Annual Actuarial Review of

The FHA Mutual Mortgage Insurance Fund

Forward Loans

Fiscal Year 2024

Submitted to:

United States Department of Housing and Urban Development

Submitted by:

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Contract Number: 86615723C00002

November 13, 2024

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

Dear Ms. Gordon,

IT Data Consulting, LLC (ITDC) has finalized and is now submitting the Fiscal Year 2024 Independent Actuarial Review of the Single-Family Forward Mortgages under the Mutual Mortgage Insurance Fund, under contract number 86615723C00002.

This report is based on data as of September 30, 2024, providing an overview of the Economic Net Worth and details regarding the Cash Flow Net Present Value (NPV) for the Mutual Mortgage Insurance (MMI) Forward Loan portfolio as of the conclusion of Fiscal Year 2024. We've included a comparison with the corresponding estimate from the end of Fiscal Year 2023, evaluation under various scenarios, and offered detailed insights into the models employed for developing this estimate.

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

Respectfully,

Benny Asnake
President and CEO
IT Data Consulting, LLC

November 13, 2024

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

Dear Ms. Gordon,

I, Min Ji, am a Professor in Actuarial Science and Risk Management at Towson University. I am a member of the American Academy of Actuaries (MAAA), fellow of the Society of Actuaries (FSA), and fellow of the Institute and Faculty of Actuaries (FIA) and I meet the Qualification Standards for Actuaries Issuing Statements of Actuarial Opinion in the United States of the American Academy of Actuaries to render the actuarial opinion contained herein.

I have reviewed the "Annual Actuarial Review of The FHA Mutual Mortgage Insurance Fund, Forward Loans, for Fiscal Year 2024". The purpose of my review was to determine the soundness of the methodology used, the appropriateness of the underlying assumptions applied, and the reasonableness of the resulting estimates derived in the Review.

The review was based upon data and information provided by the Federal Housing Administration (FHA). I have relied on FHA for the accuracy and completeness of this data. In addition, I also relied upon the reasonableness of the assumptions used in the economic projections from the FY 2025 Mid-Session Review of the President's Economic Assumptions (PEA).

It is my opinion that on an overall basis, the methodology and underlying assumptions used in the Review are reasonable and appropriate in the circumstances. In my opinion the estimates in the Review lie within a reasonable range of probable values as of this time although the actual experience in the future may not unfold as projected.

Respectfully,

Min Ji, Ph.D., MAAA, FSA, FIA
Professor, Actuarial Science and Risk Management, Towson University

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Summary of Deliverables

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

Deliverable 1: Produce a written Actuarial Study for Forward that provides actuarial central estimates of Mutual Mortgage Insurance (MMI) Fund Economic Net Worth as of the end of 2024 and assesses HUD's estimates of Economic Net Worth.

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

As of the end of 2024, ITDC's Actuarial Central Estimate (ACE) of the MMI Forward Cash Flow NPV is positive $38.016 billion.

The total capital resource as reported in the Annual Report to Congress regarding the status of the Federal Housing Administration (FHA) Mutual Mortgage Insurance Fund is a positive $115.853 billion as of the end of Fiscal Year (FY) 2024. Thus, the estimated Economic Net Worth of the MMI is $153.869 billion.

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

A review of the risk characteristics of existing MMI Forward loans and commentary of how these risk characteristics have changed is included in Section IV. Characteristics of the 2024 Insurance Portfolio and Section I.B. FHA Policy Changes.

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

Models for projecting loan terminations and loan performance are described in Appendices A to G. Cash flow summaries by major category are displayed in the table below and discussed in more detail in Sections II and V along with a detailed analysis of the cash flow calculations in Appendix D.

Exhibit SD-1. Cash Flow Summary, 2024 ($ Million)

Cash Flow Category	Net Present Value of Cash Flow
Mortgage Insurance Annual Premium	$ 75,044
Upfront Premium Refund	$ (7,472)
Loss Mitigation Expense	$ (9,312)
Claim Expenses	$ (53,038)

Cash Flow Category	Net Present Value of Cash Flow
Recoveries	$ 32,794
Net Present Value	**$ 38,016**

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

The assumptions and judgments on which the estimates are based are summarized in Appendices A to F. Various NPVs based on simulated economic scenarios are summarized in Section V. The economic conditions that could result in materially adverse changes to the Cash Flow NPV are discussed.

We have examined the vulnerabilities of our studies and compared the results under various scenarios. We will continue our investigation by comparing results and methodologies with HUD's methodologies in future research.

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

Section IV, Characteristics of the Fiscal Year 2024 Insurance Portfolio, provides historical information on changes in the MMI programs. A review of the risk characteristics of existing MMI loans and commentary of how these risk characteristics have changed are included in Section I.B. FHA Policy Changes.

Deliverable 6: The Contractor should use the FY 2025 Mid-Session Review of the President's Economic Assumptions (PEA), provided by Office of Risk Management and Regulatory Affairs (ORMRA), for the actuarial central estimates of the Studies. However, in addition to the central single path economic forecast, the Studies shall test alternative economic forecasts for stress-testing and sensitivity analysis to estimate ranges of reasonableness.

ITDC has conducted a comprehensive analysis, based on the FY 2025 Mid-Session Review provided by the Office of Management and Budget (OMB). Based on our assessment, the Cash Flow Net Present Value (NPV) by the conclusion of the 2024 fiscal year for cohort years 1994 to 2024 is a positive $38.016 billion.

In the table below, we estimate that the range of Cash Flow NPV based on the pessimistic downside and optimistic upside stochastic simulation scenarios is between positive $29.294 billion to positive $42.561 billion. These two values from the optimistic upside and pessimistic downside are two extreme scenarios that are highly unlikely to occur. Our Baseline NPV of $38.016 billion stays in the middle of $40.588 billion from the moderate upside scenario and $34.928 billion from the moderate downside scenario.

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

Economic Scenario	Fiscal Year 2024 Cash Flow NPV
Baseline PEA	$ 38,016
Alternative 1 - Optimistic Upside Scenario	$ 42,561
Alternative 2 - Moderate Upside Scenario	$ 40,588
Alternative 3 - Moderate Downside Scenario	$ 34,928
Alternative 4 - Pessimistic Downside Scenario	$ 29,294

The Cash Flow NPV estimate provided by FHA to be used in the FHA Annual Report to Congress is positive $40.914 billion. Based on ITDC's actuarial central estimate utilizing the Baseline PEA and range of results from the stochastic simulation scenarios, we conclude that the FHA estimate of Cash Flow NPV is reasonable.

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

The Executive Summary, Section III, The Current Status of the Fund, and Section V, MMI Fund Performance Under Alternative Scenarios and Sensitivity Analysis, provide the comparability to HUD estimates of Economic Net Worth and conforms to the Federal Credit Reform Act discounting assumptions and procedures.

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

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

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

Appendices A, F and G include variable specifications and statistical output from all regressions in the Studies.

Executive Summary

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

HERA also restructured several supplementary programs under the purview of MMI. There are two MMI Funds: one for forward mortgages and one for reverse mortgages. The reverse mortgages are included under the Home Equity Conversion Mortgage (HECM) program, which is excluded from this report. In the remainder of this report, the term MMI refers to forward mortgages only.

The primary purpose of this analysis is to provide an updated estimate of the Economic Net Worth of the current mortgage portfolio as of 2024. Economic Net Worth is calculated by adding the available cash in the Fund to the Net Present Value (NPV) of all anticipated future cash flows from the mortgages currently insured by the MMI Fund.

ITDC has conducted a comprehensive analysis, utilizing economic forecasts from the OMB Economic Assumptions from the Fiscal Year (FY) 2025 Mid-Session Review PEA. Based on our assessment, the Cash Flow Net Present Value (NPV) by the conclusion of the cohort year from 1994 through 2024 is a positive $38.016 billion. We also estimate that the range of Cash Flow NPV based on the pessimistic downside and optimistic upside stochastic simulation scenarios is between positive $29.294 billion and $42.561 billion.

A. Status of the MMI Forward Portfolio

To assess the adequacy of the current and future capital resources to meet estimated future liabilities, ITDC analyzed all Single Family (SF) Forwards defaults, claims, and associated recoveries using loan-level data reported by FHA through September 30, 2024. Based on historical experience, we developed loan level termination and cash flow models to estimate the future loan performance of the FY 2014 to FY 2024 books-of-business using various assumptions, including macroeconomic forecasts from the Office of Management and Budget (OMB), Moody's Analytics (Moody's), and the expected SF Forwards portfolio characteristics provided by FHA.

Using the macroeconomic inputs from FY 2025 Mid-Session Review of the President's Economic Assumptions (PEA) regarding the future trajectory of home prices, mortgage interest rates, unemployment, the 1-year Constant Maturity Treasury (CMT) rate, and the 10-year Constant Maturity Treasury (CMT) , ITDC projects the performance of the FY 1996 to 2024 books of SF Forwards loans, and estimates the SF Forwards Cash Flow Net Present Value (NPV) as of the end of FY 2024 is positive $38.016 billion. The SF Forwards portion of total capital resource as reported in the Annual Report to Congress regarding the status of the FHA Mutual Mortgage Insurance (MMI) Fund is positive $115.853 billion as of the end of FY 2024. Thus, the estimated Economic Net Worth of the SF Forwards MMI Fund is positive $153.869 billion.

ITDC also estimates that the Cash Flow NPV based on randomly generated economic scenarios is between positive $29.294 billion to positive $42.561 billion. These two values from the optimistic upside and pessimistic downside are two extreme scenarios that are unlikely to occur. Our Baseline PEA NPV of $38,016 billion stays in the middle of $40,588 billion from the moderate upside scenario and $34,928 billion from the moderate downside scenario.

The Cash Flow NPV estimate provided by FHA to be used in the FHA Annual Report to Congress is a positive $40.914 billion. Based on ITDC's actuarial central estimate utilizing the baseline PEA and range of results from the stochastic simulation scenarios, we conclude that the FHA estimate of Cash Flow NPV is reasonable.

The insurance-in-force (IIF) is calculated as the total Unpaid Principal Balance (UPB) of all SF Forwards loans remaining in the insurance portfolio as of September 30, 2024. New endorsements in 2024 are added to the portfolio and the SF Forwards IIF as of the end of FY 2024 is $1,442 billion. Exhibit ES-1 provides Actuarial Central Estimate (ACE), unamortized IIF and amortized IIF of the SF Forwards portfolio for FY 1994 through FY 2024.

Exhibit ES-1 reports the MMI Fund's projected performance and IIF for 2024.

Exhibit ES-1. Projected MMI Forward Performance for 2024 ($ Million)

Cohort Years	Cash Flow NPV	Unamortized Insurance-in-Force	Amortized Insurance-in-Force
1994-2024	$ 38,016	$ 1,632,547	$ 1,441,523

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

The FY 2023 Forward Review reported that the economic net worth of the SF Forward portfolio was $131.1 billion at the conclusion of 2023, contrasting with this review, which estimates a positive value of $153.869 billion at the end of 2024. Exhibit ES-2 compares our MMI Cash Flow NPV and IIF estimate for 2024 to the estimates in the 2023 Review.

Exhibit ES-2. Estimate of Cash Flow NPV as of 2024 ($ Million)

Item	Cash Flow NPV	Capital Resources	Unamortized Insurance-In-Force (IIF)
2023	$ 29,221	$ 101,884	$ 1,485,879
2024	$ 38,016	$ 115,853	$ 1,632,547
Dollar Difference	$ 8,795	$ 13,969	$ 146,668
Percent Change	30.10%	13.71%	9.87%

As seen in Exhibit ES-2, the Forward portion of the MMI Fund's estimated 2024 Cash Flow NPV has increased by $8.795 billion from the level estimated in Fiscal Year 2023, from positive $29.221 billion to positive $38.016 billion. The capital resources available to the MMI Fund have increased by 13.71 percent, from $101.884 billion to positive $115.853 billion. The unamortized IIF increased by 9.87 percent from $1,486 billion to $1,633 billion.

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

- The FY 2025 Mid-Session Review of the President's Economic Assumptions (PEA) projects higher house growth in the next few years and lower appreciation rates afterwards, resulting in a reduction in projected claim rates as a consequence of reduced risk of mortgages becoming "underwater" in the sense of unpaid balances exceeding property value. Based on sensitivity analysis discussed below (Section V.D), the impact of higher housing prices is relatively modest at approximately 1 percent of 2023 NPV.

- The FY 2025 PEA also projects a substantially higher 30-year fixed-rate mortgage rate, which is incorporated into our model with higher 15-year fixed rates and higher adjustable-rate mortgage interest rates as well. Higher fixed-rate mortgage interest rates reduce refinance incentives, lowering prepayment speeds, and lengthening the time over which FHA can expect to collect MIP, contributing to a NPV increase relative to 2023. When incorporating the updated PEA assumptions along with 2024 model changes, we observe an increase in the NPV on the 2023 loan data by $13.946 billion.

- Following the 2023 book of business through the end of FY 2024, we can identify the effect of the additional FY 2024 experience for all cohorts on the baseline NPV, which results in a decrease in NPV of $2.123 billion. This decrease is due to amortization and loan terminations for cohorts 1994 through 2023.

- Finally, we measure the NPV impact due to the $231.5 billion in new endorsement volume during Fiscal Year 2024. Between 2023 and 2024, there has been an overall increase in volume of the Forwards portfolio resulting in an Unamortized Insurance-In-Force increase of $146.7 billion, a year-over-year increase of 9.87 percent. Based on modeling projections, cohort 2024 is expected to have a net negative performance on the NPV, decreasing the NPV by $3.028 billion.

- The overall change in the baseline NPV from the FY 2023 Review to this Year's review is positive $8.795 billion, which is the sum of positive $13.946 billion, negative $2.123 billion, and negative $3.028 billion.

C. Impact of Economic Forecasts:

The Fund's economic net worth for 2024 will depend on the economic conditions expected to prevail over the next 30 years and, most critically, during the next 10 years. We have captured the most significant factors in the U.S. economy affecting the performance of the loans insured by the Fund using the following variables in our models:

- 30-year, 15-year, and adjustable-rate mortgage rates

- 1-year and 10-year constant maturity Treasury rates

- National and local house price indices
- Local household unemployment rates

The projected performance of FHA's current book of business, as measured by economic net worth, depends on future forecasts of these economic drivers. The baseline scenario for the primary economic drivers was developed consistent with the FY 2025 Mid-Session Review of the President's Economic Assumptions (PEA). The PEA is published by the Office of Management and Budget in compliance with the requirements of the Federal Credit Reform Act.

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

In addition to the mandated baseline PEA forecasts, we apply four alternative stochastic simulation scenarios of potential random deviations from the PEA baseline. To summarize the five scenarios for which we report estimates of economic net worth:

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

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

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

Alternative 1 – Optimistic Upside Scenario

Treasury and Mortgage Rates: 90th percentile

Unemployment Rate: 10th percentile

House Price Appreciation Rate: 90th percentile

Alternative 2 – Moderate Upside Scenario

Treasury and Mortgage Rates: 75th percentile

Unemployment Rate: 25th percentile

House Price Appreciation Rate: 75th percentile

Alternative 3 – Moderate Downside Scenario

Treasury and Mortgage Rates: 25th percentile

Unemployment Rate: 75th percentile

House Price Appreciation Rate: 25th percentile

Alternative 4 – Pessimistic Downside Scenario

Treasury and Mortgage Rates: 10th percentile

Unemployment Rate: 90th percentile

House Price Appreciation Rate: 10th percentile

The FY 2025 Mid-Session Review PEA forecast developed by OMB does not cover all the economy drivers that are included in our models. Additional economic variables that must be forecast, such as FRM 15-Year and ARM origination rates, regional and local house price indices, and local unemployment rates, are developed using the PEA and additional data from Moody's. The forecasts for all additional series are driven by the corresponding national PEA forecasts. Additional details may be found in the discussion of stochastic simulation models in Appendix F.

Exhibit ES-3 presents the actuarial central estimate of the cash flow NPV from the projections based on the PEA and four alternative scenarios. The actuarial central estimate uses the PEA for FY 2025 published by the Office of Management and Budget, in compliance with the requirements of Federal Credit Reform Act. Four alternative scenarios represent different percentile paths of interest rates and the HPI from 1000 simulations.

Stochastic scenarios are simulated using the best fitted GARCH model with mean replaced by the corresponding PEA, to ensure the simulated paths will not drift far away from the PEA while having stochastic volatilities. The loan performance estimated under each scenario excludes the identified COVID-19 impact[1].

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

Economic Scenario	Fiscal Year 2024 Cash Flow NPV*
Baseline**	$ 38,016
Alternative 1 - Optimistic Upside Scenario***	$ 42,561
Alternative 2 - Moderate Upside Scenario	$ 40,588
Alternative 3 - Moderate Downside Scenario	$ 34,928
Alternative 4 - Pessimistic Downside Scenario	$ 29,294

**All values are expressed as of the end of the fiscal year period*
***Baseline is based on PEA*
**** Description of these scenarios are in Section V and Appendix F*

Our baseline PEA Cash Flow NPV of $38.016 billion stays in the middle of the $34.928 billion moderate downside scenario and the $40.588 billion moderate upside scenario. The range of Cash Flow NPV based on the more extreme scenarios range from $29.294 billion from Alternative 4 – Pessimistic Downside Scenario to $42.561 billion from Alternative 1 – Optimistic Upside Scenario. These two values from the optimistic upside and pessimistic downside are two extreme scenarios that are unlikely to occur.

The 2024 Cash Flow NPV estimate provided by FHA is positive $40.914 billion. Based on ITDC's Cash Flow NPV estimate utilizing the Baseline PEA and range of results from the stochastic simulation scenarios, we conclude that the FHA estimate of Cash Flow NPV is reasonable.

[1] A dummy variable is added to the termination model for the Covid-19 period.

Distribution and Use

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

The distribution of this report is allowed on the condition that it is shared in its entirety, including all exhibits and appendices, without any excerpts. ITDC acknowledges that FHA will integrate this report into its Annual Report to Congress, and ITDC grants permission for this purpose. We are available to address any questions that may arise concerning this report.

Any third party receiving this report should understand that its provision does not replace their responsibility to conduct due diligence. They should not place reliance on this report or its enclosed data to establish any explicit or implicit representations, warranties, duties, or liabilities from ITDC to the third party.

I. Introduction

A. Actuarial Reviews of the FHA Mutual Mortgage Insurance Fund

The National Housing Act requires an annual independent actuarial review of the Federal Housing Administration's (FHA) Mutual Mortgage Insurance (MMI) Fund.[2] ITDC was engaged by the Department of Housing and Urban Development (HUD) to conduct an independent actuarial review of the MMI Fund for 2024. This study is required by 12 USC 1708(a)-(4) and must be completed in compliance with the Federal Credit Reform Act as implemented and all applicable Actuarial Standards of Practice (ASOPs) promulgated by the Actuarial Standards Board of the American Academy of Actuaries. This study analyzes the financial position of the MMI Fund for 2024 using data through September 30, 2024.

The MMI Fund is a group of accounts of the federal government that records transactions associated with the FHA's guarantee programs for single-family mortgages. Currently, the FHA insures approximately 7.77 million forward mortgages under the MMI Fund.

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

B. FHA Policy Changes

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

i. Revised Underwriting Guidelines and Other Policy Issues

In 1995, the FHA implemented a series of alterations to their underwriting guidelines to remove needless obstacles to homeownership. These changes were designed to offer more flexibility in evaluating the creditworthiness of nontraditional and underserved borrowers while also providing more explicit guidance to prevent discriminatory application of underwriting requirements. While these adjustments did expand homeownership opportunities for many households, the more lenient

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

underwriting standards also played a role in the subsequent rise in FHA claim rates for loans that originated after 1995.

In 1998, modifications were introduced to the underwriting guidelines governing adjustable-rate mortgages (ARMs) in response to the elevated loss rates that the FHA encountered with these loans. An in-depth study of ARM claim rates by the FHA revealed the necessity for credit policy changes to uphold the MMI Fund's actuarial stability. Consequently, because of these adjustments, ARM applicants were mandated to qualify based on a mortgage payment amount calculated using the highest potential second-year interest rate. Additionally, any temporary interest rate reduction method for ARMs could no longer be applied to establish qualifying payment ratios.

In 2008, HERA set the minimum borrower cash equity requirement to 3.5 percent for purchase loans.[3] FHA also established a minimum FICO score of 500 for loans with 90 percent or higher loan-to-value ratios (LTVs). This rule was further tightened in 2010.[4] Starting October 4, 2010, borrowers with credit scores below 500 were no longer eligible for FHA insurance, and the maximum loan-to-value ratio for borrowers with credit scores between 500 and 579 was limited to 90 percent. In 2011, FHA removed eligibility for loans on investor property.[5] In 2012, the FHA modified documentation requirements for self-employed borrowers. Starting April 1, 2012, profit-loss and balance sheets of self-employed borrowers have been required in most cases.[6] Also, for identity-of-interest transactions, the family member definition was expanded to include the extended family, including brothers, sisters, uncles, and aunts.

For manually underwritten loans assigned on or after April 21, 2014, HUD clarified a series of maximum qualifying ratios for different lowest minimum decision credit scores and acceptable compensating factors.[7] It also revised the compensating factors that must be cited to exceed FHA's standard qualifying ratios for manually underwritten loans.

ii. Changes to Homeownership Counseling Prerequisites

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

[3] Mortgagee Letter 2008-23, September 5, 2008: Revised Downpayment and Maximum Mortgage Requirements.
[4] Mortgagee Letter 2010-29, September 3, 2010: Minimum Credit Scores and Loan-to-Value Ratios.
[5] HUD 4155.1, Section B. Property Ownership Requirements and Restrictions. 4155.1 4.B.1.a: Occupancy Restrictions.
[6] Mortgagee Letter 2012-03, February 28, 2012: Miscellaneous Underwriting Issues.
[7] Mortgagee Letter 2014-02, January 21, 2014: Manual Underwriting.

- In 1993 a pilot counseling program for pre-purchase and pre-foreclosure situations was announced.[8]

- In 1996, after the pilot counseling program, the upfront Mortgage Insurance Premium (MIP) was decreased by 25 basis points for first-time homebuyers who completed homeownership counseling.[9] One year later, in 1997, the upfront MIP further decreased by another 25 basis points for first-time homebuyers who completed homeownership counseling.[10] This discount was provided to recognize the expected improvement in default experience.

- In 1998, a mortgagee letter was released indicating that the homeownership counseling program would be reviewed. This was in response to homeownership counseling programs that were being used that did not meet FHA guidelines. While the counseling program required that it should involve 15 to 20 hours of instruction, there were cases where homebuyers were provided with workbooks without additional interaction or instruction. The guidelines of the homeownership counseling program were reiterated in this letter.[11]

- In 2000, in conjunction with an overall reduction in upfront MIP, the homeownership counseling discount was discontinued.[12]

iii. Adoption of Automated Underwriting Systems

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

- In 1995, HUD approved the usage of AUSs. Mortgagors had to request permission to use these systems and receive approval from HUD.[13]

- In 1996, criteria were established for the approval of AUSs by HUD.[14]

- In 1998, the FHA approved using Freddie Mac's Loan Prospector in underwriting FHA-insured mortgages. A specific scorecard tailored for FHA-endorsed loans was introduced.

[8] Mortgagee Letter 93-28, September 20, 1993: Prepurchase and Foreclosure Prevention Counseling Demonstration.
[9] Mortgagee Letter 96-48, August 28, 1996: Single Family Production - Reduction in Up-Front Mortgage Insurance Premiums (UFMIP) for First-Time Homebuyers Who Receive Housing Counseling.
[10] Mortgagee Letter 97-37, August 13, 1997: Single Family Production - Further Reduction in Up-Front Mortgage Insurance Premiums (UFMIP) for First-Time Homebuyers Who Receive Housing Counseling
[11] Mortgagee Letter 98-1, January 2, 1998: Single Family Loan Production - Underwriting Adjustable Rate Mortgages, Interest Buydowns, Homeownership Counseling and Other Credit Policy Issues.
[12] Mortgagee Letter 2000-38, October 27, 2000: Single Family Loan Production - Further Reduction in Upfront Mortgage Insurance Premiums and Other Mortgage Insurance Premium Changes
[13] Mortgagee Letter 95-7, January 27, 1995: Single Family Loan Production - Revised Underwriting Guidelines and Other Policy Issues
[14] Mortgagee Letter 96-34, July 10, 1996: Single Family Loan Production - Automated Underwriting Systems.

Additionally, FHA made significant alterations to its credit policies and lessened documentation prerequisites for loans assessed by the Loan Prospector. This marked the inaugural inclusion of an Automated Underwriting System (AUS) in FHA's insurance endorsement process.

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

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

iv. Alteration in Mortgage Insurance Premium Structures

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

- In 1991, FHA decided to calculate the Mortgage Insurance Premium (MIP) as a combination of an upfront MIP and an annual premium, with the latter being a percentage of the remaining outstanding mortgage balance each year.[15] This adjustment led to an overall increase in MIP, which was necessary to fulfill the new capital requirement by NAHA.

- In 1994, the upfront MIP decreased by 75 basis points to 2.25 percent.[16] This was in response to the improved financial experience of the MMI Fund.

- In 1996, the upfront MIP decreased by 25 basis points to 2.00 percent for first-time homebuyers who received mortgage counseling before purchasing their home.[17] This was implemented based on the pilot program's success, which showed that first-time homebuyers who received this counseling had better default experiences.

- In 1997, the upfront MIP was decreased by an additional 25 basis points to 1.75 percent for first-time homebuyers who received mortgage counseling before purchasing their

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

home. The upfront MIP was 50 basis points lower than it would be for a homebuyer who did not receive counseling.[18]

- In 2000, several changes were implemented in recognition of the improved experience of the MMI Fund. First, the upfront MIP was reduced by 75 basis points to 1.50 percent. Second, the upfront MIP refund schedule was shortened to five years instead of seven. Third, a provision to cancel the annual MIP once the loan-to-value (LTV) ratio was 78 percent or less was implemented. Also, the discount in the upfront MIP for first-time homebuyers who received counseling was discontinued.[19]

- In April 2010, upfront MIP was increased by 75 basis points to 2.25 percent.[20] This premium increase was in response to the housing and economic crisis in 2008 and was the first in a series of increases over the next three years.

- In October of 2010, upfront MIP was decreased, but annual MIP was increased significantly.[21] Overall, this increased MIP.

- In 2011, the annual MIP was increased by 25 basis points.[22]

- In 2012, the annual MIP was increased by ten basis points.[23]

- In 2013, several changes were implemented related to the annual MIP. First, the term for collection of MIPs was extended to 11 years for mortgages with an initial LTV ratio of 90 percent or less and 30 years for mortgages with an initial LTV ratio greater than 90 percent. Second, mortgages with terms of 15 years or less and an LTV ratio of 78 percent or less at the time of origination, which were exempt from MIP, would no longer be exempt. Lastly, the annual MIP was increased by 5 to 10 basis points for mortgages with terms of 15 years or less and LTV ratios of 78 percent or less at origination.[24]

- As a result of improved financial experience, in 2015, annual MIP rates were decreased by 50 basis points for loans with terms greater than 15 years.[25]

[18] Mortgagee Letter 97-37, August 13, 1997: Single Family Production – Further Reduction in Up-Front Mortgage Insurance Premiums (UFMIP) for First-Time Homebuyers Who Receive Housing Counseling.
[19] Mortgagee Letter 2000-38, October 27, 2000: Single Family Loan Production – Further Reduction in Upfront Mortgage Insurance Premiums and Other Mortgage Insurance Premium Changes.
[20] Mortgagee Letter 2010-02, January 21, 2010: Increase in Upfront Premiums for FHA Mortgage Insurance.
[21] Mortgagee Letter 2010-28, September 1, 2010: Changes to FHA Mortgage Insurance Premiums.
[22] Mortgagee Letter 2011-10, February 14, 2011: Annual Mortgage Insurance Premium Changes and Guidance on Case Numbers.
[23] Mortgagee Letter 2012-04, March 6, 2012: Single Family Mortgage Insurance: Annual and Up-Front Mortgage Insurance Premium – Changes.
[24] Mortgagee Letter 2013-04, January 31, 2013: Revision of Federal Housing Administration (FHA) policies concerning cancellation of the annual Mortgage Insurance Premium (MIP) and increase to the annual MIP.
[25] Mortgagee Letter 2015-01, January 9, 2015: Reduction of Federal Housing Administration (FHA) annual Mortgage Insurance Premium (MIP) rates and Temporary Case Cancellation Authority.

- In 2017, a decrease was proposed for annual MIP rates,[26] but this decrease was suspended later in the year.[27]

- In 2023, FHA determined that a reduction in the annual MIP rate was necessary and appropriate to execute FHA's mission and role in the mortgage market. This resulted in a 30-basis point decrease in the annual MIP rate across most programs.[28]

v. Downpayment Assistance and Closing Costs

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

- Before 1992, closing costs could not be financed as part of the loan. In 1992, the limitation on financing closing costs was removed, but mortgages were still subject to LTV ratio limits.[29] This provision was implemented to make it easier for homebuyers to meet the down payment requirements.

- In 1996, HUD allowed family members to lend the borrower 100 percent of the down payment.[30] This also was intended to make it easier for individuals and families to achieve homeownership.

- Two provisions were implemented in 1998. First, it was prohibited for the seller or any other party to pay mortgage interest for the buyer. In addition, any interest rate buydown could not result in a lower interest rate of more than 2 percent below the note rate. These changes were implemented to avoid a significant increase in the payment amount once the seller-paid mortgage interest funds were depleted or the interest rate buydown term was complete.[31]

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

- In 2000, HUD guided mortgages to ensure that the source of the gifts to buyers is documented, and the person giving the gift must certify that the funds did not come from someone with an interest in the transaction. This was implemented to combat a practice of the sellers providing funds to family members of the buyer that would then be used for the down payment.[32]

- Section 2113 of the Housing and Economic Recovery Act of 2008 prohibited down payment contributions from a seller or any other person or entity that would financially benefit from the transaction.[33]

- In 2019, guidance by HUD was provided to clarify the rules associated with funds being provided by a governmental source for down payment assistance. The mortgagee letter requires the mortgagee to verify that the funds provided by the government agency were transferred to the Borrower before or at the time of closing and that the governmental agency was acting in its legal capacity in providing these funds. Documentation is also required from the government that the agency has the authority to provide the funds and from an attorney for the government entity verifying that the property is within the government agency's jurisdiction. There can be no direct transfer of assistance from the government agency to the mortgagee, and there can be no requirement that the loan be transferred to a specific mortgage as a condition of receiving assistance from the government agency.[34] This guidance was subsequently suspended until further notice and ultimately rescinded.[35]

vi. Foreclosure Avoidance and Loss Mitigation Programs

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

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

- In 1996, a mortgagee letter was released to provide information on the loss mitigation procedures, including unique forbearance plans, mortgage modifications, PFSs, deeds

[32] Mortgagee Letter 2000-28, August 7, 2000: Gift Documentation, Mortgage Forms and other Credit Policy and Appraisal Issues.
[33] https://www.congress.gov/110/plaws/publ289/PLAW-110publ289.pdf
[34] Mortgagee Letter 19-06, April 18, 2019: Downpayment Assistance and Operating in a Governmental Capacity.
[35] Mortgagee Letter 19-12, August 13, 2019: Rescission of Mortgagee Letters 2019-06, Downpayment Assistance And Operating in a Governmental Capacity; 2019-07, Extension of the Effective Date of Mortgagee Letter 2019-06, Downpayment Assistance and Operating in a Governmental Capacity; and 2019-10, Suspension of the Effective Date of Mortgagee Letter 2019-06, Downpayment Assistance and Operating in a Governmental Capacity.

instead of foreclosure, and partial claims. The primary objective was to keep the homeowner in the home, and if that was not possible, then the objective was the disposition of the property without full foreclosure.[36]

- In 2008, due to the increase in defaults resulting from the housing crisis, FHA released a mortgagee letter reminding mortgages of PFS as an option and consolidated the provisions of the PFS program into one place. This letter also updated the provisions of the PFS to address the mortgage crisis better.[37]

- In 2010, FHA released a mortgagee letter announcing enhancements to the FHA refinance program to allow responsible borrowers an opportunity to stay in their homes. This could occur if the lender agreed to write off at least 10 percent of the principal balance and if the remaining loan provisions were met.[38]

- In 2011, FHA issued guidance requiring a trial payment program before completing a permanent loan modification or partial claim. During the trial payment period, the borrower must complete three months of payments at the amount that will continue under the modification.[39]

- In 2012, FHA revised the Loss Mitigation Home Retention Options to reduce the claims against the MMI Fund and help more borrowers stay in their homes. These revisions included eliminating the maximum back-end debt-to-income ratio, the restriction on the principal, interest, taxes, and insurance that can be included in the claim, and the requirement that the existing mortgage be no more than 12 months past due.[40]

- In 2013 FHA established updated PFSs and Deed in Lieu (DIL) requirements. These changes included using the Deficit Income Test (DIT) – a test to determine if expenses exceed income and whether a hardship exists – and eliminating the financial hardship/deficit income PFS requirement for service members who have received a Permanent Change of Station order.[41] In 2013, additional modifications were made to the FHA Loss Mitigation Home Retention Options. These changes included defining continuous income that can be considered in the transaction, allowing for arrearages to be included in partial claims, and allowing for modifications for mortgagors in bankruptcy.[42]

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

- In 2014, the updated PFS guideline required a minimum marketing period of 15 calendar days for all PFS transactions. It also clarified that non-arms-length transactions are permitted only if necessary to comply with state law.[43] Also, in 2014, FHA issued a mortgagee letter to increase the use of Claims Without Conveyance of Title (CWCOT) procedures. This letter also established that the Commissioner's Adjusted Fair Market Value must be used for all foreclosure sales and PFS efforts.[44]

- In 2018, FHA issued a mortgagee letter implementing unique loss mitigation processes for Hurricanes Irma, Harvey, and Maria victims and the California Wildfires. These procedures were implemented to help homeowners stay home and reduce losses to FHA.[45] Later, in 2018, FHA issued a mortgagee letter in response to continued elevated default rates and lower utilization of loss mitigation options in Puerto Rico and the U.S. Virgin Islands. This mortgagee letter expanded loss mitigation assistance to borrowers in default.[46]

- In 2019, HUD incorporated additional changes to streamline and revise Loss Mitigation Procedures for Presidentially Declared Major Disaster Areas (PDMDAs).[47]

vii. COVID-19

On March 13, 2020, in Proclamation 9994, the President of the United States declared the COVID-19 outbreak in the United States as a national emergency, effective from March 1, 2020. This declaration prompted numerous jurisdictions to scale back services, close businesses, and restrict various activities. Additionally, the pandemic hindered the ability of Americans to work and support their families, directly affecting the financial stability of individuals, families, and businesses. Moreover, many Americans were required to stay in their homes to mitigate the spread of COVID-19, with several states implementing shelter-in-place orders. In response to the national

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

emergency of COVID-19, FHA released multiple mortgagee letters to safeguard families from displacement during this pivotal period.

Starting on March 18, 2020, a 60-day foreclosure moratorium was implemented for properties secured by FHA-insured mortgages, covering both the initiation of foreclosures and those already in progress.[48] Subsequently, this moratorium was extended several times, with the final extension on July 30, 2021, setting the end date as September 30, 2021.[49] During this period, the first legal action deadlines and reasonable diligence times were extended by 90 days from the moratorium's expiration. On February 7, 2022, it was further clarified that these deadlines would be extended 180 days from the end of the borrower's COVID-19 forbearance or the expiration of the foreclosure moratorium.[50]

On March 27, 2020, modifications were introduced to the rules governing employment re-verification, recognizing the widespread closure of businesses during shelter-in-place orders. Concurrently, adjustments to FHA Appraisal Protocols were made to permit exterior-only and desktop appraisals, ensuring compliance with necessary social distancing measures.[51] These changes were initially effective until June 30, 2020, but were successively extended through various dates: August 31, 2020 (June 29, 2020), October 31, 2020 (August 28, 2020), December 31, 2020 (October 28, 2020), February 28, 2021 (December 17, 2020), and June 30, 2021 (February 23, 2021).[52]

As of April 1, 2020, borrowers facing hardships that impacted their ability to make timely mortgage payments became eligible for an initial six-month forbearance period, which could be extended for six months. During the forbearance, borrowers underwent evaluations for potential loss mitigation solutions.[53]

On July 8, 2020, HUD issued a mortgagee letter outlining a comprehensive array of loss mitigation options available to borrowers affected by COVID-19.[54]

[48] Mortgagee Letter 2020-04, March 18, 2020: Foreclosure and Eviction Moratorium in connection with the Presidentially Declared COVID-19 National Emergency.
[49] Mortgagee Letter 2021-03, January 21, 2021: Extension of Foreclosure and Eviction Moratorium in Connection with the Presidentially-Declared COVID-19 National Emergency.
[50] Mortgagee Letter 2022-02, February 7, 2022: Technical Update to the Extension of the Deadlines for the First Legal Action and Reasonable Diligence Time Frame.
[51] Mortgagee Letter 2020-05, March 27, 2020: Re-verification of Employment and Exterior-Only and Desktop-Only Appraisal Scope of Work Options for FHA Single Family Programs Impacted By COVID-19.
[52] Mortgagee Letter 2021-06, February 23, 2021: Extension of Re-verification of Employment and Exterior-Only Appraisal scope of work (SOW) option for Federal Housing Administration (FHA) Single Family programs impacted by the Coronavirus Disease of 2019 (COVID-19).
[53] Mortgagee Letter 2020-06, April 1, 2020: FHA's Loss Mitigation Options for Single Family Borrowers Affected by the Presidentially-Declared COVID-19 National Emergency in Accordance with the CARES Act.
[54] Mortgagee Letter 2020-22, July 8, 2020: FHA's COVID-19 Loss Mitigation Options.

Subsequently, the approval deadline for COVID-19 forbearance was extended to December 31, 2020, on October 20, 2020, and extended to February 28, 2021, on December 17, 2020.[55]

On January 26, 2021, the approval deadline for COVID-19 forbearance was extended to March 31, 2021, and on February 16, 2021, it was extended to June 30, 2021. This last extension also broadened the range of mitigation options, including adding extra forbearance choices, expanding borrower eligibility for COVID-19 forbearance, and removing restrictions that limited borrowers to just one COVID-19 home retention option.[56]

As of June 4, 2020, mortgages under forbearance due to the impacts of COVID-19 were eligible for HUD endorsement, provided that the buyer met all requirements at the time of closing and that the mortgage remained current during the forbearance period.[57]

This endorsement guidance was subsequently extended through December 31, 2020, on November 25, 2020, and further extended through March 31, 2021, on December 17, 2020.[58]

On June 12, 2020, claims for loss mitigation options were allowed to be submitted electronically.[59]

On July 23, 2021, HUD introduced a range of COVID-19 Recovery Loss Mitigation Options, encompassing the COVID-19 Standalone Partial Claim, the COVID-19 Recovery Modification,

On April 18, 2022, HUD introduced a 40-year loan modification as one of the COVID-19 recovery loss mitigation choices.[60]

Effective April 30, 2023, the Federal Housing Administration (FHA) continued expanding its COVID-19 loss mitigation options by making it available to all eligible borrowers, regardless of the cause of their delinquency. Fundamental changes include extending COVID-19 Recovery loss mitigation options to all eligible borrowers, increasing the maximum partial claim amount to 30 percent (up from 25 percent) to aid borrowers facing difficulty making current mortgage payments, extending the availability of COVID-19 Recovery loss mitigation options for 18 months beyond April 30, 2023, expanding the definition of imminent default to include those who qualified for or used Homeowner Assistance Funds (HAF), providing incentive payments to servicers for completing COVID-19 Recovery options, and temporarily suspending the use of FHA-Home

[55] Mortgagee Letter 2020-44, December 17, 2020: Second Update to the COVID-19 Forbearance Start Date and the COVID19 Home Equity Conversion Mortgage (HECM) Extension Period.
[56] Mortgagee Letter 2021-24, September 27, 2021: Extension for COVID-19 Forbearance and COVID-19 Home Equity Conversion Mortgage (HECM) Extensions.
[57] Mortgagee Letter 2020-16, June 4, 2020: FHA Catalyst: Case Binder Module – Single Family Forward and Home Equity Conversion Mortgage (HECM) Electronic Endorsement Submission.
[58] Mortgagee Letter 2020-45, December 17, 2020: Extension of Temporary Guidance for Endorsement of Mortgages Under Forbearance for Borrowers Affected by the Presidentially-Declared COVID19 National Emergency consistent with the Coronavirus Aid, Relief, and Economic Security (CARES) Act
[59] Mortgagee Letter 2020-18, June 12, 2020: FHA Catalyst: Claims Module - Single Family Forward Loss Mitigation Home Retention Claims.
[60] Mortgagee Letter 2022-07, April 18, 2022: Update to the COVID-19 Recovery Loss Mitigation Options.

Affordable Modification (FHA-HAMP) options to simplify and transition to COVID-19 Recovery loss mitigation options.[61] Mortgagee Letter 2024-02 extends the COVID-19 Recovery Options through April 30, 2025.

viii. Payment Supplement Loss Mitigation Option

Mortgagee Letter 2024-02, released February 2024, introduces a policy update aimed at providing new loss mitigation options for FHA fixed-rate borrowers. The program is motivated by concerns regarding challenges borrowers face in the current economic environment, particularly those who are struggling with rising interest rates and the aftermath of pandemic-related financial stress.

Unlike permanent loan modifications, which alter the terms of the mortgage, the Payment Supplement provides a temporary reduction in the borrower's monthly payment. This reduction is achieved through a combination of a standalone Partial Claim and a Monthly Principal Reduction (MoPR).

The aim is to offer immediate financial relief to borrowers for a period of up to 36 months without modifying the original loan terms. By doing so, FHA ensures that borrowers have a manageable payment structure while they work toward regaining their financial footing. The strategy behind this policy is to prevent borrowers from falling into default and potential foreclosure, thereby protecting both the borrower’s homeownership status and the financial health of the Mutual Mortgage Insurance Fund (MMIF).

Mortgagees are tasked with a detailed assessment process to determine the appropriateness and extent of the Payment Supplement for eligible borrowers. This involves calculating the maximum Partial Claim amount available, determining the arrearages that need to be covered, and establishing the amount required for the Monthly Principal Reduction (MoPR). The MoPR must be sufficient to provide meaningful relief to the borrower while ensuring that the mortgage remains viable for the duration of the Payment Supplement period.

Additionally, there must be sufficient Partial Claim funds available to cover both the arrearages and the MoPR over the 36-month period. This ensures that the borrower is not placed under undue financial strain during the Payment Supplement period.

The implementation of this policy is staggered, with mortgagees given the option to adopt the Payment Supplement starting on May 1, 2024, with full mandatory implementation by January 1, 2025. This phased approach allows mortgagees to gradually integrate the new policy into their loss mitigation strategies, ensuring a smooth transition for both the lenders and borrowers.

[61] https://www.hud.gov/press/press_releases_media_advisories/hud_no_23_023

ix. LIBOR to SOFR Transition

In the context of FHA policy changes, it is important to acknowledge the transition from the London Interbank Offered Rate (LIBOR) to the Secured Overnight Financing Rate (SOFR), as outlined in Mortgagee Letter 2023-09. The transition is a result of global financial market reforms and the discontinuation of LIBOR as a benchmark rate. FHA has implemented provisions to ensure a smooth transition for existing and new adjustable-rate mortgages (ARMs) that were previously indexed to LIBOR.

While the adoption of SOFR is essential for aligning with global financial benchmarks, it is important to note that SOFR is fundamentally different from LIBOR in that it is a secured rate and is based on overnight transactions, whereas LIBOR was an unsecured rate with a term structure. This change affects the way interest rates are calculated for ARMs, affecting both new originations and existing mortgages.

The suite of transition models utilized in this report does not directly consume LIBOR or SOFR for its analysis, as we have aggregated adjustable-rate mortgages (ARMs) for our purpose. Hence, we have opted not to delve deeper into the intricacies of this shift.

C. Structure of this Report

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

Section II. Summary of Findings: Presents the economic net worth and insurance-in-force of the Forward portfolio as of the end of FY 2024.

Section III. The Current Status of SF Forwards in the MMI Fund: Analyzes the estimated economic net worth in further detail.

Section IV. Characteristics of the MMI SF Forwards Books of Business: Presents various characteristics of the SF Forwards portfolio for FYs 1994 through 2024.

Section V. MMI Fund Performance under Alternative Scenarios and Sensitivity Testing: Presents the SF Forwards portfolio economic net worth using alternative economic scenarios.

Section VI. List of Methodology Appendices: Provides a summary of the models utilized in the analysis.

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

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

Appendix B. Model Validation: Describes steps taken to verify the predictive reliability of the estimated econometric models for predicting conditional transition rates.

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

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

Appendix E. Tables of Historical and Projected Termination Rates: Provides finger tables of conditional and cumulative claim and prepayment terminations by endorsement cohort years and policy years for each mortgage product. These are provided in spreadsheet files as a separate addendum to the report.

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

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

Appendix H. Econometric Results: Data Sources, Processing and Reconciliation: This section provides the data sources, processing and reconciliation tables used for this model.

II. Summary of Findings

This section presents the projected economic net worth and insurance-in-force of the FY 2024 SF Forwards MMI portfolios endorsed in FY 1994 or later. In addition to the capital resources as of the end of the fiscal year, the economic net worth of the SF Forwards MMI portfolio depends on the discounted net present value of the future cash flows from the surviving portfolio of loans existing at the start of the valuation forecast (the end of the fiscal year under review). A fiscal year's economic net worth calculation does not include the effect of endorsements in future fiscal years. According to NAHA, the economic net worth of the Fund is defined as the "cash available to the Fund, plus the net present value of all future cash inflows and outflows expected to result from the outstanding mortgages in the Fund." We estimated the current economic net worth for the Forwards portfolio as the sum of the amount of capital resources and the net present value of all expected future cash flows of the active Forwards loans as of the end of FY 2024.

