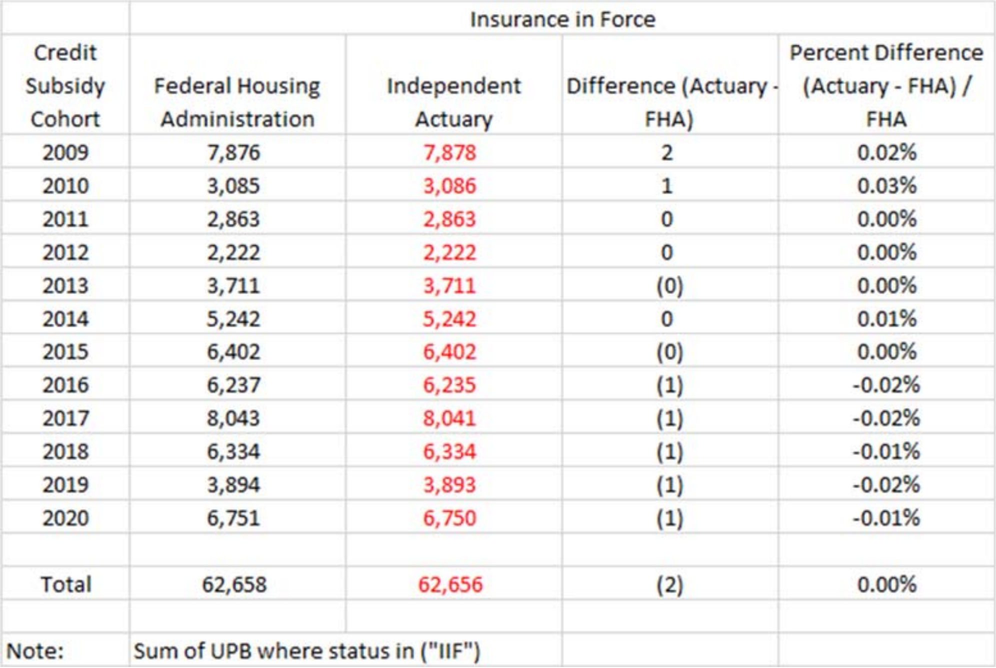
1. Pre-Processing: fields from supplemental tables were added to main HECM case file
2. HECM Quarterly: a number of calculated fields and flags are added to the dataset
3. Transaction Processing: quarterly historical transactions are then processed
4. Claim Processing: historical claim amounts are calculated based on claims 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 – 9 are joined to the main table created in step 2

Data Reconciliation

To reconcile the data processed by Pinnacle with the data provided by FHA, Pinnacle 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. The data processed by Pinnacle matches the FHA data totals within 1%.

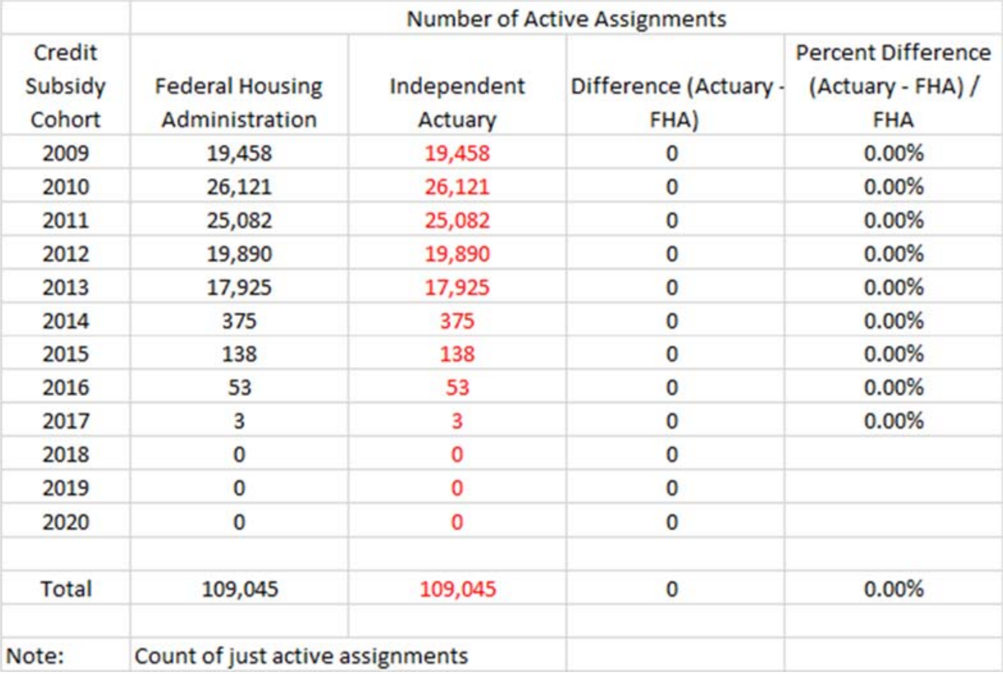
The reconciliation tables were based on data as of September 30, 2020.

Table 21: Data Validation – Insurance in Force



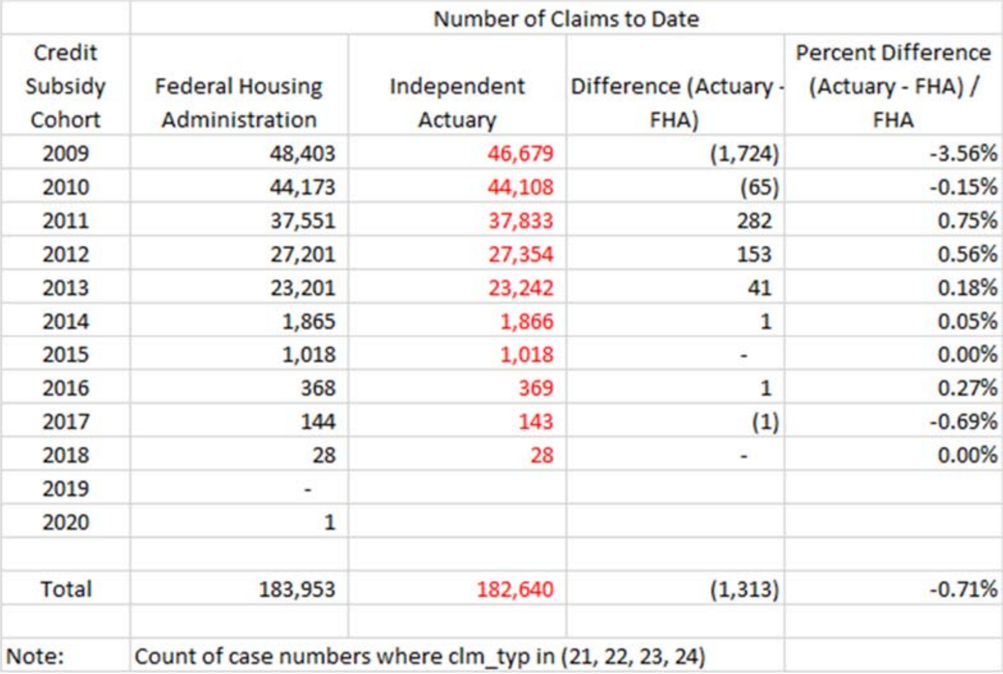
	Insurance in Force			
Credit Subsidy Cohort	Federal Housing Administration	Independent Actuary	Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
2009	7,876	7,878	2	0.02%
2010	3,085	3,086	1	0.03%
2011	2,863	2,863	0	0.00%
2012	2,222	2,222	0	0.00%
2013	3,711	3,711	(0)	0.00%
2014	5,242	5,242	0	0.01%
2015	6,402	6,402	(0)	0.00%
2016	6,237	6,235	(1)	-0.02%
2017	8,043	8,041	(1)	-0.02%
2018	6,334	6,334	(1)	-0.01%
2019	3,894	3,893	(1)	-0.02%
2020	6,751	6,750	(1)	-0.01%
Total	62,658	62,656	(2)	0.00%
Note:	Sum of UPB where status in ("IIF")			

Table 22: Data Reconciliation - Number of Active Assignments



	Number of Active Assignments			
Credit Subsidy Cohort	Federal Housing Administration	Independent Actuary	Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
2009	19,458	19,458	0	0.00%
2010	26,121	26,121	0	0.00%
2011	25,082	25,082	0	0.00%
2012	19,890	19,890	0	0.00%
2013	17,925	17,925	0	0.00%
2014	375	375	0	0.00%
2015	138	138	0	0.00%
2016	53	53	0	0.00%
2017	3	3	0	0.00%
2018	0	0	0	
2019	0	0	0	
2020	0	0	0	
Total	109,045	109,045	0	0.00%
Note:	Count of just active assignments			

Table 23: Data Reconciliation – Number of Claims to Date



	Number of Claims to Date			
Credit Subsidy Cohort	Federal Housing Administration	Independent Actuary	Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
2009	48,403	46,679	(1,724)	-3.56%
2010	44,173	44,108	(65)	-0.15%
2011	37,551	37,833	282	0.75%
2012	27,201	27,354	153	0.56%
2013	23,201	23,242	41	0.18%
2014	1,865	1,866	1	0.05%
2015	1,018	1,018	-	0.00%
2016	368	369	1	0.27%
2017	144	143	(1)	-0.69%
2018	28	28	-	0.00%
2019	-			
2020	1			
Total	183,953	182,640	(1,313)	-0.71%
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 borrowers 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.

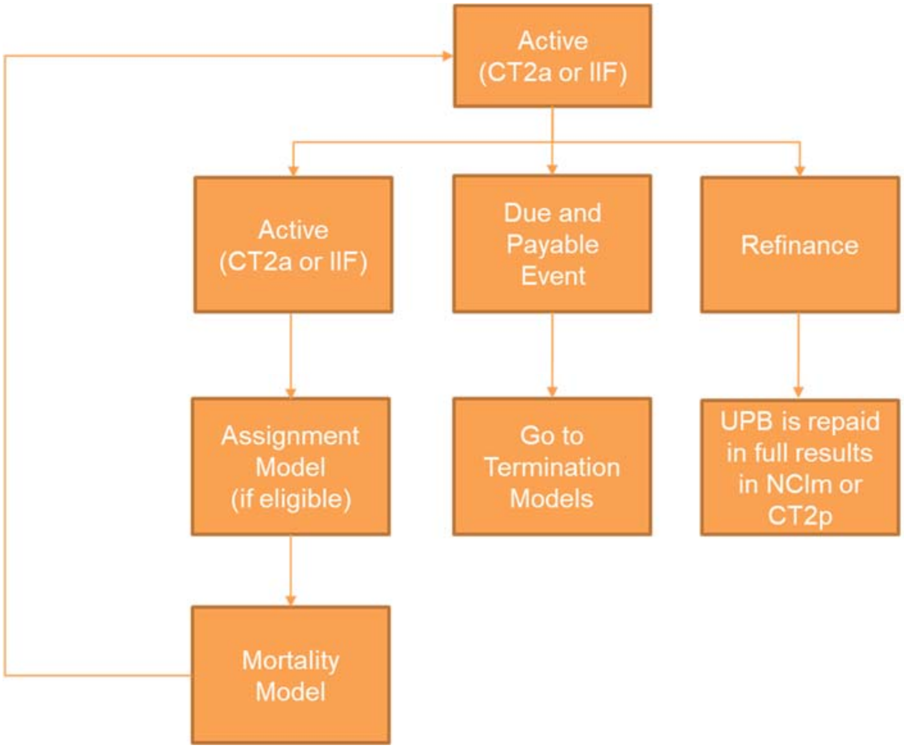
The available FHA historical HECM termination data was used to develop the base termination model. This data includes mortgages that were endorsed under the GI Fund between Fiscal Years 1990 and 2008, and mortgages endorsed under the MMI from Fiscal Year 2009 through September 30, 2020. Only mortgages 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 (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.

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 $(MCA_t \times PLF - (init\_MIP_t + orig\_fee_t) - curr\_prncpl\_lmt\_pinni)/(init\_MIP_t + orig\_fee_t)$. 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. Pinnacle 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

Likelihood of Refinance

The model parameters for the likelihood of refinance are shown below.

Table 24: Model Parameters – Likelihood of Refinance

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
Intercept				-10.0685	0.3408	0.0000
vminage_refi_pw2		Variate piecewise min_age	median(0,min_age-64,71-64)	0.0181	0.0031	0.0000
vminage_refi_pw3		Variate piecewise min_age	median(0,min_age-71,87-71)	0.0111	0.0016	0.0000

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
vminage_refi_pw4		Variate piecewise min_age	median(0,min_age-87,90-87)	-0.0407	0.0138	0.0032
vminage_refi_pw5		Variate piecewise min_age	max(0,min_age-90)	-0.0284	0.0124	0.0216
vrefi_refi_pw1		Variate piecewise refi_var[1]	min(max(-17,refi_var),-9)	0.0562	0.0170	0.0010
vrefi_refi_pw2		Variate piecewise refi_var[1]	median(0,refi_var+9,-3+9)	0.3003	0.0102	0.0000
vrefi_refi_pw3		Variate piecewise refi_var[1]	median(0,refi_var+3,-2+3)	0.1828	0.0292	0.0000
vrefi_refi_pw4		Variate piecewise refi_var[1]	median(0,refi_var+2,0+2)	0.5370	0.0132	0.0000
vrefi_refi_pw5		Variate piecewise refi_var[1]	max(0,(min(refi_var,18)))	0.2628	0.0081	0.0000
vrefi_refi_pw5*vrefi_refi_pw5		Interacted refi_var[1]	max(0,(min(refi_var,18)))	-0.0152	0.0009	0.0000
vperiodnbr_pw1		Variate piecewise period number	min(7,period_number)	0.2378	0.0050	0.0000
vperiodnbr_pw2		Variate piecewise period number	median(0,period_number-7,19-7)	-0.0631	0.0018	0.0000
vperiodnbr_pw3		Variate piecewise period number	median(0,period_number-19,30-19)	-0.0562	0.0032	0.0000
vperiodnbr_pw4		Variate piecewise period number	median(0,period_number-30,38-30)	-0.0468	0.0057	0.0000
vperiodnbr_pw5		Variate piecewise period number	median(0,period_number-38,65-38)	-0.0122	0.0034	0.0003
mSeason	L01	Categorical Season	mod(period,100) = 1	-0.2501	0.0156	0.0000
mSeason	L02	Categorical Season	mod(period,100) = 2	-0.1663	0.0153	0.0000
mSeason	L03	Categorical Season	mod(period,100) = 3	-0.2830	0.0158	0.0000
mSeason	z_Base	Categorical Season	Base level: else	0.0000		
mloantyp	L01_01	Categorical Loan Type	loan_typ ="01"	0.3204	0.0623	0.0000
mloantyp	L02_05	Categorical Loan Type	loan_typ ="05"	0.4005	0.0381	0.0000
mloantyp	z_Base	Categorical Loan Type	Base level: else	0.0000		
vltv_pw1		Variate piecewise Loan to Value[2]	min(LTV,3)	0.2867	0.1105	0.0095
vltv_pw2		Variate piecewise Loan to Value[2]	median(0,LTV-3,9-3)	-0.1018	0.0341	0.0028
vltv_pw3		Variate piecewise Loan to Value[2]	median(0,LTV-9,62-9)	0.0246	0.0010	0.0000
vltv_pw4		Variate piecewise Loan to Value[2]	median(0,LTV-62,86-62)	0.0195	0.0013	0.0000
vltv_pw5		Variate piecewise Loan to Value[2]	median(0,LTV-86,94-86)	0.0421	0.0038	0.0000
vltv_pw6		Variate piecewise Loan to Value[2]	median(0,LTV-94,99.5-94)	0.0278	0.0044	0.0000
vltv_pw7		Variate piecewise Loan to Value[2]	median(0,LTV-99.5,116-99.5)	-0.2269	0.0131	0.0000
vmob_pw1		Variate piecewise Mobility	median(0,mobility_2,10)	-0.0354	0.0065	0.0000
vmob_pw2		Variate piecewise Mobility	median(0,mobility_2-10,28-10)	0.0162	0.0025	0.0000

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
vmob_pw3		Variate piecewise Mobility	median(0,mobility_2-28,50-28)	0.0126	0.0013	0.0000
mDeltaTy1Init	L02_3.0	Categorical Change in 1 Year Treasury Rate Initial	Delta_T1Y_Init_p>3	0.1264	0.0167	0.0000
mDeltaTy1Init	z_Base	Categorical Change in 1 Year Treasury Rate Initial	Base level: else	0.0000		
MGender	L01_M	Categorical Gender	(gender = 1 and borr_alive = 1) or (gender = 3 and coborr_gender_1=1 and coborr_1_alive=1)	0.0812	0.0119	0.0000
MGender	z_Base	Categorical Gender	Base level: else	0.0000		
mAlive	L02_2	Categorical Number Alive	else	-0.0941	0.0117	0.0000
mAlive	z_Base	Categorical Number Alive	Base level: num_alive=1	0.0000		
vdelta_T1Y_4Q_pw1		Variate piecewise Change in 1 Year Treasury Rate 4Q	min(delta_T1Y_4Q,.271)	5.6559	0.1589	0.0000
vdelta_T1Y_4Q_pw2		Variate piecewise Change in 1 Year Treasury Rate 4Q	median(0,delta_T1Y_4Q-.271,.44-.271)	-8.7500	0.1263	0.0000
vdelta_T1Y_4Q_pw3		Variate piecewise Change in 1 Year Treasury Rate 4Q	median(0,delta_T1Y_4Q-.44,2-.44)	0.2592	0.0145	0.0000
vdelta_T1Y_4Q_pw4		Variate piecewise Change in 1 Year Treasury Rate 4Q	median(0,delta_T1Y_4Q-2,2.57-2)	0.2442	0.0408	0.0000
vMCA_pw1		Variate piecewise max_clm_amt	median(0,max_clm_amt/1000,312)	0.0034	0.0001	0.0000
vMCA_pw2		Variate piecewise max_clm_amt	median(0,(max_clm_amt-312000)/1000,495-312)	0.0022	0.0001	0.0000
vMCA_pw3		Variate piecewise max_clm_amt	median(0,(max_clm_amt-495000)/1000,700-495)	-0.0026	0.0002	0.0000
vp_appr_infl_1_pw1		Variate piecewise appr_infl_1	median(0,p_appr_infl_1--.1,-.04--.1)	-24.8898	2.5689	0.0000
vp_appr_infl_1_pw2		Variate piecewise appr_infl_1	median(0,p_appr_infl_1--.04,.05--.04)	-4.5003	0.3337	0.0000
vp_appr_infl_1_pw3		Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.05,.2-.05);	-5.1988	0.1583	0.0000
vp_appr_infl_1_pw4		Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.2,.3-.2);	1.6235	0.4197	0.0001
vp_appr_infl_1_pw5		Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.3,.4-.3);	4.8804	0.6754	0.0000

Likelihood of Non-Mortality Termination

The model parameters for the likelihood of non-mortality termination are shown below.

