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ACTUARIAL RESOURCES, INC.

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November 10, 2017

Dana Wade
General Deputy Assistant Secretary
Office of Housing
U.S. Department of Housing and Urban Development
451 Seventh Street, S.W., Room 9100
Washington, D.C. 20410

Dear Ms. Wade:

Pinnacle Actuarial Resources, Inc. (Pinnacle) has completed the final report for the Fiscal Year 2017 Independent Actuarial Review of the Mutual Mortgage Insurance Fund Forward Loans. The attached report details our estimate of the Cash Flow Net Present Value for fiscal year 2017.

Roosevelt C. Mosley, Jr., FCAS, MAAA and Thomas R. Kolde, FCAS, MAAA are responsible for the content and conclusions set forth in the report. We are Fellows of the Casualty Actuarial Society and Members of the American Academy of Actuaries, and are qualified to render the actuarial opinion contained herein.

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

Respectfully Submitted,

Roosevelt Mosley

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

Thomas R. Kolde

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Fiscal Year 2017 Independent Actuarial Review of the Mutual Mortgage Insurance Fund: Cash Flow Net Present Value from Forward Mortgage Insurance-In-Force

November 10, 2017

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Commitment Beyond Numbers

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Summary of Findings

This report presents the results of Pinnacle Actuarial Resources, Inc.'s (Pinnacle's) independent actuarial review of the Cash Flow Net Present Value (NPV) associated with forward mortgages insured by the Mutual Mortgage Insurance Fund (MMIF) for fiscal year 2017. The Cash Flow NPV associated with Home Equity Conversion Mortgages (HECMs) are analyzed separately and are excluded from this report. In the remainder of this report, the term MMIF refers to forward mortgages and excludes HECMs.

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

Deliverable 1: The Actuary's conclusion regarding the reasonableness of Federal Housing Administration's (FHA's) estimate of Cash Flow Net Present Value from Forward Mortgage Insurance-In-Force as presented in FHA's Annual Report to Congress and the Actuary's best estimate of the range of reasonable estimates, including the 90th, 95th and 99th percentiles.

As of the end of Fiscal Year 2017, Pinnacle's Actuarial Central Estimate (ACE) of the MMIF Cash Flow NPV is \$1.893 billion.

Pinnacle's ACE is based on the Economic Assumption for the 2018 Budget Fall Baseline 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 1.

Table 1: Range of Cash Flow NPV Outcomes Based on Moody's Scenarios

Economic Scenario	Fiscal Year 2017 Cash Flow NPV
Pinnacle ACE	1,892,909,014
Moody's Baseline	6,003,059,790
Moody's Stronger Near Term Growth	8,699,780,859
Moody's Slower Near Term Growth	1,834,075,258
Moody's Moderate Recession	-13,243,008,137
Moody's Protracted Slump	-36,309,405,864
Moody's Below-Trend Long-Term Growth	-204,715,004
Moody's Stagflation	-8,214,525,624
Moody's Next Cycle Recession	-1,801,986,274
Moody's Low Oil Price	5,665,577,819

The range of results based on the Moody's estimates is negative \$36.31 billion to positive \$8.70 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, we estimate that the range of reasonable Cash Flow NPV estimates is negative \$5.0 billion to positive \$8.5 billion. This range is based on an 80% likelihood that the ultimate Cash Flow NPV will fall within the lower and upper bound of the range.

The 90th, 95th and 99th percentiles of the stochastic simulations are shown below:

- 90th percentile: $8.5 billion
- 95th percentile: $11.9 billion
- 99th percentile: $13.7 billion

The Cash Flow NPV estimate provided by FHA to be used in the FHA's Annual Report to Congress is $1.4 billion. Based on Pinnacle's Actuarial Central Estimate and range of reasonable estimates, we conclude that the FHA estimate of Cash Flow NPV to be used in the FHA's Annual Report to Congress is reasonable.

Deliverable 2: The Actuary's best estimate and range of reasonable estimates of Cash Flow Net Present Value by cohort from Forward (Home Equity Conversion) Mortgage Insurance-In-Force as presented in FHA's Annual Report to Congress.

Pinnacle's range of reasonable estimates of the Cash Flow NPV by cohort are shown below. The range of estimates are based on the stochastic simulation results.

Table 2: Range of Reasonable Cash Flow NPV Estimates – Forward Portfolio

Cohort	10th Percentile	90th Percentile	Pinnacle ACE
1992	-1,906,956	-1,746,653	-2,510,064
1993	-2,371,960	-1,688,818	-2,587,302
1994	-4,580,119	-3,189,831	-6,483,734
1995	-3,939,164	-2,759,241	-5,998,983
1996	-8,923,993	-5,319,929	-11,976,154
1997	-13,185,713	-7,451,770	-19,158,651
1998	-22,915,694	-13,328,571	-31,623,846
1999	-38,745,528	-19,210,096	-49,412,869
2000	-40,628,914	-21,986,375	-52,489,704
2001	-99,064,250	-63,251,762	-129,956,227
2002	-164,822,389	-105,502,037	-205,837,102
2003	-247,414,669	-159,321,261	-290,254,163
2004	-397,544,640	-245,860,927	-458,386,429
2005	-379,568,136	-226,727,363	-438,741,118
2006	-411,332,460	-243,440,736	-484,933,531
2007	-500,103,398	-290,730,486	-628,461,485
2008	-1,267,113,133	-733,480,868	-1,672,216,832
2009	-1,885,337,601	-988,195,126	-2,277,550,884
2010	-1,911,328,910	-747,758,761	-1,911,996,837
2011	-958,442,763	-166,809,657	-904,394,273
2012	-442,033,701	560,370,195	-126,950,483
2013	-2,384,120	1,391,930,042	674,180,337
2014	523,887,918	1,436,894,167	1,320,408,633
2015	1,334,256,456	2,818,195,082	2,941,476,574
2016	1,064,695,471	3,063,683,900	3,167,486,685
2017	870,489,901	3,246,590,819	3,501,277,456
Total	-5,010,358,466	8,469,903,938	1,892,909,014

Deliverable 3: Reconciliation of the data used to prepare Pinnacle's estimates with data used by FHA to prepare its estimated MMIF Cash Flow NPV.

Section 4 shows the reconciliation of the data used by Pinnacle with the data used by FHA. Please see the section titled Data Reconciliation.

Deliverable 4: Assumptions and judgments on which estimates are based, support for the assumptions and sensitivity of the estimates to alternative assumptions and judgments.

The assumptions and judgments on which the Cash Flow NPV estimates are based are summarized in Section 4 of this report. The sections titled Specification of Mortgage Transition Models and Estimation Sample show the specifications and assumptions related to the transition models. The Loss Severity Model section details the loss severity models. Section 3 describes the economic assumptions incorporated into the Cash Flow NPV estimates and the sensitivity of the estimates to alternative economic scenarios. Lastly, the Cash Flow Projections section of Section 4 summarizes the assumptions associated with the cash flow analysis.

Deliverable 5: Narrative component that provides detail to explain to FHA and HUD management and auditors, OMB and Congressional offices the findings and their significance, and technical component that traces the analysis from the data to the conclusions.

Sections 1 and 2 provide an explanation of the findings and discusses the significance of the findings. Also, Section 4 traces the analysis from data to conclusions.

Deliverable 6: Commentary on the likelihood of risks and uncertainties that could result in material adverse changes in the condition of the MMIF as measured by the Cash Flow NPV.

Section 3 provides a discussion of the economic conditions that could result in material adverse change to the Cash Flow NPV.

Executive Summary

The 1990 Cranston-Gonzalez National Affordable Housing Act (NAHA) requires an independent actuarial analysis of the economic value of the FHA and Department of Housing and Urban Development's (HUD's) MMIF. Enacted on July 30, 2008, the Housing and Economic Recovery Act of 2008 (HERA) moved the requirement for an independent actuarial review into 12 USC 1708(a)-(4).

HERA also moved several additional programs into the MMIF. One of them, Home Equity Conversion Mortgages, which are reverse mortgages, are analyzed separately and are excluded from this report. In the remainder of this report, the term MMIF refers to forward mortgages and excludes HECMs.

The primary purpose of this actuarial analysis is to estimate the Cash Flow NPV of the current book of business.

We have calculated a range of estimates using economic projections from the OMB Economic Assumptions for Fiscal Year 2018, nine economic projection scenarios from Moody's and a stochastic simulation approach to test variation around economic scenarios.

Based on our analysis, we estimate that the Cash Flow NPV as of the end of fiscal year 2017 is $1.893 billion. We also estimate that the reasonable range of Cash Flow NPV is between negative $5.0 billion and positive $8.5 billion.

Impact of Economic Forecasts

The Cash Flow NPV of the MMIF depends on many factors. One of the most important set of factors is the prevailing economic conditions over the next 30 years, and most critically during the next 10 years. We incorporate the most significant factors in the U.S. economy affecting the performance of the mortgages insured by the MMIF through the use of the following variables in our models:

- 30-year fixed-rate home mortgage effective rates
- 10-year Constant Maturity Treasury (CMT) rates
- 1-year CMT rates
- Housing price index (HPI)
- Unemployment rates
- Gross Domestic Product (GDP)

The projected Cash Flow NPV of FHA's books of business is affected by changes in these economic variables. The ACE results in this report is derived from using the OMB Economic Assumptions.

We also estimated the Cash Flow NPV of the MMIF under nine additional economic scenarios from Moody's. These scenarios are:

- Moody's Baseline
- Stronger Near-Term Growth
- Slower Near-Term Growth

- Moderate Recession
- Protracted Slump
- Below-Trend Long-Term Growth
- Stagflation
- Next-Cycle Recession
- Low Oil Price

These scenarios do not represent the full range of possible future economic paths. They represent a considerable variation of economic conditions. Therefore they provide insights into the projected Cash Flow NPV of the MMIF under a range of economic environments.

The summary of estimated Cash Flow NPV resulting from each approach is shown in Table 3.

Table 3: Projected Forward Cash Flow NPV Using Alternative Economic Scenarios

Economic Scenario	Fiscal Year 2017 Cash Flow NPV
Pinnacle ACE	1,892,909,014
Moody's Baseline	6,003,059,790
Moody's Stronger Near Term Growth	8,699,780,859
Moody's Slower Near Term Growth	1,834,075,258
Moody's Moderate Recession	-13,243,008,137
Moody's Protracted Slump	-36,309,405,864
Moody's Below-Trend Long-Term Growth	-204,715,004
Moody's Stagflation	-8,214,525,624
Moody's Next Cycle Recession	-1,801,986,274
Moody's Low Oil Price	5,665,577,819

We also randomly generated 100 stochastic simulations of key economic variables. Based on these simulations, we estimate that the range of reasonable Cash Flow NPV estimates is negative $5.0 billion to positive $8.5 billion. This range is based on an 80% likelihood that the ultimate Cash Flow NPV will fall within the lower and upper bound of the range.

Distribution and Use

This report is being provided to FHA for its 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 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 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 subsequent sections of the 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 4 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 from external sources without audit or verification. This includes economic data projected over the next 30 years from Moody's and the OMB. However, we did review as many elements of the data and information as practical for reasonableness and consistency with our knowledge of the mortgage insurance industry. It is possible 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 the realized experience deviates significantly from these assumptions, the actual results may differ, perhaps significantly, from projected results.

The predictive models used in this analysis are based on a theoretical framework and certain assumptions. This model structure predicts the rates of default, claim, loss and prepayment based on a number of individual mortgage characteristics and economic variables. The models are built using predictive modeling techniques, analyzing data from actual historical experience of FHA-insured mortgages. The parameters of the predictive models are estimated over a wide variety of mortgages originated since 1975 and their performance under the range of economic conditions and mortgage market environments experienced during the past 40 years. The predictive models are combined with assumptions about future behavior of current mortgage endorsements and certain key economic assumptions to produce future projections of the performance of the existing mortgages insured by 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 the 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). This study provides an analysis of the Cash Flow NPV of the MMIF as of September 30, 2017.

The MMIF is a group of accounts of the federal government which records transactions associated with the FHA's guarantee programs for single family mortgages. Currently, the FHA insures approximately 7.83 million forward mortgages under the MMIF and 440,000 reverse mortgages under the HECM program.

Per 12 USC 1711-(f), the FHA must endeavor to 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 the MMIF obligations on outstanding mortgages (insurance-in-force, or IIF). Capital is defined as cash available to the MMIF plus the Cash Flow NPV of all future cash outflows and inflows that are expected to result from the mortgages currently insured by the MMIF.

The deliverables included in this study are:

1. The Actuary's conclusion regarding the reasonableness of FHA's estimate of Cash Flow Net Present Value from Forward (Home Equity Conversion) Mortgage Insurance-In-Force as presented in FHA's Annual Report To Congress and the Actuary's best estimate of the range of reasonable estimates, including the 90^{th}, 95^{th} and 99^{th} percentiles.

2. The Actuary's best estimate and range of reasonable estimates of Cash Flow Net Present Value by cohort from Forward (Home Equity Conversion) Mortgage Insurance-In-Force as presented in FHA's Annual Report to Congress.

3. Reconciliation of the data used to prepare Pinnacle's estimates with data used by FHA to prepare its estimated MMIF Cash Flow NPV.

4. Assumptions and judgments on which estimates are based, support for the assumptions and sensitivity of the estimates to alternative assumptions and judgments.

5. Narrative component that provides detail to explain to FHA and HUD management and auditors, OMB and Congressional offices the findings and their significance, and technical component that traces the analysis from the data to the conclusions.

6. Commentary on the likelihood of risks and uncertainties that could result in material adverse changes in the condition of the MMIF as measured by the Cash Flow NPV.

Background

The MMIF provides guarantees for traditional forward mortgages and HECMs. This report focuses on Cash Flow NPV projections for forward mortgages. Cash Flow NPV projections for HECMs are discussed in a separate report.

Congress created FHA in 1934. The FHA "provides mortgage insurance on mortgages provided by FHA-approved lenders throughout the United States and its territories. FHA insures mortgages on single family and multifamily homes including manufactured homes and hospitals. It is the largest insurer of mortgages in the world, insuring over 34 million properties since its inception in 1934."[1] The mortgage insurance provided was done so through the establishment of the MMIF.

NAHA, enacted in 1990, introduced a minimum capital requirement for the MMIF[2]. 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 IIF. NAHA also implemented the requirement that an independent actuarial study of the MMIF be completed annually. HERA moved the requirement for the annual actuarial study to 12 USC 1708(a)-(4).

Report Structure

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

- **Section 2. Summary of Findings** – presents the MMIF estimated Cash Flow NPV for fiscal year 2017. This section also shows the projected Cash Flow NPV by cohort and product.

- **Section 3. Cash Flow NPV Based on Alternative Scenarios** – presents estimates of the MMIF Cash Flow NPV using a range of alternative economic assumptions.

- **Section 4. Summary of Methodology** – presents an overview of the data processing, transition, loss severity and cash flow models used in the analysis.

[1] https://portal.hud.gov/hudportal/HUD?src=/program_offices/housing/fhahistory
[2] Public Law 101-625, 101st Congress, November 28, 1990, Section 332.

Section 2: Summary of Findings

This section presents Pinnacle's estimates of the Cash Flow NPV of the MMIF Forward Mortgage portfolio as of September 30, 2017.

Fiscal Year 2017 Cash Flow NPV Estimate

This analysis estimates the Cash Flow NPV of the MMIF as of the end of fiscal year 2017 using data through September 30, 2017. We developed this estimate by analyzing historical mortgage performance using data provided by FHA, developing predictive models for mortgage transition and losses, and using these model results along with economic projections from the OMB and Moody's to project future cash flows of the MMIF. The Cash Flow NPV along with the MMIF's capital resources represent the economic value of the MMIF.

The predictive models used in this report are similar conceptually to the econometric models developed in the 2016 Actuarial Review; however, there is one difference in the modeling approach. We have developed multinomial logistic models which predict the likelihood of all possible transitions simultaneously. In the 2016 Actuarial Review, multiple binomial models were developed for each individual transition, and the multinomial likelihood was then estimated from the individual binomial models.

Section 4 summarizes the mortgage-level models, the assumptions used and the detailed projection model results.

The Cash Flow NPV is computed from the projected cash flows occurring during fiscal year 2018 and subsequent years. It is computed based on economic projections associated with the OMB Economic Assumptions. **As of the end of Fiscal Year 2017, Pinnacle estimates that the MMIF Cash Flow NPV is $1.893 billion.** The Cash Flow NPV estimate provided by FHA to be used in FHA's Annual Report to Congress is $1.4 billion.

In addition to the overall estimate of the Cash Flow NPV, we have estimated the Cash Flow NPV by cohort. The Pinnacle estimate compared to the FHA estimate by cohort is shown below.

Table 4: Cash Flow NPV by Cohort

	Cash Flow NPV ($ in billions)		
Cohort	Pinnacle	FHA	Dollar Difference
1992	0.0	0.0	0
1993	0.0	0.0	0
1994	0.0	0.0	0
1995	0.0	0.0	0
1996	0.0	0.0	0
1997	0.0	0.0	0
1998	0.0	-0.1	0
1999	0.0	-0.1	0
2000	-0.1	-0.1	0
2001	-0.1	-0.2	0
2002	-0.2	-0.3	0
2003	-0.3	-0.4	0
2004	-0.5	-0.7	0
2005	-0.4	-0.8	0
2006	-0.5	-0.8	0
2007	-0.6	-1.0	0
2008	-1.7	-2.4	1
2009	-2.3	-3.4	1
2010	-1.9	-2.8	1
2011	-0.9	-1.2	0
2012	-0.1	-0.4	0
2013	0.7	1.1	0
2014	1.3	2.2	-1
2015	2.9	3.8	-1
2016	3.2	4.3	-1
2017	3.5	4.7	-1
Total	1.9	1.4	0.5

The Pinnacle estimates by cohort are higher (less negative) through 2012, and then conversely are lower (less positive) for cohorts 2013 and later. The total Pinnacle Cash Flow NPV estimate is $0.5 billion higher than the FHA estimate, which as a percentage of IIF is 0.04%. The current IIF is $1,265 billion.

The housing and economic crisis that occurred in 2008 has resulted in higher claim rates for mortgages originated during fiscal years 2005 - 2010. Given that their upfront mortgage insurance premium (MIP) has already been collected and is included as part of the current capital resources, and due to their large origination volume, the fiscal year 2008 - 2010 cohorts are estimated to experience larger negative Cash Flow NPVs than any other cohorts. However, at the end of the housing recession, house prices bottomed out and then turned positive, and as a result mortgages originated in fiscal years 2013 - 2017 have positive Cash Flow NPVs. The NPV is also being positively impacted for these more recent cohorts due to MIP now being collected over the life of the mortgage.

The table below shows Pinnacle's Cash Flow NPV estimates by cohort and product.

Table 5: Cash Flow NPV by Cohort and Product

Cohort	Fixed Rate 30	Fixed Rate 30 - Streamlined Refinance	Fixed Rate 15	Fixed Rate 15 - Streamlined Refinance	Adjustable Rate Mortgage	Adjustable Rate Mortgage - Streamlined Refinance	Total
1992	-1,564,549	-55,055	0	0	-274,186	-15,632	-1,909,421
1993	-1,995,836	-501,792	0	0	-207,039	-35,225	-2,739,891
1994	-2,889,882	-1,953,034	0	0	-523,847	-124,419	-5,491,182
1995	-4,489,312	-194,733	0	0	-1,073,422	-67,198	-5,824,664
1996	-7,835,515	-599,954	0	0	-1,324,726	-15,717	-9,775,912
1997	-14,435,660	-325,844	0	0	-2,941,692	-198,632	-17,901,828
1998	-21,852,966	-2,267,404	0	0	-2,697,113	-265,348	-27,082,830
1999	-38,382,860	-6,156,413	0	0	-998,613	-295,316	-45,833,203
2000	-45,690,875	-583,222	0	0	-4,257,838	-542,564	-51,074,500
2001	-88,710,692	-10,030,521	0	0	-1,632,274	-609,213	-100,982,699
2002	-157,407,408	-25,105,347	0	0	-7,258,766	-3,644,391	-193,415,912
2003	-238,974,383	-95,699,688	-41,667	-83,257	-7,694,833	-3,762,925	-346,256,753
2004	-347,308,558	-82,455,649	-171,235	-347,819	-18,878,768	-9,224,400	-458,386,429
2005	-345,355,030	-59,235,881	-301,583	-400,148	-27,669,869	-5,778,608	-438,741,118
2006	-440,580,559	-30,164,849	-760,921	-259,907	-12,287,872	-879,424	-484,933,531
2007	-593,106,589	-25,933,646	-1,603,683	-112,279	-7,407,586	-297,703	-628,461,485
2008	-1,552,891,936	-94,088,585	-6,724,643	-488,120	-15,974,033	-2,049,515	-1,672,216,832
2009	-1,769,741,843	-471,328,586	-11,260,891	-2,027,871	-14,254,211	-8,937,482	-2,277,550,884
2010	-1,602,139,494	-227,394,837	-17,993,261	-1,678,730	-41,920,416	-20,870,098	-1,911,996,837
2011	-699,767,865	-134,190,348	-19,698,403	-1,373,237	-35,347,887	-14,016,534	-904,394,273
2012	-29,918,110	-52,852,842	-28,156,613	-3,092,321	-7,682,784	-5,247,814	-126,950,483
2013	789,700,135	-100,589,385	-17,602,748	-2,973,585	5,519,897	126,024	674,180,337
2014	1,273,799,719	-5,494,166	10,612,291	3,107,851	31,050,201	7,332,738	1,320,408,633
2015	2,370,351,127	498,165,330	28,951,021	3,928,924	32,367,957	7,712,214	2,941,476,574
2016	2,632,213,636	485,804,735	28,860,872	7,013,080	12,585,856	1,008,505	3,167,486,685
2017	3,035,450,464	412,248,912	28,750,096	10,570,005	14,013,990	243,987	3,501,277,456
Total	2,096,475,161	-30,982,802	-7,141,368	11,782,586	-116,769,873	-60,454,689	1,892,909,014

The value of the overall Cash Flow NPV is influenced primarily by the fixed rate 30-year mortgage product, which has the largest volume of mortgages historically. The total Cash Flow NPV is positive for the Fixed Rate 30 and Fixed Rate 15 Streamlined Refinance products, and is negative for the remaining products.