A. The FY 2024 Actuarial Review

The 2024 Review estimates the economic net worth of the SF Forwards portfolio as of the end of FY 2024 (September 30, 2024). The objectives of our analysis include:

- Analysis of the historical loan performance using data provided by FHA, developing econometric models, estimating their parameters, and generating future performance based on economic forecasts in the FY 2025 Mid-Session Review of the PEA. The economic net worth of the Fund is determined by comparing estimates from the models with the Fund's capital resources.
- Evaluation of the historical experience of the Fund, including loan termination experience due to claims and prepayments and losses associated with claims.
- Projection of future loan termination rates and their corresponding cash flows of the existing Fund portfolio.
- Estimation of the present economic net worth and insurance-in-force of the Fund.

This Review is carried out by examining historical loan performance data supplied by FHA, creating econometric models with the estimation of their parameters, and generating economic scenarios consistent with the FY 2025 Mid-Session Review of the President's Economic Assumptions (PEA). Econometric models are employed to forecast the Fund's future cash flows, and their present value is compared to the Fund's financial resources to determine the economic worth of the Fund.

Estimation of the loan status transition models utilized loan-level data on the Fund's historical loan performance from the mid-1990s through to the end of 2024. The performance of FHA loans through the 2007-2010 mortgage crises, the period of recovery and declining interest rates that followed the crisis, and the recent COVID-19 emergency have all provided real-world "stress tests" upon which to train our econometric models and develop forecasts of future performance. Further discussion and in-depth descriptions of the individual models, their underlying assumptions, and comprehensive econometric outputs are provided in a series of appendices to the report.

B. Economic Net Worth

Exhibit II-1 presents the components of the economic net worth for Fiscal Year 2024, ITDC projects the Actuarial Central Estimate (ACE) of the MMI Forward Cash Flow NPV to be a positive $38.016 billion. Forward MMI Capital Resources is a positive $115.853 billion, and the estimated Economic Net Worth is $153.869 billion.

Exhibit II-1: Estimated Economic Net Worth of the Forward Portfolio in the MMI Fund at the End of FY 2024 ($ Million)

Item	End of 2024
Total Capital Resources*	$ 115,853
+ NPV of Future Cash Flows on Outstanding Business	$ 38,016
Economic Net Worth	$ 153,869
Insurance-In-Force	$ 1,632,547

*Source: FHA Financial Statements for 2024

Data through September 2024 was used for the total capital resources. The total economic net worth consists of the following components:

> *Total Capital Resources* equals assets less liabilities in the Fund's balance sheet. The total capital resources are projected to be $115.853 billion at the end of FY 2024.
>
> *Net Present Value of Future Cash Flows on Outstanding Business* consists of discounted cash inflows and outflows. Forward cash inflows consist of premiums and recoveries. Cash outflows consist of claims, loss mitigation, and premium refund expenses. The cash flow model projects quarterly cash inflows and outflows using economic forecasts and loan performance projections. The net present value of future cash flows is estimated to be *positive $*38.016 billion as of the end of FY 2024

C. Changes in the Economic Net Worth

As illustrated in Exhibit II-2, the projected Cash Flow NPV of the MMI Fund for FY 2024 increased by $8.795 billion compared to the Fiscal Year 2023 estimate, shifting from positive $29.221 billion to a positive $38.016 billion. The capital resources available to the MMI Fund have grown, marking a 13.71 percent increase from a positive $101.884 billion to a positive $115.853 billion. The unamortized IIF increased 9.87 percent, from $1,486 billion to $1,633 billion. Exhibit II-2 compares our estimate of the MMI's Cash Flow NPV and IIF as of the end of Fiscal Year 2024 to the Cash Flow NPV estimate in the 2023 Review.

Exhibit II-2. Cash Flow NPV, Insurance-In-Force, and Capital Resources for FY 2024 ($ Million)

Item	Cash Flow NPV	Capital Resources	Unamortized Insurance-In-Force
2023	$ 29,221	$ 101,884	$ 1,485,879
2024	$ 38,016	$ 115,853	$ 1,632,547
Dollar Difference	$ 8,795	$ 13,969	$ 146,668
Percent Change	30.10%	13.71%	9.87%

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

- The FY 2025 Mid-Session Review of the President's Economic Assumptions (PEA) projects higher house growth in the next few years and lower appreciation rates afterwards, resulting in a reduction in projected claim rates as a consequence of reduced risk of mortgages becoming "underwater" in the sense of unpaid balances exceeding property value. Based on sensitivity analysis discussed below (Section V.D), the impact of higher housing prices is relatively modest at approximately 1 percent of 2023 NPV.

- The FY 2025 PEA also projects a substantially higher 30-year fixed-rate mortgage rate, which is incorporated into our model with higher 15-year fixed rates and higher adjustable-rate mortgage interest rates as well. Higher fixed-rate mortgage interest rates reduce refinance incentives, lowering prepayment speeds, and lengthening the time over which FHA can expect to collect MIP, contributing to a NPV increase relative to 2023. When incorporating the updated PEA assumptions along with 2024 model changes, we observe an increase in the NPV on the 2023 loan data by $13.946 billion.

- Following the 2023 book of business through the end of FY 2024, we can identify the effect of the additional FY 2024 experience for all cohorts on the baseline NPV, which results in a decrease in NPV of $2.123 billion. This decrease is due to amortization and loan terminations for cohorts 1994 through 2023.

- Finally, we measure the NPV impact due to the $231.5 billion in new endorsement volume during Fiscal Year 2024. Between 2023 and 2024, there has been an overall increase in volume of the Forwards portfolio resulting in an Unamortized Insurance-In-Force increase of $146.7 billion, a year-over-year increase of 9.87 percent. Based on modeling projections, cohort 2024 is expected to have a net negative performance on the NPV, decreasing the NPV by $3.028 billion.

- The overall change in the baseline NPV from the FY 2023 Review to this Year's review is positive $8.795 billion, which is the sum of positive $13.946 billion, negative $2.123 billion, and negative $3.028 billion.

III. The Current Status of SF Forwards in the MMI Fund

In this section, we present an analysis of the Fund's status. The analysis examines the status of the Fund at the end of FY 2024. This section describes the components of the Fund's economic net worth in FY 2024.

A. Estimating the Current Economic Net Worth of the MMI Fund

The Economic Net Worth is calculated as the sum of available cash in the Fund and the Cash Flow NPV of all anticipated future cash inflows and outflows related to the mortgages currently insured by the MMI Fund. For the 2024 Review, we determined the Cash Flow NPV of the MMI Fund using data through September 30, 2024. This estimation involved an analysis of historical loan performance based on data from FHA, the creation of predictive models for loan transitions and losses, and the utilization of these model outcomes in conjunction with economic projections from OMB and Moody's to forecast the future cash flows of the MMI Fund. The NPV of these cash flows, combined with the MMI's capital resources, constitutes the economic net worth of the MMI Fund.

i. Capital Resources

Capital resources represent the Fund's net assets that can be converted into cash to fulfill the Fund's obligations, such as the payment of claims as they become due. These resources are determined by subtracting total liabilities from total assets and are documented in the year-end financial statements of the Fund. The estimated capital resources of the Fund as of the conclusion of FY 2024 are projected to amount to $115.853 billion as shown in Exhibit III-1.

Exhibit III-1: Estimated Economic Net Worth of the MMI Fund at the End of FY 2023 and 2024 ($ Million)

Item	Cash Flow NPV	Capital Resources	Economic Net Worth
2023	$ 29,221	$ 101,884	$ 131,105
2024	$ 38,016	$ 115,853	$ 153,869

B. Present Value of Future Cash Flows in FY 2024

The Fund's present value of future cash flows is aggregated from separate estimates of the present value of future cash flows from each book of business and for each of the six mortgage product types. Exhibit III-2 shows the present values of future cash flows for each of the six mortgage product types from FY 1994 through the FY 2024 books of business estimated to have survived to the end of FY 2024. From Exhibit III-2, the total present value of these future cash flows is a positive $38.016 billion.

The housing and economic downturn of 2008 led to elevated claim rates for mortgages that originated during Fiscal Years 2005 to 2010. Due to the upfront MIP having already been collected and being part of the current capital resources, and considering their substantial origination volume, the Fiscal Year 2008 to 2012 cohorts are expected to incur more significant negative Cash Flow NPVs than other cohorts. Nevertheless, with the conclusion of the housing recession, property values hit a low point and subsequently began to rise. Consequently, mortgages originating in Fiscal Years 2013 through 2023 exhibit positive Cash Flow NPVs. This positive trend is further bolstered by the collection of MIPs over the mortgage's entire duration. Additionally, the historically low mortgage interest rates on loans originated in 2020, 2021, and the initial quarter of 2022 reduced the refinance incentives, resulting in extended MIP collection periods in the simulation.

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

Interest rates had remained historically low during the first half of Fiscal Year 2022, which tended to increase the NPV on loans originated during that time period due to the reduced likelihood of refinancing. As interest rates started to rise in the latter part of Fiscal Year 2022, the refinance probability for these loans was expected to decline. With the resulting interest rate increase, the refinance rate remained relatively stable for mortgages originated in Fiscal Year 2022. The rising interest rates and subsequent mortgage rates throughout Fiscal Years 2022 and 2023 have reduced the projected level of prepayment rates for loans originating prior to 2023, due to the widely noted “lock-in” effect. However, loans originated in 2023-2024 carry higher mortgage interest rates, leading to greater refinance incentives, contributing to a reversal of post- 2013 NPV increases driven by the potential for lost MIP on loans subject to refinance risk.

Exhibit III-2. Present Value of Future Cash Flows by Origination Fiscal Year & Mortgage Type as of the End of FY 2024 ($ Millions)

Fiscal Year	FRM 30	FRM 15	ARM	SR 30	SR 15	SR ARM	Total
1994	$ -	$ -	$ -	$ -	$ -	$ -	$ -
1995	$ (0.0)	$ -	$ (0.0)	$ (0.0)	$ -	$(0.0)	$ (0.0)
1996	$ (0.0)	$ -	$ (0.0)	$ (0.0)	$ -	$(0.0)	$ (0.1)
1997	$ 0.2	$ -	$ (0.1)	$ (0.0)	$ -	$(0.0)	$ 0.1
1998	$ (0.3)	$ -	$ (0.1)	$ (0.1)	$ -	$(0.0)	$ (0.5)
1999	$ 2.4	$ -	$ 0.1	$ (0.5)	$ -	$(0.0)	$ 2.0
2000	$ 3.1	$ -	$ 0.2	$ (0.0)	$ -	$(0.0)	$ 3.3
2001	$ (3.3)	$ -	$ 0.1	$ (0.7)	$ -	$(0.0)	$ (3.9)
2002	$ (7.7)	$ -	$ (0.6)	$ (1.4)	$ -	$(0.4)	$ (10.1)
2003	$ (11.5)	$ -	$ (0.5)	$ (6.2)	$ -	$(0.4)	$ (18.6)
2004	$ (11.9)	$ -	$ (2.1)	$ (3.0)	$ -	$(0.8)	$ (17.8)
2005	$ (19.9)	$ -	$ (3.9)	$ (2.1)	$ -	$(0.9)	$ (26.7)
2006	$ (29.8)	$ -	$ (1.5)	$ (2.2)	$ -	$(0.0)	$ (33.5)
2007	$ (44.9)	$ -	$ (0.6)	$ (0.5)	$ -	$(0.0)	$ (46.0)
2008	$ (140.5)	$ -	$ (2.2)	$ (9.5)	$ -	$(0.1)	$ (152.3)

Fiscal Year	FRM 30	FRM 15	ARM	SR 30	SR 15	SR ARM	Total
2009	$ (191.9)	$ -	$ (1.9)	$ (67.8)	$ -	$(1.4)	$ (263.0)
2010	$ (227.1)	$ (0.1)	$(17.2)	$ (31.8)	$ -	$(1.5)	$ (277.7)
2011	$ (141.1)	$ (0.5)	$(15.4)	$ (22.0)	$(0.0)	$(1.3)	$ (180.3)
2012	$ (167.3)	$ (0.2)	$ (3.1)	$ (10.6)	$(0.0)	$ 0.0	$ (181.2)
2013	$ 305.0	$ 1.0	$ 2.6	$ 42.4	$ 0.1	$ 0.0	$ 351.1
2014	$ 1,061.2	$ 0.2	$ 13.1	$ 24.4	$ 0.0	$ 0.6	$ 1,099.5
2015	$ 1,653.9	$ 1.8	$ 10.7	$ 169.3	$ 0.0	$ 0.5	$ 1,836.3
2016	$ 2,243.9	$ 1.3	$ 5.8	$ 118.1	$ 0.1	$ -	$ 2,369.2
2017	$ 2,644.1	$ 2.3	$ 4.7	$ 58.8	$ 0.1	$ -	$ 2,709.9
2018	$ 2,265.4	$ 2.4	$ 5.9	$ 5.7	$ 0.0	$ -	$ 2,279.5
2019	$ 2,455.0	$ 2.9	$ 5.6	$ 17.7	$ 0.0	$ -	$ 2,481.2
2020	$ 6,191.7	$ 7.2	$ 0.8	$ 648.9	$ 0.1	$ -	$ 6,848.6
2021	$ 10,507.5	$ 14.6	$ 1.5	$ 1,402.0	$ 0.6	$ -	$ 11,926.2
2022	$ 7,740.5	$ 8.5	$ 10.9	$ 147.2	$ 0.1	$ -	$ 7,907.3
2023	$ 2,444.8	$(15.8)	$ 12.0	$ 0.1	$ -	$ -	$ 2,441.1
2024	$ (3,059.5)	$ 6.2	$ 40.8	$ (15.0)	$ -	$ -	$ (3,027.5)
Total	$ 35,462.0	$ 31.7	$ 65.7	$ 2,461.3	$ 1.0	$(5.9)	$ 38,015.9

C. Amortization of Outstanding Books of Business

Both the unamortized and the amortized IIF are presented in this Review. From 1994 to 2024, the total Unamortized IIF was $1,632 billion, and the total Amortized IIF was $1,442 billion. Unamortized IIF is the original mortgage amount of all active endorsements. The amortized IIF reflects the current outstanding loan balance of all active endorsements. Exhibit III-3 shows the total volume of new mortgage endorsements for each book of business, the unamortized IIF, and the amortized IIF as of the end of FY 2024.

Exhibit III-3. Endorsements and Insurance-in-Force as of the End of FY 2024 ($ Millions)*

Fiscal Year	Mortgage Endorsement	Unamortized Insurance-in-Force	Amortized Insurance-in-Force
1994	$ 71,942.1	$ 154.9	$ 0.0
1995	$ 41,240.7	$ 329.3	$ 13.3
1996	$ 59,500.9	$ 764.8	$ 82.8
1997	$ 61,082.9	$ 933.0	$ 166.8
1998	$ 90,474.0	$ 1,573.5	$ 380.0
1999	$ 113,169.2	$ 2,505.2	$ 745.7
2000	$ 86,275.7	$ 1,532.7	$ 565.1
2001	$ 107,549.7	$ 2,159.7	$ 902.6
2002	$ 136,141.5	$ 3,960.5	$ 1,756.6
2003	$ 147,310.5	$ 7,916.1	$ 3,669.8
2004	$ 107,620.5	$ 8,387.5	$ 4,147.2
2005	$ 57,975.0	$ 6,287.0	$ 3,338.4

Fiscal Year	Mortgage Endorsement	Unamortized Insurance-in-Force	Amortized Insurance-in-Force
2006	$ 51,732.5	$ 5,368.4	$ 3,153.6
2007	$ 56,515.7	$ 5,609.7	$ 3,573.7
2008	$ 171,805.8	$ 14,409.6	$ 9,593.2
2009	$ 330,384.6	$ 30,886.2	$ 20,726.0
2010	$ 297,502.1	$ 36,001.7	$ 24,318.5
2011	$ 217,641.7	$ 29,485.3	$ 19,904.8
2012	$ 213,272.2	$ 39,214.5	$ 26,515.0
2013	$ 240,115.4	$ 57,564.4	$ 40,761.4
2014	$ 135,216.1	$ 20,515.4	$ 15,632.7
2015	$ 213,121.3	$ 40,235.7	$ 31,809.6
2016	$ 245,405.2	$ 60,755.4	$ 49,447.3
2017	$ 250,954.3	$ 70,348.4	$ 59,025.7
2018	$ 209,049.6	$ 57,640.1	$ 50,390.0
2019	$ 214,620.7	$ 61,252.2	$ 55,182.5
2020	$ 310,321.2	$ 143,920.7	$ 130,491.3
2021	$ 342,822.9	$ 266,305.3	$ 245,343.8
2022	$ 255,504.5	$ 234,003.9	$ 222,674.7
2023	$ 208,728.5	$ 195,343.9	$ 191,683.0
2024	$ 231,485.7	$ 226,798.8	$ 225,528.0
Total	$ 5,276,482.7	$ 1,632,163.9	$ 1,441,523.2

*Data for this table is from FY 2014 through FY 2024, a small percentage of volume for Unamortized IIF falls in years prior to FY 2014.

IV. Characteristics of the MMI SF Forwards Books of Business

In this section, we examined the characteristics of the loan portfolio insured by the MMI Fund for 2024. Our analysis is divided into three key areas:

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

Furthermore, we conducted a comprehensive assessment of the FY2024 cohort and compared it to prior cohorts to assess its potential impact on the future performance of the MMI Fund.

A. Volume and Share of Mortgage Originations

FHA endorsed $231.5 billion in single-family forward mortgages in Fiscal Year 2024, bringing the MMI Fund's total unamortized IIF to $1.633 trillion. Exhibit IV-1 shows the FHA's count and volume of originations by fiscal year and mortgage product type.

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

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

Exhibit IV-1. Total Count and Volume of FHA-Insured Originations

Fiscal Year	Count of Originations						Volume of Originations ($ Million)					
	FRM 30	FRM 15	ARM	FRM 30 SR	FRM 15 SR	ARM SR	FRM 30	FRM 15	ARM	FRM 30 SR	FRM 15 SR	ARM SR
1994	484,854	29,745	148,513	373,684	140,529	29,996	36,807	1,673	13,994	27,744	7,957	2,594
1995	340,064	11,967	128,379	24,765	12,986	4,165	25,659	636	12,054	1,821	667	346
1996	457,701	13,407	146,263	62,022	18,408	10,677	36,930	787	14,324	5,336	1,038	1,064
1997	456,475	11,753	189,884	24,397	8,848	10,345	37,596	727	18,928	2,224	495	1,101
1998	612,331	14,690	169,911	135,823	17,047	21,775	54,432	990	17,631	13,890	1,097	2,424
1999	853,332	17,501	34,300	217,941	31,022	9,412	82,644	1,286	4,083	22,042	2,027	1,070
2000	712,249	8,397	78,953	21,590	4,989	5,264	72,709	632	9,879	2,159	304	582
2001	760,351	11,234	18,268	160,269	7,537	4,856	83,136	971	2,447	19,752	620	618
2002	806,823	17,279	50,421	238,885	26,535	28,218	92,750	1,622	7,295	28,741	2,014	3,718
2003	638,121	18,968	39,622	432,007	54,966	35,232	77,156	1,927	6,059	52,986	4,295	4,886
2004	547,260	14,708	56,309	200,251	39,461	34,406	66,921	1,474	8,715	23,129	2,796	4,583
2005	329,787	7,491	34,096	81,430	12,939	12,579	40,081	730	5,255	9,375	815	1,715
2006	349,138	6,856	9,291	29,786	3,933	865	45,570	702	1,476	3,602	249	128
2007	370,413	6,632	4,329	19,791	843	252	52,059	692	754	2,895	63	42
2008	934,877	21,963	10,872	59,869	2,537	1,318	155,941	2,760	2,434	10,147	242	260
2009	1,439,633	51,850	10,257	315,176	9,978	4,186	254,719	7,206	2,613	63,624	1,235	947
2010	1,342,614	77,109	34,159	191,530	8,450	12,838	234,971	10,807	8,408	39,151	1,080	3,046
2011	900,408	80,417	35,457	156,868	7,883	15,456	157,304	12,270	9,119	33,652	1,356	3,912
2012	812,118	86,033	12,214	251,299	14,552	8,148	139,489	13,601	3,179	52,326	2,516	2,138
2013	778,759	48,515	5,645	490,411	17,713	3,667	139,922	7,399	1,665	87,856	2,306	938
2014	631,599	24,849	14,714	105,149	5,262	4,604	111,478	3,392	4,006	14,887	498	922
2015	847,241	26,796	9,360	225,913	3,489	3,406	158,689	3,552	2,769	46,744	397	966
2016	1,014,558	26,269	4,190	207,172	5,395	463	199,123	3,295	1,351	40,894	604	138
2017	1,053,874	24,711	3,749	155,980	8,071	48	214,953	3,197	1,010	30,879	903	12
2018	940,820	17,526	3,745	49,198	3,255	57	195,635	2,357	1,000	9,741	302	14
2019	914,816	14,292	3,384	56,180	1,727	26	197,041	1,930	934	14,554	155	7
2020	1,000,990	9,826	344	319,166	2,823	1	230,205	1,359	113	78,227	417	0
2021	1,018,183	10,849	174	397,176	6,476	5	249,496	1,462	64	90,955	845	1
2022	887,761	8,252	1,166	83,310	1,698	7	235,753	1,143	383	18,012	211	2
2023	727,148	3,379	641	1,125	25	-	207,592	546	236	352	2	-
2024	747,683	3,686	1,485	13,946	18	-	225,238	673	636	4,936	3	-

Exhibit IV-2 displays FHA's origination volume and market share in home purchase mortgages from calendar 2000 through 2024Q2.

Exhibit IV-2: FHA's Market Share in the Home Purchase Mortgage Market[62]

Calendar Year	FHA Market Shares (Percent)			Origination Volume ($ Billions)					
				Purchase		Refinance		All	
	Purchase	Refinance	All	FHA	Market	FHA	Market	FHA	Market
2000	9.90	3.20	8.60	89	897	7	220	96	1,117

[62] https://www.hud.gov/sites/dfiles/Housing/images/FHA_SF_Market_Share_2024Q2.pdf

Calendar Year	FHA Market Shares (Percent)			Origination Volume ($ Billions)					
				Purchase		Refinance		All	
	Purchase	Refinance	All	FHA	Market	FHA	Market	FHA	Market
2001	10.20	5.80	8.20	97	951	49	841	146	1,792
2002	8.50	3.20	5.40	90	1,056	49	1,526	139	2,582
2003	6.40	2.60	3.70	78	1,221	77	2,970	155	4,191
2004	4.40	2.00	3.20	58	1,314	29	1,415	87	2,729
2005	2.60	1.10	1.90	40	1,512	16	1,514	56	3,026
2006	2.70	1.30	2.00	38	1,399	17	1,326	55	2,725
2007	3.90	2.90	3.40	44	1,140	33	1,166	77	2,306
2008	19.50	12.90	16.10	143	731	100	777	243	1,508
2009	28.10	12.80	17.90	187	664	171	1,331	358	1,995
2010	27.40	8.60	14.90	165	602	103	1,203	268	1,805
2011	25.32	6.46	13.09	128	505	60	931	188	1,436
2012	21.28	7.38	11.38	125	587	108	1,456	233	2,044
2013	15.94	7.84	11.07	117	734	87	1,111	204	1,845
2014	13.83	5.62	10.56	105	760	28	503	133	1,263
2015	16.74	10.60	13.90	151	903	82	776	233	1,679
2016	16.39	8.09	12.35	173	1,053	81	1,000	253	2,053
2017	14.95	9.64	13.09	171	1,143	59	616	230	1,759
2018	12.86	9.10	11.81	155	1,209	42	467	198	1,676
2019	13.66	7.58	10.88	167	1,225	78	1,029	245	2,254
2020	12.83	4.35	7.41	190	1,482	114	2,625	304	4,107
2021	10.85	4.83	7.35	202	1,863	124	2,575	326	4,438
2022	11.06	7.77	10.08	174	1,578	52	667	226	2,245
2023	14.22	15.69	14.44	176	1,239	34	218	210	1,457
2024Q2	14.38	11.02	13.64	90	627	20	179	110	806

FHA's market share declined to a low of 1.9 percent in 2005. However, this trend reversed over the next several years, and by Fiscal Year 2009, FHA's market share had risen to 17.9 percent. Capital limitations encumbered private mortgage insurers and non-conforming lenders, effectively establishing FHA as the sole viable avenue for high Loan-to-Value (LTV) loans. Subsequently, the market share experienced a decline from 2018 through 2021 when it reached 7.35 percent. It has since increased, to 10.08 percent as of 2022 and 14.44 percent in 2023, currently standing at 13.64 percent as of end of the second quarter of 2024.

B. Originations by Location

FHA insures loans in all regions of the U.S., but about half of FHA's total dollar volume is concentrated in only ten states. Exhibit IV-3 shows the percentage of FHA's total dollar volume originated in these ten states from FY 2019 through FY 2024. The states are ordered based on the dollar volume endorsed during FY 2024 to highlight the most recent changes.

Exhibit IV-3. Percentage of Origination Volume by the Top 10 States

State	2019	2020	2021	2022	2023	2024
TX	8.3%	9.4%	9.6%	9.1%	10.9%	11.6%
FL	8.9%	8.9%	9.1%	9.1%	10.5%	11.3%
CA	14.3%	14.4%	12.4%	11.3%	10.5%	10.7%
GA	4.0%	4.1%	4.2%	4.5%	5.1%	4.9%
AZ	3.2%	3.4%	3.2%	3.1%	3.7%	3.9%
NC	2.2%	2.3%	2.4%	2.6%	3.1%	3.4%
TN	2.4%	2.2%	2.0%	2.2%	2.6%	2.8%
NJ	3.5%	3.7%	4.0%	3.8%	3.0%	2.7%
CO	3.7%	3.5%	3.1%	2.8%	2.7%	2.7%
VA	2.9%	3.0%	3.3%	3.1%	2.7%	2.6%

Since FY 2019, Texas has continued its trend of growing market share of FHA volume, moving from 8.3 percent up to 11.6 percent in FY 2024. Florida has followed a similar trend as Texas and now also stands above California at an 11.3 percent share of FHA loans by volume.

C. Originations by Mortgage Type

Exhibit IV-4 illustrates that the fully underwritten 30-year fixed-rate mortgage (FRM) has consistently constituted most of FHA's single-family business, averaging 75.6 percent over FYs 1994-2024. The proportion of total mortgages represented by 30-year FRMs began to evolve in the early 1990s when the FHA introduced insurance for adjustable-rate mortgages (ARMs) and streamline-refinancing mortgages (SRs). Over the following years, ARM and SR mortgages gradually claimed a more significant portion of annual loan originations, causing a decrease in the fully underwritten 30-year FRM share. FYs 1993, 1994, and 2003 marked the periods with the lowest shares of fully underwritten 30-year FRMs. This proportion has exceeded 90 percent each year starting FY 2018 through the present except for 2020-2021.

The ARM share of the portfolio, including SR ARMs, has declined substantially since reaching 11.8 percent in 2000, remaining less than 1 percent since 2015. Liquidity injected into the financial system in the context of the 2000-2001 recession and the 2008-2009 financial crisis, combined with declining inflationary expectations and a narrowing of spreads between mortgage interest rates and long-term Treasury yields, brought long-term primary mortgage to historic lows, incentivizing borrowers to shift from ARM to FRM products. FRM-30 mortgage rates have risen sharply since 2022 as noted earlier, but this increase has been accompanied by a simultaneous increase in ARM rates, explaining the continuation of market share trends from the prior low mortgage interest rate period.[63]

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

Meanwhile, 15-year FRMs grew from 1.2 percent in Fiscal Year 2007 to 6.4 percent in Fiscal Year 2012 but have generally declined since then, currently standing at 0.3 percent in Fiscal Year 2024. The 15-year SR continues to represent a negligible product type in the MMI Fund.

Exhibit IV-4. Percentage of Origination Volume by Mortgage Type

Fiscal Year	Fully Underwritten Mortgages			Streamline Refinancing		
	30-Year FRMs	15-Year FRMS	ARMs	30-Year SRs	15-Year SRs	ARMs SRs
1994	40.5%	1.8%	15.6%	30.6%	8.3%	3.1%
1995	62.4%	1.5%	29.3%	4.4%	1.5%	0.8%
1996	62.3%	1.3%	23.9%	9.0%	1.7%	1.9%
1997	61.7%	1.2%	30.9%	3.6%	0.8%	1.9%
1998	59.9%	1.1%	19.7%	15.4%	1.2%	2.8%
1999	72.9%	1.1%	3.7%	19.5%	1.7%	1.0%
2000	84.0%	0.7%	11.8%	2.5%	0.3%	0.7%
2001	77.4%	0.9%	2.4%	18.2%	0.6%	0.6%
2002	68.1%	1.2%	5.7%	20.9%	1.4%	2.8%
2003	52.6%	1.3%	4.4%	35.5%	2.8%	3.4%
2004	62.2%	1.3%	8.6%	21.1%	2.5%	4.3%
2005	69.0%	1.2%	9.6%	15.9%	1.4%	2.9%
2006	88.1%	1.3%	3.0%	6.9%	0.5%	0.3%
2007	92.1%	1.2%	1.4%	5.1%	0.1%	0.1%
2008	90.8%	1.6%	1.5%	5.9%	0.1%	0.2%
2009	77.1%	2.2%	0.8%	19.3%	0.4%	0.3%
2010	79.0%	3.6%	2.8%	13.2%	0.4%	1.0%
2011	72.3%	5.6%	4.2%	15.5%	0.6%	1.8%
2012	65.4%	6.4%	1.5%	24.5%	1.2%	1.0%
2013	58.3%	3.1%	0.7%	36.6%	1.0%	0.4%
2014	82.5%	2.5%	3.0%	11.0%	0.4%	0.7%
2015	74.5%	1.7%	1.3%	21.9%	0.2%	0.5%
2016	81.1%	1.3%	0.6%	16.7%	0.2%	0.1%
2017	85.7%	1.3%	0.4%	12.3%	0.4%	0.0%
2018	93.6%	1.1%	0.5%	4.7%	0.1%	0.0%
2019	91.8%	0.9%	0.4%	6.8%	0.1%	0.0%
2020	74.2%	0.4%	0.0%	25.2%	0.1%	0.0%
2021	72.8%	0.4%	0.0%	26.5%	0.2%	0.0%
2022	92.3%	0.4%	0.2%	7.0%	0.1%	0.0%
2023	99.5%	0.3%	0.1%	0.2%	0.0%	0.0%
2024	98.0%	0.3%	0.3%	1.5%	0.0%	0.0%
Total	77.2%	1.7%	3.3%	16.2%	0.7%	0.8%

D. Initial Loan-to-Value Ratio Distributions

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

Exhibit IV-5. Percentage of Origination Volume by Original LTV Category*

Fiscal Year	Unknown LTV	<= 80	> 80% <=90%	>90 <= 95	> 95% <97%	>=97%
1994	34.6%	3.6%	9.7%	16.4%	19.8%	16.0%
1995	5.9%	3.2%	10.4%	22.9%	31.7%	26.0%
1996	9.7%	3.0%	10.6%	23.1%	30.8%	22.9%
1997	4.8%	3.4%	11.3%	24.9%	32.5%	23.1%
1998	13.5%	3.6%	11.8%	23.3%	29.1%	18.7%
1999	13.3%	4.0%	10.9%	14.8%	25.2%	31.9%
2000	2.4%	2.7%	6.9%	7.3%	31.9%	48.9%
2001	18.4%	3.6%	8.8%	8.6%	22.8%	37.9%
2002	11.6%	4.7%	11.1%	10.0%	23.7%	39.0%
2003	9.4%	6.0%	12.6%	11.7%	23.7%	36.6%
2004	12.9%	6.6%	11.7%	10.3%	22.5%	36.0%
2005	15.1%	6.4%	10.7%	9.1%	22.2%	36.5%
2006	15.2%	7.1%	10.7%	14.3%	19.9%	32.8%
2007	14.3%	7.4%	11.7%	21.2%	18.2%	27.2%
2008	21.9%	6.2%	12.2%	24.0%	14.1%	21.6%
2009	9.7%	5.0%	13.3%	18.8%	35.7%	17.4%
2010	0.1%	4.8%	14.5%	12.6%	58.8%	9.1%
2011	0.1%	4.9%	14.8%	14.1%	59.9%	6.3%
2012	0.0%	5.5%	13.4%	20.0%	57.2%	3.8%
2013	0.0%	5.7%	16.1%	27.2%	48.6%	2.3%
2014	0.0%	6.1%	14.1%	12.9%	65.0%	1.8%
2015	0.1%	6.1%	14.8%	12.9%	63.8%	2.2%
2016	0.0%	6.9%	16.1%	11.1%	64.1%	1.7%
2017	0.0%	7.9%	17.2%	10.1%	63.7%	1.2%
2018	0.0%	7.8%	16.8%	8.1%	66.2%	1.1%
2019	0.0%	7.6%	17.5%	7.8%	65.5%	1.7%
2020	0.1%	10.5%	12.1%	12.3%	62.7%	2.4%
2021	0.0%	12.5%	11.2%	14.5%	60.8%	0.9%
2022	0.0%	20.7%	7.5%	10.8%	60.8%	0.2%
2023	0.0%	18.9%	7.1%	9.7%	64.1%	0.2%
2024	0.0%	17.7%	7.1%	9.7%	64.3%	1.0%

The distribution among original LTV categories had undergone significant shifts after FY1998. During the period spanning from FY 2000 to FY 2006, over a third of insured loans had LTVs equal to or greater than 97 percent. However, this concentration in the highest-risk category gradually waned over the following years. In 2008, MMI imposed a 96.5 percent limit on the original LTV, with no additional allowances for financing closing costs. Loans with LTV greater than or equal to 97 percent have remained low for each FY since 2017. Since 2014, over 60 percent of mortgages have had LTV ratios falling between 95 percent and 97 percent.

In FY 2022, nearly 20 percent of mortgages had an initial LTV of 80 percent or lower, possibly related to refinance incentives in a historically low mortgage rate environment. Such loans have remained more than 15 percent of the total in each of the subsequent years.

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

E. Borrower Credit History Distributions

Since May 2004, all lenders originating loans for FHA insurance have been required to report borrower credit scores directly to HUD if any credit scores were ordered as part of the underwriting process. All loans going through the FHA TOTAL scorecard have credit scores obtained electronically by the affiliated automated underwriting systems. This provides a reliable source of credit score data. There are no exceptions to this requirement, so the credit scores collected through this channel are comprehensive and unbiased. These loans have become the primary source of credit score information. Credit scores pre-2004 were derived by UNICON or obtained from Fannie Mae as discussed below in Appendix A2.

Exhibit IV-6 shows the distributions of fully underwritten FHA mortgage loans by borrower credit score categories and origination years. The distribution among credit score categories remained stable for the FY 2005 through FY 2008 books. For loans originating after FY 2008, the credit score distribution significantly improved over the previous years. FY 2011 witnessed the highest percentage (62.5%) of people with credit scores above 680. Loans with credit scores below 600 have remained less than 10 percent since 2009, currently standing at 4.8 percent.

Exhibit IV-6. Percentage of Origination Volume by Credit Score among Fully Underwritten Loans*

Fiscal Year	Missing	300-499	500-599	600-639	640-679	680-719	>720
1994	98.0%	0.0%	0.6%	0.4%	0.4%	0.2%	0.3%
1995	97.5%	0.0%	0.8%	0.6%	0.4%	0.3%	0.3%
1996	97.4%	0.0%	0.8%	0.6%	0.5%	0.3%	0.4%

Fiscal Year	Missing	300-499	500-599	600-639	640-679	680-719	>720
1997	97.4%	0.0%	0.8%	0.6%	0.5%	0.4%	0.4%
1998	97.2%	0.1%	0.9%	0.6%	0.5%	0.4%	0.4%
1999	97.1%	0.1%	0.9%	0.6%	0.6%	0.4%	0.4%
2000	86.6%	0.1%	3.3%	2.8%	2.8%	2.1%	2.2%
2001	77.9%	0.2%	5.2%	4.7%	4.6%	3.5%	3.9%
2002	71.1%	0.2%	6.8%	6.4%	6.0%	4.4%	5.1%
2003	64.1%	0.3%	8.7%	8.1%	7.5%	5.3%	6.0%
2004	44.3%	0.4%	14.0%	13.6%	12.0%	7.6%	8.1%
2005	6.5%	0.9%	26.1%	24.3%	20.0%	11.3%	10.9%
2006	5.0%	0.9%	25.4%	24.5%	20.7%	11.5%	12.0%
2007	4.4%	1.5%	31.2%	25.1%	18.9%	9.5%	9.3%
2008	2.5%	0.8%	21.0%	24.2%	22.7%	13.6%	15.1%
2009	1.5%	0.0%	6.2%	18.0%	24.8%	20.6%	28.8%
2010	1.6%	0.0%	1.0%	12.4%	25.0%	23.1%	36.9%
2011	1.4%	0.0%	0.5%	8.4%	27.1%	24.0%	38.5%
2012	1.1%	0.0%	0.6%	8.2%	30.7%	24.8%	34.6%
2013	1.0%	0.0%	0.5%	6.5%	36.4%	27.7%	27.9%
2014	0.7%	0.0%	1.0%	11.3%	41.5%	27.6%	17.8%
2015	0.7%	0.0%	1.7%	14.5%	37.9%	27.4%	17.8%
2016	0.7%	0.0%	1.9%	15.5%	36.4%	27.1%	18.4%
2017	0.7%	0.0%	2.7%	17.7%	36.1%	25.8%	17.1%
2018	0.6%	0.0%	4.3%	21.0%	36.9%	23.2%	14.1%
2019	0.5%	0.0%	5.2%	22.5%	37.6%	21.6%	12.5%
2020	0.5%	0.0%	3.4%	18.7%	39.2%	23.6%	14.6%
2021	0.5%	0.0%	2.0%	18.6%	42.4%	23.1%	13.4%
2022	0.5%	0.0%	4.5%	23.3%	40.5%	20.4%	10.8%
2023	0.6%	0.0%	4.7%	19.5%	36.3%	23.3%	15.6%
2024	0.7%	0.0%	4.8%	17.0%	31.2%	24.0%	22.4%

* Excludes streamlined refinanced.

F. Initial Relative Loan Size Distributions

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

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

Exhibit IV-7 displays the percentage of new fully underwritten mortgage originations within each relative loan size category. The distribution had remained reasonably stable over time, with the most substantial share in the 100 percent and 125 percent of area loan size categories. Nevertheless, since Fiscal Year 2000, there has been a continuous increase in the variance among loan size categories. The proportion in the highest loan size category (above 150 percent of average loan size) had risen from 11.94% in Fiscal Year 2000 to 26% in Fiscal Year 2013 but decreased to 16.12% in 2020. As of 2024, the proportion in the highest loan size category is 16.38%.

The share in the lowest loan size category (less than or equal to 50% of average loan size) peaked at 5.20% in 2012, dropping to 2.77% in 2024.

Exhibit IV-7. Percentage of Origination Count by Relative Loan Size

Cohort Year	<=50% Loan Size	75% Loan Size	100% of Loan Size	125% of Loan Size	150% of loan Size	>150% Loan Size
1994	1.27%	9.65%	23.06%	29.97%	24.40%	11.66%
1995	1.64%	11.49%	24.85%	30.87%	22.52%	8.62%
1996	1.59%	11.32%	24.77%	31.36%	22.90%	8.05%
1997	1.68%	11.58%	24.64%	32.15%	22.16%	7.79%
1998	1.74%	11.58%	24.97%	32.86%	21.47%	7.37%
1999	1.80%	11.27%	24.15%	30.09%	20.95%	11.73%
2000	2.07%	11.84%	24.70%	29.24%	20.20%	11.94%
2001	2.19%	11.91%	25.57%	29.67%	19.49%	11.17%
2002	2.05%	11.08%	24.52%	29.76%	19.94%	12.64%
2003	1.81%	10.27%	23.61%	29.92%	20.68%	13.71%
2004	1.81%	10.14%	22.55%	28.93%	21.41%	15.16%
2005	1.92%	10.95%	22.97%	28.28%	21.03%	14.84%
2006	2.18%	12.04%	23.14%	28.07%	20.01%	14.56%
2007	2.50%	12.59%	23.37%	27.67%	19.36%	14.51%
2008	2.79%	13.00%	24.30%	25.47%	16.95%	17.49%
2009	3.98%	14.66%	23.51%	21.67%	15.08%	21.10%
2010	4.33%	15.02%	22.40%	20.43%	14.20%	23.62%
2011	5.09%	15.43%	21.49%	19.26%	13.71%	25.02%
2012	5.20%	15.67%	21.85%	19.68%	13.83%	23.78%
2013	4.16%	13.90%	21.20%	20.03%	14.70%	26.00%
2014	3.58%	13.16%	21.47%	20.94%	15.49%	25.35%
2015	3.83%	13.88%	22.98%	21.77%	15.64%	21.90%
2016	3.39%	12.94%	22.78%	22.41%	16.63%	21.85%
2017	3.17%	12.50%	22.91%	23.30%	17.50%	20.62%
2018	3.10%	12.50%	23.35%	24.31%	17.15%	19.59%
2019	3.16%	12.63%	24.21%	24.94%	16.98%	18.09%
2020	2.85%	12.37%	24.99%	25.99%	17.68%	16.12%
2021	2.46%	10.82%	23.14%	26.25%	18.79%	18.53%
2022	2.81%	11.58%	22.63%	25.49%	18.72%	18.77%
2023	3.02%	12.10%	23.91%	26.26%	17.40%	17.32%
2024	2.77%	12.07%	24.88%	26.62%	17.28%	16.38%

*Excludes streamlined refinanced.

G. Initial Contract Interest Rate

Exhibit IV-8 presents the average mortgage contract rate by type since FY 1993. Before FY 2020, the average contract rates in FY 2013 had been the lowest in this entire period. Rates had risen since FY 2013 but declined substantially in FY 2020 and FY 2021. Interest rates for 30-year SRs in FY 2021 were at their lowest level since FY 1993, reaching 2.88 percent and contributing significantly to a surge in refinance activity in FY 2020 and FY 2021.

Interest rates increased rapidly in FY 2022 in response to anti-inflation action by the Federal Reserve Board of Governors, rising to 6.6% as of FY 2024.

In general, an FRM with a lower initial contract rate tends to prepay at a slower speed. As interest rates continue to rise or remain steady, the prepayment rates of the recent originations are likely to remain low. The longer duration of these loans is reflected in our econometric models, so that additional insurance premium income is forecasted, thereby increasing the economic net worth of recent books with historically low contract rates. We note that there will be some level of prepayments associated with employment change and residential mobility, regardless of the level of interest rates.[64] Our econometric models fall under the general descriptions of the logit models that include both baseline and systematic components that determine conditional transition rates, so that projected transition rates will never reach either 0 or 1.

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

Exhibit IV-8. Average Contract Interest Rate by Loan Type (Percent)

Fiscal Year	30-Year FRMS	15-Year FRMs	ARMs	30-Year SRs	15-Year SRs	ARM SRs
1994	7.71%	7.25%	6.25%	7.81%	7.48%	6.15%
1995	8.29%	8.02%	7.06%	8.36%	8.21%	7.05%
1996	7.88%	7.58%	6.54%	8.00%	7.69%	6.80%
1997	7.89%	7.67%	6.47%	8.19%	7.94%	6.75%
1998	7.29%	7.10%	6.11%	7.46%	7.09%	6.47%
1999	7.39%	7.07%	6.21%	7.23%	6.97%	6.02%
2000	8.30%	8.07%	6.99%	8.18%	7.89%	6.38%
2001	7.41%	6.97%	6.03%	7.31%	6.74%	5.93%
2002	6.95%	6.45%	5.27%	6.82%	6.30%	5.26%
2003	6.08%	5.51%	4.42%	5.99%	5.48%	4.44%
2004	6.08%	5.52%	4.41%	5.92%	5.46%	4.34%
2005	5.94%	5.64%	4.78%	5.85%	5.65%	4.67%
2006	6.29%	6.14%	5.36%	6.10%	6.02%	5.03%

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

Fiscal Year	30-Year FRMS	15-Year FRMs	ARMs	30-Year SRs	15-Year SRs	ARM SRs
2007	6.51%	6.40%	5.62%	6.37%	6.22%	5.60%
2008	6.33%	5.95%	5.39%	6.09%	5.63%	5.33%
2009	5.62%	5.14%	5.05%	5.26%	4.81%	4.54%
2010	5.14%	4.62%	3.98%	5.13%	4.65%	4.28%
2011	4.65%	4.16%	3.51%	4.63%	4.16%	3.69%
2012	3.98%	3.46%	3.14%	3.98%	3.53%	3.38%
2013	3.62%	3.16%	2.82%	3.71%	3.35%	2.86%
2014	4.30%	3.71%	3.31%	4.51%	3.90%	3.39%
2015	4.03%	3.47%	3.26%	3.99%	3.67%	3.36%
2016	3.91%	3.40%	3.23%	3.87%	3.52%	3.35%
2017	4.03%	3.50%	3.18%	3.75%	3.59%	3.02%
2018	4.54%	3.87%	3.51%	4.07%	4.03%	3.49%
2019	4.68%	4.15%	4.00%	4.23%	4.44%	4.02%
2020	3.63%	3.49%	3.47%	3.50%	3.41%	3.50%
2021	3.04%	2.67%	2.65%	2.88%	2.81%	2.33%
2022	4.06%	3.16%	3.11%	3.08%	2.99%	2.52%
2023	6.18%	5.53%	4.93%	5.74%	3.94%	N/A
2024	6.57%	6.02%	5.38%	6.43%	5.60%	N/A

V. MMI Fund Performance under Alternative Scenarios and Sensitivity Testing

The Fund's economic net worth for FY 2024 depends on the economic conditions expected to prevail over the next 30 years and, most critically, during the next 10 years.

