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November 12, 2019

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

Commissioner Montgomery:

Pinnacle Actuarial Resources, Inc. (Pinnacle) has completed the final report for the Final Fiscal Year 2019 Independent Actuarial Review of the Mutual Mortgage Insurance Fund. The attached report details our estimate of the Cash Flow Net Present Value for Fiscal Year 2019 as of September 30, 2019.

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 the report and its conclusions.

Respectfully Submitted,

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

Fiscal Year 2019 Independent Actuarial Review of the Mutual Mortgage Insurance Fund: Economic Net Worth from Home Equity Conversion Mortgage Insurance-In-Force

November 12, 2019

PINNACLE
ACTUARIAL RESOURCES, INC.

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Commitment Beyond Numbers

Fiscal Year 2019 Independent Actuarial Review of the Mutual Mortgage Insurance Fund: Economic Net Worth from Home Equity Conversion Mortgage Insurance In Force

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Fiscal Year 2019 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) independent actuarial review of the Economic Net Worth associated with Home Equity Conversion Mortgages (HECM) insured by the Mutual Mortgage Insurance Fund (MMIF) for fiscal year 2019. 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 MMIF 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 MMIF economic net worth as of the end of the subject fiscal year and assesses the Department of Housing and Urban Development's (HUD) estimates of economic net worth.

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

As of the end of Fiscal Year 2019, Pinnacle's Actuarial Central Estimate (ACE) of the MMIF HECM Cash Flow NPV is negative $11.228 billion.

The total capital resource as reported in FHA's audited financial statement is $1.694 billion at the end of Fiscal Year 2019. Thus, the estimated economic net worth of the MMIF is negative $9.534 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 MMIF loans, and a commentary of how these risk characteristics have changed is 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: Cash Flow Summaries

Cash Flow Category	Net Present Value of Cash Flow
Mortgage Insurance Premium	4,554,178,527
Claim Type 1 Loss Incurred	9,623,783,815
Claim Type 2 Loss Incurred	28,480,934,313
Claim Type 2c Recovery	8,235,319,564
Claim Type 2p Recovery	14,796,961,288
Note Holding Expense	709,809,162

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 summarizes the specifications and assumptions related to the base termination models. The HECM Cash Flow Draw Projection Models section summarizes the cash draw models for HECM mortgages with lines of credit. Section 4 discusses the economic assumptions incorporated into the estimates. Lastly, the HECM Cash Flow Analysis 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 MMIF loans, and a commentary of how these risk characteristics have changed is 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: Cash Flow NPV Outcomes Based on OMB Economic Assumptions and Moody's Scenarios

Economic Scenario	Fiscal Year 2019 Cash Flow NPV
Pinnacle ACE	-11,228,067,911
Moody's Baseline	-8,198,761,602
Moody's Exceptionally Strong Growth	-5,049,327,532
Moody's Stronger Near-Term Rebound	-6,879,123,176
Moody's Slower Near Term Growth	-8,874,685,757
Moody's Moderate Recession	-8,550,636,786
Moody's Protracted Slump	-15,330,817,802
Moody's Below-Trend Long-Term Growtl	-8,991,022,827
Moody's Stagflation	-11,895,753,572
Moody's Next Cycle Recession	-9,235,362,904
Moody's Low Oil Price	-8,224,199,763

The range of results based on Moody's economic scenarios is negative $15.331 billion to negative $5.049 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 $41.093 billion to positive $0.316 billion.

The Cash Flow NPV estimate provided by FHA to be used in the FHA's Annual Report to Congress is negative $7.613 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 second largest negative outcome and the largest positive outcome based on the stochastic simulation results.

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

Cohort	Largest Negative	Largest Positive	Pinnacle ACE
2009	-5,035,441,182	-504,772,684	-2,191,486,758
2010	-2,061,585,640	-289,900,508	-835,448,342
2011	-1,819,000,642	-175,970,147	-707,058,238
2012	-1,730,872,698	-105,310,904	-663,032,616
2013	-3,586,024,999	-43,266,600	-1,355,618,442
2014	-3,380,334,109	185,674,491	-747,659,333
2015	-4,340,752,452	295,828,017	-801,060,519
2016	-4,912,131,760	403,174,446	-852,575,746
2017	-6,507,951,077	448,526,732	-1,396,103,219
2018	-4,816,702,464	33,713,108	-1,128,232,942
2019	-2,902,491,495	68,785,032	-549,791,756
Total	-41,093,288,518	316,480,983	-11,228,067,911

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 Fair 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 and Real Estate Sales models. 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 MMIF effective October 1, 2008.

The Cranston-Gonzalez National Affordable Housing Act (NAHA), enacted in 1990, introduced a minimum capital requirement for MMIF[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 MMIF 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 MMIF. In this report, we analyze the HECM portion of the MMIF, which is mortgages endorsed in fiscal year 2009 and later.

Pinnacle projects that, as of the end of fiscal year 2019, the HECM Cash Flow NPV is negative $11.228 billion. The total capital resource as reported in FHA's audited financial statement is $1.694 billion at the end of Fiscal Year 2019. Thus, the estimated economic net worth of the MMIF is negative $9.534 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, 2019. 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 2019 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.
- 1-year and 10-year Constant Maturity Treasury (CMT) rates and 1-year London Interbank Offered Rate (LIBOR) rate: Interest rates impact the growth rate of mortgage balances and the amount of equity

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

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.

- 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 Center 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 negative $15.331 billion to negative $5.049 billion.

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

Economic Scenario	Fiscal Year 2019 Cash Flow NPV
Pinnacle ACE	-11,228,067,911
Moody's Baseline	-8,198,761,602
Moody's Exceptionally Strong Growth	-5,049,327,532
Moody's Stronger Near-Term Rebound	-6,879,123,176
Moody's Slower Near Term Growth	-8,874,685,757
Moody's Moderate Recession	-8,550,636,786
Moody's Protracted Slump	-15,330,817,802
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Moody's Stagflation	-11,895,753,572
Moody's Next Cycle Recession	-9,235,362,904
Moody's Low Oil Price	-8,224,199,763

The scenario that produces the highest (least negative) HECM Cash Flow NPV is the Exceptionally Strong Growth scenario. The Protracted Slump scenario produces the worst (most negative) 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 $41.093 billion to positive $0.316 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 MMIF. 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.

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 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 MMIF.

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 MMIF. 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 MMIF starting in fiscal year 2009. Therefore, an actuarial review must also be conducted on the HECM portfolio within the MMIF. This report provides the estimated HECM Cash Flow NPV as of September 30, 2019.

The MMIF 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 8.04 million forward mortgages and 353,000 HECMs in the MMIF.

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

The deliverables required for this study are:

1. Produce a written Actuarial Study for HECM that provides an actuarial central estimate of MMIF economic net worth as of the end of fiscal year 2019 and assesses HUD's estimate of economic net worth.

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

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).

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 Study.

5. The Study 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).

6. The Contractor should use the President's Economic Assumptions (provided by ORMRA) for the actuarial central estimates of the Studies. However, in addition to the central single path economic forecast, the Study should 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. The Study 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.

9. Provide econometric appendices to the Study that include variable specifications and statistical output from all regressions in the Study. Individual estimation equations may 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

[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 or 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 2019. 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 2019.

- **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 MMIF 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 2019. 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 2019. Data through September 30, 2019 was used to estimate the Cash Flow NPV.

Fiscal Year 2019 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 $11.228 billion as of the end of fiscal year 2019. This estimate is the result of the cash flow projections based on the 2020 OMB Mid-Term Review of the President's Economic Assumptions.

The total capital resource as reported in FHA's audited financial statement is $1.694 billion at the end of Fiscal Year 2019. Thus, the ACE of the economic net worth of the MMIF is negative $9.534 billion.

According to 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, 2019. Table 5 shows the Cash Flow NPV and IIF for active HECM's 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	-2,191	9,759
2010	-835	3,942
2011	-707	3,717
2012	-663	3,163
2013	-1,356	5,993
2014	-748	5,486
2015	-801	6,667
2016	-853	6,481
2017	-1,396	8,332
2018	-1,128	6,795
2019	-550	3,879
Total	-11,228	64,212

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	-2,191	-3,265	1,074
2010	-835	-1,086	251
2011	-707	-809	102
2012	-663	-638	-25
2013	-1,356	-1,066	-290
2014	-748	-429	-318
2015	-801	-252	-549
2016	-853	298	-1,151
2017	-1,396	197	-1,593
2018	-1,128	-284	-844
2019	-550	-278	-272
Total	-11,228	-7,613	-3,615

The difference between the Pinnacle and FHA estimate is negative $3.615 billion, which is 5.63% of the HECM IIF. The Pinnacle estimates of Cash Flow NPV by cohort are lower (more negative) than the FHA estimates for cohort 2012 and later, and are higher (less negative) for the cohorts 2009 – 2011.

Change in the Cash Flow NPV

Table 7 shows the comparison of our estimate of the Cash Flow NPV, Capital Resources available to HUD, and estimated Economic Value at the end of fiscal year 2018 and the current estimate. The present value of future cash flows of the current book of business is estimated to be negative $11.228 billion.

Table 7: Estimate of Cash Flow NPV as of the end of Fiscal Year 2019 ($ in millions)

Item	2018	2019	Percent Change
Cash Flow NPV	-14,217	-11,228	21.0%
Capital Resources	2,113	1,694	-19.8%
Economic Net Worth	-12,104	-9,534	21.2%
Insurance-In-Force	72,378	64,212	-11.3%

As seen in Table 7, the estimated fiscal year 2019 Cash Flow NPV has increased by $3.0 billion from the level estimated in fiscal year 2018, from -$14.217 billion to -$11.228 billion. The unamortized IIF decreased by 11.3% – from $72.378 billion to $64.212 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 2018 Review to the Fiscal Year 2019 Review

Table 8 provides a summary of the decomposition of changes in the Cash Flow NPV of the MMIF as of the end of fiscal year 2019 as compared to the Cash Flow NPV in the fiscal year 2018 report. The overall net change in the

Cash Flow NPV is positive.

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

	Change in NPV	Cash Flow NPV - 9/30/19
Baseline FY2009-FY2018		-14,217,158,723
Impact of assumption change	1,396,782,011	-12,820,376,712
Impact of model change	-1,318,392,535	-14,138,769,247
Impact of book change	3,460,493,092	-10,678,276,155
FY2009-FY2018	3,538,882,568	
FY2019	-549,791,756	-11,228,067,911
Cumulative Change	2,989,090,812	

This section describes the sources of change in estimates of Cash Flow NPV between this year's review and last year's 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 2018 review by source of change.

Update Economic Scenario Forecast

For this decomposition step, we updated the forecasts for the purchase-only HPI, and the interest and unemployment rates from 2019 PEA forecast to the 2020 PEA forecast. There was a slight increase in the rate of annual increase for the HPI projection, ranging from 0.1% to 0.7% higher. Short term treasury rate projections are slightly lower than the projections used in the 2018 Actuarial Report, ranging from 0.1% to 0.7% lower. The projected mortgage rates are also slightly lower through 2029, and then slightly higher after 2029 in the forecast this year. This leads to lower prepayment and claim rates, both resulting in higher economic value. The unemployment rate projections are also slightly lower this year than in the 2018 Actuarial Report. The net impact of these changes is an increase of $1.397 billion in the projected Cash Flow NPV.

Update Predictive Models

In fiscal year 2019, we continued to refine the predictive models to better capture the termination and cash draw behavior of loans in the MMIF. We re-estimated the models using updated data and revised variable specifications. The model changes with the largest impacts include modifications to the Tax and Insurance default models and the models determining the probability of a cash draw. For details about these model updates and refinements, refer to Appendices B, C and E.

These model changes led to a decrease in estimated economic value in the Cash Flow NPV of $1.318 billion.

Actual Performance of Fiscal Year 2018 to Fiscal Year 2019

The actual performance of the MMIF for cohorts 2009 – 2018 realized during fiscal year 2019 affects the Cash Flow NPV of the MMIF estimate of the in-force portfolio. The actual experience for this period was $3.460 billion better than expected.

Fiscal Year 2019 Origination Volume

The addition of the origination volume for the fiscal year 2019 book of business decreased the Cash Flow NPV projection by $550 million.

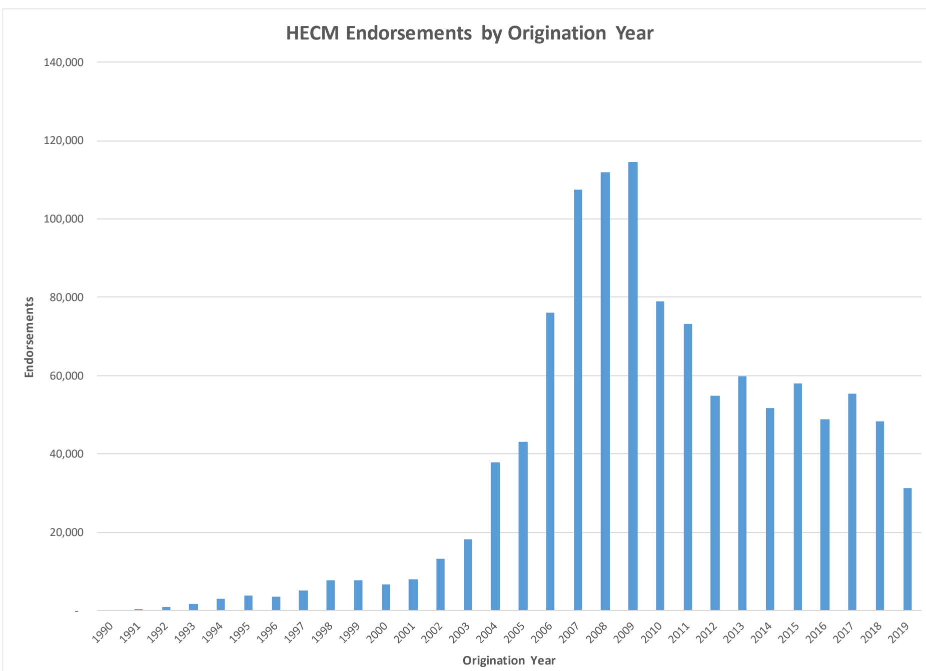
Section 3. Characteristics of HECM Fund Endorsements

This section presents the characteristics of the HECM portfolio for the HECM loans endorsed from fiscal year 2009 through fiscal year 2019. HECM loans were first included in the MMIF 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 2019. A review of the characteristics of these cohorts helps define the current risk profile of HECM Fund. Some of the characteristics of previous books are shown as well to demonstrate trends.

Volume and Share of Mortgage Originations

FHA endorsed 31,260 HECM loans in fiscal year 2019, with a total MCA of $10.856 billion. This is a 35.3% decrease in the number of loans endorsed, and a 32.9% decrease in the MCA of loans endorsed. The total number of endorsements for fiscal years 2009 to 2019 was 674,685. The corresponding MCA was $186.254 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 fiscal year.

Figure 1: Number of HECM Endorsements by Cohort



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.

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%	93.3%	1.4%	3.0%	1.6%
2015	0.7%	93.7%	1.1%	2.8%	1.7%
2016	0.7%	93.4%	1.2%	3.0%	1.7%
2017	0.7%	93.3%	1.2%	3.0%	1.8%
2018	0.8%	93.9%	1.0%	2.7%	1.7%
2019	0.8%	94.7%	1.0%	2.1%	1.3%

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 2019 it has dropped to 6%.

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 2019, this percentage has increased to 94%. Monthly adjustable LIBOR loans were more popular in fiscal year 2014 and 2015, however in fiscal years 2016 - 2019 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.

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%	0.07%	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%	78.92%	0.00%	0.00%	18.67%
2015	39.97%	44.26%	0.01%	0.01%	15.75%
2016	75.41%	13.90%	0.04%	0.00%	10.64%
2017	86.13%	3.53%	0.00%	0.00%	10.34%
2018	88.44%	1.42%	0.01%	0.00%	10.14%
2019	93.72%	0.22%	0.01%	0.00%	6.05%

Product Type

Almost all the loans endorsed in fiscal years 2009 through 2019 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. The percentage of HECMs for Purchase with first month cash draws over 90% has increased since 2009. In our analysis, the traditional and for-purchase HECMs are treated the same, as the volume of for-purchase HECM's 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%	0.14%	4.02%
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%

State

Among all endorsements in fiscal years 2009 through 2019, 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 6.0% in fiscal year 2019. 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
California	13.7%	14.0%	13.5%	12.7%	14.1%	17.5%	20.3%	21.8%	23.7%	22.7%	21.1%
Florida	13.2%	9.0%	6.8%	6.1%	6.5%	6.9%	8.3%	8.8%	8.7%	8.4%	8.6%
Texas	6.6%	8.0%	9.1%	8.9%	8.6%	7.4%	7.0%	7.6%	7.6%	7.4%	7.4%
Colorado	1.8%	1.8%	1.9%	2.0%	2.1%	2.3%	2.4%	3.7%	5.4%	5.9%	6.0%
Arizona	3.1%	2.1%	2.0%	1.8%	2.4%	2.9%	3.2%	3.6%	3.7%	4.0%	4.8%
New York	5.3%	5.9%	5.9%	7.2%	6.4%	5.9%	5.7%	4.8%	4.2%	3.8%	4.0%
Washington	2.8%	3.0%	2.5%	2.3%	2.3%	2.1%	2.3%	2.7%	3.2%	4.3%	4.0%
Utah	1.5%	1.3%	1.4%	1.8%	2.0%	1.7%	1.7%	1.8%	1.9%	2.4%	2.8%
Pennsylvania	3.2%	3.7%	4.5%	4.8%	4.7%	4.5%	3.9%	2.9%	2.5%	2.5%	2.6%
North Carolina	1.8%	2.0%	2.6%	2.8%	3.1%	2.6%	2.4%	2.5%	2.3%	2.5%	2.5%

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 73% by fiscal year 2012. Since then, the percentage of endorsements less than $300,000 have decreased steadily to 49% for fiscal year 2019.

The percentage of endorsements with an MCA greater than $300,000 and less than or equal to $417,000 dropped from 23% in 2009 and had been around 12% - 13% percent for fiscal years 2010 through 2014, but has since risen to 19.5% in 2019. The percentage of endorsements with an MCA greater than $417,000 has increased consistently since 2012, and now is at 31.1%.

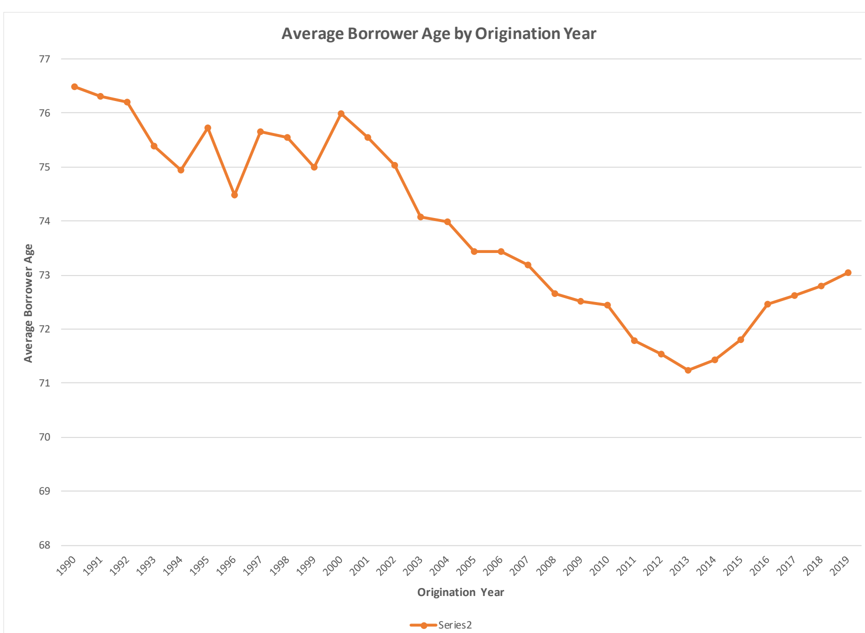
Table 13: Distribution of HECM Loans by MCA

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%	21.8%	24.2%	19.5%	31.1%

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 over fiscal years 1990 through 2019. 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. To manage this risk, the PLFs, which limits the percentage of initial equity available to the borrower, are lower for younger borrowers, limiting their cash draws to a smaller portion of the equity in the house. The average borrower age is just over 73 years old in fiscal year 2019.

Figure 2: Average Borrower Age at Origination Year



Borrower Gender

Gender also affects termination behavior due to differences in mortality rates. The gender distribution of the HECM portfolio has remained steady over time. 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 years 2013 to 2015, couples comprise 39%, surpassing single females to become the largest gender cohort. The single female share is currently 38% while single males remains the lowest at 21%. The concentration in couples rose to 41% in 2016, but has decreased to 39% in 2019.

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%	37.08%	1.80%
2012	21.22%	39.16%	37.35%	2.28%
2013	21.15%	37.56%	38.95%	2.35%
2014	20.62%	38.73%	38.65%	1.99%
2015	21.86%	38.52%	38.91%	0.71%
2016	21.65%	36.81%	41.04%	0.49%
2017	20.92%	37.13%	40.91%	1.04%
2018	20.69%	36.67%	40.20%	2.44%
2019	21.06%	37.88%	38.60%	1.90%

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 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 first-month draw over 60% fell from 80% in fiscal year 2013 to 48% in fiscal year 2019.