Section 3: 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:

- Moody's Baseline
- Stronger Near-Term Growth
- 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 6. 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 consistently between 2.0% and 3.5%. This is different from the OMB Economic Assumptions in that Moody's baseline grows more slowly for the first four years, and then increases at a faster rate through 2027. The mortgage interest rate increases more slowly than the OMB Economic Assumptions scenario, and settles at a longer term average of about 5.5%, which is lower than the OMB Economic Assumptions long term estimate of just over 6.0%. The unemployment rate decreases slightly to 3.7% over the next year, and then increases to a long-term average of around 5.0%. The OMB estimate decreases to about 4.4% over the next year, and then increases to a long-term average of 4.8%.

Stronger Near-Term Growth Scenario

In Moody's Stronger Near-Term Growth scenario, the HPI is projected to increase more quickly than under the OMB scenario. In addition, mortgage interest rates are projected to be lower than the OMB estimates through 2018, then projected to be higher than OMB through 2020, then decrease to a long-term average of just under 5.5%. The unemployment rate also is lower than projected in the OMB scenario and remains lower throughout the entire projection period.

Slower Near-Term Growth Scenario

In Moody's Slower Near-Term Growth scenario, the HPI increases more slowly than in the OMB scenario, and near the end of the projection period recovers to the level of the OMB assumptions. Mortgage interest rates are projected to be lower than the OMB assumptions throughout the projection period, settling at a long-term average of just over 5.5%. The unemployment rate is projected to be almost 0.70 percentage points higher than the OMB assumptions scenario by 2021, and then recovers to just 0.25 percentage points higher than the OMB assumptions in the long-term.

Moderate Recession Scenario

In the Moderate Recession scenario, the HPI decreases over the next 18 months, and then begins to increase. Despite the recovery, the projected HPI is lower than the OMB assumptions for the entire projection period. Mortgage interest rates spike sharply in the fourth quarter of 2017, and then drop significantly through the first quarter of 2019. Mortgage rates then begin to slowly increase until they reach the long-term average of just over 5.5%. The unemployment rate spikes to almost 8% by 2019, and then recovers to a long-term average of just over 5%. The projected unemployment rate is higher than the OMB assumptions for the entire projection period.

Protracted Slump

In Moody's Protracted Slump scenario, the HPI decreases significantly over the next 18 months, and then begins to increase again. Despite the recovery, the projected HPI is lower than the OMB assumptions for the entire projection period. Mortgage interest rates spike sharply in the fourth quarter of 2017, and then drop until the fourth quarter of 2019. They begin to slowly increase until they reach the long-term average of just over 5.5%. The unemployment rate spikes to over 10% by 2020, and then recovers to a long-term average of approximately 5.4%. The projected unemployment rate is higher than the OMB assumptions scenario for the entire projection period.

Below-Trend Long-Term Growth

In Moody's Below-Trend Long-Term Growth scenario, the HPI increases more slowly than in the OMB assumptions and remains lower for the entire projection period. Mortgage interest rates increase gradually and settle at a long-term average of about 5.7%. The projected mortgage interest rate is lower than the OMB projection over the entire period. The unemployment rate increases to 5.6% by 2020, and then decreases to a long-term average of approximately 5.0%.

Stagflation

In Moody's Stagflation scenario, the HPI decreases through the third quarter of 2019, and then begins to increase. Despite the recovery, the projected HPI is lower than the OMB assumptions for the entire projection period. Mortgage interest rates increase sharply to 6.8% by the second quarter of 2018, and then drop through the second quarter of 2019. They then begin to slowly increase to the long-term average of just over 5.5%. Unemployment rates increase significantly to just over 8% by 2019, and then decrease to a long-term average of just over 5%.

Next-Cycle Recession

In Moody's Next-Cycle Recession scenario, the HPI increases at the same rate as the OMB assumptions through the first quarter of 2020, and then decreases significantly through the second quarter of 2021. The HPI then increases again until it is equal to the OMB assumptions by 2027. The mortgage interest rates are approximately equal to the OMB assumptions through 2020, and then increase significantly to 7.7% by 2022. The rates then drop slightly and settle in at a long term average of 7.4%. The unemployment rate is lower than the OMB assumptions through the third quarter of 2019, and then increases sharply to over 8% by 2021. It then decreases to the level of the OMB assumptions by 2024.

Low Oil Price

In Moody's Low Oil Price scenario, the HPI increases at a rate similar to the OMB assumptions throughout the entire projection period. Mortgage interest rates decrease slightly through the first quarter of 2018, and then increase significantly through 2020. The rate then levels off at a long-term average of about 5.8%. Unemployment rates decrease through 2019, and then increase for the remainder of the projection period, settling at a long-term average of just over 5%.

Summary of Alternative Scenarios

Table 6 shows the projected Cash Flow NPV from the ten deterministic scenarios. The range of projected results is between negative $36.31 billion and positive $8.70 billion.

Table 6: Cash Flow NPV Summaries from Alternative Scenarios

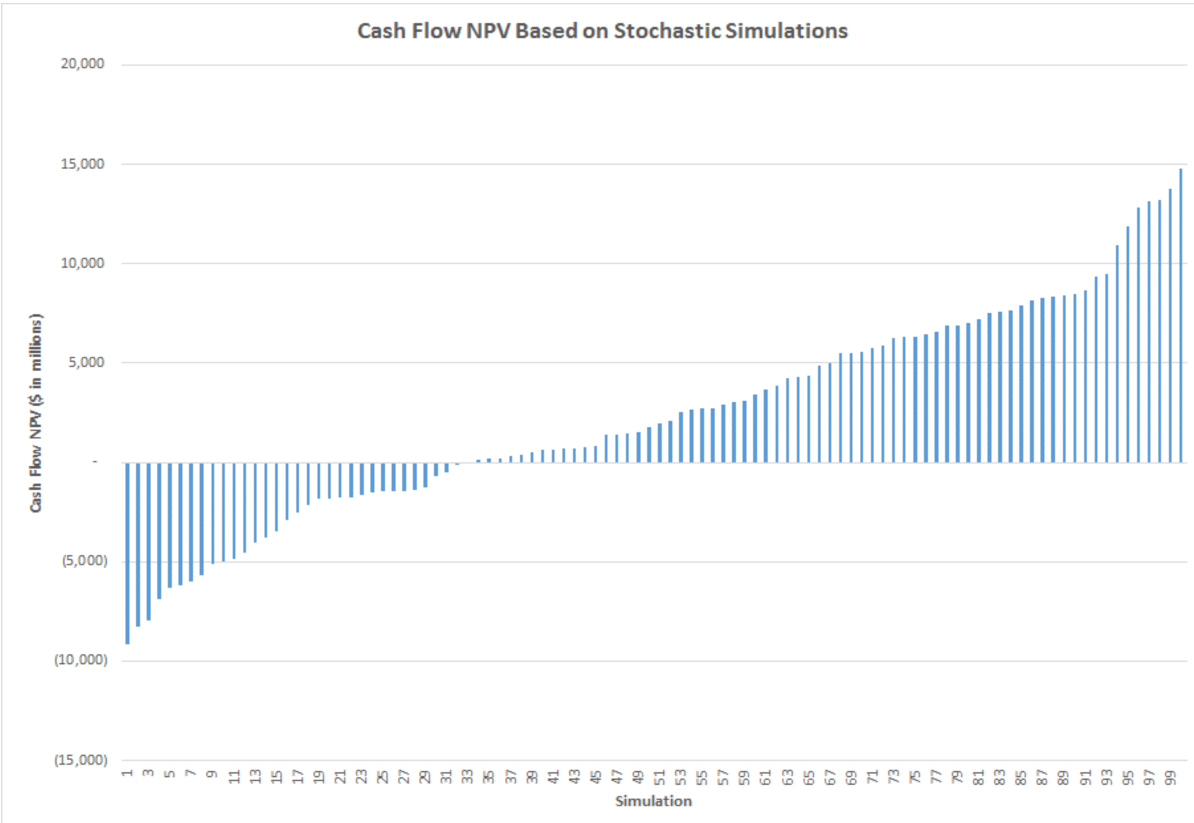
Cohort	Pinnacle ACE	Moody's Baseline	Moody's Stronger Near-Term Growth	Moody's Slower Near-Term Growth	Moody's Moderate Recession	Moody's Protracted Slump	Moody's Below-Trend Long-Term Growth	Moody's Stagflation	Moody's Next Cycle Recession	Moody's Low Oil Price
1992	-1,909,421	-1,629,189	-1,412,913	-2,000,042	-2,204,692	-2,571,325	-1,912,976	-2,041,695	-1,558,058	-1,495,958
1993	-2,739,891	-2,687,384	-2,395,768	-2,510,494	-3,526,298	-5,051,868	-2,866,324	-2,724,010	-2,265,570	-2,411,136
1994	-5,491,182	-4,986,935	-3,823,972	-5,593,247	-8,851,174	-12,858,243	-5,777,251	-6,974,514	-5,011,214	-4,650,445
1995	-5,824,664	-4,642,111	-5,248,017	-6,041,639	-10,113,015	-12,777,703	-5,658,464	-9,006,915	-5,785,758	-4,821,992
1996	-9,775,912	-9,388,559	-8,307,782	-11,451,981	-18,678,384	-25,698,604	-10,859,286	-14,629,402	-11,372,364	-8,680,949
1997	-17,901,828	-13,843,115	-13,090,234	-17,792,370	-29,180,164	-41,983,205	-18,874,053	-25,761,067	-16,559,130	-15,405,585
1998	-27,082,830	-22,386,906	-22,031,428	-26,349,872	-46,052,645	-66,181,226	-27,645,116	-39,313,572	-27,637,701	-22,840,747
1999	-45,833,203	-41,384,404	-36,870,254	-47,516,408	-85,044,228	-124,860,878	-51,227,638	-73,655,607	-49,285,443	-40,295,432
2000	-51,074,500	-45,629,306	-42,155,701	-53,121,577	-84,440,089	-135,740,137	-57,004,603	-80,298,157	-57,447,771	-44,291,191
2001	-100,982,699	-89,481,211	-85,332,023	-102,679,374	-152,042,207	-223,820,021	-110,089,323	-143,582,533	-107,929,441	-89,289,815
2002	-193,415,912	-178,747,880	-167,066,567	-201,638,597	-295,202,104	-419,582,183	-206,460,681	-284,075,275	-218,457,781	-176,321,352
2003	-346,256,753	-313,111,244	-300,928,551	-366,921,431	-531,424,093	-750,675,747	-379,585,087	-520,629,809	-406,851,069	-311,020,093
2004	-458,386,429	-424,475,362	-402,799,173	-482,043,787	-693,606,549	-1,022,044,426	-506,472,822	-698,861,126	-519,107,416	-423,667,303
2005	-438,741,118	-394,490,835	-374,692,237	-459,634,301	-656,048,684	-967,024,693	-485,117,216	-673,784,985	-486,922,432	-391,951,205
2006	-484,933,531	-443,275,941	-415,757,742	-513,981,332	-736,214,158	-1,056,557,117	-530,332,608	-724,203,295	-552,453,114	-447,101,774
2007	-628,461,485	-578,849,291	-538,307,287	-650,801,815	-952,488,279	-1,362,754,439	-693,778,693	-932,900,252	-704,102,440	-577,376,093
2008	-1,672,216,832	-1,521,933,495	-1,400,206,474	-1,740,538,913	-2,548,126,972	-3,724,735,182	-1,810,922,936	-2,492,284,944	-1,889,270,549	-1,483,581,489
2009	-2,277,550,884	-2,022,507,659	-1,857,705,912	-2,406,200,217	-3,675,365,742	-5,661,175,793	-2,503,801,217	-3,595,376,279	-2,719,194,598	-1,992,562,971
2010	-1,911,996,837	-1,685,093,871	-1,484,372,506	-2,075,507,146	-3,451,922,262	-5,711,182,025	-2,211,532,348	-3,475,377,330	-2,267,079,145	-1,650,266,407
2011	-904,394,273	-699,020,581	-576,900,456	-996,927,820	-1,938,343,935	-3,461,453,640	-1,077,072,495	-1,808,729,264	-1,203,329,713	-710,273,466
2012	-126,950,483	58,837,286	233,427,134	-223,329,932	-1,317,790,209	-3,024,841,831	-367,355,262	-1,121,944,363	-426,128,773	8,862,911
2013	674,180,337	991,593,677	1,198,860,441	591,475,522	-876,122,970	-3,163,818,237	403,614,009	-349,722,689	313,563,023	876,983,401
2014	1,320,408,633	1,606,356,302	1,792,860,020	1,332,363,971	163,624,522	-1,369,728,676	1,139,097,591	1,012,660,702	1,264,990,975	1,549,002,834
2015	2,941,476,574	3,599,444,521	3,958,940,139	3,115,818,065	1,336,374,456	-1,378,570,189	2,781,758,351	2,260,348,720	2,677,780,336	3,594,463,051
2016	3,167,486,685	3,933,322,068	4,402,725,353	3,392,768,881	1,479,404,477	-1,663,488,963	3,050,217,714	2,466,355,639	2,707,598,179	3,848,779,705
2017	3,501,277,456	4,311,071,214	4,852,372,770	3,794,231,113	1,890,377,263	-920,229,512	3,484,943,729	3,121,986,398	2,911,830,693	4,185,791,319
Total	1,892,909,014	6,003,059,790	8,699,780,859	1,834,075,258	-13,243,008,137	-36,309,405,864	-204,715,004	-8,214,525,624	-1,801,986,274	5,665,577,819

Stochastic Simulation

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

Figure 1 below shows the range of Cash Flow NPV for the 100 scenarios.

Figure 1: Stochastic Simulation Results



Based on the stochastic simulation results, we estimate that the range of reasonable Cash Flow NPV estimates is negative $5.0 billion to positive $8.5 billion. This range is based on an 80% likelihood that the ultimate Cash Flow NPV will fall within the lower and upper bound of the range. The 90th, 95th and 99th percentiles of the stochastic simulations are shown below:

- 90th percentile: $8.5 billion
- 95th percentile: $11.9 billion
- 99th percentile: $13.7 billion

The range of reasonable 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 Annual Report to Congress is $1.368 billion. Based on Pinnacle's Actuarial Central Estimate and range of reasonable estimates, we conclude that the FHA estimate of Cash Flow NPV is reasonable.

Sensitivity Tests of Economic Variables

The above scenario analyses were conducted to estimate the distribution of the Cash Flow NPV of the MMIF with different combinations of the interest rate and house price movements in the future. It is also useful to understand the marginal impact of 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 three sets of economic variables:

- House Price Appreciation (HPA)
- Interest rates, including:
    - 10-year CMT rate
    - 1-year CMT rate
    - Commitment rate on 30-year fixed-rate mortgages
- Unemployment Rate

The marginal impact is measured by the change in Cash Flow NPV from the OMB Economic Assumption scenario result. These simulations change each of these variables one at a time from the baseline scenario. The changes are parallel shifts in the path of each variable in the OMB Economic Assumption scenario, where all three interest rates are shifted together and at the same magnitudes, but are kept from going negative.

Figure 2 shows 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 results show a small upward trend in the Change in Cash Flow NPV projections, with a more significant impact for the 200 basis point increase and decrease. This shows that there is a more moderate increasing trend for the -100 basis point to 100 basis point changes. The large negative HPA shift results in lower recoveries on homes sold by FHA, and thus a lower Cash Flow NPV is realized. Conversely, the large positive HPA shift causes HPA recovery rates to increase on FHA disposed properties, and thus results in a higher Cash Flow NPV for the MMIF. Figure 3 shows the range of the impact of the sensitivity tests as a percentage of the IIF. For the HPA sensitivity, the range of Cash Flow NPV impacts are -0.02% to +0.03% of IIF.

Figure 2 also shows the sensitivity of the Cash Flow NPV with respect to changes in future interest rates. Specifically, we applied parallel shift to the 1-year CMT rate, 10-year CMT rate and the mortgage rates up and down from the base scenario by 20, 50, 100 and 200 basis points. Interest rates are not allowed to be negative. The results show a positive slope, indicating that the Cash Flow NPV of the MMIF is positively related to future interest rates. Higher future interest rates benefit the MMIF in two ways. First, a higher future interest rate means lower refinance incentive for existing borrowers. Thus, there would be fewer prepayments, which lead to a longer stream of annual MIP revenue. Second, higher future interest rates imply that the mortgage payments of existing borrowers would be lower than that of a new mortgage with the market interest rate. The below-market mortgage payment serves as an incentive for borrowers to keep their mortgages longer and thus is a disincentive to default in order to continue to benefit from their below-market payments. A 100 basis point fall in interest rates will incur a decrease in Cash Flow NPV of $7.0 billion, and a positive 100 basis point change in interest rates will result in an increase in Cash Flow NPV of $7.2 billion. For the interest rate sensitivity, the range of Cash Flow NPV impacts are -1.14% to +1.14% of IIF.

Finally, Figure 2 reports the sensitivity of the Cash Flow NPV with respect to the unemployment rate. A negative 100 basis point change in the unemployment rates will produce an increase in Cash Flow NPV of positive $5.9 billion, and a positive 100 basis point change in the unemployment rate will result in a decrease in Cash Flow NPV of $7.9 billion. This results from the fact that as unemployment increases, the likelihood of defaults and claims increase, and the average net loss increases as well. For the unemployment rate sensitivity, the range of Cash Flow NPV impacts are -1.43% to +0.78% of IIF.

These sensitivity analyses show that Cash Flow NPV of the MMIF portfolio would be significantly affected by changes in interest rates and unemployment, while a change in HPA has a smaller impact.