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

- 30-year, 15-year, and adjustable-rate mortgage rates
- 30-year, 15-year, and adjustable-rate mortgage rates
- National and local house price indices
- National and local unemployment rates

The projected performance of FHA's current book of business, as measured by economic net worth, depends on future forecasts of these economic drivers. The baseline scenario for the primary economic drivers was developed consistent with the FY 2025 Mid-Session Review of the President's Economic Assumptions (PEA). The PEA is published by the Office of Management and Budget in compliance with the requirements of the Federal Credit Reform Act.

A. FHFA House Price Indices

The actuarial central estimates are based on the PEA for the quarterly future performance of the FHFA Purchase Only (PO) seasonally adjusted HPI for the period FY 2024 FQ3 to FY 2034 FQ4 and 3% annualized HPA for years after FY 2034.

Consistent with the PEA, house price indices (HPIs) produced and published by FHFA were applied in loan status transition model estimation. FHFA publishes both purchase-only (PO) and all-transactions (AT) versions of their HPIs. We have applied the AT version of the FHFA HPIs in model estimation, due to the significantly broader regional coverage provided by the AT version of the HPI, including more than 300 additional Metropolitan Statistical Area (MSA) level HPIs.

Prior reviews have expressed the view that the HPI PO version is necessarily more accurate than the HPI AT version due to the reliance of the latter on appraisal valuations in addition to observed sale prices. The actual evidence is limited, mixed, and sometimes points to the opposite conclusion as it regards HPI availability and accuracy. One must keep in mind that the choice between PO and AT versions of the HPI is not an either-or proposition, as the AT version still uses a blended sample of sale and refinance transactions.

Calhoun (1991) first noted the benefits of having appraisal based HPIs during periods when sales transactions are limited or in locations where they are non-existent. Calhoun (1991) also examined the potential for greater sample-selection bias when only sales transaction data are used. Simply stated, mortgage borrowers may be willing to refinance at appraised values well below their reservation prices for selling, so that relying solely on sales prices draws from the higher end of the house price distribution at any point in time. In our view, geographic aggregation bias far outweighs concerns about appraisal bias, particularly given the overall consistency between AT and PO versions of the HPI at the same level of geography. Later research by Calhoun, Harter-Dreiman, VanderGoot (1998) and Leventis (2006) indicate that the actual evidence for systematic appraisal bias is mixed or inconclusive. On the other hand, geographic bias is large, immediate, and certain if the HPI PO version must be applied at the state level when no MSA-level HPI is available, Therefore, we opted for broader geographic coverage at the MSA level.

Nevertheless, we were required to apply the PEA for the national FHFA PO HPI in developing our baseline forecast of portfolio economic net worth. To meet this requirement, we applied the following two-step procedure to obtain regional HPI forecasts from the PEA national forecasts: (1) compute the period-by-period differentials between national forecast HPI appreciation rates and the corresponding appreciation rates for each regional HPI from the same forecast; and then (2) apply these differential appreciation rates to the PEA national HPI forecast to obtain regional HPIs forecasts consistent with the PEA. So as the PEA national forecast varies period-by-period, our regional HPIs vary in a consistent manner, and will maintain the regional dispersion based on historical patterns.

To implement step (1), we use appreciation rates for the Moody's baseline forecasts of the FHFA AT version HPIs at the national and regional levels. This enables us to retain the broader geographic coverage of the AT version of the FHFA HPIs that we applied in estimation. We note that using the Moody's regional forecasts of the FHFA PO version HPI for step (1) would result in loss of the regional coverage we seek to preserve. Step (2) is implemented by adding the respective appreciation rate differentials from step (1) to the appreciation rates of the mandated PEA national forecast of the FHFA PO version HPI.

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

B. Stochastic Scenarios

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

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

- Optimistic Upside Scenario in Simulation, the path that is most favorable to the SF Forwards MMI Fund.
- Moderate Upside Scenario in Simulation, the path that is moderately favorable to the SF Forwards MMI Fund.
- Moderate Downside Scenario in Simulation, the path that is moderately unfavorable to the SF Forwards MMI Fund.
- Pessimistic Downside Scenario in Simulation, the path that is most unfavorable to the SF Forwards MMI Fund.

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

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

Scenario 1 – Optimistic Upside Scenario

Treasury and Mortgage Rates: 90th percentile

Unemployment Rate: 10th percentile

House Price Appreciation Rate: 90th percentile

Scenario 2 – Moderate Upside Scenario

Treasury and Mortgage Rates: 75th percentile

Unemployment Rate: 25th percentile

House Price Appreciation Rate: 75th percentile

Scenario 3 – Moderate Downside Scenario

Treasury and Mortgage Rates: 25th percentile

Unemployment Rate: 75th percentile

House Price Appreciation Rate: 25th percentile

Scenario 4 – Pessimistic Downside Scenario

Treasury and Mortgage Rates: 10th percentile

Unemployment Rate: 90th percentile

House Price Appreciation Rate: 10th percentile

The PEA forecast developed by the White House Council of Economic Advisors, Treasury, and OMB does not cover all the economy drivers that are included in our models. Additional economic variables that must be forecasted, such as FRM 15-Year and ARM origination rates, regional and local house price indices, and local unemployment rates, are developed using the PEA and additional forecast data from Moody's. Additional details may be found in the discussion of stochastic simulation models in Appendix F.

C. NPV Values

The summary of the estimated Cash Flow NPV resulting from the Baseline PEA is $38.016 billion. This projection constitutes the baseline against which the projections from the alternative scenarios are compared. Each scenario is shown in Exhibit V-2. The range of projected results is between positive $29.294 billion and positive $42.561 billion.

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

Economic Scenario	Fiscal Year 2024 Cash Flow NPV
Baseline PEA	$ 38,016
Alternative 1 - Optimistic Upside Scenario	$ 42,561
Alternative 2 - Moderate Upside Scenario	$ 40,588
Alternative 3 - Moderate Downside Scenario	$ 34,928
Alternative 4 - Pessimistic Downside Scenario	$ 29,294

Exhibit V-3 presents a breakdown of the Cash Flow NPV by Cohort for the baseline PEA scenario along with the 4 simulated alternative scenarios.

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

Cohort Year	Baseline PEA	Alternative - 1 Optimistic Upside	Alternative 2 - Moderate Upside	Alternative 3 - Moderate Downside	Alternative 4 - Pessimistic Downside
1995	$ (0)	$ (0)	$ (0)	$ (0)	$ (0)
1996	$ (0)	$ (0)	$ (0)	$ (0)	$ (0)
1997	$ 0	$ 0	$ 0	$ 0	$ 0
1998	$ (0)	$ (0)	$ (0)	$ (0)	$ (0)
1999	$ 2	$ 2	$ 2	$ 2	$ 2
2000	$ 4	$ 4	$ 4	$ 4	$ 4
2001	$ (7)	$ (7)	$ (7)	$ (7)	$ (7)
2002	$ (11)	$ (11)	$ (11)	$ (11)	$ (11)
2003	$ (16)	$ (16)	$ (16)	$ (16)	$ (16)
2004	$ (18)	$ (18)	$ (18)	$ (18)	$ (18)
2005	$ (27)	$ (26)	$ (26)	$ (27)	$ (28)
2006	$ (34)	$ (33)	$ (33)	$ (34)	$ (35)
2007	$ (46)	$ (44)	$ (45)	$ (47)	$ (49)
2008	$ (152)	$ (146)	$ (148)	$ (157)	$ (164)
2009	$ (263)	$ (257)	$ (259)	$ (267)	$ (275)
2010	$ (278)	$ (272)	$ (275)	$ (280)	$ (286)
2011	$ (180)	$ (176)	$ (178)	$ (182)	$ (185)
2012	$ (181)	$ (175)	$ (178)	$ (184)	$ (188)
2013	$ 351	$ 362	$ 357	$ 346	$ 338
2014	$ 1,099	$ 1,105	$ 1,102	$ 1,097	$ 1,093
2015	$ 1,836	$ 1,852	$ 1,844	$ 1,829	$ 1,817
2016	$ 2,369	$ 2,399	$ 2,384	$ 2,356	$ 2,332
2017	$ 2,710	$ 2,760	$ 2,735	$ 2,687	$ 2,643
2018	$ 2,280	$ 2,349	$ 2,316	$ 2,244	$ 2,168
2019	$ 2,481	$ 2,586	$ 2,536	$ 2,427	$ 2,298
2020	$ 6,849	$ 7,062	$ 6,960	$ 6,738	$ 6,542
2021	$ 11,926	$ 12,413	$ 12,177	$ 11,670	$ 11,271
2022	$ 7,907	$ 8,614	$ 8,284	$ 7,516	$ 6,726
2023	$ 2,441	$ 3,672	$ 3,169	$ 1,466	$ (431)
2024	$ (3,028)	$ (1,438)	$ (2,089)	$ (4,224)	$ (6,247)
Total	$ 38,016	$ 42,561	$ 40,588	$ 34,928	$ 29,294

The 2024 Cash Flow NPV estimate provided by FHA is positive $40.914 billion. Based on ITDC's Cash Flow NPV estimate utilizing the Baseline PEA and range of results from the stochastic simulation scenarios, we conclude that the FHA estimate of Cash Flow NPV is reasonable.

D. Sensitivity Tests for Economic Variables and Important Assumptions

The stochastic scenario test results revealed the HPA/HPI and interest rates as important economic assumptions driving the NPV. Exhibit V-4 illustrates NPV changes from baseline to 10 percent increases and decreases in home price appreciation, interest rates (including Treasury and mortgage interest rates) and loss severity.

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

Description	NPV (% Change from the Baseline NPV)*	
	Down 10%	Up 10%
House Price Appreciation	37,512 (-1.3%)	38,675 (1.7%)
Interest Rates	32,949 (-13.3%)	38,831 (2.1%)
Loss Severity Rates	40,040 (5.3%)	35,991 (-5.3%)

The direction and magnitude of NPV impacts of shocks to these key model inputs are broadly consistent with economic intuition. Faster home price appreciation contributes to rising property values and falling LTV ratios, reducing borrower propensity to default, reducing claim rates. At the same time, higher LTV may facilitate refinancing behavior, resulting in the reduction of MIP, mitigating the NPV benefits associated with lower claim rates. Conversely, the dominant effect of lower HPA is reduction in claim rates, mitigated by a slowdown in prepayment speeds.

Rising mortgage interest rates to reduce refinance incentives relative to baseline, contributing to a slowdown in prepayment speeds, extending the period over which MIP can be collected. Conversely, borrowers are very sensitive to any drop in mortgage rates as evidenced by prepayment acceleration in 2024Q1. Because Treasury rates are incorporated into transition models as a measure of curve slope, simultaneous increases in 10-year and 1-year rates will not be significantly impactful on model-predicted transition outcomes.

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

VI. List of Methodological Appendices

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

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

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

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

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

The transition models adopt four main categories of explanatory variables:

> Fixed initial loan characteristics, e.g. credit score, original loan size, loan size, loan purpose, spread relative to market mortgage rates at origination, and debt-to-income ratio;
>
> Dynamic variables based entirely on loan history, e.g. mortgage age, burnout, and default duration;
>
> Dynamic variables incorporating macroeconomic data separately or in conjunction with loan characteristics such as fixed-rate refinance incentive, local/national home price appreciation, current loan-to-value ratio, unemployment, and Treasury curve slope;
>
> Indicator variables designed to capture the impacts of the Covid-19 pandemic as well as policy responses.

Transition models are estimated for each of the following six products: FRM-30 non-streamlined-refinance (NSR); FRM-15 NSR; ARM NSR; FRM-30 streamlined refinance (SR); FRM-15 SR; and ARM SR. For loans that are "current" as of the beginning of a quarterly period (i.e. less than 90 days delinquent), binomial logistic models are estimated for transitions to default, SR, and

NSR. For "defaulted" loans that are 90 days or more delinquent, binomial models are estimated for cure, NSR, and claim.

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

Model Validation (Appendix B)

This section describes steps taken to verify the predictive reliability of the estimated econometric models for predicting conditional transition rates, namely model re-estimation using smaller samples and preparation of plots comparing predicted and realized transition rates for each of the 48 transition models along a variety of relevant covariates. Results confirm the robustness of the transition model econometric modeling design.

Estimation, Forecasting, and Actuarial Projections (Appendix C)

This section describes the loan status transition framework as it relates to the estimated probability models, how those models are applied in forecasting, and the application of the forecasted probabilities to the actuarial calculations that summarize future loan performance. 30-year projections are developed utilizing regression models and coefficients described in Appendix A together with macroeconomic risk factor values for housing prices, long-term mortgage rates, unemployment, and Treasury interest rates from the PEA forecast, supplemented by data from Moody's DataBuffet.

Loss Severity Model and Cash Flow Analysis (Appendix D)

This section provides a technical description of our econometric model of FHA mortgage loss severity rates.

Tables of Historical and Projected Termination Rates (Appendix E)

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

Stochastic Simulation Models (Appendix F)

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

Logistic Model Estimation Results (Appendix G)

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

Data Sources, Processing and Reconciliation (Appendix H)

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

VII. Qualifications and Limitations

The actuarial models used in this review are based on a theoretical framework and certain assumptions. This framework relates the default, claim, loss, and prepayment rates to several individual loan characteristics and certain critical macroeconomic variables. The models are estimated using econometric regression techniques based on data from actual historical experience regarding the performance of FHA-insured mortgage loans. The parameters of the econometric models are estimated over a wide variety of loans originated starting fiscal 1996 and their performance under the range of economic conditions and mortgage market environments experienced during the past 30 years or less. The estimated models are used together with assumptions about future loan performance and certain key economic assumptions to produce future projections of the performance of the Fund.

The financial estimates presented in this Review require projections of events up to 30 years into the future.[65] These projections depend on the validity and robustness of the underlying models and the assumptions about future economic environments and loan characteristics. These include projections of future outcomes for key economic inputs to the models based on economic forecasts provided as components of the FY 2025 Mid-Session Review of the President's Economic Assumptions (PEA). If the realized experience deviates from these or other assumptions, the actual results may differ, perhaps significantly, from current projections.

A. Model Sensitivity to Economic Projections

Three critical economic variables used in making these projections are future house prices, interest rates, and unemployment rates. We conducted a sensitivity analysis to examine how the Fund's economic net worth may change with these macroeconomic factors to gain insights into the possible magnitude of the impacts. Specifically, we investigated the changes in economic net worth by applying the four alternative combinations of percentile paths outlined previously. The benchmark for these sensitivity tests is the deterministic base case, using the FY 2025 Mid-Session Review of the President's Economic Assumptions.

Recent circumstances suggest that the alternative projections should not be expected to yield dramatically different results from the PEA baseline. Mortgage interest rates have been at historically low levels since FY2012 and reached their lowest values as recently as FY2021. Rates have since risen rapidly in response to anti-inflationary actions by the Federal Reserve, roughly doubling over a two-year period. The mandated PEA assumptions applied as the baseline scenario in our analysis stipulate that mortgage rates will rise a bit further and recede only slightly to remain close to their present level for the next 30 years.

[65] As such, the review does not consider cashflows past 2054 on extended term ("ET") modifications where the term to maturity is extended to 40 years.

A quick glance at the historical pattern of mortgage rates suggests this is highly unlikely, and that rates are likely to vary significantly over time. To allow for this likelihood, our analysis applies four alternative scenarios for mortgage interest rates, treasury rates, unemployment rates, and housing prices to examine the potential impact on portfolio performance. However, recent circumstances would be expected to dampen the sensitivity of the models to these alternative scenarios. For example, alternative scenarios that lead to even higher interest rates than the PEA will only further reduce prepayment speeds on outstanding loans, and even a substantial decline in interest rates is unlikely to create a refi boom among current borrowers with historically low-rate mortgages.

B. Basic Data Inputs

The econometric analysis in this Review uses data extracted from FHA's Single-Family Data Warehouse (SFDW). The volume and composition of the existing portfolio are based on FHA data as of September 30, 2024. While we have reviewed the integrity and consistency of these data and believe them to be reasonable, we have not audited them for accuracy. The information in this Review may not correspond exactly with other published analyses that rely on FHA data compiled at different dates or obtained from other data sources.

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

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

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

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

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

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

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

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

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

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

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

claims_601_case_dta - This table contains data to support the accelerated claims disposition programs. Data is provided on the 12th of each month.

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

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

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

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Appendix A: Econometric Analysis of Mortgage Status Transitions and Terminations

A1. Model Specification and Estimation

A1.1. Specification of FHA Mortgage Status Transition and Termination Models

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

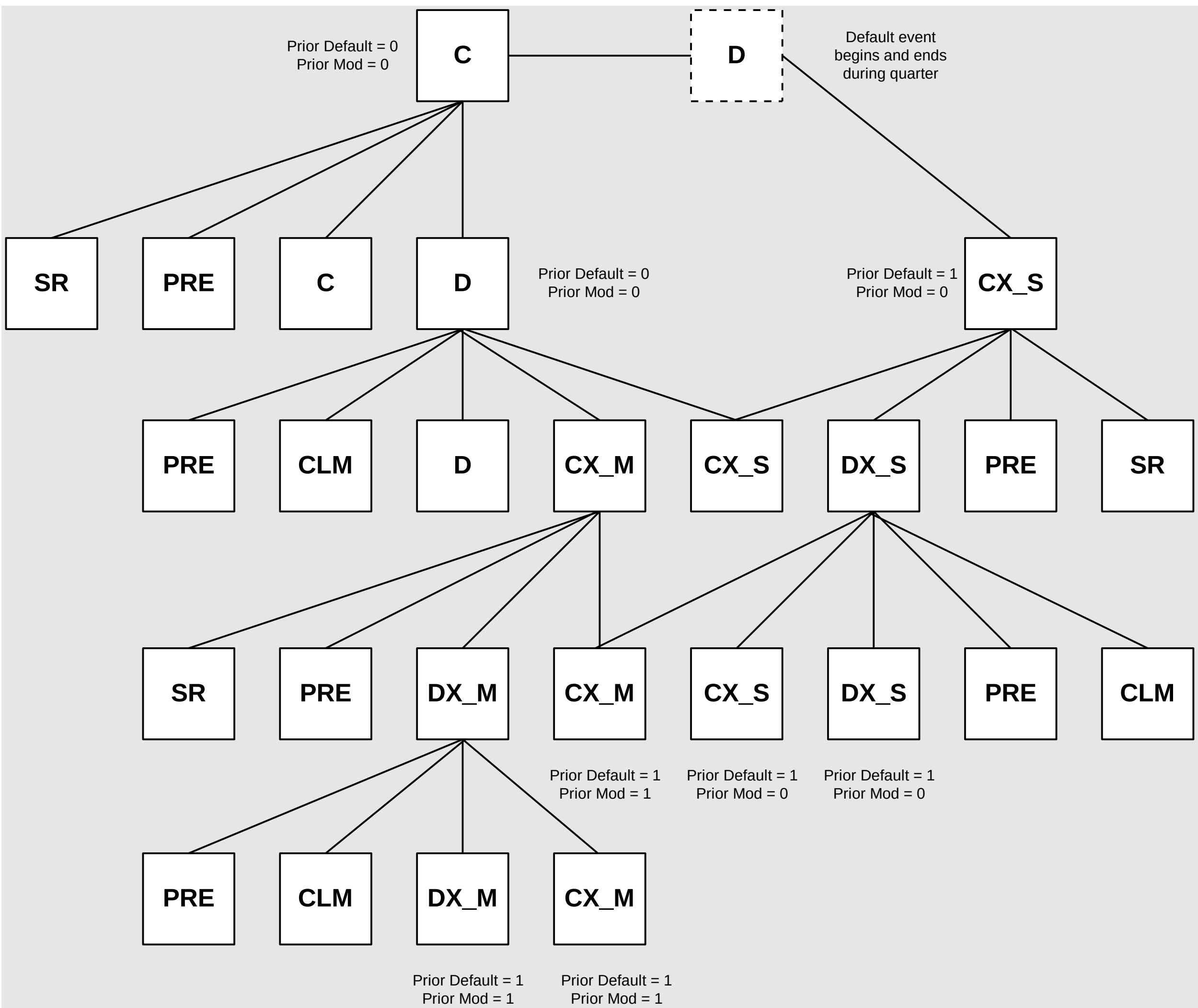
Starting in FY 2010, the modeling utilized FHA historical data on new 90-day default episodes on outstanding mortgages beginning with FY 1990 Q1 originations. The date at which a loan is first reported to be 90 or more days in arrears is used to define the start of a 90-day default episode, which continues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

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

Exhibit A-1 summarizes the loan status transitions we modeled for the FY 2024 review. As described above, we track loans with and without prior default episodes and with and without prior self- or mod-cures as separate loan status categories to introduce path dependence into the analysis. We also account for duration dependence in transition rates by controlling for the duration of default for loans in default status and the duration of cure for loans in self-cure or mod-cure status.

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

Exhibit A-1: Loan Status Transitions Framework



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

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

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

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

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

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

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

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

Current loans that have had one-or-more prior defaults and at least one mod-cure (CX_M) may remain in that status, transition back to default (DX_M), or terminate as prepayment (PRE) or streamline refinance (SR). It is important to emphasize that our prior default and mod indicators correspond to "one or more prior defaults" and "one or more prior mods." Thus, CX_M does not necessarily describe the most recent cure type for loans with multiple cures status. Conversely, self-cure status (CX_S) only applies when all prior defaults are self-cured, and there has been no prior mod-cure.

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

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

Graphic Illustrations of the Timeline of Status Transitions

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

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

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

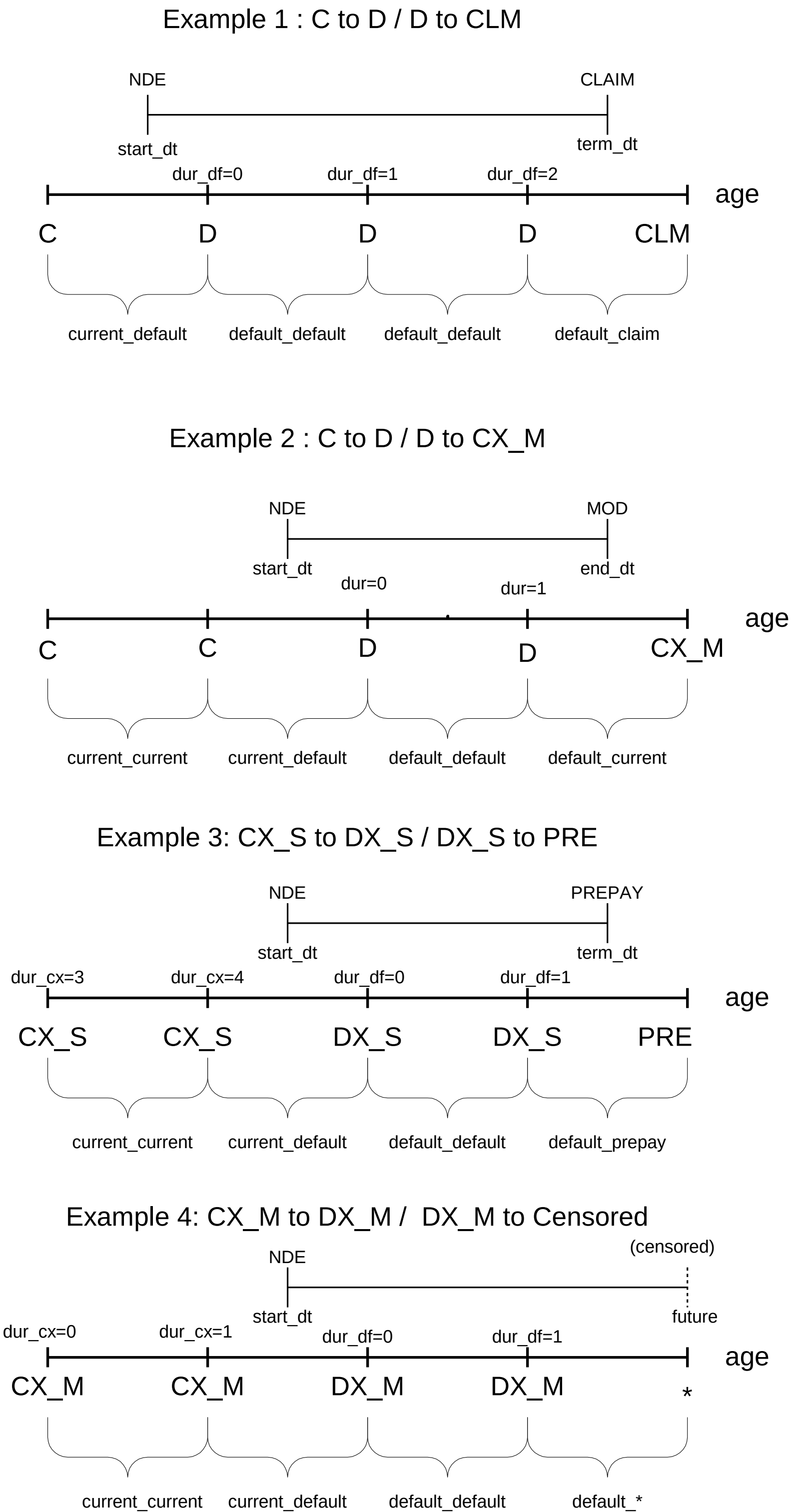
Example 3 starts with a previously defaulted and self-cured loan spending four quarters in current status (CX_S), defaulting again, and remaining in default status DX_S for one quarter before terminating in prepayment (PRE).

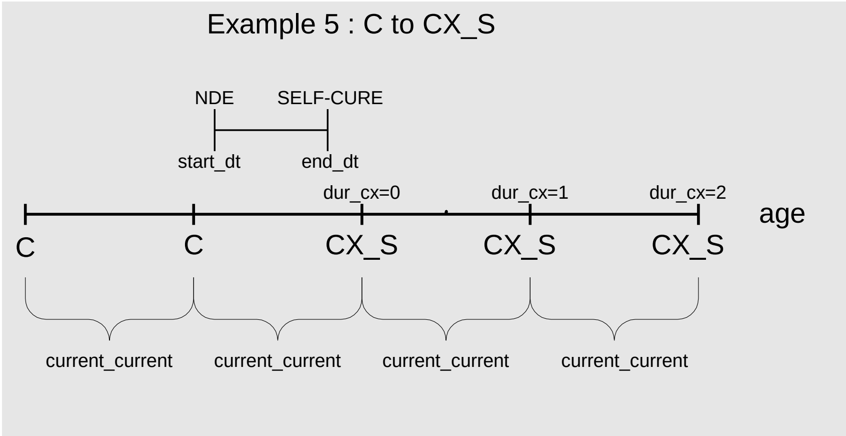
Example 4 has a recently mod-cured loan in current status (CX_M) defaulting again and remaining in default status DX_M until the historical sample ends. This results in the censoring of that default episode, so we do not yet know how long the episode will continue or the ultimate status of the loan.

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

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

Exhibit A-2: Examples of Loan Transition Types





A1.2. Specification of Multinomial Logit Models

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

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

$$B_{DEF}^{CUR} = \left(\beta_0^{CUR\_DEF},\ \beta_1^{CUR\_DEF}, \dots, \beta_k^{CUR\_DEF}\right)\ ;\ X = (\mathbf{1}_n,\ X_1, \dots, X_k\ )^T$$

Where $X_i = (X_{i1}, X_{i2}, \dots,\ X_{in}\ )^T$, n : number of observations ; X = Extended design matrix of explanatory variables.

$$B = \left\{B_{DEF}^{CUR},\ B_{PRE\_NSR}^{CUR},\ B_{PRE\_SR}^{CUR},\ B_{CUR\_X}^{CUR}\right\}$$

Here the transition CUR_CUR is the baseline category.

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

Here *i* is *CUR* and $j \in \{DEF, PRE\_NSR, PRE\_SR, CUR\_X\}$

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

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

$$\pi_{CUR\_X}^{CUR}(t \mid X) = \frac{exp\,(B_{CUR\_X}^{CUR}X)}{1 + \sum_{\forall B} exp\,(BX)} \tag{1b}$$

$$\pi_{PRE\_NSR}^{CUR}(t \mid X) = \frac{exp\,(B_{PRE\_NSR}^{CUR}X)}{1 + \sum_{\forall B} exp\,(BX)} \tag{1c}$$

$$\pi_{PRE\_SR}^{CUR}(t \mid X) = \frac{exp\,(B_{PRE\_SR}^{CUR}X)}{1 + \sum_{\forall B} exp\,(BX)} \tag{1d}$$

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

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

Here $B = \left\{B_{PRE}^{DEF}, B_{CUR\_S}^{DEF}, B_{CUR\_M}^{DEF}, B_{CLM}^{DEF}\right\}$, and *DEF_DEF* is the baseline category.

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

$$\pi_{CUR\_S}^{DEF}(t \mid X) = \frac{exp\,(B_{CUR\_S}^{DEF}X)}{1 + \sum_{\forall B} exp\,(BX)} \tag{2b}$$

$$\pi_{CUR\_M}^{DEF}(t \mid X) = \frac{exp\,(B_{CUR\_M}^{DEF}X)}{1 + \sum_{\forall B} exp\,(BX)} \tag{2c}$$

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

The coefficient vectors B_j^i are the unknown parameters to be estimated for the multinomial logit model for initial status *i* indicating current (CUR) or default (DEF) and ending status *j* indicating prepayment (PRE_NSR or PRE_SR), default (DEF), or current (CUR) when *i* is current, and *j* is prepayment (PRE), current (CUR_S or CUR_M), or claim (CLM) when i is default. It is important to note that j is not CUR when i is CUR and j is not DEF when i is DEF, because CUR_CUR and DEF_DEF are baseline categories for transitions starting from CUR and DEF respectively. We denote by X the vector of explanatory variables for the conditional probability of transitioning from starting status CUR and DEF. Some components of X are constant over the life of the loan and therefore do not vary with time. The "dynamic" or time-varying explanatory components (variables) of X include mortgage age, the duration of the default episode for loans in default status, and the duration of cure for current loans with a prior default. They also include an array of time-varying economic factors that predict default, prepay, cure, and claim, which will be described in detail below.

As illustrated in Exhibit A-1, for the FY 2024 review actuarial projections, we ultimately stratify initial current status (CUR) by whether the loan has had a prior default or prior mod (or both). As discussed further below, the econometric equations (1a) - (1d) and (3.1a) - (3.2c) for loans in current statuses (C, CX_S, CX_M) presented above were jointly estimated using pooled samples of loans with and without prior default episodes and prior loan modifications, and the explanatory variables in X include indicators (dummy variables) for prior events.

A1.3. Computation of Multinomial Logit Probabilities from Binomial Logit Parameters

As in prior-year reviews, we apply an approach first proposed by Begg and Gray (1984), in which we estimate separate independent binomial logit models for each possible transition type and then recombine the estimates to derive multinomial logit probabilities. Begg and Gray (1984) applied Bayes Law for conditional probabilities to demonstrate that the values of parameters B estimated from separate independent binomial logit (BNL) models are parametrically equivalent to those for the corresponding multinomial logit (MNL). Here we have 4 BNL models for loans in current status at the start of quarter t, the pairs in each of the 4 BNL are (CUR_DEF, CUR_CUR), (CUR_PRE_NSR, CUR_CUR) ,(CUR_PRE_SR, CUR_CUR), and (CUR_CUR_X, CUR_CUR). Here C in the below equations is equivalent B in MNL.

Hence,

For Binomial Model 1, we have

$$\Pi_{DEF}^{CUR}(t \mid X) = \frac{exp\ (C_{DEF}^{CUR} X)}{1 + exp\ (C_{DEF}^{CUR} X)} \quad (3.1a)$$

$$\Pi_{CUR}^{CUR}(t \mid X) = \frac{1}{1 + exp\ (C_{DEF}^{CUR} X)} \quad (3.2a)$$

The C_{DEF}^{CUR} computed from this binomial model will be substituted for B_{DEF}^{CUR} in multinomial logit model in (1a)

For Binomial Model 2, we have

$$\Pi_{CUR\_X}^{CUR}(t \mid X) = \frac{exp\ (C_{CUR\_X}^{CUR}X)}{1 + exp\ (C_{CUR\_X}^{CUR}X)} \quad (3.1b)$$

$$\Pi_{CUR}^{CUR}(t \mid X) = \frac{1}{1 + exp\ (C_{CUR\_X}^{CUR}X)} \quad (3.2b)$$

The $C_{CUR\_X}^{CUR}$ computed from this binomial model will be substituted for $B_{CUR\_X}^{CUR}$ in multinomial logit model in (1b)

For Binomial Model 3, we have

$$\Pi_{PRE\_NSR}^{CUR}(t \mid X) = \frac{exp\ (C_{PRE\_NSR}^{CUR}X)}{1 + exp\ (C_{PRE\_NSR}^{CUR}X)} \quad (3.1c)$$

$$\Pi_{CUR}^{CUR}(t \mid X) = \frac{1}{1 + exp\ (C_{PRE\_NSR}^{CUR}X)} \quad (3.2c)$$

The $C_{PRE\_NSR}^{CUR}$ computed from this binomial model will be substituted for $B_{PRE\_NSR}^{CUR}$ in multinomial logit model in (1c)

For Binomial Model 4, we have

$$\Pi_{PRE\_SR}^{CUR}(t \mid X) = \frac{exp\ (C_{PRE\_SR}^{CUR}X)}{1 + exp\ (C_{PRE\_SR}^{CUR}X)} \quad (3.1d)$$

$$\Pi_{CUR}^{CUR}(t \mid X) = \frac{1}{1 + exp\ (C_{PRE\_SR}^{CUR}X)} \quad (3.2d)$$

The $C_{PRE\_SR}^{CUR}$ computed from this binomial model will be substituted for $B_{PRE\_SR}^{CUR}$ in multinomial logit model in (1d)

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

For Binomial Model 5, we have

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

$$\Pi_{DEF}^{DEF}(t \mid X) = \frac{1}{1 + exp\,(C_{PRE}^{DEF} X)} \quad (4.2a)$$

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

For Binomial Model 6, we have

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

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

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

For Binomial Model 7, we have

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

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

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

For Binomial Model 8, we have

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

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

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

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

A1.4. Loan Transition and Event Data

We used loan-level data to construct quarterly loan event histories by combining mortgage origination information with contemporaneous values of time-dependent factors. In the process of creating quarterly event histories, each loan contributed an additional observed "transition" for every quarter from origination up to and including the period of mortgage termination, or until the last time of the historical data sample. The term "transition" is used here to refer to any situation in which a loan remains active, and the loan status is observed at the start of the next quarter, or in which terminal claim or prepayment events are observed in the current quarter.

The FHA single-family data warehouse (SFDW) records each loan for which insurance was endorsed and includes additional data fields updating the timing of changes in the status of the loan. The historical data used in model estimation for this Actuarial Review are from an extract from FHA's database as of 2024.

A1.5. Data Samples

A full 100-percent sample of loan-level data from the FHA single-family data warehouse was extracted for the FY 2024 analysis. This produced a very large sample of approximately 42 million single-family loans originated between the first quarter of FY 1975 and the fourth quarter of FY 2024. While our analysis of economic net worth will ultimately focus on those loans originated since FY 1994 that continue as active MMI Fund exposures, we include data as far back as FY 1975 to support the process of linking FHA streamline refinance (SR) loans to information associated with the original fully underwritten mortgage to the same borrower. Model estimation is based on data samples from the more recent FY 1996 through FY 2024 cohorts comprising those that impact the current economic net worth of the MMI Fund. Approximately 32 million loans have been endorsed for insurance during those years. For estimation, these data were used to generate quarterly loan-level event histories extending to the age at which the loan would mature based on the original term of the loan product or the end of the historical sample period. Forecasting the future performance of loans still active at the end of FY 2024 extends an additional 30 years out to FY 2054.[66]

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

Product 1	FRM30	Fixed-rate 30-year fully underwritten purchase and refinance
Product 2	FRM15	Fixed-rate 15-year fully underwritten purchase and refinance

[66] As noted above, the review does not consider cashflows past 2054 on extended term ("ET") modifications where the term to maturity is extended to 40 years. Such loans are less than 1 percent of the current book of business.

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

A1.5.1. Random Sampling for Estimation

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

Product 1	FRM30	25 percent
Product 2	FRM15	100 percent
Product 3	ARM	100 percent
Product 4	FRM30_SR	100 percent
Product 5	FRM15_SR	100 percent
Product 6	ARM_SR	100 percent

Proportional random sampling was applied to Product 1 for model estimation. All other products models were estimated using 100 percent samples. Utilization of 100 percent samples is a known limitation of the model mitigated by validation as discussed in Appendix B.

A1.5.2 Random Sampling for Forecasting

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

We have attempted to minimize issues of choice-based sampling bias by using simple random sampling in developing the data for estimation and forecasting. FHA loan data include significant numbers of loans across all product types to support random sampling. There are two main channels through which choice-based sampling affected prior year reviews: (1) the use of alternative sources of credit score data for FHA loans with missing credit scores (primarily before

2004); and (2) over-sampling of default events and under-sampling of more prevalent non-default events.

The use of alternative sources of credit score data from the 1990s and early 2000s from a study conducted by Unicon Corporation raised issues of choice-based sampling related to over-sampling of defaulted loans. Further oversampling of these loans to increase the share of loans having usable credit scores further magnified the potential bias issue. However, research by Manski (etc.) and others indicates that the impact of choice-based sampling bias in logit models is limited to estimates of the intercept terms. In a mixed sample of choice-based and randomly sampled non-choice-based loans it is possible to control for the choice-based loans by including an indicator (0/1 dummy) for these loans (i.e., an indicator for the source of credit score). While we continue to utilize the Unicon data, as well as additional credit score data provided to FHA by Fannie Mae, we do not oversample these loans relative to FHA loans with still missing credit scores, and they are randomly sampled along with all other FHA loans. In addition, we continue to control the source of credit score for individual loans as was done in prior reviews.

Regarding over-sampling of quarterly default versus non-default events we have not implemented that approach out of concern that this applies to all loans and there is no longer a simple approach to controlling for choice-based sampling bias in the intercept terms. Unlike the case of the supplemental credit score data, there is no subset of loans not subject to choice-based sampling that can provide an unbiased baseline reference category since all loans are subject to choice-based sampling.

A1.5.3. Sample Periods for Transition Model Estimation

We used loans originated from FY 1996 through FY 2024 to estimate the status transition models. This covers the loan cohorts for which complete data were available on new 90-day default episodes. Quarterly observations from FY 2006 FQ 2 and FY 2007 FQ 3 were excluded from the estimation of transition probabilities for loans in default status (D, DX_S, DX_M) due to data issues associated with changes in the default episode tracking system in FY 2006.

A2. Explanatory Variables

Four main categories of explanatory variables were employed:

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

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

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

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

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

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

A2.1 Fixed Initial Loan Characteristics

A2.1.1. Mortgage Product Types

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

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

A2.1.2. Loan-to-Value Ratio at Origination

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

A2.1.3. Relative Loan Size

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

A2.1.4. Relative House Price

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

A2.1.5. Spread at Origination

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

A2.1.6. Property Type

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

A2.1.7. Judicial Foreclosure State Indicators

The duration of default and foreclosure is likely to be longer for loans originating in states providing borrowers with a right to judicial foreclosure proceedings. We include an indicator of judicial foreclosure taking the value 1 for loans originated in judicial foreclosure states and 0 otherwise. We find that this variable has a positive impact on current-to-default probabilities for all FHA fixed-rate products and a strong negative impact on default-to-claim probabilities for fixed-rate non-SR and ARM SR products. This suggests borrowers are more inclined to default and slower to transition to claim, as expected, in states providing for the longer judicial foreclosure process.

A2.1.8. Deficiency Judgment State Indicators

We expect that lenders having the option to seek personal deficiency judgments against borrowers following foreclosure will discourage borrowers from defaulting. Some states that allow deficiency judgments on consumer and business loans may prohibit them in the case of residential foreclosures on mortgages that were secured by residential properties.

A2.7. Fixed Initial Borrower Characteristics

A2.7.1. First-Time Buyer

An indicator for first-time buyers is included to distinguish these buyers from more experienced and seasoned buyers. The FHA single-family was originally developed to support first-time buyers with lower downpayments. The program has evolved over the years to include a broader cross-section of borrowers, particularly during the mortgage crisis years of 2007-2010 as emergency provisions were implemented to expand the availability of FHA-insured loans following the implosion of the subprime market and withdrawal of several private mortgage insurance providers. Nevertheless, first-time buyers still comprised around 84 percent of new originations.

A2.7.2. Source of Downpayment Assistance

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

A2.7.3. Borrower Credit Scores

Our primary source of credit scores on FHA single-family mortgages are those collected by FHA since 2004 and available from the SFDW. We supplement these data with additional credit score information collected through internal studies conducted for HUD that retrospectively obtained scores for FHA loan applications. The studies were conducted by UNICON Corporation and Fannie Mae. The UNICON study included credit scores collected for a sample of FHA applications from FY 1992, FY 1994, and FY 1996, and subsequently extended to loan applications during FY 1997 through FY 2004. This set of credit score data is useful because these loans have existed for many years and provide valuable historical delinquency, claim, and prepayment performance information. The Fannie Mae data provides additional credit score coverage for the loans originated from FY 2000 to FY 2004. There is surprisingly little overlap between the two sources resulting in substantial credit score coverage during these years. Together the two data sources provide credit score information on hundreds of thousands of loans during a period in which none was being collected by FHA. There are some limitations to the data. First, the data do not provide credit score data on all FHA loans originated during those years, so missing data remains an issue. Second, the data were initially collected for policy research purposes and were not randomly selected from all FHA loan applications. For example, there was an over-sampling of early-default loans among applications from FY 1997 through FY 2004. As a standalone dataset these loans are a choice-based sample. This does not translate directly to our analysis as our loan samples are randomly selected based on all endorsed FHA loans. However, use of the data does imply that scores are not assigned to all FHA loans, and those that are assigned are not randomly selected. We address these issues by controlling the source of credit score data among our three sources (FHA, UNICON, Fannie Mae) and whether credit score remains missing.

These three sets of FICO data represent the most reliable sources of borrower credit history information available for historical FHA-endorsed loans before FY 2005 when FHA credit scores became available for almost all loans.

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

A2.7.4 Debt-to-Income (DTI) Ratio

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

A3. Dynamic Variables Based on Loan Information

A3.1 Mortgage Age

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

Exhibit A-3: Example of a 6-Segment Mortgage Age Functions

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

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

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

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

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

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

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

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

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

A3.2. Prior Loan Default Indicator

A loan that experiences a 90-day default episode and later returns to the current status is then classified as having had a prior default episode. Once this occurs and the dummy (0/1) variable for prior default is set to 1, it remains at this value for the remainder of the loan life. This enables us to distinguish these loans from those that have never entered the 90-day default status, a strong predictor of subsequent default, and a negative factor for the likelihood of prepayment.

A3.3. Prior Loan Modification Indicator

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

A3.4. Duration of Default Episode

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

A3.5. Duration of Cure Episode

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

A3.6. Seasonality Indicator

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

A3.7. Time-Period Indicators for Unique Market Conditions or Policy Changes

The loan status transition models employed selected time-period indicator variables to account for periods of significant economic turmoil and major changes in FHA policies related to loss mitigation activities. These included the following six periods:

Early Loss Mitigation Period Prior to FY 2004 - Period of introduction and implementation of expanded FHA standalone loan modification and partial claim practices and procedures.

Subprime Market Period FY 2004 to FY 2006 – Period of rapid expansion in the subprime market which greatly reduced FHA market share and altered the geographic footprint of FHA lending.

Mortgage Crisis Period FY 2007 to FY 2009 – Period of increasing default and foreclosure resulting from the mortgage crisis.

Home Affordable Modification Program (HAMP) Period FY 2010 FY 2020 – Period of recovery and implementation of additional programs to manage default, foreclosure, and loss including the HAMP combination loan modification and partial claim. The policies and procedures emerging from the HAMP program established a new standard in the approach to loss mitigation in subsequent years.

COVID Onset FY 2020 FQ3 to FY 2021 FQ3 – Period of onset of the COVID crisis leading to rapid spike in mortgage default rates during this time period. The increase in conditional default rates was rapidly attenuated as a result of the emergency forbearance and foreclosure moratoria policies adopted during this period.

COVID Loss Mitigation FY 2021 FQ3 to FY 2025 FQ2 – Period of extended COVID loss mitigation procedures extended through April 30, 2025 per Mortgagee Letter 2024-02, a change reflected in the covid_lossmit indicator variable included in the transition models. This variable impacts the projected loan status transition rates into the first year of the forecast period. The forecasting assumptions then revert to the HAMP period loss mitigation procedures that preceded the onset of the COVID crisis. Any ongoing impacts of the COVID crisis are represented by the changes in the emerging loan status distribution following the crisis.

A4. Dynamic Variables Incorporating External Economic Data

A4.1. FHFA House Price Indices

Consistent with the FY 2025 Mid-Session Review PEA, house price indices (HPIs) produced and published by FHFA were applied in loan status transition model estimation. FHFA publishes both purchase-only (PO) and all-transactions (AT) versions of their HPIs. We have applied the AT version of the FHFA HPIs in model estimation, due to the significantly broader regional coverage provided by the AT version of the HPI, including more than 300 additional MSA-level HPIs.

Prior reviews have expressed the view that the HPI PO version is necessarily more accurate than the HPI AT version due to the reliance of the latter on appraisal valuations in addition to observed sale prices. The actual evidence is limited, mixed, and sometimes points to the opposite conclusion as it regards HPI availability and accuracy. One must keep in mind that the choice between PO and AT versions of the HPI is not an either-or proposition, as the AT version still uses a blended sample of sale and refinance transactions.