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

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
Intercept				-5.0039	0.0513	0.0000
vminage_pw1		Variate piecewise Minimum Age	median(0,min_age-72,79-72)	0.0822	0.0022	0.0000
vminage_pw2		Variate piecewise Minimum Age	median(0,min_age-79,92-79)	0.0794	0.0010	0.0000
vminage_pw3		Variate piecewise Minimum Age	max(0,min_age-92)	0.0491	0.0043	0.0000
vmob_pw0		Variate piecewise Mobility	min(0,mobility_2)	0.0098	0.0007	0.0000
vmob_pw1		Variate piecewise Mobility	median(0,mobility_2-0,30-0)	0.0116	0.0004	0.0000
vmob_pw2		Variate piecewise Mobility	max(0,mobility_2-30)	0.0373	0.0006	0.0000
vmob_pw0*vmob_pw0		Interacted Mobility	min(0,mobility_2)	0.0000	0.0000	0.0000
vminage_pw1*vmob_pw2		Interacted piecewise Minimum Age and Mobility	median(0,min_age-72,79-72) and max(0,mobility_2-30)	-0.0038	0.0001	0.0000
vmob_pw0*mSeason	L02	Interacted piecewise Mobility and Season	min(0,mobility_2) and mod(period,100) = 2	0.0037	0.0011	0.0014
vmob_pw0*mSeason	L03	Interacted piecewise Mobility and Season	min(0,mobility_2) and mod(period,100) = 3	0.0063	0.0012	0.0000
vmob_pw0*mSeason	z_Base	Interacted piecewise Mobility and Season	min(0,mobility_2) and mSeason Base Level	0.0000		
vmob_pw2*mSeason	L02	Interacted piecewise Mobility and Season	max(0,mobility_2-30) and mod(period,100) = 2	0.0022	0.0008	0.0032
vmob_pw2*mSeason	L03	Interacted piecewise Mobility and Season	max(0,mobility_2-30) and mod(period,100) = 3	0.0066	0.0007	0.0000
vmob_pw2*mSeason	z_Base	Interacted piecewise Mobility and Season	max(0,mobility_2-30) and mSeason Base Level	0.0000		
vltv_pw1		Variate piecewise Loan to Value	min(5,LTV)	-0.0849	0.0095	0.0000
vltv_pw2		Variate piecewise Loan to Value	median(0,LTV-5,88-5)	-0.0079	0.0002	0.0000
vltv_pw3		Variate piecewise Loan to Value	median(0,LTV-88,96.5 - 88)	-0.0162	0.0016	0.0000
vltv_pw4		Variate piecewise Loan to Value	median(0,LTV-96.5,99.5-96.5)	0.1254	0.0041	0.0000
vltv_pw5		Variate piecewise Loan to Value	max(0,LTV-99.5)	0.1031	0.0013	0.0000
min_age65	L01__62	Categorical Minimum Age	min_age = 62	-0.3624	0.0725	0.0000
min_age65	L02__63	Categorical Minimum Age	min_age = 63	-0.3074	0.0383	0.0000
min_age65	L03__64	Categorical Minimum Age	min_age = 64	-0.2500	0.0302	0.0000
min_age65	L04__65	Categorical Minimum Age	min_age = 65	-0.1834	0.0260	0.0000

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
min_age65	L05__72	Categorical Minimum Age	65 < min_age <= 72	-0.0670	0.0131	0.0000
min_age65	z_Base	Categorical Minimum Age	Base level: else	0.0000		
mloantyp	L01_01	Categorical Loan Type	loan_typ in ("01","03","04","05","06")	-0.0391	0.0096	0.0000
mloantyp	z_Base	Categorical Loan Type	Base level: else	0.0000		
MGender	L01_M	Categorical Gender	(gender = 1 and borr_alive = 1) or (gender = 3 and coborr_gender_1=1 and coborr_1_alive=1)	0.0201	0.0065	0.0020
MGender	z_Base	Categorical Gender	Base level: else	0.0000		
mSeason	L02	Categorical Season	mod(period,100) = 2	0.0610	0.0088	0.0000
mSeason	L03	Categorical Season	mod(period,100) = 3	0.0656	0.0087	0.0000
mSeason	z_Base	Categorical Season	Base level: else	0.0000		
mOrigFY	L01_2001	Categorical Origination Fiscal Year	Orig_FY = 2001	0.0397	0.0514	0.4397
mOrigFY	L02_2002	Categorical Origination Fiscal Year	Orig_FY = 2002	0.0635	0.0381	0.0956
mOrigFY	L03_2003	Categorical Origination Fiscal Year	Orig_FY = 2003	0.2270	0.0318	0.0000
mOrigFY	L04_2004	Categorical Origination Fiscal Year	Orig_FY = 2004	0.1170	0.0212	0.0000
mOrigFY	L05_2005	Categorical Origination Fiscal Year	Orig_FY = 2005	0.0186	0.0188	0.3227
mOrigFY	L06_2006	Categorical Origination Fiscal Year	Orig_FY = 2006	0.0357	0.0127	0.0049
mOrigFY	L07_2007	Categorical Origination Fiscal Year	Orig_FY = 2007	-0.1442	0.0116	0.0000
mOrigFY	L08_2008	Categorical Origination Fiscal Year	Orig_FY = 2008	-0.2020	0.0114	0.0000
mOrigFY	L09_2009	Categorical Origination Fiscal Year	Orig_FY = 2009	-0.0937	0.0111	0.0000
mOrigFY	L10_2010	Categorical Origination Fiscal Year	Orig_FY = 2010	-0.0477	0.0116	0.0000
mOrigFY	z_Base	Categorical Origination Fiscal Year	Base level: else	0.0000		
mperiod_num	L01_02	Categorical Period Number	period_number = 2	-1.0117	0.0269	0.0000
mperiod_num	L02_03	Categorical Period Number	period_number = 3	-0.5454	0.0223	0.0000

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
mperiod_num	L03_04	Categorical Period Number	period_number = 4	-0.2756	0.0203	0.0000
mperiod_num	L04_05	Categorical Period Number	period_number = 5	-0.1345	0.0194	0.0000
mperiod_num	z_Base	Categorical Period Number	Base level: else	0.0000		
vperiodnbr_othr_pw1		Variate piecewise Period Number	median(0,period_number-6,20-6)	0.0155	0.0009	0.0000
vperiodnbr_othr_pw2		Variate piecewise Period Number	median(0,period_number-20,44-20)	0.0111	0.0005	0.0000
vperiodnbr_othr_pw3		Variate piecewise Period Number	max(0,period_number-44)	-0.0221	0.0013	0.0000
vp_appr_infl_1_pw2		Variate piecewise appr_infl_1	median(0,p_appr_infl_1--.04,.05--.04)	0.6448	0.2060	0.0018
vp_appr_infl_1_pw3		Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.05,.2-.05);	-0.2057	0.0811	0.0112
vp_appr_infl_1_pw4		Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.2,.3-.2);	-0.9373	0.1681	0.0000
vp_appr_infl_1_pw5		Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.3,.4-.3);	-1.5660	0.3225	0.0000

CT2c Claim

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

Table 26: Model Parameters – Likelihood of CT2c

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
Intercept				-13.1853	0.5252	0.0000
vUPBRatio_MRA_pw1		Variate piecewise UPB Ratio1	median(0,UPB_Ratio,.85)	9.8746	0.2558	0.0000
vUPBRatio_MRA_pw2		Variate piecewise UPB Ratio1	median(0,UPB_Ratio-.85,1.5-.85)	5.0443	0.2133	0.0000
mMinage	L01_Miss	Categorical Minimum Age	min_age=.	0.7876	0.0554	0.0000
mMinage	z_Base	Categorical Minimum Age	Base level: else	0.0000		
vmin_age_pw1		Variate piecewise Minimum Age	median(0,min_age-62,95-62)	0.0509	0.0048	0.0000
vmin_age_pw2		Variate piecewise Minimum Age	max(0,min_age-95)	-0.0789	0.0384	0.0399
vp_appr_infl_1_pw1		Variate piecewise appr_infl_1	median(0,p_appr_infl_1--.1,-.04--.1)	33.8760	8.3821	0.0001
vp_appr_infl_1_pw2		Variate piecewise appr_infl_1	median(0,p_appr_infl_1--.04,.05--.04)	17.3423	1.2164	0.0000
vp_appr_infl_1_pw3		Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.05,.2-.05);	2.9705	0.4819	0.0000
vp_appr_infl_1_pw4		Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.2,.3-.2);	5.8662	1.0312	0.0000

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 below. This model includes an offset term of the natural log of the UPB.

Table 27: Model Parameters – CT2c Sales Price Model

Variable	Description	Description Detail	Estimate	StdErr	ProbChiSq
Intercept			2.4353	0.1740	<.0001
vperiodnbr_pw1	Variate piecewise Period Number	min(43,period_number)	-0.0048	0.0010	<.0001
vpropval_pw1	Variate piecewise Property Value[1]	min(8,vpropval)	-0.3436	0.0113	<.0001
vpropval_pw2	Variate piecewise Property Value[1]	median(0,vpropval-8,10-8)	0.1770	0.0190	<.0001
vpropval_pw3	Variate piecewise Property Value[1]	median(0,vpropval-10,15-10)	0.0298	0.0055	<.0001
vpropval_pw4	Variate piecewise Property Value[1]	median(0,vpropval-15,30-15)	0.0087	0.0013	<.0001
vpropval_pw5	Variate piecewise Property Value[1]	median(0,vpropval-30,50-30)	-0.0030	0.0016	0.0639
vpropval_pw6	Variate piecewise Property Value[1]	max(0,vpropval-50)	-0.0041	0.0001	<.0001
vp_appr_infl_1_pw1	Variate piecewise appr_infl_1	median(0,p_appr_infl_1--.1,-.04--.1)	-4.5591	2.7275	0.0946
vp_appr_infl_1_pw2	Variate piecewise appr_infl_1	median(0,p_appr_infl_1--.04,.05--.04)	-2.5239	0.3611	<.0001
vp_appr_infl_1_pw3	Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.05,.2-.05);	-0.8037	0.1555	<.0001
vp_appr_infl_1_pw4	Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.2,.3-.2);	-0.9339	0.4274	0.0289
vp_appr_infl_1_pw5	Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.3,.4-.3);	-1.8472	0.9423	0.0500
Scale			6.2024	0.0000	

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 below.

Table 28: Model Parameters – Likelihood of CT1 Claim

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
Intercept				-15.6391	0.7345	0.0000
vUPBRatio_MRA_pw1		Variate piecewise UPB Ratio[1]	median(0,UPB_Ratio,.2)	-6.8537	0.5446	0.0000
vUPBRatio_MRA_pw2		Variate piecewise UPB Ratio[1]	median(0,UPB_Ratio-.2,.35-.2)	-5.8142	0.5284	0.0000
vUPBRatio_MRA_pw3		Variate piecewise UPB Ratio[1]	median(0,UPB_Ratio-.35,.6-.35)	9.0085	0.1784	0.0000
vUPBRatio_MRA_pw4		Variate piecewise UPB Ratio[1]	median(0,UPB_Ratio-.6,.95-.6)	10.5036	0.0721	0.0000
vUPBRatio_MRA_pw5		Variate piecewise UPB Ratio[1]	median(0,UPB_Ratio-.95,1.5-.95)	5.3221	0.1882	0.0000

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
mMinage	L01_Miss	Categorical Minimum Age	min_age=.	1.1314	0.0130	0.0000
mMinage	z_Base	Categorical Minimum Age	Base level: else	0.0000		
vmin_age_pw1		Variate piecewise Minimum Age	median(0,min_age-62,67-62)	0.3028	0.0633	0.0000
vperiodnum_mra_pw1		Variate piecewise period number	median(0,period_number-1,6-1)	0.7817	0.1229	0.0000
vperiodnum_mra_pw2		Variate piecewise period number	median(0,period_number-6,9-6)	0.5739	0.0334	0.0000
vperiodnum_mra_pw3		Variate piecewise period number	median(0,period_number-9,22-9)	0.1319	0.0026	0.0000
vperiodnum_mra_pw4		Variate piecewise period number	median(0,period_number-22,35-22)	0.0438	0.0019	0.0000
vperiodnum_mra_pw5		Variate piecewise period number	median(0,period_number-35,44-35)	0.0064	0.0030	0.0306
vperiodnum_mra_pw6		Variate piecewise period number	max(0,period_number-44)	0.0206	0.0028	0.0000
vp_appr_infl_1_pw1		Variate piecewise appr_infl_1	median(0,p_appr_infl_1--.1,-.04--.1)	41.9719	5.4190	0.0000
vp_appr_infl_1_pw2		Variate piecewise appr_infl_1	median(0,p_appr_infl_1--.04,.05--.04)	20.3083	0.5721	0.0000
vp_appr_infl_1_pw3		Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.05,.2-.05);	5.7064	0.1598	0.0000
vp_appr_infl_1_pw4		Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.2,.3-.2);	6.9890	0.3291	0.0000
vp_appr_infl_1_pw5		Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.3,.4-.3);	3.3852	0.6088	0.0000

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 below. This model includes an offset term of the natural log of the UPB.

Table 29: Model Parameters – CT1 Sales Price Model

Variable	Description	Description Detail	Estimate	StdErr	ProbChiSq
Intercept			-0.5963	0.2514	0.017699
vperiodnbr_pw1	Variate piecewise Period Number	median(0,period_number-1,6-1)	-0.0118	0.0010	9.34E-32
vperiodnbr_pw3	Variate piecewise Period Number	median(0,period_number-9,22-9)	0.0009	0.0002	4.13E-05
vpropval_pw1	Variate piecewise Property Value[1]	min(8,vpropval)	0.0273	0.0065	2.57E-05
vpropval_pw2	Variate piecewise Property Value[1]	median(0,vpropval-8,10-8)	0.0778	0.0081	5.49E-22
vpropval_pw3	Variate piecewise Property Value[1]	median(0,vpropval-10,15-10)	0.0344	0.0023	7.85E-51
vpropval_pw4	Variate piecewise Property Value[1]	median(0,vpropval-15,30-15)	0.0086	0.0006	1.55E-50
vpropval_pw6	Variate piecewise Property Value[1]	max(0,vpropval-50)	-0.0022	0.0006	0.000236

Variable	Description	Description Detail	Estimate	StdErr	ProbChiSq
vUPB_Ratio_pw3	Variate piecewise UPB Ratio^2	median(0,UPB_Ratio-47.8,59-47.8)	0.0076	0.0025	0.001973
vUPB_Ratio_pw4	Variate piecewise UPB Ratio^2	median(0,UPB_Ratio-59,65.5-59)	0.0134	0.0026	2.36E-07
vUPB_Ratio_pw5	Variate piecewise UPB Ratio^2		0.0026	0.0005	6.47E-09
vUPB_Ratio_pw6	Variate piecewise UPB Ratio^2	median(0,UPB_Ratio-88,121-88)	-0.0029	0.0003	1.21E-16
vmin_age_pw3	Variate piecewise Minimum Age	median(0,min_age-70,77-70)	0.0043	0.0016	0.006404
vmin_age_pw4	Variate piecewise Minimum Age	median(0,min_age-77,91-77)	0.0085	0.0007	2.54E-35
vmin_age_pw5	Variate piecewise Minimum Age	max(0,min_age-91)	-0.0044	0.0027	0.105632
vp_appr_infl_1_pw1	Variate piecewise appr_infl_1	median(0,p_appr_infl_1--.1,-.04--.1)	-7.9674	4.1868	0.057045
vp_appr_infl_1_pw2	Variate piecewise appr_infl_1	median(0,p_appr_infl_1--.04,.05--.04)	-0.8386	0.2746	0.00226
vp_appr_infl_1_pw3	Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.05,.2-.05);	-1.2646	0.0673	1.16E-78
vp_appr_infl_1_pw4	Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.2,.3-.2);	-0.6707	0.1260	1.02E-07
vp_appr_infl_1_pw5	Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.3,.4-.3);	-2.4016	0.2093	1.79E-30
Scale			4.9448	0.0000	

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 below.