Figure 2: Sensitivity Test of Selected Economic Variables

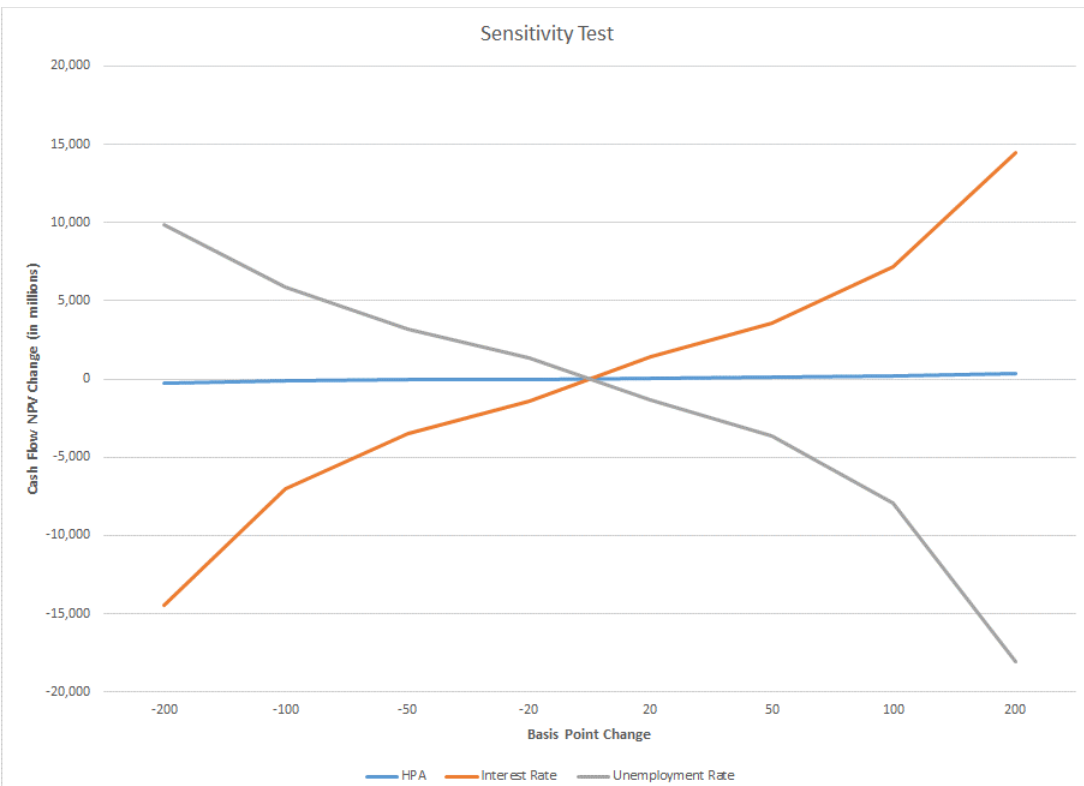
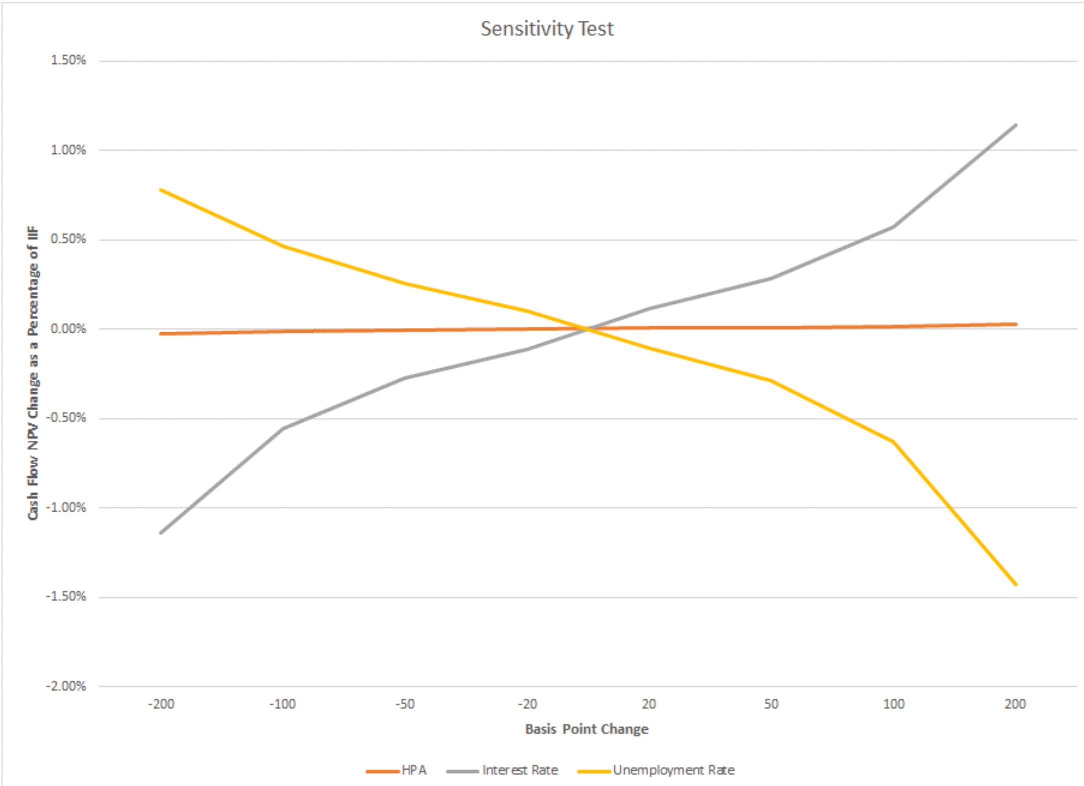


Figure 3: Sensitivity Test of Selected Economic Variables as a Percentage of IIF



Section 4: Summary of Methodology

This section provides an overview of the analytical approach used in this analysis.

Data Sources

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

From FHA, we have received the following data:

1. Claims_601_Case_Data: used for the cash entry from note sales
2. IDB: core case data, this table is derived based on fields from IDB_1, IDB_2, and the Decision_FICO_Score (one file each for 1975 – 2017)
3. Lossmit_Costs: derived table based on the Loss Mitigation table and IDB_1, used to obtain mitigation claim amounts
4. Sams_case_record: used to determine the status of the conveyances, the capital income/expense amounts, the sales and REO expenses and sales proceeds to FHA, where applicable
5. SFDW_Default_History: used to create period information related to default histories
6. Fannie_FICO_pre2004: used for supplemental credit data
7. SFDW Dictionary for Pinnacle: data dictionary for the data tables provided by FHA
8. LoanCounts_by_Year
9. 022317 fiscal year18 Budget Model Active Loan Panel Data Dictionary

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

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

From OMB, we have received the Economic Assumptions for the 2018 Budget Fall Baseline (updated as of March, 2017).

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

1. HPI
2. Mortgage rates
3. Treasury rates
4. Unemployment rates
5. GDP

Data Processing – Mortgage Level Modeling (Appendix A)

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.

The first step in preparing the data for analysis was the processing of the economic data. Historical economic data was imported by quarter, additional data elements were derived, and data was joined to the FHA mortgage data.

Once the economic data was prepared, the core data processing occurred. We used mortgage-level data to reconstruct quarterly mortgage-event histories by relating mortgage origination information to other data reflecting events that occurred over the history of the mortgage. In the process of creating quarterly event histories, each mortgage contributed an observed transition for every quarter from origination up to and including the period of mortgage termination, or until the end of the end of fiscal year 2017 if the mortgage remained active.

Data Reconciliation

To reconcile the data processed by Pinnacle with the data provided by FHA, Pinnacle compared summaries of key data elements with summaries provided by FHA. The summaries for the number of active mortgages, IIF, number of 90 day delinquencies, and the number of claims to date are shown in the following tables. The data processed by Pinnacle matches the FHA data totals within 1%.

The following tables are based on data as of June 30, 2017, as this was the data used to develop the transition and net loss models.

Table 7: Data Validation – Number of Active Mortgages

	Number of Active Mortgages		
Credit Subsidy Cohort	Federal Housing Administration	Independent Actuary	Absolute Difference (Actuary - FHA)
1992	15,787	15,787	0
1993	25,388	25,388	0
1994	36,350	36,350	0
1995	17,268	17,268	0
1996	27,749	27,749	0
1997	29,767	29,767	0
1998	47,399	47,399	0
1999	59,857	59,857	0
2000	32,696	32,696	0
2001	57,229	57,229	0
2002	86,431	86,431	0
2003	135,145	135,145	0
2004	167,933	167,933	0
2005	120,326	120,326	0
2006	95,422	95,422	0
2007	91,885	91,885	0
2008	219,218	219,218	0
2009	505,018	505,018	0
2010	651,683	651,683	0
2011	522,944	522,944	0
2012	638,408	638,408	0
2013	880,300	880,300	0
2014	441,568	441,568	0
2015	831,831	831,831	0
2016	1,138,319	1,138,319	0
2017	909,036	909,036	0
Total	7,784,957	7,784,957	0

Table 8: Data Validation – Insurance in Force

Insurance in Force ($M)				
= Original Loan Amount on Active Loans				
Credit Subsidy Cohort	Federal Housing Administration	Independent Actuary	Absolute Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
1992	965	965	0	0%
1993	1,660	1,660	0	0%
1994	2,430	2,430	0	0%
1995	1,097	1,097	0	0%
1996	1,829	1,829	0	0%
1997	2,017	2,017	0	0%
1998	3,474	3,474	0	0%
1999	4,621	4,621	0	0%
2000	2,503	2,503	0	0%
2001	4,945	4,945	0	0%
2002	8,065	8,065	0	0%
2003	14,068	14,068	0	0%
2004	17,507	17,507	0	0%
2005	12,989	12,989	0	0%
2006	10,871	10,871	0	0%
2007	11,283	11,283	0	0%
2008	30,776	30,776	0	0%
2009	77,525	77,525	0	0%
2010	98,904	98,904	0	0%
2011	81,884	81,884	0	0%
2012	102,200	102,200	0	0%
2013	145,068	145,068	0	0%
2014	63,979	63,979	0	0%
2015	148,133	148,133	0	0%
2016	217,030	217,030	0	0%
2017	182,327	182,327	0	0%
Total	1,248,150	1,248,150	0	0%

Table 9: Data Validation – Number of 90 Day Delinquencies

Number of 90 Day Delinquencies				
= Current Number of 90 Day Delinquencies				
Credit Subsidy Cohort	Federal Housing Administration	Independent Actuary	Absolute Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
1992	634	630	(4)	-1%
1993	951	947	(4)	0%
1994	1,439	1,436	(3)	0%
1995	1,114	1,110	(4)	0%
1996	1,848	1,841	(7)	0%
1997	2,267	2,252	(15)	-1%
1998	3,342	3,332	(10)	0%
1999	4,624	4,608	(16)	0%
2000	3,406	3,388	(18)	-1%
2001	4,974	4,953	(21)	0%
2002	6,919	6,881	(38)	-1%
2003	8,738	8,687	(51)	-1%
2004	12,044	11,969	(75)	-1%
2005	10,427	10,373	(54)	-1%
2006	10,504	10,442	(62)	-1%
2007	12,744	12,690	(54)	0%
2008	30,556	30,407	(149)	0%
2009	42,912	42,715	(197)	0%
2010	35,359	35,088	(271)	-1%
2011	22,149	21,992	(157)	-1%
2012	21,235	21,006	(229)	-1%
2013	23,843	23,580	(263)	-1%
2014	18,502	18,291	(211)	-1%
2015	23,176	22,868	(308)	-1%
2016	15,713	15,520	(193)	-1%
2017	1,641	1,631	(10)	-1%
Total	321,061	318,637	(2,424)	-1%

Table 10: Data Validation – Number of Claims to Date

Number of Claims To Date			
Federal Housing Administration	Independent Actuary	Absolute Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
36,631	36,634	3	0%
52,004	52,007	3	0%
65,539	65,543	4	0%
44,321	44,324	3	0%
62,868	62,869	1	0%
59,101	59,102	1	0%
66,319	66,319	0	0%
82,575	82,576	1	0%
70,014	70,014	0	0%
83,339	83,340	1	0%
87,529	87,529	0	0%
87,464	87,464	0	0%
110,234	110,234	0	0%
86,785	86,785	0	0%
88,259	88,259	0	0%
98,984	98,984	0	0%
206,201	206,201	0	0%
200,798	200,798	0	0%
95,656	95,656	0	0%
36,205	36,205	0	0%
19,137	19,137	0	0%
14,249	14,249	0	0%
5,767	5,767	0	0%
2,503	2,503	0	0%
347	347	0	0%
1	1	0	0%
1,762,830	1,762,847	17	0%

Specification of Mortgage Transition Models (Appendix B)

The purpose of the transition predictive models is to estimate the future incidences of claim and prepayment terminations for FHA forward mortgages in the MMIF portfolio. The models are used to project future outstanding balances, cash flows, and ultimately the Cash Flow NPV.

The predictive models reflect the fact that mortgage borrowers possess two mutually exclusive options, one to prepay the mortgage and the other to default by permanently ceasing payment. From FHA's point of view, prepayment and claim events are the corresponding outcomes of "competing risks" in the sense that they are mutually exclusive, and realization of one of these events precludes the other. Prepayment means cessation of cash inflows from MIP, but at the same time eliminates any chance of incurring claim losses. Conversely, termination through foreclosure means claim costs are incurred and MIP inflows cease, but uncertainty about the possibility and timing of prepayment is eliminated.

The models developed for this analysis also include additional transitions. These include the transition from current to 90 days or more delinquent (Default), cures from Default separated into cures by mortgage modification, and self-cures with no modification or with "light" modifications. We track the post-cure behavior of modified mortgages and self-cured mortgages separately with modification-related variables, namely a modification flag and the payment reduction ratio. We also track the status of mortgages post-default by including a prior default flag and the time since the most recent default.

We model five possible transitions from a mortgage in current status: remain current, default (enter 90+ days delinquent), prepay by streamline refinance (SR) or other prepayments, cure with a mortgage modification or self-cure. Given that these are mutually exclusive outcomes, the sum of the probabilities for all five transitions is unity. For a mortgage in default status at the beginning of a particular time period, the possible transitions are that it may be prepaid, transition into a claim, self-cure, cure with a mortgage modification, or remain in default.

We use multinomial logistic models to estimate the probability of transition for current and default mortgages. There are several benefits to using multinomial logistic models. First, they ensure that the event probabilities sum to unity. This means that at any point in time, a mortgage must experience only one of the possible transitions over the next period. Second, the possible values of each probability are constrained to be between zero and one. Third, as the probability of one transition type increases, the probabilities of the others are automatically reduced, reflecting the competing-risk nature among the transition events. Finally, they allow the conditional termination rates using mortgage-level data to be estimated. With mortgage-level observations, the possible outcomes at each point in time are either 0 (the event did not happen), or 1 (the event happened).

Estimation Sample

The entire population of mortgage-level data from the FHA single-family data warehouse was provided to Pinnacle for this analysis. This data represents the history of almost 33 million single family mortgages originated between fiscal year 1975 through the end of fiscal year 2017.

We have applied random sampling to improve the efficiency of the model estimation. For the transition models with the initial condition of Current, we used the following sampling percentages:

Table 11: Current Transition Model Sampling Percentages

Ending Condition	Sampling Percentage
Current	2.5%
Current with Self-Cure	50%
Current with Mortgage Modification	100%

Claim	50%
Pre-payment	50%
Streamline Refinance	50%

For transition models with the initial condition of Default, we sampled 25% of the records with ending condition of Default. For all other ending conditions, we used 100% of the data.

The sampling percentages were selected as a balance between having a credible amount of data to estimate the probability of the transition and efficiently running the models.

Loss Severity Model (Appendix C)

FHA incurs a loss from a mortgage claim event. This loss amount depends on many factors, including the disposition channel. In practice, foreclosed properties generally have higher severity compared to pre-foreclosure-sales (PFS). Foreclosure mortgages can be further separated into real-estate-owned (REO) and Claims Without Conveyance of Title (CWCOT). We have developed multiple models to predict loss severity: a model to predict whether the property is disposed by PFS, REO or CWCOT, and separate loss severity models for REO, PFS and CWCOT cases. The loss severity models capture characteristics of the mortgage, the collateral, the borrower, and the housing market environment when a claim occurs. The claim disposition selection model was estimated using multinomial logistic regression, while Generalized Linear Models (GLM) were developed for loss severity models.

In addition to the loss severity models, we have also developed a model to project the severity associated with loss mitigation claims.

Cash Flow Projections (Appendix E)

After projecting the future transitions and severities using the predictive models, we use this information to project the corresponding cash flows. The cash flow model includes the calculation of five types of cash flows:

1. Upfront MIP
2. Annual MIP
3. Claim payments
4. Loss mitigation related expenses
5. Premium refunds

The federal credit subsidy present value conversion factors provided by OMB are used to discount future cash flows to determine their present value as of the end of fiscal year 2017.

FHA executed a note sale in November 2015 and launched another one in September 2016. There are no current planned or pending note sales. Therefore, we have not projected any future note sales in our analysis.

We have calculated the Cash Flow NPV based on multiple deterministic economic scenario paths. The ACE projection is based on the OMB Economic Assumptions, and the variation in the estimate is calculated by using nine alternative economic projection scenarios from Moody's. These scenarios includes both more favorable than expected and less favorable than expected economic assumptions. The resulting Cash Flow NPV is then calculated based on these varying assumptions. The following are the economic variables that drive the variation in the MMIF Cash Flow NPV:

- 1-year CMT rates
- 10-year CMT rates
- 30-year Fixed Rate Mortgage (FRM) rates
- FHFA national purchase-only HPI
- Unemployment rates

Appendices

A. Data - Sources, Processing and Reconciliation
B. Transition Models
C. Loss Severity Models
D. Economic Scenarios
E. Cash Flow Analysis

Appendix A: Data – Sources, Processing and Reconciliation

Data Sources

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

From FHA, we have received the following data:

1. Claims_601_Case_Data: used for the cash entry from note sales
2. IDB: core case data, this table is derived based on fields from IDB_1, IDB_2, and the Decision_FICO_Score (one file each for 1975 – 2017)
3. Lossmit_Costs: derived table based on the Loss Mitigation table and IDB_1, used to obtain mitigation claim amounts
4. Sams_case_record: used to determine the status of the conveyances, the capital income/expense amounts, the sales and Real Estate Owned (REO) expenses and sales proceeds to FHA, where applicable
5. SFDW_Default_History: used to create period information related to default histories
6. Fannie_FICO_pre2004: used for supplemental credit data
7. SFDW Dictionary for Pinnacle: data dictionary for the data tables provided by FHA
8. LoanCounts_by_Year
9. 022317 fiscal year18 Budget Model Active Loan Panel Data Dictionary

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

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

From OMB, we have received the Economic Assumptions for the 2018 Budget Fall Baseline (updated as of March 2017).

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

1. HPI
2. Mortgage rates
3. Treasury rates
4. Unemployment rates
5. GDP

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 first step in preparing the data for analysis was the processing of the economic data. Historical economic data was imported by quarter, additional data elements were derived, and data was joined to the FHA mortgage data.

Once the economic data was prepared, the core data processing occurred. We used mortgage-level data to reconstruct quarterly mortgage-event histories by relating mortgage origination information to other data reflecting events that occurred over the history of the mortgage. In the process of creating quarterly event histories, each mortgage contributed an observed transition for every quarter from origination up to and including the period of mortgage termination, or until the end of the end of fiscal year 2017 if the mortgage remained active.

Data Reconciliation

To reconcile the data processed by Pinnacle with the data provided by FHA, Pinnacle compared summaries of key data elements with summaries provided by FHA. The summaries for the number of active mortgages, IIF, number of 90 day delinquencies, and the number of claims to date are shown in the following tables. The data processed by Pinnacle matches the FHA data totals within 1%.

The following tables are based on data as of June 30, 2017, as this was the data used to develop the transition and net loss models.

Table 12: Data Validation – Number of Active Mortgages

Number of Active Loans				
Credit Subsidy Cohort	Federal Housing Administration	Independent Actuary	Absolute Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
1992	15,787	15,787	0	0%
1993	25,388	25,388	0	0%
1994	36,350	36,350	0	0%
1995	17,268	17,268	0	0%
1996	27,749	27,749	0	0%
1997	29,767	29,767	0	0%
1998	47,399	47,399	0	0%
1999	59,857	59,857	0	0%
2000	32,696	32,696	0	0%
2001	57,229	57,229	0	0%
2002	86,431	86,431	0	0%
2003	135,145	135,145	0	0%
2004	167,933	167,933	0	0%
2005	120,326	120,326	0	0%
2006	95,422	95,422	0	0%
2007	91,885	91,885	0	0%
2008	219,218	219,218	0	0%
2009	505,018	505,018	0	0%
2010	651,683	651,683	0	0%
2011	522,944	522,944	0	0%
2012	638,408	638,408	0	0%
2013	880,300	880,300	0	0%
2014	441,568	441,568	0	0%
2015	831,831	831,831	0	0%
2016	1,138,319	1,138,319	0	0%
2017	909,036	909,036	0	0%
Total	7,784,957	7,784,957	0	0%

Table 13: Data Validation – Insurance-in-Force

Insurance in Force ($M) = Original Loan Amount on Active Loans				
Credit Subsidy Cohort	Federal Housing Administration	Independent Actuary	Absolute Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
1992	965	965	0	0%
1993	1,660	1,660	0	0%
1994	2,430	2,430	0	0%
1995	1,097	1,097	0	0%
1996	1,829	1,829	0	0%
1997	2,017	2,017	0	0%
1998	3,474	3,474	0	0%
1999	4,621	4,621	0	0%
2000	2,503	2,503	0	0%
2001	4,945	4,945	0	0%
2002	8,065	8,065	0	0%
2003	14,068	14,068	0	0%
2004	17,507	17,507	0	0%
2005	12,989	12,989	0	0%
2006	10,871	10,871	0	0%
2007	11,283	11,283	0	0%
2008	30,776	30,776	0	0%
2009	77,525	77,525	0	0%
2010	98,904	98,904	0	0%
2011	81,884	81,884	0	0%
2012	102,200	102,200	0	0%
2013	145,068	145,068	0	0%
2014	63,979	63,979	0	0%
2015	148,133	148,133	0	0%
2016	217,030	217,030	0	0%
2017	182,327	182,327	0	0%
Total	1,248,150	1,248,150	0	0%

Table 14: Data Validation – Number of 90 Day Delinquencies

Number of 90 Day Delinquencies = Current Number of 90 Day Delinquencies				
Credit Subsidy Cohort	Federal Housing Administration	Independent Actuary	Absolute Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
1992	634	630	(4)	-1%
1993	951	947	(4)	0%
1994	1,439	1,436	(3)	0%
1995	1,114	1,110	(4)	0%
1996	1,848	1,841	(7)	0%
1997	2,267	2,252	(15)	-1%
1998	3,342	3,332	(10)	0%
1999	4,624	4,608	(16)	0%
2000	3,406	3,388	(18)	-1%
2001	4,974	4,953	(21)	0%
2002	6,919	6,881	(38)	-1%
2003	8,738	8,687	(51)	-1%
2004	12,044	11,969	(75)	-1%
2005	10,427	10,373	(54)	-1%
2006	10,504	10,442	(62)	-1%
2007	12,744	12,690	(54)	0%
2008	30,556	30,407	(149)	0%
2009	42,912	42,715	(197)	0%
2010	35,359	35,088	(271)	-1%
2011	22,149	21,992	(157)	-1%
2012	21,235	21,006	(229)	-1%
2013	23,843	23,580	(263)	-1%
2014	18,502	18,291	(211)	-1%
2015	23,176	22,868	(308)	-1%
2016	15,713	15,520	(193)	-1%
2017	1,641	1,631	(10)	-1%
Total	321,061	318,637	(2,424)	-1%

Table 15: Data Validation – 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
1992	36,631	36,634	3	0%
1993	52,004	52,007	3	0%
1994	65,539	65,543	4	0%
1995	44,321	44,324	3	0%
1996	62,868	62,869	1	0%
1997	59,101	59,102	1	0%
1998	66,319	66,319	0	0%
1999	82,575	82,576	1	0%
2000	70,014	70,014	0	0%
2001	83,339	83,340	1	0%
2002	87,529	87,529	0	0%
2003	87,464	87,464	0	0%
2004	110,234	110,234	0	0%
2005	86,785	86,785	0	0%
2006	88,259	88,259	0	0%
2007	98,984	98,984	0	0%
2008	206,201	206,201	0	0%
2009	200,798	200,798	0	0%
2010	95,656	95,656	0	0%
2011	36,205	36,205	0	0%
2012	19,137	19,137	0	0%
2013	14,249	14,249	0	0%
2014	5,767	5,767	0	0%
2015	2,503	2,503	0	0%
2016	347	347	0	0%
2017	1	1	0	0%
Total	1,762,830	1,762,847	17	0%

Appendix B: Transition Models

This appendix describes the technical details of the predictive models used to estimate the transition behavior of forward mortgages.