Calhoun (1991) first noted the benefits of having appraisal based HPIs during periods when sales transactions are limited or in locations where they are non-existent. Calhoun (1991) also examined the potential for greater sample-selection bias when only sales transaction data are used. Simply stated, mortgage borrowers may be willing to refinance at appraised values well below their reservation prices for selling, so that relying solely on sales prices draws from the higher end of the house price distribution at any point in time. In our view, geographic aggregation bias far outweighs concerns about appraisal bias, particularly given the overall consistency between AT and PO versions of the HPI at the same level of geography. Later research by Calhoun, Harter-Dreiman, VanderGoot (1998) and Leventis (2006) indicate that the actual evidence for systematic appraisal bias is mixed or inconclusive. On the other hand, geographic bias is large, immediate, and certain if the HPI PO version must be applied at the state level when no MSA-level HPI is available, Therefore, we opted for broader geographic coverage at the MSA level.

The forward-looking actuarial central estimates are based on the PEA for the quarterly future performance of the FHFA Purchase Only (PO) seasonally adjusted HPI for the period FY 2024 to FY 2034 FQ4, pursuant to HUD requirements. We extended the quarterly PEA forecast series out to FY 2054 Q4 based on the PEA assumption of 3% annualized HPA for years after FY 2034.

We applied the following two-step procedure to obtain regional HPI forecasts from the PEA national forecasts: (1) compute the period-by-period differentials between national forecast HPI appreciation rates and the corresponding appreciation rates for each regional HPI from the same forecast; and then (2) apply these differential appreciation rates to the PEA national HPI forecast to obtain regional HPIs forecasts consistent with the PEA. So as the PEA national forecast varies period-by-period, our regional HPIs vary in a consistent manner, and will maintain the regional dispersion based on historical patterns.

To implement step (1), we use appreciation rates for the Moody's baseline forecasts of the FHFA AT version HPIs at the national and regional levels. This enables us to retain the broader geographic coverage of the AT version of the FHFA HPIs that we applied in estimation. We note that using the Moody's regional forecasts of the FHFA PO version HPI for step (1) would result in loss of the regional coverage we seek to preserve. Step (2) is implemented by adding the respective appreciation rate differentials from step (1) to the appreciation rates of the mandated PEA national forecast of the FHFA PO version HPI.

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

A4.2. Current Loan-to-Value (CLTV) Ratio

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

A4.3. House Price Volatility

House price volatility parameter estimates are a byproduct of the estimation of the FHFA weighted-repeat-sales HPIs. FHFA publishes the estimated volatility parameters at the state-level and has provided FHA with MSA-level volatility parameter estimates for application to the FY 2024 review. The volatility parameters can be used to derive the expected dispersion of individual house price appreciation around the market average represented by HPI. Higher dispersion makes it more likely that an individual housing value may be too low to enable a borrower to qualify for refinancing. This will reduce the probability of prepayment and increase the probability of default for borrowers subject to higher and higher levels of volatility. Since the dispersion of individual housing values increases over time, so does the probability of negative equity. While these estimates are developed over time as parameters of the house price diffusion process, we apply than as cross-sectional indicators of relative market volatility in the borrower's location.

A4.4. House Price Appreciation

The FHFA HPIs are used to compute short-term rates of local and national house price appreciation as proxies for borrower expectations regarding future house price changes. These measures provide alternative indicators of market conditions that may impact the likelihood of prepayment, default, or cure in different directions. For example, borrowers whose personal or loan factors may increase their chances of default may have greater opportunities to sell their property and avoid default through prepayment if local markets are appreciating. Conversely, borrowers in declining markets may be less mobile in the face of strong national appreciation, thus reducing the likelihood of prepayment and increasing the risk of default. The local house and national house price appreciation (HPA) measures are computed as the ratio of the region-specific HPI one-year ahead to the value of the same HPI one-year prior:

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

A4.5. Refinance Incentive

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

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

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

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

A4.6. Unemployment Rate Change

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

$$delta\_ue = ue\_rate(t-1) - ue\_rate(t-3)$$

A4.7. Refinance Burnout

Refinance burnout is the tendency for borrowers who have missed refinance opportunities in the past to have lower conditional probabilities of prepayment going forward. A burnout factor is included to identify borrowers who have foregone recent opportunities to refinance. The burnout factor is quantified as the moving average number of basis points the borrower was in the money, for all quarters during which the borrower was in the money, during the preceding 8 quarters. The refinance burnout factor is included to account for individual differences in propensity to prepay, often characterized as unobserved heterogeneity. Empirical evidence now suggests that borrowers who refinance now tend to do so at much lower thresholds than in the past.

A4.8. Credit Burnout

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

A4.9. ARM Coupon Rate Dynamics

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

$$\begin{aligned} C(t) = \max \{&\min [\mathrm{Index(t-S)} + Margin, \\ &C(t-1) + A(t) \cdot Period\_UpCap, C(0) + Life\_UpCap], \\ &C(t-1) - A(t) \cdot Period\_DownCap(t), \max (C(0) - Life\_DownCap, Life\_Min)\} \end{aligned}$$

where *Index(t)* is the underlying rate index value at time *t*, *S* is the "look back" period, and *Margin* is the amount added to *Index(t – S)* obtain the "fully indexed" coupon rate. The periodic adjustment caps are given by *Period_UpCap* and *Period_DownCap*, and are multiplied by a dummy variable *A(t)* which equals zero except during scheduled adjustment periods. Maximum lifetime adjustments are determined by *Life_UpCap* and *Life_DownCap*, and *Life_Min* is the overall minimum lifetime rate level. Any initial discounts in ARM coupon rates are reflected in the original interest rate represented by *C(0)* in equation (12).

A4.10. ARM Payment Shock

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

$$arm\_pmt\_shock(t) = 100\ x\ \frac{PMT(t) - PMT(0)}{PMT(0)}$$

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

A4.11. Yield Curve Slope

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

A4.12. Current Exposure-Period FRM Offer Rate

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

A5. Prior Loan Information for Streamline Refinance Mortgages

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

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

Once the first match is obtained, we create a new combined match group/match sequence code to uniquely identify matched loans. We can then repeat the entire process for the newly matched prior SR loan using its **old_case_nbr**. Some borrowers undertake more than a dozen SRs, so we repeat the process again and again until we match with the original FUWM. Along the way, we create a two-digit refi-type sequence number that identifies the two product types involved in each match. This also enables us to later distinguish SR from non-SR prepayment terminations for the last SR in the sequence. If the sorting-matching process fails to identify the original FUWM, we attempt a direct match of **old_case_nbr** for any unmatched SR loan to the **case_nbr** values of unmatched non-SR loans to obtain a few additional matches. The entire process yields match rates in the range of 92 to 98 percent of SR loans depending on the vintages and state locations of the SR loan.

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

Appendix B: Model Validation

Model validation is required to comply with Actuarial Standards of Practice 23 (Data Quality) and 56 (Modeling). ASOP 23 applies when an actuary is selecting, using, or relying on data provided by others, all of which are relevant to our review of MMI Fund performance. ASOP 56 provides guidance on designing, developing, selecting, modifying, and using models when performing actuarial services. We employ models that are descended from those originally developed by members of our team and applied in the 2004 to 2016 actuarial reviews. As such, the models we use are the culmination of a multi-year process of model design, development, and application that we feel contributes meaningfully to the current validation process. This ongoing process has also provided us with considerable past experience with the data required for estimation and forecasting the performance of FHA single-family mortgages. Nevertheless, we are not simply relying on prior models and past experience. We have undertaken an expansive and fresh look at data and model development to support the FY 2024 review.

The primary data source for our analysis is the FHA Single-Family Data Warehouse (SFDW). We consider that the SFDW is compliant with ASOP 23 with regard to the appropriateness, availability of current information, internal consistency of the data, and comprehensive coverage of current and past FHA mortgages. The data are well documented by the SFDW Meta Data workbook that ITDC requested from HUD to better understand the available data. The SFDW is an appropriate and sufficient source of FHA loan data, including detailed information on over 60 million single-family mortgages.

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

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

To avoid data attrition on variables that have missing value we attempt to retain as many observations as possible through the use of indicator (0/1 dummy variables) of missing values. For example, we include an indicator of missing credit score for loans originated prior to 2004 and for which the alternative data sources provided no information on credit score for that loan. In addition, we use dummy variables to control for the source of credit score across the different possible source of credit score data.

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

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

The actual estimation of loan performance models applied in forecasting utilized a 25 percent sample for FRM 30Y mortgages and 100 percent samples for each of the other five FHA loan products. Even the size of the 25 percent sample for FRM 30Y loans is somewhat excessive for this purpose confirming the relative accuracy of the model in a hold-out sample, which can be achieved with a smaller, but still large, sample of loans, and a comparably sized hold-out sample.

The risk of overfitting as well as the need to validate model estimation results using a holdout sample are mitigated by the following steps executed for each of the transition models used across all six FHA single-family loan products:

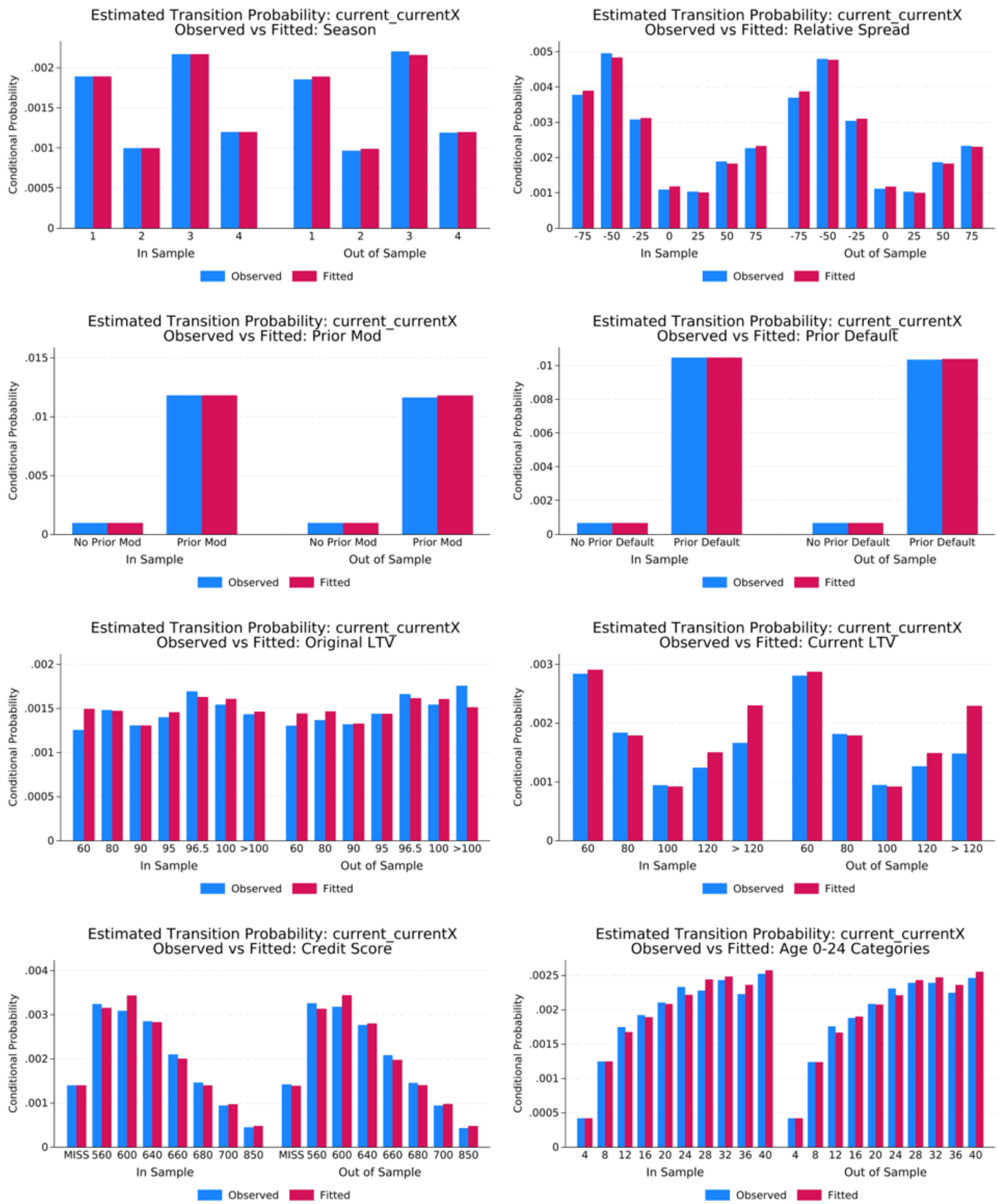
1. We drew a 2*P-percent sample of loans and randomly assigned these loans to two separate P-percent samples to serve as our estimation and hold-out samples. P was 5-percent for the FRM 30Y product, and 50-percent for all other products.
2. We used one of the P-percent samples to estimate the 8 loan status transition models for a specification identical to our final model.
3. We then applied the estimated coefficients to compute the predicted or "fitted" loan status transition probabilities for the separate P-percent estimation and hold-out samples.
4. We then developed graphical comparisons of fitted and observed mean transition rates for each loan-status transition type across a number of explanatory factors.
5. Because of close similarities between coefficient estimates and model-predicted transition probabilities comparing production and sample-based models, the holdout sample testing results reported below can be interpreted as supporting the robustness of the production models.

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

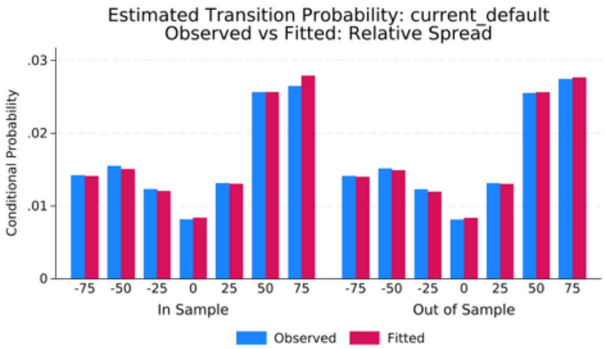
The model fits indicated by these comparisons appear quite good, with little deviation of the average fitted rates from the average observed rates of transition in most comparisons, confirming the effectiveness of transition model regression specifications, and that model outputs reasonably represent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