Figure 7: Model Validation – Likelihood of Refinance

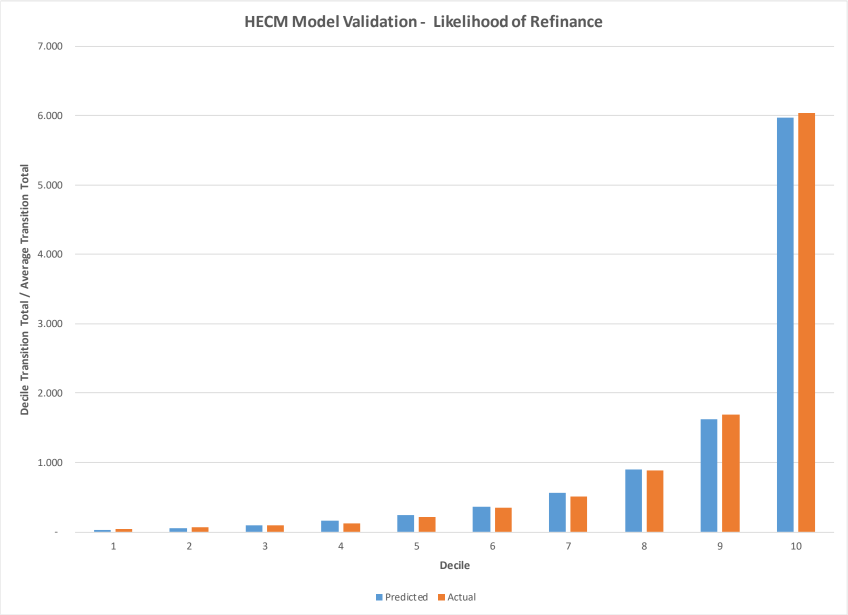


Figure 8: Model Validation - Likelihood of Non-Mortality Termination

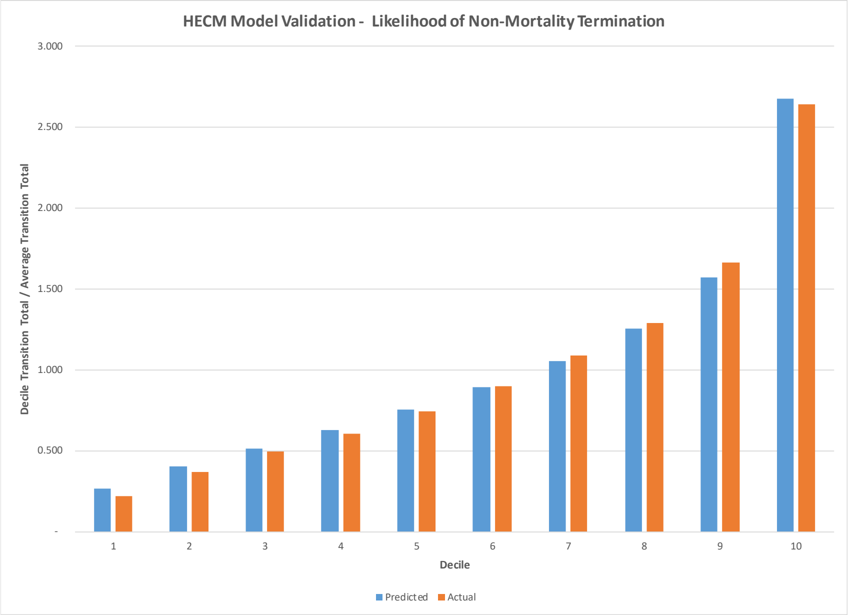


Figure 9: Model Validation - Likelihood of CT2c Claim

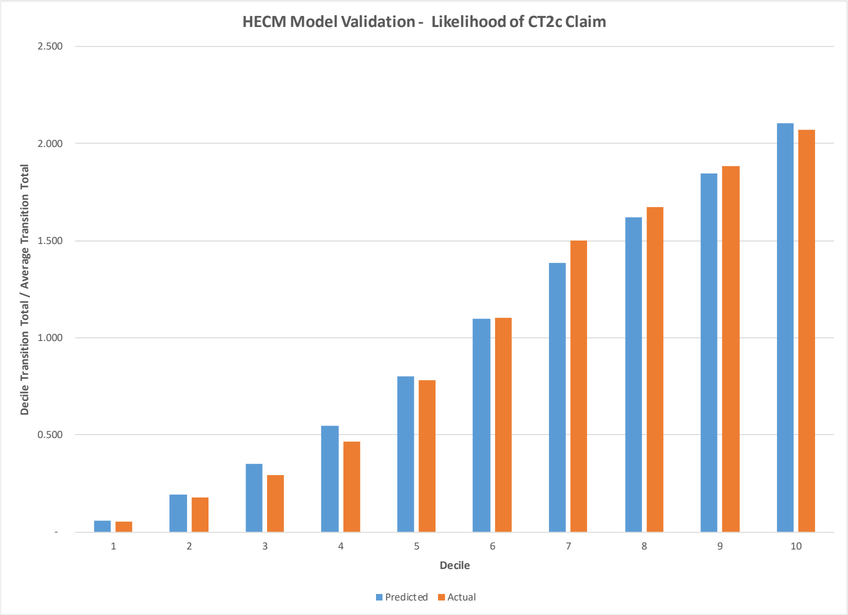


Figure 10: Model Validation – CT2c Sales Price Model

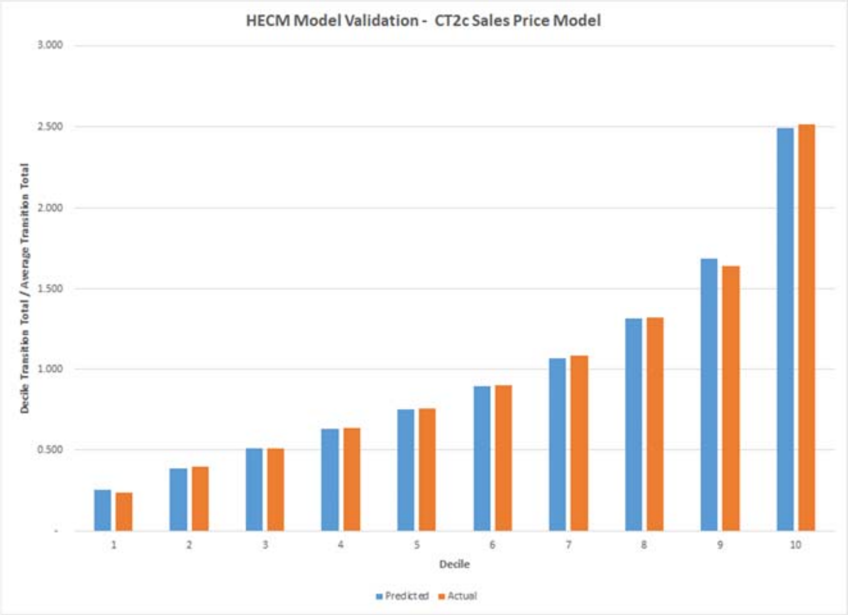


Figure 11: Model Validation – Likelihood of CT1 Claim

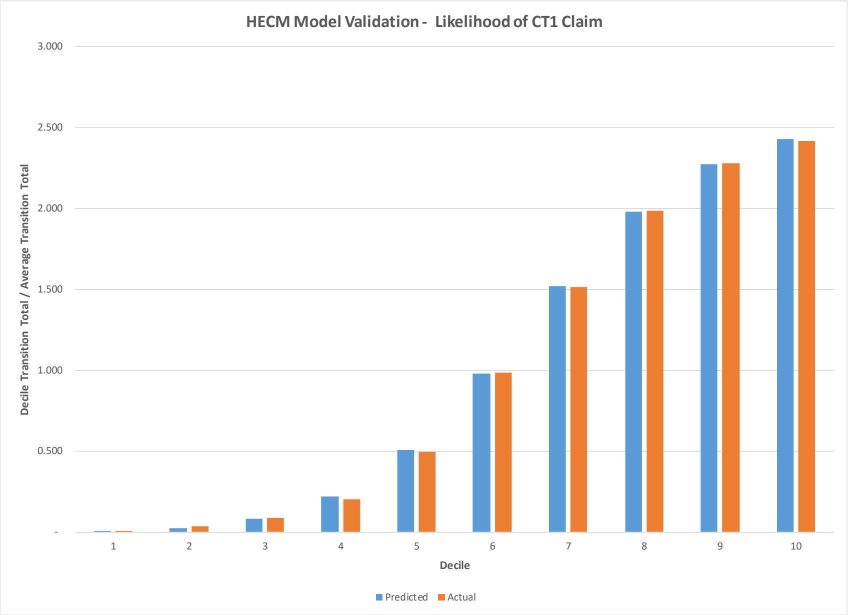
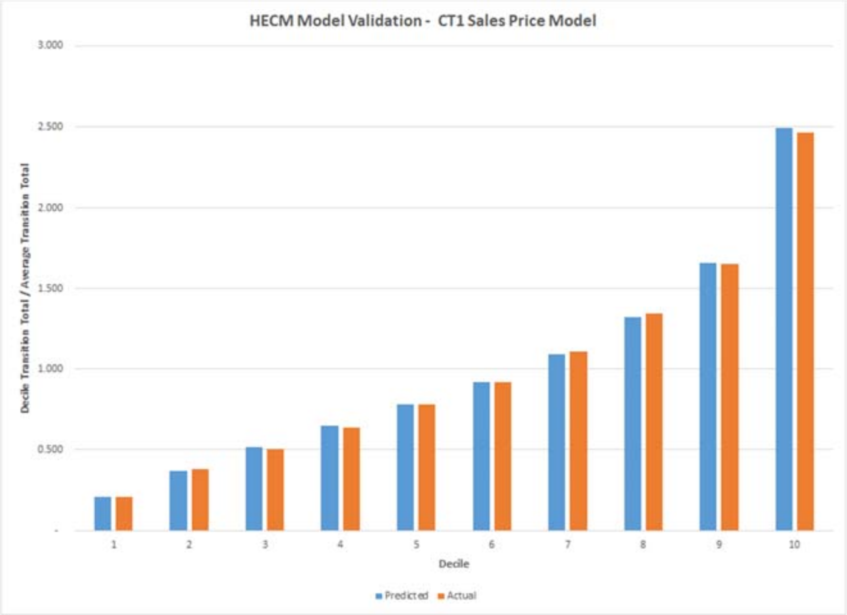


Figure 12: Model Validation – CT1 Sales Price Model



Appendix C: HECM Cash Draw Models

Over 90% of HECM‘s 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 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 or not a net positive unscheduled cash draw was taken from the line of credit during that quarter, and also the amount of the cash draw. We use 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 that has been 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, Pinnacle 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 - 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.
- **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. Pinnacle 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

Likelihood of Cash Draw

The model parameters for the likelihood of a cash draw are shown below.

Table 30: Model Parameters – Likelihood of Cash Draw

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
Intercept				-2.7509	0.0187	0.0000
mMinage	L01_62	Categorical Minimum Age	min_age=62	0.1626	0.0144	0.0000
mMinage	L02_63	Categorical Minimum Age	min_age=63	0.1599	0.0087	0.0000
mMinage	L03_64	Categorical Minimum Age	min_age=64	0.1024	0.0073	0.0000
mMinage	L04_65	Categorical Minimum Age	min_age=65	0.0346	0.0065	0.0000
mMinage	L05_95	Categorical Minimum Age	90<min_age<=95	-0.0246	0.0063	0.0001
mMinage	L06_99	Categorical Minimum Age	min_age>95	-0.0034	0.0146	0.8161
mMinage	z_Base	Categorical Minimum Age	Base level: else	0.0000		
mSeason	A01	Categorical Season	period <201300 and mod(period,100) = 1	-0.1449	0.0047	0.0000
mSeason	A02	Categorical Season	period <201300 and mod(period,100) = 2	-0.0799	0.0046	0.0000
mSeason	A03	Categorical Season	period <201300 and mod(period,100) = 3	-0.0215	0.0046	0.0000
mSeason	A04	Categorical Season	period <201300 and mod(period,100) = 4	0.0087	0.0046	0.0558
mSeason	B01	Categorical Season	period >=201300 and mod(period,100) = 1	-0.1528	0.0039	0.0000
mSeason	B02	Categorical Season	period >=201300 and mod(period,100) = 2	-0.1604	0.0039	0.0000
mSeason	B03	Categorical Season	period >=201300 and mod(period,100) = 3	-0.0973	0.0039	0.0000
mSeason	z_Base	Categorical Season	Base level: else	0.0000		
mAlive	L02_2	Categorical Alive	Else	-0.2212	0.0022	0.0000
mAlive	z_Base	Categorical Alive	Base level: num_alive=1	0.0000		
MGender	L01_M	Categorical Gender	(gender = 1 and borr_alive = 1) or (gender = 3 and coborr_gender_1=1 and coborr_1_alive=1)	-0.0500	0.0024	0.0000
MGender	z_Base	Categorical Gender	Base level: else	0.0000		
mDeltaTy1Init	L01_2.0	Categorical Change in 1 year Treasury from Initial	Delta_T1Y_Init_p>2	0.0395	0.0030	0.0000
mDeltaTy1Init	z_Base	Categorical Change in 1 year Treasury from Initial	Base level: else	0.0000		

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
mloantyp	L01_01	Categorical Loan Type	loan_typ in ('01", "03", "04", "05", "06")	-0.4400	0.0044	0.0000
mloantyp	z_Base	Categorical Loan Type	Base level: else	0.0000		
vLOCCap_pw1		Variate piecewise Line of Credit[1]	min(4500,loc_capped_i)	0.0010	0.0000	0.0000
vLOCCap_pw1*vLOCCap_pw1		Interacted Line of Credit	min(4500,loc_capped_i)	0.0000	0.0000	0.0000
vLOCCap_pw2		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-4500,12500-4500)	0.0001	0.0000	0.0000
vLOCCap_pw3		Variate piecewise Line of Credit[1]	max(0,loc_capped_i-12500)	0.0000	0.0000	0.0000
vLOCRemain_pw2		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-.45,1.4-.45)	1.1282	0.0116	0.0000
vLOCRemain_pw3		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-1.4,4.1-1.4)	-0.0286	0.0040	0.0000
vLOCRemain_pw4		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-4.1,15.5-4.1)	-0.0165	0.0006	0.0000
vLOCRemain_pw5		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-15.1,40.5-15.5)	-0.0165	0.0002	0.0000
vLOCRemain_pw6		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-40.5,77-40.5)	-0.0184	0.0001	0.0000
vLOCRemain_pw7		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-77,93.4-77)	-0.0251	0.0004	0.0000
vLOCRemain_pw8		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-93.4,99-93.4)	-0.1148	0.0017	0.0000
vLOCRemain_pw9		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-99,99.9-99)	-0.4554	0.0141	0.0000
vLOCRemain_pw10		Variate piecewise Line of Credit Remaining[2]	max(0,loc_remaining-99.9)	1.1951	0.0996	0.0000
mperiod_num	L01_02	Categorical Period Number	period_number = 2	0.6567	0.0061	0.0000
mperiod_num	L02_03	Categorical Period Number	period_number = 3	0.3730	0.0059	0.0000
mperiod_num	L03_04	Categorical Period Number	period_number = 4	0.2683	0.0060	0.0000
mperiod_num	L04_05	Categorical Period Number	period_number = 5	0.5552	0.0053	0.0000
mperiod_num	z_Base	Categorical Period Number	Base level: else	0.0000		
vPeriodNbr_pw1		Variate piecewise Period Number	median(0,period_number-5,24-5)	-0.0479	0.0002	0.0000
vPeriodNbr_pw2		Variate piecewise Period Number	median(0,period_number-24,40-24)	-0.0257	0.0004	0.0000
vPeriodNbr_pw3		Variate piecewise Period Number	median(0,period_number-40,52-40)	-0.0375	0.0009	0.0000
vPeriodNbr_pw4		Variate piecewise Period Number	max(0,period_number-52)	-0.0180	0.0021	0.0000
vLTV_CDF_pw1		Variate piecewise Loan to Value	median(0,LTV-20,20)	0.0256	0.0007	0.0000

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
vLTV_CDF_pw2		Variate piecewise Loan to Value	median(0,LTV-20,75-20)	-0.0022	0.0001	0.0000
vLTV_CDF_pw3		Variate piecewise Loan to Value	median(0,period_number-75,95.5-75)	-0.0206	0.0003	0.0000
vLTV_CDF_pw4		Variate piecewise Loan to Value	median(0,LTV-95.5,98-95.5)	-0.0857	0.0025	0.0000
mLTV	0	Categorical Loan to Value	LTV <99.5	-0.1486	0.0078	0.0000
mLTV	z_Base	Categorical Loan to Value	Base level: else	0.0000		
vp_appr_infl_1_pw2		Variate piecewise appr_infl_1	median(0,p_appr_infl_1--.04,.05--.04)	1.9689	0.0716	0.0000
vp_appr_infl_1_pw3		Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.05,.2-.05);	0.2887	0.0262	0.0000
vp_appr_infl_1_pw4		Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.2,.3-.2);	-0.7430	0.0605	0.0000
vp_appr_infl_1_pw5		Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.3,.4-.3);	-0.6619	0.1275	0.0000

Likelihood of Full Cash Draw

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

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

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
Intercept				-1.7058	0.1813	0.0000
mperiod_num	L01_02	Categorical Period Number	period_number = 2	-0.6618	0.1528	0.0000
mperiod_num	L02_03	Categorical Period Number	period_number = 3	-0.7372	0.1512	0.0000
mperiod_num	L03_04	Categorical Period Number	period_number = 4	0.8268	0.0676	0.0000
mperiod_num	L04_05	Categorical Period Number	period_number = 5	0.7624	0.1207	0.0000
mperiod_num	L05_06	Categorical Period Number	period_number = 6	0.2188	0.0389	0.0000
mperiod_num	L06_07	Categorical Period Number	period_number = 7	0.0727	0.0407	0.0736
mperiod_num	z_Base	Categorical Period Number	Base level: else			
vLOCCap_cd100_pw1		Variate piecewise Line of Credit[1]	min(3500,loc_capped_i)	-0.0004	0.0000	0.0000
vLOCCap_cd100_pw2		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-3500,10000-3500)	-0.0001	0.0000	0.0000
vLOCCap_cd100_pw3		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-10000,20000-10000)	-0.0001	0.0000	0.0000
vLOCCap_cd100_pw4		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-20000,100000-20000)	0.0000	0.0000	0.0000
vLOCCap_cd100_pw6		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-165000,300000-165000)	0.0000	0.0000	0.0002
vltv_cd100_pw1		Variate piecewise Loan to Value	min(55,LTV)	-0.0187	0.0035	0.0000
vltv_cd100_pw2		Variate piecewise Loan to Value	median(0,LTV-55,60-55)	0.6327	0.0210	0.0000

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
vltv_cd100_pw3		Variate piecewise Loan to Value	median(0,LTV-60,64-60)	-0.5870	0.0211	0.0000
vltv_cd100_pw4		Variate piecewise Loan to Value	median(0,LTV-64,95-64)	0.0550	0.0031	0.0000
vltv_cd100_pw5		Variate piecewise Loan to Value	max(0,LTV-95)	0.1744	0.0163	0.0000
vminage_cd100_pw1		Variate piecewise Minimum Age	median(0,min_age-62,78-62)	0.0063	0.0022	0.0033
vminage_cd100_pw2		Variate piecewise Minimum Age	max(0,min_age-78)	0.0360	0.0035	0.0000
mSeason	L01	Categorical Season	mod(period,100) = 1	0.0184	0.0278	0.5092
mSeason	L02	Categorical Season	mod(period,100) = 2	0.0324	0.0278	0.2426
mSeason	L03	Categorical Season	mod(period,100) = 3	0.0948	0.0274	0.0005
mSeason	z_Base	Categorical Season	Base level: else			
MGender	L01_M	Categorical Gender	(gender = 1 and borr_alive = 1) or (gender = 3 and coborr_gender_1=1 and coborr_1_alive=1)	0.1815	0.0209	0.0000
MGender	z_Base	Categorical Gender	Base level: else			
mAlive	L02_2	Categorical Alive	Else	0.1416	0.0212	0.0000
mAlive	z_Base	Categorical Alive	Base level: num_alive=1			
mloantyp	L01_01	Categorical Loan Type	loan_typ in ('01", "03", "04", "05", "06")	0.8543	0.0861	0.0000
mloantyp	z_Base	Categorical Loan Type	Base level: else			
vltv_cd100_pw2*mperiod_num5	L01_5	Interacted Loan to Value and Period Number	median(0,LTV-55,60-55) and period_number = 5	0.1169	0.0247	0.0000
vltv_cd100_pw3*mperiod_num5	L01_5	Interacted Loan to Value and Period Number	median(0,LTV-60,64-60) and period_number = 5	0.2211	0.0254	0.0000
vltv_cd100_pw4*mperiod_num5	L01_5	Interacted Loan to Value and Period Number	median(0,LTV-64,95-64) and period_number = 5	-0.0273	0.0037	0.0000
vltv_cd100_pw5*mperiod_num5	L01_5	Interacted Loan to Value and Period Number	max(0,LTV-95) and period_number = 5	-0.3208	0.0190	0.0000
vltv_cd100_pw5*mperiod_num5	z_Base	Interacted Loan to Value and Period Number	max(0,LTV-95) and period_number <> 5			
vp_appr_infl_1_pw2		Variate piecewise appr_infl_1	median(0,p_appr_infl_1--.04,.05--.04)	-1.3275	0.4300	0.0020
vp_appr_infl_1_pw4		Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.2,.3-.2);	3.5039	1.2194	0.0041
vp_appr_infl_1_pw5		Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.3,.4-.3);	-4.8724	2.6443	0.0654