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

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%	10.67%	62.09%	0.09%	13.01%
	71-75	18.63%	11.32%	58.67%	0.01%	11.36%
	76-85	24.66%	11.91%	53.48%	0.03%	9.92%
	86+	36.24%	10.20%	46.05%	0.03%	7.48%
	Total	18.73%	10.93%	58.72%	0.07%	11.54%
2010	62-65	7.35%	4.29%	8.39%	0.19%	79.77%
	66-70	9.07%	5.24%	9.88%	0.13%	75.68%
	71-75	13.30%	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	14.17%	6.47%	9.54%	0.07%	69.75%
	76-85	20.68%	7.13%	10.05%	0.14%	61.99%
	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%	5.71%	20.96%	0.31%	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	19.35%	7.04%	19.31%	0.28%	54.02%
	86+	31.37%	7.36%	16.57%	0.38%	44.33%
	Total	13.15%	6.26%	20.01%	0.32%	60.27%
2014	62-65	12.26%	26.84%	38.20%	2.03%	20.68%
	66-70	15.15%	25.08%	39.04%	1.93%	18.80%
	71-75	18.81%	25.82%	37.33%	1.93%	16.12%
	76-85	24.69%	26.32%	34.83%	2.10%	12.07%
	86+	36.77%	27.36%	26.52%	2.51%	6.83%
	Total	18.38%	26.09%	36.86%	2.03%	16.65%
2015	62-65	12.71%	38.02%	30.62%	0.67%	17.98%
	66-70	14.57%	35.36%	31.66%	0.60%	17.80%
	71-75	18.03%	34.04%	31.84%	0.55%	15.54%
	76-85	23.60%	35.02%	29.70%	0.66%	11.01%
	86+	33.99%	36.04%	23.29%	1.10%	5.58%
	Total	18.04%	35.72%	30.49%	0.65%	15.10%
2016	62-65	16.76%	36.73%	32.69%	0.81%	13.01%
	66-70	18.02%	33.15%	35.73%	0.49%	12.62%
	71-75	19.11%	32.64%	37.18%	0.25%	10.81%
	76-85	24.21%	33.44%	35.38%	0.40%	6.57%
	86+	34.90%	34.75%	27.05%	0.66%	2.63%
	Total	20.65%	33.97%	34.74%	0.50%	10.15%
2017	62-65	17.78%	34.09%	34.80%	0.98%	12.36%
	66-70	16.75%	30.30%	40.27%	0.47%	12.21%
	71-75	19.07%	28.79%	41.44%	0.43%	10.27%
	76-85	21.88%	30.72%	40.28%	0.40%	6.71%
	86+	32.28%	33.82%	30.79%	0.41%	2.71%
	Total	19.78%	31.05%	38.82%	0.54%	9.81%
2018	62-65	18.39%	33.58%	35.85%	0.69%	11.49%
	66-70	17.12%	29.30%	40.64%	0.53%	12.40%
	71-75	19.86%	28.64%	41.09%	0.31%	10.08%
	76-85	22.06%	31.10%	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	18.04%	31.84%	42.99%	0.42%	6.71%
	66-70	17.35%	28.82%	46.82%	0.20%	6.80%
	71-75	20.08%	28.58%	44.66%	0.18%	6.50%
	76-85	24.03%	31.98%	39.21%	0.31%	4.47%
	86+	34.09%	32.68%	30.55%	0.60%	2.09%
	Total	21.09%	30.43%	42.42%	0.29%	5.76%

Section 4. HECM Cash Flow NPV Based on Alternative Scenarios

The Cash Flow NPV of the MMIF will vary from our estimates if the actual 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 and associated percentiles. These alternative estimates were then 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.

The Moody's scenarios are:

- Baseline
- Exceptionally Strong Growth
- Stronger Near-Term Rebound
- Slower Near-Term Growth
- Moderate Recession
- Protracted Slump
- Below-Trend Long-Term Growth
- Stagflation
- Next-Cycle Recession
- Low Oil Price

The resulting Cash Flow NPV associated with each alternative scenario is summarized in Table 16. Below, we discuss the characteristics of each Moody's scenario.

Moody's Baseline Assumptions

In this scenario, the HPI increases over the entire projection period, and the rate of change is between 2.5% and 5.0%. The mortgage interest rate increases as well and settles at a long-term average of about 5.5%. The unemployment rate is flat at 3.6% over the next year, increases to 4.5% by 2023, and then decreases to 4.3% by 2030.

Exceptionally Strong Growth Scenario

In Moody's Exceptionally Strong Growth scenario, the HPI is projected to increase more quickly than under the

Baseline scenario. In addition, mortgage interest rates are projected to be higher than the Baseline scenario throughout the entire projection period. The unemployment rate is lower than projected in the Baseline scenario throughout the entire projection period.

Stronger Near-Term Rebound Scenario

In Moody's Stronger Near-Term Rebound scenario, the HPI is projected to increase at a slightly higher rate than the Baseline scenario through the entire projection period. In addition, mortgage interest rates are projected to be higher than the Baseline scenario through 2023, then projected to be the same as the Baseline for the remainder of the projection period. The unemployment rate also is lower than projected in the Baseline scenario throughout the entire projection period.

Slower Near-Term Growth Scenario

In Moody's Slower Near-Term Growth scenario, the HPI increases slower than the Baseline scenario, but is still increasing throughout the entire projection period. Mortgage interest rates are projected to be flat through 2020, and then increase for the remainder of the projection period. The unemployment rate is projected to be higher than the Moody's assumptions for the entire projection period.

Moderate Recession Scenario

In the Moderate Recession scenario, the HPI decreases through the end of 2020, and then begins to increase. Mortgage interest rates drop significantly through the end of 2020, and then begin to slowly increase until they reach the long-term average of about 5.8%. The unemployment rate spikes to 7.4% by 2021, and then recovers to a long-term average of 4.5%.

Protracted Slump

In Moody's Protracted Slump scenario, the HPI decreases significantly over the next 18 months, and then begins to increase again. Mortgage interest rates drop until the end of 2020, then begin to slowly increase until they reach the long-term average of 5.6%. The unemployment rate spikes to 8.3% by 2021, and then recovers to a long-term average of 4.5%.

Below-Trend Long-Term Growth

In Moody's Below-Trend Long-Term Growth scenario, the HPI increases more slowly than in the Baseline scenario. Mortgage interest rates increase gradually and settle at a long-term average of about 5.4%. The unemployment rate increases to 5.7% by 2021, and then decreases to a long-term average of approximately 4.5%.

Stagflation

In Moody's Stagflation scenario, the HPI decreases through the third quarter of 2021, and then begins to increase. Mortgage interest rates increase sharply to 5.4% by the second quarter of 2020, and then drop through the second quarter of 2021. They then begin to slowly increase to the long-term average of 5.7%. Unemployment rates increase significantly to just over 7.4% by 2021, and then decrease to a long-term average of 4.3%.

Next-Cycle Recession

In Moody's Next-Cycle Recession scenario, the HPI increases through the beginning of 2022, and then decreases significantly through the second quarter of 2023. The HPI then increases again. The mortgage interest rates increase through the first quarter of 2021, and then increase significantly to 6.1% by the end of 2021. The rates then drop significantly, and settle in at a long-term average of about 5.7%. The unemployment rate is equal to the Baseline assumptions through 2021, and then increases sharply to 7.6% by 2023. It then decreases to 4.5% by 2026.

Low Oil Price

In Moody's Low Oil Price scenario, the HPI increases throughout the entire projection period. Mortgage interest rates increase at a slow rate through 2021, and then increase at a higher rate through the remainder of the projection period. Unemployment rates decrease through the second quarter of 2020, and then increase for the remainder of the projection period, settling at a long-term average of 4.4%.

Summary of Alternative Scenarios

Table 16 shows the projected Cash Flow NPV from the ten deterministic scenarios. The range of projected results is between negative $15.331 billion and negative $5.049 billion.

Table 16: Cash Flow NPV Summaries from Alternative Scenarios

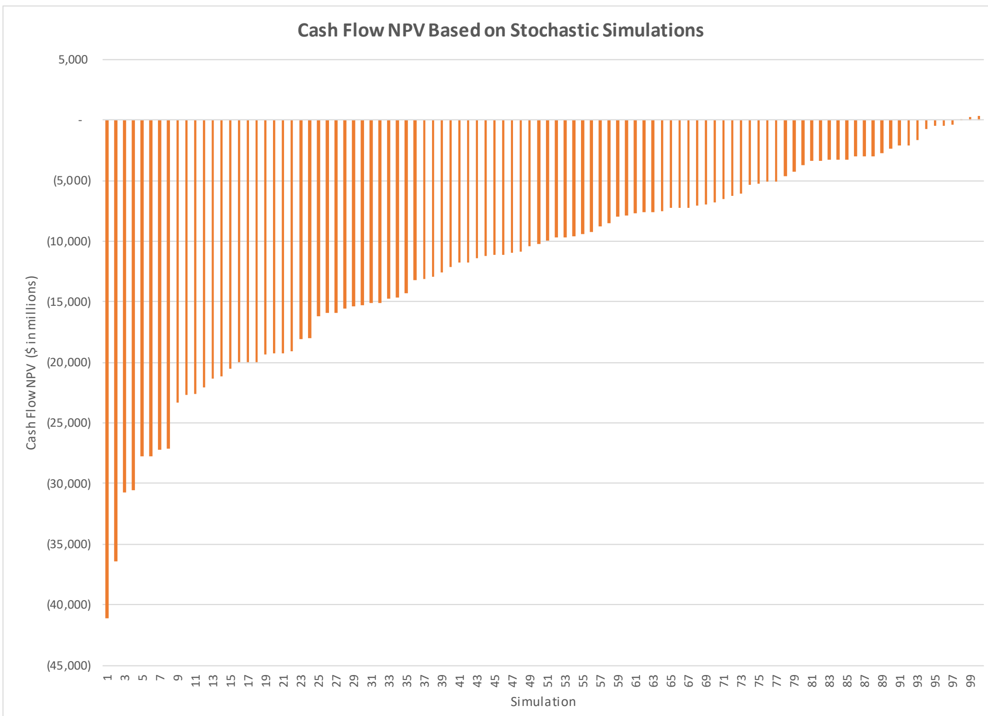
Cohort	Pinnacle ACE	Moody's Baseline	Moody's Exceptionally Strong Growth	Moody's Stronger Near-Term Rebound	Slower Near Term Growth	Moderate Recession	Protracted Slump	Below-Trend Long-Term Growth	Stagflation	Next Cycle Recession	Low Oil Price
2009	-2,191,486,758	-1,830,154,161	-1,465,615,877	-1,677,952,244	-1,881,308,552	-1,769,917,134	-2,462,520,102	-1,879,466,225	-2,366,881,389	-2,000,676,487	-1,808,085,465
2010	-835,448,342	-726,363,830	-557,137,649	-645,570,757	-733,751,066	-767,160,065	-1,046,093,311	-760,197,610	-893,767,449	-781,652,985	-713,276,938
2011	-707,058,238	-590,553,540	-443,200,973	-516,156,667	-625,542,621	-621,599,609	-883,094,949	-634,442,621	-764,990,281	-654,720,983	-593,732,126
2012	-663,032,616	-566,639,592	-420,316,200	-509,577,040	-600,556,842	-619,484,918	-885,179,060	-602,730,782	-717,871,369	-617,140,776	-577,076,395
2013	-1,355,618,442	-1,112,169,727	-813,261,959	-995,318,391	-1,187,752,639	-1,213,750,171	-1,827,121,573	-1,190,397,581	-1,449,239,275	-1,208,460,834	-1,141,611,716
2014	-747,659,333	-467,281,043	-204,813,280	-361,901,198	-544,637,841	-492,611,558	-1,059,404,566	-521,756,385	-797,305,241	-551,465,764	-466,765,610
2015	-801,060,519	-464,316,606	-138,097,721	-323,606,338	-551,522,933	-527,938,327	-1,298,668,318	-576,522,537	-873,878,021	-580,553,804	-480,594,809
2016	-852,575,746	-467,422,468	-45,016,706	-302,287,336	-565,384,906	-544,511,645	-1,511,374,206	-598,765,369	-902,468,758	-560,549,401	-469,862,692
2017	-1,396,103,219	-864,892,675	-287,137,149	-623,494,549	-1,001,323,378	-963,723,460	-2,257,175,702	-1,041,492,413	-1,463,986,769	-1,059,632,963	-872,598,502
2018	-1,128,232,942	-783,173,492	-484,590,621	-656,864,222	-832,706,846	-753,461,628	-1,483,227,809	-853,547,068	-1,152,321,238	-872,693,087	-771,703,189
2019	-549,791,756	-325,794,468	-190,139,397	-266,394,434	-350,198,133	-276,478,271	-616,958,206	-331,704,236	-513,043,782	-347,815,820	-328,892,321
Total	-11,228,067,911	-8,198,761,602	-5,049,327,532	-6,879,123,176	-8,874,685,757	-8,550,636,786	-15,330,817,802	-8,991,022,827	-11,895,753,572	-9,235,362,904	-8,224,199,763

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 Cash Flow NPV to different economic conditions.

The figure 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 $41.093 billion to positive $0.317 billion. The range of Cash Flow NPV estimates may not include all conceivable outcomes. For example, it would not include conceivable 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 $7.613 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 MMIF 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 of the Cash Flow NPV based on the OMB scenario. These simulations change each of these variables one at a time from the OMB scenario. The changes are parallel shifts in the path of each variable in the OMB 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 forecast. Specifically, we applied a parallel shift to the annualized HPA rates from the base scenario up and down by 20, 50, 100 and 200 basis points. The sensitivity to shifts in the annualized HPA from the base scenario has a positive slope. A negative 100 basis points parallel shift in HPA will decrease Cash Flow NPV by $4.294 billion, and a positive 100 basis points parallel shift in HPA will increase Cash Flow NPV by $4.275 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 -13.3% to +12.6%.

Figure 4 also reports the sensitivity of the Cash Flow NPV with respect to changes in interest rates. Specifically, we applied a parallel shift to the annualized CMT and mortgage rates from the base scenario up and down by 20, 50, 100 and 200 basis points. The sensitivity to shifts in the interest rates from the base scenario has a negative slope. A negative 100 basis points parallel shift in interest rates will increase Cash Flow NPV by $1.548 billion, and a positive 100 basis points parallel shift in HPA will decrease Cash Flow NPV by $1.023 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 -2.8% to +5.2%.

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

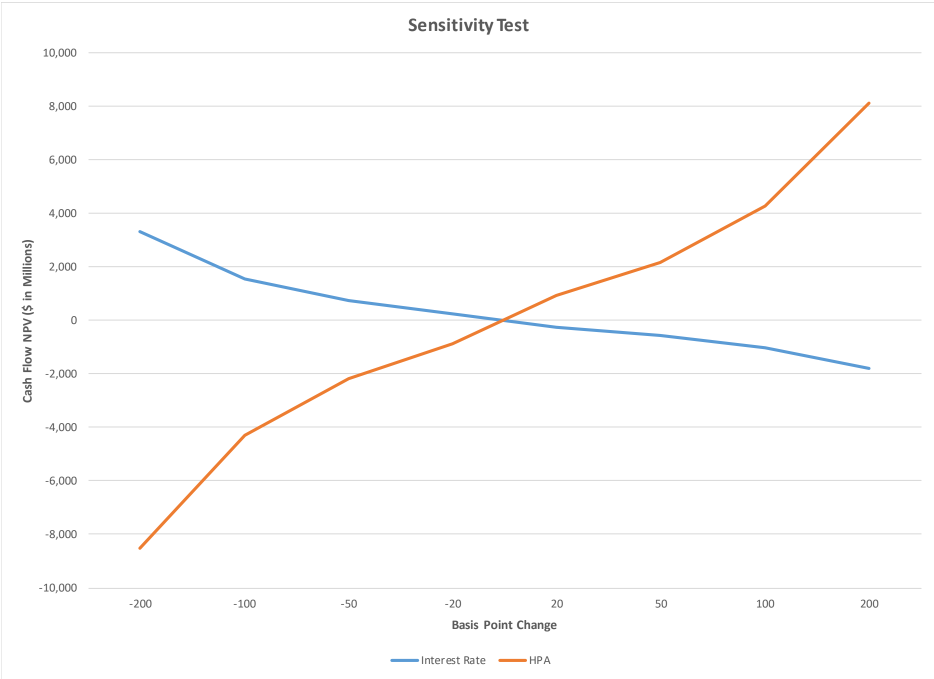
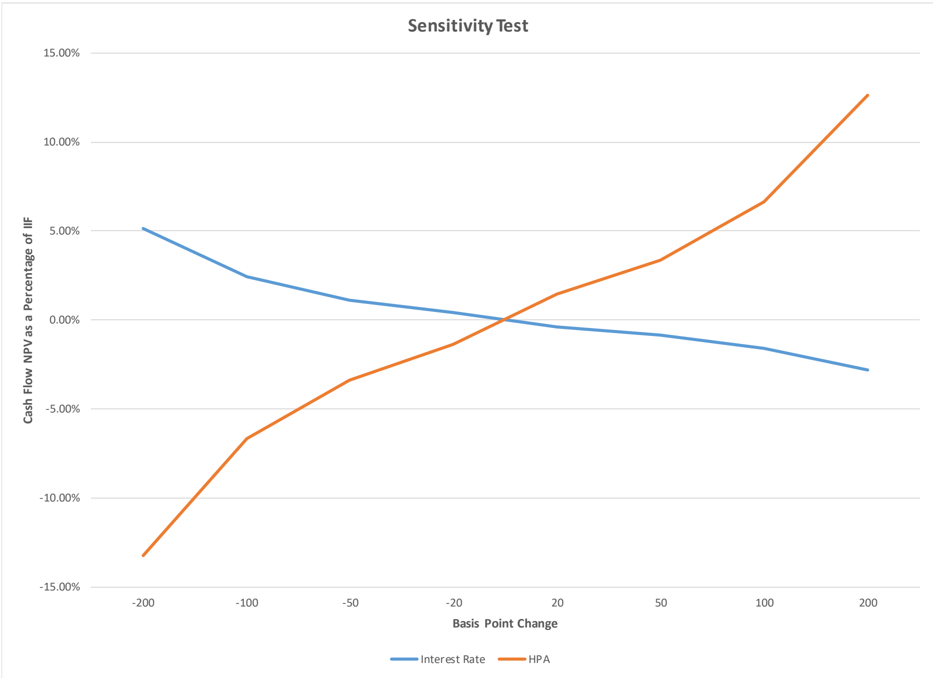


Figure 5: HECM Sensitivity Analysis – Change in Cash Flow NPV as a Percentage of IIF



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, Moody's and OMB.

From FHA, we have received the following data tables.

1. hermit_case_detail: case level data for HECM's.
2. hermit_claim_detail: data for electronically processed HECM claims.
3. hermit_transactions_balance: HECM balance transactions data.
4. hermit_transactions_setaside: HECM setaside transactions data.
5. hermit_transactions_growth: HECM growth transactions data.
6. hermit_payment_plan: payment plan information on HECM's.
7. hermit_lender_detail: supporting lender information for HECM's.
8. sams_case_record: Union of sams_monthly_record and sams_archive_record.
9. hecm_claim_detail: data for paper claims for HECM's.
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

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 received the Economic Assumptions for the 2020 Mid-Term Review as of March, 2019.

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 and loss severity models. The steps below describe the data processing that occurred to prepare the data that was used for this analyses.

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. 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 File
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 were 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.[3]

The reconciliation tables were based on data as of September 30, 2019.

[3] Comparison data from FHA was not available as of the date of this draft report

Table 17: Data Validation – Insurance in Force

Insurance in Force ($M)				
= Total Loan Amount on Active Loans				
Credit Subsidy Cohort	Federal Housing Administration	Independent Actuary	Absolute Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
2009	$ 9,757	$9,762	5	0.05%
2010	$ 3,942	$3,944	2	0.04%
2011	$ 3,720	$3,720	0	0.00%
2012	$ 3,164	$3,165	1	0.03%
2013	$ 5,993	$5,993	(0)	0.00%
2014	$ 5,486	$5,486	0	0.01%
2015	$ 6,664	$6,667	3	0.05%
2016	$ 6,422	$6,481	59	0.91%
2017	$ 8,269	$8,332	63	0.76%
2018	$ 6,757	$6,795	38	0.56%
2019	$ 3,872	$3,879	7	0.19%
Total	$ 64,046	64,223	177	0.28%
Note:	tot_loan_bal from tmod_cd_full_20190930 where status i= 'IIF'			

Table 18: Data Reconciliation - Number of Active Assignments

Number of Active Assignments				
Credit Subsidy Cohort	Federal Housing Administration	Independent Actuary	Absolute Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
2009	15,222	15,222	-	0.00%
2010	25,159	25,159	-	0.00%
2011	23,827	23,827	-	0.00%
2012	17,409	17,409	-	0.00%
2013	9,401	9,401	-	0.00%
2014	81	81	-	0.00%
2015	8	8	-	0.00%
2016	1	1	-	0.00%
2017	-	-	-	
2018	-	-	-	
2019	-	-		
Total	91,108	91,108	-	0.00%
Note:	Count of case numbers with status as CT2a in tmod_cd_full_20190930			

Table 19: Data Reconciliation – Number of Claims to Date

Number of Claims to Date				
Credit Subsidy Cohort	Federal Housing Administration	Independent Actuary	Absolute Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
2009	58,491	58,491	-	0.00%
2010	51,132	51,132	-	0.00%
2011	41,738	41,738	-	0.00%
2012	27,374	27,374	-	0.00%
2013	16,267	16,267	-	0.00%
2014	2,072	2,072	-	0.00%
2015	999	999	-	0.00%
2016	290	290	-	0.00%
2017	80	80	-	0.00%
2018	4	4	-	
2019				
Total	198,447	198,447	-	0.00%
Note:	Count of case numbers with clm_typ 21,22,23, or 24 from hermit_claim_detail and hecm_claim_detail			

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 ("othr" 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 the there are no borrowers remaining on the loan. If a termination is simulated then the loan follows the non-mortality termination path described in #4.

3. If the loan ends up 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 Projection Models (Appendix C)

Over 90% of HECM's have a line of credit associated with them. To estimate the present value of future cash flows on the existing portfolio of HECM's, we need to estimate the future cash draws associated with the line of credit. As these cash draws are not certain as they would be for a term product, 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 12-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 July 2019 forecasts of interest, 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 Base Termination Model section. 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, and
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 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 aggregated 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

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

From FHA, we have received the following data tables.

1. hermit_case_detail: case level data for HECM mortgages.
2. hermit_claim_detail: data for electronically processed HECM claims.
3. hermit_transactions_balance: HECM balance transactions data.
4. hermit_transactions_setaside: HECM setaside transactions data.
5. hermit_transactions_growth: HECM growth transactions data.
6. hermit_payment_plan: payment plan information on HECM mortgages.
7. hermit_lender_detail: supporting lender information for HECM mortgages.
8. sams_case_record: Union of sams_monthly_record and sams_archive_record.
9. hecm_claim_detail: data for paper claims for HECM mortgages.
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 HECM 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 received the Economic Assumptions for the 2020 Budget Fall Baseline as of March 2019.