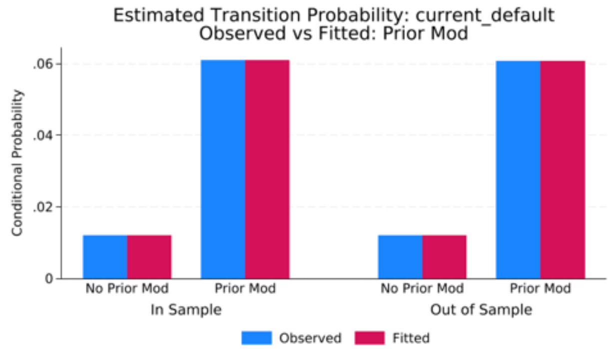
B1. Product 1

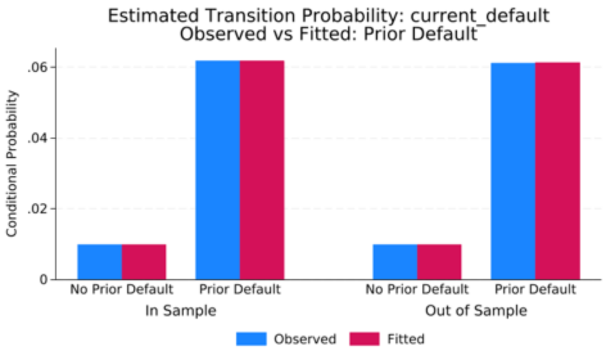
Product 1 - current_currentX

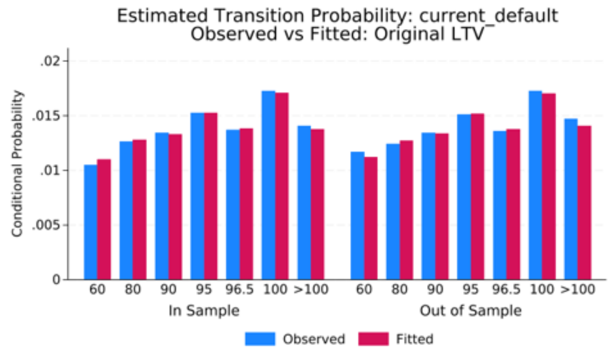


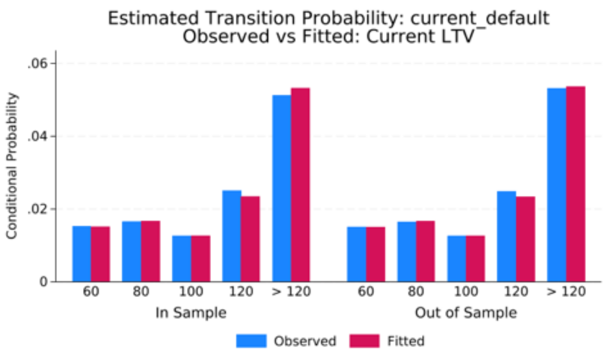
Product 1 - current_default

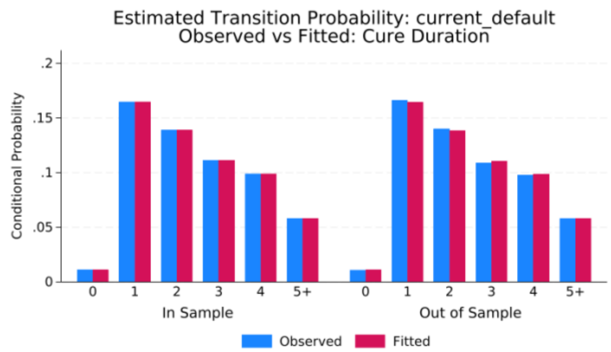


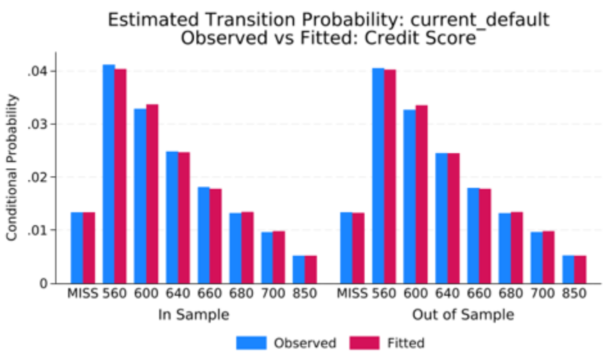


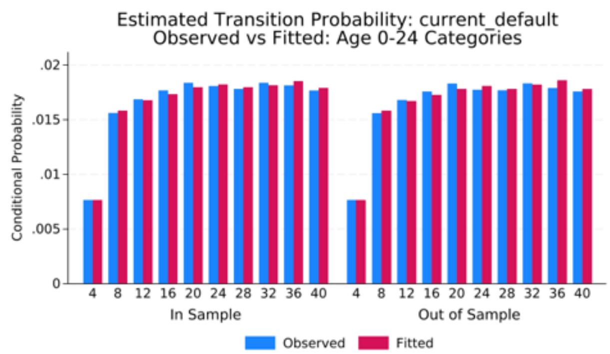




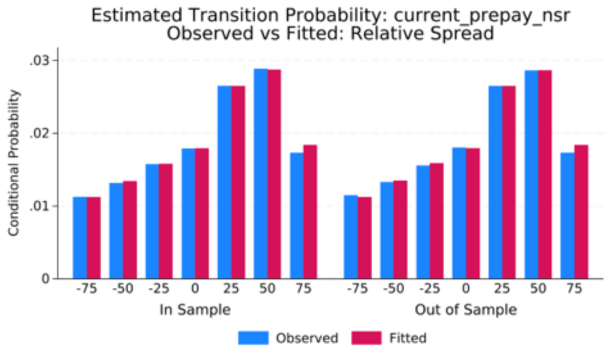


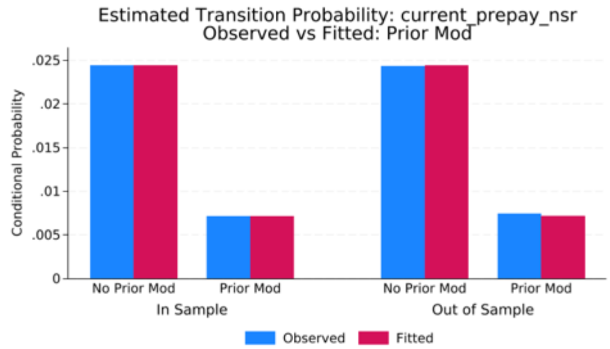


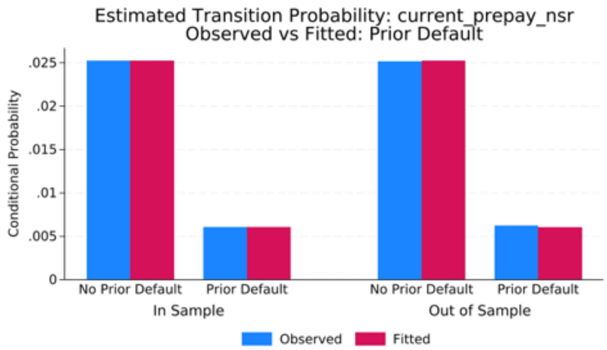


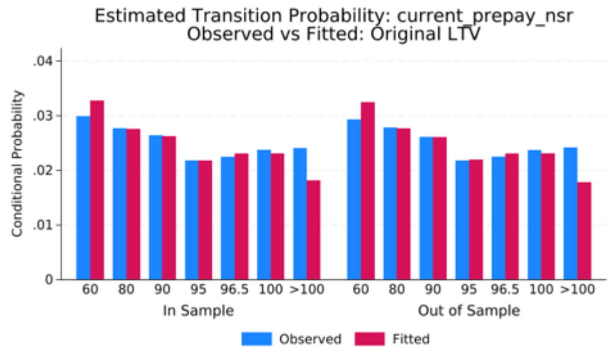


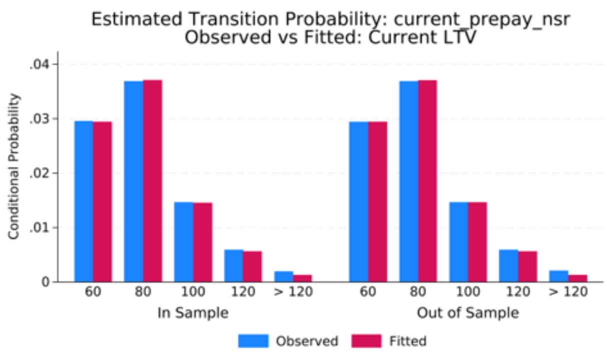
Product 1 - current_prepay_nsr

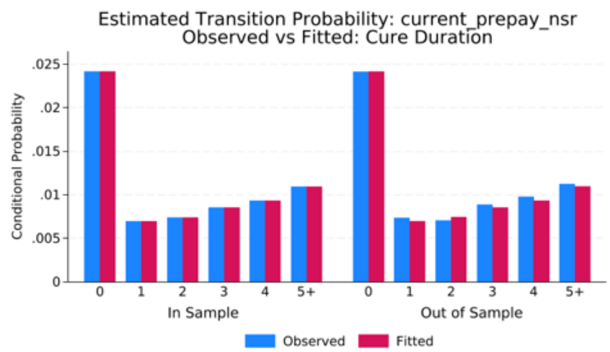


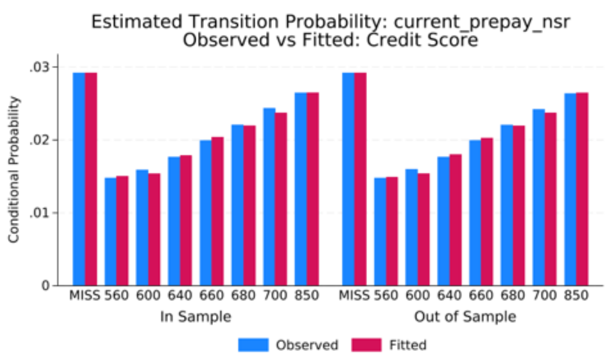


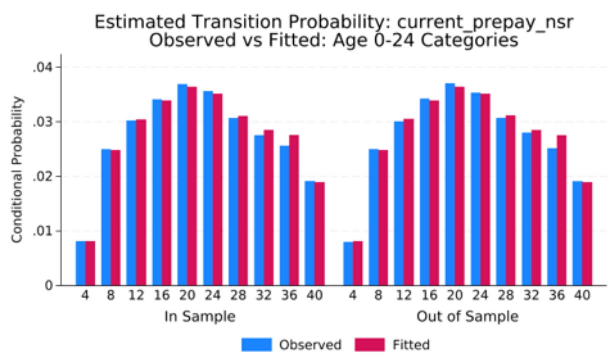




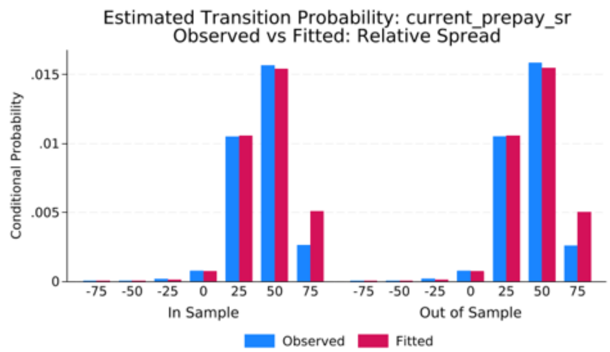


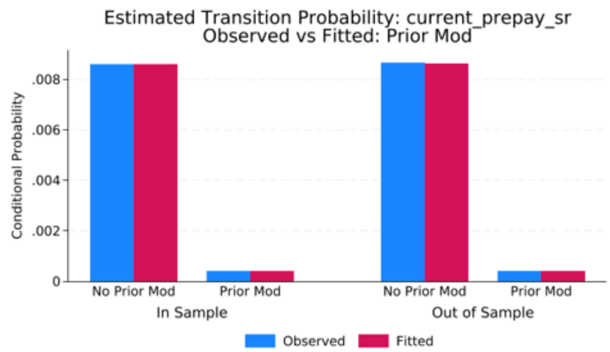


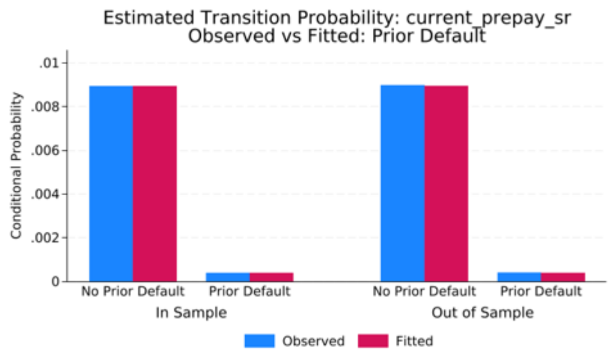


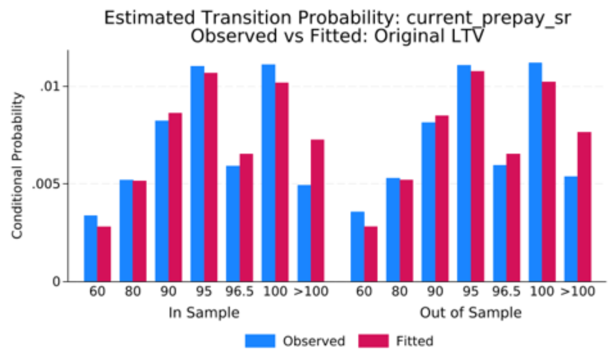


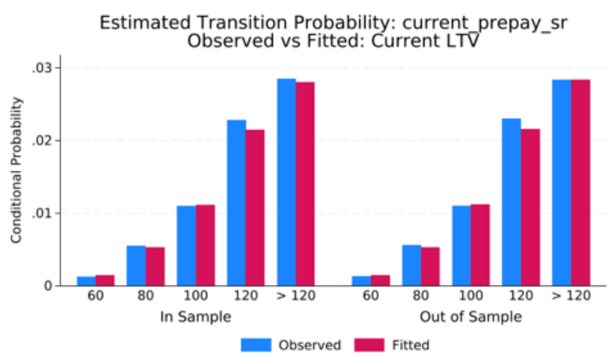
Product 1 - current_prepay_sr

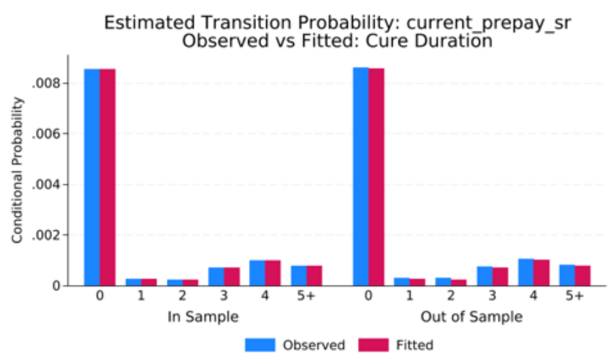


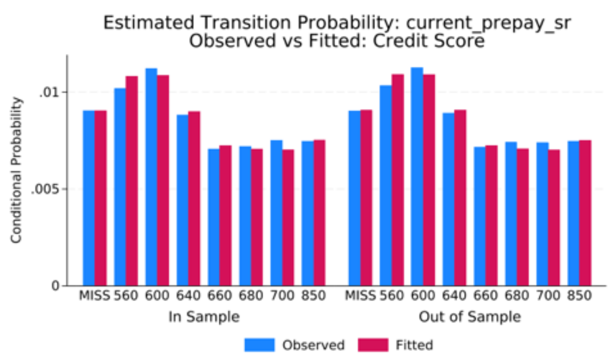


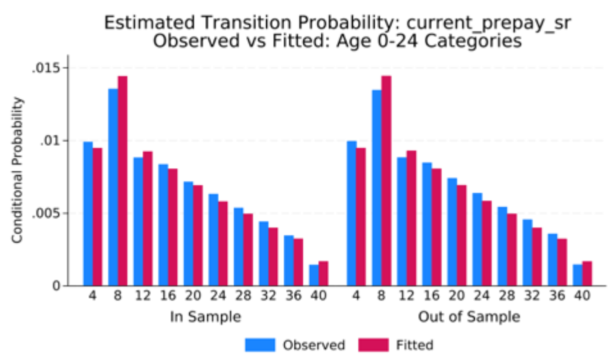




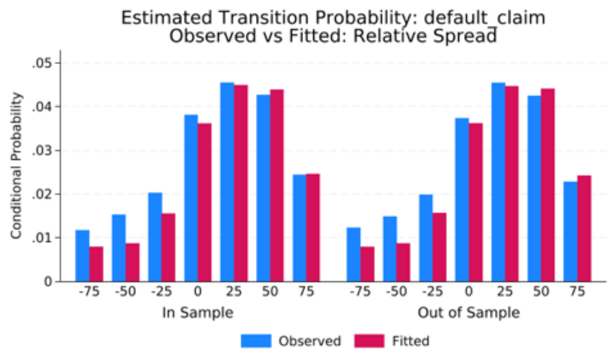


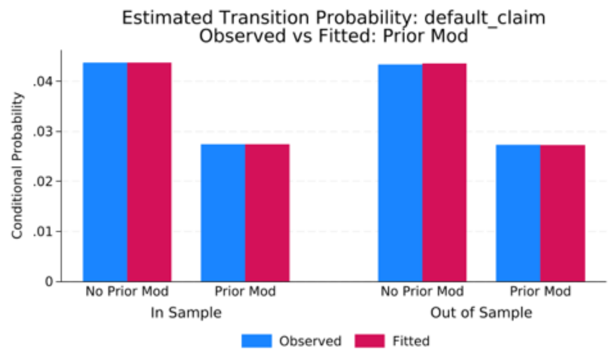


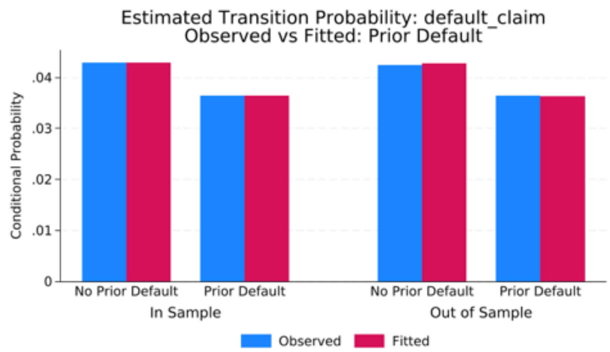


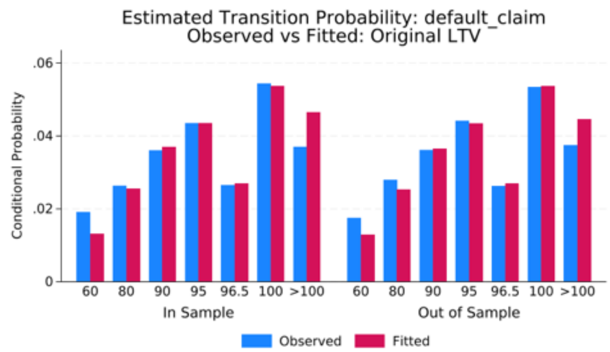


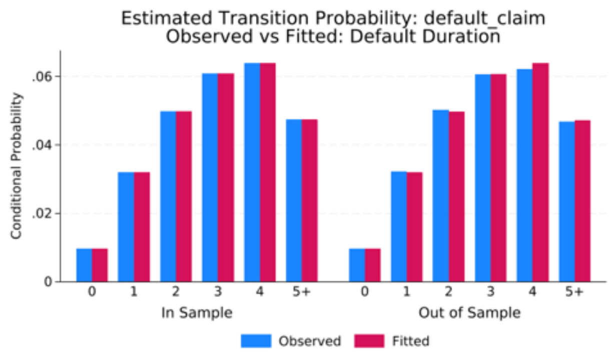
Product 1 - default_claim

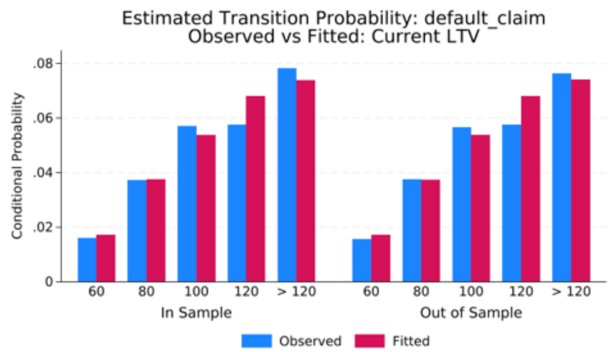


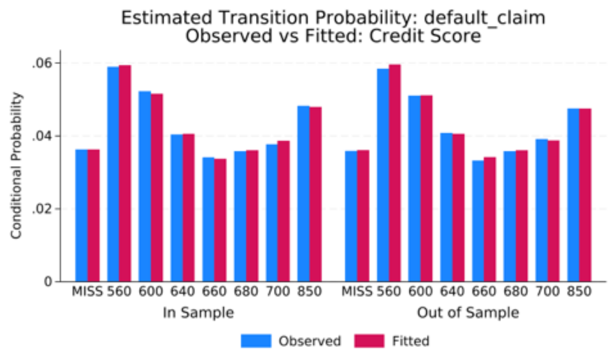


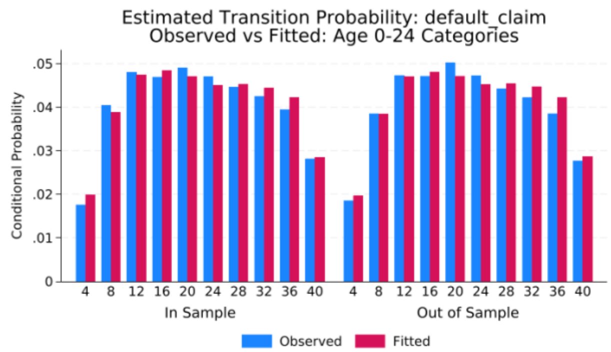




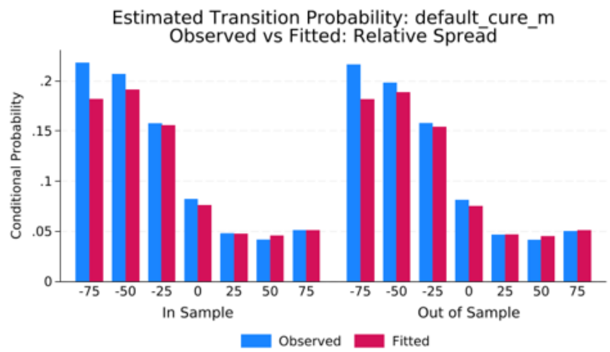


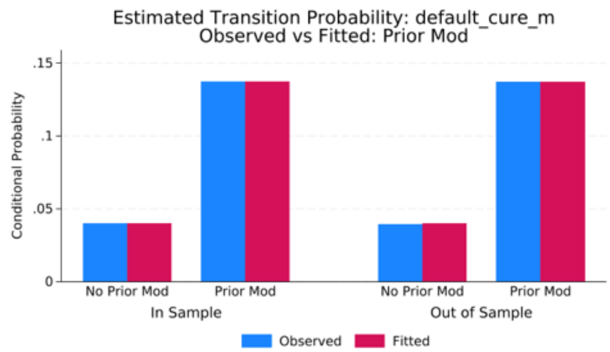


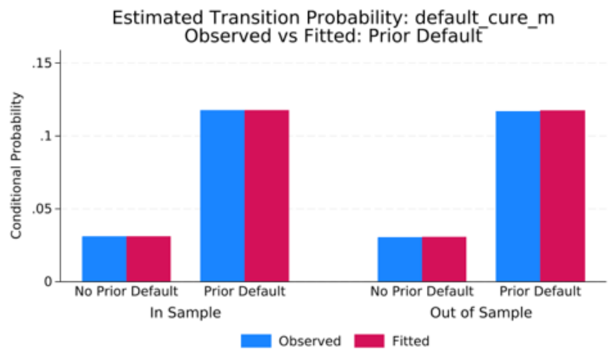


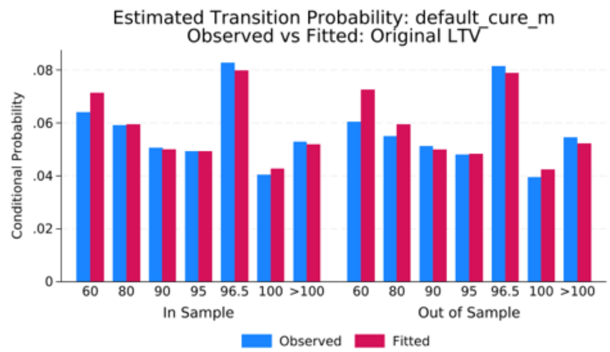


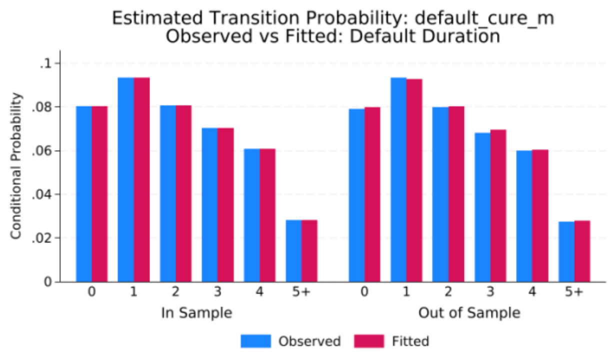
Product 1 - default_cure_m

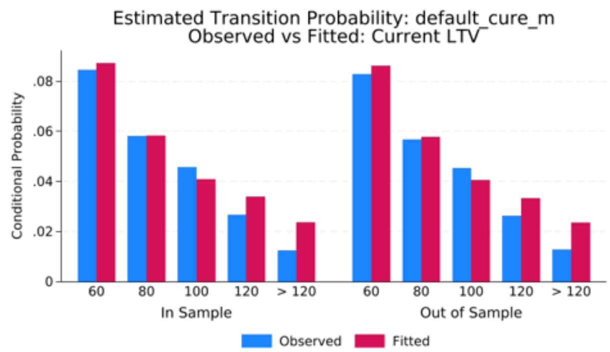


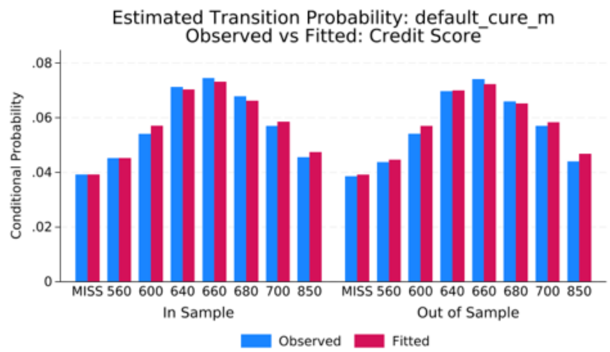


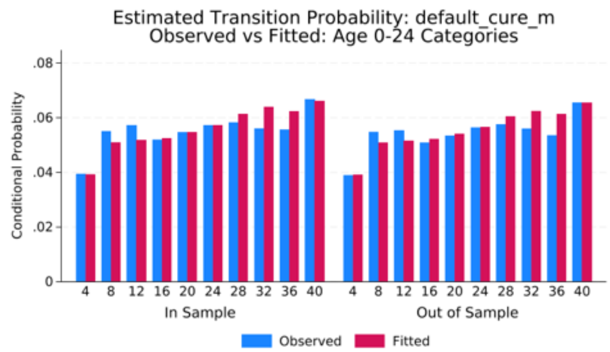




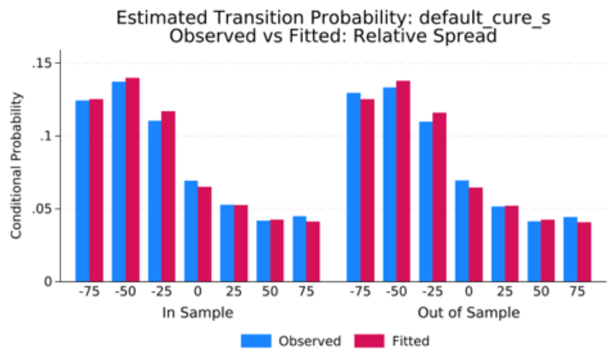


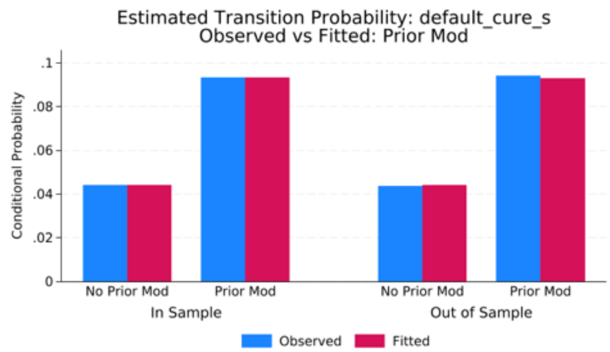


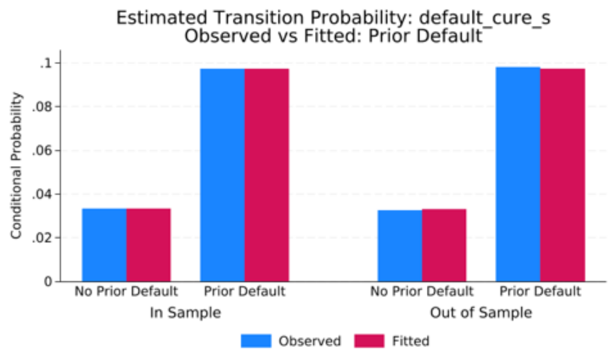


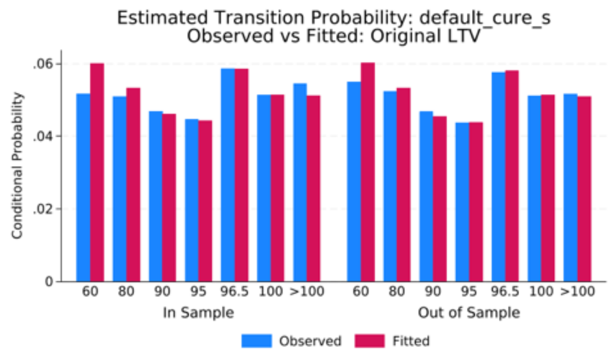


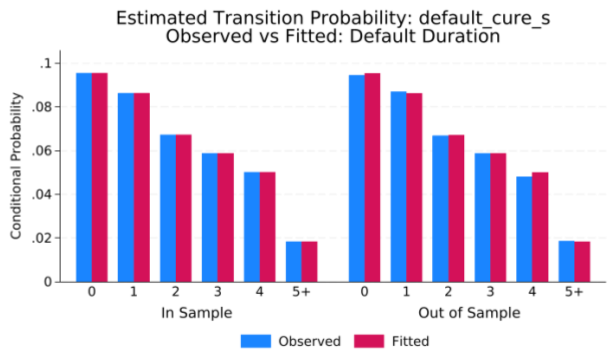
Product 1 - default_cure_s

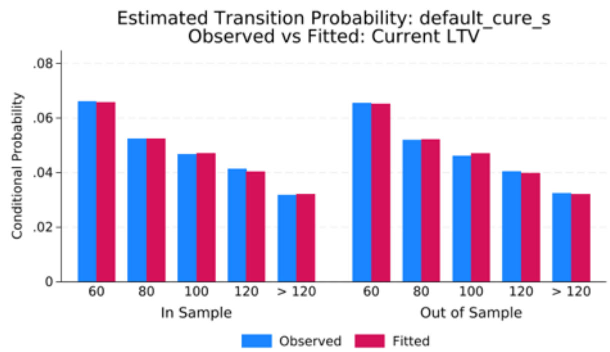


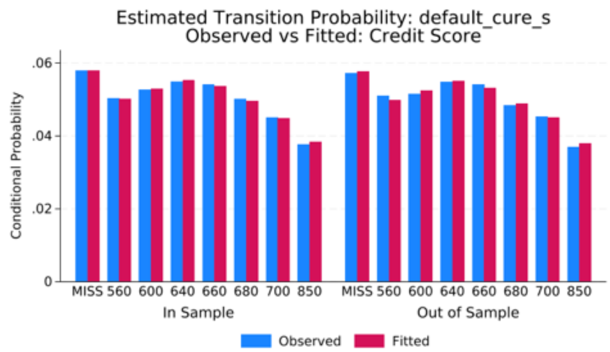


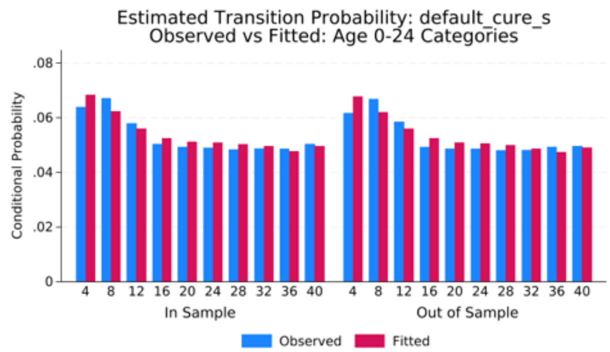




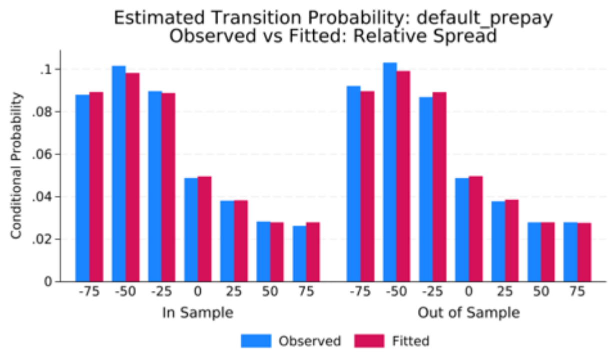


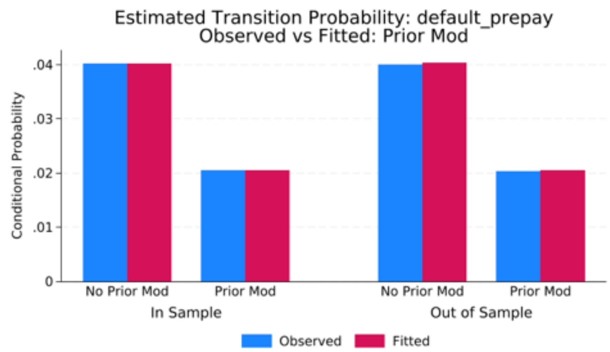


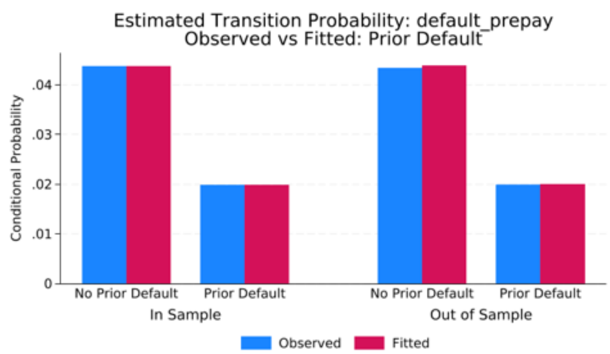


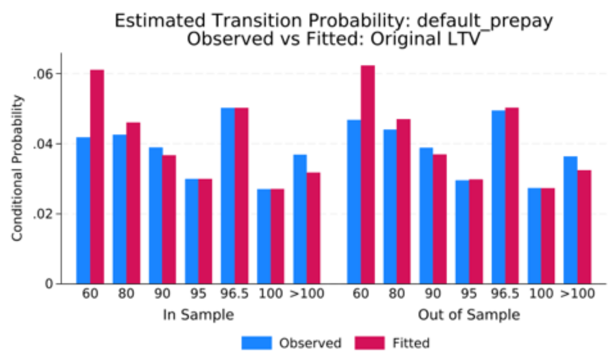


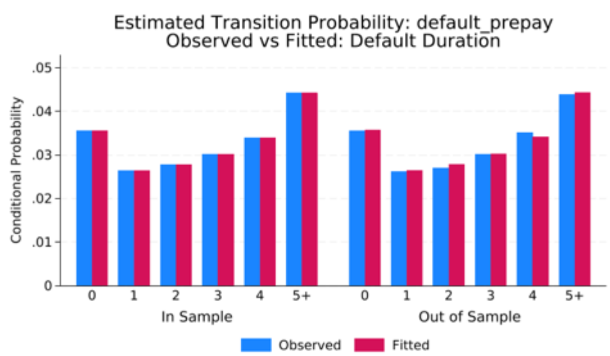
Product 1 - default_prepay

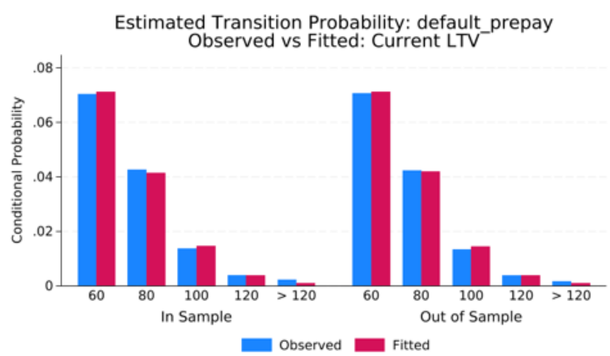


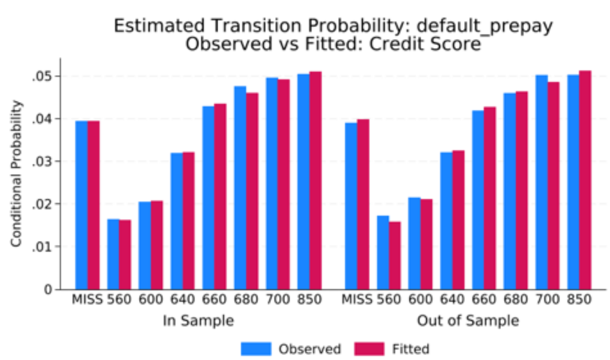


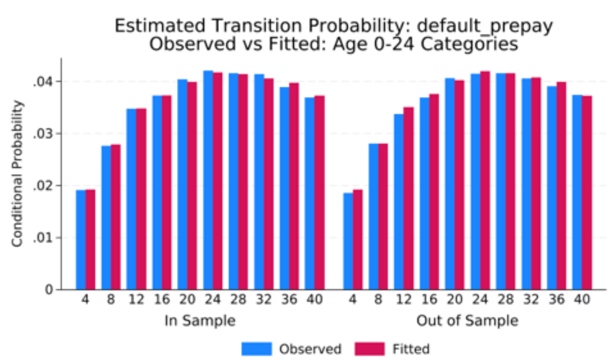






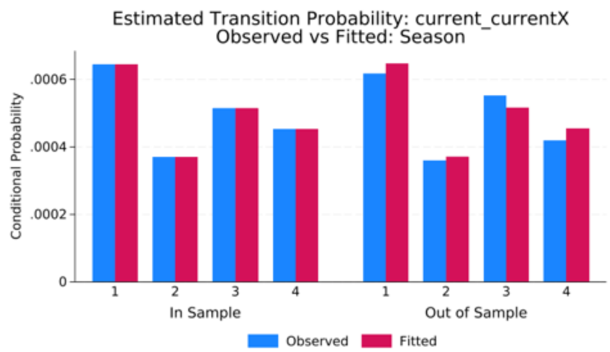


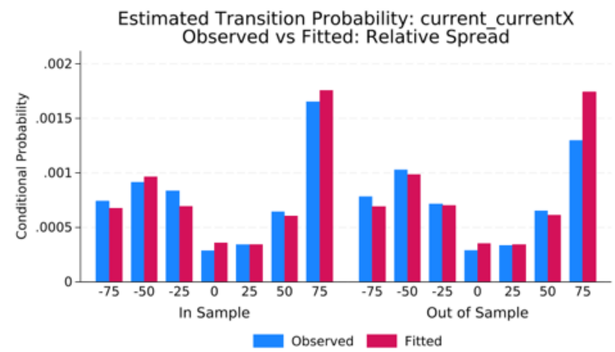


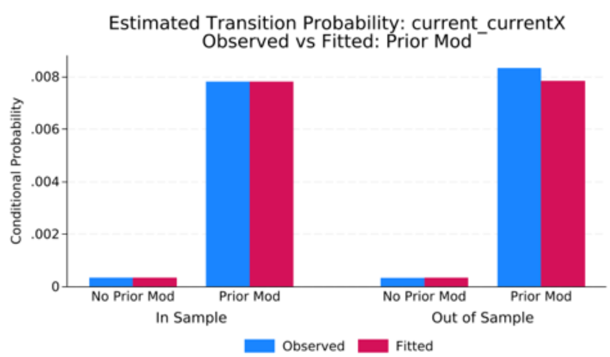


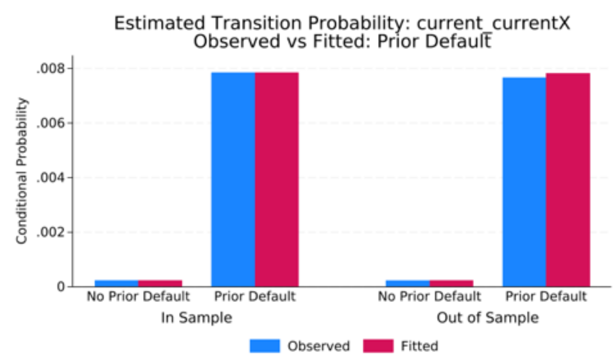
B2. Product 2

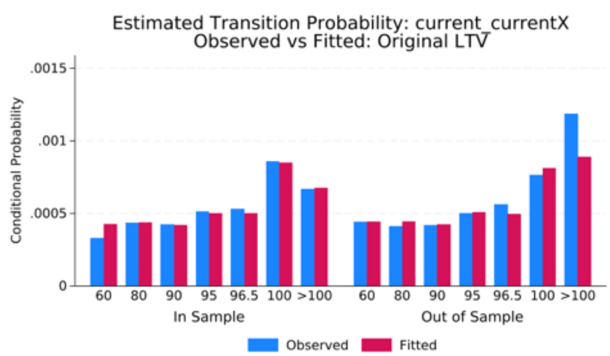
Product 2 - current_currentX

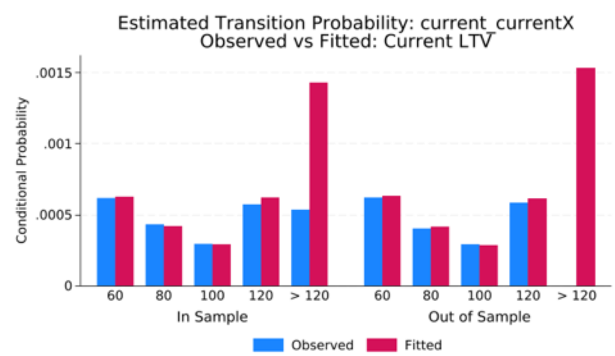


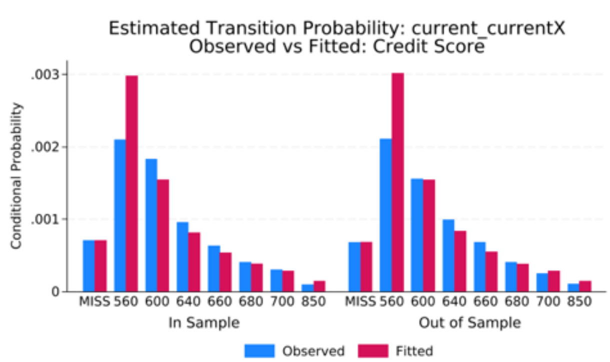


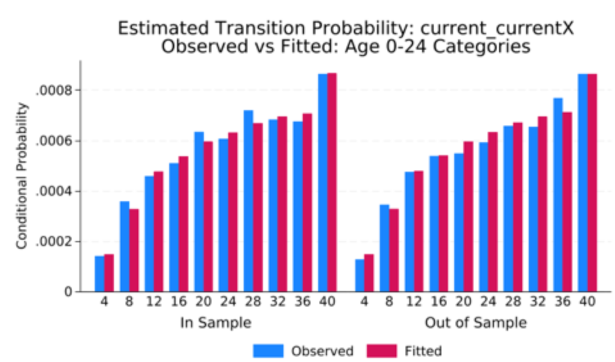




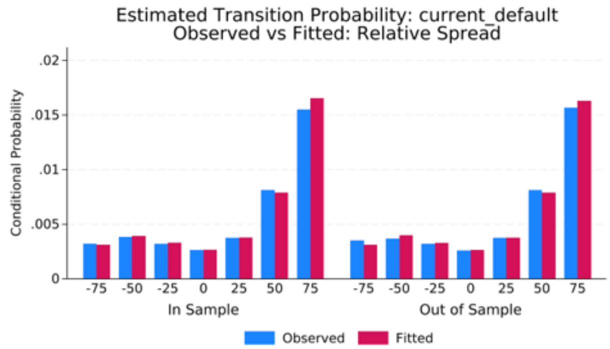


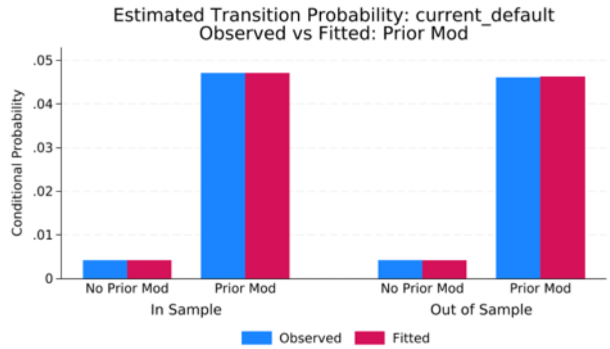


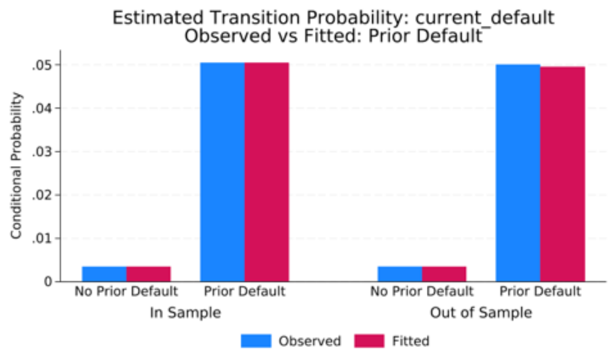


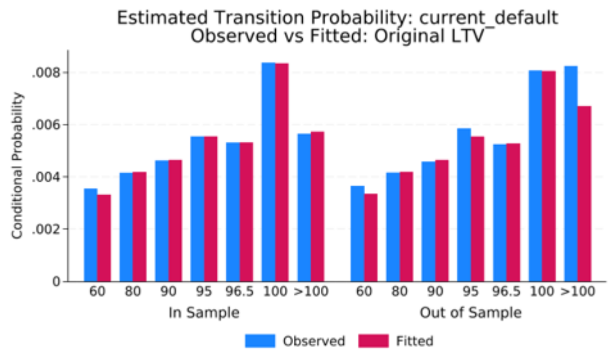


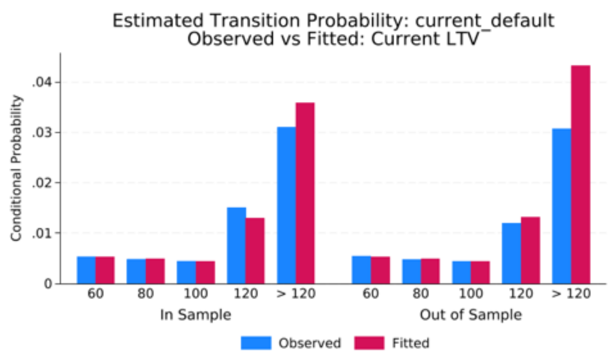
Product 2 - current_default

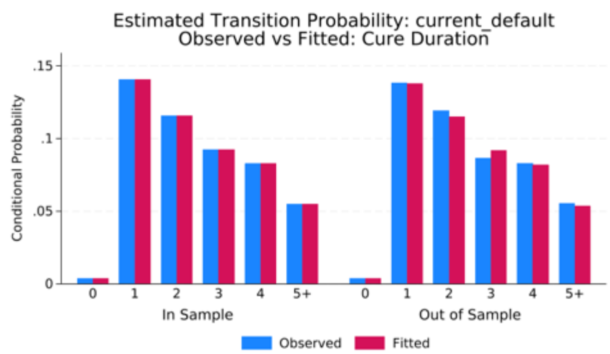


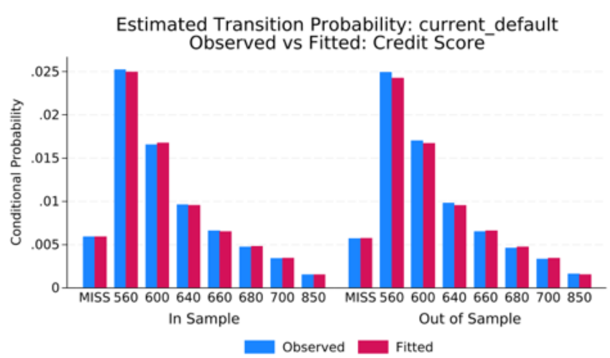


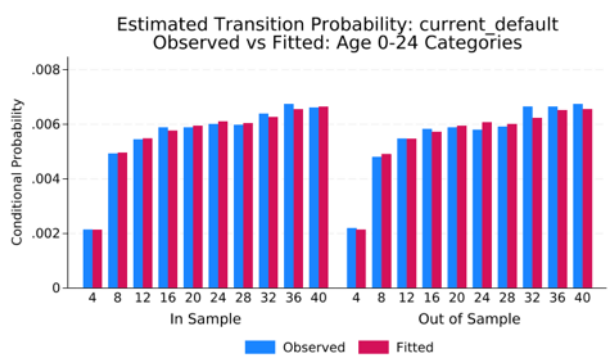




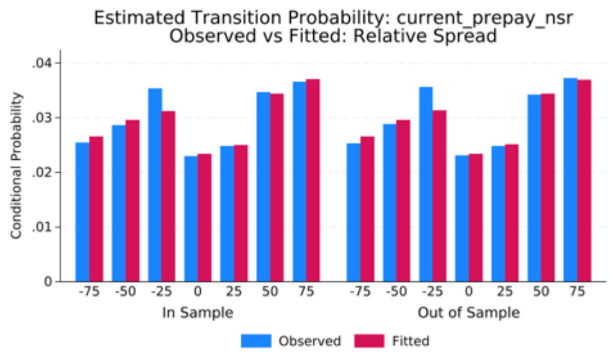


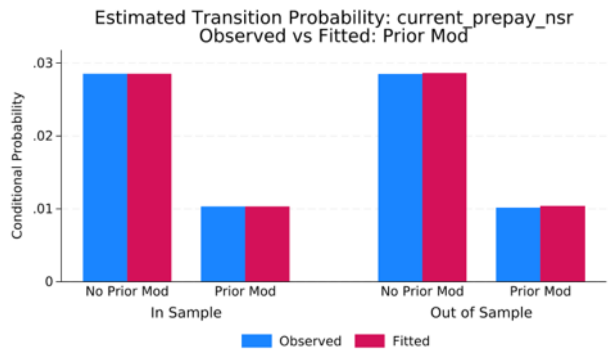


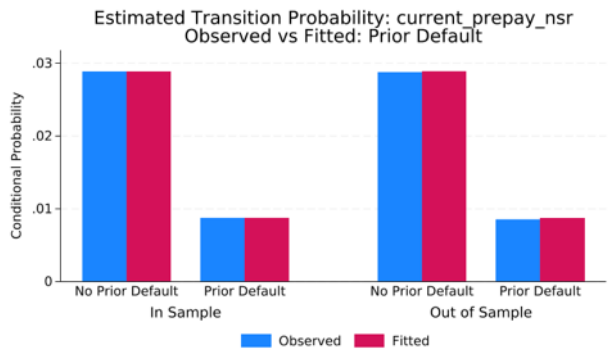


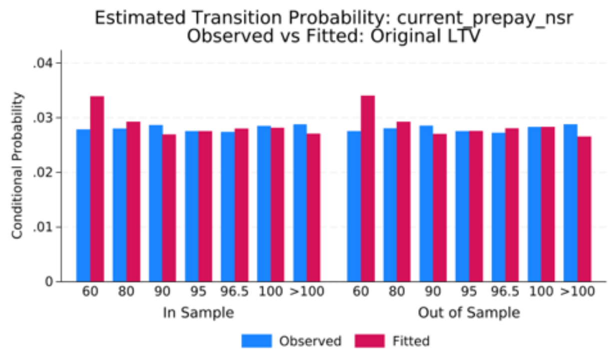


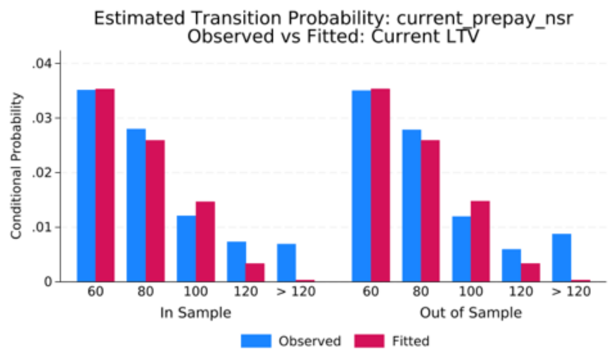
Product 2 - current_prepay_nsr

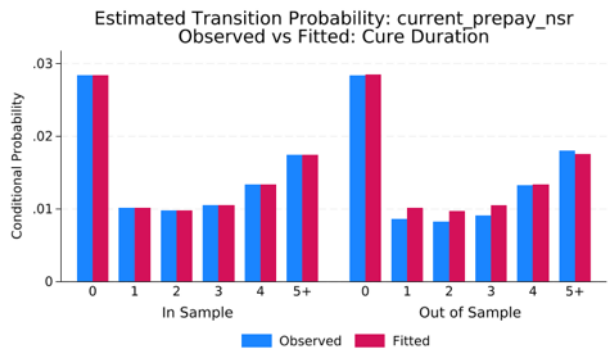


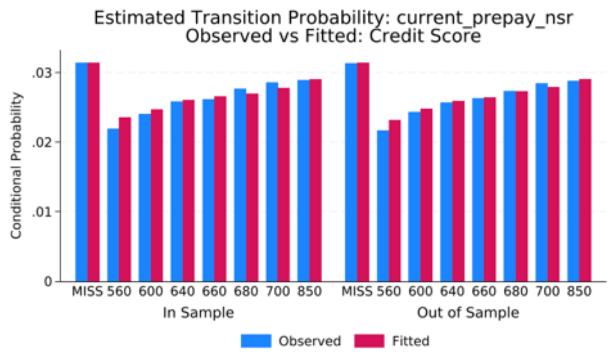


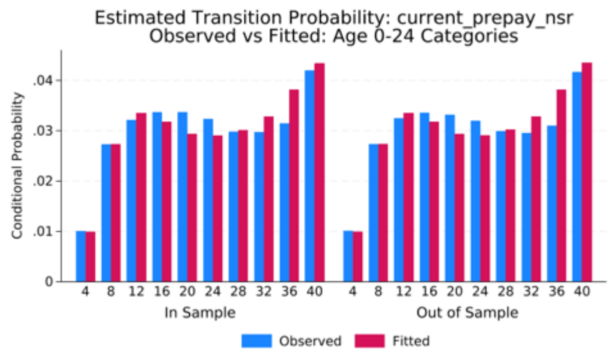












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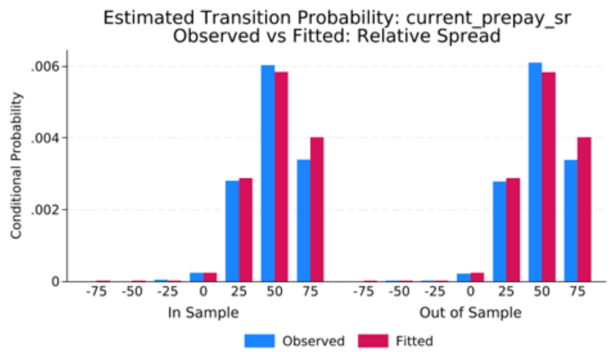

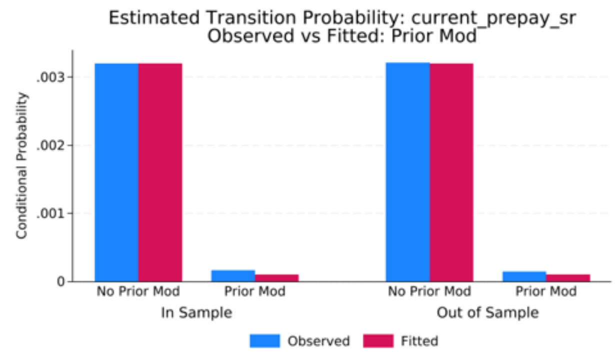

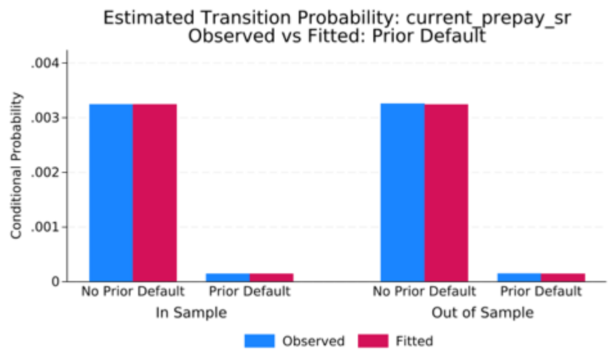

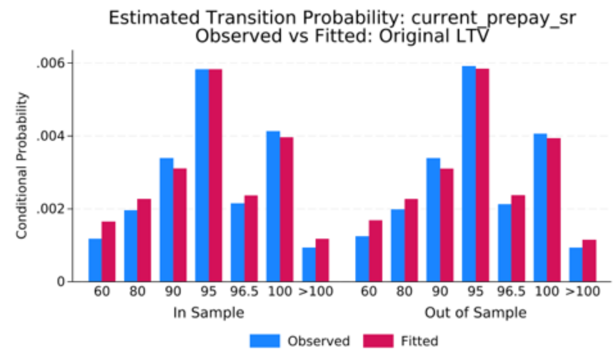

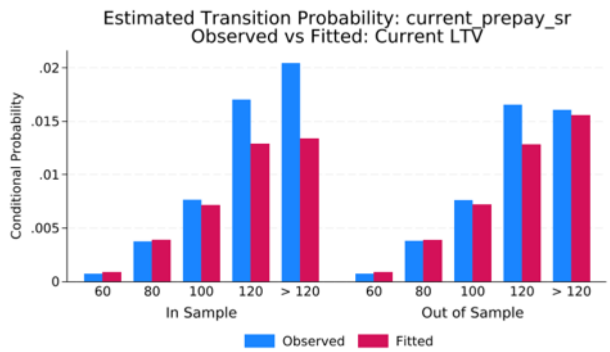

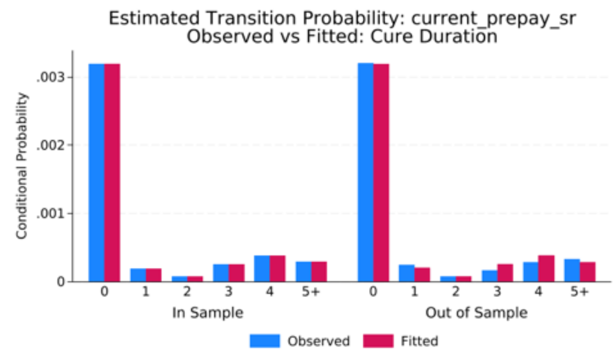

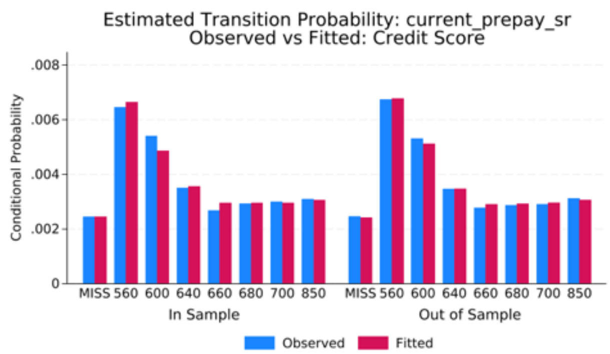

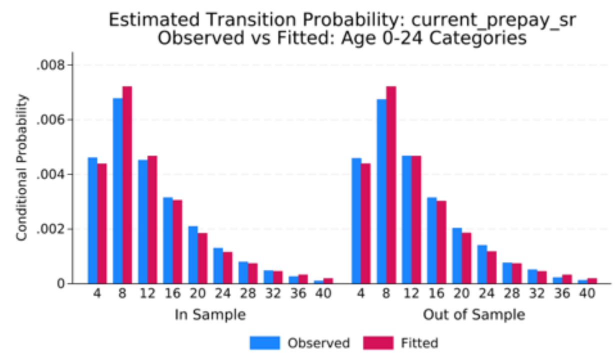

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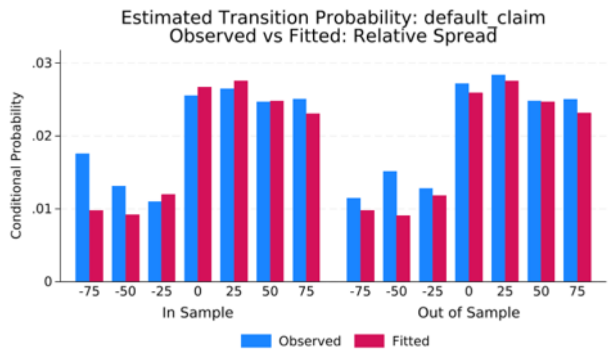

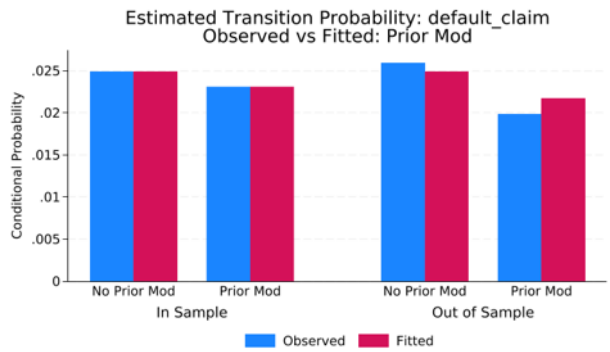

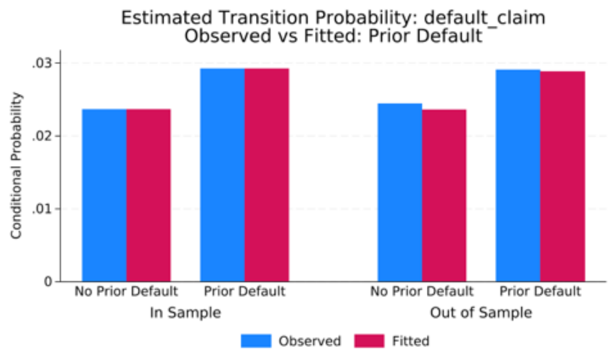

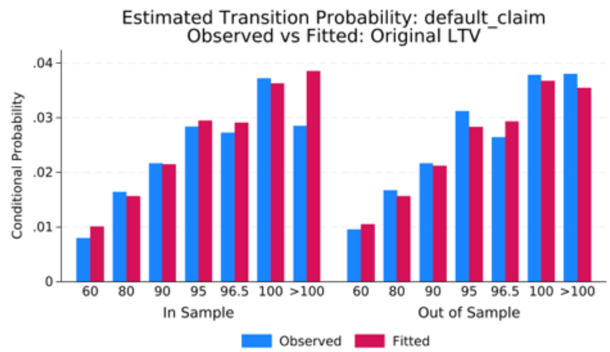

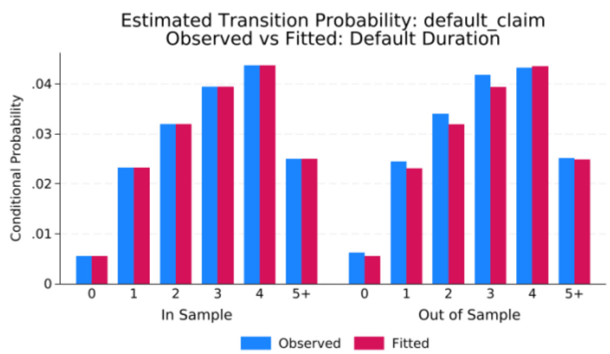

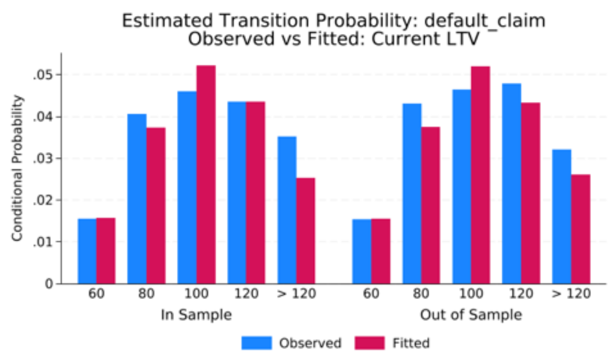

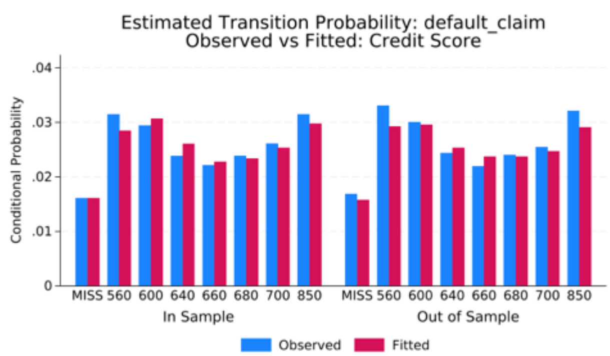

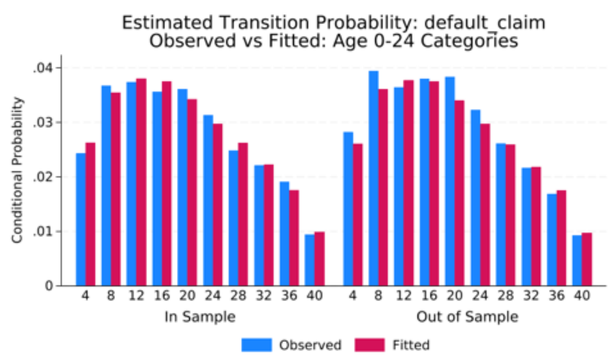

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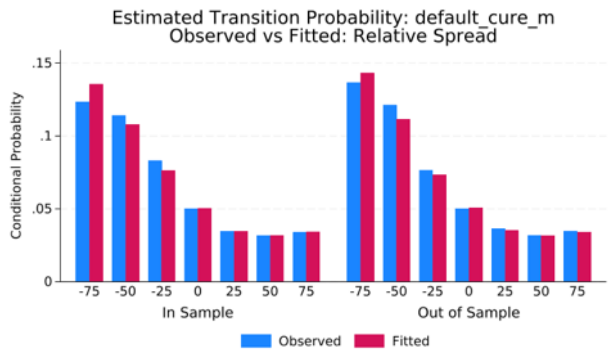

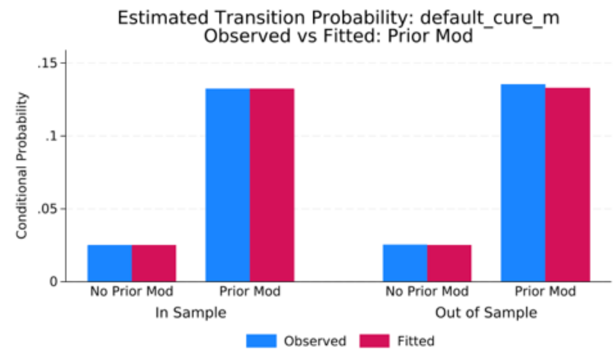

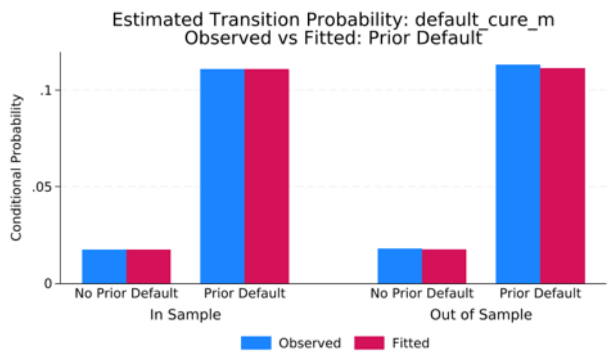

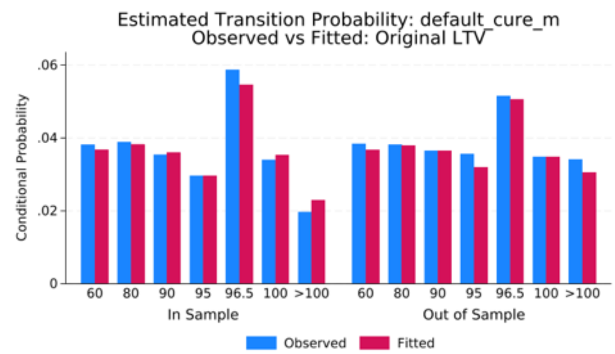

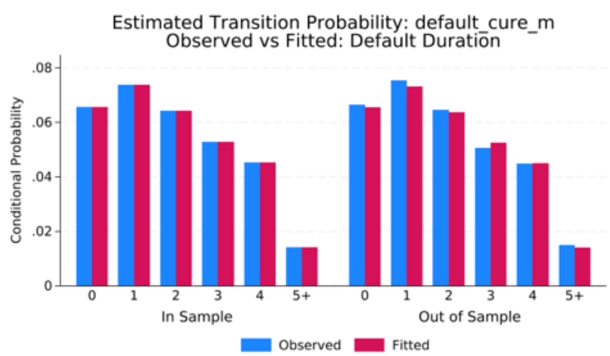

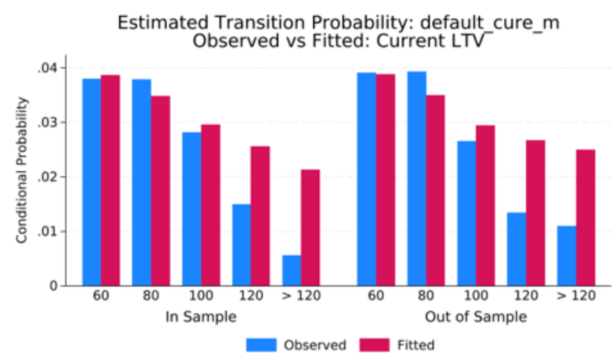

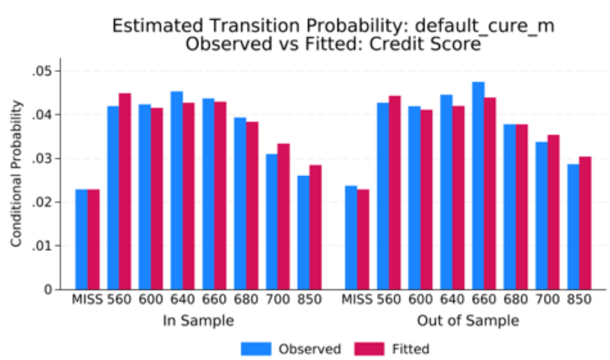

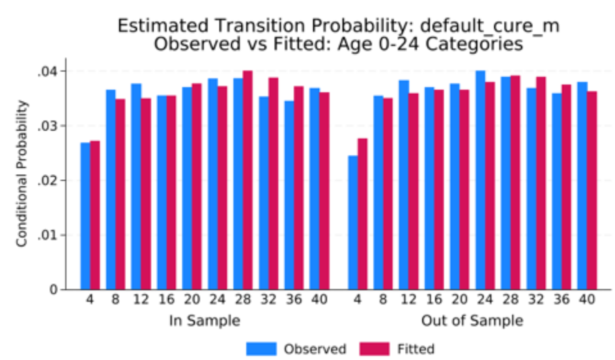

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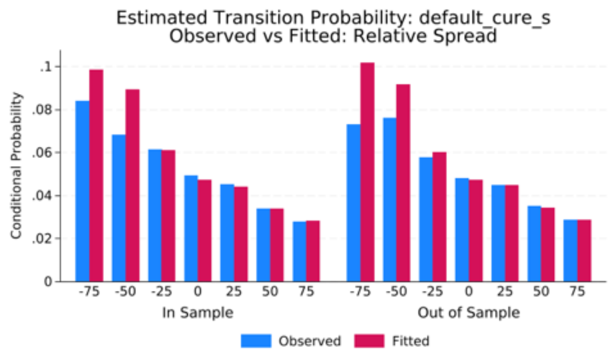
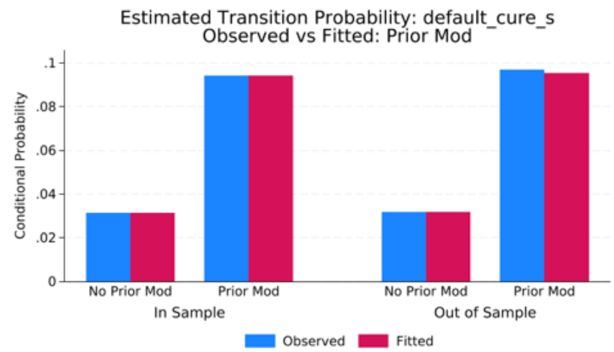
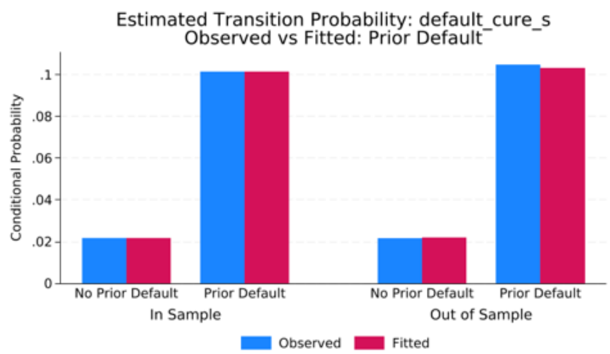
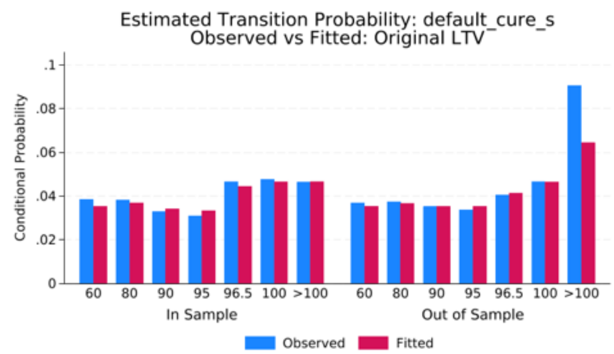
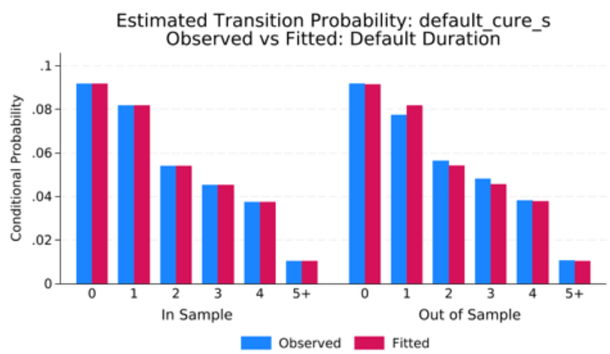
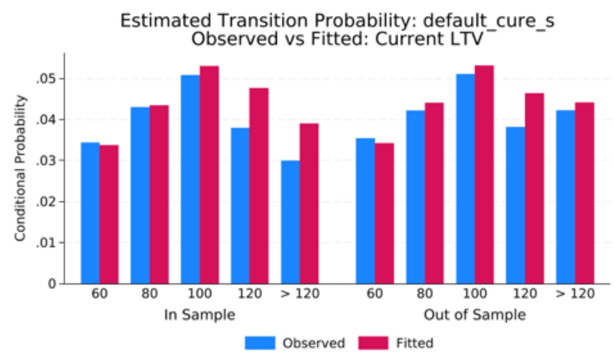