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

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

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
Intercept				-0.5919	0.2490	0.0174
vLOCCap_cd1009_pw0		Variate piecewise Line of Credit[1]	min(1000,loc_capped_i)	-0.0010	0.0000	0.0000
vLOCCap_cd1009_pw1		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-1000,3500-1000)	-0.0005	0.0000	0.0000
vLOCCap_cd1009_pw2		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-3500,10000-3500)	-0.0001	0.0000	0.0000
vLOCCap_cd1009_pw3		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-10000,20000-10000)	-0.0001	0.0000	0.0000
vLOCCap_cd1009_pw4		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-20000,100000-20000)	0.0000	0.0000	0.0000
vLOCCap_cd1009_pw5		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-100000,185000-100000)	0.0000	0.0000	0.0002
vLOCCap_cd1009_pw6		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-185000,300000-185000)	0.0000	0.0000	0.0004
vltv_cd1009_pw2		Variate piecewise Loan to Value	median(0,LTV-66,95-66)	0.0078	0.0011	0.0000
vltv_cd1009_pw3		Variate piecewise Loan to Value	max(0,LTV-95)	-0.0520	0.0044	0.0000
vminage_cd1009_pw1		Variate piecewise Minimum Age	median(0,min_age-62,78-62)	0.0084	0.0015	0.0000
vminage_cd1009_pw2		Variate piecewise Minimum Age	max(0,min_age-78)	0.0328	0.0016	0.0000
vperiodnbr_pw1		Variate piecewise Period Number	median(0,period_number-9,25-9)	-0.0508	0.0012	0.0000
vperiodnbr_pw2		Variate piecewise Period Number	max(0,period_number-25)	-0.0154	0.0012	0.0000
mSeason	L01	Categorical Season	mod(period,100) = 1	0.0755	0.0158	0.0000
mSeason	L02	Categorical Season	mod(period,100) = 2	0.1265	0.0156	0.0000
mSeason	L03	Categorical Season	mod(period,100) = 3	0.0000		
mSeason	z_Base	Categorical Season	Base level: else	0.1929	0.0153	0.0000
MGender	L01_M	Categorical Gender	(gender = 1 and borr_alive = 1) or (gender = 3 and coborr_gender_1=1 and coborr_1_alive=1)	0.0512	0.0124	0.0000
MGender	z_Base	Categorical Gender	Base level: else	0.0000		
mAlive	L02_2	Categorical Alive	Else	0.1396	0.0123	0.0000
mAlive	z_Base	Categorical Alive	Base level: num_alive=1	0.0000		
mloantyp	L01_01	Categorical Loan Type	loan_typ in ('01", "03", "04", "05", "06")	0.5834	0.0267	0.0000
mloantyp	z_Base	Categorical Loan Type	Base level: else	0.0000		
vp_appr_infl_1_pw1		Variate piecewise appr_infl_1	median(0,p_appr_infl_1--.1,-.04--.1)	12.2021	4.2195	0.0038
vp_appr_infl_1_pw2		Variate piecewise appr_infl_1	median(0,p_appr_infl_1--.04,.05--.04)	-4.3963	0.4027	0.0000
vp_appr_infl_1_pw3		Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.05,.2-.05);	-2.0327	0.1352	0.0000

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
vp_appr_infl_1_pw4		Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.2,.3-.2);	2.0384	0.2686	0.0000

Cash Draw Amount Model

The model parameters for the cash draw amount are shown below.

Table 33: Model Parameters – Cash Draw Amount

Parameter	Level1	Description	Description Detail	Estimate	StdErr	ProbChiSq
Intercept				6.4553	0.0180	0.0000
vLOCCap_cds_pw1		Variate piecewise Line of Credit[1]	min(1,loc_capped_i)	0.0497	0.0112	0.0000
vLOCCap_cds_pw2		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-1,3.5-1)	-0.0180	0.0034	0.0000
vLOCCap_cds_pw3		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-3.5,10-3.5)	-0.0321	0.0011	0.0000
vLOCCap_cds_pw4		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-10,15-10)	-0.0223	0.0012	0.0000
vLOCCap_cds_pw5		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-15,30-15)	-0.0169	0.0003	0.0000
vLOCCap_cds_pw6		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-30,125-30)	-0.0049	0.0000	0.0000
vLOCCap_cds_pw7		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-125,200-125)	-0.0010	0.0001	0.0000
vLOCCap_cds_pw8		Variate piecewise Line of Credit[1]	max(0,loc_capped_i-200)	-0.0008	0.0001	0.0000
vminage_cds_pw1		Variate piecewise Min Age	median(0,min_age-62,67-62)	-0.0112	0.0013	0.0000
vminage_cds_pw2		Variate piecewise Min Age	median(0,min_age-67,75-67)	-0.0073	0.0004	0.0000
vminage_cds_pw3		Variate piecewise Min Age	median(0,min_age-75,85-75)	0.0081	0.0004	0.0000
vminage_cds_pw4		Variate piecewise Min Age	max(0,min_age-85)	0.0270	0.0006	0.0000
vperiodnbr_pw1		Variate piecewise Period Number	median(0,period_number-5,10-5)	-0.0766	0.0007	0.0000
vperiodnbr_pw2		Variate piecewise Period Number	median(0,period_number-10,20-10)	-0.0243	0.0003	0.0000
vperiodnbr_pw3		Variate piecewise Period Number	median(0,period_number-20,54-20)	-0.0085	0.0002	0.0000
vperiodnbr_pw4		Variate piecewise Period Number	max(0,period_number-54)	-0.0155	0.0024	0.0000
vltv_cds_pw1		Variate piecewise Loan to Value	min(20,LTV)	-0.0032	0.0006	0.0000
vltv_cds_pw2		Variate piecewise Loan to Value	median(0,LTV-20,80-20)	0.0092	0.0001	0.0000
vltv_cds_pw3		Variate piecewise Loan to Value	max(0,LTV-80)	0.0014	0.0003	0.0000
mltv	L01_60	Categorical Loan to Value	LTV=60 and orig_fy>2014 and period_number=5 and loan_typ="02"	0.5567	0.0140	0.0000
mltv	z_Base	Categorical Loan to Value	Base level: else	0.0000		

Parameter	Level1	Description	Description Detail	Estimate	StdErr	ProbChiSq
mSeason	L01	Categorical Season	mod(period,100) = 1	0.0001	0.0026	0.9720
mSeason	L02	Categorical Season	mod(period,100) = 2	0.0240	0.0025	0.0000
mSeason	L03	Categorical Season	mod(period,100) = 3	0.0323	0.0025	0.0000
mSeason	z_Base	Categorical Season	Base level: else	0.0000		
MGender	L01_M	Categorical Gender	(gender = 1 and borr_alive = 1) or (gender = 3 and coborr_gender_1=1 and coborr_1_alive=1)	0.0378	0.0021	0.0000
MGender	z_Base	Categorical Gender	Base level: else	0.0000		
mAlive	L02_2	Categorical Alive	Else	0.0490	0.0020	0.0000
mAlive	z_Base	Categorical Alive	Base level: num_alive=1	0.0000		
mloantyp	L01_01	Categorical Loan Type	loan_typ in ('01", "03", "04", "05", "06")	-0.1017	0.0042	0.0000
mloantyp	z_Base	Categorical Loan Type	Base level: else	0.0000		
vLOCRemain_pw1		Variate piecewise Line of Credit Remaining[2]	min(6.4,loc_remaining)	-0.0201	0.0016	0.0000
vLOCRemain_pw2		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-6.4,14.6-6.4)	-0.0236	0.0009	0.0000
vLOCRemain_pw3		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-14.6,29-14.6)	-0.0125	0.0004	0.0000
vLOCRemain_pw4		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-29,53.5-29)	-0.0068	0.0002	0.0000
vLOCRemain_pw5		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-53.5,85.5-53.5)	-0.0061	0.0001	0.0000
vLOCRemain_pw6		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-85.5,88.5-85.5)	-0.0164	0.0021	0.0000
vLOCRemain_pw7		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-88.5,96.25-88.5)	-0.0112	0.0012	0.0000
vLOCRemain_pw8		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-96.25,97.5-96.25)	0.1165	0.0094	0.0000
vLOCRemain_pw9		Variate piecewise Line of Credit Remaining[2]	max(0,loc_remaining-97.5)	0.1882	0.0041	0.0000
vp_appr_infl_1_pw2		Variate piecewise appr_infl_1	median(0,p_appr_infl_1--.04,.05--.04)	-0.4857	0.0627	0.0000
vp_appr_infl_1_pw3		Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.05,.2-.05);	-0.3561	0.0224	0.0000
vp_appr_infl_1_pw4		Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.2,.3-.2);	0.5845	0.0526	0.0000
vp_appr_infl_1_pw5		Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.3,.4-.3);	-0.4004	0.1138	0.0004
Scale				0.9233	0.0000	

Tax and Insurance Default Frequency Model

The model parameters for the tax and insurance default frequency model are shown below.

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

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
Intercept				-4.4243	0.0132	0.0000
mSeason	L01	Categorical Season	mod(period,100) = 1	-0.0819	0.0051	0.0000
mSeason	L02	Categorical Season	mod(period,100) = 2	0.0259	0.0050	0.0000
mSeason	L03	Categorical Season	mod(period,100) = 3	0.0501	0.0050	0.0000
mSeason	z_Base	Categorical Season	Base level: else	0.0000		
mTICnt	L01	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 1	2.2073	0.0050	0.0000
mTICnt	L02	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 2	2.8212	0.0059	0.0000
mTICnt	L03	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 3	3.0662	0.0068	0.0000
mTICnt	L04	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 4	3.2105	0.0079	0.0000
mTICnt	L05	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 5	3.3045	0.0091	0.0000
mTICnt	L06	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 6	3.4147	0.0106	0.0000
mTICnt	L07	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 7	3.5096	0.0124	0.0000
mTICnt	L08	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 8	3.5784	0.0147	0.0000
mTICnt	L09	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 9	3.6177	0.0174	0.0000
mTICnt	L10	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 10	3.6880	0.0208	0.0000
mTICnt	L11	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 11	3.8032	0.0247	0.0000
mTICnt	L12	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 12	3.7432	0.0294	0.0000
mTICnt	L13	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 13	3.8646	0.0360	0.0000

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
mTICnt	L14	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 14	3.9607	0.0440	0.0000
mTICnt	L15	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 15	3.9483	0.0540	0.0000
mTICnt	L16	Categorical Count of Tax and Ins Default[1]	Else	4.0224	0.0401	0.0000
mTICnt	z_Base	Categorical Count of Tax and Ins Default[1]	Base level: TI_Debit_Cnt_i = 0	0.0000		
vperiodnbr_TIDF_pw1		Variate piecewise Period Number	median(0,period_number-5,20-5)	-0.0153	0.0005	0.0000
vperiodnbr_TIDF_pw2		Variate piecewise Period Number	median(0,period_number-20,29-20)	-0.0253	0.0008	0.0000
vperiodnbr_TIDF_pw3		Variate piecewise Period Number	median(0,period_number-29,44-29)	-0.0273	0.0006	0.0000
vperiodnbr_TIDF_pw4		Variate piecewise Period Number	max(0,period_number-44)	-0.0121	0.0011	0.0000
vp_appr_infl_1_pw2		Variate piecewise appr_infl_1	median(0,p_appr_infl_1--.04,.05--.04)	0.9697	0.1572	0.0000
vp_appr_infl_1_pw3		Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.05,.2-.05);	0.4474	0.0451	0.0000
vp_appr_infl_1_pw4		Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.2,.3-.2);	1.1124	0.0868	0.0000
vp_appr_infl_1_pw5		Variate piecewise appr_infl_1	median(0,p_appr_infl_1-.3,.4-.3);	0.4798	0.1361	0.0004

Tax and Insurance Default Amount Model

The model parameters for the tax and insurance default amount model are shown below.

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

Variable	Description	Description Detail	Estimate	StdErr	ProbChiSq
Intercept			1.6807	0.0839	0.0000
vperiod_number	Period Number	period	-0.0108	0.0021	0.0000
vProperty_Value_Curr	Property Value	property_value_curr	0.0002	0.0000	0.0001
Scale			0.6364	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 below.

Figure 13: Model Validation - Likelihood of Cash Draw

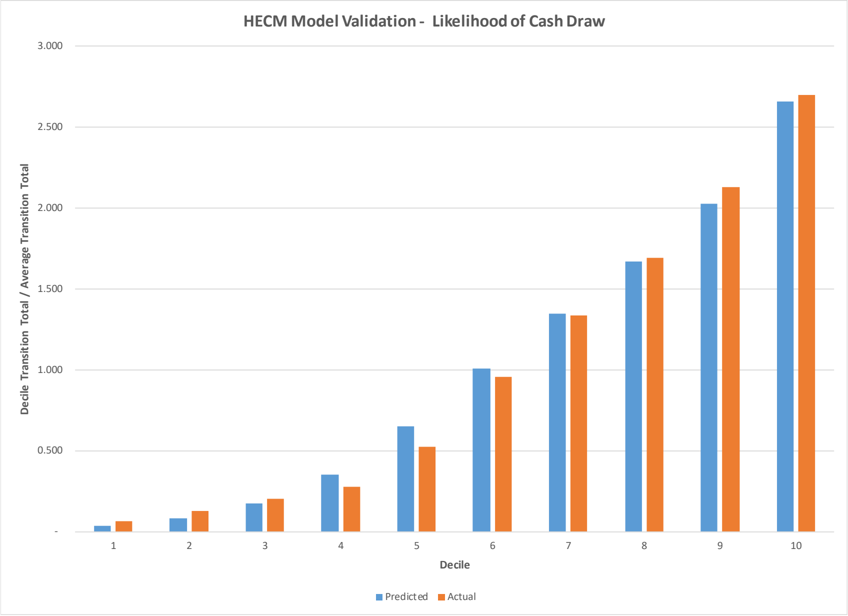


Figure 14: Model Validation - Likelihood of Full Cash Draw (Quarters 1 – 8)

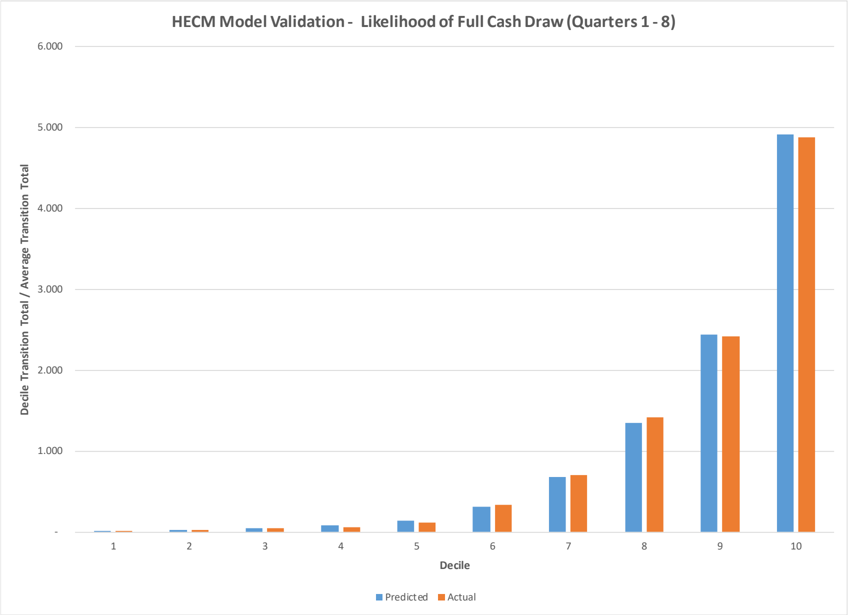


Figure 15: Model Validation - Likelihood of Full Cash Draw (Quarters 9+)

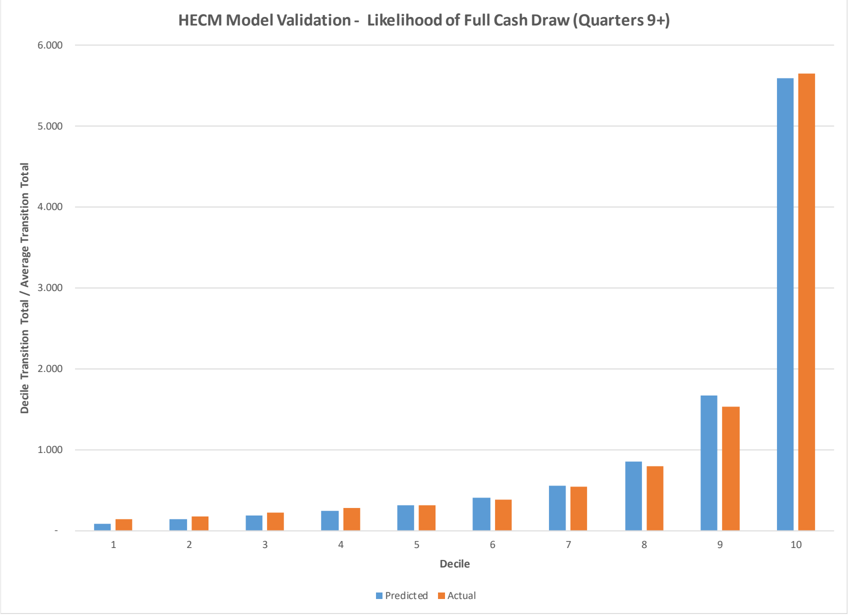
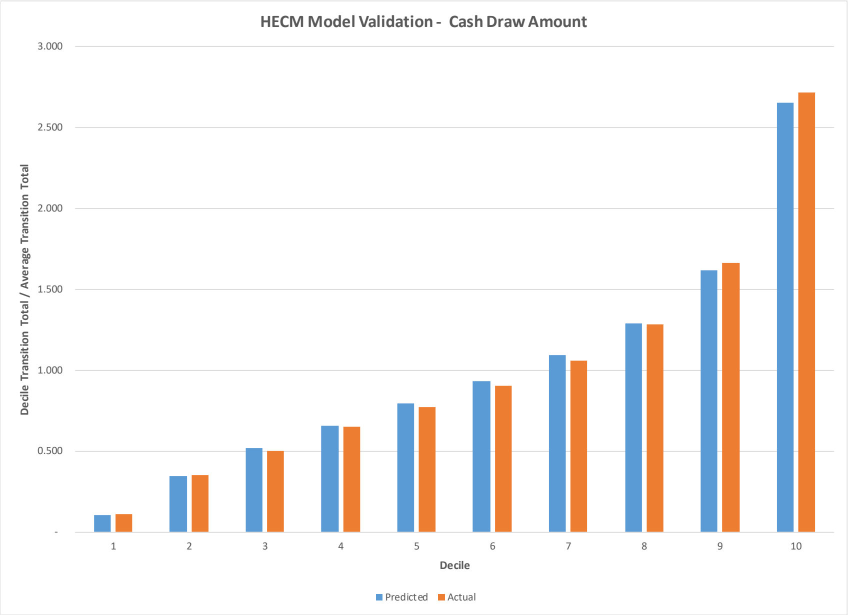


Figure 16: Model Validation – Cash Draw Amount



The validation chart for the tax and insurance default model is shown below.