Section 1 summarizes the model specifications used to analyze FHA mortgage status transitions and the subsequent ultimate claim and prepayment rates. This section also presents the statistical theory behind multinomial logistic models.

Section 2 describes the explanatory variables used in the models.

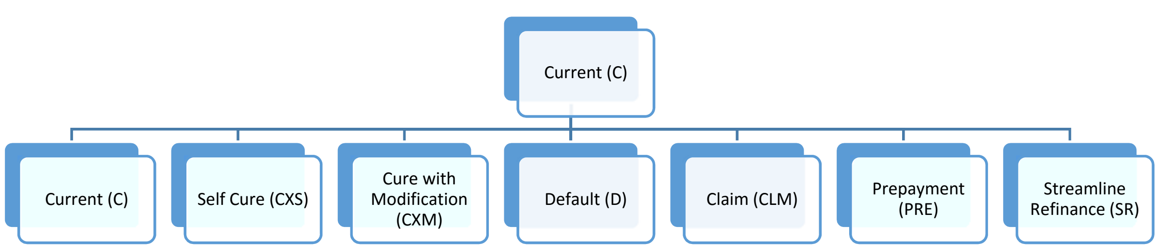
Section 3 shows the model validation of the multinomial logistic models.

Section 1: Model Specification

Prior to the 2010 Actuarial Review, a competing-risk framework based on multinomial logistic models for quarterly conditional probabilities of prepayment and claim terminations was used. Starting with the 2010 Review, a third "competing risk" was introduced: 90-day delinquency, or default. The date from which a mortgage is first reported to be 90 or more days late is used to identify the start of a default episode, and this episode continues until ended by cure or the mortgage terminates through claim or prepayment. Active mortgages that are not in a 90-day default episode at the beginning of the quarter are classified as current.

Figure 4 below shows the possible "current" status transitions that have been modeled using the multinomial framework.

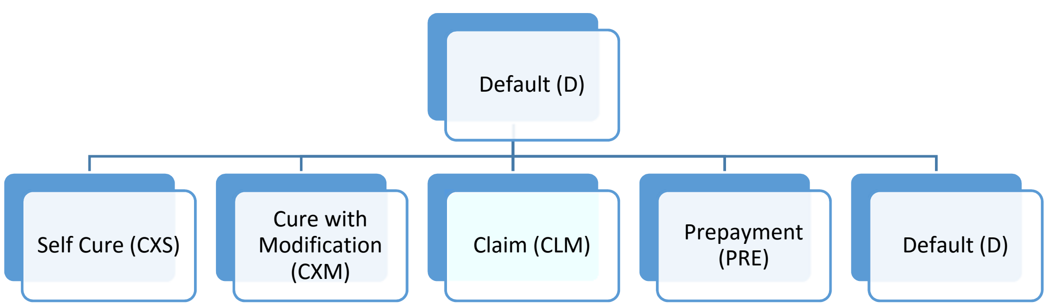
Figure 4: Transition Models - Initial Current Status



Mortgages in current status (C) at the beginning of the quarter can default and cure in the same quarter (CXS and CXM), transition to default status (D) at the start of the next quarter, result in a claim (CLM) or terminate as a prepayment due to an FHA SR (SR) or as a prepayment (PRE) for any reason other than SR. There are two types of cures, a self-cure (CXS) and a cure that includes a mortgage modification (CXM). For the purpose of building the multinomial models, we have combined PRE and SR into one category (END), as the distinction is not important for the transition models. Also, due to the very low likelihood of a current mortgage transitioning into to a CLM in one quarter, we have combined D and CLM into one category (DCLM).

The figure below shows the possible default status transitions that have been modeled using the multinomial framework.

Figure 5: Transition Models – Initial Default Status



For mortgages that begin the quarter in default, they can cure either by the borrower becoming current on their own (CXS), or they can cure with a modification in the terms of the mortgage (CXM). The mortgage can also terminate as a prepayment due to a streamlined refinance or as a prepayment (PRE) for any reason other than SR, turn into a claim (CLM) for the MMIF or remain in default (D).

As the mortgage transitions through multiple stages, the historical status of the mortgage is retained. At any point in the life of the mortgage, we track both the number of prior times the mortgage was either in default or modified as well as the length of time since the mortgage was in the prior stage.

Multinomial Logistic Regression Theory and Model Specification

Multinomial logistic regression is used to model the relationship between a collection of predictor variables and the distributional behavior of a polytomous response variable. It is a likelihood-based methodology and may be viewed as the generalization of logistic regression for a response variable with more than two levels.

To formalize its description, let the response variable Y take m possible levels, denoted for simplicity as 1,…,m, and assume there is a collection of g predictors $\mathrm{X}_1,\ldots,\mathrm{X}_\mathrm{g}$, that is used to model Y's distribution. We assume that Y and $\mathrm{X}_1,\ldots,\mathrm{X}_\mathrm{g}$ are jointly observed n times with the i^{th} random observation being labeled as

$$\mathrm{Y}_i,\ \mathrm{X}_{1i},\ldots,\mathrm{X}_{\mathrm{gi}} \text{ and its realized value } \mathrm{y}_i,\ \mathrm{x}_{1i},\ldots,\mathrm{x}_{\mathrm{gi}}.$$

In a multinomial logistic regression, the mathematical structure of the model is set by the following two assumptions:

1. The g+1 length random vectors $<\mathrm{Y}_i, \mathrm{X}_{1i},\ldots,\mathrm{X}_{\mathrm{gi}}>$ are jointly independent across all i
2. Given that $\mathrm{X}_{1i},\ldots,\mathrm{X}_{\mathrm{gi}}$ have been observed at $\mathrm{x}_{1i},\ldots,\mathrm{x}_{\mathrm{gi}}$, Y_i's distribution is assumed to be multinomial with

$$\mathrm{P}(\mathrm{Y}_i = \mathrm{l}) = \exp(\mu^{\mathrm{l}} + \textstyle\sum_{k=1}^{g} \beta_k^{\mathrm{l}} \cdot \mathrm{x}_{\mathrm{ki}}) / (\sum_{j=1}^{m} \exp(\mu^j + \sum_{k=1}^{g} \beta_k^j \cdot \mathrm{x}_{\mathrm{ki}}))\ ,$$

where the β_k^j are unknown regression parameters and the μ^{j} are unknown intercept parameters. [Note: To prevent over-specification of the model due to the constraint that the above probabilities sum to 1 over l=1,…,m, a base level j is chosen such that β_k^j and μ^j are set equal to zero.] Thus, if j = 1, then

$$\mathrm{P}(\mathrm{Y}_i = 1) = 1/(1 + \textstyle\sum_{j=2}^{g} \exp(\mu^j + \sum_{k=1}^{g} \beta_k^j \cdot \mathrm{x}_{\mathrm{ki}}))\ .$$

It now follows the likelihood equation for this model is given by

$$\textstyle\prod_{i=1}^{n} \mathrm{P}(\mathrm{Y}_i = \mathrm{y}_i) = \prod_{i=1}^{n} \exp(\mu^{\mathrm{y}_i} + \sum_{k=1}^{g} \beta_k^{\mathrm{y}_i} \cdot \mathrm{x}_{\mathrm{ki}}) / (\sum_{j=1}^{m} \exp(\mu^j + \sum_{k=1}^{g} \beta_k^j \cdot \mathrm{x}_{\mathrm{ki}})).$$

The multinomial logistic regression procedure optimizes the above likelihood over the unknown parameters in order to find those parameters that are most likely to have given rise to the data.

The target variables for the current and default transition models are shown above in Figure 4 and Figure 5. The independent variables used in the models are described in the following section. Twelve models were built, six for the current (C) transitions and six for the Default (D) transitions. Three products are modeled: fixed rate 30-year term, fixed rate 15-year term and adjustable rate mortgages. Each of the three products are further sub-divided if they are a result of SR. The model development was completed using a train/validate approach. A random sample of the data is used to train the multinomial model, to determine inclusion and exclusion of explanatory variables, and to calculate model parameters. The remaining sample, the validation data, is used as a final validation step to test the predictive power of the final model.

To generate the random sample, random numbers were added to the dataset at the case level using a random number generator. The random numbers were drawn from a uniform distribution between 0 and 1. Based on these random numbers, 70% of the cases were assigned to the train dataset, and 30% were assigned to the validation dataset.

There are approximately 33 million single-family mortgages insured by FHA originated between the first quarter of fiscal year 1975 and the third quarter of fiscal year 2017. Sampling enhances the efficiency of model estimation. In predictive modeling, a choice-based sample is commonly used for large populations with relatively rare events of interest. We use a sampling process for estimating the transition equations where the sampling rates are determined by the ending condition of each mortgage at each period.

For the transition models with the initial condition of C, we sample ending conditions using the following sampling percentages:

Table 16: Current Transition Model Sampling Percentages

Ending Condition	Sampling Percentage
Current (C)	2.5%
Current with Self-Cure (CXS)	100%
Current with Mortgage Modification (CSM)	100%
Default/Claim (DCLM)	100%
Pre-payment (PRE)	50%
Streamline Refinance (SR)	50%

For transition models with the initial condition of D, we sample 50% of the records with ending condition of D. For all other ending conditions, we used 100% of the data.

Section 2: Transition Model Explanatory Variables

Multiple categories of explanatory variables were used in development of the transition models.

- Fixed initial mortgage characteristics: market rate, initial mortgage size, spread at origination
- Fixed initial borrower characteristics: down payment assistance, first-time home buyer, credit score, cohort year
- Property characteristics: the number of living units, initial home values
- Dynamic variables based on mortgage information: prior default indicator, prior mortgage modification, LTV ratio, interest rate spread, TEI (expense to income ratio), mortgage period

- Dynamic variables derived by combining mortgage information and external economic data: spread, spread at origination
- Dynamic macroeconomic variables: ten-year average unemployment rate, change in the unemployment rate, HPI, treasury rates, GDP measures
- Geographic variables: judicial state, collateral state

The overall percentage of records in each final condition category for the initial condition of Current is shown in the table below.

Table 17: Distribution of Final Condition – Current Transition Models

Final Condition	Percentage
CXS	0.29%
DCLM	0.99%
CXM	0.02%
END	3.01%
C	95.70%

The overall percentage of records in each final condition category for the initial condition of Default is shown in the table below.

Table 18: Distribution of Final Condition - Default Transition Models

Final Condition	Percentage
CLM	6.13%
CXM	5.39%
CXS	11.57%
END	1.38%
D	75.53%

Section 3: Model Validation

Model validation was accomplished applying the model structure developed using the training set to the validation dataset. The application of the model to the validation data produces the probability of each type of transition. The actual target variable is then compared to the predicted target variable to ensure the model fits the transition process without over-fitting the actual data.

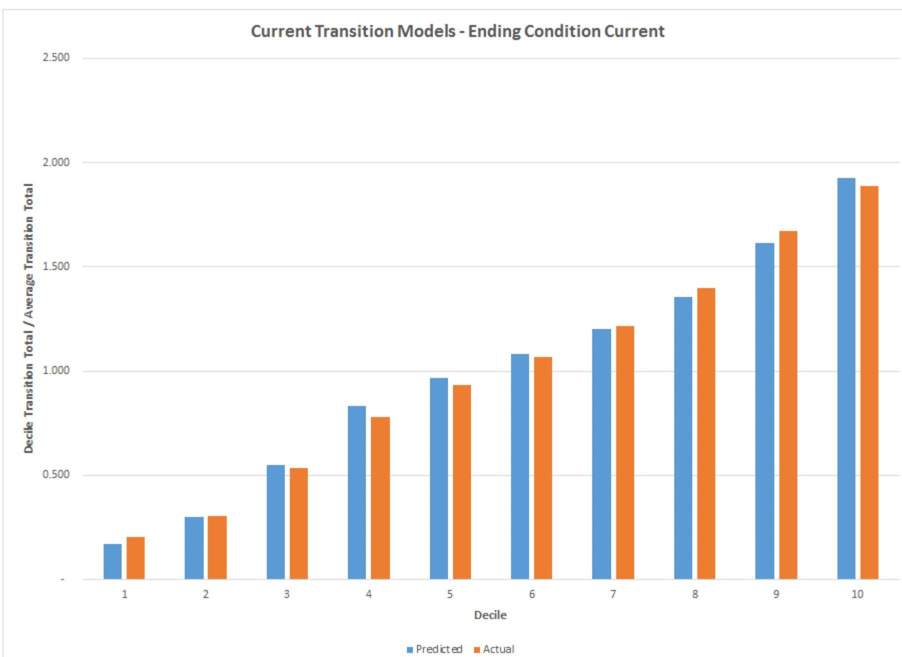
Specifically, for the final condition transition state, we calculate the actual transition rate and the predicted transition rate. The actual transition is 1.0 for the final transition state of the record and 0.0 for all other transition states. The probability of each final transition state for each record in the validation dataset is derived from the model parameters. The sum of all predicted final condition transition states' probabilities is 1.0 for each record.

Decile charts are then created for each final condition transition state. All records are sorted, or ranked, in increasing order by the predicted probability. Ten equal sized decile groups are created with 10% of the records in each group. The sum of the actual probability and the sum of the predicted probability for each ending condition within each decile is calculated. The total number of actual and predicted transitions are 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.

Current Transition Models

The validation chart for the ending condition of Current is shown below.

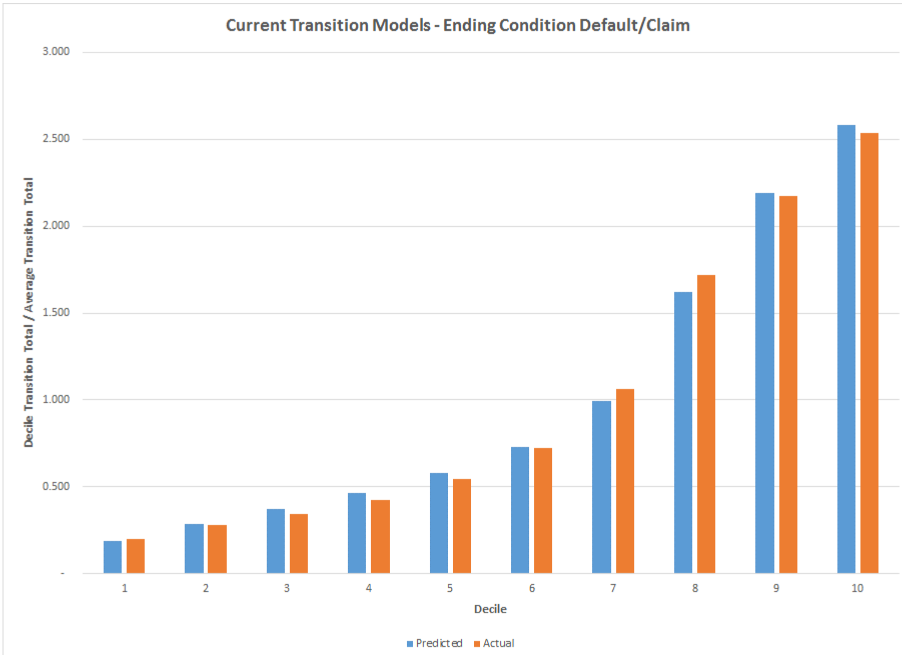
Figure 6: Current Transition Model Validation - Ending Condition Current



The spread in prediction of the ending condition of Current has a range of roughly 10 to 1. In addition, the actual and predicted ratio by decile for ending condition of Current are consistent.

The validation chart for the ending condition of Default/Claim is shown below.

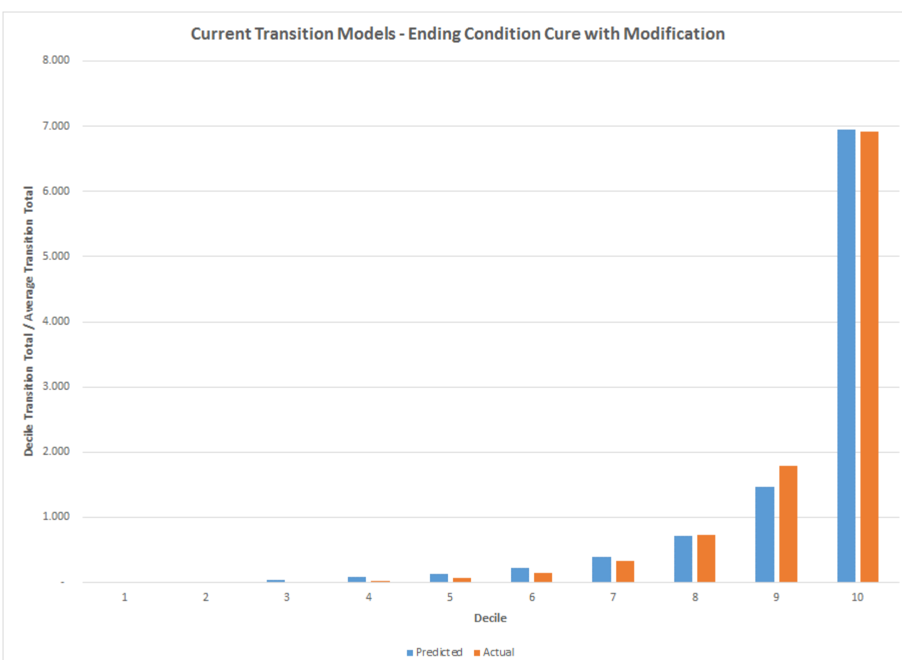
Figure 7: Current Transition Model Validation - Ending Condition Default/Claim



The spread in prediction of the ending condition of Default/Claim has a range of approximately 13 to 1. In addition, the actual and predicted ratio by decile for ending condition of Default/Claim are consistent.

The validation chart for the ending condition of Cure with Modification is shown below.

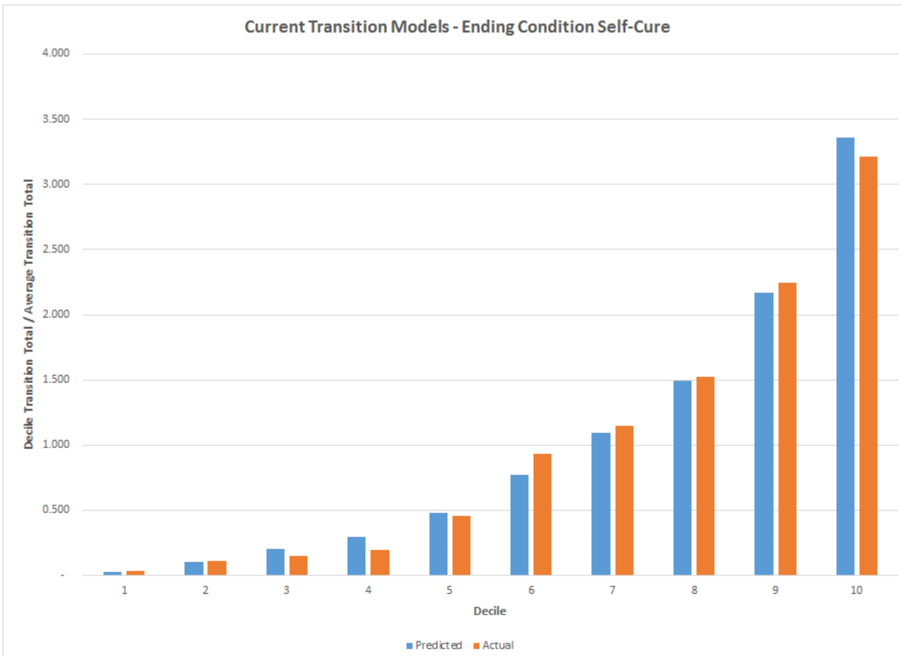
Figure 8: Current Transition Model Validation - Ending Condition Cure with Modification



The number of CXM ending conditions in the historical data is relatively small, so the validation results are volatile. However, there is a significant spread in segmentation between deciles, and there is also a consistent relationship between the actual and predicted transitions by decile.