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

1. HPI
2. CMT rates
3. LIBOR

Data Processing – Mortgage Level Modeling

Beginning with the data tables provided by FHA, the data was processed to create datasets for developing the mortgage level transition and cash draw models. The steps below describe the data processing that occurred to prepare the data that was used for these analyses.

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. 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 File
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 were 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, 2019.

Table 20: Data Validation – IIF

Insurance in Force ($M)				
= Total Loan Amount on Active Loans				
Credit Subsidy Cohort	Federal Housing Administration	Independent Actuary	Absolute Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
2009	$ 9,757	$9,762	5	0.05%
2010	$ 3,942	$3,944	2	0.04%
2011	$ 3,720	$3,720	0	0.00%
2012	$ 3,164	$3,165	1	0.03%
2013	$ 5,993	$5,993	(0)	0.00%
2014	$ 5,486	$5,486	0	0.01%
2015	$ 6,664	$6,667	3	0.05%
2016	$ 6,422	$6,481	59	0.91%
2017	$ 8,269	$8,332	63	0.76%
2018	$ 6,757	$6,795	38	0.56%
2019	$ 3,872	$3,879	7	0.19%
Total	$ 64,046	64,223	177	0.28%
Note:	tot_loan_bal from tmod_cd_full_20190930 where status i= 'IIF'			

Table 21: Data Reconciliation - Number of Active Assignments

Number of Active Assignments				
Credit Subsidy Cohort	Federal Housing Administration	Independent Actuary	Absolute Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
2009	15,222	15,222	-	0.00%
2010	25,159	25,159	-	0.00%
2011	23,827	23,827	-	0.00%
2012	17,409	17,409	-	0.00%
2013	9,401	9,401	-	0.00%
2014	81	81	-	0.00%
2015	8	8	-	0.00%
2016	1	1	-	0.00%
2017	-	-	-	
2018	-	-	-	
2019	-	-		
Total	91,108	91,108	-	0.00%
Note:	Count of case numbers with status as CT2a in tmod_cd_full_20190930			

Table 22: Data Reconciliation – Number of Claims to Date

Number of Claims to Date				
Credit Subsidy Cohort	Federal Housing Administration	Independent Actuary	Absolute Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
2009	58,491	58,491	-	0.00%
2010	51,132	51,132	-	0.00%
2011	41,738	41,738	-	0.00%
2012	27,374	27,374	-	0.00%
2013	16,267	16,267	-	0.00%
2014	2,072	2,072	-	0.00%
2015	999	999	-	0.00%
2016	290	290	-	0.00%
2017	80	80	-	0.00%
2018	4	4	-	
2019				
Total	198,447	198,447	-	0.00%
Note:	Count of case numbers with clm_typ 21,22,23, or 24 from hermit_claim_detail and hecm_claim_detail			

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.

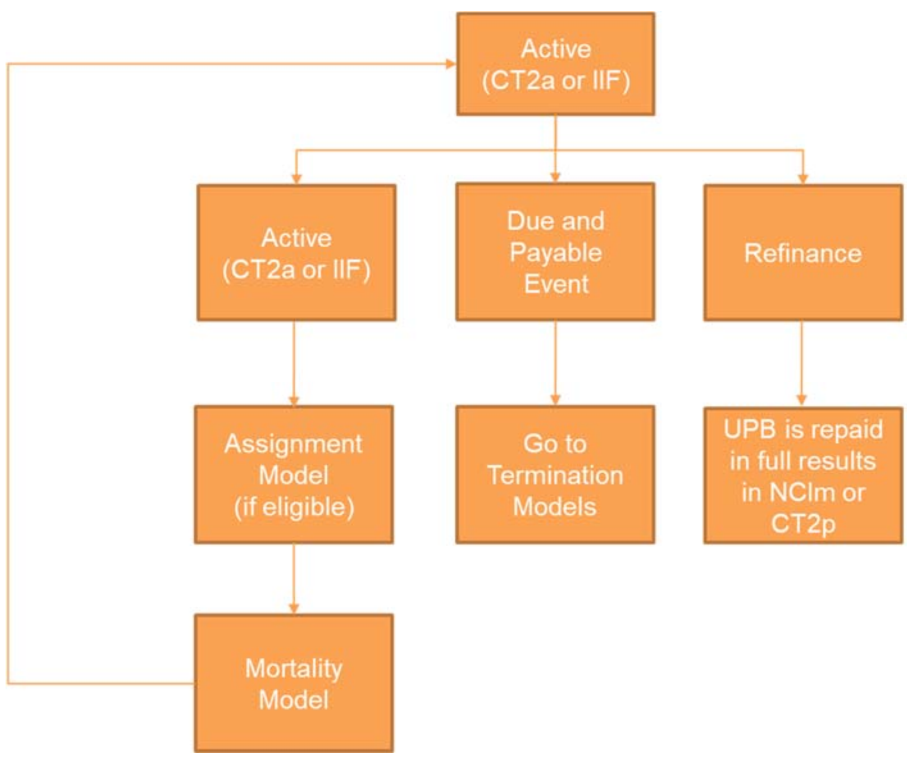
The available FHA historical HECM termination data was used to develop the base termination model. This data includes mortgages that were endorsed under the GI Fund between fiscal years 1990 and 2008, and mortgages endorsed under the MMIF from fiscal year 2009 through September 30, 2019. Only mortgages endorsed under the MMIF, 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 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.
- **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 $(MCA_t * PLF - (init\_MIP_t + orig\_feet) - curr\_prncpl\_lmt\_pinni)/(init\_MIP_t + orig\_feet)$. 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 1-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.

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 23: Model Parameters – Likelihood of Refinance

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
Intercept				-13.6300	0.0916	0.0000
vminage_refi_pw2		Variate piecewise min_age	median(0,min_age-63,72-63)	0.0121	0.0023	0.0000
vminage_refi_pw4		Variate piecewise min_age	max(0,min_age-90)	-0.0194	0.0109	0.0743
vrefi_refi_pw2		Variate piecewise refi_var[1]	median(0,refi_var+9,6)	0.6562	0.0142	0.0000

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
vrefi_refi_pw3		Variate piecewise refi_var[1]	median(0,refi_var+3,1)	0.2502	0.0556	0.0000
vrefi_refi_pw4		Variate piecewise refi_var[1]	max(0,(min(refi_var,6)+2))	0.6958	0.0161	0.0000
vrefi_refi_pw4*vrefi_refi_pw4		Interacted refi_var[1]	max(0,(min(refi_var,6)+2))	-0.0592	0.0019	0.0000
vperiodnbr_pw1		Variate piecewise period number	min(9,period_number)	0.0573	0.0033	0.0000
vperiodnbr_pw2		Variate piecewise period number	median(0,period_number-9,30-9)	-0.0773	0.0013	0.0000
vperiodnbr_pw3		Variate piecewise period number	median(0,period_number-30,50-30)	0.0210	0.0026	0.0000
vperiodnbr_pw4		Variate piecewise period number	max(0,period_number-50)	0.0350	0.0101	0.0005
vltv_pw1		Variate piecewise Loan to Value[2]	min(66,LTV)	0.0210	0.0009	0.0000
vltv_pw2		Variate piecewise Loan to Value[2]	median(0,LTV-66,94-66)	0.0198	0.0010	0.0000
vltv_pw3		Variate piecewise Loan to Value[2]	median(0,LTV-94,99.5-94)	0.0293	0.0046	0.0000
vltv_pw4		Variate piecewise Loan to Value[2]	median(0,LTV-99.5,100.5-99.5)	-0.0768	0.0360	0.0330
vltv_pw5		Variate piecewise Loan to Value[2]	max(0,LTV-100.5)	-0.2396	0.0195	0.0000
vMob_pw		Variate piecewise Mobility	max(mobility_2,-10)+20;	-0.2673	0.0121	0.0000
mDeltaTy14Q	L01_.35	Categorical Change in 1 Year Treasury Rate 4Q	delta_T1Y_4Q<=0.35	1.5897	0.0181	0.0000
mDeltaTy14Q	z_Base	Categorical Change in 1 Year Treasury Rate 4Q	Base level: else	0.0000		
mDeltaTy1Init	L02_2.0	Categorical Change in 1 Year Treasury Rate Initial	Delta_T1Y_Init_p>2	0.3167	0.0166	0.0000

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
mDeltaTy1Init	z_Base	Categorical Change in 1 Year Treasury Rate Initial	Base level: else	0.0000		
mloantyp	L01_01	Categorical Loan Type	loan_typ in ('01", "03", "04", "05", "06")	0.3548	0.0227	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	0.0771	0.0129	0.0000
MGender	z_Base	Categorical Gender	Base level: else	0.0000		
mAlive	L02_2	Categorical Number Alive	else	-0.0572	0.0126	0.0000
mAlive	z_Base	Categorical Number Alive	num_alive=1	0.0000		
vMCA_pw1		Variate piecewise max_clm_amt	min(165,max_clm_amt/1000);	0.0058	0.0003	0.0000
vMCA_pw2		Variate piecewise max_clm_amt	median(0,max_clm_amt/1000-165,250);	0.0032	0.0001	0.0000

Likelihood of Non-Mortality Termination

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

Table 24: Model Parameters – Likelihood of Non-Mortality Termination

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
Intercept				-4.8538	0.0538	0.0000
vminage_pw1		Variate piecewise Minimum Age	median(0,min_age-72,79-72);	0.0799	0.0024	0.0000
vminage_pw2		Variate piecewise Minimum Age	median(0,min_age-79,92-79);	0.0829	0.0011	0.0000
vminage_pw3		Variate piecewise Minimum Age	max(0,min_age-92);	0.0567	0.0046	0.0000
vmob_pw0		Variate piecewise Mobility	min(0,mobility_2)	0.0092	0.0007	0.0000
vmob_pw1		Variate piecewise Mobility	median(0,mobility_2-0,30-0)	0.0115	0.0004	0.0000
vmob_pw2		Variate piecewise Mobility	max(0,mobility_2-30)	0.0376	0.0011	0.0000

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
vmob_pw2*vmob_pw2		Interacted Mobility	max(0,mobility_2-30)	-0.0001	0.0000	0.0271
vmob_pw0*vmob_pw0		Interacted Mobility	min(0,mobility_2)	0.0000	0.0000	0.0000
vminage_pw1*vmob_pw2		Interacted piecewise Mobility	median(0,mobility_2-0,30-0) and max(0,mobility_2-30)	-0.0038	0.0001	0.0000
vmob_pw0*mSeason	L02	Interacted piecewise Mobility and Season	mod(period,100) = 2	0.0028	0.0010	0.0070
vmob_pw0*mSeason	L03	Interacted piecewise Mobility and Season	mod(period,100) = 3	0.0070	0.0012	0.0000
vmob_pw0*mSeason	z_Base	Interacted piecewise Mobility and Season	Base level: else			
vmob_pw2*mSeason	L02	Interacted piecewise Mobility and Season	mod(period,100) = 2	0.0028	0.0008	0.0004
vmob_pw2*mSeason	L03	Interacted piecewise Mobility and Season	mod(period,100) = 3	0.0055	0.0008	0.0000
vmob_pw0*mSeason	z_Base	Interacted piecewise Mobility and Season	Base level: else			
vltv_pw1		Variate piecewise Loan to Value	min(5,LTV)	-0.1192	0.0104	0.0000
vltv_pw2		Variate piecewise Loan to Value	median(0,LTV-5,88-5)	-0.0083	0.0002	0.0000
vltv_pw3		Variate piecewise Loan to Value	median(0,LTV-88,96.5 - 88)	-0.0168	0.0017	0.0000
vltv_pw4		Variate piecewise Loan to Value	median(0,LTV-96.5,99.5-96.5)	0.1390	0.0044	0.0000
vltv_pw5		Variate piecewise Loan to Value	max(0,LTV-99.5)	0.0975	0.0013	0.0000
min_age65	L01__62	Categorical Minimum Age	62	-0.3651	0.0745	0.0000
min_age65	L02__63	Categorical Minimum Age	63	-0.2328	0.0387	0.0000

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
min_age65	L03__64	Categorical Minimum Age	64	-0.2468	0.0318	0.0000
min_age65	L04__65	Categorical Minimum Age	65	-0.2224	0.0280	0.0000
min_age65	L05__72	Categorical Minimum Age	65 < min_age <= 72	-0.0705	0.0142	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")	-0.0326	0.0103	0.0015
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	0.0394	0.0070	0.0000
MGender	z_Base	Categorical Gender	Base level: else	0.0000		
mSeason	L02	Categorical Season	mod(period,100) = 2	0.1199	0.0091	0.0000
mSeason	L03	Categorical Season	mod(period,100) = 3	0.0486	0.0096	0.0000
mSeason	z_Base	Categorical Season	Base level: else	0.0000		
mOrigFY	L01_2001	Categorical Origination Fiscal Year	2001	-0.1647	0.0518	0.0015
mOrigFY	L02_2002	Categorical Origination Fiscal Year	2002	-0.1012	0.0389	0.0093
mOrigFY	L03_2003	Categorical Origination Fiscal Year	2003	0.0955	0.0330	0.0038
mOrigFY	L04_2004	Categorical Origination Fiscal Year	2004	-0.0044	0.0221	0.8412
mOrigFY	L05_2005	Categorical Origination Fiscal Year	2005	-0.0375	0.0194	0.0535
mOrigFY	L06_2006	Categorical Origination Fiscal Year	2006	0.0463	0.0132	0.0004
mOrigFY	L07_2007	Categorical Origination Fiscal Year	2007	-0.1259	0.0124	0.0000
mOrigFY	L08_2008	Categorical Origination Fiscal Year	2008	-0.1926	0.0120	0.0000
mOrigFY	L09_2009	Categorical Origination Fiscal Year	2009	-0.1083	0.0113	0.0000
mOrigFY	L10_2010	Categorical Origination Fiscal Year	2010	-0.0265	0.0121	0.0284

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
mOrigFY	z_Base		Base level: else	0.0000		
mperiod_num	L01_02	Categorical Period Number	2	-0.9382	0.0278	0.0000
mperiod_num	L02_03	Categorical Period Number	3	-0.4989	0.0234	0.0000
mperiod_num	L03_04	Categorical Period Number	4	-0.2344	0.0213	0.0000
mperiod_num	L04_05	Categorical Period Number	5	-0.0758	0.0203	0.0002
mperiod_num	z_Base	Categorical Period Number	Base level: else	0.0000		
vperiodnbr_othr_pw1		Variate piecewise Period Number	median(0,period_number-5,20-5);	0.0185	0.0009	0.0000
vperiodnbr_othr_pw2		Variate piecewise Period Number	max(0,period_number-20);	0.0097	0.0005	0.0000

CT2c Claim

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

Table 25: Model Parameters – Likelihood of CT2c

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
Intercept				-9.0407	0.2624	0.0000
vUPBRatio_MRA_pw1		Variate piecewise UPB Ratio1	median(0,UPB_Ratio,.85)	9.7405	0.2951	0.0000
vUPBRatio_MRA_pw2		Variate piecewise UPB Ratio1	median(0,UPB_Ratio-.85,1.5-.85)	4.3626	0.2182	0.0000
mMinage	L01_Miss	Categorical Minimum Age	min_age=.	1.3513	0.1530	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)	0.0373	0.0058	0.0000
vmin_age_pw2		Variate piecewise Minimum Age	max(0,min_age-62)	-0.1158	0.0392	0.0032

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 26: Model Parameters – CT2c Sales Price Model

Variable	Description	Description Detail	Estimate	StdErr	Pr > ChiSq
Intercept			1.8442	0.0839	<.0001
vperiodnbr_pw1	Variate piecewise Period Number	min(45,period_number)	-0.0029	0.0010	0.0041
vpropval_pw1	Variate piecewise Property Value[1]	min(8,vpropval)	-0.3514	0.0123	<.0001
vpropval_pw2	Variate piecewise Property Value[1]	median(0,vpropval-8,10-8)	0.2220	0.0206	<.0001
vpropval_pw3	Variate piecewise Property Value[1]	median(0,vpropval-10,15-10)	0.0263	0.0061	<.0001
vpropval_pw4	Variate piecewise Property Value[1]	median(0,vpropval-15,30-15)	0.0126	0.0016	<.0001
vpropval_pw5	Variate piecewise Property Value[1]	median(0,vpropval-30,50-30)	-0.0105	0.0022	<.0001
vpropval_pw6	Variate piecewise Property Value[1]	max(0,vpropval-50)	-0.0040	0.0001	<.0001
Scale			5.5974	0.0000	

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 27: Model Parameters – Likelihood of CT1 Claim

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
Intercept				-10.0572	0.8711	0.0000
vUPBRatio_MRA_pw1		Variate piecewise UPB Ratio[1]	median(0,UPB_Ratio,.2)	-6.9590	0.5363	0.0000

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
vUPBRatio_MRA_pw2		Variate piecewise UPB Ratio[1]	median(0,UPB_Ratio-.2,.35-.2)	-6.4824	0.5262	0.0000
vUPBRatio_MRA_pw3		Variate piecewise UPB Ratio[1]	median(0,UPB_Ratio-.35,.6-.35)	9.7216	0.1838	0.0000
vUPBRatio_MRA_pw4		Variate piecewise UPB Ratio[1]	median(0,UPB_Ratio-.6,.95-.6)	9.6996	0.0732	0.0000
vUPBRatio_MRA_pw5		Variate piecewise UPB Ratio[1]	median(0,UPB_Ratio-.95,1.5-.95)	3.2111	0.1661	0.0000
mMinage	L01_Miss	Categorical Minimum Age	min_age=.	1.1146	0.0135	0.0000
mMinage	z_Base	Categorical Minimum Age	Base level: else	0.0000		
vmin_age_pw1		Variate piecewise Minimum Age	median(0,min_age-62,69-62)	0.0920	0.0212	0.0000
vperiodnum_mra_pw1		Categorical Minimum Age	median(0,period_number-9,30-9)	0.8690	0.2207	0.0001
vperiodnum_mra_pw2		Variate piecewise period number	median(0,period_number-1,5-1)	0.5969	0.0286	0.0000
vperiodnum_mra_pw3		Variate piecewise period number	median(0,period_number-5,9-5)	0.1408	0.0026	0.0000
vperiodnum_mra_pw4		Variate piecewise period number	median(0,period_number-9,22-9)	0.0457	0.0023	0.0000
vperiodnum_mra_pw5		Variate piecewise period number	median(0,period_number-22,33-22)	-0.0173	0.0026	0.0000
vperiodnum_mra_pw6		Variate piecewise period number	median(0,period_number-33,44-.33)	-0.0222	0.0041	0.0000
vperiodnum_mra_pw7		Variate piecewise period number	median(0,period_number-44,60-44)	0.1108	0.0208	0.0000

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 28: Model Parameters – CT1 Sales Price Model

Variable	Description	Description Detail	Estimate	StdErr	Pr > ChiSq
Intercept			-1.2411	0.0318	<.0001
vperiodnbr_pw1	Variate piecewise Period Number	median(0,period_number-8,22-8)	-0.0102	0.0010	<.0001
vperiodnbr_pw2	Variate piecewise Period Number	median(0,period_number-22,40-22)	0.0029	0.0003	<.0001
vperiodnbr_pw3	Variate piecewise Period Number	median(0,period_number-40,44-40)	-0.0008	0.0002	<.0001
vperiodnbr_pw4	Variate piecewise Period Number	median(0,period_number-44,57-44)	-0.0003	0.0002	0.0523
vperiodnbr_pw5	Variate piecewise Period Number	max(0,period_number-57)	-0.0124	0.0031	<.0001
vpropval_pw1	Variate piecewise Property Value[1]	min(8,vpropval)	0.0213	0.0039	<.0001
vpropval_pw2	Variate piecewise Property Value[1]	median(0,vpropval-8,10-8)	0.0653	0.0049	<.0001
vpropval_pw3	Variate piecewise Property Value[1]	median(0,vpropval-10,15-10)	0.0316	0.0014	<.0001
vpropval_pw4	Variate piecewise Property Value[1]	median(0,vpropval-15,30-15)	0.0107	0.0004	<.0001
vpropval_pw5	Variate piecewise Property Value[1]	median(0,vpropval-30,50-30)	-0.0014	0.0005	0.0088
vpropval_pw6	Variate piecewise Property Value[1]	max(0,vpropval-50)	-0.0024	0.0006	<.0001
vUPB_Ratio_pw1	Variate piecewise UPB Ratio[2]	median(0,UPB_Ratio-39,39);	0.0022	0.0002	<.0001
vUPB_Ratio_pw3	Variate piecewise UPB Ratio[2]	median(0,UPB_Ratio-47.8,59-47.8);	0.0047	0.0014	0.0006
vUPB_Ratio_pw4	Variate piecewise UPB Ratio[2]	median(0,UPB_Ratio-59,65.5-59);	0.0102	0.0015	<.0001

Variable	Description	Description Detail	Estimate	StdErr	Pr > ChiSq
vUPB_Ratio_pw7	Variate piecewise UPB Ratio^2	median(0,UPB_Ratio-98.6,135-98.6);	-0.0013	0.0003	0.0001
vUPB_Ratio_pw8	Variate piecewise UPB Ratio^2	Min(200,UPB_Ratio_100)-135;	0.0044	0.0007	<.0001
vmin_age_pw2	Variate piecewise Minimum Age	median(0,min_age-65,68-65);	-0.0199	0.0046	<.0001
vmin_age_pw3	Variate piecewise Minimum Age	median(0,min_age-68,77-68);	0.0081	0.0015	<.0001
vmin_age_pw4	Variate piecewise Minimum Age	median(0,min_age-77,90-77);	0.0069	0.0007	<.0001
vmin_age_pw5	Variate piecewise Minimum Age	max(0,min_age-90);	-0.0067	0.0019	0.0005
Scale			4.9395	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 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