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

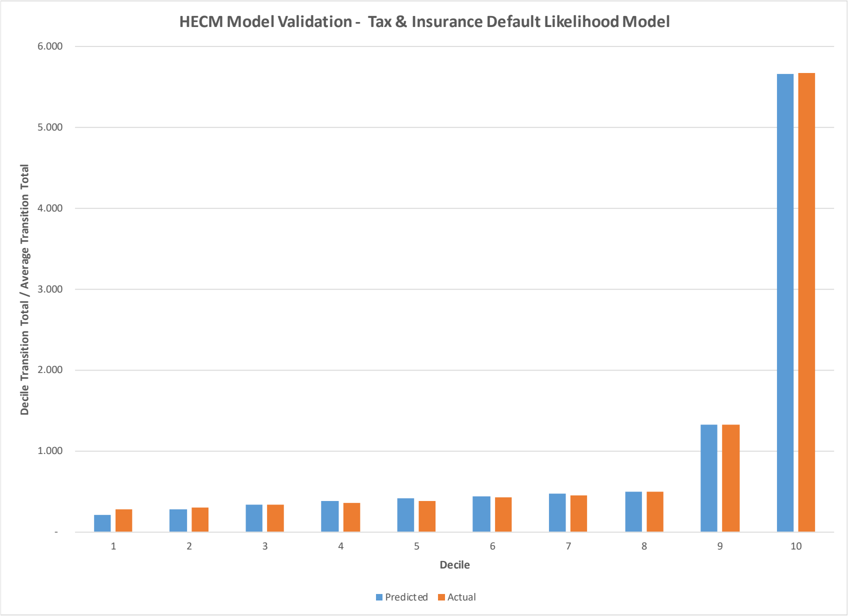
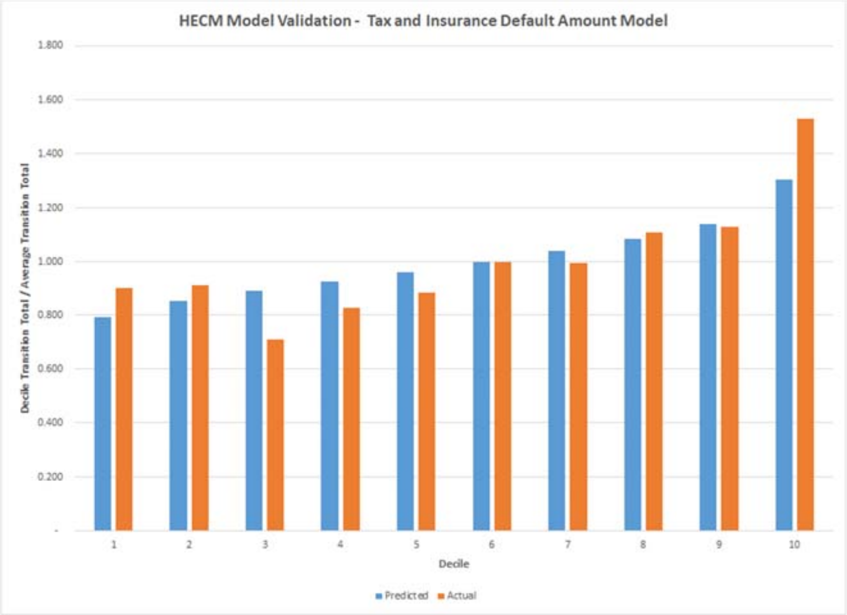


Figure 18: Model Validation - Tax and Insurance Default Amount Model



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 also projections for ten additional deterministic economic scenarios from Moody's. For this analysis, we used the Moody's August 2020 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 Moody's Baseline scenario, the HPI is flat through the third quarter of 2021, and then increases over the remainder of the projection period. The rate of increase is about 5% per year through 2030, and then decreases to about 3% per year for the remainder of the projection period.

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

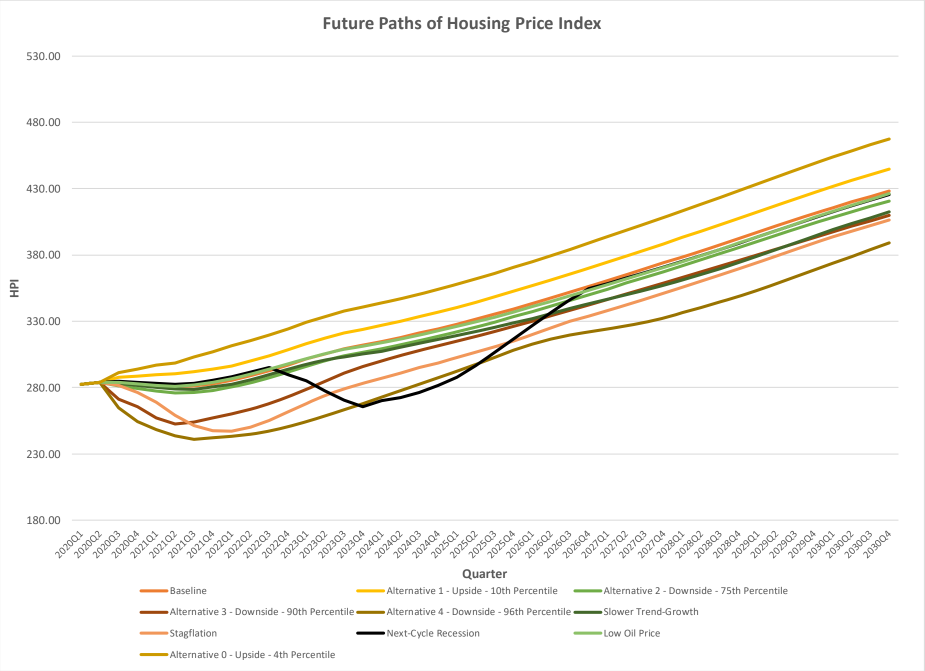


Figure 20 shows the forecasted mortgage rate of 30-year fixed-rate mortgages for the ten Moody's scenarios. Moody's Baseline forecast for the 30-year fixed interest rate decreases to about 3% through the second quarter of 2021 and then increases for the remainder of the projection period. The mortgage rate levels off at approximately 5.5% by 2026.

Figure 20: Paths of the Future Mortgage Rate

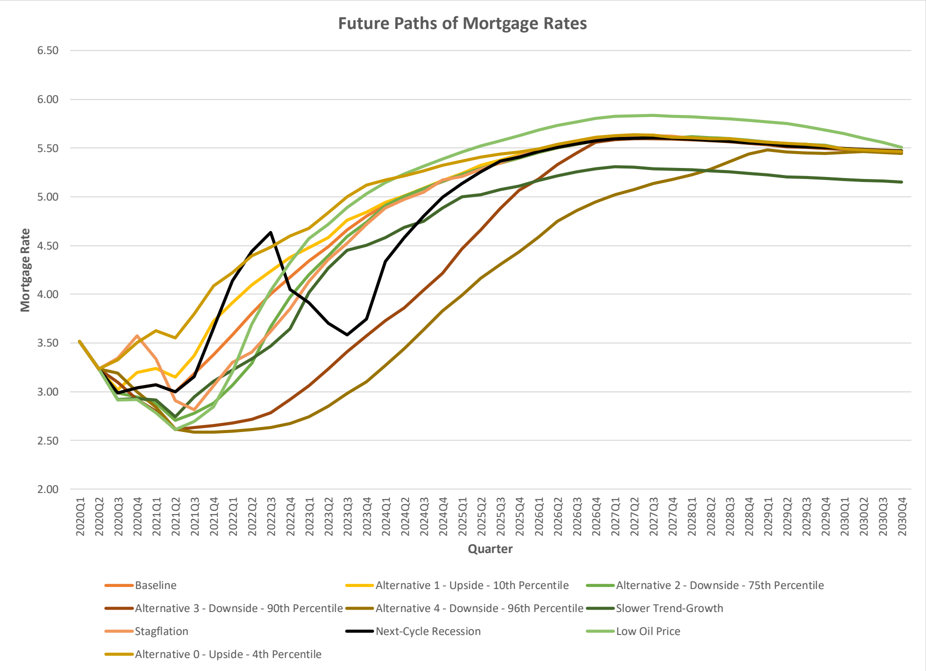
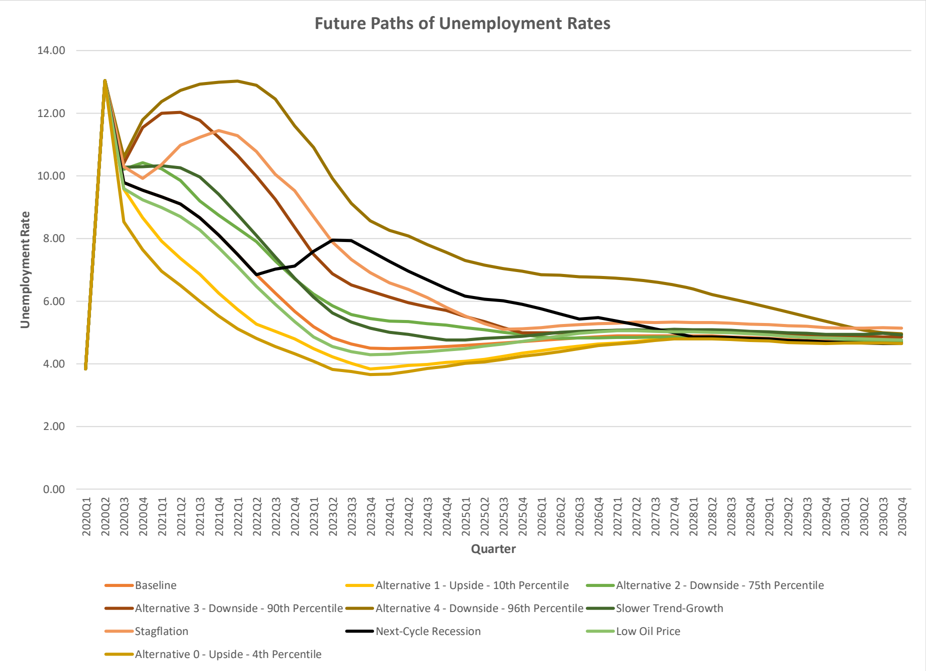


Figure 21 shows the forecasted unemployment rate under alternative economic scenarios. The Moody's Baseline forecast projects that the unemployment rate decreases through 2023 to approximately 4.5%, and then remains steady at that level for the remainder of the projection period. Under this scenario, it is projected that it will take approximately three years for unemployment to fully return to more stable levels, and it is projected to stabilize at a level higher than pre-COVID-19 unemployment levels.

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:

- Six-Month CMT Rates
- One-Year CMT Rates
- 10-Year CMT Rates
- 30-Year CMT Rates
- 30-Year FRM Rates
- FHFA National Purchase Only House Price Index (HPI-PO)
- Unemployment Rates
- GDP
- Small Business Normalized Optimism Index (NOI)
- Consumer Confidence Index (CCI)

Historical Data

A. Interest Rates

Figure 22 shows historical interest rates since 1971. This graph illustrates 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 were the major cause of the historically high interest rates in early 1980's. The Federal Reserve shifted its monetary policy from managing interest rates to managing the money supply as a way to influence interest rates after this period of time. The tr1y was around 5% in Calendar Year 1971 and increased steadily to its peak of 16.31% in the third quarter of Calendar Year 1981. Subsequently, tr1y followed a decreasing trend and reached an all-time low of 0.10% in the second quarter of Calendar Year 2014. Since that time, rates had started a slow upward trend until recently, where there is a sharp downturn due to the COVID-19 pandemic.

Figure 22: Historical Interest Rates (%)

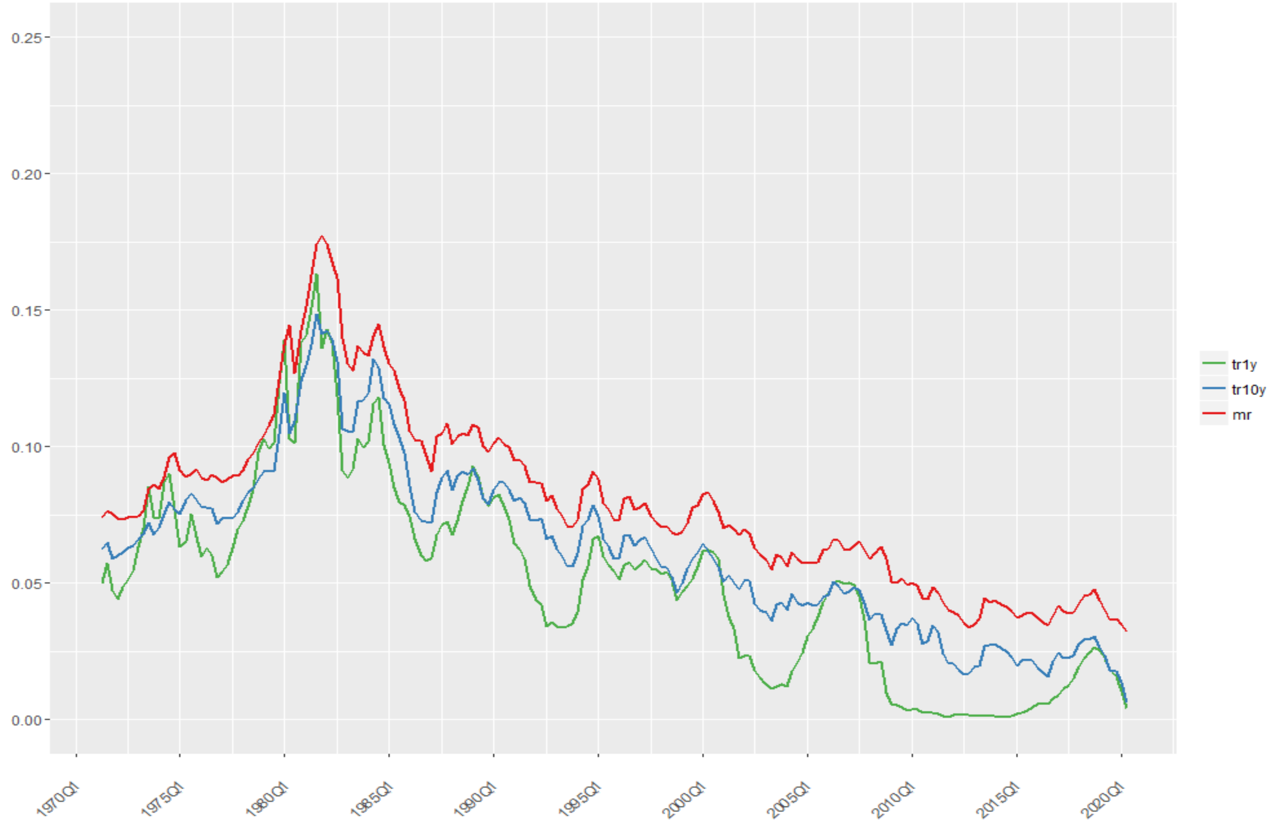
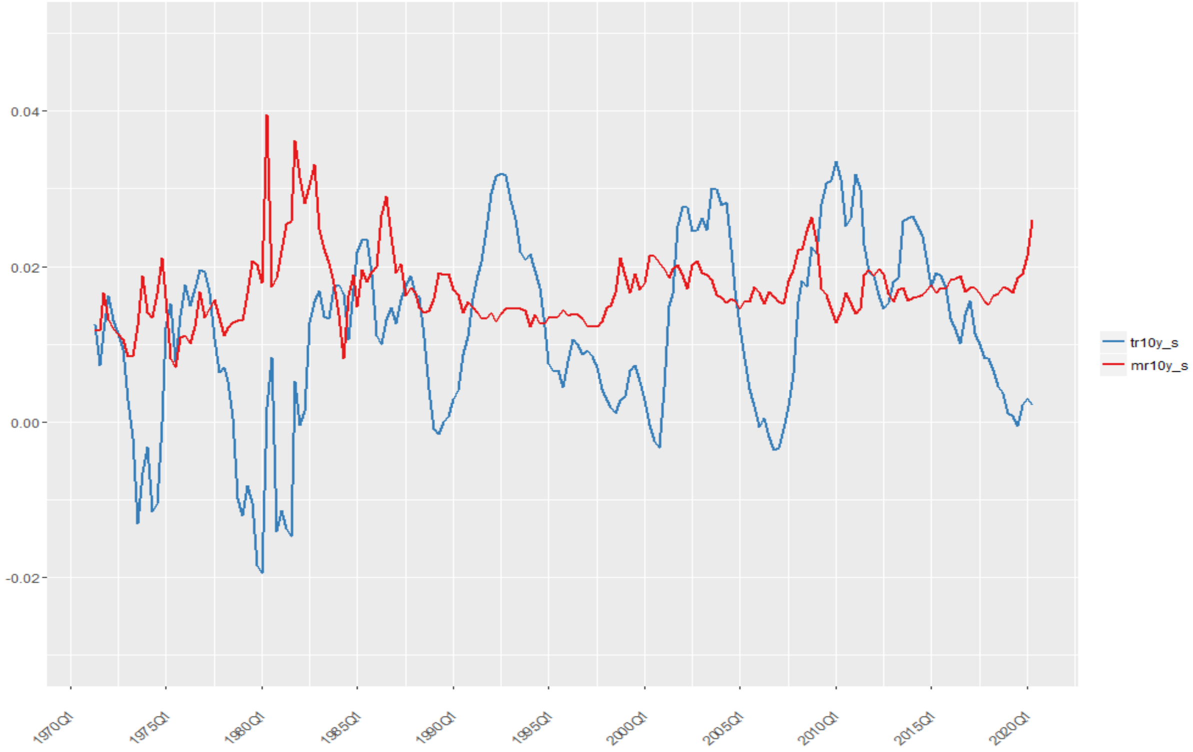


Figure 23 shows historical interest rate spreads, including the spread between 10-year and one-year CMT rates (tr10y_s) and the spread between the 30-year mortgage rate and the 10-year CMT rate (mr10y_s). Both spreads have primarily positive value with long cycles. Smaller positive and negative spreads typically correspond with economic downturns, an example being the downturn during the late 1970's through early 1980's. The spread of the mortgage rate over the 10-year CMT rate is always positive, reflecting the premium for credit risk.

Figure 23: Historical Interest Rate Spreads (%)



B. House Price Appreciation Rates

The national HPA is derived from the FHFA repeat sales 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 24 shows the national quarterly HPA from the first quarter of Calendar Year 1991 to the second quarter of Calendar Year 2020. The long-term average quarterly HPA is approximately 0.87% (3.30% annual rate).

Figure 24: Historical National HPI and Quarterly HPA

The HPI increased steadily before 2004, and the quarterly appreciation rate was approximately 1.14%. Then house prices rose sharply starting in 2004. The average quarterly HPA rate was 1.88% during the subprime mortgage expansion period from 2004 to 2006, and reached its peak of 2.59% in the second quarter of Calendar Year of 2005. After 2006, the average growth rate of house prices turned negative until 2011 when appreciation returned to a positive value. Following an almost eight quarter period of a nearly flat appreciation rate, the last quarter showed an sharp decrease to nearly 0% appreciation, again, resulting from the economic shock of COVID-19.