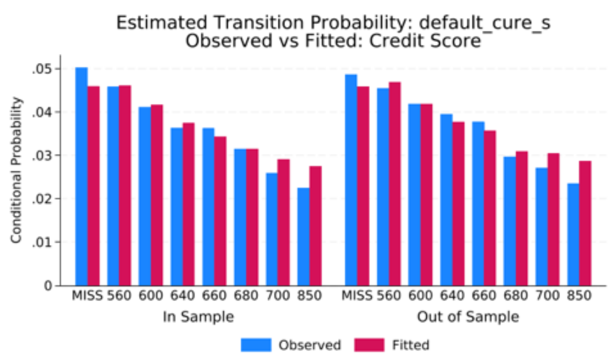


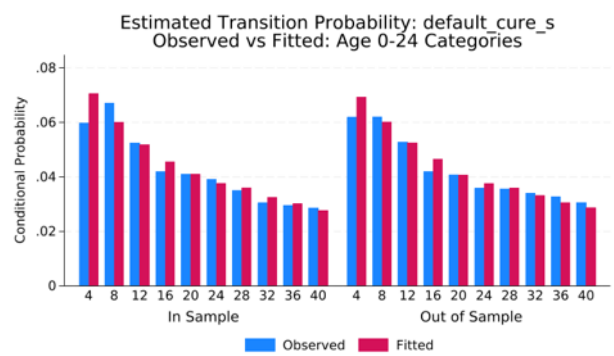




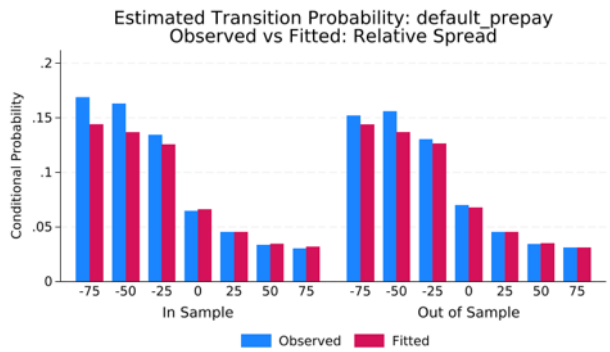


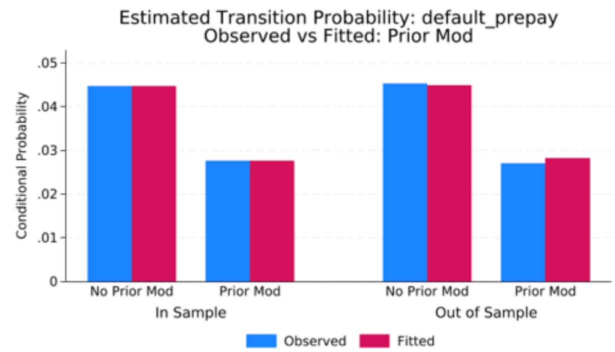


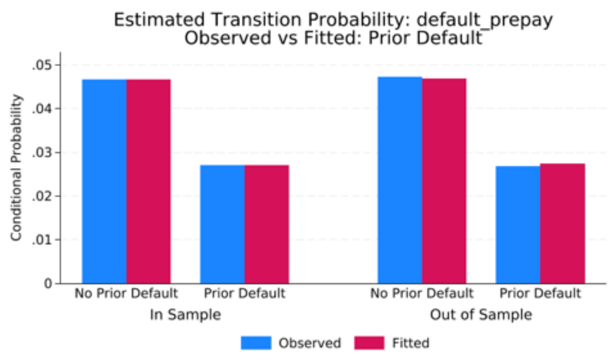


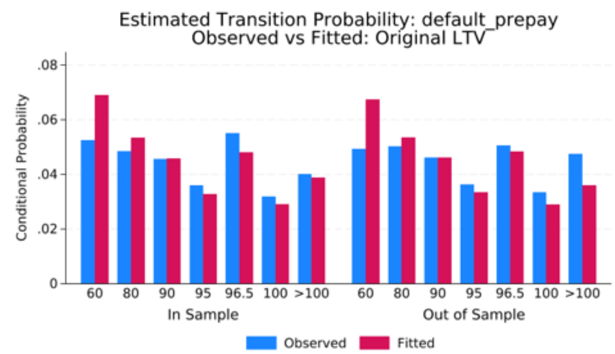


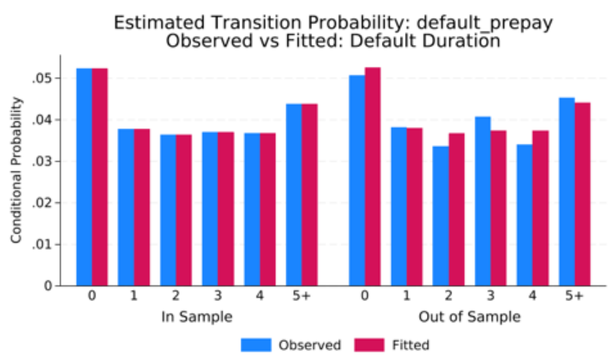
Product 2 - default_prepay

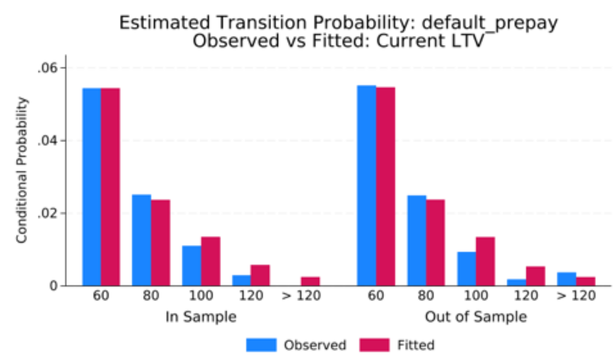


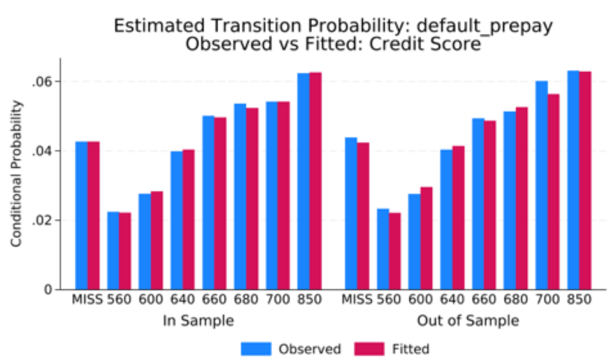


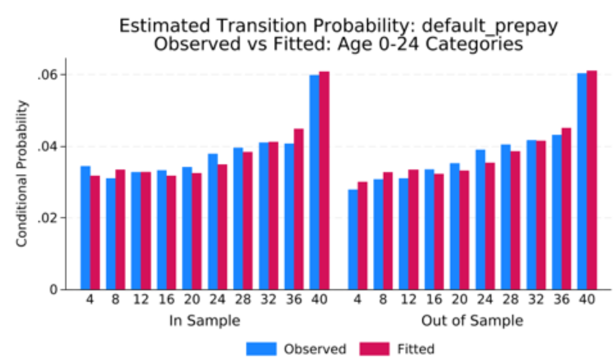






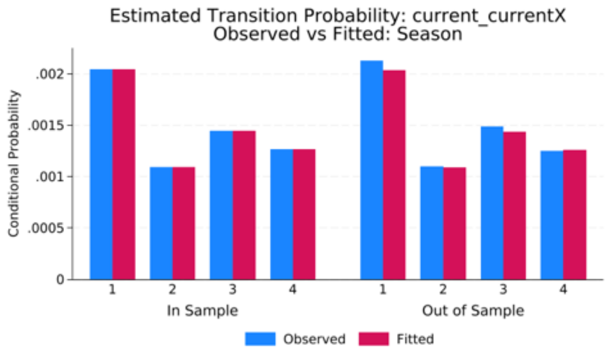


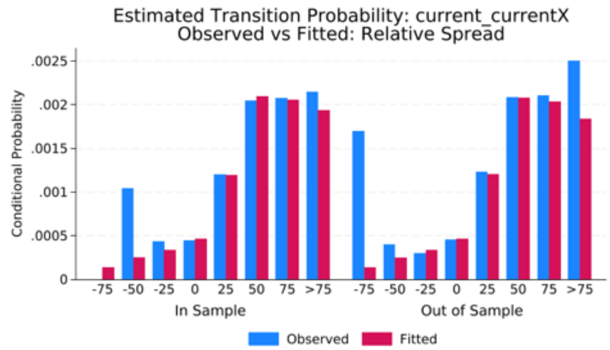


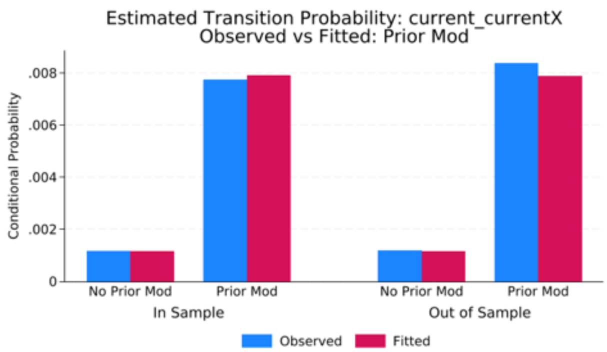


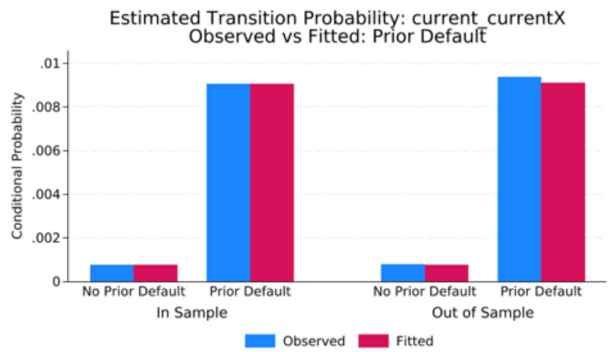
B3. Product 3

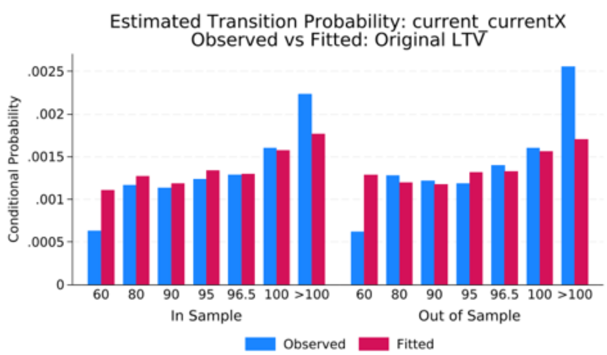
Product 3 - current_currentX

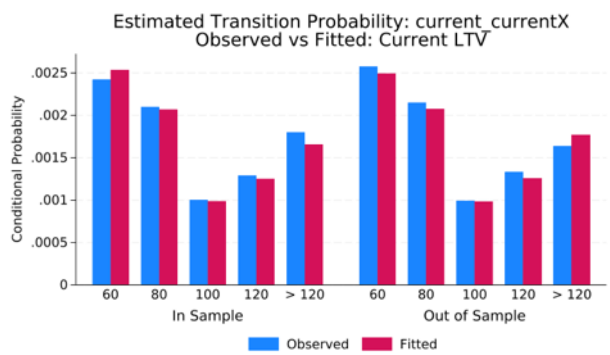


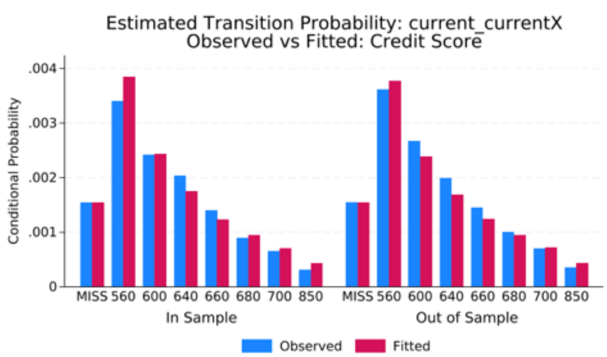


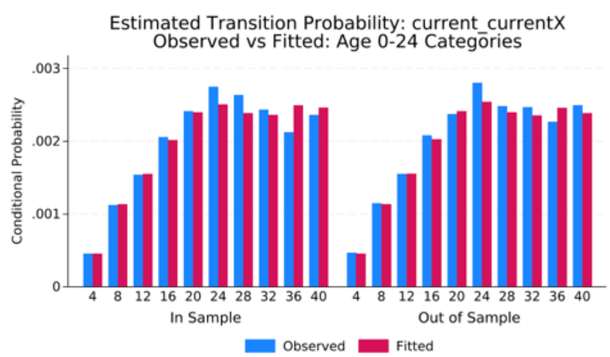




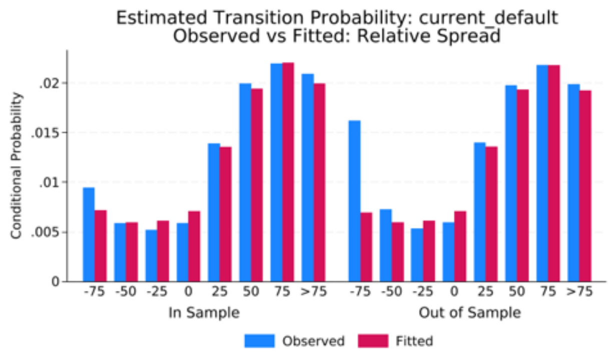


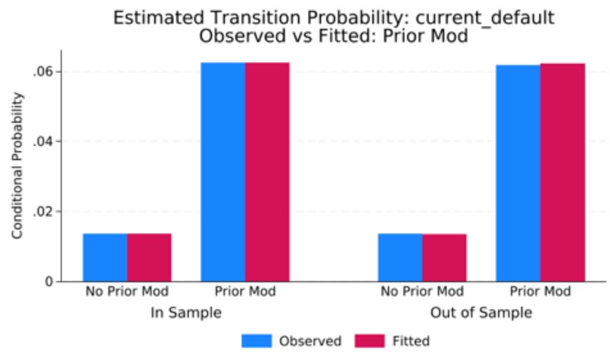


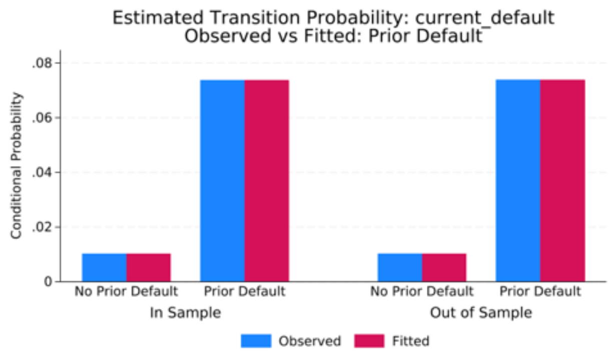


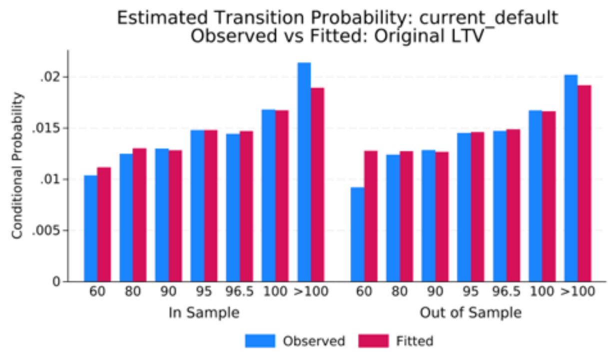


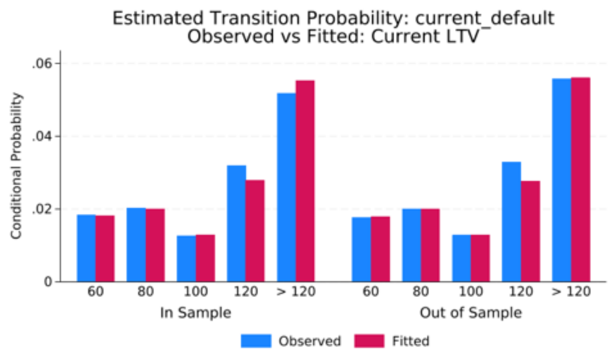
Product 3 - current_default

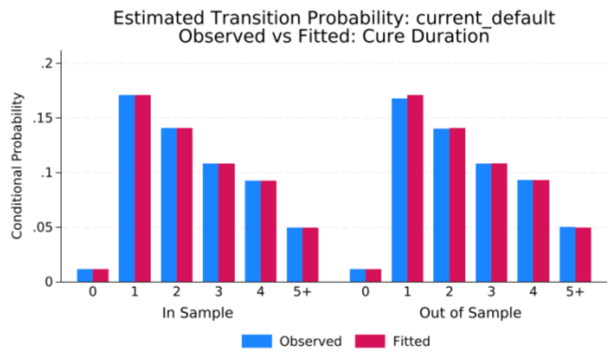


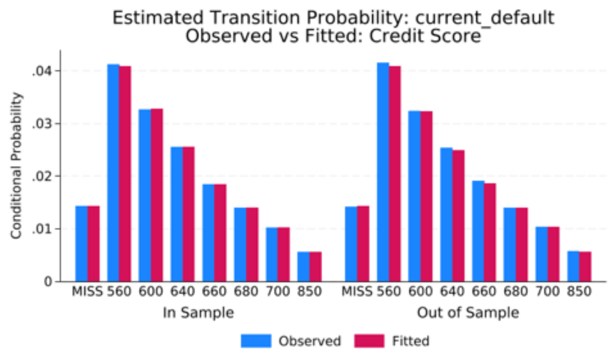


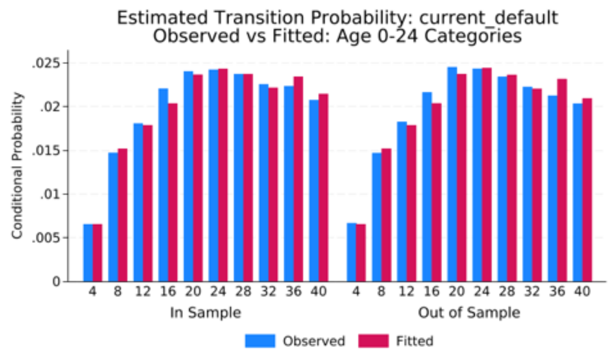




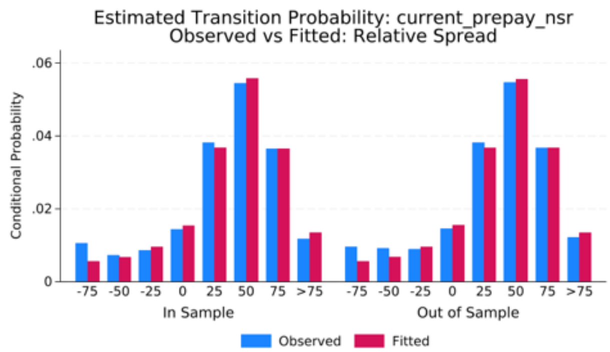


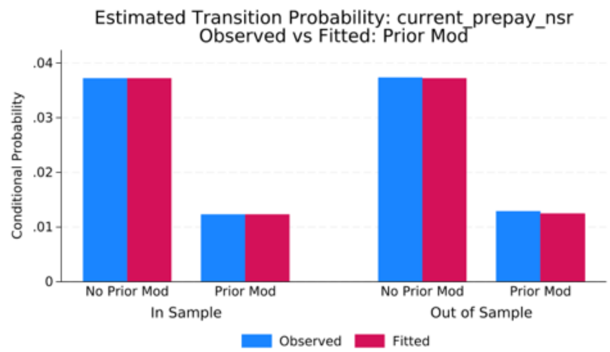


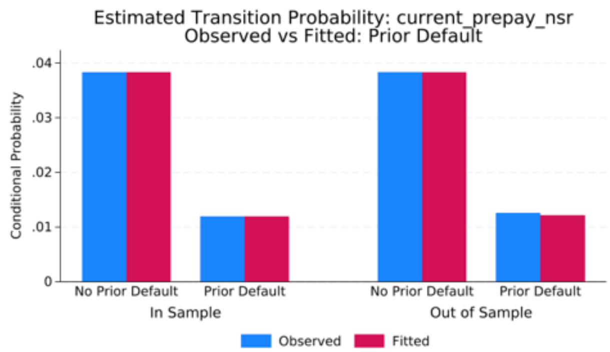


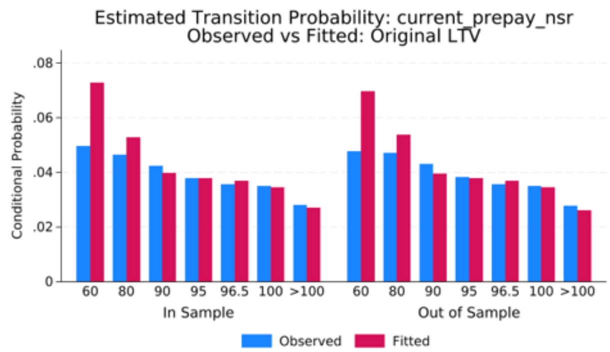


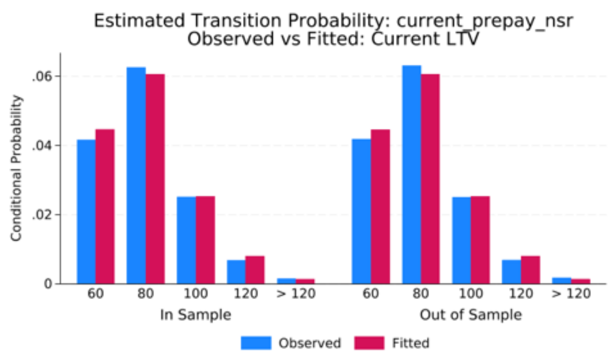
Product 3 - current_prepay_nsr

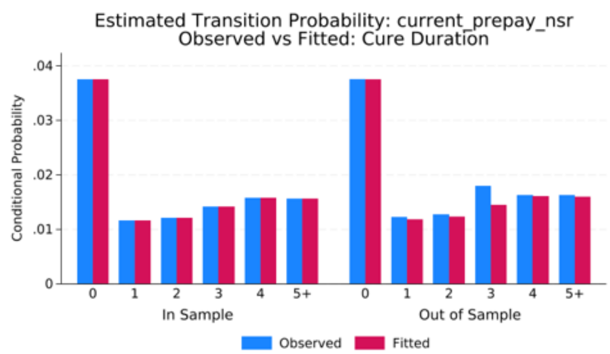


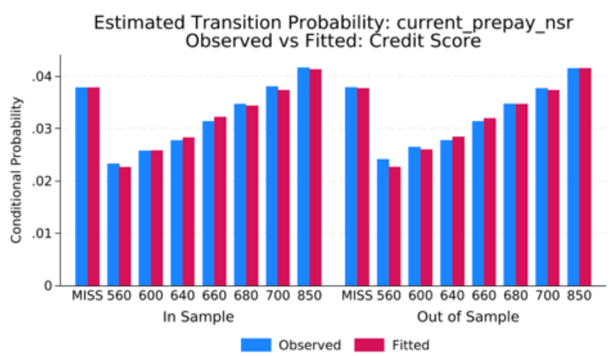


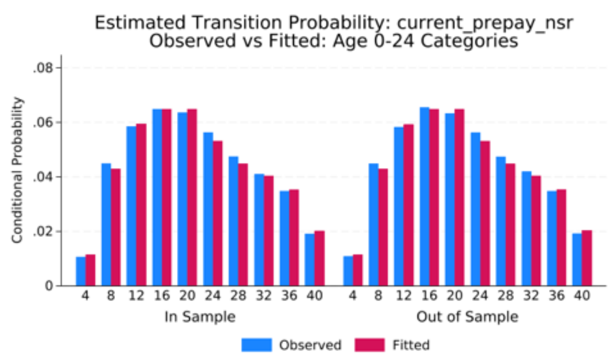




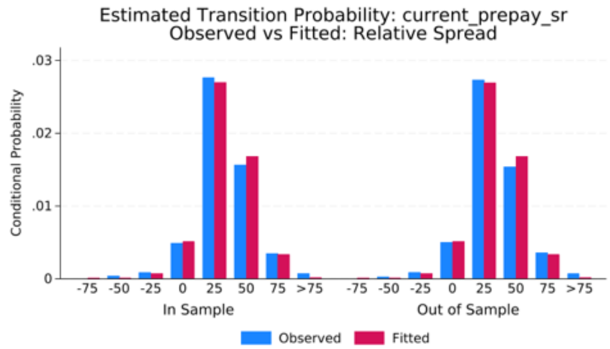


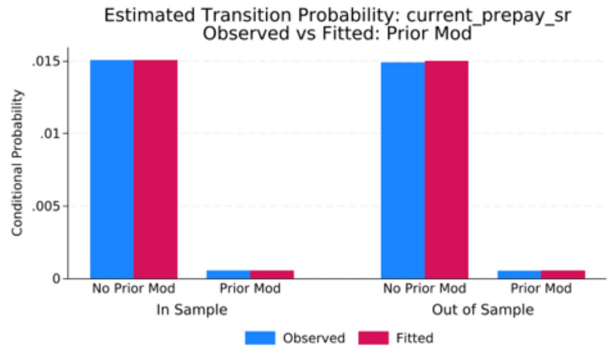


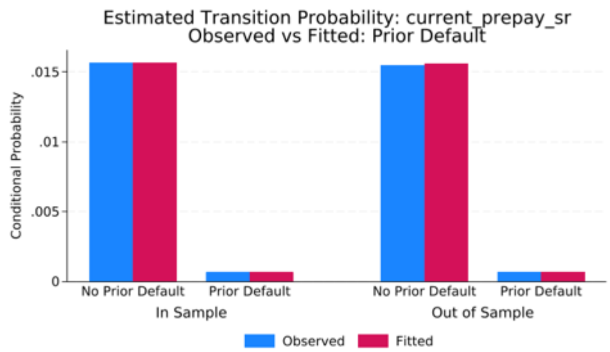


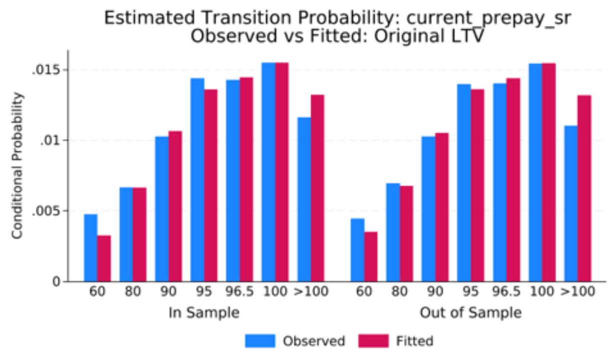


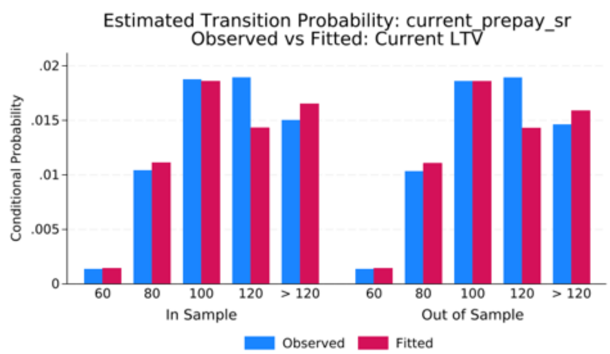
Product 3 - current_prepay_sr

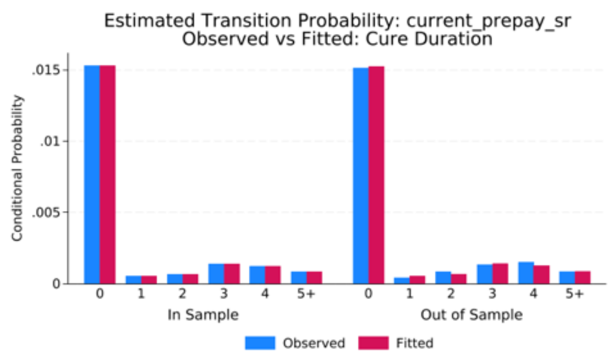


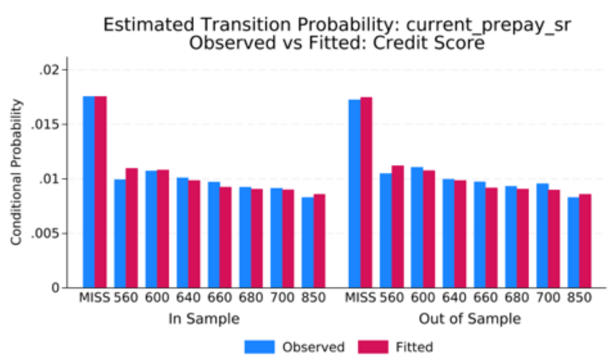


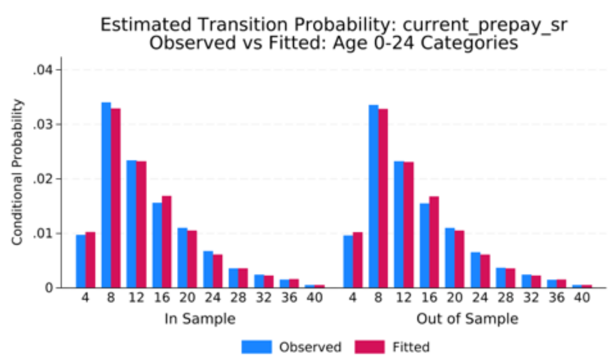




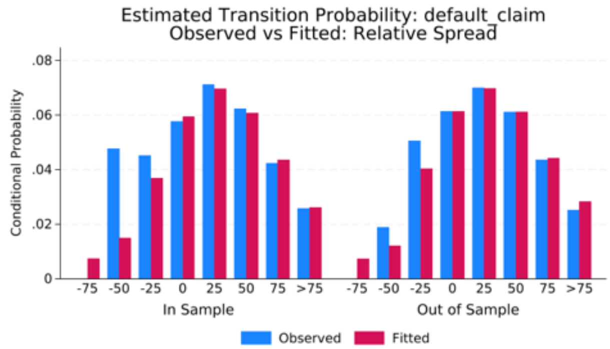


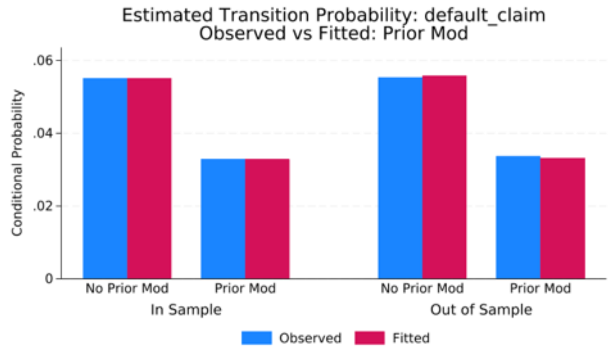


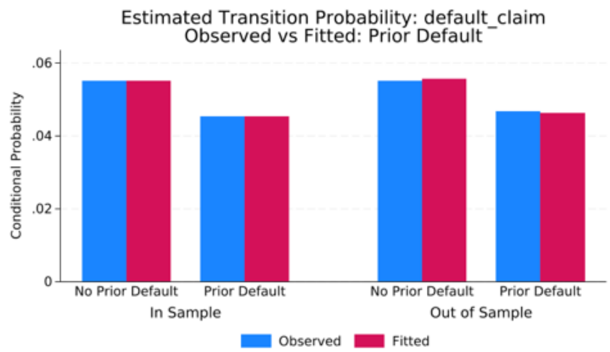


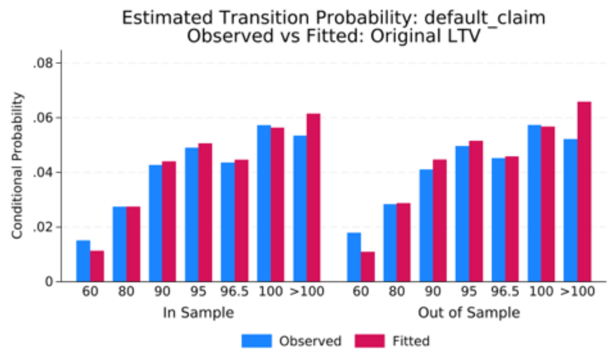


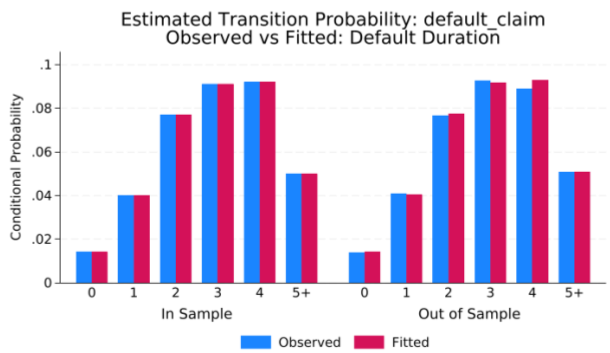
Product 3 - default_claim

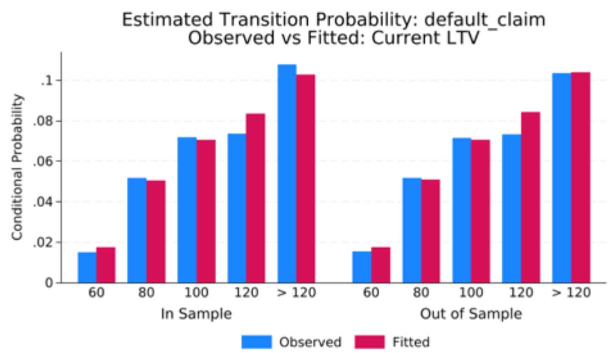


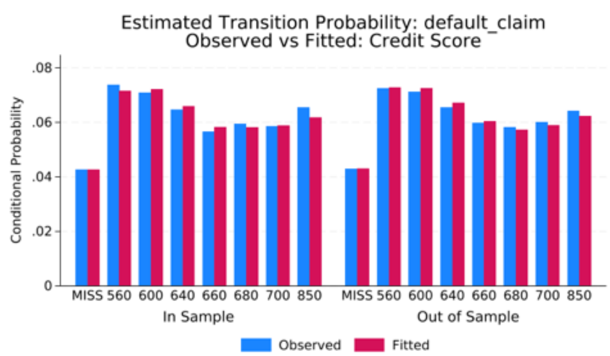


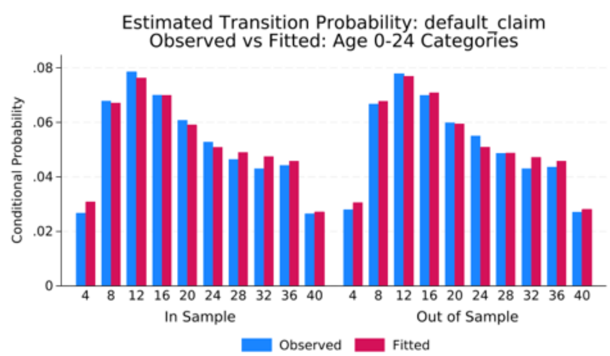












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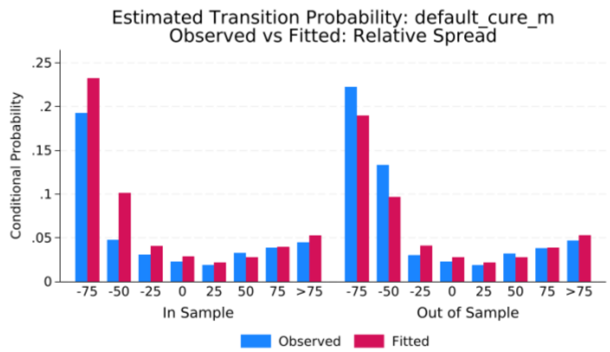

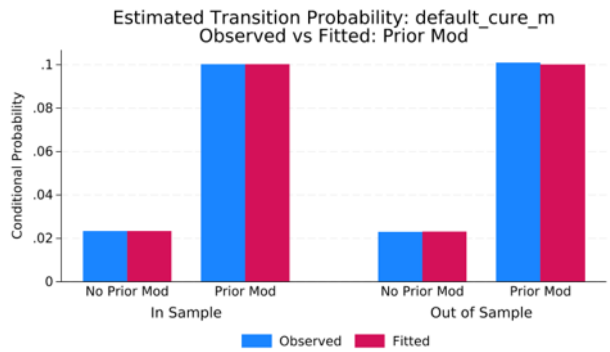

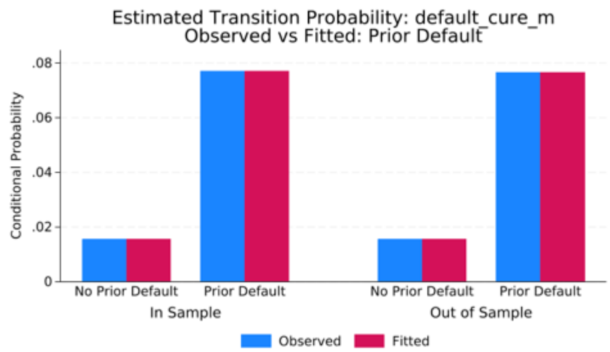

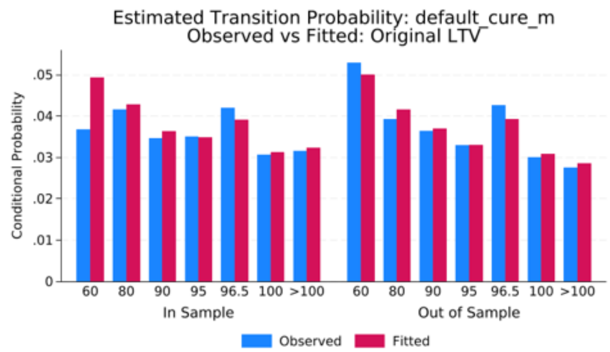

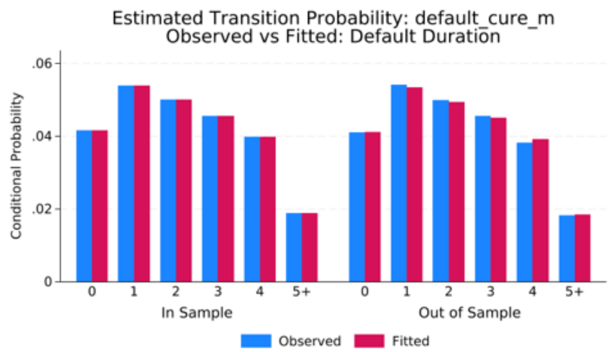

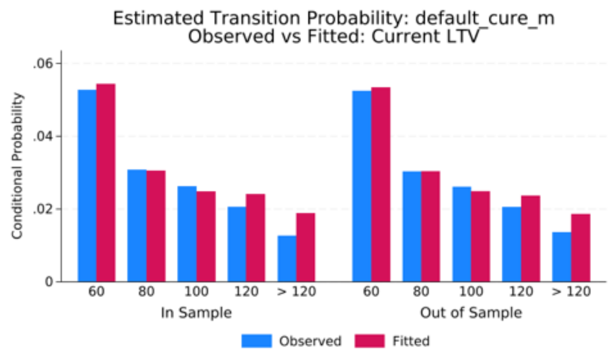

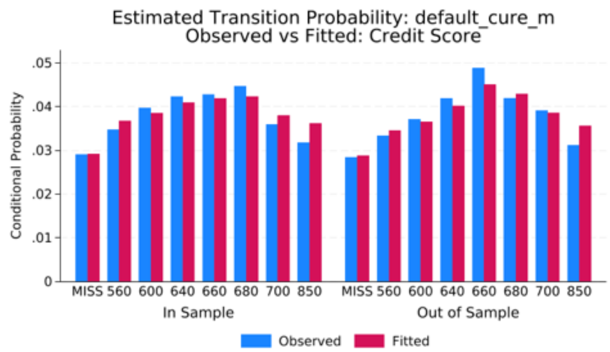

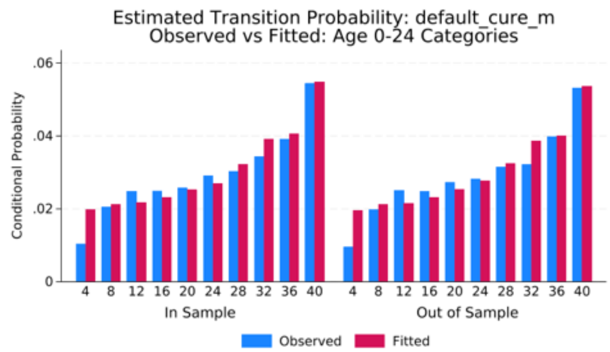

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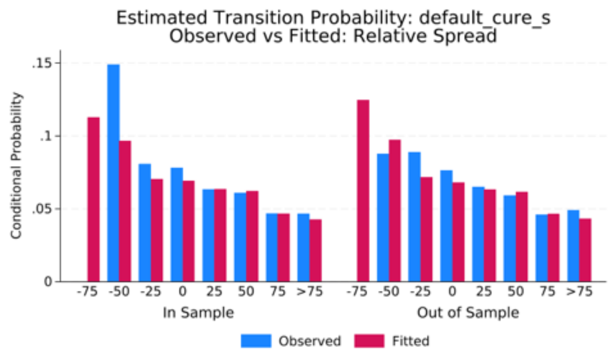
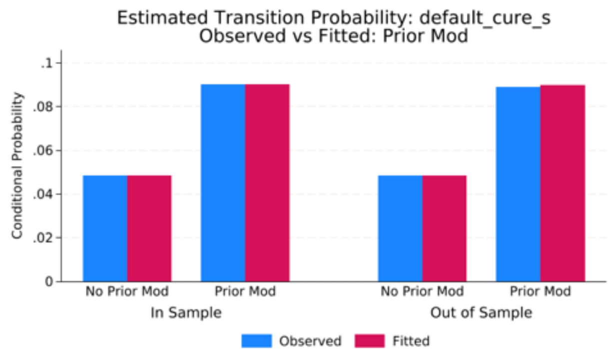
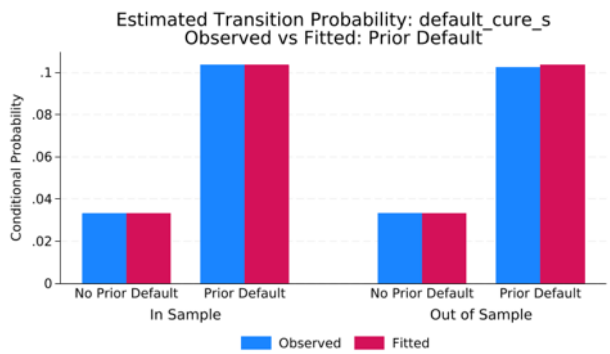
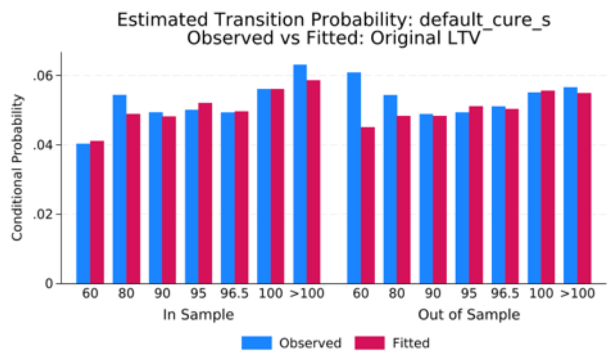
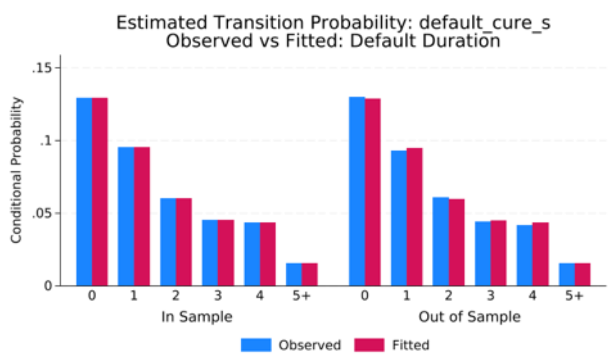
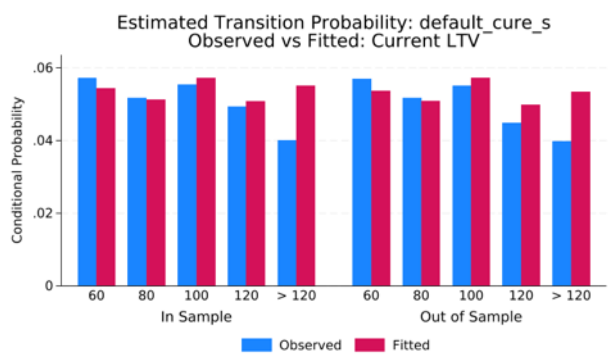