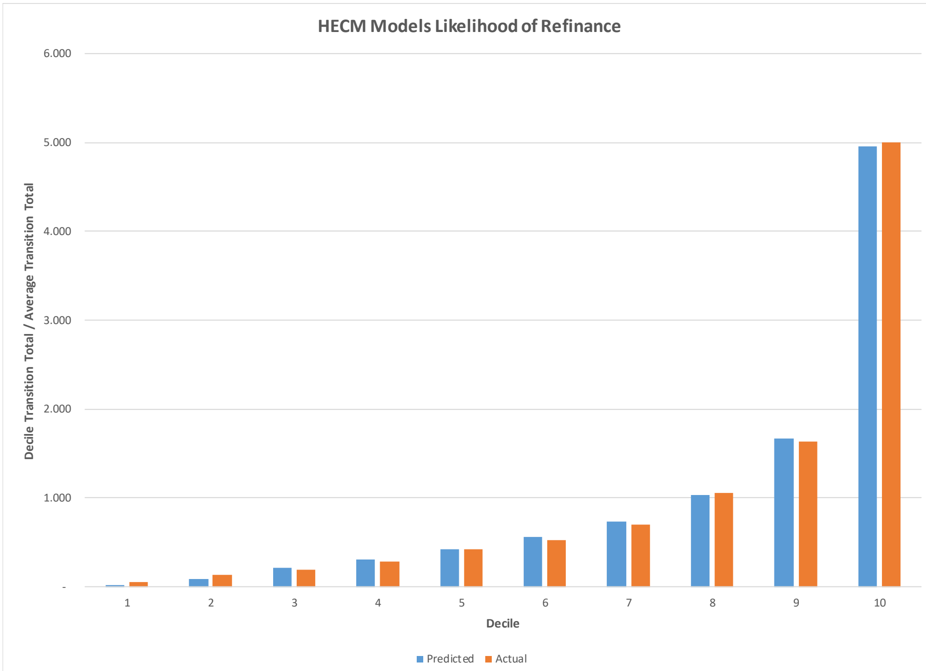


Figure 8: Model Validation - Likelihood of Non-Mortality Termination

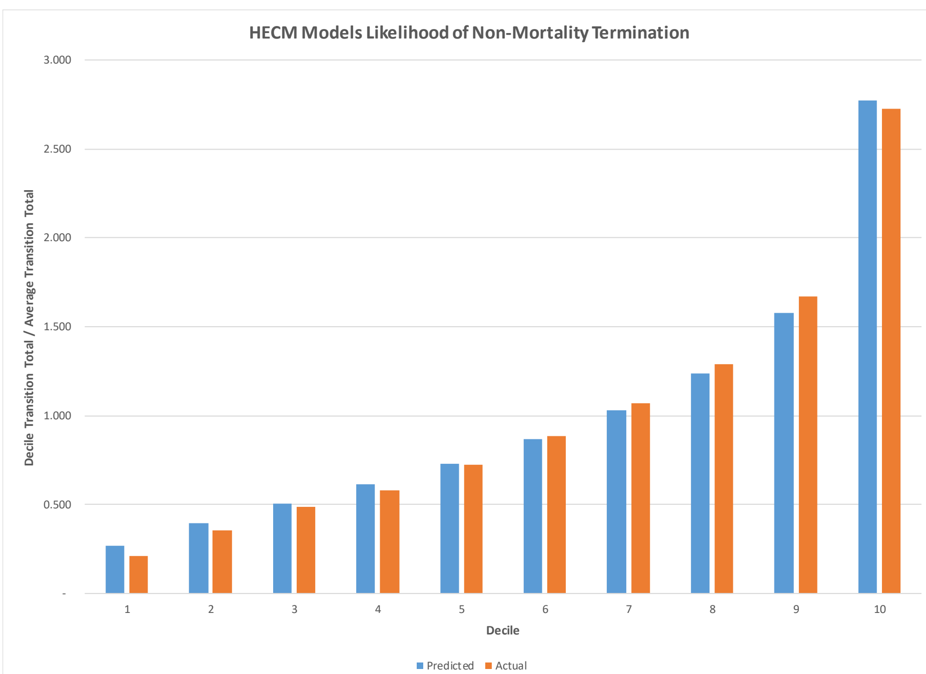


Figure 9: Model Validation - Likelihood of CT2c Claim

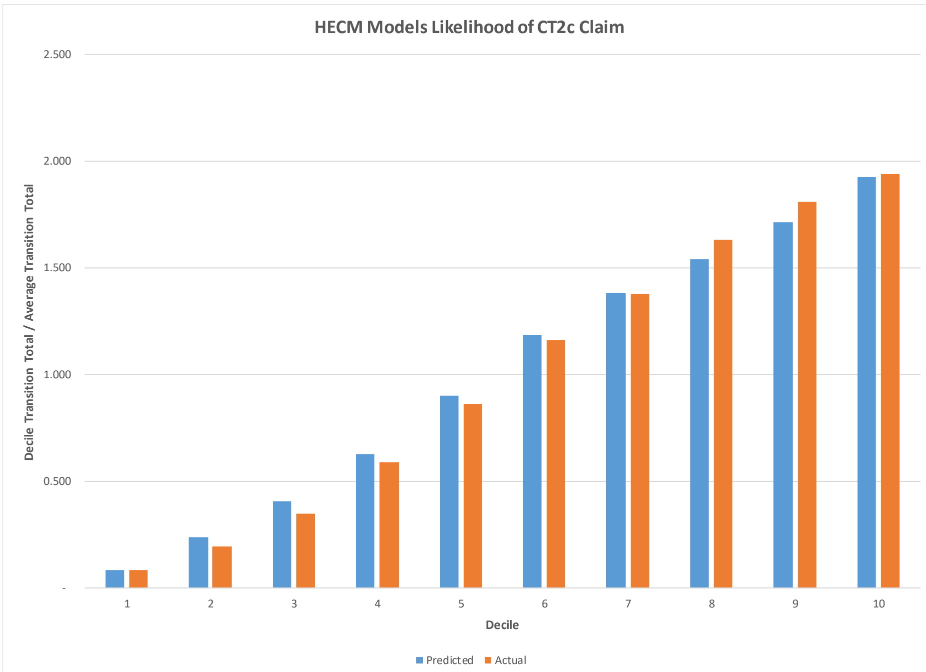


Figure 10: Model Validation – CT2c Sales Amount Model

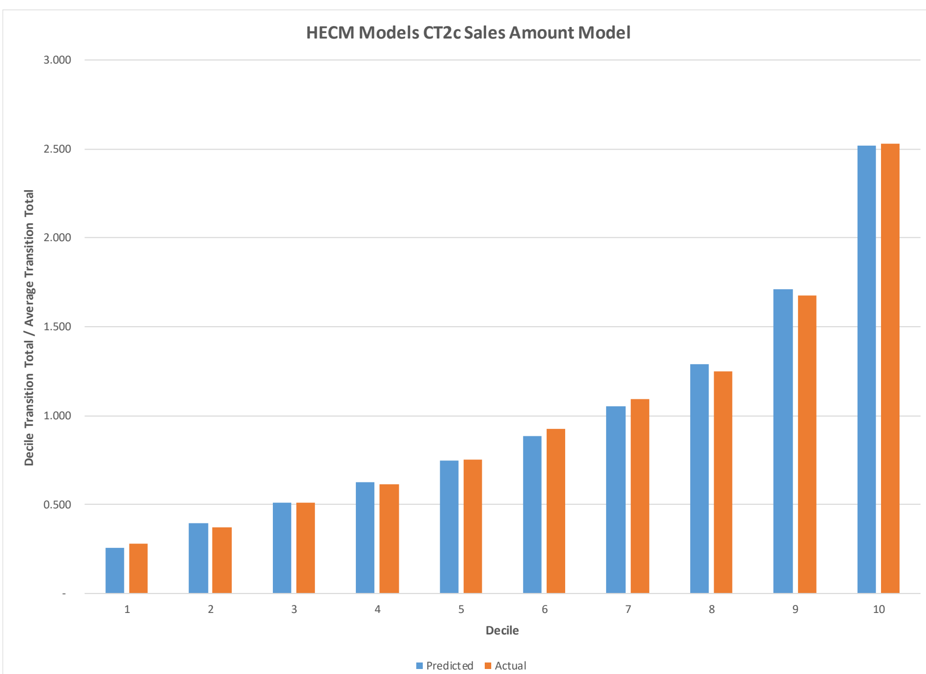


Figure 11: Model Validation – Likelihood of CT1 Claim

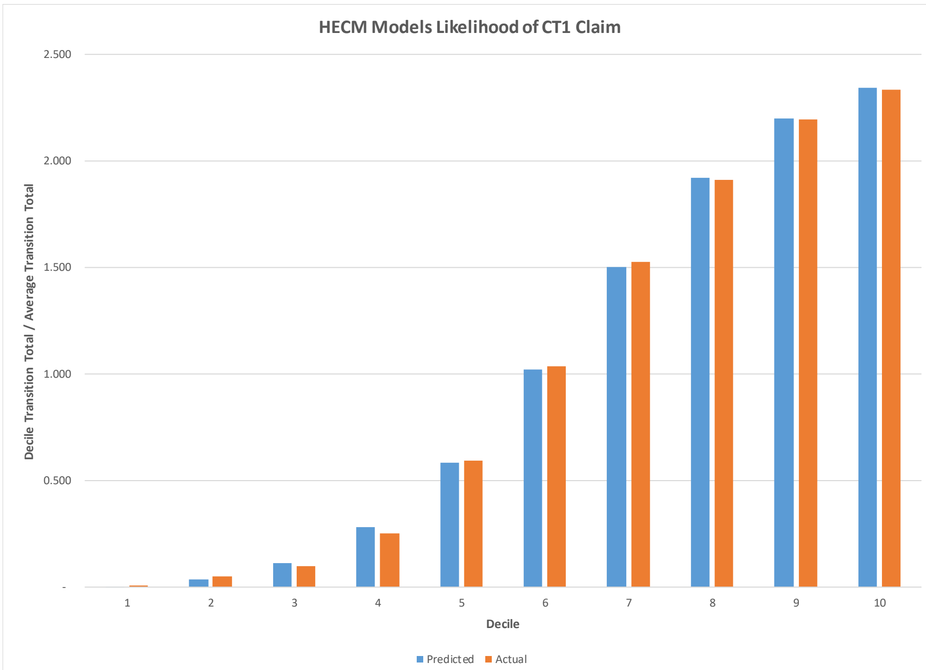
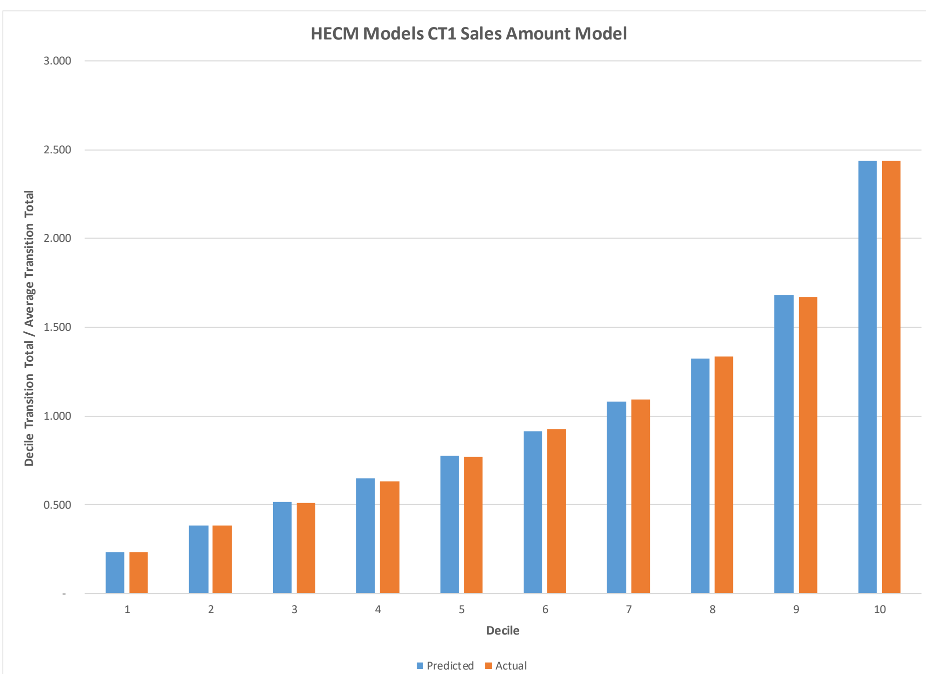


Figure 12: Model Validation – CT1 Sales Amount Model



Appendix C: HECM Cash Draw Projection 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 unscheduled cash draws for HECM with a line of credit. 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 12-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.

For the historical HECM database, for each quarter we develop an indicator of whether or not a net positive unscheduled cash draw was taken from the line of credit during that quarter. 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 (LOCCap) 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 database. 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 (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 1-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 * 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 tge count of prior periods where i_TI_Debit_Amt is greater than $100. This variable is incorporated as a grouped categorical variable.

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 29: Model Parameters – Likelihood of Cash Draw

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
Intercept				-2.8912	0.0100	0.0000
mMinage	L01_62	Categorical Minimum Age	min_age=62	0.1932	0.0144	0.0000
mMinage	L02_63	Categorical Minimum Age	min_age=63	0.1640	0.0089	0.0000
mMinage	L03_64	Categorical Minimum Age	min_age=64	0.1008	0.0075	0.0000
mMinage	L04_65	Categorical Minimum Age	min_age=65	0.0423	0.0067	0.0000
mMinage	L05_95	Categorical Minimum Age	90<min_age<=95	-0.0268	0.0067	0.0001
mMinage	L06_99	Categorical Minimum Age	min_age>95	0.0101	0.0155	0.5150
mMinage	z_Base	Categorical Minimum Age	Base level: else	0.0000		
mSeason	A01	Categorical Season	period <201300 and mod(period,100) = 1	-0.1900	0.0048	0.0000
mSeason	A02	Categorical Season	period <201300 and mod(period,100) = 2	-0.1203	0.0048	0.0000
mSeason	A03	Categorical Season	period <201300 and mod(period,100) = 3	-0.0623	0.0047	0.0000
mSeason	A04	Categorical Season	period <201300 and mod(period,100) = 4	-0.0286	0.0047	0.0000
mSeason	B01	Categorical Season	period >=201300 and mod(period,100) = 1	-0.1717	0.0041	0.0000
mSeason	B02	Categorical Season	period >=201300 and mod(period,100) = 2	-0.1196	0.0041	0.0000
mSeason	B03	Categorical Season	period >=201300 and mod(period,100) = 3	-0.0661	0.0043	0.0000
mSeason	z_Base	Categorical Season	Base level: else	0.0000		
mAlive	L02_2	Categorical Alive	else	-0.2146	0.0023	0.0000
mAlive	z_Base	Categorical Alive	Base level: 1	0.0000		
MGender	L01_M	Categorical Alive	gender=1 and borr_alive=1 or gender = 3 and coborr_gender_1=1 and coborr_1_alive=1	-0.0416	0.0025	0.0000
MGender	z_Base	Categorical Alive	Base level: else	0.0000		
mDeltaTy1Init	L02_2.0	Categorical Change in 1 year Treasury from Initial	Delta_T1Y_Init_p>2	-0.0115	0.0032	0.0004
mDeltaTy1Init	z_Base	Categorical Change in 1 year	Base level: else	0.0000		

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
		Treasury from Initial				
mloantyp	L01_01	Categorical Loan Type	loan_typ in ('01", "03", "04", "05", "06")	-0.4402	0.0046	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 Cretit	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)	0.0000	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)	1.1620	0.0121	0.0000
vLOCRemain_pw3		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-1.4,4.1-1.4)	-0.0354	0.0041	0.0000
vLOCRemain_pw4		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-4.1,15.5-4.1)	-0.0148	0.0007	0.0000
vLOCRemain_pw5		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-15.1,40.5-15.5)	-0.0172	0.0002	0.0000
vLOCRemain_pw6		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-40.5,77-40.5)	-0.0185	0.0001	0.0000
vLOCRemain_pw7		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-77,93.4-77)	-0.0253	0.0004	0.0000
vLOCRemain_pw8		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-93.4,99-93.4)	-0.1235	0.0017	0.0000
vLOCRemain_pw9		Variate piecewise Line of	median(0,loc_remaining-99,99.9-99)	-0.4255	0.0145	0.0000

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
		Credit Remaining[2]				
vLOCRemain_pw10		Variate piecewise Line of Credit Remaining[2]	max(0,loc_remaining-99.9)	1.2807	0.1019	0.0000
mperiod_num	L01_02	Categorical Period Number	2	0.6541	0.0062	0.0000
mperiod_num	L02_03	Categorical Period Number	3	0.3644	0.0061	0.0000
mperiod_num	L03_04	Categorical Period Number	4	0.2584	0.0061	0.0000
mperiod_num	L04_05	Categorical Period Number	5	0.5039	0.0054	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)	-0.0484	0.0002	0.0000
vPeriodNbr_pw2		Variate piecewise Period Number	median(0,period_number-24,40-24)	-0.0316	0.0004	0.0000
vPeriodNbr_pw3		Variate piecewise Period Number	median(0,period_number-40,52-40)	-0.0278	0.0011	0.0000
vPeriodNbr_pw4		Variate piecewise Period Number	max(0,period_number-52)	-0.0196	0.0031	0.0000
vLTV_cdf_pw1		Variate piecewise Loan to Value	median(0,LTV-20,20)	0.0244	0.0007	0.0000
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)	-0.0204	0.0003	0.0000
vLTV_cdf_pw4		Variate piecewise Loan to Value	max(0,period_number-95.5)	-0.0756	0.0022	0.0000
mLTV	0	Categorical Loan to Value	else	0.1833	0.0165	0.0000

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
mLTV	z_Base	Categorical Loan to Value	LTV <99.5	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 30: Model Parameters – Likelihood of Full Cash Draw (Quarters 1 – 8)

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
Intercept				-1.1279	0.1969	0.0000
mperiod_num	L03_04	Categorical Period Number	4	0.0233	0.1196	0.8453
mperiod_num	L05_06	Categorical Period Number	6	-0.6039	0.1242	0.0000
mperiod_num	L06_07	Categorical Period Number	7	-0.7720	0.1260	0.0000
mperiod_num	L07_08	Categorical Period Number	8	-0.8642	0.1269	0.0000
mperiod_num	Z01_02	Categorical Period Number	2	-1.3049	0.1663	0.0000
mperiod_num	Z02_03	Categorical Period Number	3	-1.3595	0.1656	0.0000
mperiod_num	z_Base	Categorical Period Number	else	0.0000		
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	0.0004
vltv_cd100_pw1		Variate piecewise	min(55,LTV)	-0.0178	0.0036	0.0000

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
		Loan to Value				
vltv_cd100_pw2		Variate piecewise Loan to Value	median(0,LTV-55,60-55)	0.6320	0.0220	0.0000
vltv_cd100_pw3		Variate piecewise Loan to Value	median(0,LTV-60,64-60)	-0.5910	0.0231	0.0000
vltv_cd100_pw4		Variate piecewise Loan to Value	median(0,LTV-64,95-64)	0.0528	0.0034	0.0000
vltv_cd100_pw5		Variate piecewise Loan to Value	max(0,LTV-95)	0.2003	0.0173	0.0000
vminage_cd100_pw1		Variate piecewise Minimum Age	median(0,min_age-62,78-62)	0.0093	0.0023	0.0001
vminage_cd100_pw2		Variate piecewise Minimum Age	max(0,min_age-78)	0.0291	0.0038	0.0000
mSeason	L01	Categorical Season	mod(period,100) = 1	0.0482	0.0296	0.1032
mSeason	L02	Categorical Season	mod(period,100) = 2	0.0837	0.0292	0.0042
mSeason	L03	Categorical Season	mod(period,100) = 3	0.0941	0.0302	0.0018
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	0.1334	0.0224	0.0000
MGender	Z_Base	Categorical Gender	Base level: else	0.0000		
mAlive	L02_2	Categorical Alive	else	0.1521	0.0226	0.0000
mAlive	Z_Base	Categorical Alive	Base level: 1	0.0000		
mloantyp	L01_01	Categorical Loan Type	loan_typ in ('01", "03", "04", "05", "06")	0.8748	0.0883	0.0000
mloantyp	Z_Base	Categorical Loan Type	Base level: else	0.0000		
vltv_cd100_pw2*mperiod_num5	L01_5	Interacted Loan to Value and Period Number	Period Number 5	0.0941	0.0258	0.0003
vltv_cd100_pw3*mperiod_num5	L01_5	Interacted Loan to Value and Period Number	Period Number 5	0.2304	0.0277	0.0000

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
vltv_cd100_pw4*mperiod_num5	L01_5	Interacted Loan to Value and Period Number	Period Number 5	-0.0258	0.0040	0.0000
vltv_cd100_pw5*mperiod_num5	L01_5	Interacted Loan to Value and Period Number	Period Number 5	-0.3319	0.0202	0.0000
vltv_cd100_pw5*mperiod_num5	z_Base	Interacted Loan to Value and Period Number	Base Period Number 5: else	0.0000	0.0202	0.0000

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

Table 31: Model Parameters – Likelihood of Full Cash Draw (Quarters 9+)

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
Intercept				-0.3554	0.0424	0.0000
vLOCCap_cd100_pw0		Variate piecewise Line of Credit[1]	min(1000,loc_capped_i)	-0.0011	0.0000	0.0000
vLOCCap_cd100_pw1		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-1000,3500-1000)	-0.0005	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_pw5		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-100000,165000-100000)	0.0000	0.0000	0.0050
vLOCCap_cd100_pw6		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-165000,300000-165000)	0.0000	0.0000	0.0020
vltv_cd100_pw2		Variate piecewise Loan to Value	median(0,LTV-64,95-64)	0.0060	0.0011	0.0000