Table 36 shows the quarterly HPA by selected historical time-periods.

Table 36: Average Quarterly HPA by Time Span

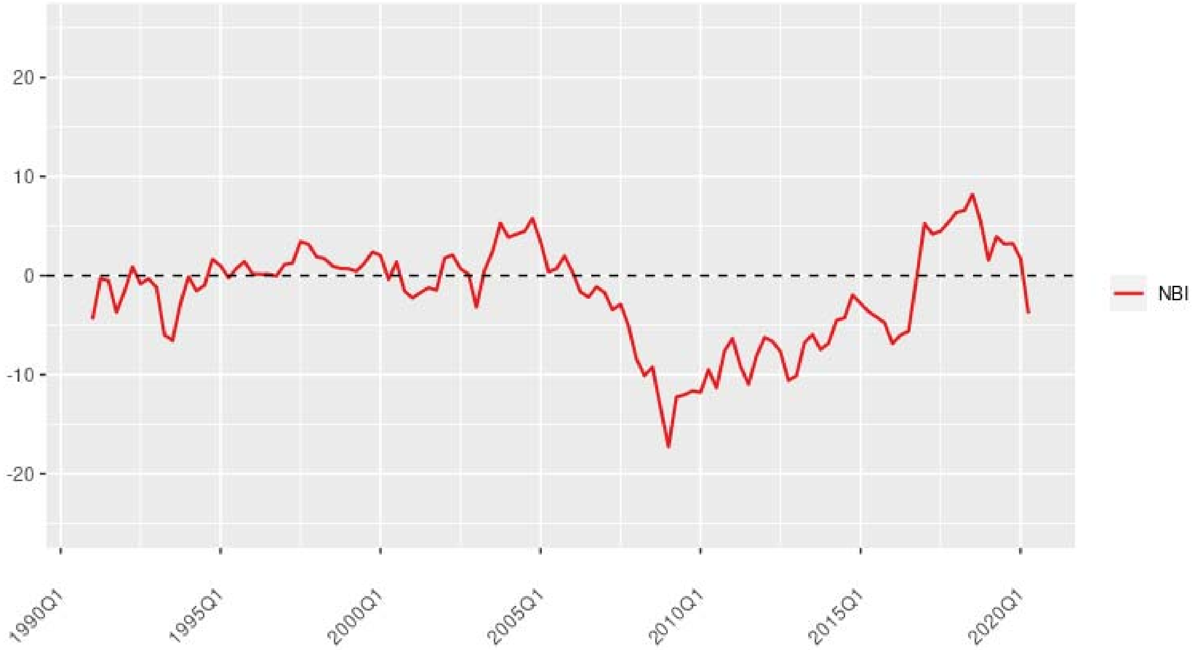
Period	Average Quarterly HPA
1991 – 2003	1.13%
2004 – 2006	1.87%
2007 – 2010	-1.23%
2011 – 2020-Q2	1.12%

C. Confidence Indices

The Small Business Normalized Optimism Index (NOI) and Consumer Confidence Index (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, and values below 100 indicate relative pessimism. Figure 25 and Figure 26 show CCI and NOI, with noted sharp drops in confidence associated with the 2008 mortgage crisis and the recent COVID-19 pandemic.

Figure 25: Consumer Confidence Index

Figure 26: Small Business Normalized Optimism Index

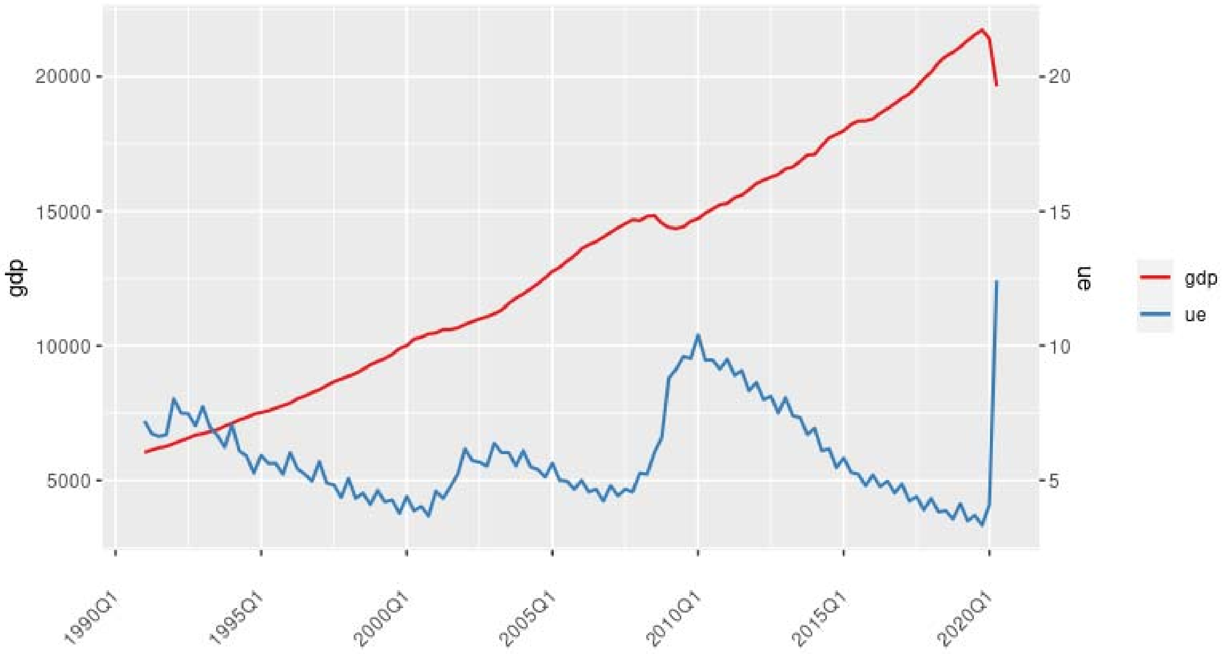


Modeling Method

In financial econometrics, 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 27, we can see two obvious examples of this following the mortgage crisis in 2008 and again with the recent COVID-19 pandemic.

Figure 27: Unemployement 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 account for these factors will lead to models that are more predictive.

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

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

Table 37 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
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	(1,1)	(1,0)	Skewed student-t

Variable	Variable Transformation	ARMA(p,q)	GARCH(p,q)	Distribution
	transformation			
NOI	First difference, log function transformation	(0,0)	(0,1)	Normal
CCI	First difference, log function transformation	(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	0.0205
tr1yr.ma1	0.7242
tr1yr.omega	0.0004
tr1yr.alpha1	0.3378
tr1yr.beta1	0.6612
tr6m.mu	-0.2407
tr6m.ar1	0.8247
tr6m.omega	0.0004
tr6m.alpha1	0.2418
tr6m.beta1	0.7572
tr10yr.mu	1.8144
tr10yr.ar1	0.9837

Variable	Estimate
tr10yr.omega	0.0406
tr10yr.alpha1	0.1780
tr10yr.beta1	0.4290
tr30yr.mu	2.0151
tr30yr.ar1	0.9846
tr30yr.omega	0.0736
tr30yr.alpha1	0.2932
tr30yr.beta1	0.1697
mr.mu	3.1573
mr.ar1	0.9744
mr.omega	0.0447
mr.alpha1	0.3597
mr.beta1	0.2284
ue.omega	0.0051
ue.alpha1	0.0000
ue.beta1	0.9990
GDP.mu	5.5025
GDP.ar1	0.7303
GDP.ma1	-0.3175
GDP.omega	0.0080
GDP.alpha1	0.0584
GDP.beta1	0.9105
GDP.skew	0.8471
GDP.shape	0.4426
HPI.mu	0.9943
HPI.omega	0.9385
HPI.alpha1	0.3366
HPI.skew	0.6810
HPI.shape	59.9998
NOI.mu	0.0071
NOI.ar1	0.0699
NOI.omega	0.0094
NOI.alpha1	0.0000
NOI.beta1	0.9990
CCI.mu	0.1811
CCI.ar1	0.0765
CCI.omega	0.1301
CCI.alpha1	0.0000
CCI.beta1	0.9990

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

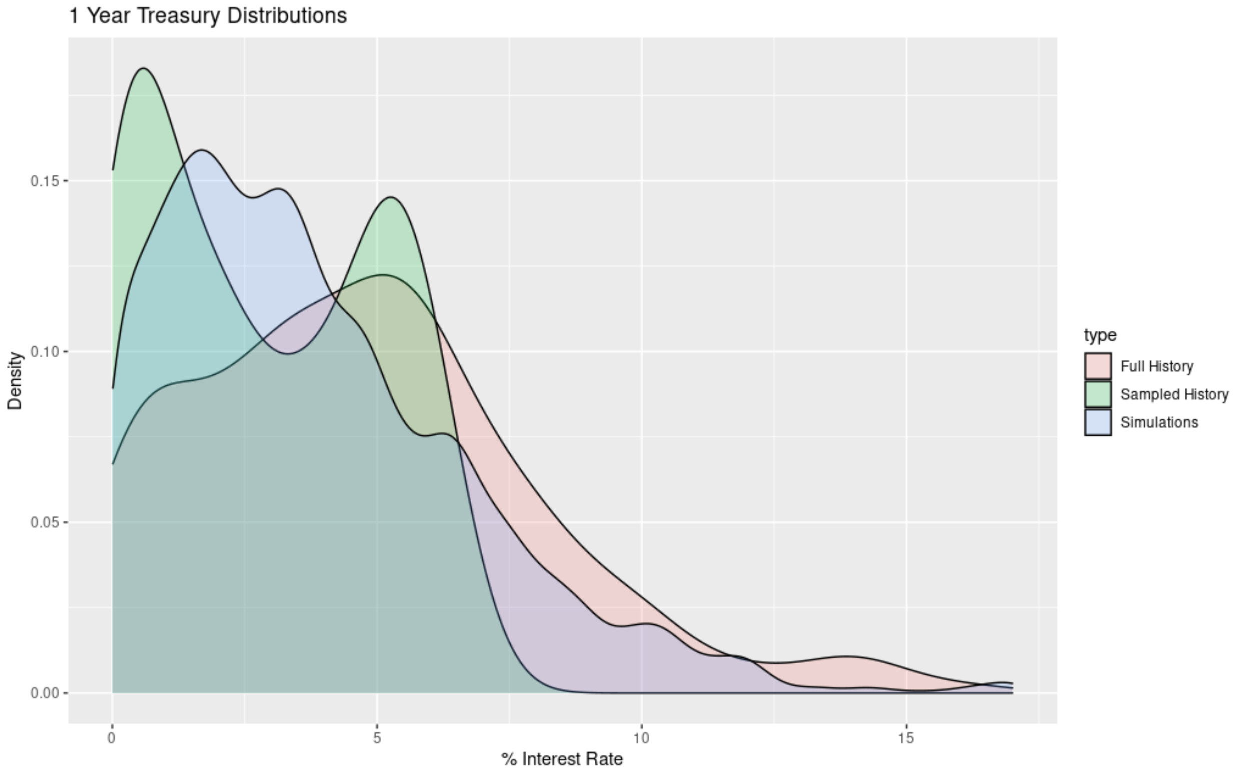
Table 39 shows the summary statistics of the historical one-year CMT rates for two different periods as well as the simulated series. We can see that in the last 50 or more years, interest rates have had a much broader range as compared to the last 25 years.

Table 39: Statistics for the One-Year Treasury Rates

Statistics	Since 1953	Since 1991	Simulations
95-Percentile	10.29%	6.14%	9.55%
90-Percentile	8.94%	5.70%	7.80%
50-Percentile	4.60%	2.41%	3.31%
25-Percentile	2.28%	0.57%	1.64%
10-Percentile	0.51%	0.18%	0.64%
5-Percentile	0.19%	0.13%	0.20%
Mean	4.78%	2.84%	3.87%
Max	16.31%	6.71%	17.00%
Min	0.10%	0.10%	0.01%
Variance	10.78%	4.71%	2.63%

Figure 28 shows density distributions for the one-year CMT rates, comparing the distribution of the historical rates, historic sample used for simulations, and the distributions of all the simulations.

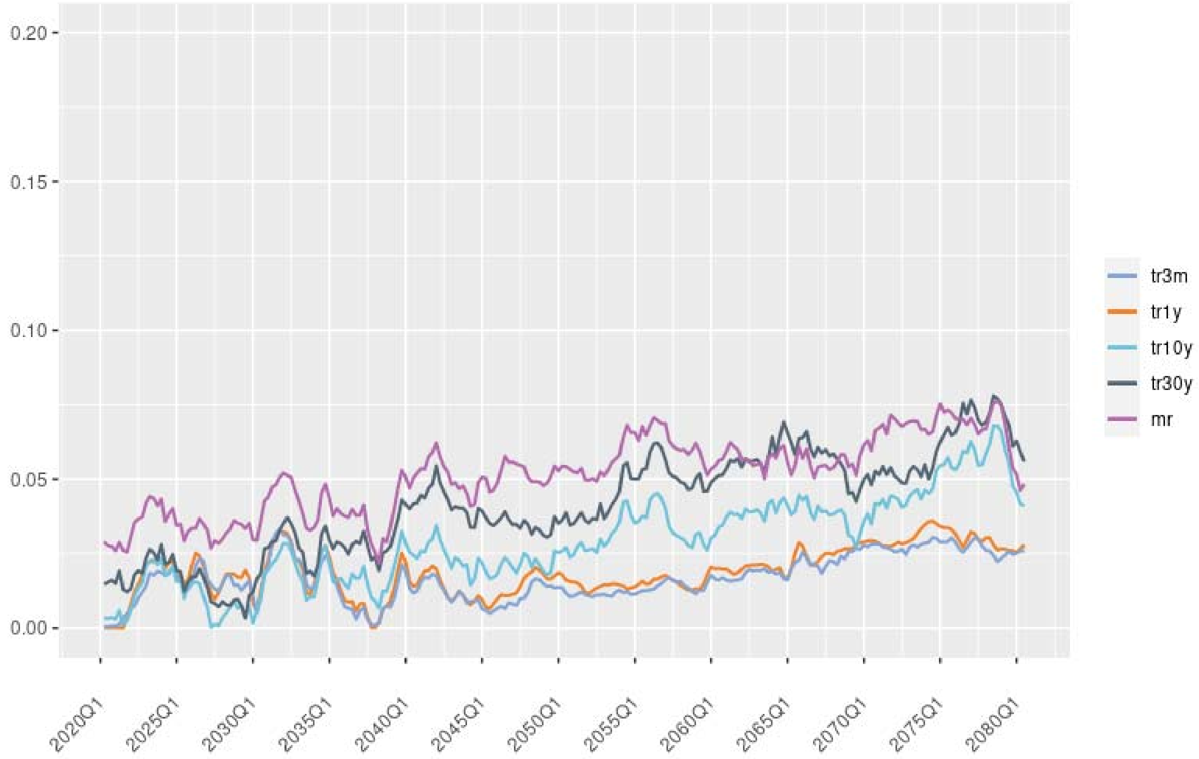
Figure 28: One-Year Treasury Rate Densities, Historical and Simulations



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

Figure 29 graphs one 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 29: Interest Rate Sample Simulation



House Price Appreciation Rate

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 trends, but when simulated trends are averaged across all series they are very close to the historical trend used in model fitting.

Table 40: HPI Simulation Statistics

	Simulated Series			
	Max trend	**Min trend**	**Mean trend**	**Historical Trend**
HPI	8.462885	0.2034	1.775645	1.8179

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:

$$Disp_{i,t}^{Base} = HPA_{i,t}^{Base} / HPA_{national,t}^{Base} \qquad (3)$$

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:

$$HPA_{i,t}^{j} = HPA_{national,t}^{j} * Disp_{i,t}^{Base} \qquad (4)$$

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.[3]

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 MMI.

Unemployment Rate

A. National Unemployment Rate

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

Table 41 – Unemployment Historical and Simulation Statistics

Statistics	Since 1953	Since 1991	Simulations
95-Percentile	9.13%	9.47%	16.36%
90-Percentile	8.08%	8.68%	14.99%
50-Percentile	5.53%	5.45%	9.68%
25-Percentile	4.53%	4.61%	7.28%
10-Percentile	3.69%	4.10%	4.15%
5-Percentile	3.38%	3.82%	2.19%
Mean	5.76%	5.89%	9.59%
Max	12.42%	12.42%	21.00%
Min	2.47%	3.33%	1.50%
Variance	2.96%	3.06%	0.08%

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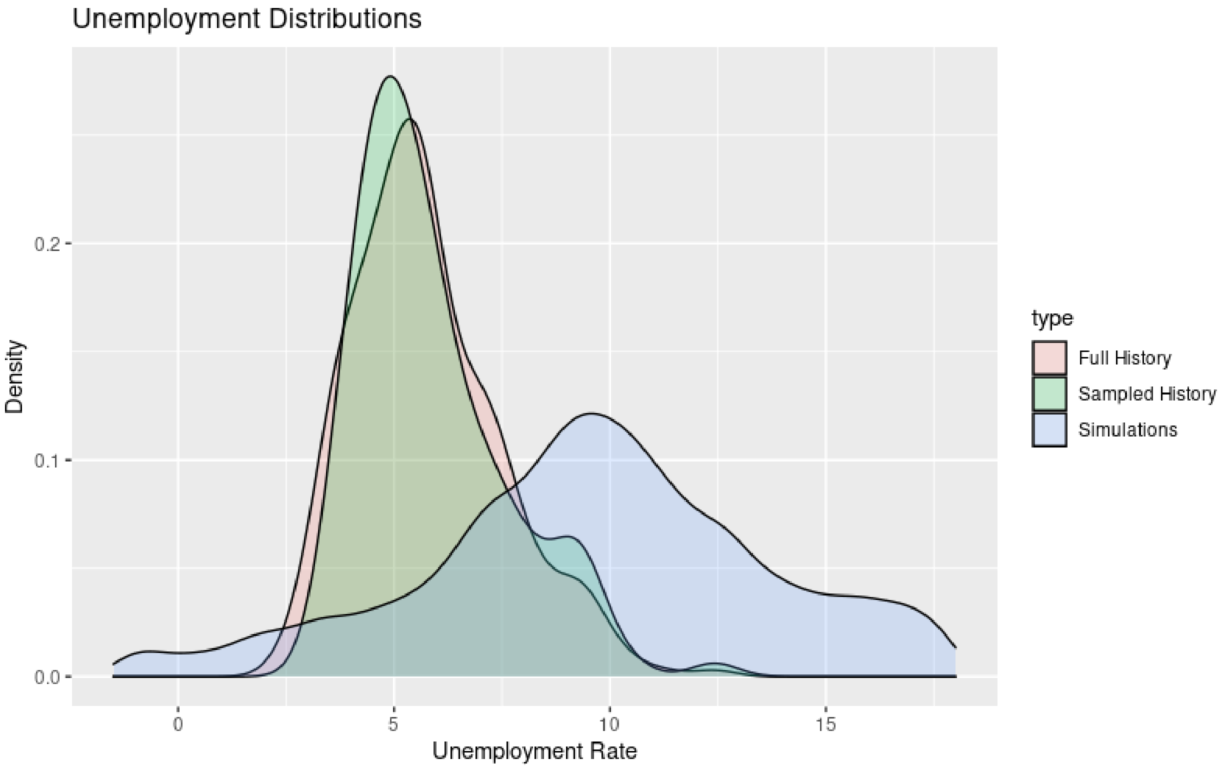
[3] The dispersion of each MSA remains constant among all alternative Moody's forecast scenarios.