The validation chart for the ending condition of Self-Cure is shown below.

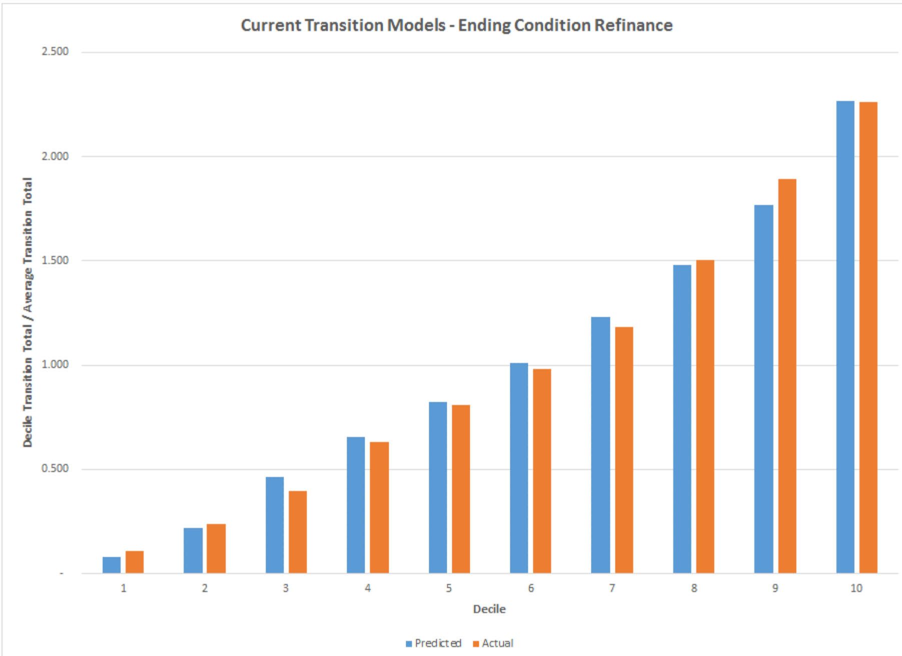
Figure 9: Current Transition Model Validation - Ending Condition Self-Cure



The spread in prediction of the ending condition of Self-Cure has a range of approximately 100 to 1. In addition, the actual and predicted ratio by decile for ending condition of Self-Cure are consistent.

The validation chart for the ending condition of Refinance is shown below.

Figure 10: Current Transition Model Validation - Ending Condition Refinance

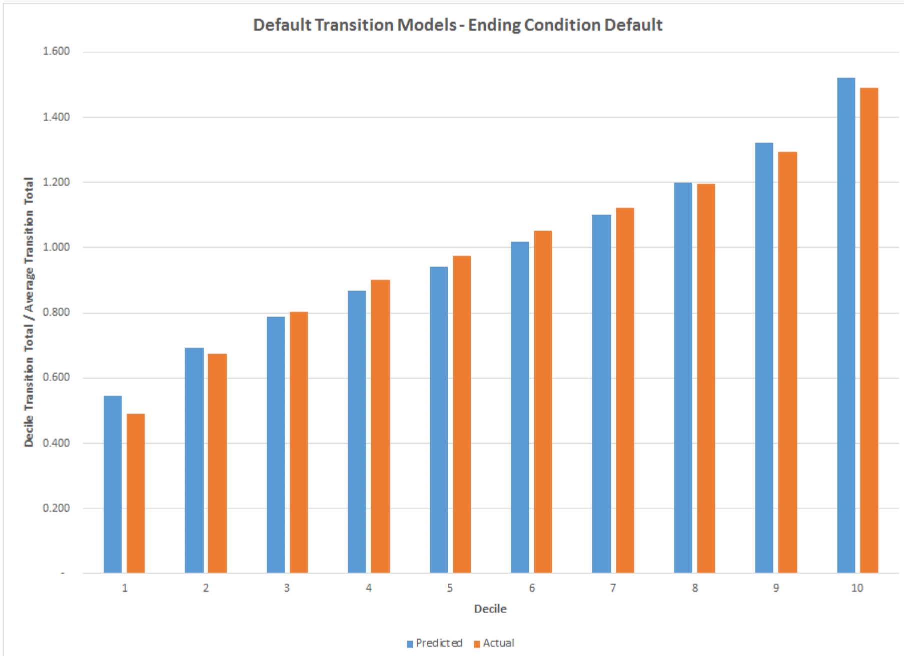


The spread in prediction of the ending condition of Refinance has a range of approximately 25 to 1. In addition, the actual and predicted ratio by decile for ending condition of Refinance are consistent.

Default Transition Models

The validation chart for the ending condition of Default is shown below.

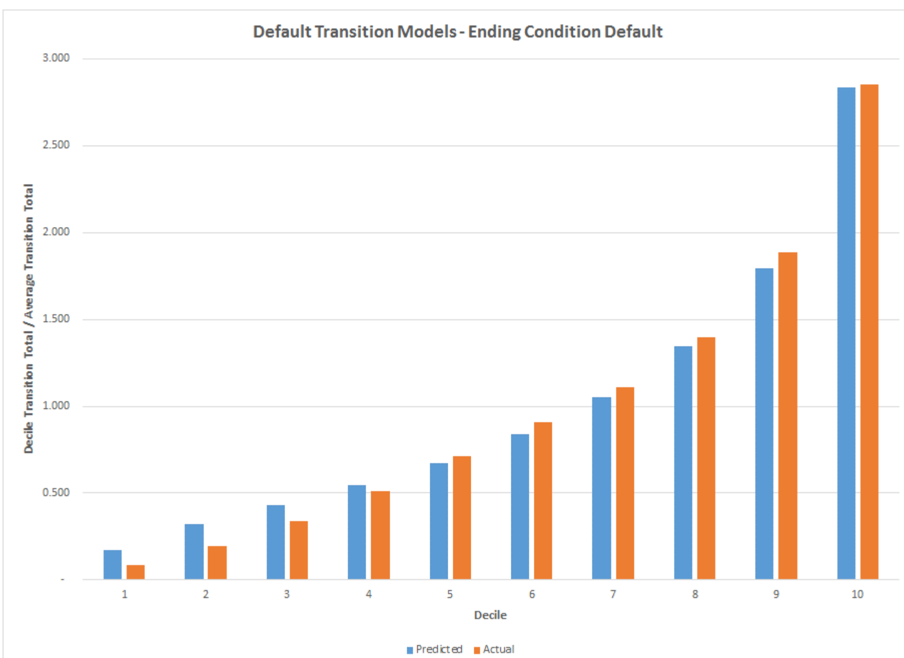
Figure 11: Default Transition Model Validation - Ending Condition Default



The spread in prediction of the ending condition of Default has a range of roughly 3 to 1. In addition, the actual and predicted ratio by decile for ending condition of Default are consistent.

The validation chart for the ending condition of Claim is shown below.

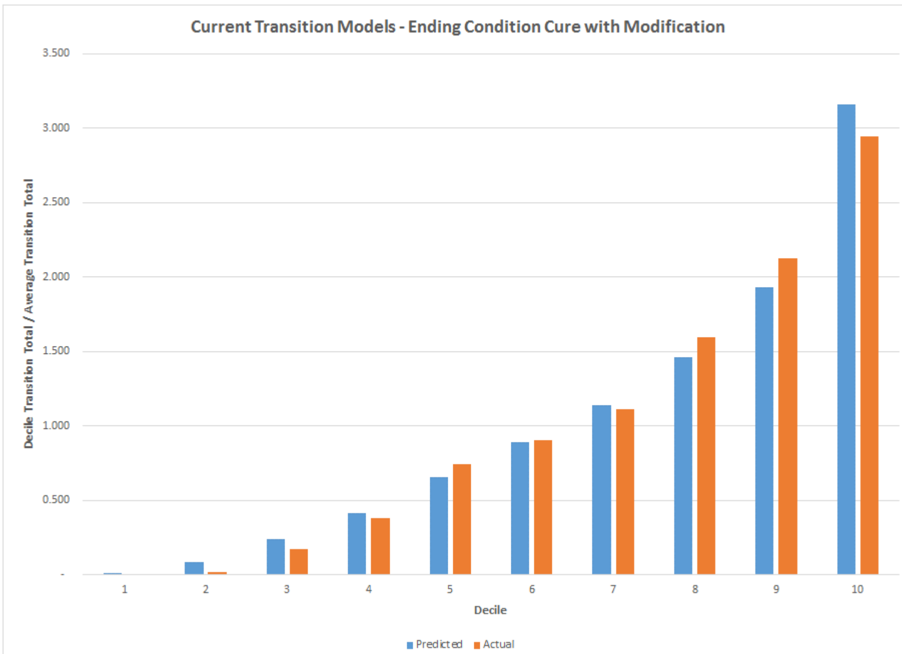
Figure 12: Default Transition Model Validation - Ending Condition Claim



The spread in prediction of the ending condition of Claim has a range of approximately 20 to 1. In addition, the actual and predicted ratio by decile for ending condition of Claim are consistent.

The validation chart for the ending condition of Cure with Modification is shown below.

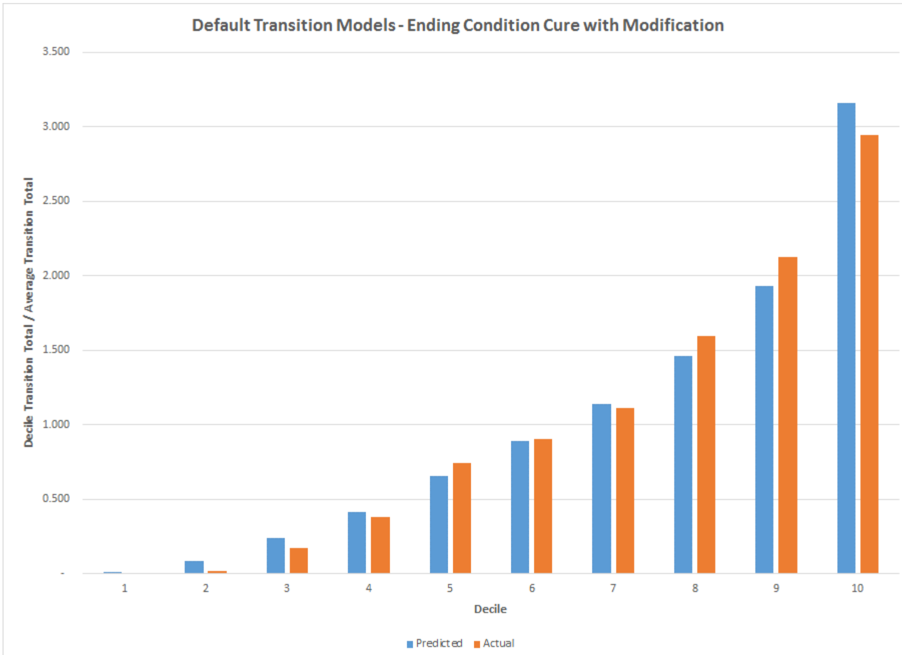
Figure 13: Default Transition Model Validation - Ending Condition Cure with Modification



The number of CXM ending conditions in the historical data is relatively small, so the validation results are volatile. However, there is a significant spread in segmentation between deciles, and there is a consistent relationship between the actual and predicted transitions by decile also.

The validation chart for the ending condition of Self-Cure is shown below.

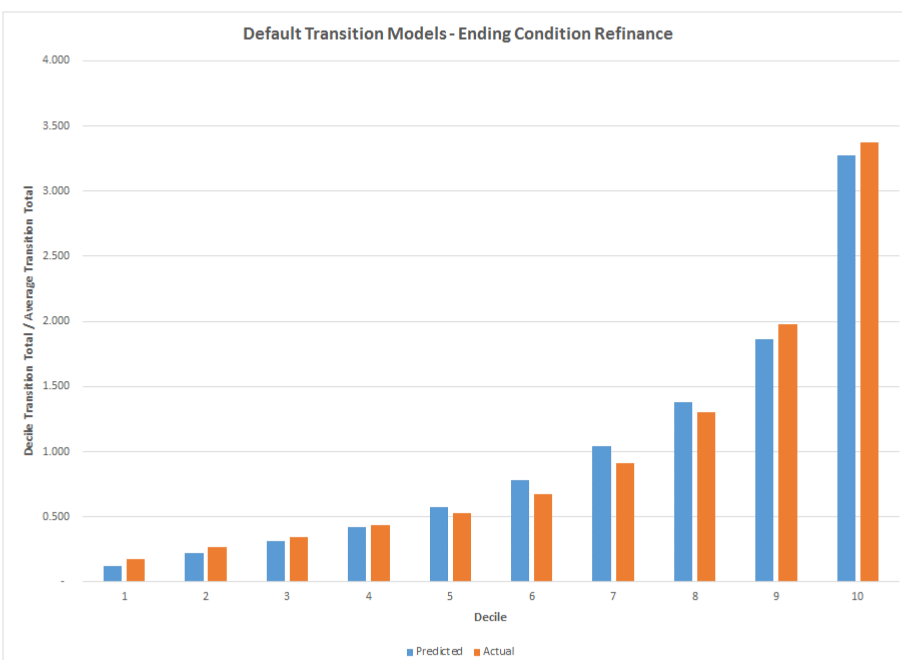
Figure 14: Default Transition Model Validation - Ending Condition Self-Cure



The spread in prediction of the ending condition of Self-Cure has a range of approximately 15 to 1. In addition, the actual and predicted ratio by decile for ending condition of Self-Cure are consistent.

The validation chart for the ending condition of Refinance is shown below.

Figure 15: Default Transition Model Validation - Ending Condition Refinance



The spread in prediction of the ending condition of Refinance has a range of approximately 22 to 1. In addition, the actual and predicted ratio by decile for ending condition of Refinance are consistent.

Appendix C: Loss Severity Models

This appendix describes the loss severity models used in this analysis. One of the primary sources of variation in the MMIF performance has been the loss severity experienced on mortgages that terminate as claims. In the case of a single mortgage, net loss is defined as the difference between the acquisition cost to HUD (acq_cost_to_HUD) from the IDB table and the recoveries realized by FHA on properties owned. We predict the net loss by modeling the probability of the type of claim that develops, modeling separately the loss for each type of claim and the recovery for REO claims.

In this appendix, we also summarize the model specifications, describe the explanatory variables used and provide validation exhibits for the final models.

Model Specifications

Typically, when an FHA-endorsed mortgage terminates as a claim, the property is conveyed to FHA, and FHA makes a payment to the lender to settle the claim and acquire the underlying property. That is, the underlying house becomes real estate owned, or REO. The claim payment FHA makes to the servicer, known as the acquisition cost, consists of three components:

1. the outstanding unpaid principal balance on the mortgage;
2. the foregone interest advanced by the servicer as a result of the mortgage default; and
3. legal and administrative costs paid by the servicer associated with foreclosure, including any expenses associated with the cost of repairing or maintaining the property prior to conveyance.

The formula for acquisition cost is:

Acquisition Cost = Unpaid Principal Balance + Foregone Interest + Foreclosure Expense

Following acquisition, FHA attempts to sell the property, sometimes at a reduced price in order to assist low-income prospective homebuyers in achieving homeownership. During the period when the property is held by FHA, but not yet sold, FHA incurs various holding costs associated with maintenance, repairs, tax payments and expenses incurred in preparing the property for sale. Upon sale of the collateral property, FHA receives the sale price less any sales expenses. In sum, the net loss amount is the net amount that FHA cannot recoup from this process:

Net Loss = Acquisition Cost + Holding Cost - Sale Price + Sale Expense

Table 19 shows the distribution of different types of FHA claim terminations. Conveyance refers to the foreclosure procedure discussed above, wherein the property is conveyed to FHA after foreclosure is completed. This is the most common type of claim.

FHA permits pre-foreclosure sales (PFS) as an alternative to the foreclosure process. In the case of a PFS, the property is sold by the borrower without the foreclosure process being completed, or even started in some cases. Instead of acquiring the foreclosed house, FHA directly pays the loss amount claimed by the lender. The loss amount of a PFS case is reported as an acquisition cost to FHA. By 2012, the percentage of PFS was just under 24%. Since then, the percentage of PFS has decreased to under 9%.

There was a significant volume of note (non-performing mortgage) sales from fiscal year 2003 through fiscal year 2006. From fiscal year 2007 to fiscal year 2012, there were few note sales. By 2014, however, the percentage of note sales rose above 27%. In these cases, the expenses of foreclosure procedures and subsequent house sales are avoided by FHA. Note sales are discretionary and highly unpredictable. For forecasting purposes, we use a note sale override to incorporate recent note sale transactions. We do not model note sales as a continuing program.

FHA changed its servicing guide in 2013 to allow foreclosure without conveyance. This consists of a TPS during the foreclosure auction. A third party, instead of FHA, acquires the property directly from the foreclosure auction. This process allows FHA to avoid the process and expenses of property disposition after conveyance including any associated holding costs.

Table 19: Percentage of Claim Termination Types by Fiscal Claim Year

Claim Year	Conveyance (REO)	Note Sales	Third Party Sales (TPS)	Pre Foreclosure Sale (PFS)
1999	94.87%	0.11%	0.00%	5.02%
2000	95.06%	0.09%	0.00%	4.85%
2001	95.03%	0.01%	0.00%	4.97%
2002	94.33%	0.00%	0.00%	5.66%
2003	86.74%	8.34%	0.00%	4.92%
2004	85.57%	8.41%	0.00%	6.02%
2005	83.30%	9.79%	0.00%	6.91%
2006	89.37%	2.83%	0.00%	7.80%
2007	92.80%	0.00%	0.00%	7.20%
2008	93.06%	0.00%	0.10%	6.83%
2009	90.06%	0.00%	0.01%	9.93%
2010	84.46%	0.31%	0.00%	15.22%
2011	76.29%	1.17%	0.02%	22.51%
2012	71.24%	1.32%	3.59%	23.85%
2013	56.74%	17.66%	6.86%	18.74%
2014	42.75%	27.32%	15.38%	14.55%
2015	54.55%	16.32%	17.95%	11.18%
2016	52.09%	12.16%	25.78%	9.97%
2017	48.50%	9.87%	32.80%	8.83%

Table 20 shows the average net loss for the combined foreclosure (REO and TPS) and PFS claims by claim fiscal year for 1991 to 2017. The average net loss increased from 1991 to 2012, reaching a high of almost $129,000 in fiscal year 2012. Since 2012, the average net loss has decreased.

Table 20: Historical Average Net Loss

Claim Year	Average Net Loss
1991	61,076
1992	62,675
1993	65,876
1994	68,629
1995	70,921
1996	73,613
1997	78,308
1998	81,260
1999	84,223
2000	85,865
2001	87,042
2002	88,196
2003	88,248
2004	89,850
2005	91,200
2006	96,330
2007	101,695
2008	109,991
2009	118,359
2010	128,091
2011	128,687
2012	128,741
2013	120,959
2014	104,382
2015	107,997
2016	106,866
2017	78,539

Net Loss Severity Model Specification

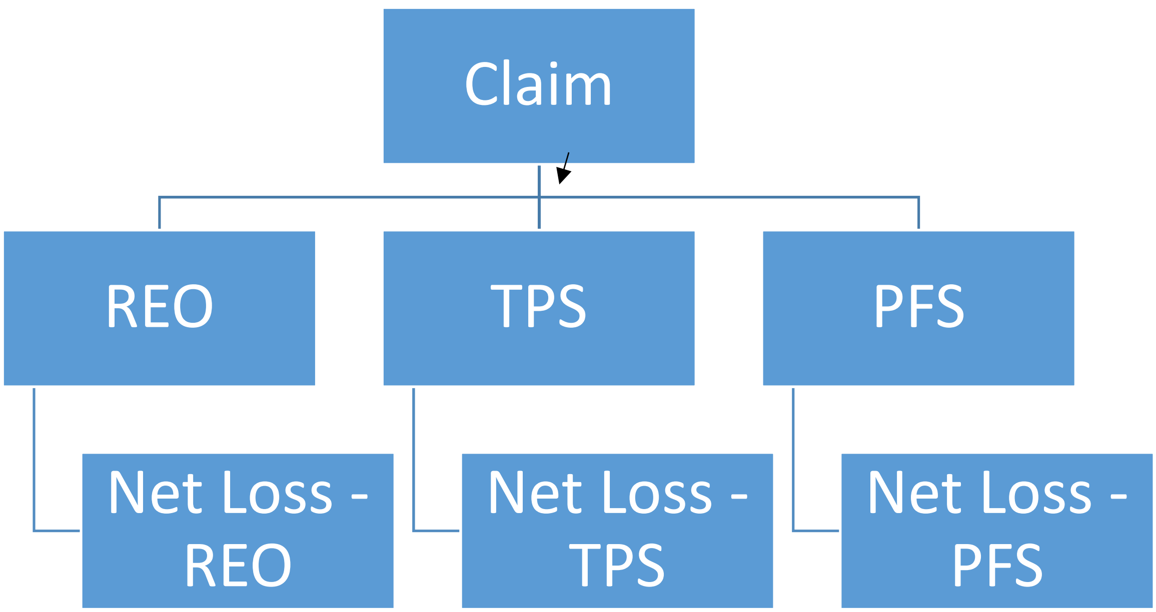
As described above, there are several components of the total loss amount, and each component is influenced by a number of factors. Foregone interest depends on the interest rate on the mortgage and on the length of the default-to-claim lag. Foreclosure expenses can vary depending on whether a judicial foreclosure process is used that can lengthen the time period of the foreclosure process. Repair expenses may be a function of the financial condition of the borrowers, which we proxy by credit scores. Sale prices are influenced by the house price appreciation since origination and by the prevailing local housing market conditions during the default and property disposition periods. Several components of the net loss amount involve expenses that are fixed across foreclosed properties. Hence, mortgages with lower values are more likely to realize higher net losses as a percentage of the sales amount, as the amount of the recovery will be smaller relative to higher value homes.