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
vltv_cd100_pw3		Variate piecewise Loan to Value	max(0,LTV-95)	-0.0588	0.0046	0.0000
vminage_cd100_pw1		Variate piecewise Minimum Age	median(0,min_age-62,78-62)	0.0071	0.0016	0.0000
vminage_cd100_pw2		Variate piecewise Minimum Age	max(0,min_age-78)	0.0332	0.0017	0.0000
vperiodnbr_pw1		Variate piecewise Period Number	median(0,period_number-9,30-9)	-0.0443	0.0010	0.0000
vperiodnbr_pw2		Variate piecewise Period Number	max(0,period_number-30)	0.0122	0.0018	0.0000
mSeason	L01	Categorical Season	mod(period,100) = 1	0.1044	0.0165	0.0000
mSeason	L02	Categorical Season	mod(period,100) = 2	0.1751	0.0163	0.0000
mSeason	L03	Categorical Season	mod(period,100) = 3	0.2478	0.0162	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	0.0451	0.0131	0.0006
MGender	z_Base	Categorical Gender	Base level: else	0.0000		
mAlive	L02_2	Categorical Alive	else	0.1164	0.0128	0.0000
mAlive	z_Base	Categorical Alive	Base level: 1			
mloantyp	L01_01	Categorical Loan Type	loan_typ in ('01", "03", "04", "05", "06")	0.5546	0.0271	0.0000
mloantyp	z_Base	Categorical Loan Type	Base level: else	0.0000		

Cash Draw Amount Model

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

Table 32: Model Parameters –Cash Draw Amount

Parameter	Level1	Description	Description Detail	Estimate	StdErr	ProbChiSq
Intercept				6.2781	0.0176	0.0000
vLOCCap_cds_pw1		Variate piecewise Line of Credit[1]	min(1,loc_capped_i)	0.1193	0.0116	0.0000

Parameter	Level1	Description	Description Detail	Estimate	StdErr	ProbChiSq
vLOCCap_cds_pw2		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-1,3.5-1)	-0.0381	0.0035	0.0000
vLOCCap_cds_pw3		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-3.5,10-3.5)	-0.0323	0.0011	0.0000
vLOCCap_cds_pw4		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-10,15-10)	-0.0219	0.0012	0.0000
vLOCCap_cds_pw5		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-15,30-15)	-0.0173	0.0003	0.0000
vLOCCap_cds_pw6		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-30,125-30)	-0.0047	0.0000	0.0000
vLOCCap_cds_pw7		Variate piecewise Line of Credit[1]	median(0,loc_capped_i-125,200-125)	-0.0014	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)	-0.0101	0.0013	0.0000
vminage_cds_pw2		Variate piecewise Min Age	median(0,min_age-67,75-67)	-0.0073	0.0005	0.0000
vminage_cds_pw3		Variate piecewise Min Age	median(0,min_age-75,85-75)	0.0087	0.0004	0.0000
vminage_cds_pw4		Variate piecewise Min Age	max(0,min_age-85)	0.0274	0.0006	0.0000
vperiodnbr_pw1		Variate piecewise Period Number	median(0,period_number-5,10-5)	-0.0762	0.0007	0.0000
vperiodnbr_pw2		Variate piecewise Period Number	median(0,period_number-10,20-10)	-0.0246	0.0003	0.0000
vperiodnbr_pw3		Variate piecewise Period Number	median(0,period_number-20,54-20)	-0.0080	0.0002	0.0000
vperiodnbr_pw4		Variate piecewise Period Number	max(0,period_number-54)	-0.0088	0.0036	0.0131
vltv_cds_pw1		Variate piecewise	min(20,LTV)	-0.0013	0.0007	0.0406

Parameter	Level1	Description	Description Detail	Estimate	StdErr	ProbChiSq
		Loan to Value				
vltv_cds_pw2		Variate piecewise Loan to Value	median(0,LTV-20,80-20)	0.0094	0.0001	0.0000
vltv_cds_pw3		Variate piecewise Loan to Value	max(0,LTV-80)	0.0031	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"	0.5798	0.0148	0.0000
mltv	z_Base	Categorical Loan to Value	Base level: else	0.0000		
mSeason	L01	Categorical Season	mod(period,100) = 1	0.0001	0.0026	0.9825
mSeason	L02	Categorical Season	mod(period,100) = 2	0.0302	0.0026	0.0000
mSeason	L03	Categorical Season	mod(period,100) = 3	0.0373	0.0026	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	0.0364	0.0021	0.0000
MGender	z_Base	Categorical Gender	Base level: else	0.0000		
mAlive	L02_2	Categorical Alive	else	0.0478	0.0020	0.0000
mAlive	z_Base	Categorical Alive	Base level: 1	0.0000		
mloantyp	L01_01	Categorical Loan Type	loan_typ in ('01", "03", "04", "05", "06")	-0.0968	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(.45,loc_remaining_i)	-0.0191	0.0016	0.0000
vLOCRemain_pw2		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-.45,1.4-.45)	-0.0219	0.0009	0.0000
vLOCRemain_pw3		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-1.4,4.1-1.4)	-0.0123	0.0004	0.0000
vLOCRemain_pw4		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-4.1,15.5-4.1)	-0.0065	0.0002	0.0000

Parameter	Level1	Description	Description Detail	Estimate	StdErr	ProbChiSq
vLOCRemain_pw5		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-15.1,40.5-15.5)	-0.0058	0.0001	0.0000
vLOCRemain_pw6		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-40.5,77-40.5)	-0.0126	0.0021	0.0000
vLOCRemain_pw7		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-77,93.4-77)	-0.0113	0.0013	0.0000
vLOCRemain_pw8		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-93.4,99-93.4)	0.1250	0.0095	0.0000
vLOCRemain_pw9		Variate piecewise Line of Credit Remaining[2]	median(0,loc_remaining-99,99.9-99)	0.1799	0.0042	0.0000
Scale				0.9580	0.0000	

Tax and Insurance Default Model

The model parameters for the Tax and Insurance Default model are shown below.

Table 33: Model Parameters – Tax and Insurance Default Frequency Model

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
Intercept				-4.3141	0.0062	<.0001
mSeason	L01	Categorical Season	mod(period,100) = 1	-0.0992	0.0054	<.0001
mSeason	L02	Categorical Season	mod(period,100) = 2	0.0370	0.0052	<.0001
mSeason	L03	Categorical Season	mod(period,100) = 3	0.0611	0.0053	<.0001
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	2.2885	0.0052	<.0001
mTICnt	L02	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 2	2.8682	0.0062	<.0001
mTICnt	L03	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 3	3.0947	0.0072	<.0001

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
mTICnt	L04	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 4	3.2389	0.0084	<.0001
mTICnt	L05	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 5	3.3237	0.0098	<.0001
mTICnt	L06	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 6	3.4417	0.0115	<.0001
mTICnt	L07	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 7	3.5209	0.0137	<.0001
mTICnt	L08	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 8	3.5997	0.0163	<.0001
mTICnt	L09	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 9	3.6799	0.0196	<.0001
mTICnt	L10	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 10	3.6962	0.0235	<.0001
mTICnt	L11	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 11	3.7673	0.0286	<.0001
mTICnt	L12	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 12	3.7769	0.0349	<.0001
mTICnt	L13	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 13	3.9234	0.0430	<.0001
mTICnt	L14	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 14	3.9881	0.0531	<.0001
mTICnt	L15	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i = 15	3.9452	0.0652	<.0001
mTICnt	L16	Categorical Count of Tax and Ins Default[1]	TI_Debit_Cnt_i >= 16	3.9616	0.0507	<.0001
mTICnt	z_Base	Categorical Count of Tax and Ins Default[1]	Base level: else	0.0000		
vperiodnbr_TIDF_pw1		Variate piecewise	median(0,period_number-5,20-5)	-0.0141	0.0005	<.0001

Variable	ClassVal0	Description	Description Detail	Estimate	StdErr	ProbChiSq
		Period Number				
vperiodnbr_TIDF_pw2		Variate piecewise Period Number	median(0,period_number-20,28-20)	-0.0236	0.0009	<.0001
vperiodnbr_TIDF_pw3		Variate piecewise Period Number	median(0,period_number-28,40-28)	-0.0296	0.0007	<.0001
vperiodnbr_TIDF_pw4		Variate piecewise Period Number	median(0,period_number-42,52-42)	-0.0205	0.0019	<.0001
vperiodnbr_TIDF_pw5		Variate piecewise Period Number	max(0,period_number-52)	-0.0415	0.0049	<.0001

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 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

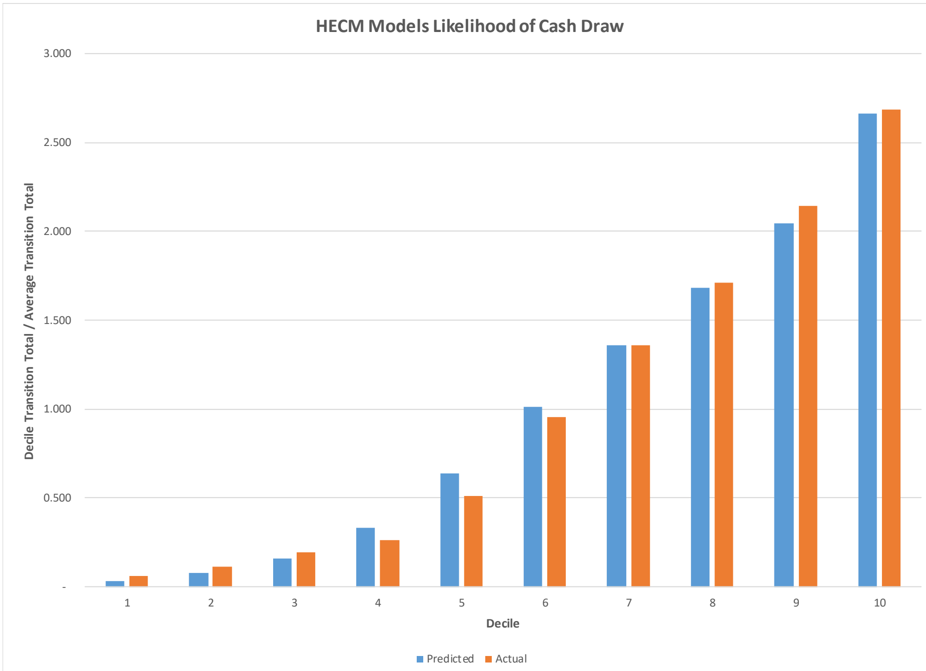


Figure 14: Model Validation - Likelihood of Full Cash Draw (Quarters 0 – 8)

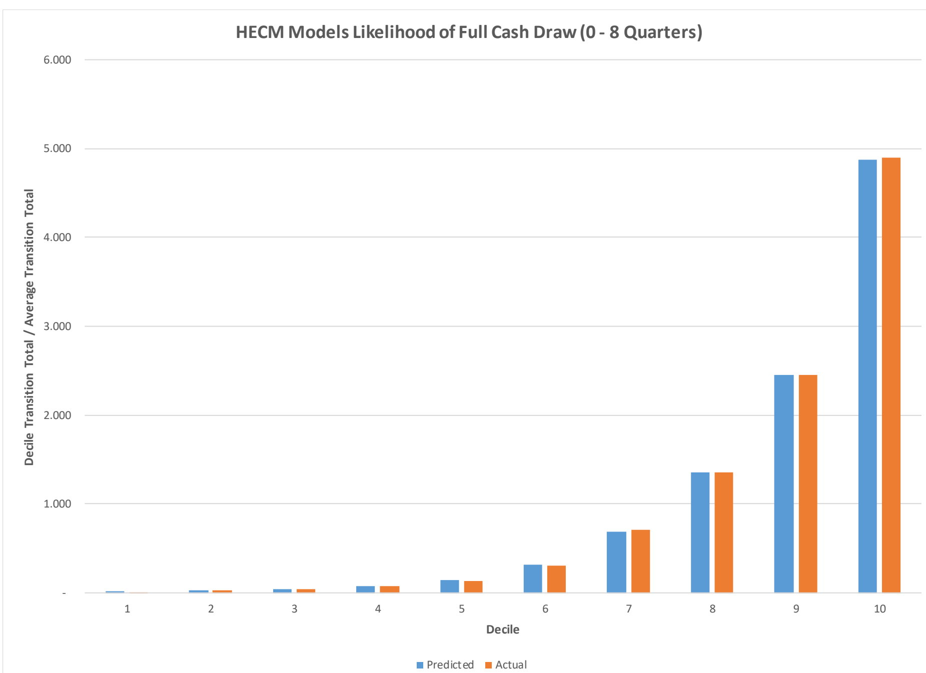


Figure 15: Model Validation - Likelihood of Full Cash Draw (Quarters 9+)

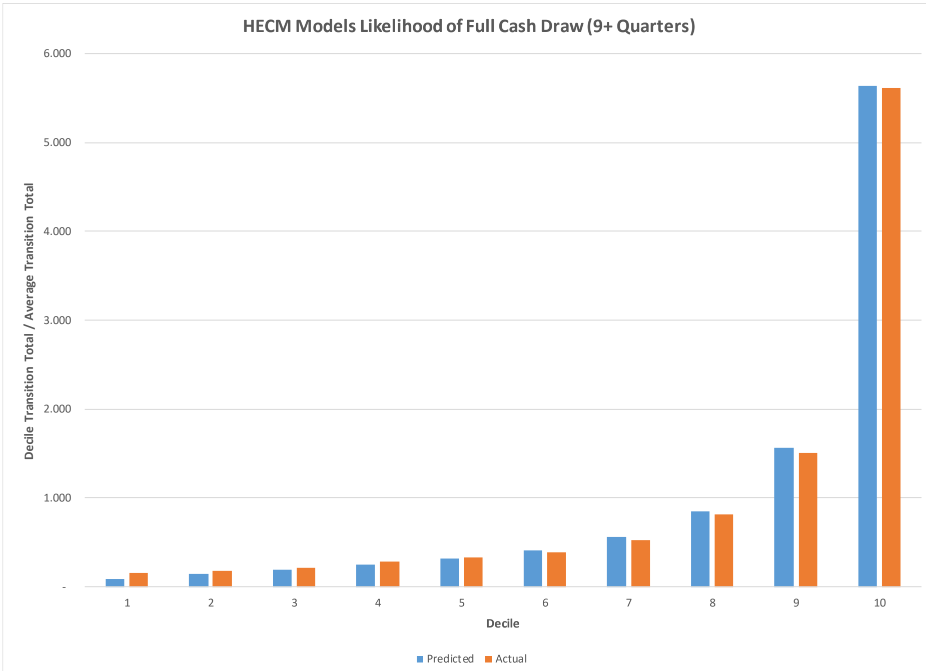
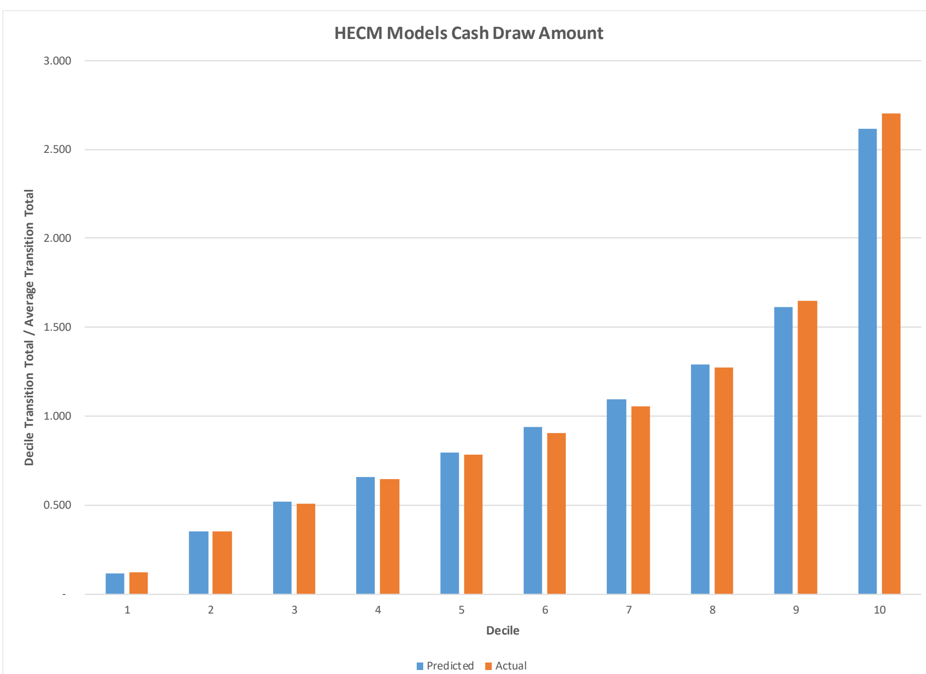
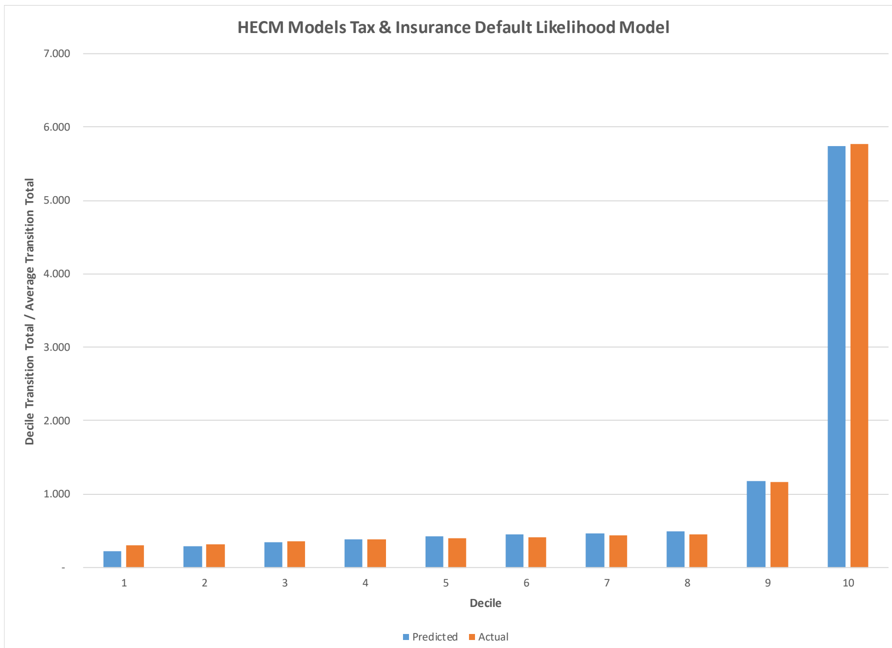


Figure 16: Model Validation – Cash Draw Amount Model



The validation chart for the Tax and Insurance Default model is shown below.

Figure 17: Model Validation – Tax and Insurance Default Model



Appendix D: Economic Scenarios

To measure the possible variation in MMIF'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 July 2019 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
- 1-year CMT rate
- 3-year CMT rate
- 5-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
- Exceptionally Strong Growth
- Stronger Near-Term Rebound
- Slower Near-Term Growth
- Moderate Recession
- Protracted Slump
- Below-Trend Long-Term 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 18 shows the future movements of the HPI under the baseline and the alternative economic scenarios. In the Moody's Baseline scenario, the HPI increases over the entire projection period, and the rate of change varies between 2.5% and 5.0%.

Figure 18: Paths of the Future National House Price Index in Different Scenarios

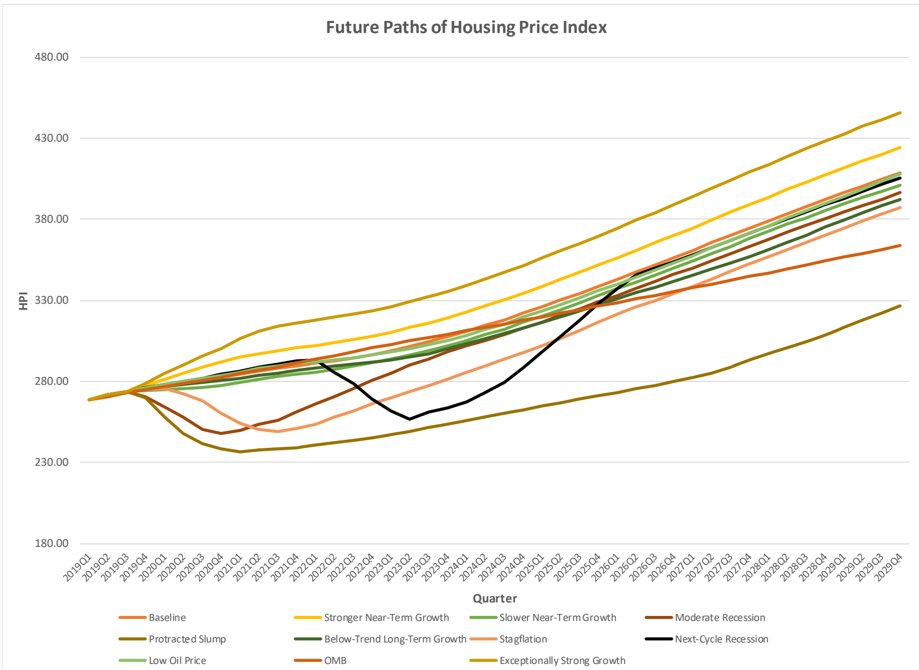


Figure 19 shows the forecasted mortgage rate of 30-year fixed-rate mortgages for the ten Moody's scenarios. Moody's Baseline forecast for the 30-year fixed interest rate shows that the mortgage interest rate increases to just under 5.4% by 2023, holds steady though 2024, then increases to a long-term average rate of around 5.5%. For the Moody's projections, we use the 30-year fixed rate as this represents the majority of the mortgage products sold.