Based on historical statistics, the national unemployment rate was capped at 20%, with a floor at 2%.

Figure 30 is a density plot comparison of the historical series and simulated sets. The unusually high unemployment within these simulated sets is a result of the increased spike in unemployment cause by the COVID-19 pandemic. The pandemic has affected all simulations, but most notably, this series. Further data and analysis is needed is needed to better determine how this outlier will affect future series data, and how best to account for this.

Figure 30: Unemployment Rate Densities Historical and Simluations



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*:

$$Disp_{i,t}^{Base} = ue_{i,t}^{Base} / ue_{national,t}^{Base} \tag{5}$$

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:

$$ue_{i,t}^{j} = ue_{national,t}^{j} * Disp_{i,t}^{Base} \tag{6}$$

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 fairly small spread between the series when comparing the largest and smallest trends, and when simulated trends are averaged across all series they are very close to the historical GDP trend used in model fitting.

Table 42 – GDP Simulation Statistics

	Simulated Series			
	Max trend	**Min trend**	**Mean trend**	**Historical Trend**
GDP	3.873	1.518	2.239	2.254

Small Business Normalized Optimism Index/ Consumer Confidence Index

The small business and consumer confidence indices are based on a 100-point scale, where values under 100 represent less confidence in the economy, and values over 100 indicate an increase in confidence.

Table 43 - Confidence Indices Statistics

	Historical NOI	Simulated NOI	Historical CCI	Simulated CCI
Max	142.11	177.35	108.18	122.21
Min	29.86	24.61	82.73	65.89
Mean	94.38	96.22	98.13	94.18

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.

REFERENCES:

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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 2020 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.[4] 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 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[5] and ML 2015-11[6]. For HECMs after assignment, FHA currently does not foreclose

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

[5] Mortgagee Letter 2015-10, April 23, 2015 – "Home Equity Conversion Mortgage (HECM) Due and Payable Policies."

[6] Mortgagee Letter 2015-11, April 23, 2015 – "Loss Mitigation Guidance for Home Equity Conversion Mortgages (HECMs) in Default due to Unpaid Property Charges."

on assigned mortgages that are in T&I default. In order 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.

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:

$$\textit{Claim Type 1 Payment} = \textit{maximum}\ (0,\ \textit{UPB} - \textit{Net Property Sales Price})$$

The net sales price of the property is:

$$\textit{Net Property Sales Price} = \textit{Estimated Property Sales Price} \times (1 - \textit{sales expenses}\ \% - \textit{other expenses}\ \%)$$

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:

$$\text{Recovery Amount} =$$

$$\begin{array}{ll} minimum\,(UPB, Net\ Property\ Sales\ Price) & if\ terminated\ with\ \text{death}\ or\ \text{move}\ out \\ UPB & if\ terminated\ with\ refinance \end{array}$$

where the net sales price of the property is:

$$Net\ Property\ Sales\ Price = Estimated\ Property\ Sales\ Price \times (1 - sales\ expenses\ \% - other\ expenses\ \%)$$

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:

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

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. Pinnacle 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 Pinnacle 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 Pinnacle, and assesses the vulnerabilities of the models developed. We have also identified potential areas of future research based on this assessment.

Deliverable 5 of the Actuarial Report states:

> ***Deliverable 5: 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:

- <u>Process risk</u>— actual results vary from projected results due to variability in the mortgage insurance process
- <u>Parameter risk</u>— the uncertainty related to the parameters selected for a given model
- <u>Specification risk</u>— the 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.

There are multiple components of the Claim & Recovery Module. Claim probability modules use a logistic regression to estimate the probability of CT1 versus NClm termination. A separate logistic regression model estimates the probability of CT2 conveyance versus payoff termination. The recovery estimation models are used to estimate sales price at claim or termination. The CT1 and CT2 sales price model is developed using linear regression. The CT1 and CT2 sales expense assumption is developed based on historical expenses as a percentage of the home sales price. S-M enhanced this year's model due to increased data availability and developed separate expense assumptions for CT1 versus CT2. Based on the data provided in the technical note, this is a reasonable and favorable change.

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), and a weighted average is calculated to determine the overall likelihood of termination. As with the Stage 1 models for the HUD Forward assessment, this required the assumption of Independent Irrelevant Alternatives (IIA). This assumption is a candidate for future research and testing. HUD also assumed a waterfall pattern to the non-mortality terminations, which is reasonable based on the available data. Again, this could be a candidate for future research as more data becomes available.

The four types of terminations are the mortality termination, refinance termination, tax and insurance default termination, and the mobility termination. For the FY2022.0 models, S-M has combined the Mobility termination and the Tax and Insurance Default termination into an all Other termination model. This is an update from model version 2021.1. Mortality tables were used to determine mortality terminations separately by gender and age. A time lag between death and termination of the loan regardless of claim type is also applied based on study of the data. 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 used 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. Additionally, with the FY2022.0 model version, S-M combined the tax and insurance default terminations into the “other” terminations category. This is an improvement since, previously, there was no way to indicate a default termination. Now, the tax and insurance default model is a predictor in the CT1 probability model instead of being used as an additive risk of termination. Based on the technical note, S-M continues to evaluate new data with FHA to determine if additional terminations will be available for use in future model versions.

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 for the FY2022.0 model, S-M has updated the HECM code to directly pull 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 made several model updates as noted below, including enhancements to changes made on the prior (FY2021.1) model version. While these are all more sophisticated than the methods applied in previous analyses, they possibly introduce some additional forecasting risk.

- Appraisal inflation is used as an input for claim severity and claim probability estimations, as was first done with the FY2021.1 model version. This parameter is determined using regression trees, which allows for identification of more factors that influence appraisal inflation. Additional data was used this year which enhanced appraisal inflation predictions for cohorts 2019 and beyond. S-M tested various approaches to estimate appraisal value, and determined that the decision/regression trees were the best balance of sophistication and results. This is a reasonable approach.

- Sales prices are estimated using multiple linear regression as introduced in the prior model version, but was enhanced with this version to estimate CT1 and CT2 separately.

- Historical cash draw data used to estimate future cash draw behaviors was previously limited at 5% and 95% of cash draw distribution data. This has been expanded to include the range of 0% to 200% cash draws based upon S-M’s updated review of borrower behavior data.

- As noted above with the enhancement to availability of certain termination data, the new model structure includes the tax and insurance default termination model and the mobility termination model combined to capture any other terminations (other termination model). The tax and insurance default probability model is used as a predictor in the CT1 probability model.

- S-M made several updates to the splines based on a review of updated data.

- Building upon the prior version's change to use a regression estimate for probability of assignment to HUD, the FY2022.0 model version includes a new regression-based estimate for loans eligible to assign as a Mortgagee Optional Election (MOE) Assignment. Based on the report, MOE assignments have a very low frequency and a minimal impact on the final net present value calculation. Due to this low frequency, S-M was unable to produce an in and out of the sample test. The potential vulnerability due to this is very small.

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 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 of time as they did 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 results showed more deviation (beyond one coefficient of variation of the model's point estimate) for recent years on a number of variables. S-M provided some possible rationale for these deviations, which were reasonable, though still could be a potential vulnerability of the model performance.

Pinnacle HECM Budget Model Commentary

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

Similar to the Pinnacle 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 Pinnacle models were built using a training/validation approach, similar to S-M's methodology. To validate the performance of the models, Pinnacle 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. Pinnacle 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%, Pinnacle 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 Pinnacle 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, Pinnacle 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. Pinnacle has also developed a T&I default model which S-M has now incorporated into an other termination model with their

FY2022.0 model version.

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, Pinnacle 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 Pinnacle utilized Moody’s data on a state and MSA level when possible to provide for a greater reflection of differences in home prices, etc. across the country.

Simulation

Pinnacle 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.

Pinnacle 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.

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

Mutual Mortgage Insurance Fund
HECM Summaries
CT1 Claim Counts

Table 1: Incremental CT1 Claim Counts

	Evaluation Year																																																
Fiscal Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49
1990	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1991	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1992	0	0	1	0	0	1	2	3	0	0	1	2	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1993	0	0	0	0	3	1	4	4	1	3	1	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1994	0	0	0	2	4	8	1	1	3	2	0	3	0	0	0	0	0	0	1	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1995	0	0	0	1	7	9	3	7	3	1	1	0	0	0	0	0	0	1	0	0	2	2	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1996	0	0	4	5	5	2	4	4	0	4	0	0	1	0	1	0	1	0	0	1	1	1	1	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1997	0	1	12	7	2	9	1	2	2	0	3	1	1	3	1	2	0	3	1	6	1	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1998	0	5	8	3	12	8	7	16	9	7	3	6	3	6	6	4	4	7	10	2	4	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1999	0	2	2	9	11	6	4	4	4	12	6	8	9	8	2	10	10	14	10	5	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2000	0	1	4	5	4	3	4	3	4	1	11	2	14	7	12	14	13	8	5	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2001	0	0	1	10	5	9	6	8	4	6	12	14	6	20	9	20	13	6	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2002	0	1	0	6	3	15	14	18	20	18	23	22	40	37	34	25	19	7	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2003	1	1	4	12	16	13	19	34	40	36	37	42	53	44	30	15	14	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2004	0	3	11	31	34	65	75	81	102	97	110	155	153	101	68	54	19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2005	0	3	23	47	65	98	131	125	159	175	278	273	174	133	131	58	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2006	0	6	41	104	159	251	249	328	394	756	713	480	386	394	191	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2007	0	14	101	177	309	297	525	645	1,325	1,330	896	755	806	384	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2008	1	27	105	237	312	580	590	1,386	1,154	931	736	778	372	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2009	1	26	73	159	452	400	1,096	885	765	650	657	305	58	31	28	32	30	33	30	42	45	43	40	38	41	41	44	43	31	36	23	28	21	17	12	14	8	4	4	2	2	1	0	0	0	1	0	0	0
2010	1	10	54	220	232	530	489	417	357	372	137	46	37	21	16	15	19	14	25	21	19	23	15	15	17	14	13	23	6	11	14	4	11	7	3	4	4	2	2	0	3	0	0	0	1	0	1	0	0
2011	0	7	77	102	317	377	346	333	320	124	26	11	12	14	11	11	21	18	20	17	13	20	24	18	14	20	15	12	19	15	9	5	5	6	5	2	2	4	1	0	0	0	0	0	1	0	0	0	0
2012	0	18	33	150	252	232	215	222	91	15	4	8	5	7	11	16	19	16	14	17	12	18	24	18	18	13	16	10	7	10	7	7	9	5	1	6	0	1	1	0	0	0	1	0	0	0	0	0	0
2013	0	5	79	188	198	222	204	109	16	11	6	8	14	14	21	19	19	18	22	36	24	24	25	26	25	25	25	27	20	13	17	8	5	3	5	2	4	0	2	0	2	0	0	1	0	0	0	0	0
2014	0	9	43	64	92	102	64	3	7	2	3	4	5	11	10	17	12	12	27	17	23	28	28	21	18	18	17	15	21	16	11	5	9	3	8	1	5	5	5	1	0	1	1	0	0	0	0	0	0
2015	0	9	34	42	77	52	6	6	5	5	2	3	11	5	11	14	20	18	21	25	27	26	27	29	27	24	31	23	13	12	17	9	16	7	6	2	0	2	1	1	1	0	0	0	0	0	0	0	0
2016	1	9	22	41	28	3	4	8	11	6	17	9	11	14	15	21	15	26	29	26	20	22	25	19	24	25	16	19	12	18	3	17	9	8	11	2	2	3	1	1	0	0	1	0	1	0	0	0	0
2017	0	5	16	20	0	5	6	11	21	19	9	20	18	27	35	29	22	36	36	28	28	29	37	31	34	14	24	23	23	21	16	17	6	9	8	3	0	1	1	1	1	0	0	0	0	0	0	0	0
2018	0	2	9	2	2	3	6	9	9	7	7	11	7	14	16	14	18	21	14	21	24	22	14	19	20	10	15	9	14	8	15	9	4	4	3	1	1	1	1	0	0	0	1	0	0	1	0	0	0
2019	0	0	0	0	0	1	3	2	2	0	3	8	6	12	6	3	10	4	9	11	9	7	10	10	9	9	7	8	2	8	5	4	1	1	0	3	1	0	0	0	0	0	0	0	0	0	0	0	0
2020	0	0	0	2	1	6	6	6	15	13	16	6	23	10	16	14	22	27	18	18	26	16	16	18	21	17	18	10	5	8	9	6	5	0	1	3	2	1	2	0	1	1	0	0	0	0	0	0	0

Table 2: Incremental CT1 Claim Percentage = Incremental CT1 Claim Counts/Active Loans as of Evaluation Year 1

	Evaluation Year																																																
Fiscal Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49
2009	0.0%	0.1%	0.1%	0.4%	0.4%	1.0%	0.8%	0.7%	0.6%	0.6%	0.3%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2010	0.0%	0.1%	0.3%	0.3%	0.7%	0.6%	0.5%	0.5%	0.5%	0.2%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2011	0.0%	0.1%	0.1%	0.4%	0.5%	0.5%	0.5%	0.4%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2012	0.0%	0.1%	0.3%	0.5%	0.4%	0.4%	0.4%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2013	0.0%	0.1%	0.3%	0.3%	0.4%	0.3%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2014	0.0%	0.1%	0.1%	0.2%	0.2%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2015	0.0%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2016	0.0%	0.0%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.0%	0.0%	0.1%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2017	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.0%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2018	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2019	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2020	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.1%	0.1%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Table 3: Cumulative CT1 Claim Percentage = Cumulative CT1 Claim Counts/Active Loans as of Evaluation Year 1

	Evaluation Year																																																
Fiscal Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49
2009	0.0%	0.0%	0.1%	0.2%	0.6%	1.0%	1.9%	2.7%	3.4%	3.9%	4.5%	4.8%	4.8%	4.9%	4.9%	4.9%	4.9%	5.0%	5.0%	5.0%	5.1%	5.1%	5.1%	5.2%	5.2%	5.2%	5.3%	5.3%	5.3%	5.4%	5.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2010	0.0%	0.0%	0.1%	0.4%	0.7%	1.3%	1.9%	2.5%	2.9%	3.4%	3.6%	3.6%	3.7%	3.7%	3.7%	3.7%	3.8%	3.8%	3.8%	3.8%	3.9%	3.9%	3.9%	3.9%	3.9%	4.0%	4.0%	4.0%	4.0%	4.0%	4.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2011	0.0%	0.0%	0.1%	0.3%	0.7%	1.2%	1.7%	2.1%	2.6%	2.7%	2.8%	2.8%	2.8%	2.8%	2.8%	2.9%	2.9%	2.9%	2.9%	3.0%	3.0%	3.0%	3.0%	3.1%	3.1%	3.1%	3.1%	3.1%	3.2%	3.2%	3.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2012	0.0%	0.0%	0.1%	0.4%	0.8%	1.2%	1.6%	2.0%	2.2%	2.2%	2.2%	2.3%	2.3%	2.3%	2.3%	2.3%	2.4%	2.4%	2.4%	2.5%	2.5%	2.5%	2.6%	2.6%	2.6%	2.6%	2.7%	2.7%	2.7%	2.7%	2.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2013	0.0%	0.0%	0.1%	0.5%	0.8%	1.2%	1.5%	1.7%	1.7%	1.7%	1.7%	1.7%	1.8%	1.8%	1.8%	1.9%	1.9%	1.9%	2.0%	2.0%	2.1%	2.1%	2.1%	2.2%	2.2%	2.3%	2.3%	2.4%	2.4%	2.4%	2.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2014	0.0%	0.0%	0.1%	0.2%	0.4%	0.6%	0.7%	0.7%	0.7%	0.7%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.9%	0.9%	0.9%	1.0%	1.0%	1.1%	1.1%	1.2%	1.2%	1.2%	1.3%	1.3%	1.3%	1.4%	1.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2015	0.0%	0.0%	0.1%	0.1%	0.3%	0.4%	0.4%	0.4%	0.4%	0.4%	0.4%	0.4%	0.4%	0.4%	0.5%	0.5%	0.5%	0.6%	0.6%	0.6%	0.7%	0.7%	0.8%	0.8%	0.9%	0.9%	1.0%	1.0%	1.0%	1.0%	1.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2016	0.0%	0.0%	0.1%	0.1%	0.2%	0.2%	0.2%	0.2%	0.3%	0.3%	0.3%	0.3%	0.3%	0.4%	0.4%	0.5%	0.5%	0.5%	0.6%	0.6%	0.7%	0.7%	0.8%	0.8%	0.9%	0.9%	1.0%	1.0%	1.0%	1.1%	1.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2017	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%	0.1%	0.2%	0.2%	0.2%	0.2%	0.3%	0.3%	0.4%	0.4%	0.5%	0.5%	0.6%	0.7%	0.7%	0.8%	0.8%	0.9%	0.9%	1.0%	1.0%	1.1%	1.1%	1.1%	1.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2018	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%	0.1%	0.2%	0.2%	0.2%	0.2%	0.3%	0.3%	0.4%	0.4%	0.4%	0.5%	0.5%	0.6%	0.6%	0.6%	0.7%	0.7%	0.7%	0.7%	0.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2019	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%	0.1%	0.2%	0.2%	0.2%	0.3%	0.3%	0.3%	0.3%	0.4%	0.4%	0.4%	0.5%	0.5%	0.5%	0.5%	0.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2020	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.2%	0.2%	0.2%	0.2%	0.3%	0.3%	0.4%	0.4%	0.5%	0.5%	0.6%	0.6%	0.7%	0.7%	0.8%	0.8%	0.8%	0.9%	0.9%	0.9%	0.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Mutual Mortgage Insurance Fund
HECM Summaries
CT2 Claim Counts