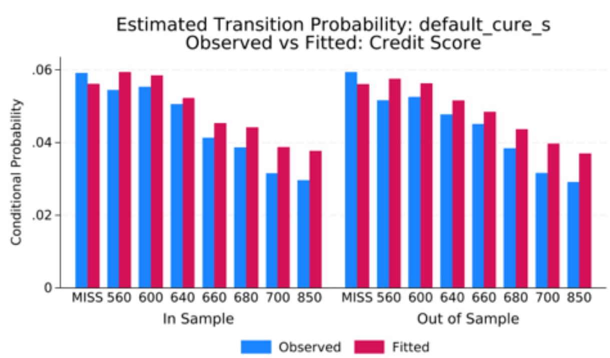


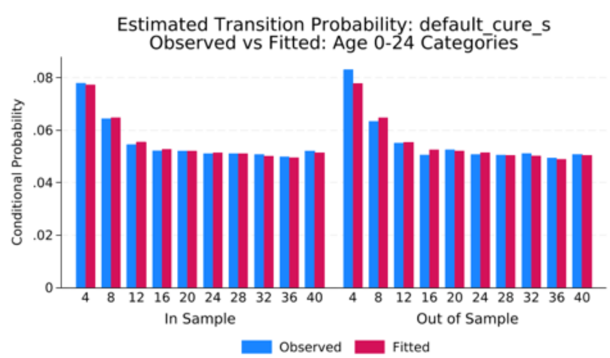




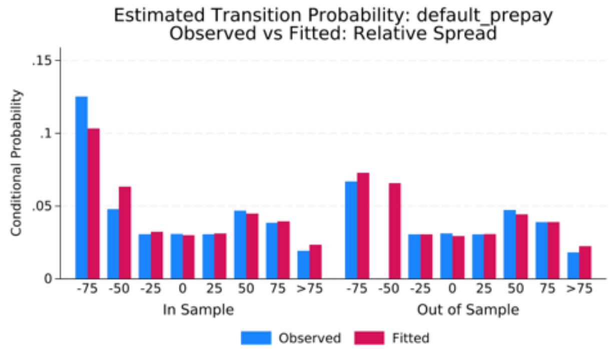


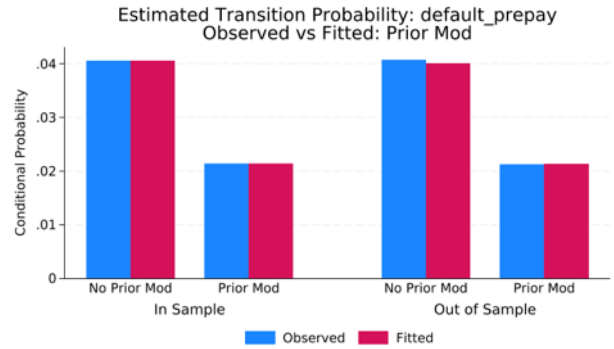


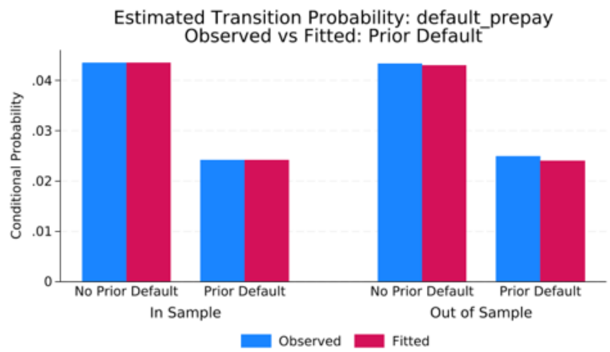


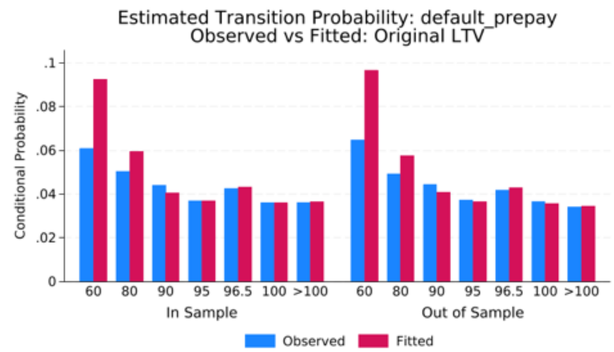


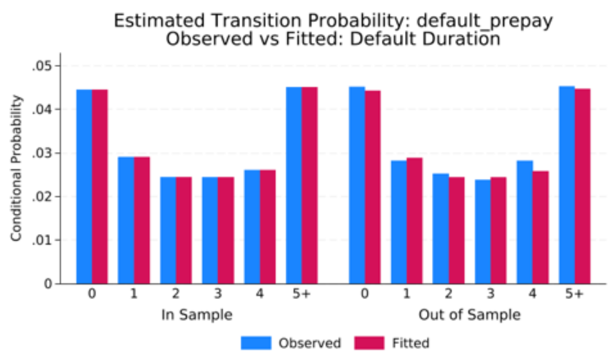
Product 3 - default_prepay

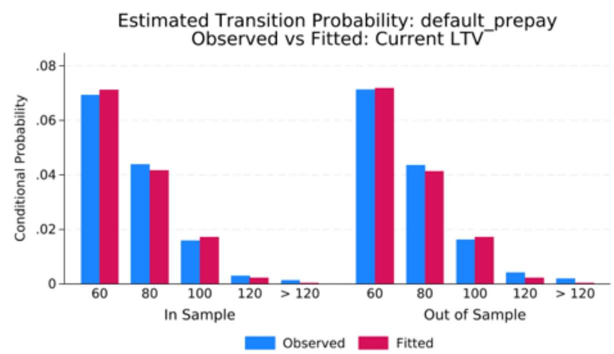


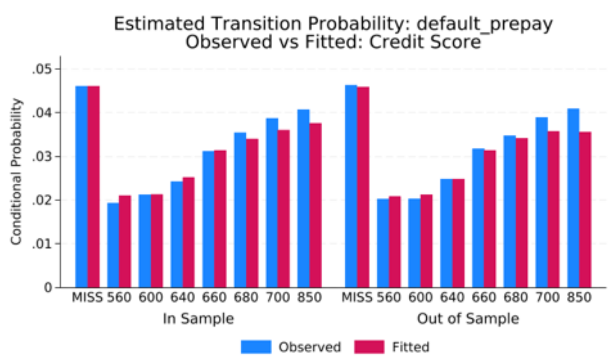


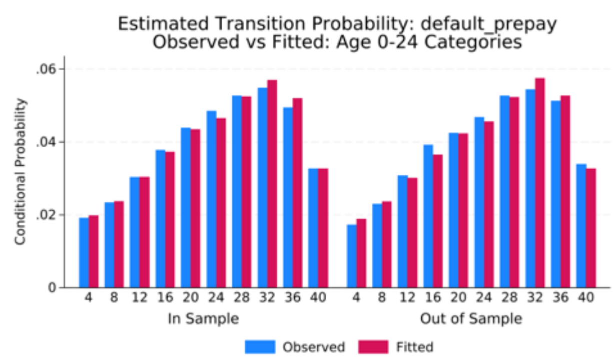






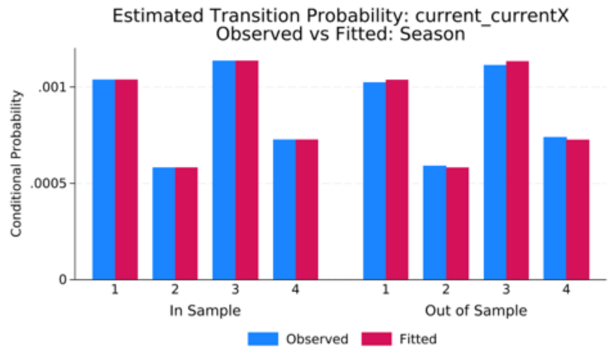


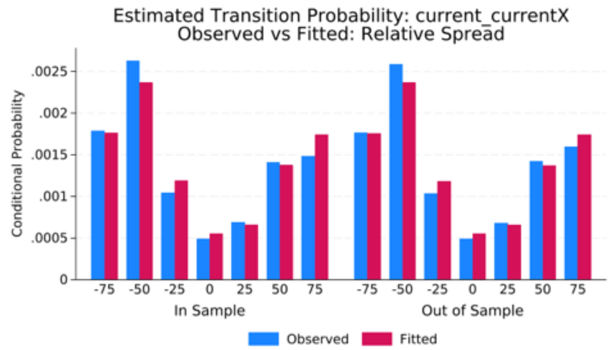


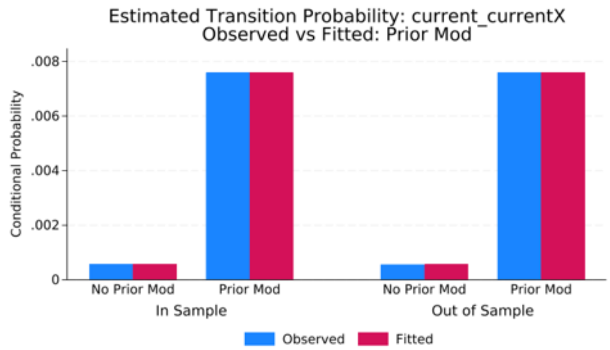


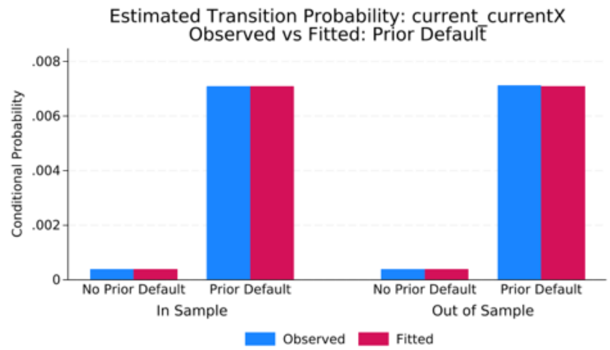
B4. Product 4

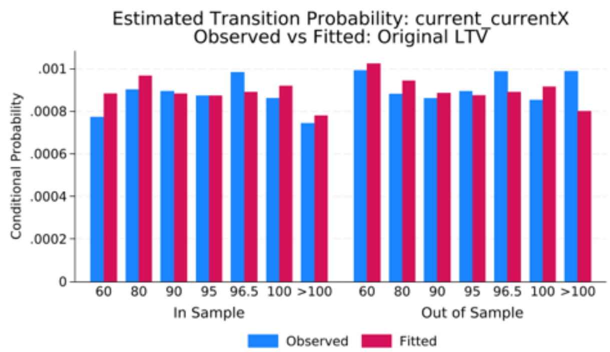
Product 4 - current_currentX

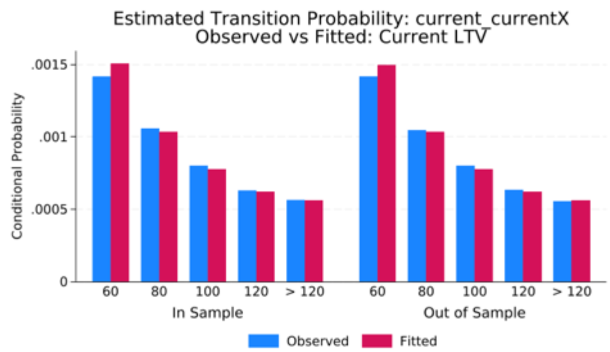


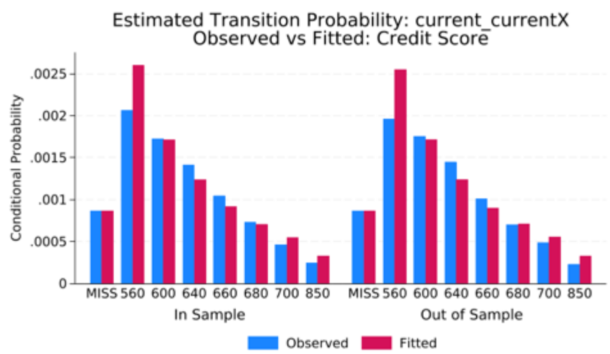


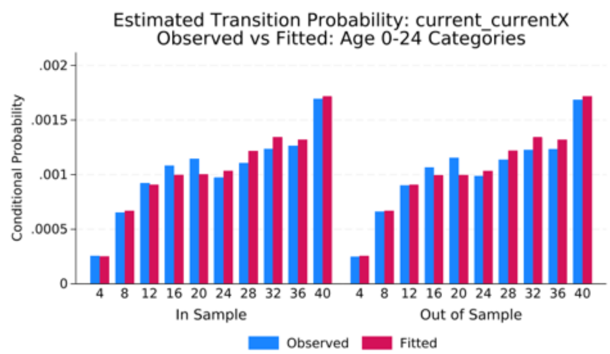




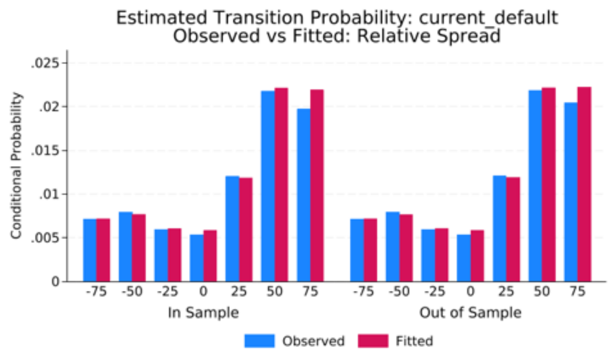


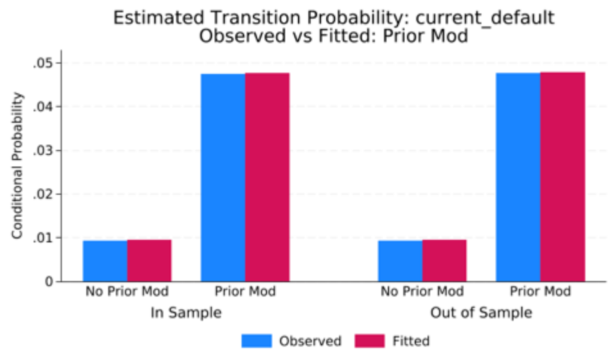


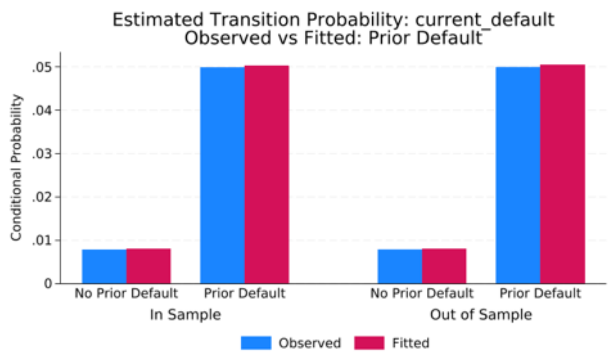


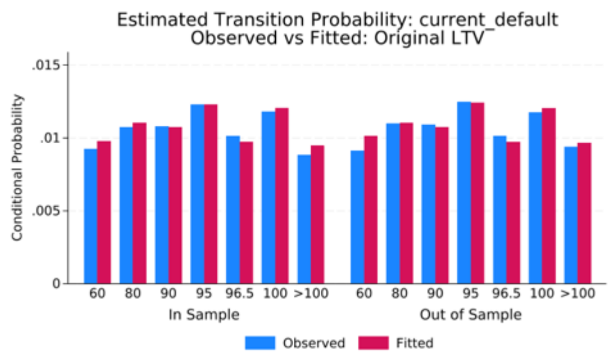


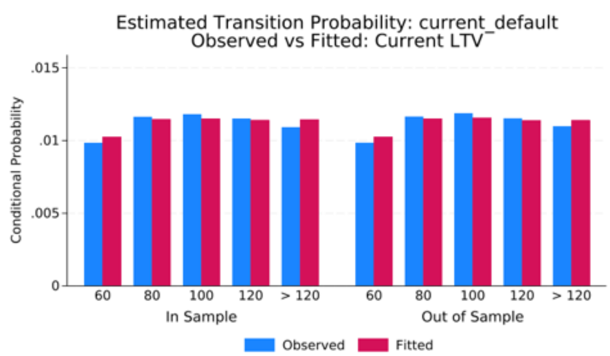
Product 4 - current_default

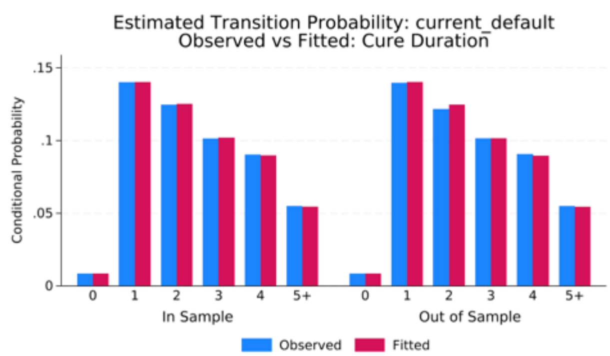


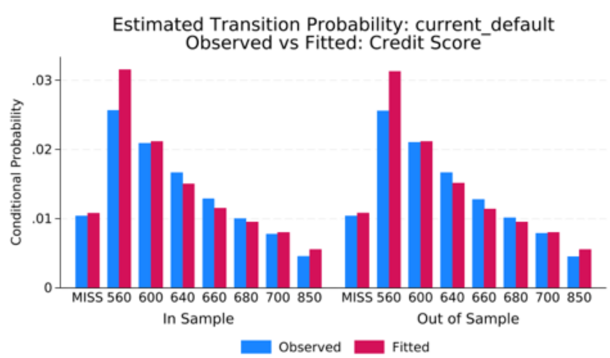


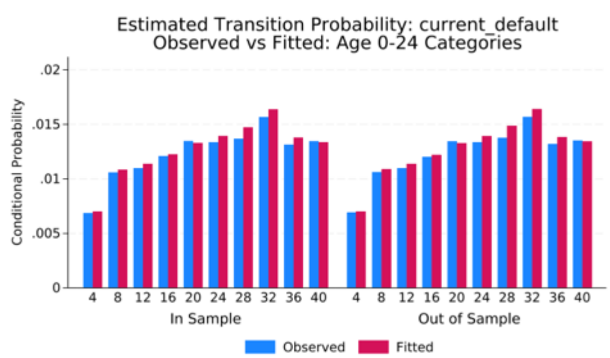




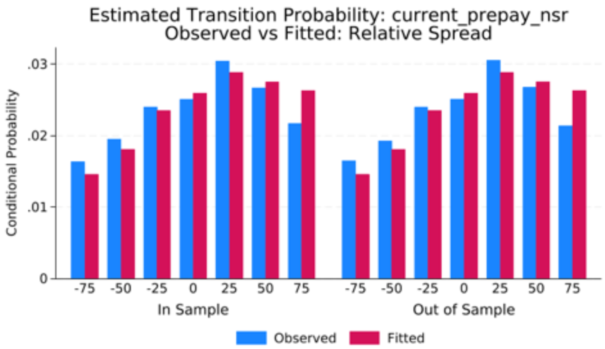


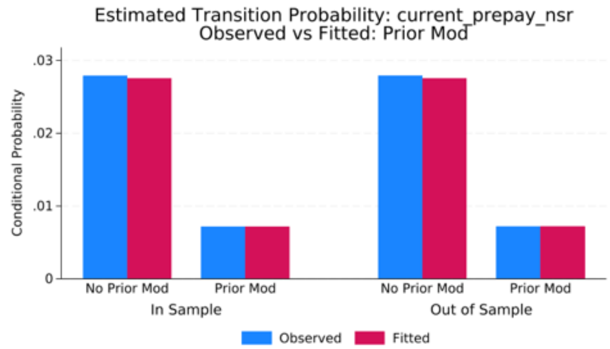


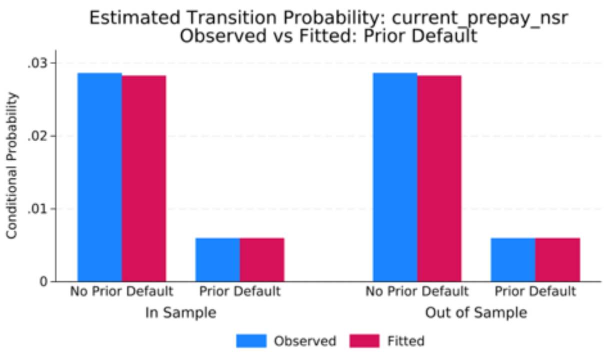


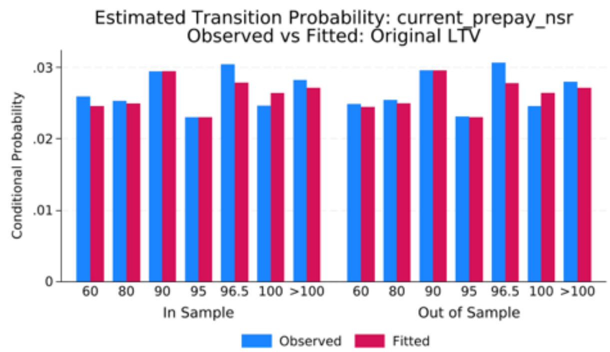


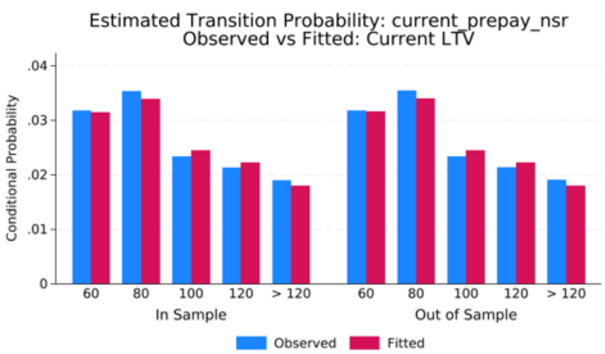
Product 4 - current_prepay_nsr

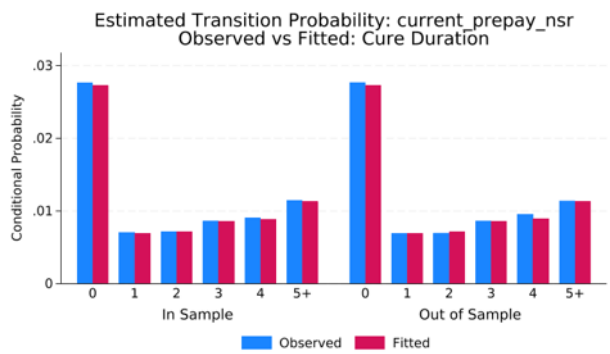


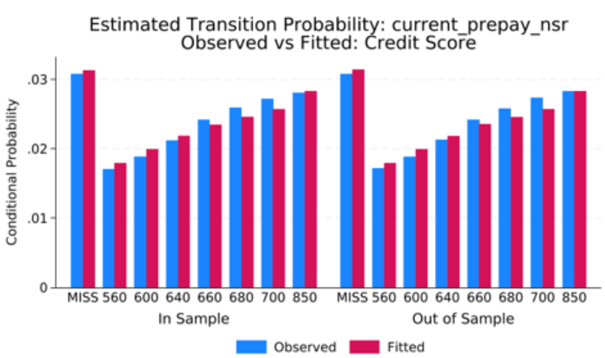


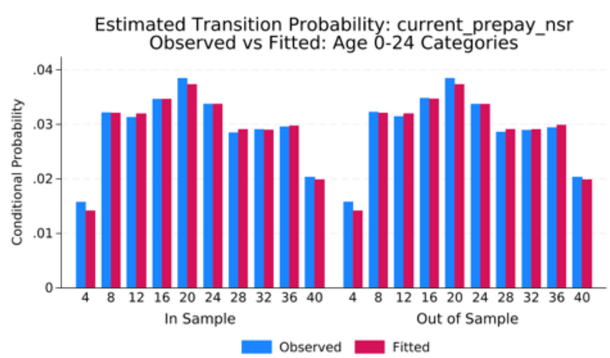




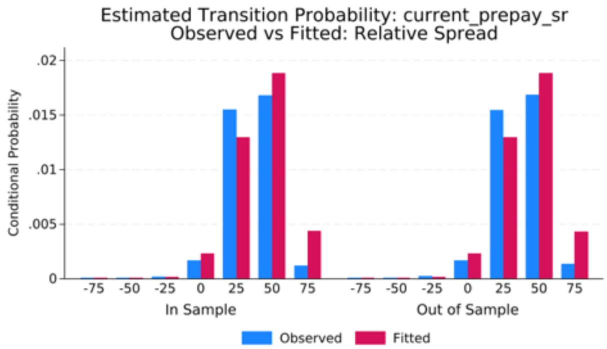


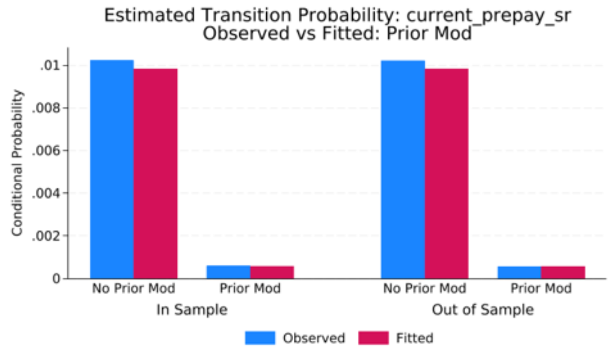


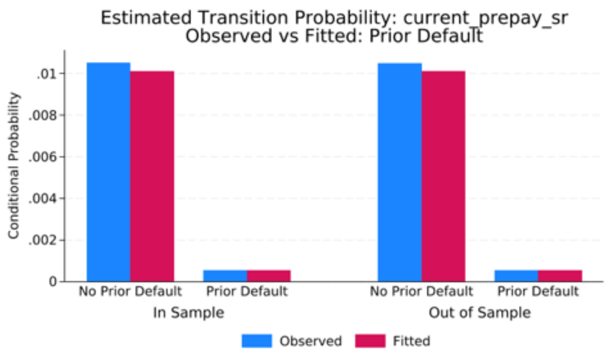


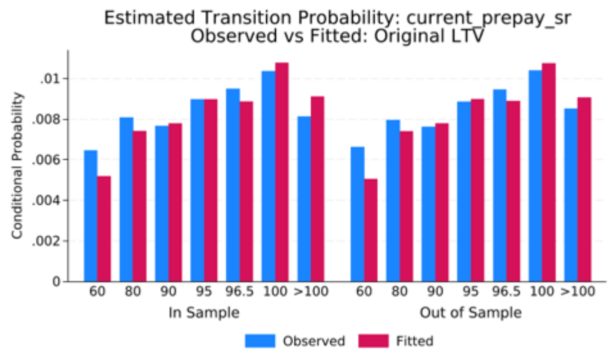


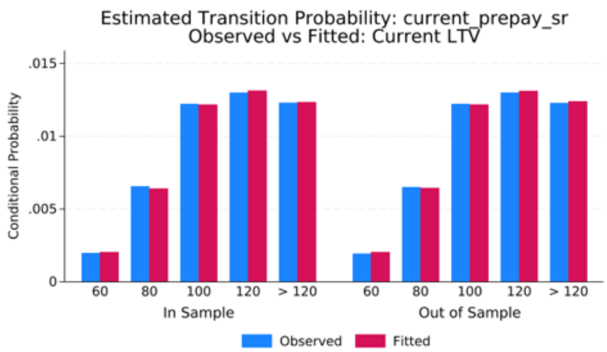
Product 4 - current_prepay_sr

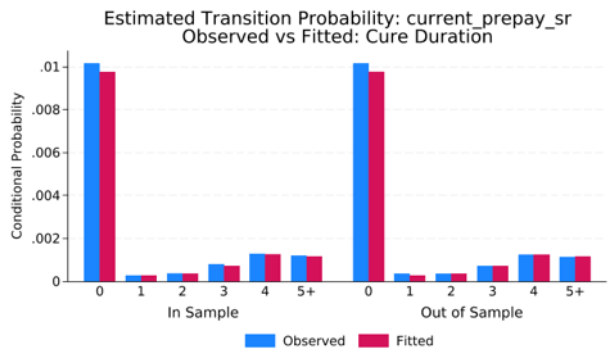


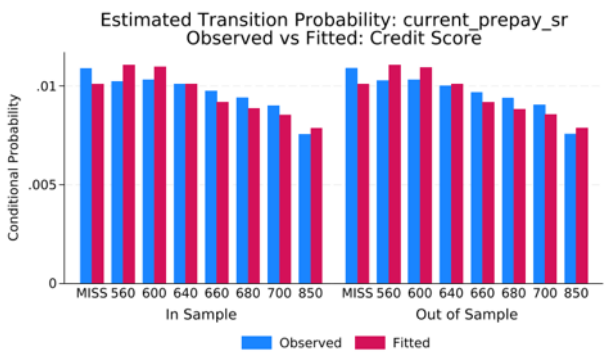


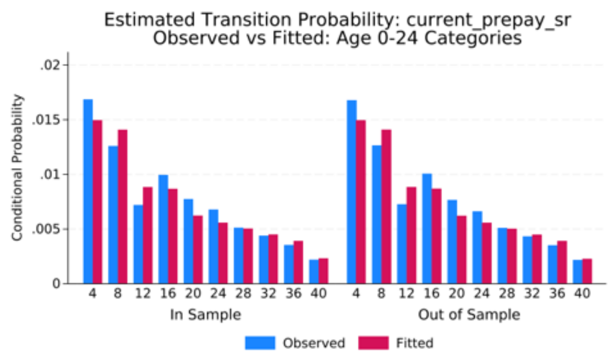




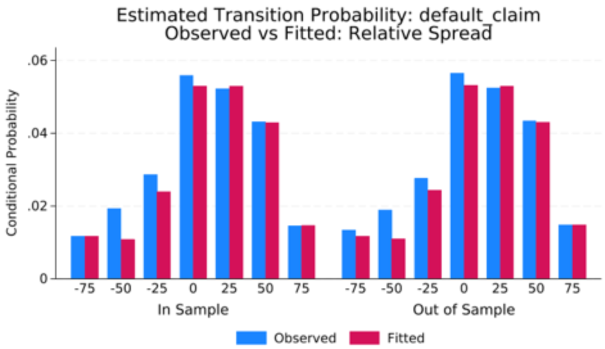


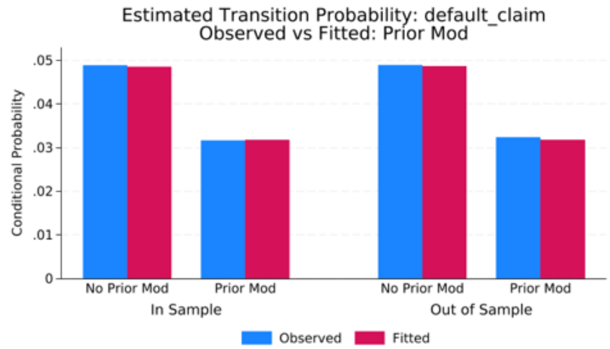


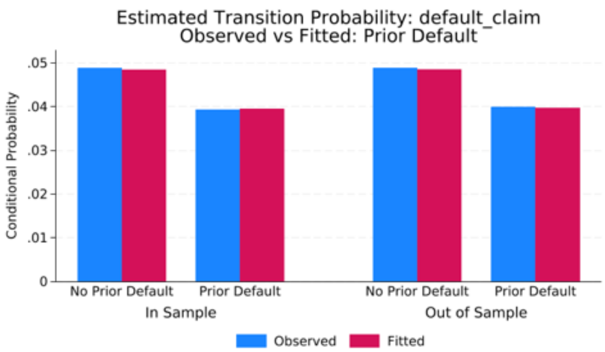


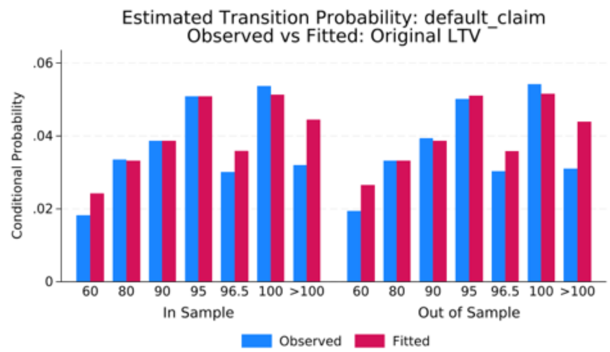


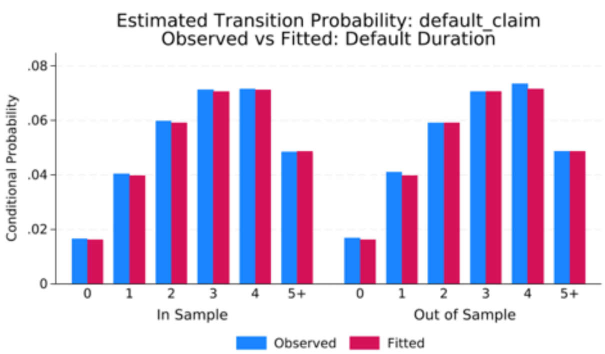
Product 4 - default_claim

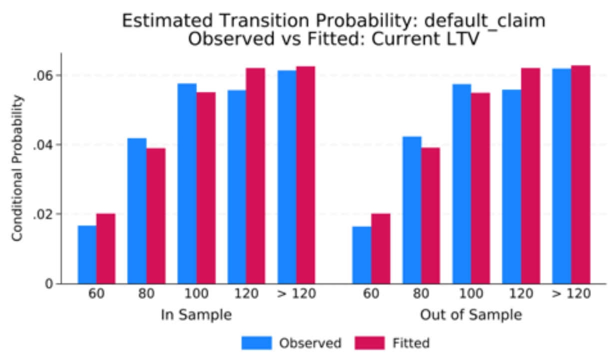


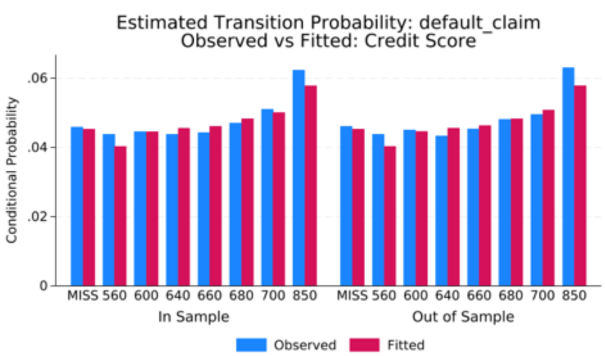


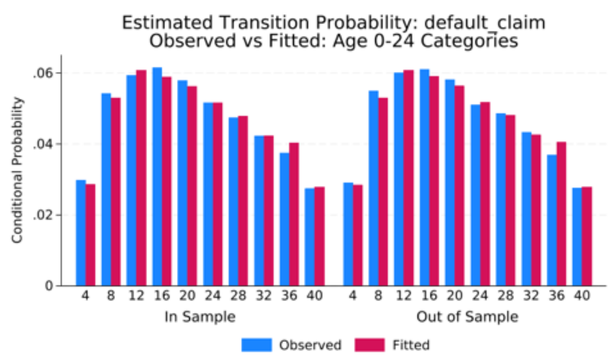




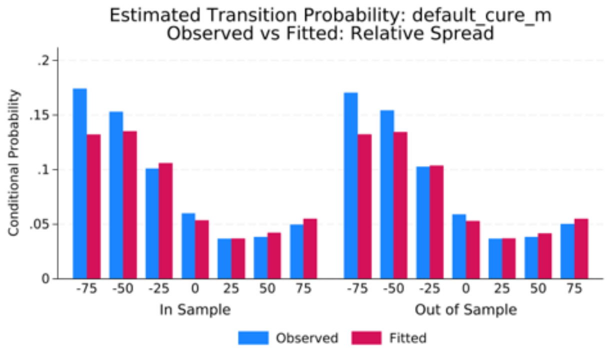


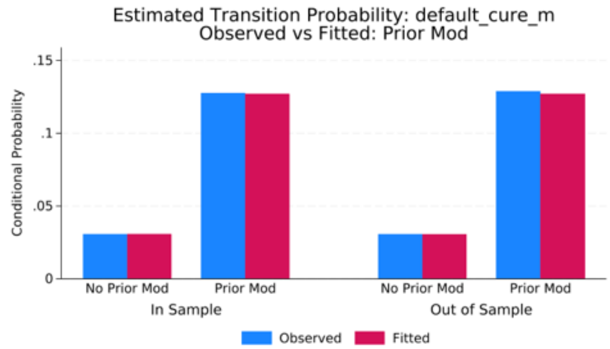


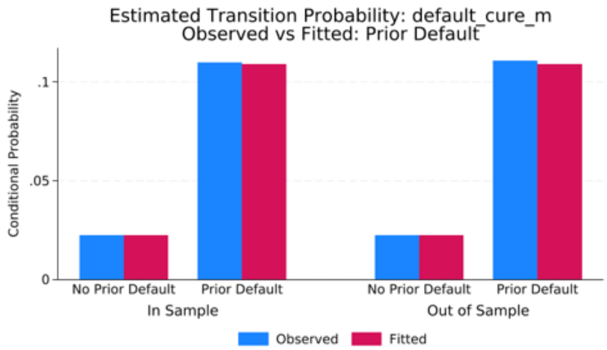


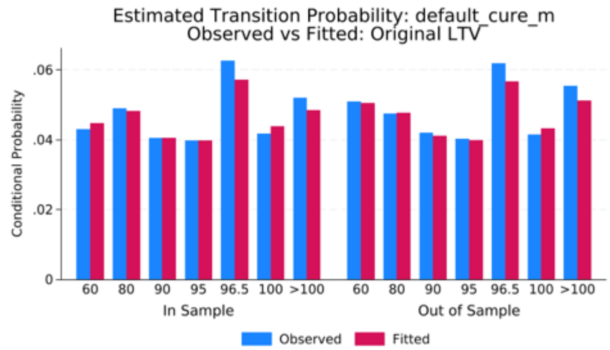


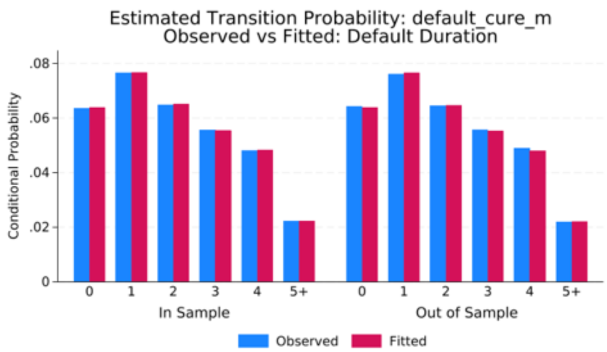
Product 4 - default_cure_m

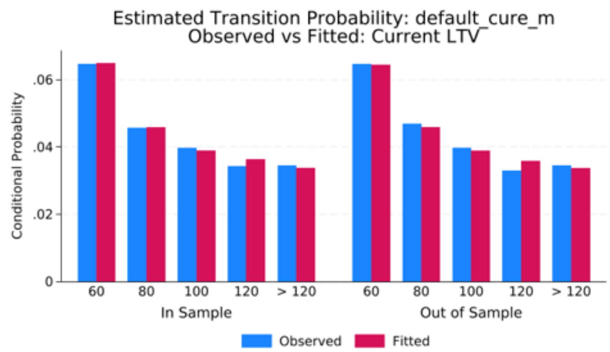


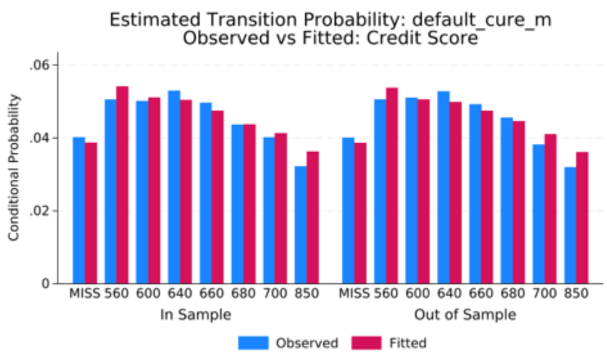


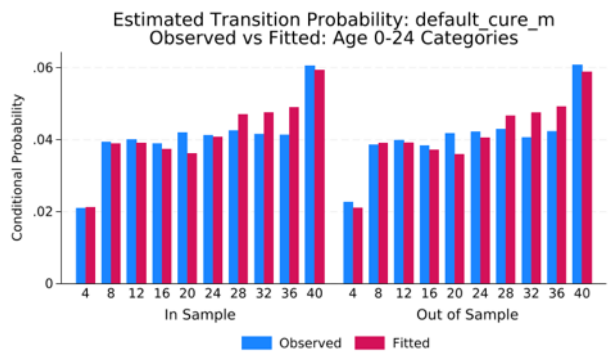




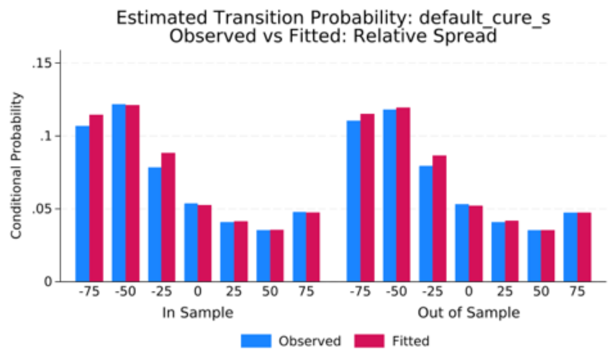


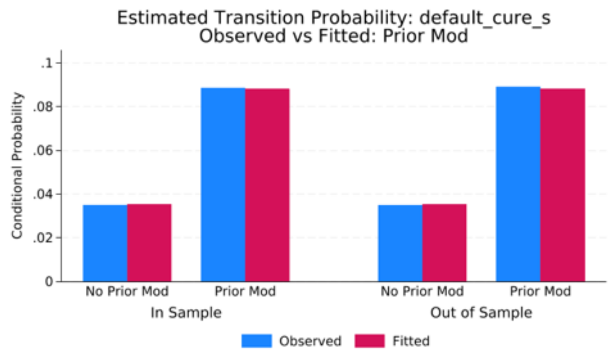