Figure 19: Paths of the Future Mortgage Rate

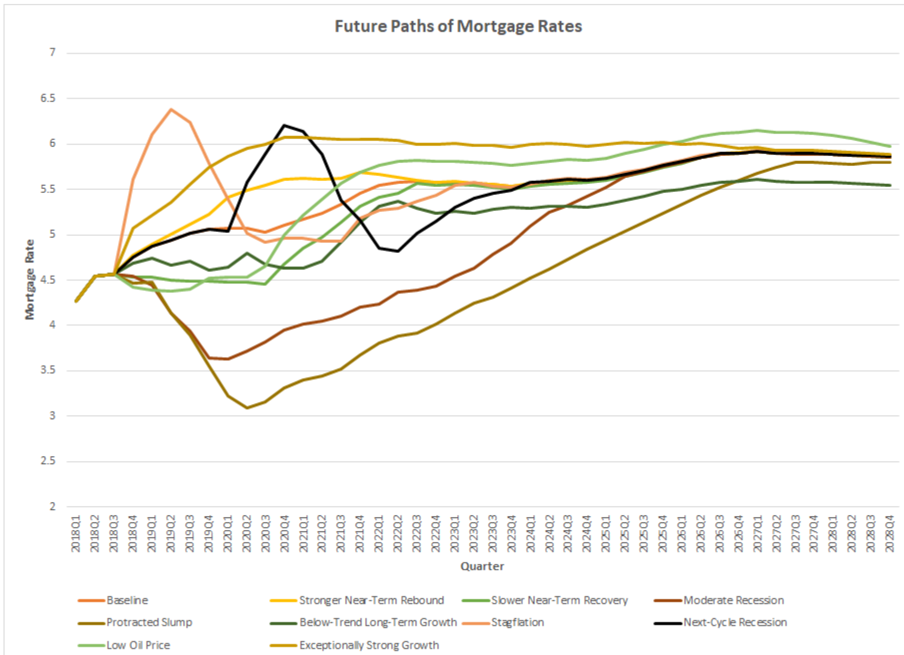
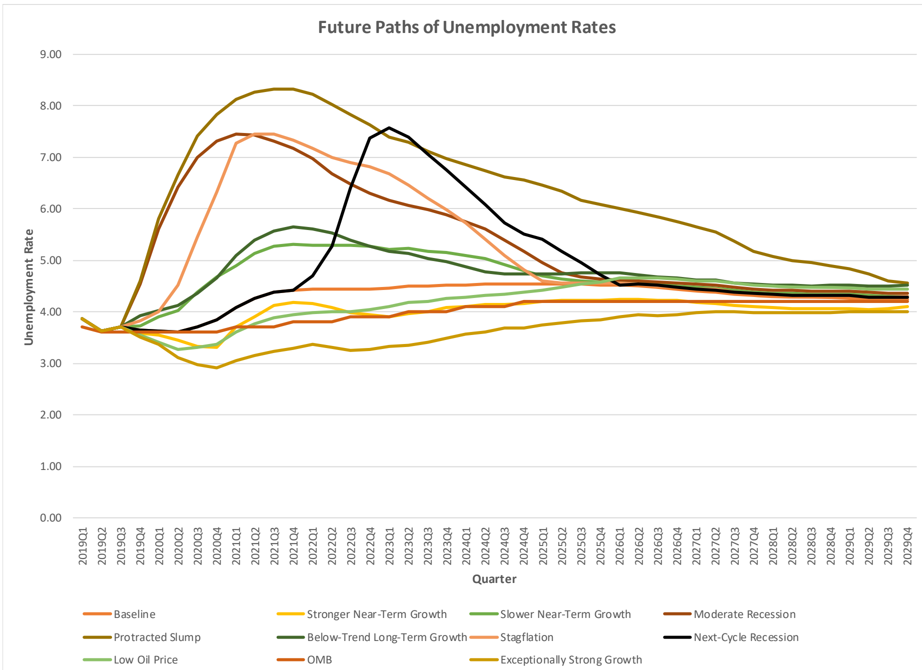


Figure 20 shows the forecasted unemployment rate under alternative economic scenarios. The Moody's Baseline forecast projects that the unemployment rate will decrease to 3.6% in 2020, and then increases to a long-term average of about 4.5%.

Figure 20: 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:

- 1-Year CMT Rates
- 3-Month CMT Rates
- 6-Month CMT Rates
- 2-Year CMT Rates
- 3-Year CMT Rates
- 5-Year CMT Rates
- 7-Year CMT Rates
- 10-Year CMT Rates
- 20-Year CMT Rates
- 30-Year CMT Rates
- 30-Year FRM Rates
- FHFA National Purchase Only House Price Index (HPI-PO)
- Unemployment Rates

- Gross Domestic Product (GDP)

Historical Data

A. Interest Rates

Figure 21 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 1-year CMT rate (tr1y), 10-year CMT rate (tr10y) and the 30-year fixed rate mortgage rate (mr).

High inflation rates caused by the global oil crisis in the late 1970's was the major factor for the historically high level in early 1980's. The Federal Reserve shifted its monetary policy from managing interest rates to managing the money supply as a way to influence interest rates after this period of time. The 1-year CMT rate (tr1y) was around 5% in CY 1971 and increased steadily to its peak of 16.31% in CY 1981 Q3. After that, it followed a decreasing trend and reached an all-time low of 0.10% in CY 2014 Q2. Since then rates have started a slow upward trend.

Figure 21: Historical Interest Rates (%)

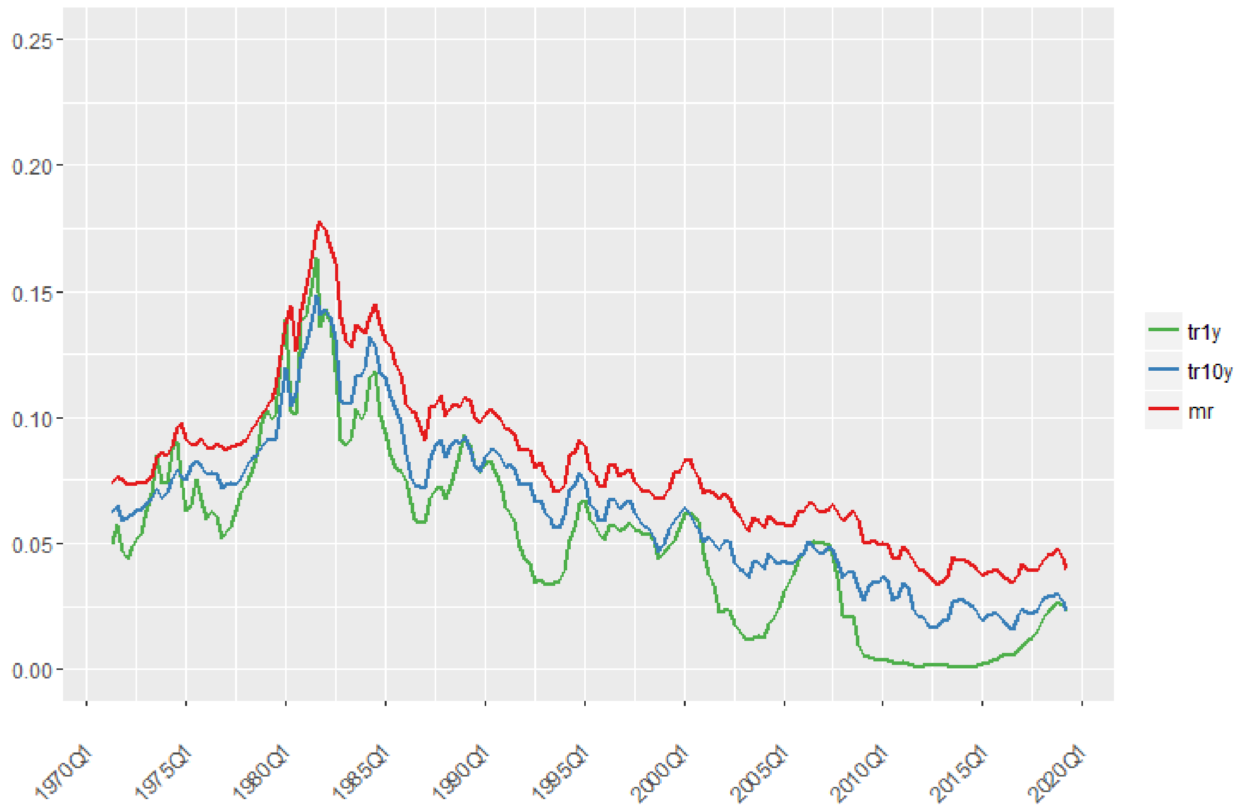
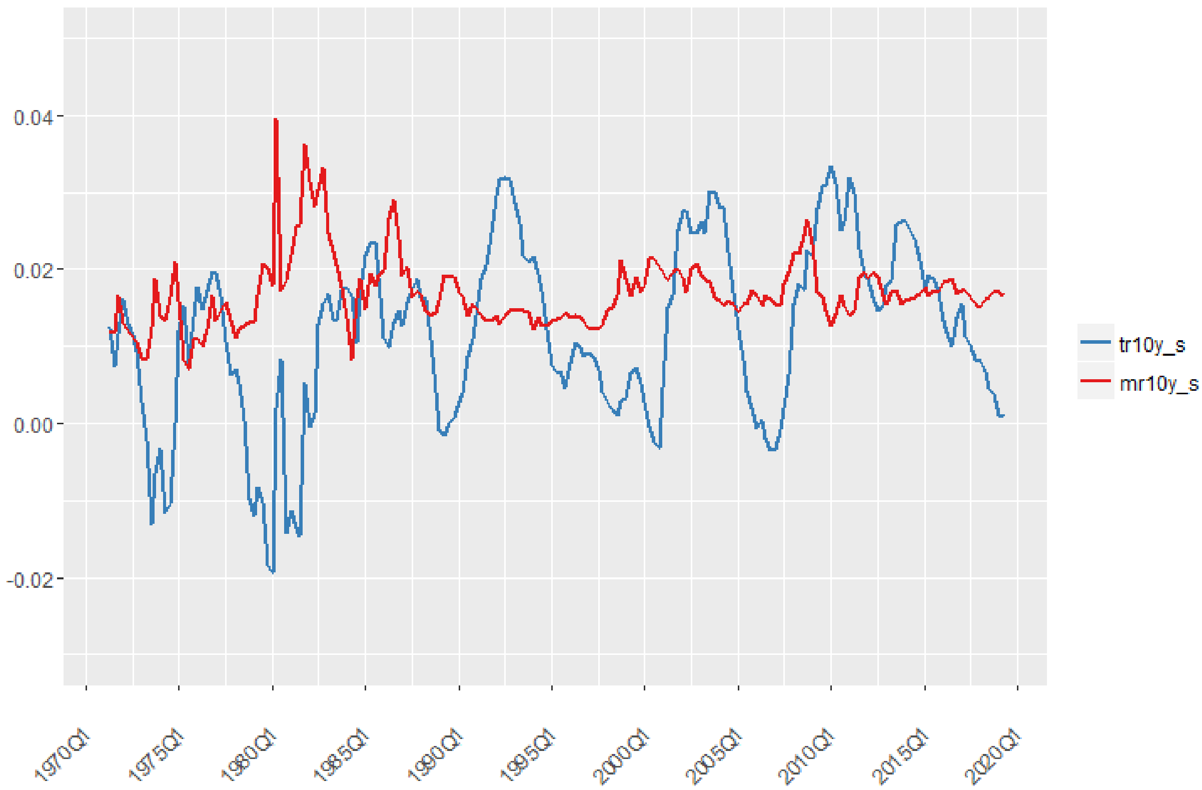


Figure 22 shows historical interest rate spreads, including the spread between 10-year and 1-year CMT rates (tr10y_s) and the spread between the 30-year mortgage rate and the 10-year Treasury rate (mr10y_s). Both spreads have a mostly positive value with long cycles. Lower, and negative spreads typically correspond with economic downturns, as occurred in the late 70's through early 80's. Also note, the spread of the mortgage rate over the 10-year CMT rate is always positive, reflecting the premium for credit risk.

Figure 22: Historical Interest Rate Spreads (%)



B. House Price Appreciation Rates

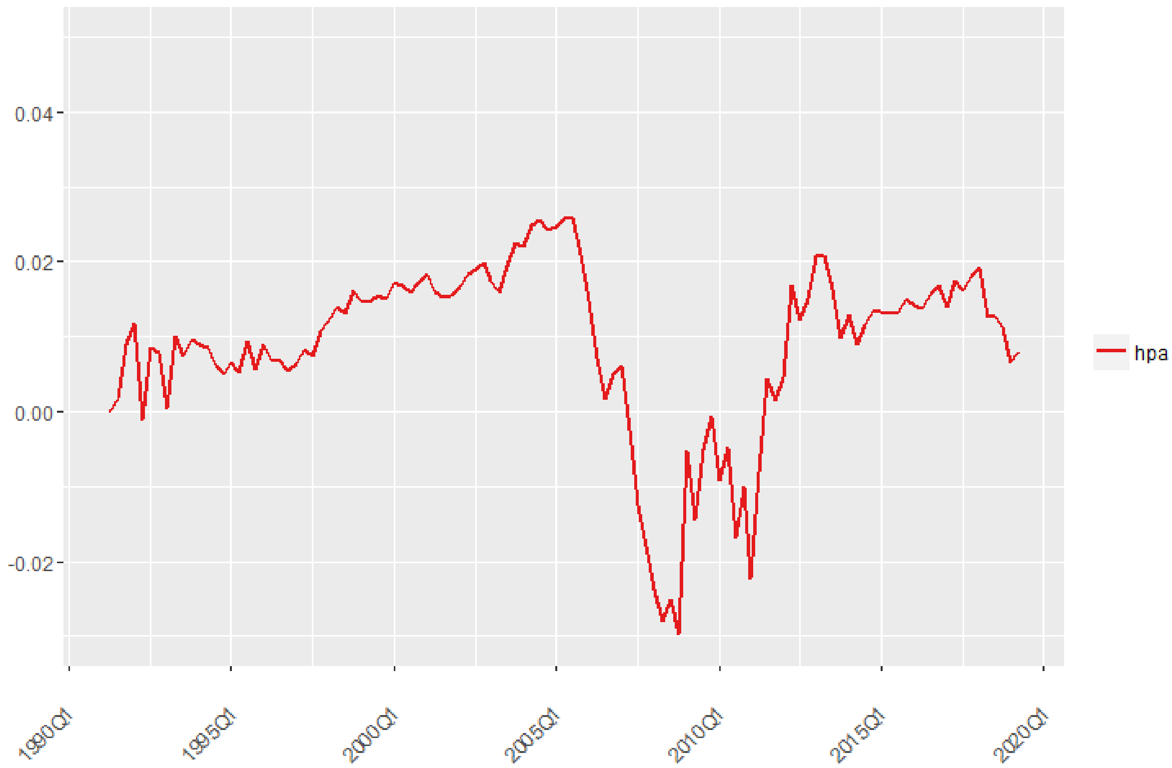
The national house price appreciation rate (HPA) is derived from the FHFA repeat sales house price indexes (HPIs) of purchase-only (PO) transactions. The PO HPI provides a reliable measure of housing market conditions, since it is based on repeat sales at market prices and does not use any appraised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

The HPA series being modeled is defined as:

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

Figure 23 shows the national quarterly HPA from CY 1991 Q1 to CY 2019 Q2. The long-term average quarterly HPA is around 0.87% (3.30% annual rate).

Figure 23: Historical National HPI and Quarterly HPA



The HPA increased steadily before 2004, and the quarterly appreciation rate was around 1.14%. Then house prices rose sharply starting in 2004. The average quarterly house price appreciation rate was 1.88% during the subprime mortgage expansion period from 2004 to 2006, and reached its peak of 2.59% in CY 2005 Q2. After 2006, the average growth rate of house price became negative until 2011 when appreciation returns to a positive value. It is interesting to note the last three quarters have shown a shrinking in this growth to almost zero (0.065) in 2019 Q1 and Q2.

Table 34 shows the quarterly HPA by selected historical time periods.

Table 34: Average Quarterly HPA by Time Span

Period	Average Quarterly HPA
1991 – 2003	1.13%
2004 – 2006	1.87%
2007 – 2010	-1.23%
2011 – 2019	1.00%

Modeling Techniques

The primary modeling techniques used in these simulations include:

- Auto Regressive Moving Average (ARMA)
- General Auto Regressive Conditional Heteroscedasticity (GARCH)

ARMA models are typically specified as ARMA(*p,q*) where *p* is the auto regressive component of the series, and *q* is the moving average.

GARCH models are typically specified as GARCH(*p,q)* where *p* is the auto regressive component of ${\sigma_t}^2$, and *q* is the AR component of the error term.

Description and examples of using an ARMA-GARCH model for time series analysis includes Engle and Mezrich (1995).

1-Year CMT Rate

In this section, we present some historical statistics on the 1-year CMT rate, and then describe the estimation model for the stochastic process, and finally report the parameter estimates and their standard errors.

Table 35 shows the summary statistics of the historical 1-year CMT rates for three 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 35: Statistics for the 1-Year Treasury Rates

Statistics	Since 1953	Since 1969	Since 1992	Simulations
Mean	4.82%	5.23%	2.46%	4.92%
Standard Deviation	3.27%	3.60%	2.27%	4.52%
Max	16.31%	16.31%	6.71%	18.25%
95- Percentile	10.30%	11.82%	5.93%	15.15%
90- Percentile	8.97%	9.94%	5.65%	12.71%
50- Percentile	4.64%	5.41%	2.40%	3.22%
25-Percentile	2.39%	2.22%	0.56%	1.64%
10- Percentile	0.54%	0.34%	0.17%	0.52%
5- Percentile	0.19%	0.16%	0.13%	0.02%
Min	0.10%	0.10%	0.10%	0.01%

An ARMA(2,4) parameterization was used to model the 1-Year CMT rate (*r1*) difference from the previous period and estimated it using data from CY 1969 Q3 to CY 2019 Q2 or the last 50 years. The process takes the following form:

$$r_{1,t} = x_1 r_{1,ar1} + x_2 r_{1,ar2} + x_3 r_{1,ar2} + x_4 w_{1,ma1} + x_5 w_{1,ma2} + x_6 w_{1,ma3} + x_7 w_{1,ma4} + x_8 w_{1,ma4} + \sigma_t dZ_1 \quad (2)$$

Where Z_1 is an independent Wiener random process with distribution N(0,.5), and where the variance (σ) of the residual term follows a GARCH(1,1) process:

$$\sigma_t{}^2 = \beta_0 + \beta_1 \varepsilon^2{}_{t-1} + \beta_2 \sigma^2{}_{t-1} \qquad (3)$$

Where ε is the error term, which equals $\sigma_t dZ_1$ from equation (2).

Full information maximum likelihood (FIML) method was used to estimate the parameters in equations (2) and (3). The results are presented in Table 36.

Table 36: Estimation Results for 1-Year CMT Rate Model

Parameter	Estimate	Std Dev	t-value	prob>t
x_1	1.0955	0.1271	8.6217	0.0000
x_2	-0.2184	0.2912	-0.7499	0.4533
x_3	0.0874	0.2168	0.4034	0.6867
x_4	-0.6172	0.3739	-1.6507	0.0988
X_5	-0.3024	0.3534	-0.8556	0.3922
X_6	0.1907	0.2488	0.7667	0.4432
X_7	-0.0366	0.2774	-0.1318	0.8952
X_8	-0.1886	0.0964	-1.9564	0.0504
β0	0.0000	0.0001	0.0010	0.9992
β1	0.3131	0.3367	0.9301	0.3523
β2	0.6859	0.7569	0.9061	0.3649
Pearson's GOF	0.2714			

The model based on these parameters is used to simulate the 1-year CMT rates for the forecast period starting in FY 2019 Q3. The model was fit using Akaike Information Criterion (AIC) and Pearson's goodness-of-fit test.

A lower bound of 0.01 percent was applied to the simulated future 1-year CMT rates to avoid negative rates in the simulation.

Additional Interest Rate Models

Additional interest rate models were developed. All are transformed as a spread (difference) between the current maturity length and prior. Table 37 describes these spreads and models.

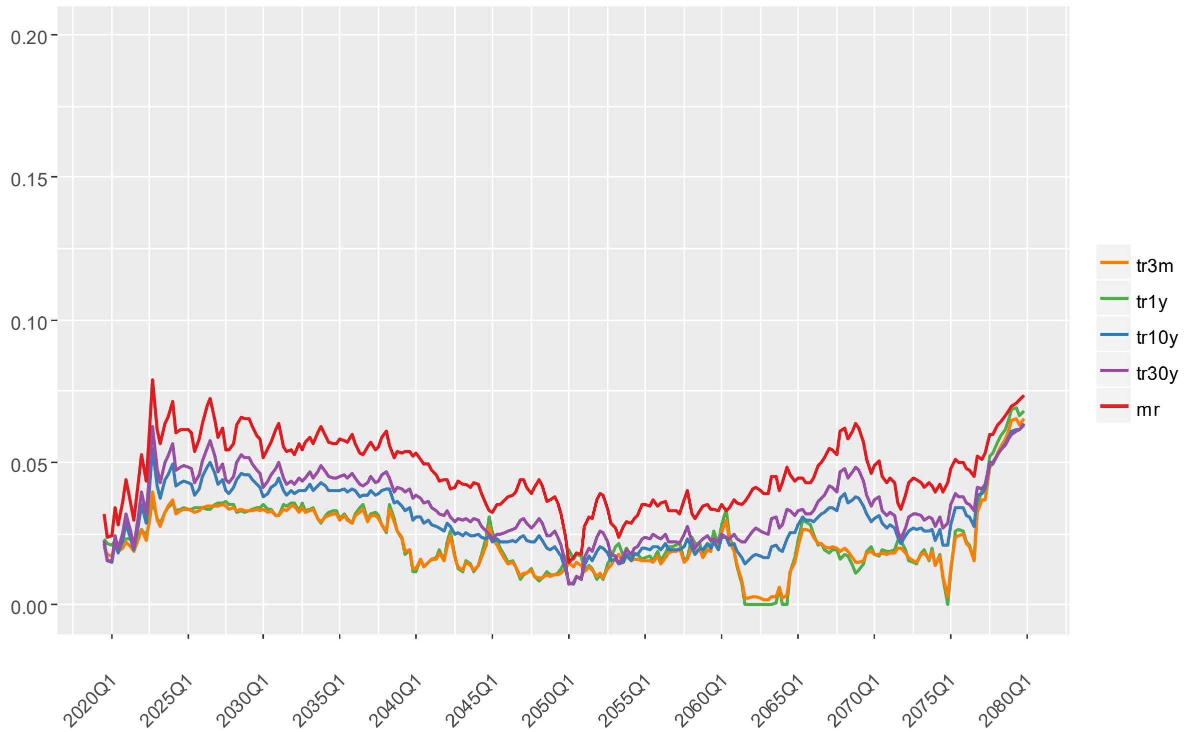
Table 37: Model Specification for Additional Interest Rates

Variable	Variable Transformation	Model Specification	*Notes
3-month	$S_{3m} = r_{3m} - r_{6m}$	AR(1)-GARCH(1,1)	
6-month	$S_{6m} = r_{6m} - r_{1y}$	ARMA(4,2)-GARCH(1,1)	
1-year	r_{1y}	ARMA(3,5)-GARCH(1,1)	*Base Interest Rate
2-year	$S_{2y} = r_{2y} - r_{1y}$	ARMA(1,2)-ARCH(1)	
3-year	$S_{3y} = r_{3y} - r_{2y}$	ARMA(2,1)-ARCH(1)	
5-year	$S_{5y} = r_{5y} - r_{2y}$	ARMA(2,1)-ARCH(1)	
7-year	$S_{7y} = r_{7y} - r_{5y}$	ARMA(2,1)-ARCH(1)	
10-year	$S_{10y} = r_{10y} - r_{7y}$	ARMA(2,1)-ARCH(1)	
20-year	$S_{20y} = r_{20y} - r_{10y}$	AR (2)	*dataset for 1980 forward producing a weaker model
30-year	$S_{30y} = r_{30y} - r_{10y}$	ARMA(1,1)-GARCH(1,1)	*used 10 year rate for spread
30-year FRM	$S_{mr} = r_{mr} - r_{30y}$	AR(1)-ARCH(1)	

All of these models also used Akaike Information Criterion (AIC) and/or Pearson's goodness-of-fit test to determine the best fitting model.