As shown in Table 19, the distribution between REO/TPS (foreclosure) and PFS was relatively stable through fiscal year 2009. Beginning in fiscal year 2010, there were widespread house price declines and a higher volume of defaults. As a result, the foreclosure claim process has been lengthened and foreclosure claims have been delayed, while the PFS process has remained relatively stable. From fiscal year 2009 to 2012, the PFS share increased significantly. Since fiscal year 2012, the PFS share has declined. Moreover, the proceeds recovered from REO and PFS sales differ significantly. To achieve more accurate estimates of net loss severities, we adopted a three-stage model:

1. Model to predict the development of an REO, TPS or PFS claims
2. Model of gross loss severity conditional on claim being an REO, TPS or PFS claim
3. Model of recovery amount conditional on claim being a foreclosure REO claim

The net loss severity model follows the flowchart in Figure 16.

Figure 16: Net Loss Severity Model



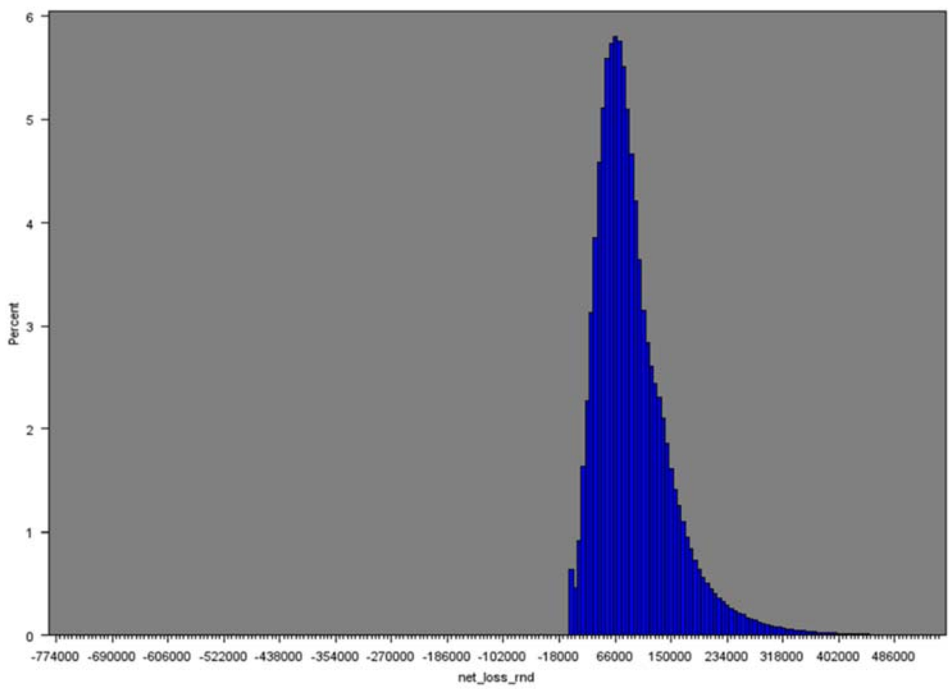
First, we estimate the probability that a claim is settled by the REO, TPS, or PFS process. To model the first-stage choice event, we used a multinomial logistic model to estimate the probability of the claim settlement type.

Second, we estimate the gross loss severity as a function of all the same explanatory factors used in the multinomial model. The gross loss severity distribution is smooth and continuous with a long right tail. Thus, we use a GLM approach with a Gamma error structure and a log link function to develop the gross loss severity models. The Gamma structure is used for each gross loss severity model (REO, TPS, PFS). For REO claims, a recovery model estimating sales proceeds net of the Capital Income Expenses is built using a similar framework.

In addition to the loss severity models described above, we also developed a set of models to project loss mitigation costs. Implemented in 1996, the loss mitigation program was designed as a way to help financially stressed borrowers stay in their homes. Loss mitigation costs can be incurred from modifying the terms of the mortgage, allowing a borrower to refinance into a new mortgage and writing off a portion of the unpaid principal (partial claim), or a forbearance, which is a written agreement with the borrower which includes a plan to reinstate the mortgage. The loss mitigation cost is modeled using a GLM with a Gamma error structure and an offset term of log(unpaid balance/1000).

Figure 17 shows the distribution of the net loss.

Figure 17: Net Loss Distribution



Thus, the estimated net loss to the MMIF is the expected value of net loss of the different claim types:

$$\text{Net Loss} = Probability\ of\ REO * (\text{GrossLoss}_{REO} - \text{Recovery}) + Probablity\ of\ TPS * \text{NetLoss}_{TPS} + Probablity\ of\ PFS * \text{NetLoss}_{PFS}$$

The probabilities of REO, TPS or PFS are predicted from the multinomial loss selection model. The $\text{GrossLoss}_{\text{REO}}$, $\text{NetLoss}_{\text{PFS}}$ and $\text{NetLoss}_{\text{TPS}}$ are predicted from the loss severity models described above.

Estimation Sample

The sample used to estimate the loss severity model consists of mortgage level data from the FHA single-family data warehouse. The available data covers the period from the first quarter of fiscal year 1975 to the fourth quarter of fiscal year 2017. In total, there are over 2.3 million claims in the FHA database.

The models were built using a traditional train/validate approach. A random sample of the data is used to train the models, and a second random sample is used to validate and refine the model parameters and to determine inclusion and exclusion of explanatory variables.

Explanatory Variables

Multiple categories of explanatory variables were used.

- Fixed initial mortgage characteristics: ARM adjustment period, mortgage product, interest rate, initial mortgage size, spread at origination
- Fixed initial borrower characteristics: down payment assistance, first time home buyer, credit score
- Property characteristics: the number of living units, initial home values
- Dynamic variables based on mortgage information: prior default indicator, prior mortgage modification, LTV ratio, interest rate spread, TEI, age of mortgage
- Dynamic variables derived by combining mortgage information and external economic data: spread, spread at origination
- Dynamic macroeconomic variables: 10-year average unemployment rate, change in the unemployment rate, prior year unemployment rate, HPI, state unemployment rate relative to countrywide unemployment rate, CMT rates, state unemployment rate
- Geographic variables: Judicial state, collateral state

The explanatory variables used in the loss severity model are the same as those used in the mortgage status transition models.

Model Validation

Model validation was accomplished by applying the models developed using the training set to the validation dataset. The application of the models to the validation data produces the probability of each type of claim settlement type and a predicted net loss. The actual target variable is then compared to the predicted target variable to ensure the model fits the claim settlement process and net loss process without over-fitting the actual data.

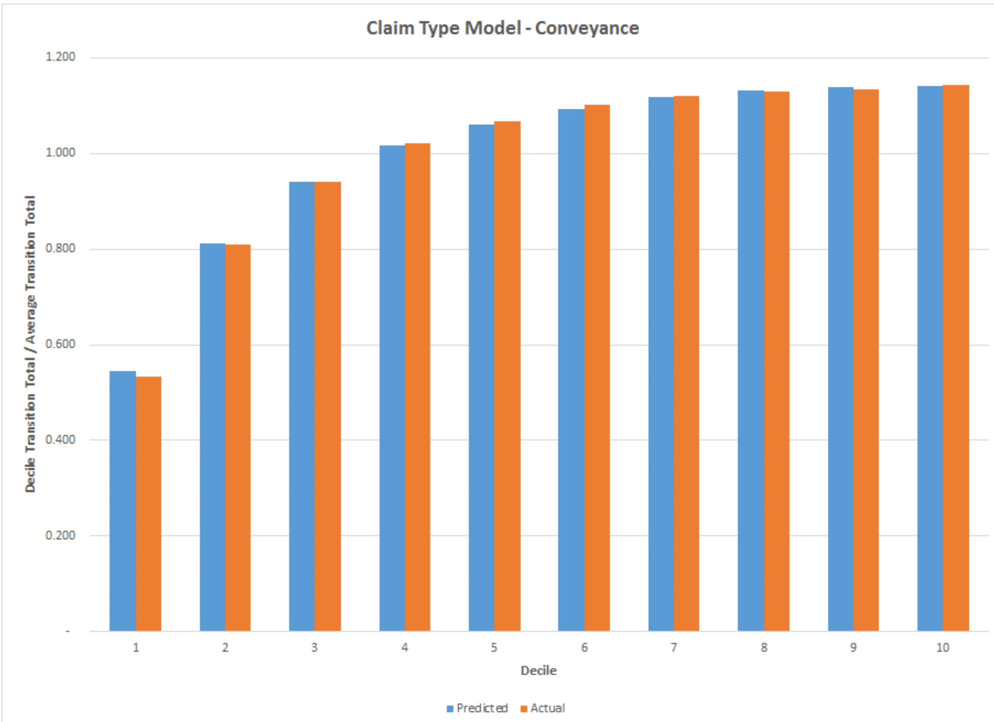
Specifically for the loss settlement models, for the final loss settlement type we calculate the predicted probability of the settlement type. The actual settlement type is 1.0 for the final type of claim and 0.0 for all other claim types. The probability of each claim type for each record in the validation dataset is derived from the model parameters. The sum of all predicted claim type probabilities is 1.0 for each record.

For the net loss severity models, we calculate a predicted net loss. We also summarize the actual net loss for each claim. The predicted loss severity for each record in the validation dataset is derived from the model parameters.

Decile charts are then created for each final claim type selection and each net loss. All records are sorted, or ranked, in ascending order by the predicted value. Ten equal-sized decile groups are created with 10% of the records in each group. The sum of the actual probability and the sum of the predicted probability for each claim type within each decile is calculated for the claim type models. The sum of the actual net loss and the sum of the predicted net loss within each decile is calculated for the loss severity models. 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 chart for claim type model target conveyance (REO) is shown below.

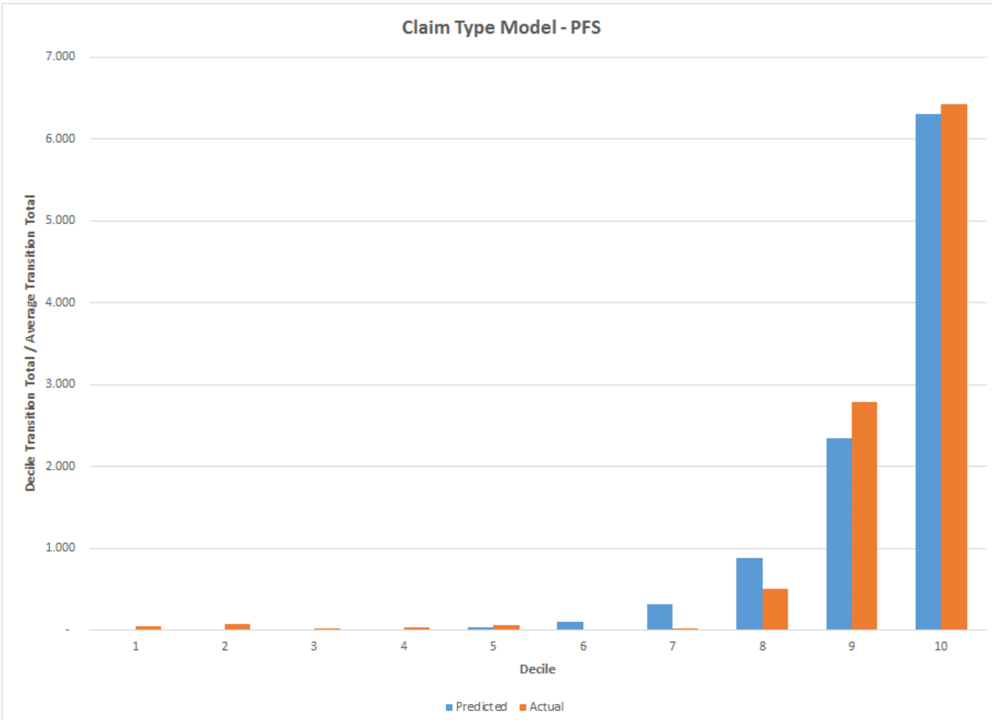
Figure 18: Net Loss Severity Claim Type Model Validation - REO



The spread in prediction for the REO claim type has a range of roughly 2 to 1. In addition, the actual and predicted ratio by decile for the REO claim type are consistent.

The validation chart for claim type model target PFS is shown below.

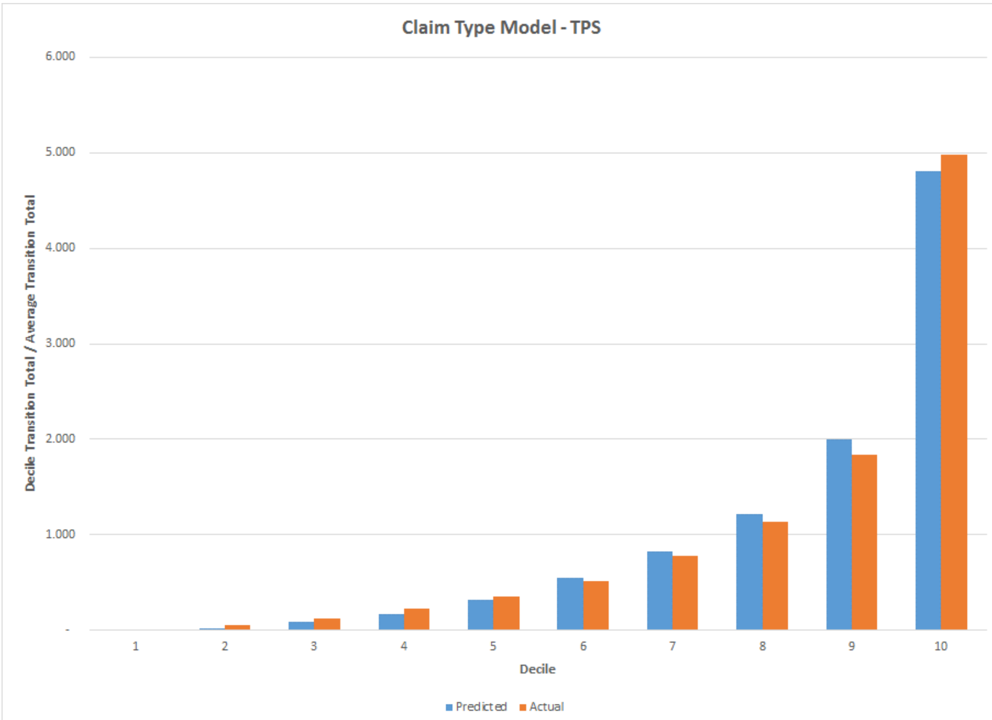
Figure 19: Net Loss Severity Claim Type Model Validation - PFS



The number of PFS claims are limited, and therefore the validation exhibits are volatile. However, the spread in prediction for the PFS claim type is significant, and the actual and predicted ratio by decile for the PFS claim type are consistent.

The validation chart for claim type model target TPS is shown below.

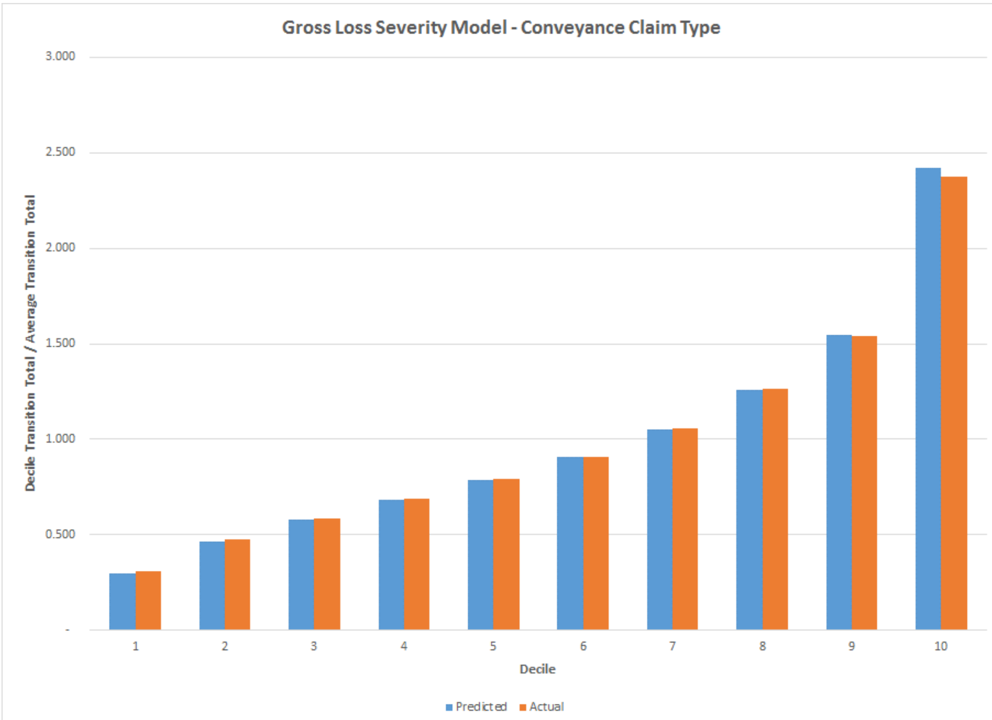
Figure 20: Net Loss Severity Claim Type Model Validation - TPS



The spread in prediction for the TPS claim type has a significant range. In addition, the actual and predicted ratio by decile for the REO claim type are consistent.

The validation chart for the REO gross loss severity model is shown below.

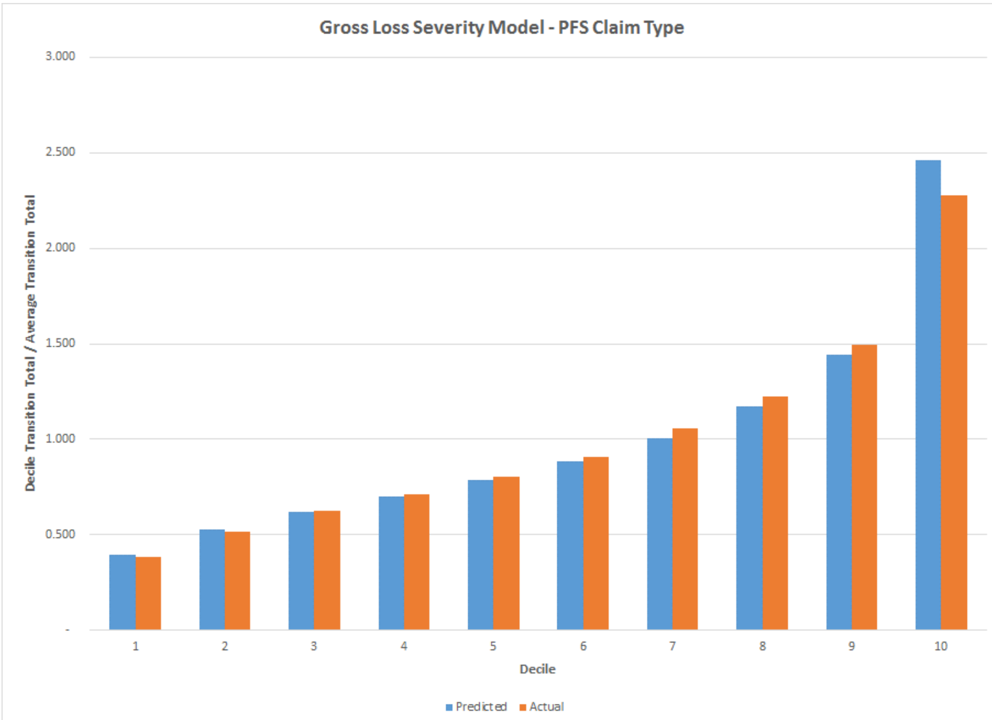
Figure 21: Gross Loss Severity Claim Type Model Validation - REO



The spread in prediction for the REO claim type has a range of approximately 8 to 1. In addition, the actual and predicted ratio by decile for the REO claim type are consistent.

The validation chart for the PFS net loss severity model is shown below.