Table 4: Incremental CT2 Claim Counts

	Evaluation Year																																																
Fiscal Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49
1990	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1991	0	0	0	0	0	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1992	0	0	0	0	0	0	2	0	0	1	2	2	1	1	3	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1993	0	0	0	0	0	2	0	0	1	7	4	4	1	3	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1994	0	0	1	0	3	0	2	6	6	11	8	6	9	10	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1995	0	0	0	2	0	0	1	6	8	11	5	18	12	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1996	1	0	4	2	0	0	3	7	14	9	21	19	4	1	0	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1997	0	0	0	0	0	0	7	13	14	36	19	6	2	6	4	1	2	1	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1998	7	1	1	1	2	4	5	12	23	28	12	4	10	10	3	3	9	7	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1999	3	0	0	2	1	8	10	37	54	20	16	12	13	4	7	4	9	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2000	42	0	1	0	2	2	10	6	3	2	8	6	2	2	7	4	4	2	2	3	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2001	49	0	0	2	1	7	11	10	10	9	11	3	8	10	13	10	6	5	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2002	82	1	1	2	8	17	20	20	23	35	15	15	29	35	39	22	18	13	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2003	48	1	4	14	79	73	87	64	93	34	52	65	99	75	25	12	10	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2004	22	1	10	49	68	67	80	155	44	91	134	197	215	134	125	75	52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2005	1	1	23	39	71	83	125	63	107	204	322	325	228	263	199	117	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2006	0	5	21	37	63	78	48	109	168	273	336	283	357	390	452	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2007	1	0	6	7	21	11	26	59	123	178	152	247	548	529	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2008	0	0	1	16	15	35	67	126	142	148	296	631	619	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2009	1	1	8	42	166	237	642	824	499	642	1,314	1,089	924	762	565	300	188	95	54	56	43	43	30	27	16	16	10	12	8	2	5	3	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2010	0	12	41	165	353	756	1,425	1,125	1,173	1,520	215	145	134	153	145	98	77	34	33	14	17	17	10	5	5	8	1	6	1	4	0	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
2011	0	0	0	7	174	1,113	1,385	2,158	832	334	228	155	120	146	76	65	41	31	21	21	21	16	8	6	10	3	3	1	3	4	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2012	2	0	1	20	269	817	1,402	2,036	352	220	208	116	97	69	43	43	29	17	14	17	8	11	8	7	11	6	5	5	3	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2013	0	0	0	30	220	586	2,106	1,718	504	418	284	162	114	71	49	45	34	32	18	27	17	14	19	10	4	9	10	2	1	1	1	1	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
2014	0	0	1	3	6	29	83	172	374	589	417	298	296	224	76	62	50	40	21	27	12	13	15	13	7	5	6	6	3	1	2	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
2015	0	0	0	1	6	36	83	201	361	563	615	531	314	151	63	60	41	41	36	30	16	13	13	11	7	7	4	4	1	3	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2016	0	0	0	0	29	62	139	279	453	668	657	309	139	75	62	50	45	37	28	30	13	13	10	13	7	9	4	3	3	1	0	1	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
2017	0	0	0	2	36	123	221	500	722	836	621	254	136	110	72	63	51	55	49	36	26	12	11	11	4	5	5	3	3	2	2	0	2	1	2	0	0	0	1	0	0	0	0	0	0	0	0	0	0
2018	0	0	0	2	22	28	52	133	244	346	288	154	126	87	118	96	82	43	30	28	15	13	6	5	7	4	4	4	2	3	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2019	0	0	0	0	0	0	1	1	5	14	19	37	63	140	162	108	47	21	11	7	6	10	11	2	3	1	0	0	0	0	1	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2020	0	0	0	0	1	1	5	12	29	76	173	318	356	211	120	63	40	20	29	14	7	15	10	5	4	4	3	1	2	3	1	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0

Table 5: Incremental CT2 Claim Percentage = Incremental CT2 Claim Counts/Active Loans as of Evaluation Year 1

	Evaluation Year																																																
Fiscal Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49
2009	0.0%	0.0%	0.0%	0.1%	0.2%	0.6%	0.7%	0.4%	0.6%	1.2%	1.0%	0.8%	0.7%	0.5%	0.3%	0.2%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2010	0.0%	0.1%	0.2%	0.5%	1.0%	1.8%	1.4%	1.5%	1.9%	0.3%	0.2%	0.2%	0.2%	0.2%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2011	0.0%	0.0%	0.0%	0.2%	1.5%	1.9%	3.0%	1.1%	0.5%	0.3%	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2012	0.0%	0.0%	0.0%	0.5%	1.5%	2.6%	3.8%	0.6%	0.4%	0.4%	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2013	0.0%	0.0%	0.1%	0.4%	1.0%	3.6%	2.9%	0.9%	0.7%	0.5%	0.3%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2014	0.0%	0.0%	0.0%	0.0%	0.1%	0.2%	0.3%	0.7%	1.2%	0.8%	0.6%	0.6%	0.4%	0.1%	0.1%	0.1%	0.1%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2015	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.4%	0.6%	1.0%	1.1%	0.9%	0.6%	0.3%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2016	0.0%	0.0%	0.0%	0.1%	0.1%	0.3%	0.6%	0.9%	1.4%	1.4%	0.6%	0.3%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2017	0.0%	0.0%	0.0%	0.1%	0.2%	0.4%	0.9%	1.3%	1.5%	1.1%	0.5%	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2018	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.3%	0.5%	0.7%	0.6%	0.3%	0.3%	0.2%	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2019	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.2%	0.5%	0.5%	0.3%	0.2%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2020	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.2%	0.4%	0.8%	0.9%	0.5%	0.3%	0.2%	0.1%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Table 6: Cumulative CT2 Claim Percentage = Cumulative CT2 Claim Counts/Active Loans as of Evaluation Year 1

	Evaluation Year																																																
Fiscal Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49
2009	0.0%	0.0%	0.0%	0.0%	0.2%	0.4%	1.0%	1.7%	2.1%	2.7%	3.8%	4.8%	5.6%	6.2%	6.7%	7.0%	7.2%	7.3%	7.3%	7.3%	7.4%	7.4%	7.5%	7.5%	7.5%	7.5%	7.5%	7.5%	7.5%	7.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2010	0.0%	0.0%	0.1%	0.3%	0.7%	1.7%	3.5%	4.9%	6.4%	8.3%	8.6%	8.8%	8.9%	9.1%	9.3%	9.4%	9.5%	9.6%	9.6%	9.6%	9.7%	9.7%	9.7%	9.7%	9.7%	9.7%	9.7%	9.7%	9.7%	9.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2011	0.0%	0.0%	0.0%	0.0%	0.2%	1.8%	3.7%	6.6%	7.8%	8.2%	8.5%	8.7%	8.9%	9.1%	9.2%	9.3%	9.3%	9.4%	9.4%	9.4%	9.5%	9.5%	9.5%	9.5%	9.5%	9.5%	9.5%	9.5%	9.5%	9.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2012	0.0%	0.0%	0.0%	0.0%	0.5%	2.0%	4.6%	8.3%	8.9%	9.3%	9.7%	9.9%	10.1%	10.2%	10.3%	10.4%	10.4%	10.5%	10.5%	10.5%	10.5%	10.6%	10.6%	10.6%	10.6%	10.6%	10.6%	10.6%	10.6%	10.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2013	0.0%	0.0%	0.0%	0.1%	0.4%	1.4%	4.9%	7.8%	8.6%	9.3%	9.8%	10.1%	10.2%	10.4%	10.4%	10.5%	10.6%	10.6%	10.7%	10.7%	10.7%	10.8%	10.8%	10.8%	10.8%	10.8%	10.8%	10.9%	10.9%	10.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2014	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.2%	0.6%	1.3%	2.4%	3.2%	3.8%	4.4%	4.8%	5.0%	5.1%	5.2%	5.3%	5.3%	5.4%	5.4%	5.4%	5.4%	5.5%	5.5%	5.5%	5.5%	5.5%	5.5%	5.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2015	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.2%	0.6%	1.2%	2.2%	3.2%	4.1%	4.7%	4.9%	5.0%	5.1%	5.2%	5.3%	5.4%	5.4%	5.4%	5.5%	5.5%	5.5%	5.5%	5.5%	5.5%	5.5%	5.5%	5.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2016	0.0%	0.0%	0.0%	0.0%	0.1%	0.2%	0.5%	1.0%	2.0%	3.3%	4.7%	5.3%	5.6%	5.8%	5.9%	6.0%	6.1%	6.1%	6.2%	6.3%	6.3%	6.3%	6.3%	6.4%	6.4%	6.4%	6.4%	6.4%	6.4%	6.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2017	0.0%	0.0%	0.0%	0.0%	0.1%	0.3%	0.7%	1.6%	2.9%	4.4%	5.5%	6.0%	6.2%	6.4%	6.6%	6.7%	6.8%	6.9%	7.0%	7.0%	7.1%	7.1%	7.1%	7.1%	7.1%	7.2%	7.2%	7.2%	7.2%	7.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2018	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.2%	0.5%	1.0%	1.7%	2.3%	2.6%	2.9%	3.1%	3.3%	3.5%	3.7%	3.8%	3.8%	3.9%	3.9%	3.9%	4.0%	4.0%	4.0%	4.0%	4.0%	4.0%	4.0%	4.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2019	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.2%	0.4%	0.9%	1.4%	1.8%	1.9%	2.0%	2.0%	2.0%	2.1%	2.1%	2.1%	2.1%	2.1%	2.1%	2.1%	2.1%	2.1%	2.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2020	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.3%	0.7%	1.5%	2.3%	2.8%	3.1%	3.3%	3.4%	3.4%	3.5%	3.5%	3.5%	3.6%	3.6%	3.6%	3.6%	3.6%	3.6%	3.6%	3.6%	3.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Mutual Mortgage Insurance Fund
HECM Summaries
CT1 Loss

Table 7: Actual CT1 Loss in Each Period/MCA at the Beginning of Each Period

	Evaluation Year																
Fiscal Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
2009	8.6%	24.7%	31.3%	34.9%	39.6%	41.5%	43.8%	42.4%	41.1%	42.7%	42.7%	43.0%	49.9%	48.8%	47.4%	49.4%	52.9%
2010	21.3%	30.8%	28.3%	36.3%	40.7%	40.5%	40.0%	46.5%	45.4%	47.3%	51.2%	65.4%	64.3%	60.1%	61.6%	66.4%	80.5%
2011	0.0%	17.0%	24.9%	34.8%	31.4%	37.4%	39.8%	42.2%	50.1%	47.1%	56.0%	48.0%	53.9%	60.9%	57.9%	62.9%	72.7%
2012	0.0%	30.8%	26.4%	31.3%	34.8%	37.1%	39.9%	45.5%	44.0%	42.5%	49.4%	40.3%	55.6%	45.1%	65.8%	53.9%	89.4%
2013	0.0%	16.7%	29.0%	29.7%	36.5%	36.7%	37.5%	39.8%	43.3%	22.9%	57.9%	47.7%	51.5%	61.0%	65.7%	72.8%	70.8%
2014	0.0%	38.6%	22.2%	25.5%	35.0%	37.7%	32.9%	10.9%	11.0%	9.1%	3.0%	25.2%	31.8%	41.0%	54.9%	57.3%	65.3%
2015	0.0%	17.6%	20.2%	28.5%	26.5%	29.8%	15.7%	24.8%	16.3%	12.3%	21.1%	33.1%	38.9%	36.2%	44.4%	52.6%	64.4%
2016	0.4%	20.4%	23.4%	23.2%	24.2%	19.5%	22.9%	29.3%	24.4%	28.7%	38.8%	38.1%	40.0%	56.9%	54.8%	69.1%	64.5%
2017	0.0%	17.0%	22.0%	23.2%	0.0%	16.8%	27.3%	16.7%	33.4%	34.3%	53.5%	43.9%	49.0%	57.8%	61.6%	65.3%	74.2%
2018	0.0%	4.1%	13.7%	6.0%	0.0%	8.3%	28.8%	17.1%	29.6%	32.3%	33.2%	35.2%	45.1%	49.0%	51.6%	56.8%	51.9%
2019	0.0%	0.0%	0.0%	0.0%	0.0%	12.0%	13.0%	14.0%	9.0%	0.0%	10.7%	21.9%	23.1%	29.8%	38.2%	38.9%	40.0%
2020	0.0%	0.0%	0.0%	5.8%	0.0%	12.3%	20.2%	15.8%	24.0%	26.7%	27.1%	31.9%	36.9%	32.3%	41.0%	48.5%	51.2%

	Evaluation Year															
Fiscal Year	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
2009	61.0%	55.4%	61.5%	64.8%	76.6%	75.4%	77.7%	80.1%	92.1%	88.4%	95.0%	96.8%	98.8%	96.3%	99.0%	99.7%
2010	81.0%	71.5%	86.3%	87.2%	83.4%	89.9%	92.2%	91.7%	93.9%	98.6%	94.6%	95.6%	98.9%	100.0%	100.0%	100.0%
2011	77.7%	74.9%	75.7%	88.1%	93.4%	88.3%	83.4%	93.8%	93.0%	100.0%	99.1%	97.2%	100.0%	100.0%	100.0%	100.0%
2012	86.5%	82.2%	96.0%	92.1%	98.2%	100.0%	98.3%	95.0%	100.0%	98.6%	94.6%	100.0%	100.0%	100.0%	100.0%	100.0%
2013	86.6%	85.0%	94.1%	96.4%	88.1%	99.2%	98.9%	97.9%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
2014	65.6%	68.2%	82.7%	84.8%	78.6%	91.6%	97.8%	98.9%	98.3%	100.0%	98.4%	99.3%	100.0%	100.0%	100.0%	100.0%
2015	66.0%	65.5%	73.4%	87.9%	90.2%	97.2%	96.5%	99.2%	96.5%	99.8%	99.8%	98.9%	100.0%	100.0%	100.0%	100.0%
2016	72.3%	81.4%	87.0%	93.9%	92.4%	97.3%	99.1%	96.6%	100.0%	99.3%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
2017	80.3%	88.1%	91.6%	92.4%	93.9%	93.4%	99.0%	99.8%	100.0%	100.0%	100.0%	99.7%	100.0%	96.0%	100.0%	100.0%
2018	68.2%	57.3%	71.3%	75.5%	82.7%	75.0%	91.8%	87.4%	91.0%	91.5%	96.5%	90.0%	95.2%	99.5%	100.0%	100.0%
2019	50.8%	39.5%	44.6%	63.8%	69.2%	65.1%	72.4%	81.8%	76.4%	87.6%	95.3%	59.6%	100.0%	100.0%	100.0%	56.7%
2020	56.3%	59.9%	60.7%	73.7%	77.1%	83.1%	91.6%	93.9%	96.7%	96.8%	99.0%	100.0%	99.5%	100.0%	100.0%	81.7%

	Evaluation Year															
Fiscal Year	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49
2009	98.0%	99.6%	99.9%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	0.0%	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%
2010	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	0.0%	100.0%	0.0%	0.0%	0.0%	100.0%	0.0%	100.0%	0.0%	0.0%
2011	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%
2012	100.0%	100.0%	100.0%	0.0%	100.0%	100.0%	0.0%	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2013	100.0%	100.0%	100.0%	100.0%	0.0%	100.0%	0.0%	100.0%	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2014	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	0.0%	100.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2015	100.0%	100.0%	100.0%	0.0%	100.0%	100.0%	100.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2016	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	0.0%	0.0%	100.0%	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%
2017	100.0%	100.0%	100.0%	0.0%	100.0%	100.0%	100.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2018	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	0.0%	0.0%	0.0%	100.0%	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%
2019	100.0%	0.0%	100.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2020	0.0%	100.0%	100.0%	100.0%	100.0%	100.0%	0.0%	100.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Mutual Mortgage Insurance Fund
HECM Summaries
CT2 Loss

Table 7: Actual CT2 Loss in Each Period/MCA at the Beginning of Each Period

	Evaluation Year																																																
Fiscal Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49
2009	0.0%	99.3%	98.8%	99.3%	98.9%	99.0%	99.3%	99.2%	99.4%	99.1%	98.8%	98.8%	99.5%	99.6%	99.6%	99.8%	99.9%	99.9%	99.9%	100.0%	99.9%	99.9%	99.9%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2010	0.0%	99.2%	99.0%	99.0%	99.0%	99.5%	99.4%	99.6%	99.5%	99.0%	99.4%	99.7%	99.6%	99.6%	99.7%	99.7%	99.8%	100.0%	99.9%	99.9%	99.9%	99.8%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	100.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2011	0.0%	0.0%	0.0%	98.5%	99.4%	99.2%	99.5%	99.4%	99.3%	99.0%	99.6%	99.7%	99.7%	99.8%	99.8%	99.9%	99.8%	100.0%	99.9%	100.0%	99.8%	99.8%	99.8%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2012	100.1%	0.0%	98.4%	98.9%	98.9%	99.4%	99.4%	99.1%	99.0%	99.7%	99.8%	99.9%	99.8%	99.9%	99.9%	100.0%	100.0%	100.0%	99.9%	100.0%	99.9%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	0.0%	100.0%	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2013	0.0%	0.0%	0.0%	98.9%	99.3%	99.3%	99.1%	98.9%	99.7%	99.7%	99.8%	99.8%	99.9%	100.0%	99.9%	99.9%	99.9%	99.9%	100.0%	99.9%	100.0%	100.0%	99.8%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	0.0%	100.0%	100.0%	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2014	0.0%	0.0%	49.6%	99.4%	89.1%	95.4%	98.1%	99.4%	99.5%	99.6%	99.7%	99.8%	99.7%	99.8%	99.8%	99.8%	100.0%	99.9%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	0.0%	100.0%	100.0%	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2015	0.0%	0.0%	0.0%	44.2%	99.4%	98.9%	99.5%	99.5%	99.6%	99.6%	99.7%	99.8%	99.8%	99.8%	99.9%	99.9%	99.9%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	99.9%	100.0%	100.0%	100.0%	0.0%	100.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2016	0.0%	0.0%	0.0%	0.0%	98.8%	99.5%	99.6%	99.6%	99.6%	99.7%	99.8%	99.8%	99.9%	99.9%	99.9%	99.9%	100.0%	99.9%	99.7%	99.9%	99.9%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	0.0%	100.0%	100.0%	100.0%	0.0%	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2017	0.0%	0.0%	0.0%	98.7%	99.7%	99.6%	99.6%	99.6%	99.6%	99.6%	99.8%	99.9%	99.9%	99.9%	99.9%	99.9%	100.0%	99.9%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	0.0%	100.0%	100.0%	100.0%	0.0%	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2018	0.0%	0.0%	0.0%	98.2%	99.7%	99.5%	99.5%	99.5%	99.6%	99.6%	99.7%	99.7%	99.8%	99.6%	99.7%	99.6%	99.5%	99.9%	99.5%	99.9%	100.0%	100.0%	100.0%	99.9%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2019	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%	100.0%	99.3%	99.3%	99.2%	99.3%	99.5%	99.4%	99.6%	99.7%	99.8%	99.9%	99.9%	100.0%	100.0%	100.0%	99.9%	100.0%	100.0%	100.0%	0.0%	0.0%	0.0%	0.0%	100.0%	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2020	0.0%	0.0%	0.0%	0.0%	98.8%	98.2%	99.0%	99.7%	99.4%	99.5%	99.5%	99.6%	99.6%	99.6%	99.6%	99.8%	99.9%	99.9%	100.0%	99.7%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%