A lower bound of 0.01 percent was applied to the simulated future Treasury rates to avoid negative rates in the simulation.

Figure 24: Interest Rate Sample Simulation



House Price Appreciation Rate (HPA)

A. National HPA

The national HPA series was fit using an ARMA(1,1)-GARCH(1,1). The 1-year CMT, 10-year CMT, and mortgage rates at time *t* and *t-1* were also included as external regressors for a model formula:

$$HPA_t = \mu + x_1 HPA_{ar1} + x_2 w_{1,ma1} + x_3 r_{1,t} + x_4 r_{1,t-1} + x_5 r_{10,t} + x_6 r_{10,t-1} + x_7 mr_t + x_8 mr_{t-1} + \sigma_t dZ_1 \quad (4)$$

Where Z_1 is an independent Wiener random process with distribution N(0,1), and where the variance (σ) of the residual term follows a GARCH(1,1) process:

$$\sigma_t{}^2 = \beta_0 + \beta_1 \varepsilon^2{}_{t-1} + \beta_2 \sigma^2{}_{t-1} \quad (5)$$

The model specification and variable inclusions were determined by achieving appropriate coefficient signs and significance, and overall model fit. FIML was used to estimate parameters in equations (4) and (5). The results are shown in Table 38.

Table 38: Estimation Results for the National HPA Model

Parameter	Estimate	Std Dev	t-value	prob>t
μ	0.0250	0.0071	3.5373	0.0004
x_1	0.9350	0.0354	26.4392	0.0000
x_2	-0.2718	0.1248	-2.1785	0.0294
x_3	-0.0440	0.0606	-0.7258	0.4680
x_4	-0.1616	0.0509	-3.1720	0.0015
x_5	0.1506	0.2367	0.6361	0.5247
x_6	-0.2497	0.1200	-2.0817	0.0374
x_7	-0.1151	0.0928	-1.2401	0.2149
x_8	-0.1368	0.0730	-1.8727	0.0611
β0	0.0000	0.0000	0.0551	0.9560
β1	0.4269	0.2372	1.7998	0.0719
β2	0.5721	0.2346	2.4387	0.0147
Pearson's GOF	0.2318			

We used these parameters to simulate future HPAs from FY 2019 Q3.

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:

$$Disp_{i,t}^{Base} = HPA_{i,t}^{Base} / HPA_{national,t}^{Base} \tag{6}$$

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

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

This approach retains the relative current housing market cycle among different geographic locations and it allows us to capture the geographical concentration of FHA's current endorsement portfolio. This approach is also consistent with Moody's logic in creating local market HPA forecasts relative to the national HPA forecast under alternative economic scenario forecasts.[4]

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

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

estimate of claim losses of the Fund.

Unemployment Rate

A. National Unemployment Rate

In our unemployment rate model, the unemployment rate depends on the prior unemployment rate, mortgage rates and Treasury rates.

We used quarterly data from CY 1971 to CY 2019 Q2 to estimate the national unemployment rate. The model we adopted was:

$$ue_t = \mu + x_1 ue_{ar1} + x_2 ue_{ar2} + x_3 ue_{ar3} + x_4 r_t + x_5 s_{mr} + \varepsilon_t \quad (8)$$

where r_t is the 1-year CMT rate,

s_{mr} is the 30-year mortgage rate to 10-year CMT rate spread,

ue_{ari} is the unemployment rate auto regressive component at the i^{th} interval.

The model specification and variable inclusions were determined by achieving appropriate coefficient signs and significance, and overall model fit. FIML was used to estimate parameters in equation (8). The results are shown in Table 39.

Table 39: Estimation Results for the National Unemployment Rate Model

Parameter	Estimate	Std Error
μ	1.6302	0.0731
x_1	-0.6095	0.1337
x_2	-0.0462	0.0734
x_3	0.0675	0.0061
X_4	-0.1391	0.0218
X_5	-0.0057	0.0404

From the simulated interest rates and house prices, we applied the parameters shown in Table 39 to calculate the corresponding national unemployment rate. Based on historical statistics, the national unemployment rate was capped at 20% with a floor at 2%.

B. Geographic Dispersion

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

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

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

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

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

Gross Domestic Product

In the Gross Domestic Product (GDP) model, the GDP depends on the prior GDP, unemployment, mortgage and Treasury rates.

We used quarterly data from CY 1971 to CY 2019 Q2 to estimate the national unemployment rate. The model tested for integration, so first difference transformations were used prior to estimations. The model adopted was an ARMA(1,2):

$$GDP_t = x_1 GDP_{ar1} + x_2 GDP_{ma1} + x_3 GDP_{ma2} + x_4 r_t + x_5 s_{mr,t} + x_6 ue_t + \varepsilon_t \quad (11)$$

where, r_t is the 1-year CMT rate,

$s_{mr,t}$ is the 30-year mortgage rate to 10-year CMT rate spread,

ue_t is the unemployment rate,

GDP_{ar1} is the unemployment rate auto regressive component,

GDP_{mai} is the unemployment rate moving average component at the *i*th interval.

The model specification and variable inclusions were determined by achieving appropriate coefficient signs and significance, and overall model fit. FIML was used to estimate parameters in equation (11). The results are shown in Table 40.

Table 40: Estimation Results for the National Gross Domestic Product Model

Parameter	Estimate	Std Error
x_1	0.7254	0.1268
x_2	-1.3616	0.1553
x_3	0.3910	0.1412
x_4	1227.5821	749.9991
X_5	-1351.2852	917.7638
X_6	-220.6296	723.6363

Simulation Selection/Moody's Baseline

A total of 10,000 simulations paths were generated using all of the economic variable models described. From these 10,000, a subset of 100 were randomly chosen.

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 surviving (active) mortgage. The variables used in the projection are derived from mortgage characteristics and economic forecasts. OMB Economic Assumptions and Moody's July 2019 forecasts of interest 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. House price forecasts are generated simultaneously with various macroeconomic variables including the local unemployment rates.

For each mortgage during future policy years, the derived mortgage variables serve as independent variables to the 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 year by different modes of termination given that it survives to the end of the prior policy year. 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, and
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. Assignment claims and note holding payments are additional outflows. Table 41 summarizes the HECM inflows and outflows.

Table 41: 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 borrower 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.[5] 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 Mortgagee Letter (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 two 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 HECM's before assignment, FHA provided additional guidance on due and payable policies and the timing

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

requirements in ML 2015-10[6] and ML 2015-11[7]. For HECM's after assignment, FHA currently does not foreclose 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 Claim Type 2 (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:

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

The net sales price of the property is:

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

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

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

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 42: 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:

$$\text{Recovery Amount} = \begin{cases} minimum\,(UPB, Net\ Property\ Sales\ Price) & if\ terminated\ with\ Death\ or\ Move-out \\ UPB & if\ terminated\ with\ refinance \end{cases}$$

where the net sales price of the property is:

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

Net Future Cash Flows

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

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

Discount Factors

The discount factors applied were provided by FHA and reflect the most recent 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. Our simulations aggregated each future year's cash flows, which are treated as being received at the end of the year.

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 4 of the Actuarial Report is stated below:

> ***Deliverable 4: 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 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.***

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

- Process risk— actual results vary from projected results due to variability in the mortgage insurance process
- Parameter risk— the uncertainty related to the parameters selected for a given model
- Specification risk— 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 Claim Type 1 (CT1) vs Non-Claim termination. A separate logistic regression model estimates the probability of Claim Type 2 (CT2) Conveyance vs. 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. Prior to this version, the sales price module used only historical averages, but S-M found that developing a model produced stronger results. The CT1 and CT2 sales expense assumption is developed based on historical expenses as a percentage of the home sales price.

The Termination Module consists of logistic models for separate termination types as part of the multinomial logistic model. Probabilities are estimated for each type, 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 seems reasonable based on the available data. Again, this could be a candidate for future research as more data becomes available in the future.

The three types of binomial termination models are the Refinance termination model, Tax and Insurance Default termination model, and the Mobility termination model. Mortality tables were used to determine mortality terminations separately by gender and age. 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 a loan level. Once the projected cash flows are determined, they are discounted to present value to arrive at the final net present value cash flow 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 evaluate 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 makes 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 data available.

There have been several policy changes made to the HECM program over the years, but it is not clear if or how well they are reflected in the HUD data across time. 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. These approaches are reasonable.

From the prior analysis, S-M made several model updates as noted below. 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. This was not used in earlier model versions. This parameter is determined using regression trees, which allows for identification of more factors that influence appraisal inflation. 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.

- S-M now uses logistic regression to estimate Claim Type 1 (CT1) vs. Non-Claim termination (NCT) probability.

- S-M now uses logistic regression to estimate Claim Type 2 (CT2) conveyance vs. payoff probability.

- S-M now uses a regression estimate for probability of assignment to HUD.

Simulation

Similar to the approach taken for Forward mortgages, S-M used stochastic simulation with the Monte Carlo method to provide confidence levels on the estimated performance of the FHA loan portfolio. S-M developed parametric distributions to simulate future default frequency (claim), recovery, and prepayment rates. Using the Monte Carlo method for this work is a reasonable approach. S-M evaluated multiple distributional curves based on analysis of historical data and other statistics. Through this, they determined to use a gamma distribution to model Claim Type 1, Claim Type 2, Claim Type 2 recovery, and premium rates. This differs from the approach Pinnacle used to develop economic scenarios, as Pinnacle developed simulations of key economic variables to test the sensitivity of the Cash Flow NPV estimate.

S-M performed 10,000 trials for their Monte Carlo simulation. Pinnacle also ran 10,000 simulations but then randomly selected 100 scenarios to incorporate into the Cash Flow NPV calculation. Finally, as discussed in the technical note, the S-M simulations are only focused on process risk and not parameter or specification risk. This is a potential source of uncertainty in the results.

Following are additional potential sources of vulnerabilities and future research.

- Sensitivity tests performed on home price appreciation 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 was done for Return on Properties.

- S-M selected the 2006 cohort due to volume and seasoning of data for performing back-testing of their model results. While this is not unreasonable, this could be a potential source of vulnerability if the results would change significantly by using different cohort years for back-testing.

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 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 using 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 refinance or non-mortality termination ("other") for a living borrower. If neither event happens, the loan continues.

- If the loan is not assigned and Unpaid Principal Balance (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 then 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 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 model is then used to estimate the amount of the cash draw if it is not a full draw. S-M does incorporate cash draws in their calculation, but does not develop models for cash draws. Pinnacle has also developed a Tax and Insurance Default model similar to S-M.

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 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 Tax & Insurance payments during their assignment period.

This is consistent with the HUD formula which is

> Upfront Premium + Annual Premium – Claim Type 1 – Claim Type 2 – 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 simulations to determine the range of cash flow NPV estimates. The process began with a pool of 10,000 randomly generated economic scenarios that were randomly sampled down to 100. 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.

For Pinnacle, we used ARMA and GARCH models to simulate various interest rates, House Price Appreciation (HPA), unemployment rates, and Gross Domestic Product to use. 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

CT1Cnt INCREMENTAL

CT1Cnt f

Incrmental Counts

ANNUAL EVALUATIONS - 2016Q4 - QUARTERS OF

Fiscal Year	4	8	12	16	20	24	28	32	36	40	44	48	52	56	60	64	68	72	76	80	84	88	92	96	100	104	108
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
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
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
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
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
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	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	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
1998	0	5	8	3	12	8	7	16	9	7	3	6	3	6	6	4	4	7	10	2	4	4	0	0	0	0	0
1999	0	2	2	9	11	6	4	4	4	12	6	8	9	8	2	10	10	14	9	5	1	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
2001	0	0	1	10	5	9	6	8	4	6	12	14	6	20	9	20	13	6	6	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	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	0	0	0	0	0	0	0	0	0	0
2004	0	3	11	31	34	65	75	82	102	97	110	155	153	101	68	54	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	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	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	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	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	485	311	200	208	250	223	217	178	184	174	147	115	103	97	63	57
2010	1	10	54	220	232	530	489	417	357	372	242	150	111	86	67	104	103	70	88	59	43	67	38	44	36	19	16
2011	0	7	77	102	317	377	346	333	320	243	138	136	129	91	98	111	102	104	77	72	67	56	45	36	29	33	17
2012	0	18	33	150	252	232	215	222	224	128	94	93	82	73	71	84	69	51	73	51	55	40	35	28	21	22	18
2013	0	5	79	188	198	222	204	247	186	163	123	140	122	119	121	131	112	109	98	91	66	71	70	65	56	36	25
2014	0	9	43	64	92	102	138	215	172	154	132	124	109	123	110	128	108	115	86	68	81	68	47	41	43	25	27
2015	0	9	34	42	77	174	188	197	205	187	157	138	142	112	101	151	117	128	80	94	70	71	62	55	39	35	28
2016	1	9	22	41	96	140	184	192	201	200	172	157	133	127	116	130	121	93	83	78	74	61	48	42	47	28	19
2017	-	5	16	64	141	223	270	269	271	257	211	193	177	155	139	167	153	136	111	108	98	64	65	59	40	41	24
2018	-	2	28	66	133	167	194	203	225	227	172	185	184	152	123	140	130	105	86	96	73	58	53	45	31	27	18
2019	-	5	17	31	58	97	102	116	141	151	148	108	117	109	95	105	80	87	74	66	51	35	24	24	23	20	17

CT1Cnt

Incrmental Percentage

Fiscal Year	4 - 8	8 - 12	12 - 16	16 - 20	20 - 24	24 - 28	28 - 32	32 - 36	36 - 40	40 - 44	44 - 48	48 - 52	52 - 56	56 - 60	60 - 64	64 - 68	68 - 72	72 - 76	76 - 80	80 - 84	84 - 88	88 - 92	92 - 96	96 - 100	100 - 104	104 - 108	108 - 112
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%	0.0%	0.0%	0.0%
1991	0.0%	0.0%	0.0%	0.0%	0.3%	0.0%	0.0%	0.0%	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%	0.0%	0.0%	0.0%	0.0%	0.0%
1992	0.0%	0.1%	0.0%	0.0%	0.1%	0.2%	0.3%	0.0%	0.0%	0.1%	0.2%	0.0%	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%
1993	0.0%	0.0%	0.0%	0.2%	0.1%	0.2%	0.2%	0.1%	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%	0.1%	0.0%	0.0%	0.0%	0.0%	
1994	0.0%	0.0%	0.1%	0.1%	0.3%	0.0%	0.0%	0.1%	0.1%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%		
1995	0.0%	0.0%	0.0%	0.2%	0.2%	0.1%	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%	0.1%	0.1%	0.0%	0.0%	0.0%			
1996	0.0%	0.1%	0.1%	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%	0.1%				
1997	0.0%	0.2%	0.1%	0.0%	0.2%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.1%	0.0%	0.1%	0.0%	0.0%	0.1%					
1998	0.1%	0.1%	0.0%	0.2%	0.1%	0.1%	0.2%	0.1%	0.1%	0.0%	0.1%	0.0%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.1%	0.1%						
1999	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.2%	0.1%	0.1%	0.1%	0.1%	0.0%	0.1%	0.1%	0.2%	0.1%	0.1%	0.0%							
2000	0.0%	0.1%	0.1%	0.1%	0.0%	0.1%	0.0%	0.1%	0.0%	0.2%	0.0%	0.2%	0.1%	0.2%	0.2%	0.2%	0.1%	0.1%	0.0%								
2001	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.2%	0.2%	0.1%	0.3%	0.1%	0.3%	0.2%	0.1%	0.1%									
2002	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.2%	0.1%	0.2%	0.2%	0.3%	0.3%	0.3%	0.2%	0.1%	0.1%										
2003	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%	0.2%	0.2%	0.2%	0.2%	0.2%	0.3%	0.2%	0.2%	0.1%	0.1%											
2004	0.0%	0.0%	0.1%	0.1%	0.2%	0.2%	0.2%	0.3%	0.3%	0.3%	0.4%	0.4%	0.3%	0.2%	0.1%												
2005	0.0%	0.1%	0.1%	0.2%	0.2%	0.3%	0.3%	0.4%	0.4%	0.7%	0.6%	0.4%	0.3%	0.3%													
2006	0.0%	0.1%	0.1%	0.2%	0.3%	0.3%	0.4%	0.5%	1.0%	0.9%	0.6%	0.5%	0.5%														
2007	0.0%	0.1%	0.2%	0.3%	0.3%	0.5%	0.6%	1.2%	1.3%	0.8%	0.7%	0.8%															
2008	0.0%	0.1%	0.2%	0.3%	0.5%	0.5%	1.2%	1.0%	0.8%	0.7%	0.7%																
2009	0.0%	0.1%	0.1%	0.4%	0.4%	1.0%	0.8%	0.7%	0.6%	0.6%	0.4%	0.3%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%
2010	0.0%	0.1%	0.3%	0.3%	0.7%	0.6%	0.5%	0.5%	0.5%	0.3%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.1%	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%	0.3%	0.2%	0.2%	0.2%	0.1%	0.1%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	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%	0.4%	0.2%	0.2%	0.2%	0.2%	0.1%	0.1%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%
2013	0.0%	0.1%	0.3%	0.3%	0.4%	0.3%	0.4%	0.3%	0.3%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%
2014	0.0%	0.1%	0.1%	0.2%	0.2%	0.3%	0.4%	0.3%	0.3%	0.3%	0.2%	0.2%	0.2%	0.2%	0.3%	0.2%	0.2%	0.2%	0.1%	0.2%	0.1%	0.1%	0.1%	0.1%	0.0%	0.1%	0.0%
2015	0.0%	0.1%	0.1%	0.1%	0.3%	0.3%	0.3%	0.4%	0.3%	0.3%	0.2%	0.2%	0.2%	0.2%	0.3%	0.2%	0.2%	0.1%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%
2016	0.0%	0.0%	0.1%	0.2%	0.3%	0.4%	0.4%	0.4%	0.4%	0.4%	0.3%	0.3%	0.3%	0.2%	0.3%	0.3%	0.2%	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%
2017	0.0%	0.0%	0.1%	0.3%	0.4%	0.5%	0.5%	0.5%	0.5%	0.4%	0.4%	0.3%	0.3%	0.3%	0.3%	0.3%	0.2%	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%
2018	0.0%	0.1%	0.1%	0.3%	0.4%	0.4%	0.4%	0.5%	0.5%	0.4%	0.4%	0.4%	0.3%	0.3%	0.3%	0.3%	0.2%	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%
2019	0.0%	0.1%	0.1%	0.2%	0.3%	0.3%	0.4%	0.5%	0.5%	0.5%	0.3%	0.4%	0.4%	0.3%	0.3%	0.3%	0.3%	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%

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Fiscal Year	MATURITY 112	116	120	124	128	132	136	140	144	148	152	156	160	164	168	172	176	180	184	188	192	196
1990	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	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1992	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	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1994	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	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1996	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	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1998	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1999	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2000	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	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2002	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2003	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2004	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2005	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2006	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2007	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	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2009	31	34	39	21	10	7	15	4	4	3	1	2	1	0	0	0	1	0	0	0	0	0
2010	11	7	13	4	5	0	3	4	2	1	0	1	0	0	0	0	0	0	0	0	0	0
2011	16	10	5	4	3	4	1	6	1	0	2	0	0	0	0	0	0	0	0	0	0	0
2012	10	13	8	11	6	6	3	1	3	2	1	0	1	0	0	0	0	0	0	0	0	0
2013	20	15	13	14	7	5	3	6	5	1	0	1	1	1	0	0	0	0	0	0	0	0
2014	15	8	8	9	5	5	1	5	1	3	1	0	0	0	0	0	0	0	0	0	0	0
2015	16	14	17	8	9	4	1	3	0	3	0	2	0	0	0	1	0	0	0	0	0	0
2016	13	14	9	7	7	6	3	0	2	0	0	0	1	0	1	0	0	0	0	0	0	0
2017	27	20	11	11	13	5	7	1	2	3	2	1	0	0	0	0	0	0	0	0	0	0
2018	17	13	8	6	4	2	4	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
2019	12	7	9	6	2	2	1	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0

CT1Cnt

Fiscal Year	112 - 116	116 - 120	120 - 124	124 - 128	128 - 132	132 - 136	136 - 140	140 - 144	144 - 148	148 - 152	152 - 156	156 - 160	160 - 164	164 - 168	168 - 172	172 - 176	176 - 180	180 - 184	184 - 188	188 - 192	192 - 196	196 - 200	Cumulative
1990	0.0%	0.0%																					
1991	0.0%																						
1992																							
1993																							
1994																							
1995																							
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2003																							
2004																							
2005																							
2006																							
2007																							
2008																							
2009	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	7.4%
2010	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	5.2%
2011	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	4.9%
2012	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	4.6%
2013	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	5.3%
2014	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	4.9%
2015	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	4.9%
2016	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	5.6%
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%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	6.5%
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%	0.0%	0.0%	0.0%	6.3%
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%	6.3%