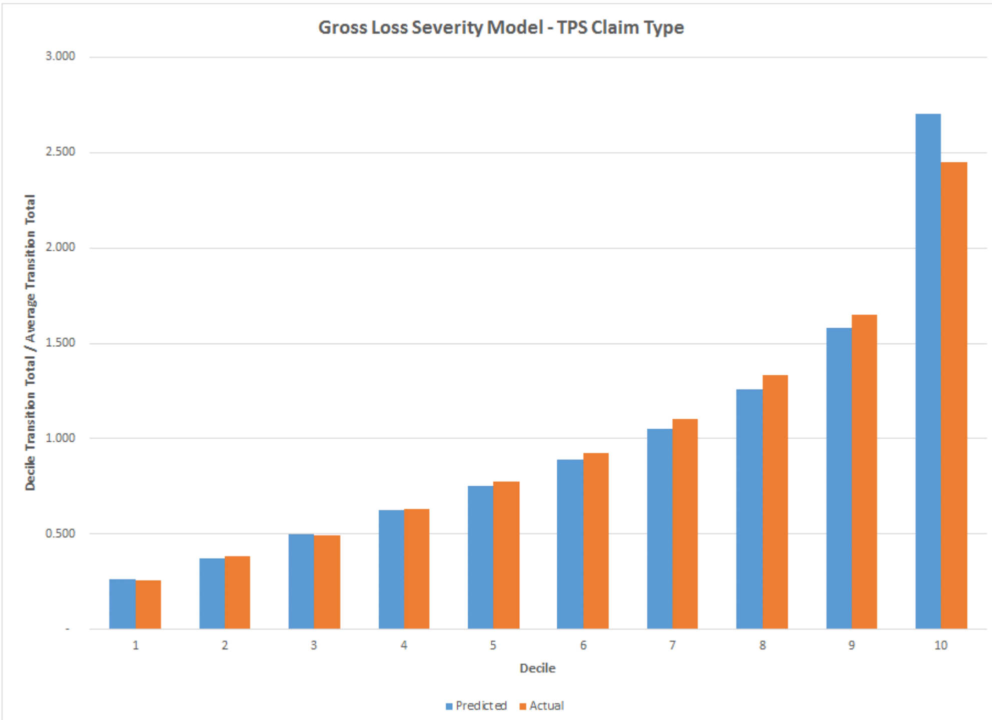
Figure 22: Net Loss Severity Claim Type Model Validation - PFS



The spread in prediction for the PFS claim type has a range of approximately 6 to 1. In addition, the actual and predicted ratio by decile for the REO claim type are consistent.

The validation chart for the TPS net loss severity model is shown below.

Figure 23: Net Loss Severity Claim Type Model Validation - TPS



The spread in prediction for the PFS claim type has a range of approximately 10 to 1. In addition, the actual and predicted ratio by decile for the REO claim type are consistent.

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 nine additional deterministic economic scenarios from Moody's. For this analysis, we used the Moody's September 2017 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
- 10-year CMT rate
- Commitment rate on 30-year fixed-rate mortgages
- Unemployment rates at the MSA, state, regional and national levels
- GDP

A summary of a portion of the economic data used in the OMB simulation is presented in Table 21. We used a quarterly frequency and local HPI and unemployment rate in deriving the Cash Flow NPV. The quarterly economic factors forecasted by Moody's are available from fiscal years 2017 through 2047.

Table 21: Summary of OMB Economic Assumptions

Fiscal Year	FHFA Purchase-Only Home Index	FHLMC Contract Rate on Conventional Mortgage Commitments	1-Year Treasury Rate (%)	10-Year Treasury Rate (%)	National Unemployment Rate (%)
2017	242.10	4.44	1.16	2.66	4.6
2018	252.52	5.19	1.94	3.28	4.4
2019	261.51	5.45	2.47	3.44	4.6
2020	269.36	5.85	3.01	3.78	4.7
2021	277.44	5.94	3.24	3.81	4.8
2022	285.21	6.00	3.33	3.83	4.8
2023	292.25	6.04	3.37	3.84	4.8
2024	299.45	6.06	3.39	3.84	4.8
2025	306.83	6.08	3.39	3.84	4.8
2026	314.50	6.09	3.39	3.84	4.8
2027	322.57	6.10	3.39	3.84	4.8

Source: OMB Economic Assumptions for the 2018 Fall Budget Baseline, March 2017

Alternative Scenarios

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

- Baseline
- Stronger Near-Term Growth
- 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 24 shows the future movements of the HPI under the baseline and the alternative economic scenarios. For the OMB projections, the HPI increases as a fairly steady rate throughout the entire projection period. For the Moody's Baseline Scenario, the HPI appreciation rate increases at a slower rate through 2022, at which time the rate of increase becomes greater than the OMB rate. The Moody's Baseline HPI projection is higher than the OMB baseline after 2024.

Figure 24: Paths of the Future National House Price Index in Different Scenarios

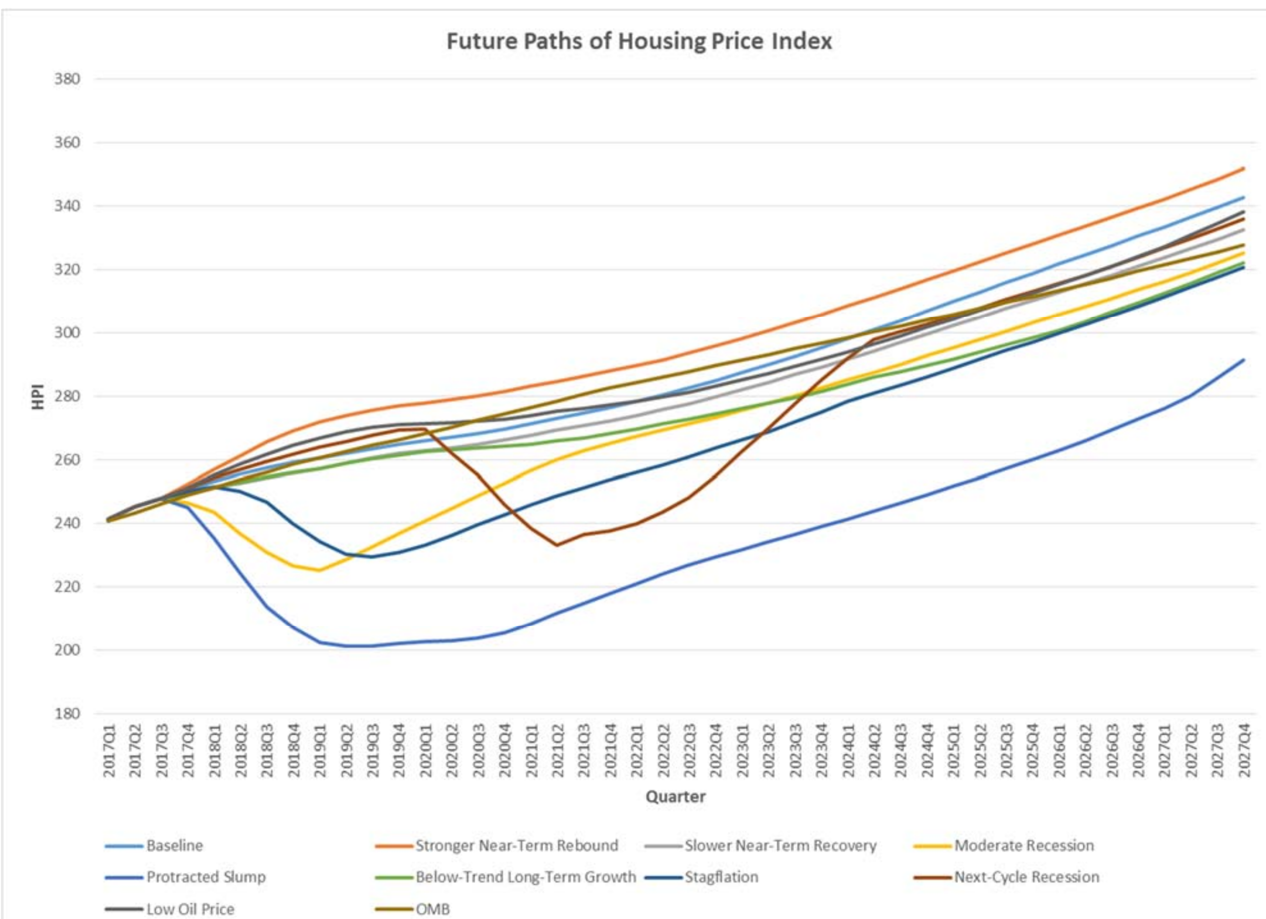


Figure 25 shows the forecasted mortgage rate of 30-year fixed-rate mortgages for the nine scenarios. OMB's forecast shows that the rate will rise steadily over the projection period to just over 6% by 2027. Moody's Baseline forecast for the 30-year fixed interest rate shows that the mortgage interest rate increases to just over 5.6% by 2020, and then hovers around a long-term average rate of around 5.5%. The OMB projection is a composite interest rate projection, whereas the Moody's projections are separate by mortgage product. Therefore, the trends in projection can be compared but the absolute value of the projected mortgage rates are not directly comparable. For the Moody's projections, we use the 30-year fixed rate as this represents the majority of the mortgage products sold.

Figure 25: Paths of the Future Mortgage Rate

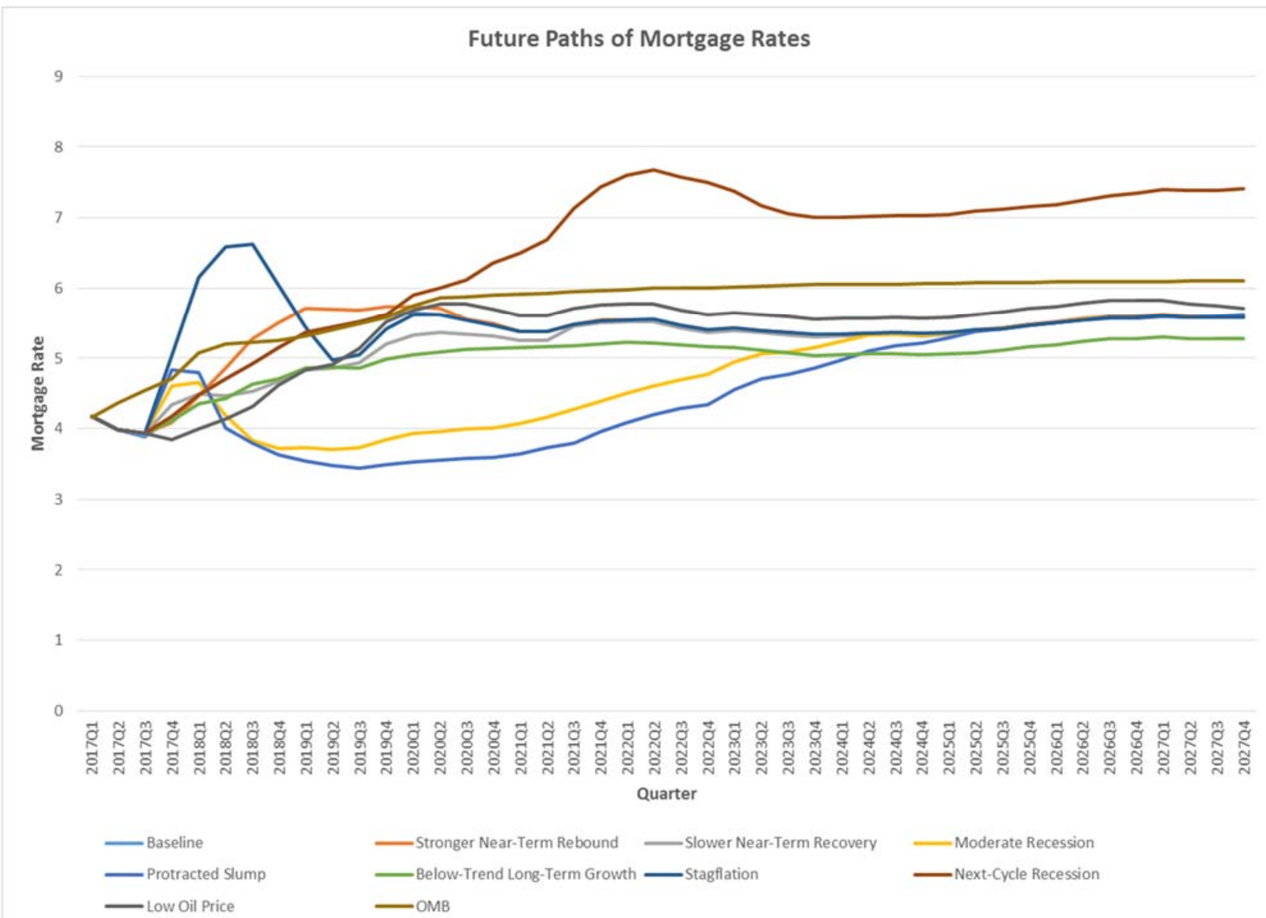
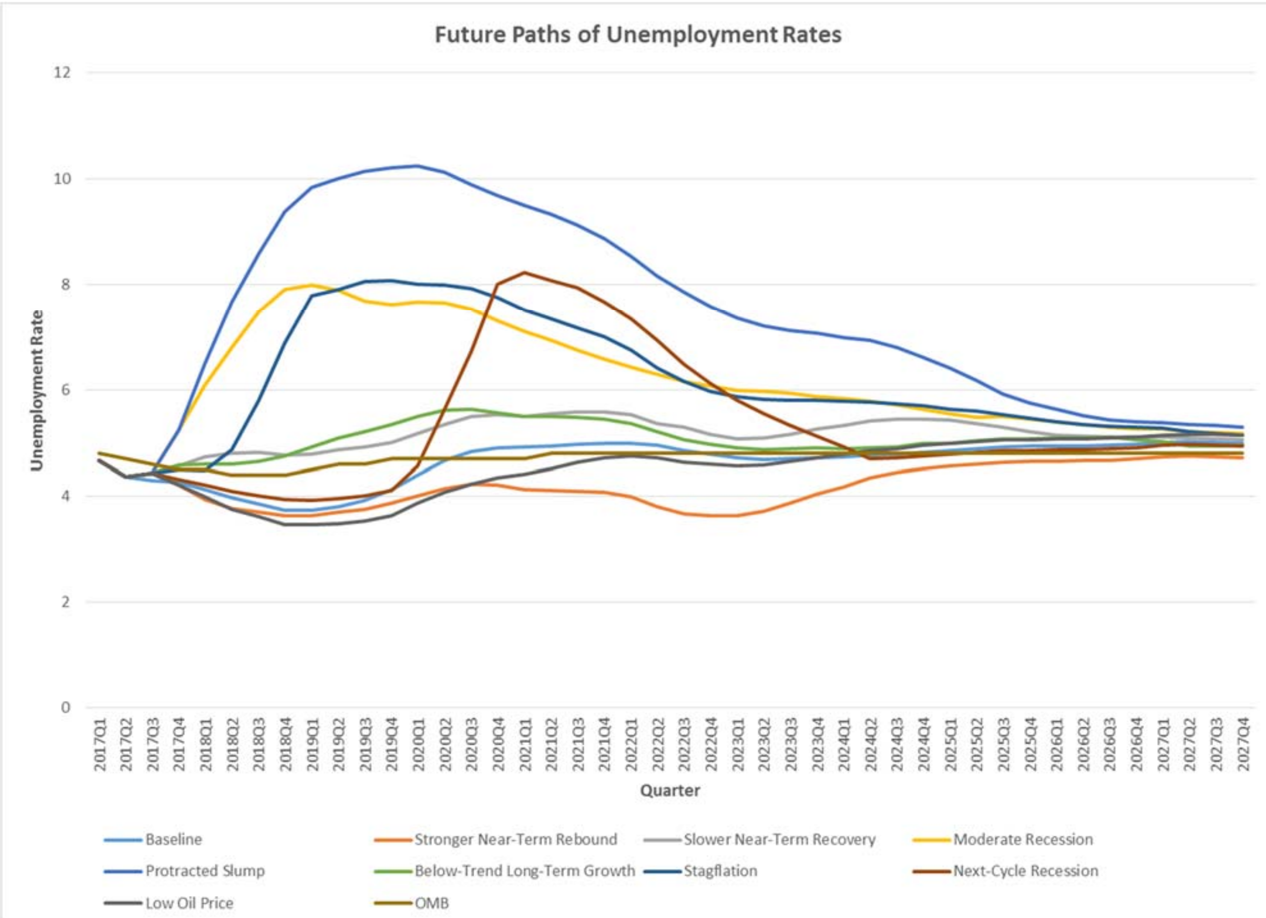


Figure 26 shows the forecasted unemployment rate under alternative economic scenarios. OMB projects the unemployment rate to essentially remain constant over the projection period, decreasing slightly to 4.4% by 2018 and then rising to 4.8%. The Moody's Baseline forecast projects that the unemployment rate will decrease to under 4% in 2019, and then increases to a long-term average of just over 5%.

Figure 26: Paths of Future National Unemployment Rate



Stochastic Simulations

This section describes the stochastic models which were fit to generate the economic variable simulations used in the analysis of the Forward Mortgage Portfolio.

The modeled economic variables 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
- GDP

Historical Data

A. Interest Rates

Figure 27 shows historical interest rates since the first quarter of 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 FRM rate (mr).

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

Figure 27: Historical Interest Rates (%)

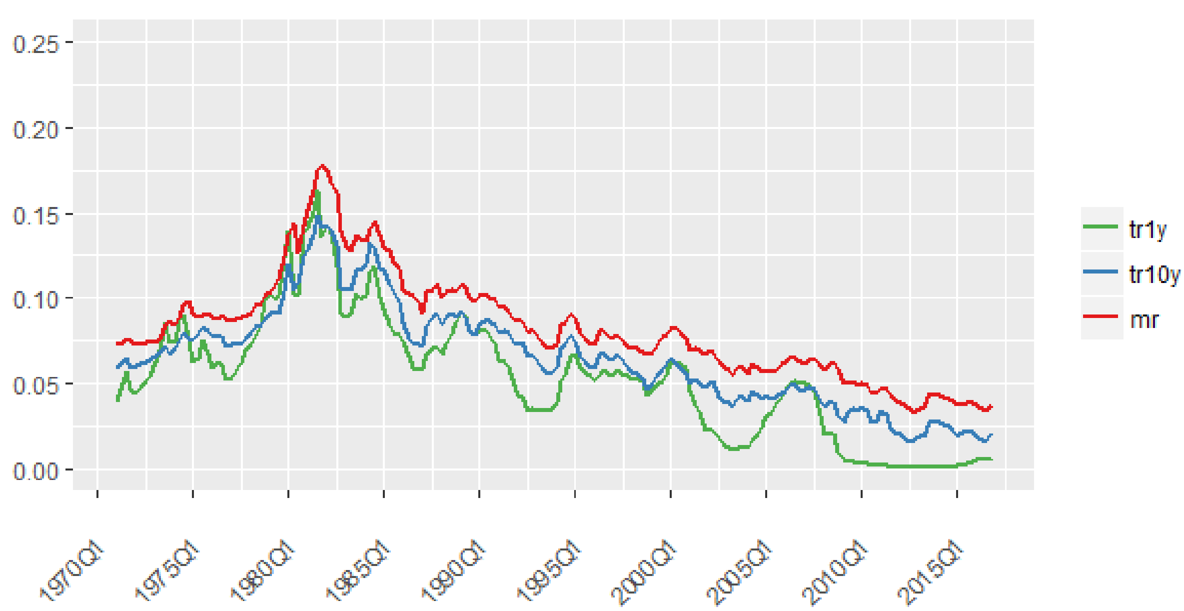
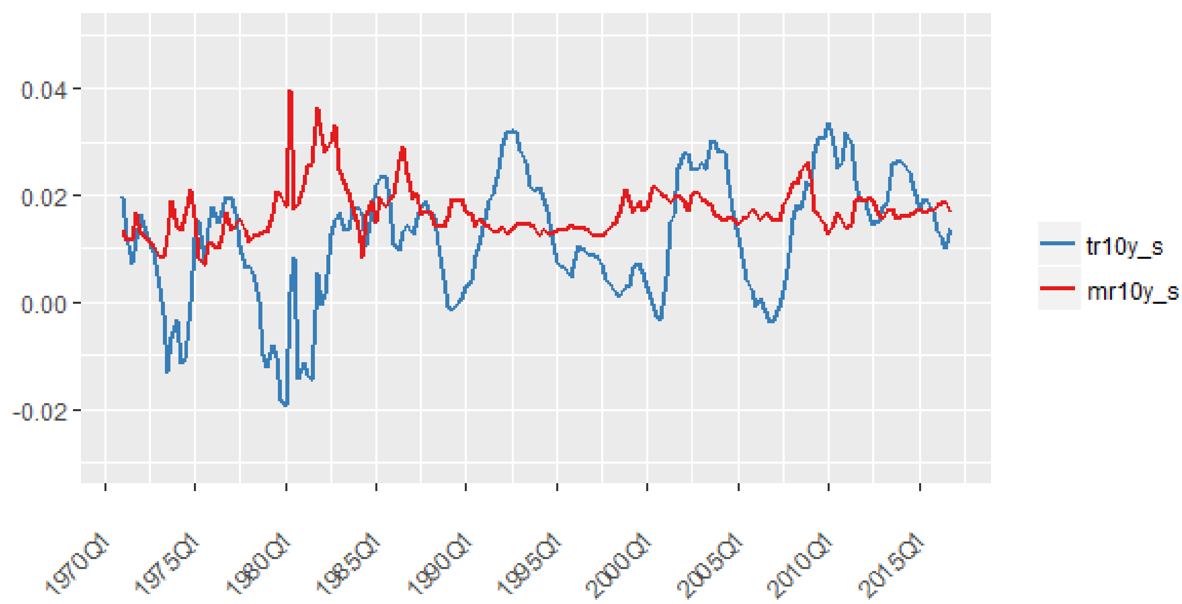


Figure 28 shows historical interest rate spreads, including the spread between 10-year and 1-year CMT rates (tr10y_s) and the spread between the 30-year mortgage rate and the 10-year CMT rate (mr10y_s). Both spreads have positive values for most of the historical periods with long cycles. Small positive and negative spreads typically correspond with economic downturns, such as those that occurred during the late 1970's through early 1980's. The spread of the mortgage rate over the 10-year CMT rate is always positive, reflecting the premium for credit risk.