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Fiscal Year	Incrmental Counts 4	8	12	16	20	24	28	32	36	40	44	48	52	56	60	64	68	72	76	80	84	88	92	96	100	104	108
																							ANNUAL EVALUATIONS - 2016Q4 - QUARTERS OF				
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
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
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
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
1994	0	0	1	0	3	0	2	6	6	12	8	6	9	10	1	0	1	1	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
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
1997	0	0	0	0	0	0	7	13	14	36	19	6	3	6	4	1	2	1	2	0	0	0	0	0	0	0	0
1998	7	1	2	1	2	4	5	13	23	30	13	5	10	10	3	3	9	7	4	0	0	0	0	0	0	0	0
1999	3	0	0	2	1	8	10	39	56	20	17	13	13	4	7	5	9	2	2	0	0	0	0	0	0	0	0
2000	42	0	1	0	2	2	10	6	3	2	8	6	2	3	7	4	4	2	2	3	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	0	0	0	0	0	0	0	0
2002	82	1	1	2	8	18	20	21	23	36	15	16	29	37	39	22	18	13	0	0	0	0	0	0	0	0	0
2003	48	1	4	14	80	73	89	67	96	34	54	66	102	77	26	12	10	0	0	0	0	0	0	0	0	0	0
2004	22	1	10	51	67	67	83	158	44	93	136	203	220	136	125	75	0	0	0	0	0	0	0	0	0	0	0
2005	1	1	23	39	74	85	126	65	111	205	329	332	229	263	197	0	0	0	0	0	0	0	0	0	0	0	0
2006	0	5	22	37	63	82	48	114	178	277	346	289	359	390	0	0	0	0	0	0	0	0	0	0	0	0	0
2007	1	0	7	8	21	10	27	62	130	189	155	247	548	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2008	0	0	1	16	15	36	73	132	147	150	297	631	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2009	1	1	8	42	170	242	654	832	506	643	1,312	1,409	1,248	770	345	212	125	99	72	57	49	34	34	18	18	12	5
2010	-	12	41	168	361	781	1,448	1,136	1,173	1,517	270	186	197	168	130	92	56	39	28	24	16	9	9	11	5	2	2
2011	-	-	-	7	184	1,135	1,391	2,159	831	346	260	226	206	125	72	55	43	32	31	22	15	12	3	2	5	3	3
2012	2	-	1	21	284	825	1,405	2,036	358	271	171	125	88	64	45	42	29	29	20	19	11	9	4	6	5	2	1
2013	-	-	-	30	225	586	2,106	1,305	617	355	287	163	129	95	79	64	49	50	30	28	20	8	11	11	9	3	3
2014	-	-	1	3	6	29	97	284	500	588	519	375	260	200	120	64	55	37	37	15	19	14	11	3	6	2	1
2015	-	-	-	1	6	37	98	245	474	706	655	417	355	180	117	81	60	48	36	19	20	14	9	10	6	3	2
2016	-	-	-	-	28	64	187	285	544	711	517	357	266	167	138	94	51	57	37	21	16	6	9	4	2	4	0
2017	-	-	-	4	45	111	244	461	715	869	577	337	244	186	143	117	92	74	33	24	22	14	12	6	8	7	4
2018	-	-	-	-	13	34	66	138	230	317	339	245	188	237	207	168	121	79	67	27	21	17	8	6	5	1	3
2019	-	-	-	-	-	1	4	8	9	25	53	84	164	219	181	132	92	49	24	27	16	12	7	5	2	2	1

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Fiscal Year	Incrmental Percentage 4 - 8	8 - 12	12 - 16	16 - 20	20 - 24	24 - 28	28 - 32	32 - 36	36 - 40	40 - 44	44 - 48	48 - 52	52 - 56	56 - 60	60 - 64	64 - 68	68 - 72	72 - 76	76 - 80	80 - 84	84 - 88	88 - 92	92 - 96	96 - 100	100 - 104	104 - 108	108 - 112
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%	0.0%	0.0%	0.0%
1991	0.0%	0.0%	0.0%	0.0%	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.3%	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%	0.0%	0.0%
1992	0.0%	0.0%	0.0%	0.0%	0.0%	0.2%	0.0%	0.0%	0.1%	0.2%	0.2%	0.1%	0.1%	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%	0.0%
1993	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.1%	0.4%	0.2%	0.2%	0.1%	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%	
1994	0.0%	0.0%	0.0%	0.1%	0.0%	0.1%	0.2%	0.2%	0.4%	0.3%	0.2%	0.3%	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%		
1995	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.2%	0.2%	0.3%	0.1%	0.5%	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%			
1996	0.0%	0.1%	0.1%	0.0%	0.0%	0.1%	0.2%	0.4%	0.3%	0.6%	0.6%	0.1%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%				
1997	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.3%	0.3%	0.7%	0.4%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%					
1998	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.2%	0.3%	0.4%	0.2%	0.1%	0.1%	0.1%	0.0%	0.0%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%						
1999	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.5%	0.7%	0.3%	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%							
2000	0.0%	0.0%	0.0%	0.0%	0.0%	0.2%	0.1%	0.0%	0.0%	0.1%	0.1%	0.0%	0.0%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%								
2001	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.1%	0.1%	0.2%	0.1%	0.1%	0.1%	0.0%									
2002	0.0%	0.0%	0.0%	0.1%	0.1%	0.2%	0.2%	0.2%	0.3%	0.1%	0.1%	0.2%	0.3%	0.3%	0.2%	0.1%	0.1%										
2003	0.0%	0.0%	0.1%	0.4%	0.4%	0.5%	0.4%	0.5%	0.2%	0.3%	0.4%	0.6%	0.4%	0.1%	0.1%	0.1%											
2004	0.0%	0.0%	0.1%	0.2%	0.2%	0.2%	0.4%	0.1%	0.2%	0.4%	0.5%	0.6%	0.4%	0.3%	0.2%												
2005	0.0%	0.1%	0.1%	0.2%	0.2%	0.3%	0.2%	0.3%	0.5%	0.8%	0.8%	0.5%	0.6%	0.5%													
2006	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.2%	0.2%	0.4%	0.5%	0.4%	0.5%	0.5%														
2007	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.2%	0.1%	0.2%	0.5%															
2008	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%	0.3%	0.6%																
2009	0.0%	0.0%	0.0%	0.2%	0.2%	0.6%	0.7%	0.4%	0.6%	1.2%	1.3%	1.1%	0.7%	0.3%	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%
2010	0.0%	0.1%	0.2%	0.5%	1.0%	1.8%	1.5%	1.5%	1.9%	0.3%	0.2%	0.3%	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%
2011	0.0%	0.0%	0.0%	0.3%	1.6%	1.9%	3.0%	1.1%	0.5%	0.4%	0.3%	0.3%	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%
2012	0.0%	0.0%	0.0%	0.5%	1.5%	2.6%	3.8%	0.7%	0.5%	0.3%	0.2%	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%
2013	0.0%	0.0%	0.1%	0.4%	1.0%	3.6%	2.2%	1.0%	0.6%	0.5%	0.3%	0.2%	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%
2014	0.0%	0.0%	0.0%	0.0%	0.1%	0.2%	0.6%	1.0%	1.2%	1.0%	0.7%	0.5%	0.4%	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%
2015	0.0%	0.0%	0.0%	0.0%	0.1%	0.2%	0.4%	0.8%	1.2%	1.2%	0.7%	0.6%	0.3%	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%
2016	0.0%	0.0%	0.0%	0.1%	0.1%	0.4%	0.6%	1.1%	1.5%	1.1%	0.7%	0.6%	0.3%	0.3%	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%
2017	0.0%	0.0%	0.0%	0.1%	0.2%	0.4%	0.8%	1.3%	1.6%	1.1%	0.6%	0.4%	0.3%	0.3%	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%
2018	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.3%	0.5%	0.7%	0.7%	0.5%	0.4%	0.5%	0.4%	0.4%	0.3%	0.2%	0.1%	0.1%	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%	0.1%	0.2%	0.3%	0.5%	0.7%	0.6%	0.4%	0.3%	0.2%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

CT2Cnt
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Fiscal	**MATURITY**																				
Year	112	116	120	124	128	132	136	140	144	148	152	156	160	164	168	172	176	180	184	188	192	196
1990	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	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1992	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	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1994	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	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1996	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	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1998	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1999	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2000	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	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2002	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2003	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2004	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2005	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2006	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2007	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	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2009	5	4	4	2	1	1	1	0	0	0	2	1	0	0	0	0	0	0	0	0	0	0
2010	4	4	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2011	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2012	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2013	1	2	1	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2014	1	2	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2015	5	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2016	2	2	1	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2017	3	2	2	0	1	1	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2018	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2019	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

CT2Cnt

Fiscal Year	112 - 116	116 - 120	120 - 124	124 - 128	128 - 132	132 - 136	136 - 140	140 - 144	144 - 148	148 - 152	152 - 156	156 - 160	160 - 164	164 - 168	168 - 172	172 - 176	176 - 180	180 - 184	184 - 188	188 - 192	192 - 196	196 - 200	Cumulative
1990	0.0%	0.0%																					
1991	0.0%																						
1992																							
1993																							
1994																							
1995																							
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2004																							
2005																							
2006																							
2007																							
2008																							
2009	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	7.9%
2010	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	10.1%
2011	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	9.9%
2012	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	10.8%
2013	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	10.6%
2014	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	6.4%
2015	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	6.3%
2016	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	7.4%
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%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	8.0%
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%	0.0%	0.0%	0.0%	5.3%
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%	3.6%

Avg CT1 LossMCA **INCREMENTAL**

Avg CT1 LossMCA **f**

Actual Average as a Percentage of Outstanding MCA at the Beginning of Each Period

Fiscal																										**ANNUAL EVALUA**
Year	4	8	12	16	20	24	28	32	36	40	44	48	52	56	60	64	68	72	76	80	84	88	92	96	100	
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%	
1991	0%	0%	0%	0%	0%	14%	0%	0%	0%	14%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	
1992	0%	0%	13%	0%	0%	50%	23%	34%	0%	0%	16%	22%	0%	30%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	
1993	0%	0%	0%	0%	34%	34%	19%	34%	30%	39%	31%	0%	13%	0%	0%	0%	0%	0%	0%	0%	0%	0%	77%	0%	0%	
1994	0%	0%	0%	33%	26%	21%	21%	52%	51%	52%	0%	19%	0%	0%	0%	0%	0%	0%	104%	0%	151%	0%	0%	0%	0%	
1995	0%	0%	0%	23%	31%	21%	32%	30%	41%	35%	7%	0%	0%	0%	0%	0%	0%	105%	0%	0%	84%	102%	101%	0%	0%	
1996	0%	0%	21%	35%	37%	41%	36%	46%	0%	31%	0%	0%	4%	0%	50%	0%	130%	0%	0%	108%	124%	101%	105%	46%	0%	
1997	0%	12%	20%	29%	31%	30%	56%	19%	23%	0%	47%	40%	7%	30%	61%	37%	0%	63%	38%	106%	54%	0%	76%	0%	0%	
1998	0%	28%	19%	18%	37%	24%	48%	36%	23%	40%	42%	86%	66%	43%	89%	109%	70%	79%	86%	102%	82%	93%	0%	0%	0%	
1999	0%	18%	27%	12%	44%	29%	67%	38%	30%	52%	68%	30%	63%	70%	91%	73%	76%	81%	79%	61%	115%	0%	0%	0%	0%	
2000	0%	35%	21%	20%	45%	21%	49%	47%	64%	11%	51%	51%	57%	85%	57%	58%	47%	56%	131%	34%	0%	0%	0%	0%	0%	
2001	0%	0%	31%	35%	19%	30%	52%	50%	36%	38%	48%	61%	58%	75%	76%	72%	58%	75%	69%	0%	0%	0%	0%	0%	0%	
2002	0%	18%	0%	21%	38%	35%	54%	39%	50%	48%	47%	61%	62%	54%	57%	53%	54%	50%	0%	0%	0%	0%	0%	0%	0%	
2003	51%	10%	27%	22%	31%	52%	40%	41%	38%	54%	58%	64%	56%	66%	48%	75%	38%	0%	0%	0%	0%	0%	0%	0%	0%	
2004	0%	17%	21%	30%	37%	36%	44%	36%	50%	49%	55%	52%	54%	44%	49%	51%	0%	0%	0%	0%	0%	0%	0%	0%	0%	
2005	0%	12%	22%	36%	36%	35%	43%	52%	48%	54%	47%	48%	43%	49%	44%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	
2006	0%	21%	29%	35%	38%	39%	46%	47%	48%	49%	46%	42%	40%	42%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	
2007	0%	26%	27%	33%	39%	48%	46%	48%	48%	46%	43%	40%	39%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	
2008	57%	25%	31%	36%	43%	46%	48%	47%	44%	40%	43%	40%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	
2009	8.6%	24.7%	31.3%	34.9%	39.6%	41.5%	43.8%	42.4%	41.1%	42.7%	41%	30%	27%	32%	36%	43%	46%	56%	61%	72%	80%	86%	91%	96%	97%	
2010	21.3%	30.8%	28.3%	36.3%	40.7%	40.5%	40.0%	46.5%	45.4%	45.2%	57%	31%	37%	42%	49%	49%	55%	62%	70%	84%	79%	85%	84%	93%	99%	
2011	0.0%	17.0%	24.9%	34.8%	31.4%	37.4%	39.8%	42.2%	48.2%	50.6%	48%	33%	33%	41%	47%	57%	64%	72%	81%	75%	91%	84%	99%	94%	98%	
2012	0.0%	30.8%	26.4%	31.3%	34.8%	37.1%	39.9%	43.5%	47.0%	47.9%	46%	35%	32%	44%	55%	61%	68%	72%	82%	89%	97%	97%	100%	100%	98%	
2013	0.0%	16.7%	29.0%	29.7%	36.5%	36.7%	35.6%	42.9%	47.8%	45.6%	51%	33%	40%	45%	55%	62%	69%	78%	85%	92%	98%	96%	99%	100%	100%	
2014	0.0%	38.6%	22.2%	25.5%	35.0%	35.7%	32.1%	34.4%	34.6%	34.8%	39%	23%	26%	32%	39%	49%	57%	64%	77%	78%	90%	94%	97%	99%	99%	
2015	0.0%	17.6%	20.2%	28.5%	24.9%	30.3%	33.2%	34.0%	35.7%	38.3%	40%	22%	24%	31%	40%	45%	55%	58%	73%	77%	90%	92%	98%	98%	97%	
2016	0.4%	20.4%	23.4%	21.8%	25.6%	31.8%	34.8%	35.7%	38.1%	43.6%	41%	27%	29%	37%	43%	50%	53%	64%	71%	84%	89%	93%	98%	99%	100%	
2017	0.0%	17.0%	21.2%	24.8%	29.8%	31.5%	37.0%	38.4%	40.7%	42.9%	45%	27%	32%	38%	43%	50%	57%	67%	74%	83%	87%	94%	99%	100%	100%	
2018	0.0%	3.4%	8.8%	23.3%	27.1%	28.9%	32.5%	34.6%	34.5%	34.3%	38%	21%	24%	27%	29%	32%	42%	44%	49%	64%	70%	75%	75%	87%	90%	
2019	0.0%	0.3%	4.0%	14.4%	19.2%	27.3%	24.3%	28.2%	29.8%	30.6%	34%	17%	20%	21%	26%	27%	30%	39%	45%	47%	58%	67%	79%	86%	86%	

Avg CT1 LossMCA

Avg CT1 LossMCA

Fiscal	**TIONS - 2016Q4 - QUARTERS OF MATURITY**																				
Year	104	108	112	116	120	124	128	132	136	140	144	148	152	156	160	164	168	172	176	180	184	188
1990	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%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1992	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%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1994	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%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1996	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%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1998	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1999	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2000	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%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2002	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2003	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2004	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2005	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2006	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2007	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%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2009	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%	0%	0%	100%	0%	0%	0%
2010	100%	100%	100%	100%	100%	100%	100%	0%	100%	100%	100%	100%	0%	100%	0%	0%	0%	0%	0%	0%	0%	0%
2011	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2012	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%	100%	0%	0%	0%	0%	0%	0%	0%
2013	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%	100%	100%	100%	0%	0%	0%	0%	0%	0%
2014	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2015	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%	100%	0%	100%	0%	0%	0%	100%	0%	0%	0%	0%
2016	99%	100%	100%	100%	100%	100%	100%	100%	100%	0%	100%	0%	0%	0%	100%	0%	100%	0%	0%	0%	0%	0%
2017	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%	0%	0%	0%	0%	0%	0%	0%
2018	99%	93%	100%	95%	100%	100%	100%	100%	100%	100%	100%	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2019	94%	99%	100%	100%	100%	100%	100%	100%	100%	0%	0%	100%	100%	0%	0%	0%	0%	0%	100%	0%	0%	0%

Avg CT2 LossMCA
Avg CT2 LossMCA

INCREMENTAL
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Actual Average as a Percentage of Outstanding MCA at the Beginning of Each Period

ANNUAL EVALUATIONS - 2016Q4 - QUARTI

Fiscal Year	4	8	12	16	20	24	28	32	36	40	44	48	52	56	60	64	68	72	76	80	84	88	92	96	100	104	108
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%
1991	0%	0%	0%	0%	0%	105%	0%	0%	0%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1992	0%	0%	0%	0%	0%	0%	109%	0%	0%	100%	99%	99%	98%	100%	99%	99%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1993	0%	0%	0%	0%	0%	103%	0%	0%	100%	99%	99%	99%	100%	100%	99%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1994	0%	0%	100%	0%	106%	0%	99%	99%	99%	99%	99%	99%	99%	100%	100%	0%	98%	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1995	0%	0%	0%	104%	0%	0%	99%	99%	99%	99%	99%	100%	99%	100%	99%	90%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1996	101%	0%	101%	109%	0%	0%	99%	99%	99%	99%	99%	99%	100%	100%	0%	95%	0%	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1997	0%	0%	0%	0%	0%	0%	100%	99%	99%	99%	99%	100%	100%	99%	93%	99%	99%	100%	99%	0%	0%	0%	0%	0%	0%	0%	0%
1998	81%	100%	99%	99%	98%	99%	99%	99%	99%	99%	100%	100%	100%	99%	100%	100%	99%	100%	99%	0%	0%	0%	0%	0%	0%	0%	0%
1999	70%	0%	0%	98%	98%	100%	99%	99%	99%	99%	99%	100%	98%	99%	99%	99%	99%	100%	100%	0%	0%	0%	0%	0%	0%	0%	0%
2000	81%	0%	98%	0%	98%	99%	99%	100%	99%	99%	98%	97%	99%	99%	99%	99%	99%	100%	100%	99%	0%	0%	0%	0%	0%	0%	0%
2001	95%	0%	0%	98%	98%	99%	99%	99%	99%	95%	98%	100%	99%	99%	99%	99%	100%	99%	98%	0%	0%	0%	0%	0%	0%	0%	0%
2002	85%	100%	98%	98%	99%	99%	99%	98%	99%	99%	99%	99%	99%	99%	99%	100%	100%	99%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2003	69%	98%	98%	99%	99%	99%	98%	99%	99%	99%	99%	98%	99%	98%	100%	100%	99%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2004	53%	99%	99%	99%	99%	98%	98%	98%	99%	99%	98%	99%	99%	99%	100%	99%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2005	98%	98%	99%	99%	98%	97%	97%	98%	99%	98%	98%	99%	99%	99%	99%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2006	0%	100%	99%	98%	99%	99%	98%	99%	98%	98%	99%	99%	99%	99%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2007	98%	0%	99%	97%	99%	98%	99%	99%	99%	98%	99%	99%	99%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2008	0%	0%	100%	99%	99%	99%	99%	99%	98%	98%	99%	99%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2009	0.0%	99.3%	98.8%	99.3%	98.9%	99.0%	99.3%	99.2%	99.3%	99.1%	99%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
2010	0.0%	99.2%	99.0%	99.0%	99.0%	99.5%	99.4%	99.6%	99.5%	99.0%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
2011	0.0%	0.0%	0.0%	98.5%	99.4%	99.2%	99.5%	99.4%	99.3%	99.7%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
2012	100.1%	0.0%	98.4%	98.9%	98.9%	99.4%	99.4%	99.1%	99.8%	99.6%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
2013	0.0%	0.0%	0.0%	98.9%	99.3%	99.3%	99.1%	99.7%	99.7%	99.8%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
2014	0.0%	0.0%	49.6%	99.4%	89.1%	95.4%	99.5%	99.6%	99.6%	99.6%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
2015	0.0%	0.0%	0.0%	44.2%	99.4%	99.4%	99.6%	99.6%	99.5%	99.7%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
2016	0.0%	0.0%	0.0%	0.0%	99.4%	99.4%	99.5%	99.6%	99.6%	99.7%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	0%
2017	0.0%	0.0%	0.0%	99.8%	99.5%	99.5%	99.6%	99.6%	99.6%	99.7%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	99%
2018	0.0%	0.0%	0.0%	0.0%	99.1%	99.2%	99.4%	99.5%	99.6%	99.6%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
2019	0.0%	0.0%	0.0%	0.0%	0.0%	99.8%	99.8%	99.7%	99.3%	99.3%	99%	99%	99%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

Avg CT2 LossMCA
Avg CT2 LossMCA

Fiscal Year	ERS OF MATURITY 112	116	120	124	128	132	136	140	144	148	152	156	160	164	168	172	176	180	184	188	192	196	200
1990	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%	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%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1993	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%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1995	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%	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%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1998	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%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2000	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%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2002	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2003	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%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2005	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%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2007	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%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2009	100%	100%	100%	100%	100%	100%	100%	0%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2010	100%	100%	100%	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2011	100%	0%	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2012	100%	100%	0%	0%	0%	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2013	100%	100%	100%	100%	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2014	100%	100%	100%	100%	100%	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2015	100%	100%	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2016	100%	100%	100%	100%	0%	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2017	100%	100%	100%	0%	100%	100%	100%	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2018	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2019	100%	0%	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%