Figure 28: Historical Interest Rate Spreads (%)



B. House Price Appreciation Rates

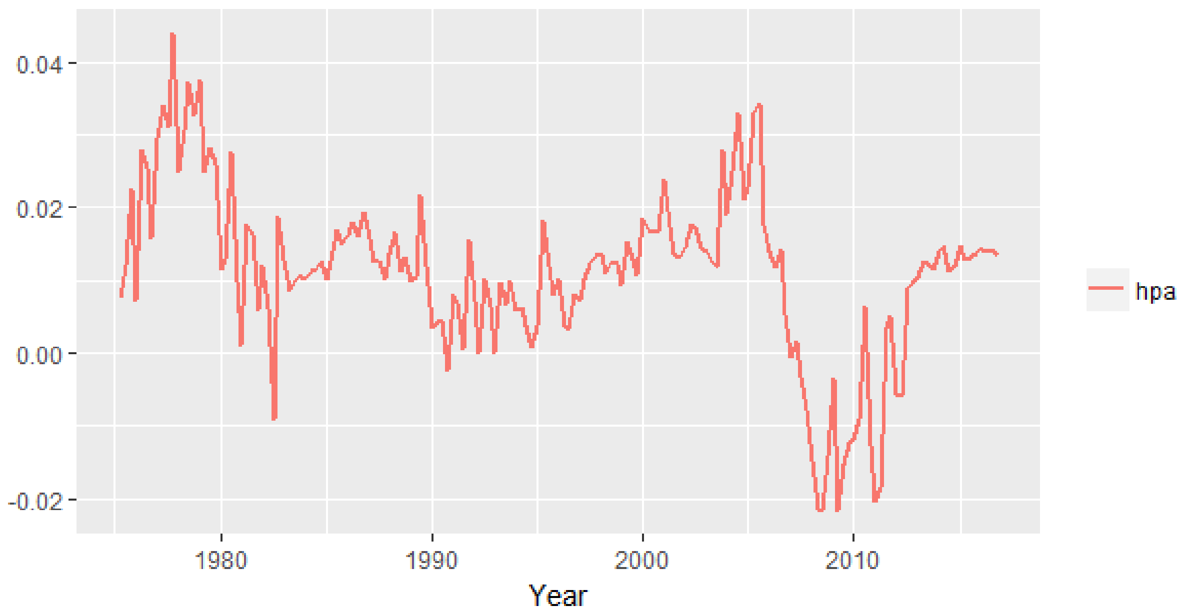
The national HPA rate is derived from the FHFA repeat sales HPI of purchase-only (PO) transactions. The PO HPI provides a reliable measure of housing market conditions, since it is based on repeat sales at market prices and does not use any appraised values.

The HPA series being modeled is defined as:

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

Figure 29 shows the national quarterly HPA from CY 1971 Q1 to CY 2016 Q4. The long-term average quarterly HPA is approximately 0.83% (an annual rate of 3.30%).

Figure 29: Historical Quarterly HPA



The HPA increased steadily before 2004, and the quarterly appreciation rate was around 1.13%. Subsequently, house prices rose sharply starting in 2004. The average quarterly house price appreciation rate was 1.87% during the subprime mortgage expansion period from 2004 to 2006, and reached its peak of 2.59% in the second quarter of CY 2005. After 2006, the average growth rate of house price became negative until 2011, when appreciation returned to a positive value. Table 22 shows the quarterly HPA by selected historical time periods.

Table 22: Average Quarterly HPA by Time Span

Period	Average Quarterly HPA
1991 – 2003	1.13%
2004 – 2006	1.87%
2007 – 2010	-1.23%
2011 – 2017	1.03%

Modeling Techniques

The primary modeling techniques used in developing the stochastic 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* 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* the AR component of the error term.

Description and examples of using an ARMA-GARCH model for time series analysis can be found in Engle and Mezrich (1995)[3].

1-Year CMT Rate

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

Table 23 shows the summary statistics of the historical 1-year CMT rates for two time periods, one from 1971 to current and the other from 1992 to current, as well as the simulated series. We can see that in the last 25 years, interest rates have been much more stable than in the past.

Table 23: Statistics for the 1-Year CMT Rates

Statistics	Since 1971	Since 1992	Simulations
Mean	5.34%	2.69%	5.13%
Standard Deviation	3.64%	2.27%	2.37%
Max	16.31%	6.71%	28.21%
95th Percentile	11.83%	5.94%	12.31%
90th Percentile	10.02%	5.66%	10.31%
50th Percentile	5.44%	2.12%	4.24%
25th Percentile	2.30%	0.36%	2.05%
10th Percentile	0.27%	0.15%	1.13%
5th Percentile	0.15%	0.12%	0.81%
Minimum	0.10%	0.10%	0.01%

[3] Engle, R. F. and J. Mezrich (1995), "Grappling with GARCH", *Risk Magazine*, 8 (9), 112 – 17.

An ARMA(2,4) parameterization was used to model the 1-Year CMT rate (*r1*) difference from the previous period. The model was estimated using data from the first quarter of CY 1971 to the third quarter of CY 2017. The process takes the following form:

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

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

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

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

The Full information maximum likelihood (FIML) method was used to estimate the parameters in equations (2) and (3). The results are presented in Table 24.

Table 24: Estimation Results for 1-Year CMT Rate Model

Parameter	Estimate	Std Dev	t-value	prob>t
μ	0.0003	0.0002	1.4052	0.1600
x_1	0.0424	1.5880	0.0267	0.9787
x_2	0.3361	1.3910	0.2416	0.8091
x_3	0.3517	1.5558	0.2261	0.8212
x_4	-0.4119	0.7487	-0.5502	0.5822
x_4	0.1358	0.4423	0.3070	0.7589
x_5	0.3051	0.3723	0.8195	0.4125
β_0	0.0000	0.0000	0.0110	0.9912
β_1	0.3094	0.0512	6.0382	0.0000
β_2	0.6896	0.0424	16.2677	0.0000
Pearson's GOF	0.9380			

The model based on these parameters is used to simulate the 1-year CMT rates for the forecast period starting in the fourth quarter of FY 2017. The model fit was evaluated 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

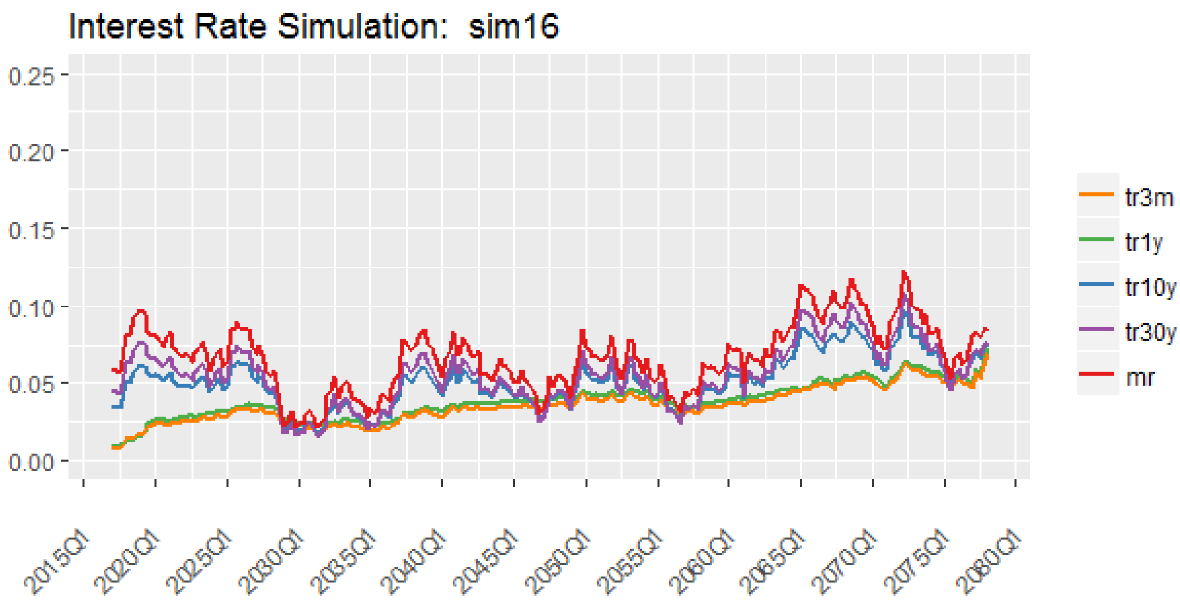
Additional models were developed to simulate the other interest rates. All models were estimated as a spread (difference) between the current maturity length and prior. Table 25 describes these spreads and models.

Table 25: 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(3,1)-ARCH(1)	
1-year	r_{1y}	ARMA(2,4)-GARCH(1,1)	Base Interest Rate
2-year	$S_{2y} = r_{2y} - r_{1y}$	AR(1)-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 did not produce a statistically significant 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 models used AIC and/or Pearson's goodness-of-fit test to determine the best fitting model. A lower bound of 0.01% was applied to the simulated future Treasury rates to avoid negative rates in the simulation. Figure 30 shows the projected interest rate values from a sample simulation.

Figure 30: Interest Rate Sample Simulation



HPA

A. National HPA

The national HPA series was fit using as 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 in the following model formula:

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

Z_1 is an independent Wiener random process with distribution N(0,1), and 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 26.

Table 26: Estimation Results for the National HPA Model

Parameter	Estimate	Std Dev	t-value	prob>t
μ	0.0369	0.0070	5.3041	0.0000
x_1	0.9552	0.0168	56.7543	0.0000
x_2	-0.5776	0.0765	-7.5524	0.0000
x_3	-0.4629	0.0867	-5.3379	0.0000
x_4	0.2687	0.0858	3.1322	0.0017
x_4	-0.5277	0.1804	-2.9248	0.0034
x_5	0.1464	0.1378	1.0624	0.2880
x_6	-0.6007	0.1463	-4.1058	0.0000
x_7	0.2862	0.1405	2.0373	0.0416
x_8	0.0369	0.0070	5.3041	0.0000
β_0	0.0000	0.0000	0.6067	0.5441
β_1	0.3277	0.1120	2.9262	0.0034
β_2	0.6447	0.0754	8.5510	0.0000
Pearson's GOF	0.9125			

We used these parameters to simulate future HPAs from the first quarter of FY 2017.

B. Geographic dispersion

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

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

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:

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

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 mortgage portfolio. This approach is also consistent with Moody's logic in creating local market HPA forecasts relative to the national HPA forecast under alternative economic scenario forecasts.

We understand this approach is equivalent to assuming perfect correlation of dispersions among different locations across simulated national HPA paths, which creates systematic house price decreases during economic downturns and vice versa during booms. Due to Jensen's Inequality, this tends to generate a more conservative estimate of the Cash Flow NPV.

Unemployment Rate

A. National Unemployment Rate

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

We used quarterly data from CY 1971 through the first quarter of CY 2017 to estimate the national unemployment rate. The model we adopted was:

$$ue_t = x_1 ue_{ar1} + x_2 r_t + x_3 s_{mr} + \varepsilon_t \tag{8}$$

where r_t is the 1-year CMT rate,

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

ue_{ar1} is the unemployment rate auto regressive component.

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 27.

Table 27: Estimation Results for the National Unemployment Rate Model

Parameter	Estimate	Std Error
x_1	0.0551	0.7039
x_2	0.021	-0.1273
x_3	0.0376	0.041

From the simulated interest rates and house prices, we applied the parameters shown in Table 27 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 applied to the MSA-level HPA forecasts, we first calculated the dispersion of unemployment rates between the i^{th} MSA or state level and the national level from Moody's July base-case forecast at each time *t*:

$$Disp_{i,t}^{Base} = ue_{i,t}^{Base} - ue_{national,t}^{Base} \tag{9}$$

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

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

For the simulation, we capped the unemployment rate at the local level at a maximum of 30% and a minimum of 1%.

Gross Domestic Product

For the GDP model, the GDP depends on the prior GDP, unemployment, mortgage and CMT rates.

We used quarterly data from CY 1971 through the first quarter of CY 2017 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(1,1):

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

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, and

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

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 (6). The results are shown in Table 28.

Table 28: Estimation Results for the National Gross Domestic Product Model

Parameter	Estimate	Std Error
x_1	0.3878	0.0822
x_2	-0.9383	0.0371
x_3	1135.458	739.7173
x_4	-1298.61	899.3981
x_5	-12.5117	672.9905

Final Simulation Selection

A total of 1,000 simulation paths were generated using all of the economic variable models described to create a large sample pool. From this pool, a random sample of 100 simulated series was drawn to be used for the Cash Flow NPV stochastic simulations.

Appendix E: Cash Flow Analysis

Introduction

The calculation of the Cash Flow NPV of the MMIF involves the estimation of the present value of future cash flows generated by the existing portfolio. The analysis requires the projection of future prepayment and claim incidences, and severity and cash flow items associated with each type of outcome. The Cash Flow NPV represents future revenue and expenses associated with the existing book of mortgage guarantees. This appendix describes the components of these cash flow calculations.

To develop the estimated Cash Flow NPV, our model incorporates projections of mortgage performance and information about the existing portfolio composition to project the MMIF's various cash flow sources. The cash flow projection model uses projections from predictive models as discussed in Appendix B (Transition Models), Appendix C (Loss Severity Models), and the economic scenarios described in Appendix D. We developed predictive models for conditional transition probabilities for individual mortgages depending on a number of mortgage and economic characteristics. From these models and using detailed mortgage-level characteristics, we estimated the various transition probabilities and then generated respective cash flows for individual mortgages.

Based on the mortgage termination rates projected by the predictive models, individual components of cash flows are projected into the future. These cash flows are discounted to present value based on the single discount rate provided by the OMB. Based on the specific characteristics of the mortgage, the probability of each transition 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 prepayment, claim or reaches maturity.

The cash flow components are shown in the following table:

Table 29: Cash Flow Components

Cash Inflows	Cash Out Flows
Upfront MIP	Net Claim Payments
Annual MIP	Loss Mitigation Expenses
Interest Income	Refunded Upfront Premiums

These cash flows were projected quarterly for individual mortgages and then aggregated by product type and origination year. Below, we discuss the development of each of these cash flows.

Definitions

The following definitions are applicable to the projection of cash flow components:

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

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

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

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

- **Unpaid Principal Balance (UPB) Factor**: the principal balance outstanding at a given time divided by the original mortgage amount. The UPB factor is calculated based only on amortization, given the original maturity, the type of mortgage, and the mortgage contract rate. For FRMs, the UPB factor for each quarter in the future can be directly computed using the initial contract rate and the amortization term. For ARMs, the UPB factor changes depending on the interest rate of the mortgages, which is updated according to the contractual rate-adjustment rule. In our model, the contract interest rates of ARM mortgages are updated by using changes in the 1-year CMT rate as an approximation for changes in the underlying index, subject to limits implied by FHA annual and lifetime rate-adjustment caps.

Cash Flow Components

The components of cash flow are discussed below.

MIP

The primary source of revenue to the MMIF is insurance premiums. If the MMIF's mortgage insurance is priced to meet the expected liabilities, the MIP collected and interest earned on the MIP will cover all costs associated with mortgage mortgages insured by the MMIF under a normal or expected economic environment. The MIP structure and the premium rates have changed over the period under evaluation. Details of MIP changes are as follows:

- For mortgages originated prior to September 1, 1983, the MIP was collected on a monthly basis at an annualized rate of 0.50% of the outstanding principal balance for the period. To align this change with fiscal quarters, we assumed that this annual MIP policy was in effect through September 30, 1983.

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

- Effective July 1, 1991, NAHA implemented a new MIP structure. An upfront MIP of 3.80% was charged for all product types except for 15-year non-SR mortgages, for which the upfront MIP was set at 2.00%. An annual MIP of 0.50% per year on the outstanding balance was also implemented. The annual MIP would cease at different policy years depending on the initial LTV of the mortgage.

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

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

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

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

- Effective October 1, 2008, FHA charged an upfront premium rate of 1.75% for home purchase and full-credit qualifying refinances; and 1.50% for all types of streamline refinance mortgages. A varying annual MIP, collected on a monthly basis, was charged based on the initial LTV ratio and maturity of the mortgage.

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

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

- Effective April 18, 2011, the annual MIP for mortgages with 30-year terms was increased to 1.10% for LTV ratios up to 95% and to 1.15% for LTV ratios greater than 95%. For mortgages with 15-year terms, the annual MIP was increased to 0.25% for LTV ratios up to 90% and to 0.50% for LTV ratios greater than

90%. To align this change with fiscal quarters, we started applying this policy change on April 1, 2011.

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

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

- Effective April 1, 2013, the annual MIP for mortgages with 30-year terms and base mortgage amounts below $625,500 was increased to 1.30% for LTV ratios up to 95%, and to 1.35% for LTV ratios greater than 95%. The annual MIP for mortgages with 30-year terms and base mortgage amounts above $625,500 was increased to 1.50% for LTV ratios up to 95%, and to 1.55% for LTV ratios greater than 95%. For mortgages with 15-year terms and base mortgage amounts below $625,500, the annual MIP was increased to 0.45% for LTV ratios up to 90%, and to 0.70% percent for LTV ratios greater than 90%. For mortgages with 15-year terms and base mortgage amounts above $625,500, the annual MIP was increased to 0.70% for LTV ratios up to 90%, and to 0.95% for LTV ratios greater than 90%. This increase was effective for all forward mortgages except single family forward SR transactions that refinance existing FHA mortgages that were endorsed on or before May 31, 2009.

- Effective June 3, 2013, the annual MIP rates for mortgages with an LTV of less than or equal to 78% and with terms of up to 15 years was 0.45%. The new payment period for annual MIP for mortgages with case numbers assigned on or after June 3, 2013 and with an LTV up to 90% was 11 years, and the annual MIP applied for the life of the mortgage for LTVs greater than 90%. To align this change with fiscal quarters, we started applying these policy changes on July 1, 2013.

- Effective January 26, 2015, the annual MIP rates for mortgages with a term greater than 15-years have been reduced by 50 basis points. To align this change with fiscal quarters, we applied these policy changes on January 1, 2015.

Upfront MIP

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

*Upfront MIP = Origination Mortgage Amount * Upfront MIP Rate*

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

Annual Premium

The annual MIP is calculated as follows:

*Monthly MIP = UPB (excluding any upfront MIP) * Annual MIP Rate / 12*

The MIP is actually collected on a monthly basis. For purposes of the simulation, the monthly MIP is aggregated by quarter, and this quarterly premium is used to discount MIP for the simulation.

Refunded MIP

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

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

Refund payments at each quarter are calculated based on the number of mortgages prepaid in that quarter and the origination date of the mortgage. In the past, borrowers always received the upfront MIP refund when they prepaid their mortgages before the maturity of the mortgage contract. In 2000, FHA changed its policy so that borrowers would obtain refunds only if they prepaid within the first five years of their mortgage contracts. The most recent policy change at the end of 2004 eliminated refunds for early prepayments of any mortgages endorsed after that date, except for those borrowers who refinanced into a new FHA mortgage within three years following the original endorsement date.

Losses Associated with Claims

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

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

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

We have estimated the net loss as discussed in Appendix C separately for PFS, TPS and REO. Based on the specific characteristics of the mortgage, the net loss for each claim is calculated. Then, a random number between 0 and 1 is generated, and based on this random draw the net loss is determined.

Loss Mitigation Expenses

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

The loss mitigation program includes Forbearance and HAMP, which has Loan Modification and Partial Claim options. A Special Forbearance is a written repayment agreement between the mortgagee, acting on behalf of FHA, and the borrower that contains a plan to reinstate a mortgage. A Loan Modification modifies the contractual terms of the mortgage permanently, such as lowering the interest rate, or increasing the mortgage term. Under the partial claim option, a mortgagee will advance funds on behalf of a mortgagor in an amount necessary to reinstate a delinquent mortgage. The borrowers are required to sign a promissory note and a subordinated mortgage payable to FHA of the amount advanced.

Loss mitigation cases have decreased from fiscal year 2007 to fiscal year 2016, the latest fiscal year with finalized cash flows. There were 16,042 loss mitigation claims in FY 2007 which has decreased to 5,485 cases in fiscal year 2016. The amount FHA paid in these cases after all adjustments and curtailments was $85.8 million in FY 2007, which decreased to $54 million in fiscal year 2016. Loss mitigation payments made by FHA include administrative fees and costs of title searches, recording fees and subordinated mortgage note amounts.

As discussed in Appendix C, we have developed models to project loss mitigation expenses.

Net Present Value

Once all the above future cash flow components are estimated, their present value is computed by discounting them at an appropriate rate.

The discount factors applied were provided by FHA and reflect the OMB discount factors and the expected timing of future cash flows. The rates are constant and vary by mortgage cohort year. The discount factors 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 by quarter, and treat the cash flows as being received at the end of the quarter.