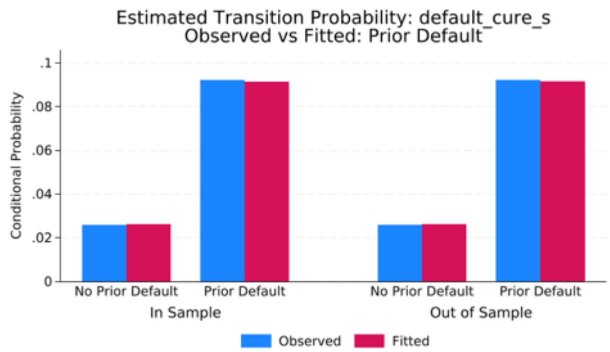


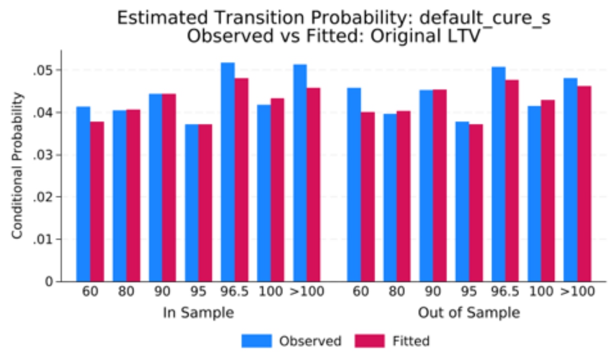


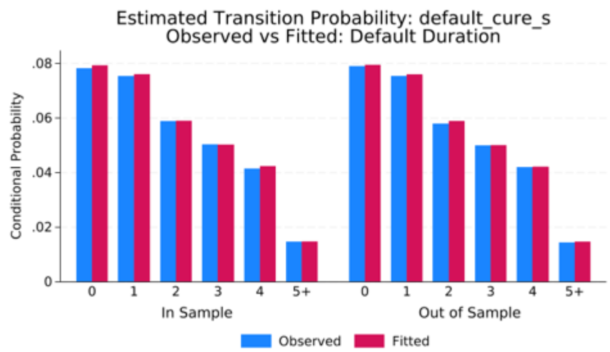
Product 4 - default_cure_s

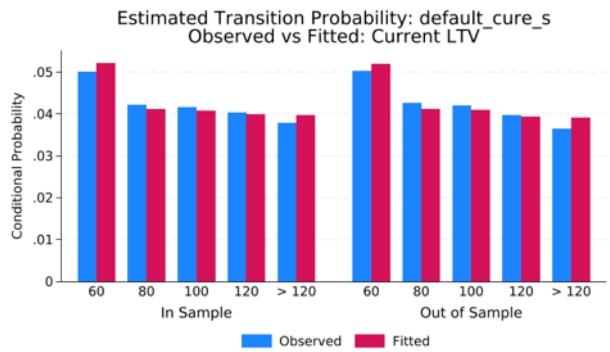


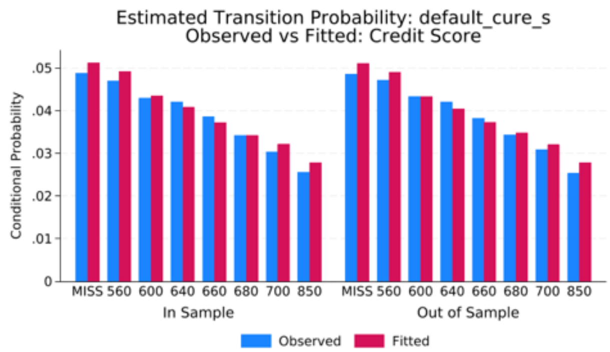


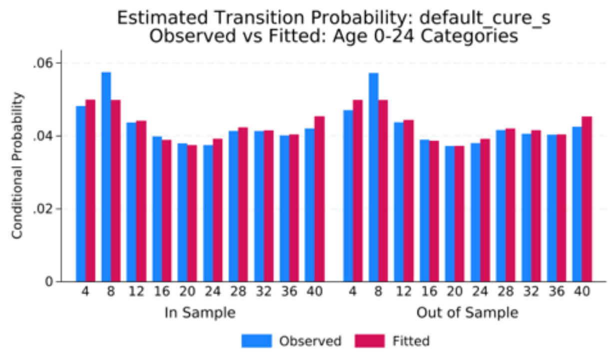




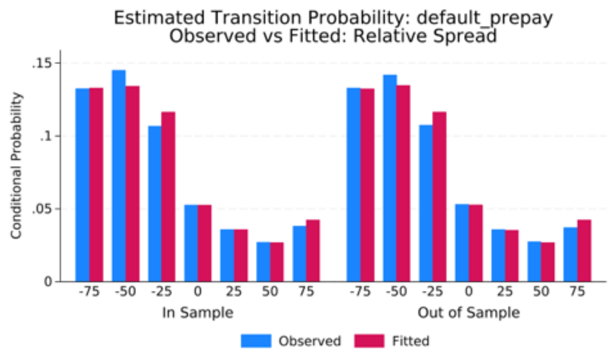


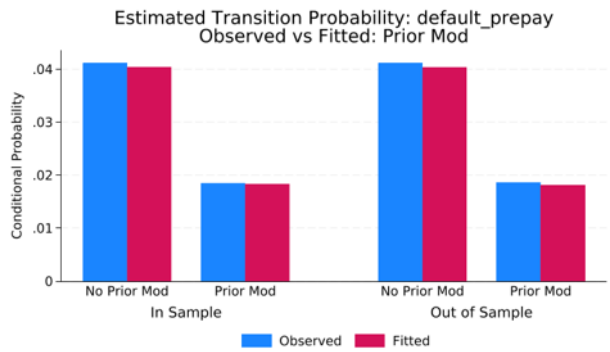


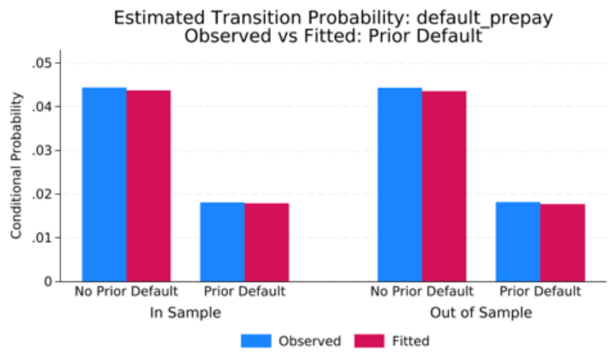


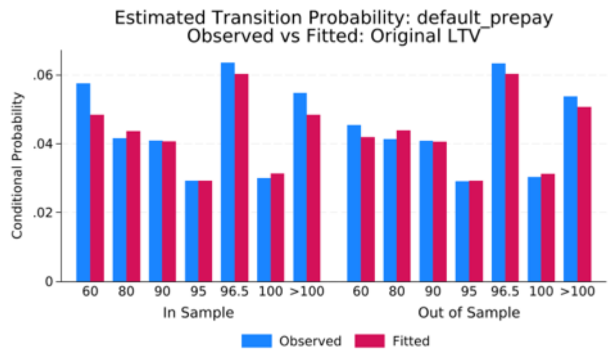


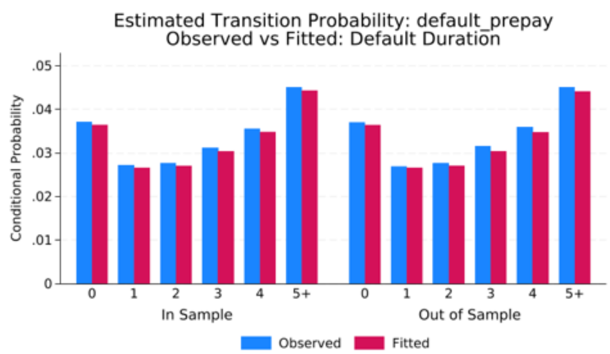
Product 4 - default_prepay

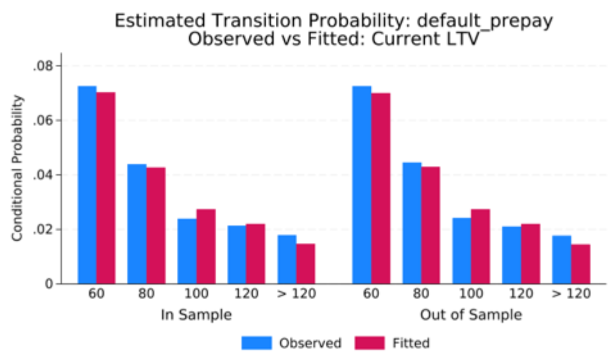


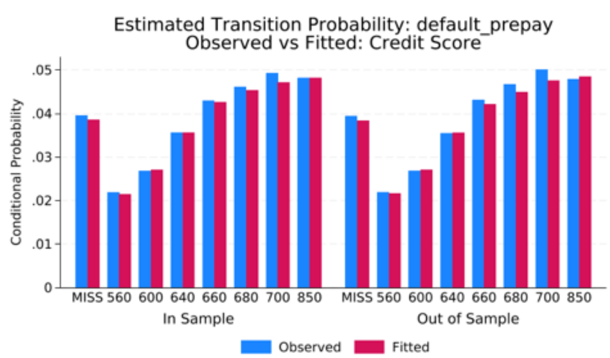


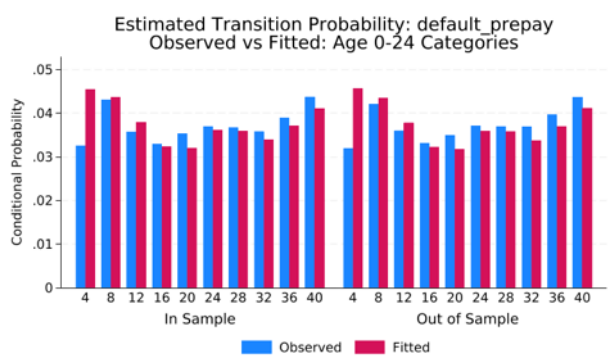






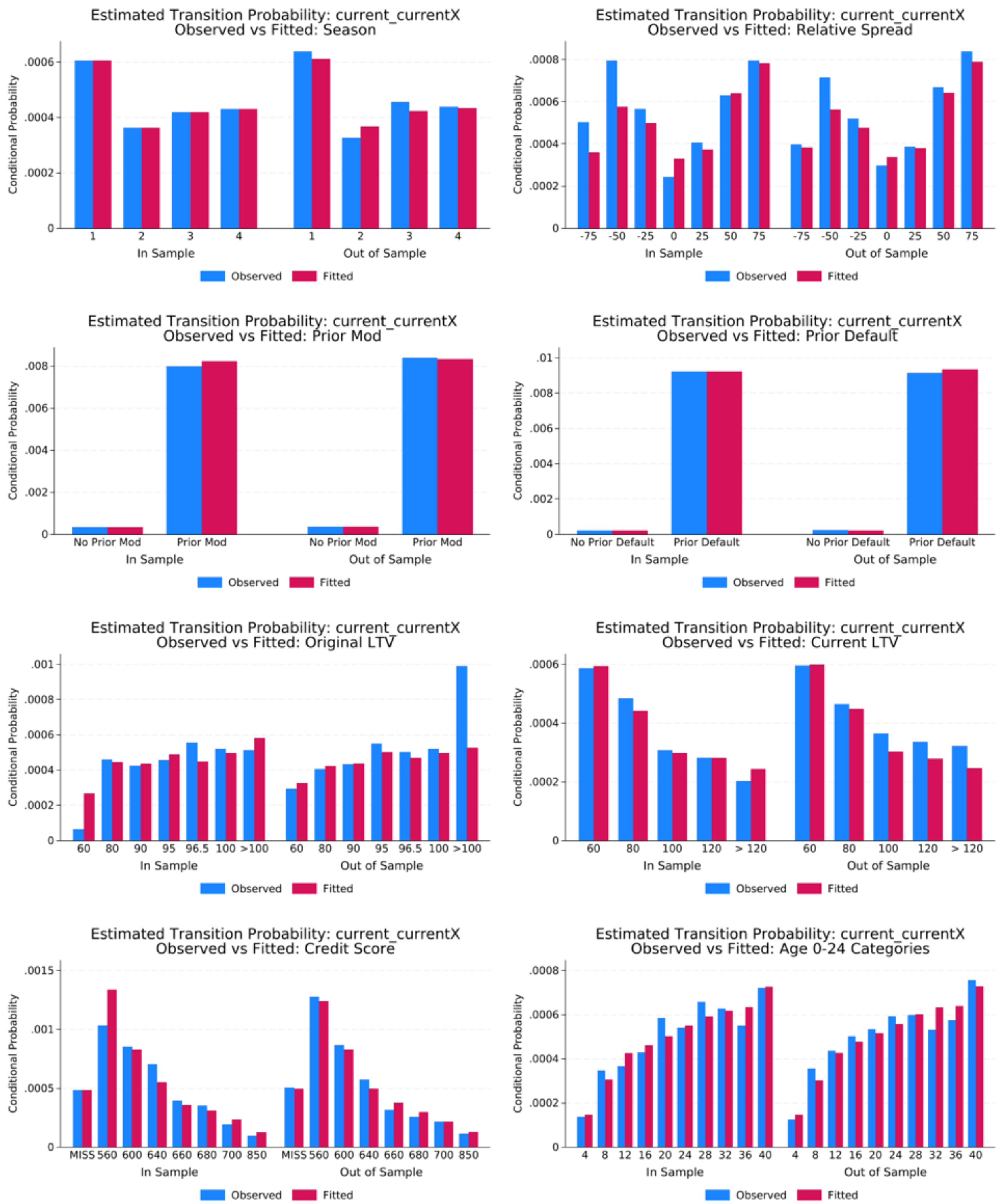




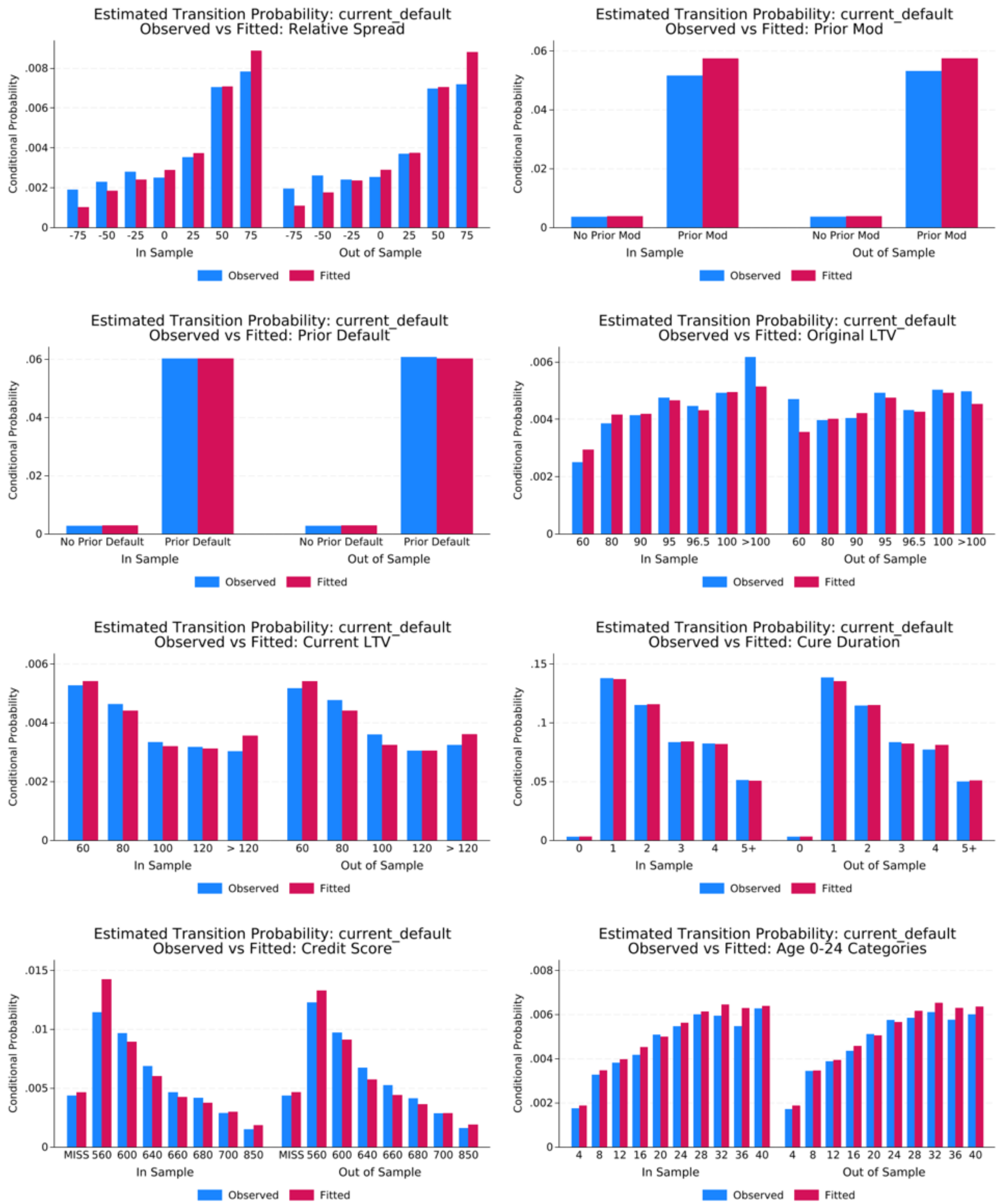


B5. Product 5

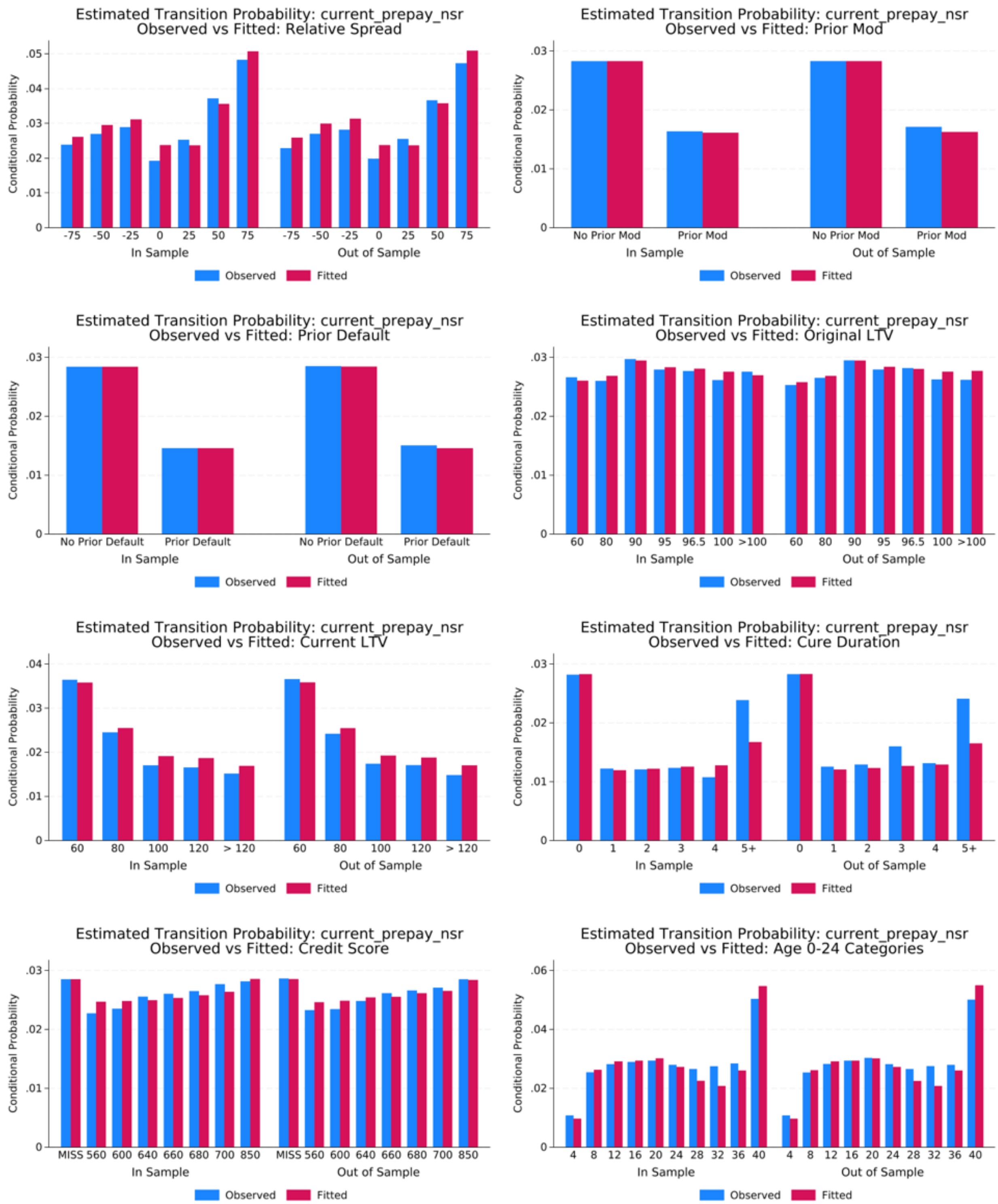
Product 5 - current_currentX



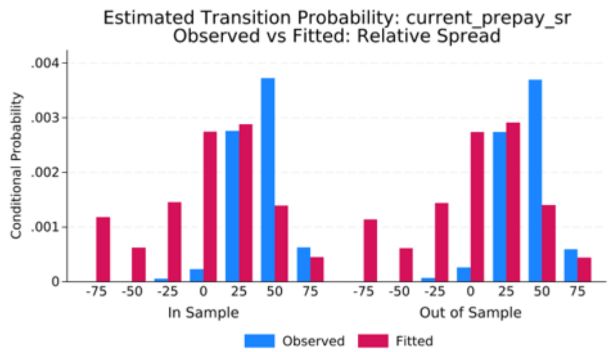
Product 5 - current_default

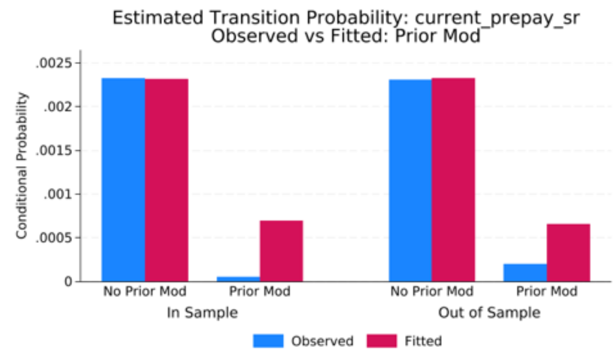


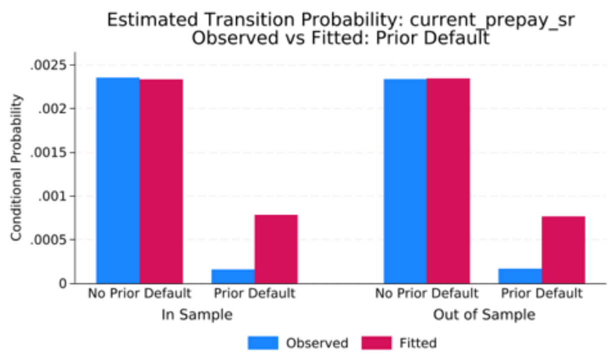
Product 5 - current_prepay_nsr

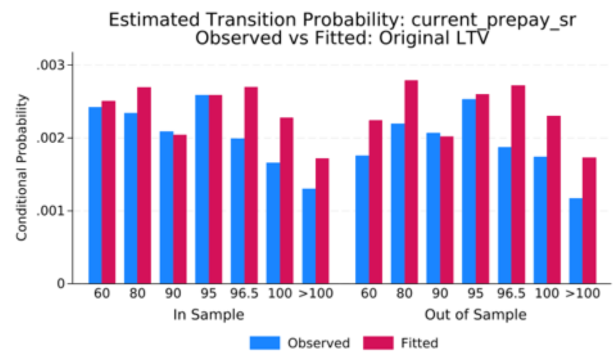


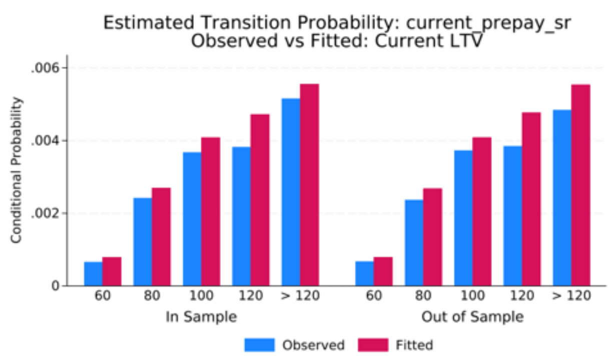
Product 5 - current_prepay_sr

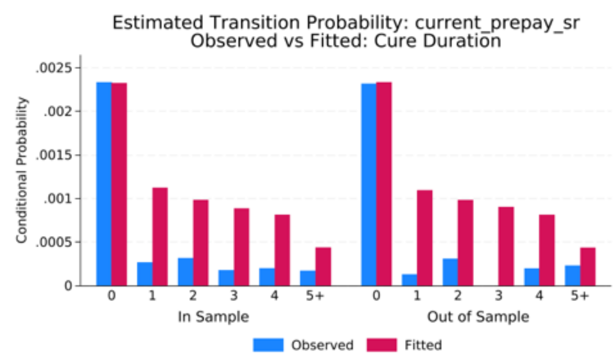


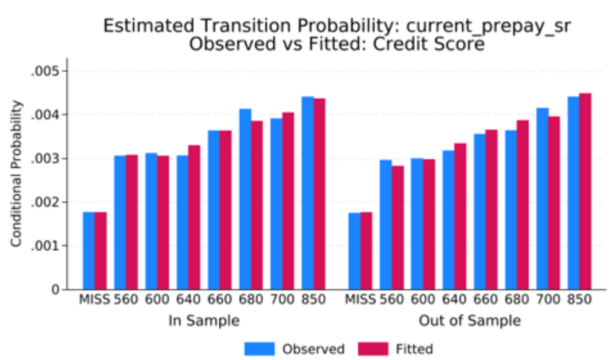


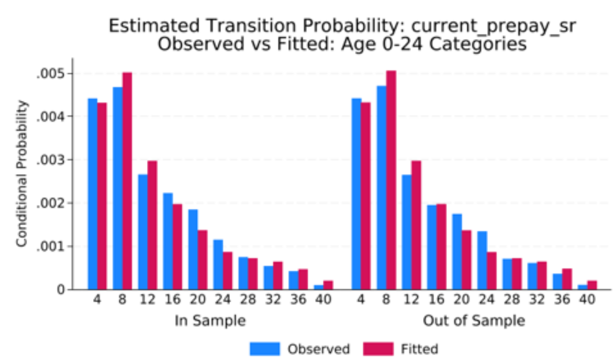




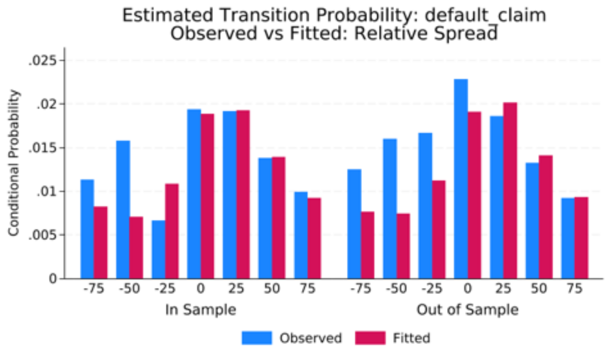


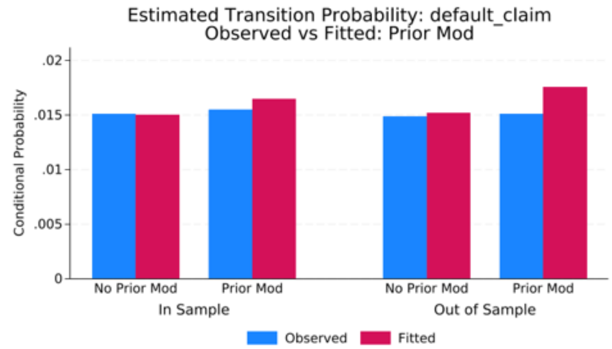


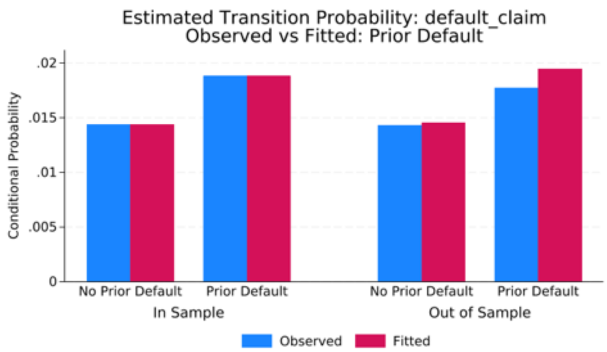


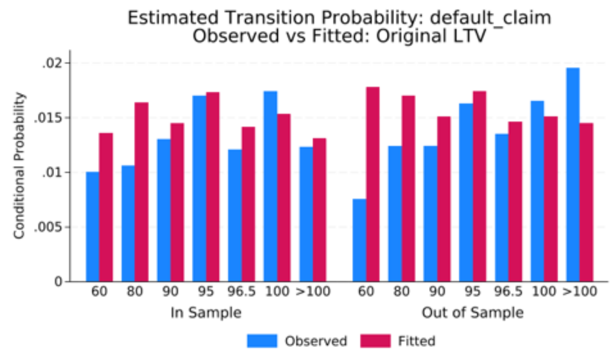


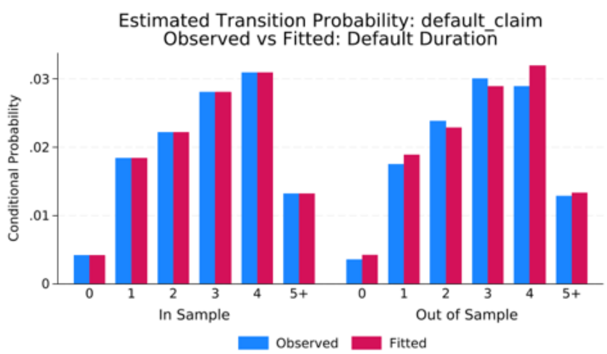
Product 5 - default_claim

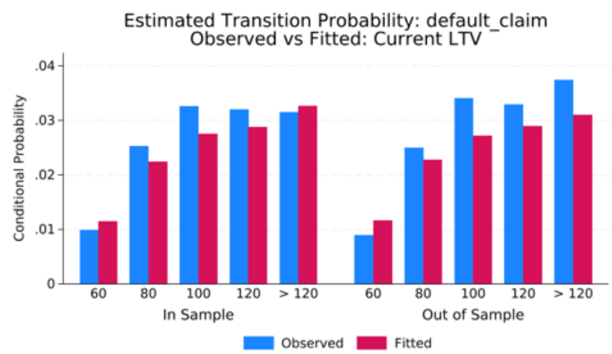


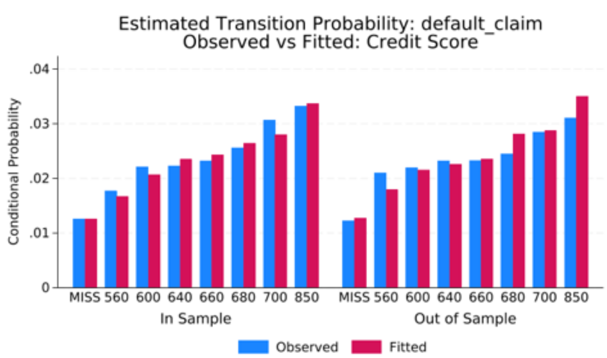


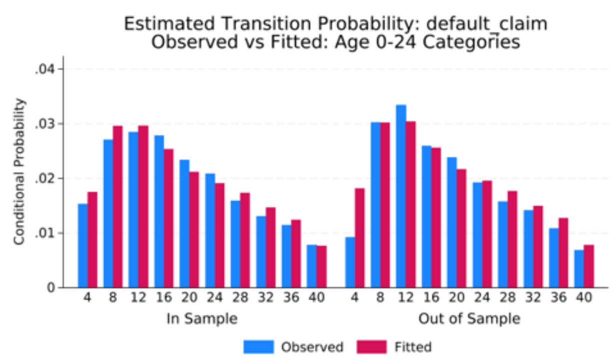




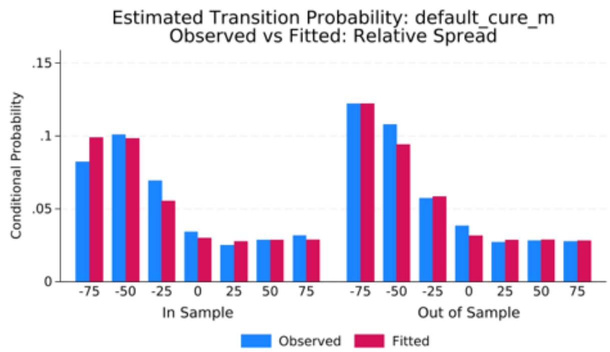


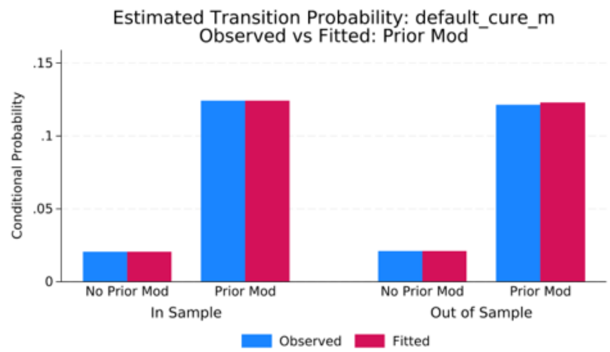


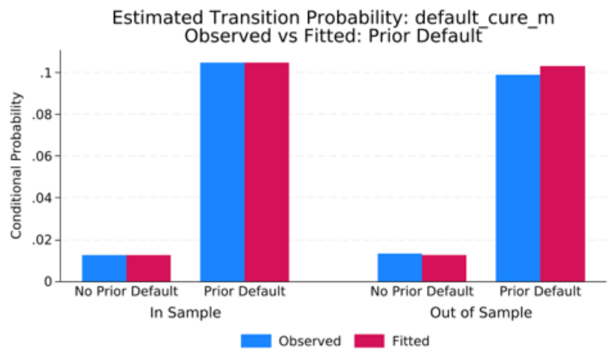


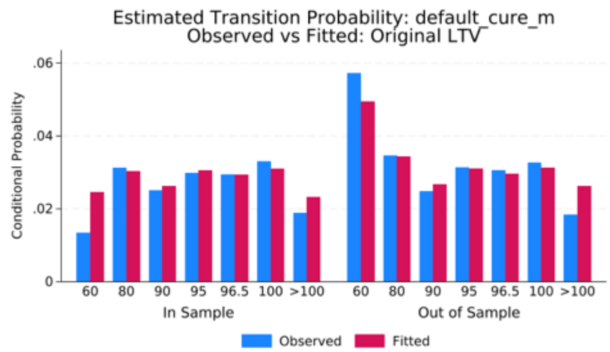


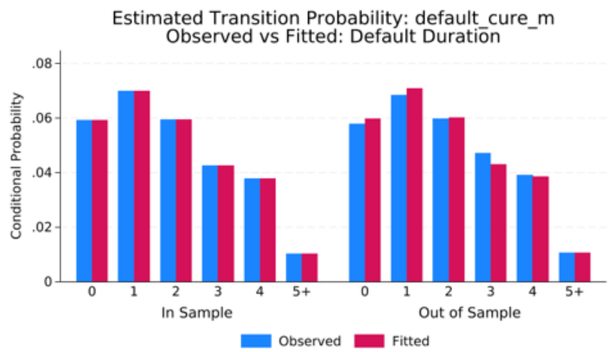
Product 5 - default_cure_m

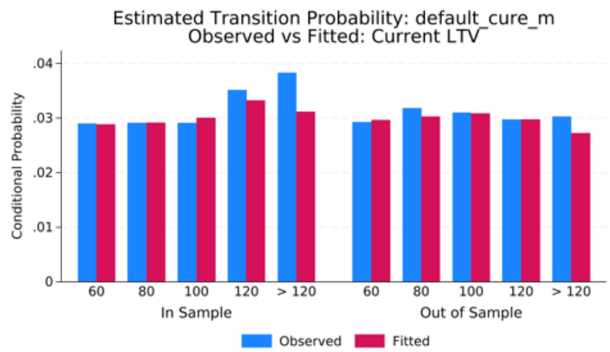


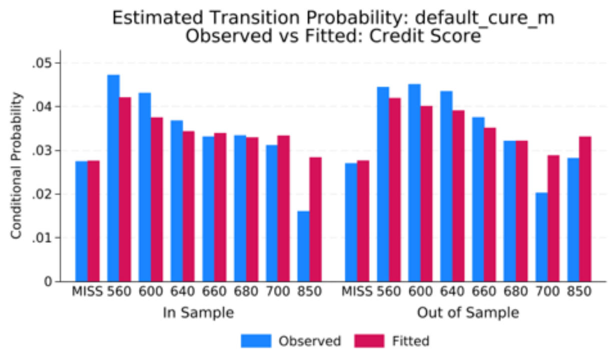


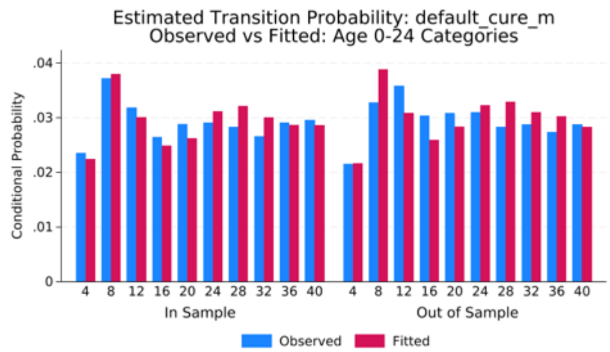




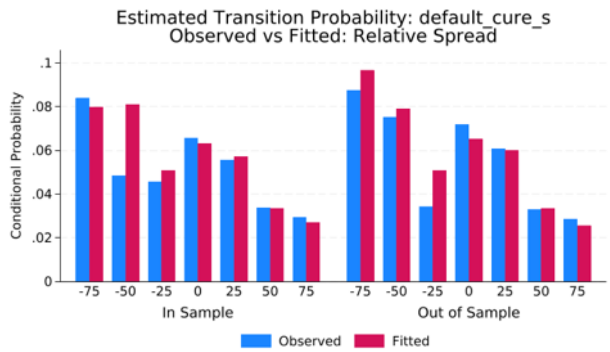


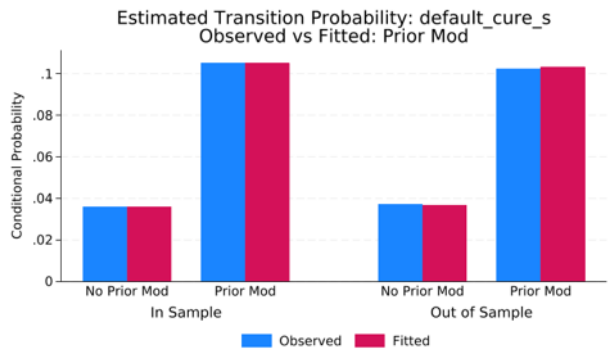


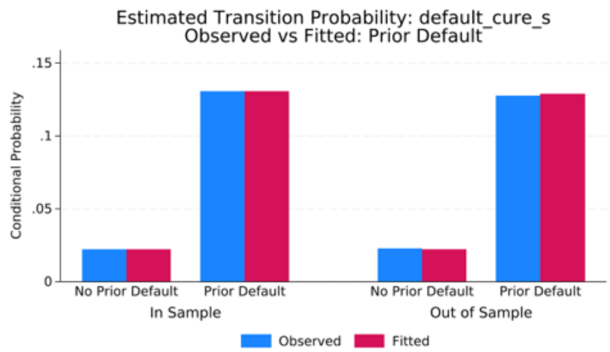


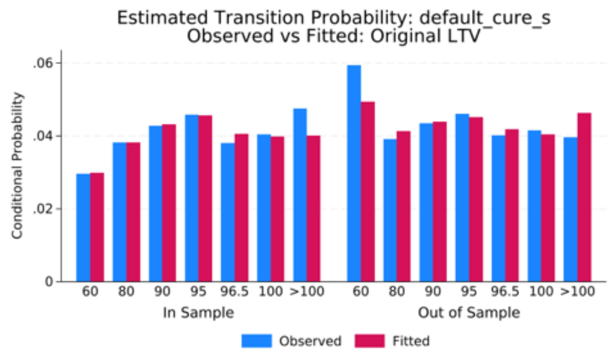


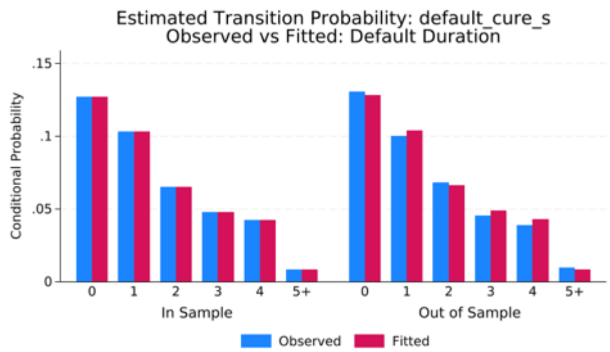
Product 5 - default_cure_s

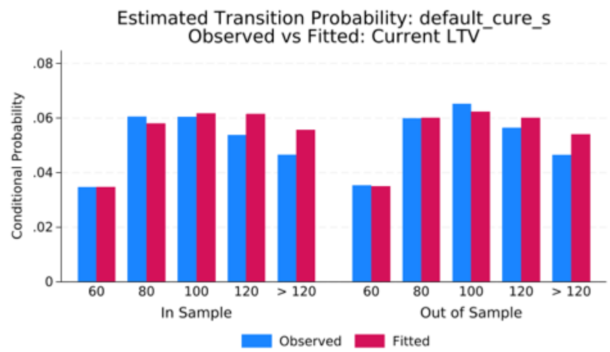


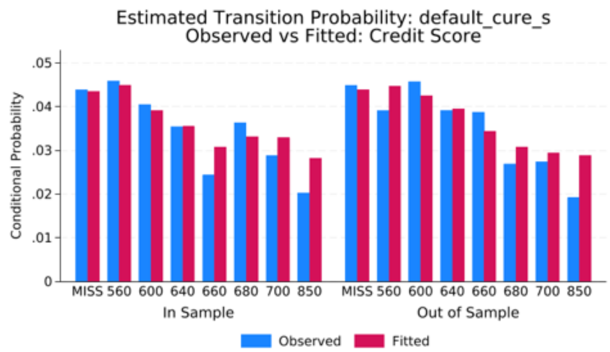


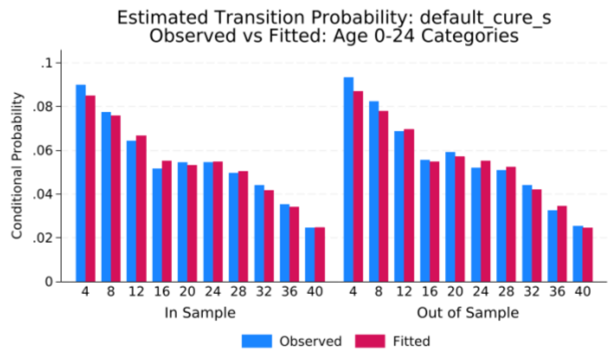




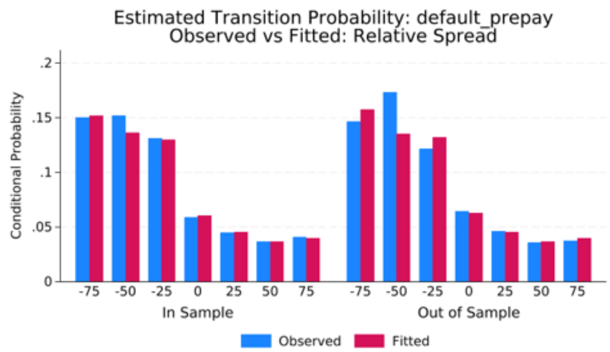


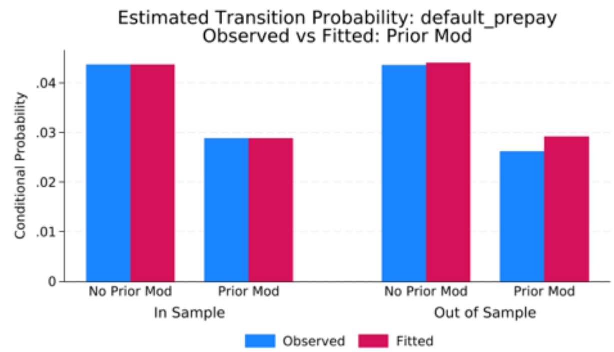


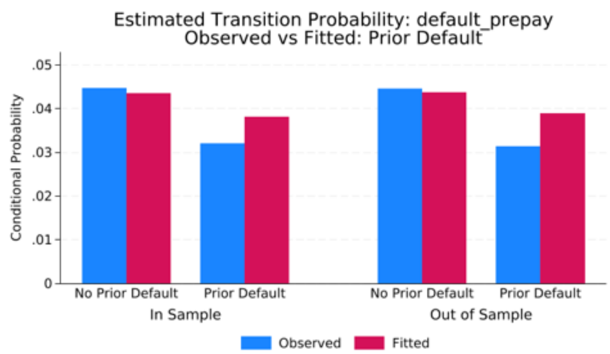


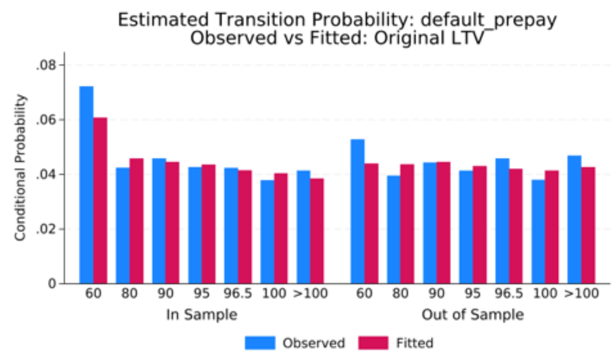


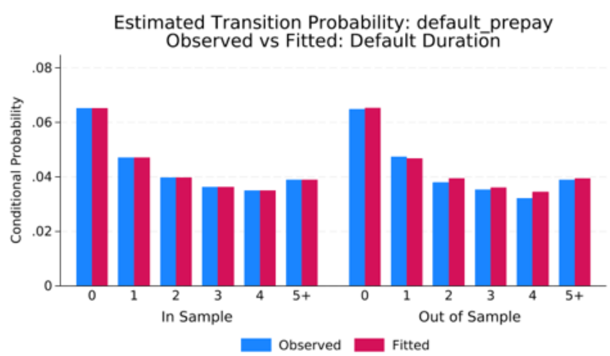
Product 5 - default_prepay

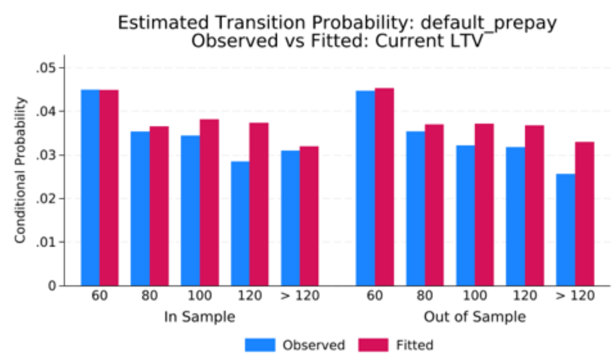


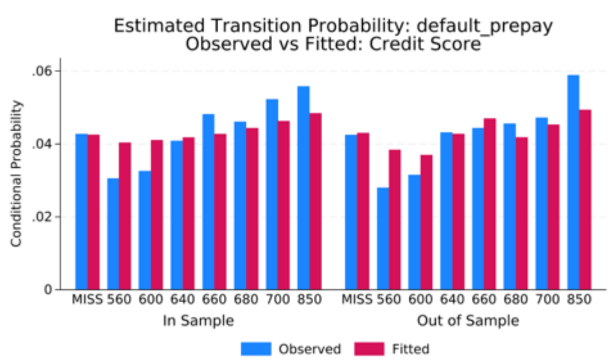


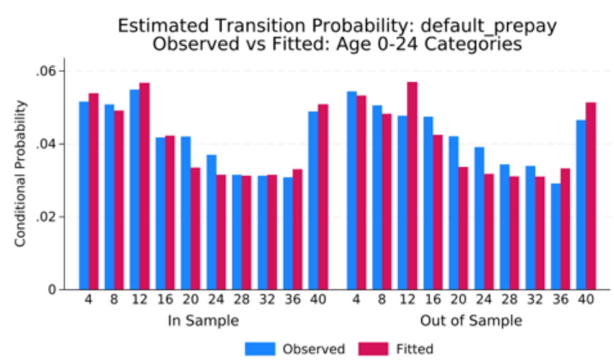






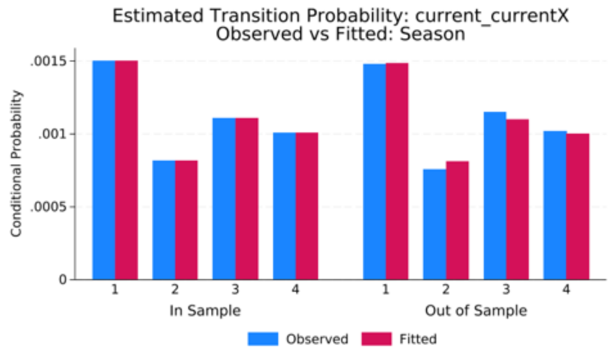


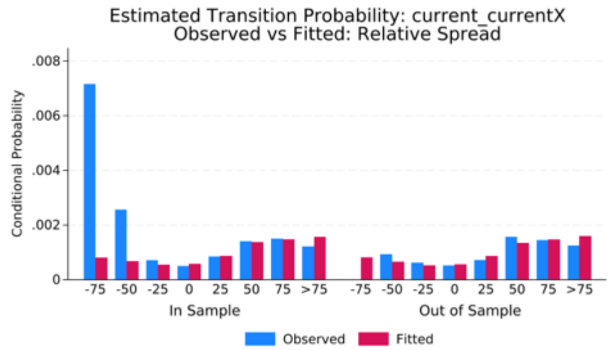


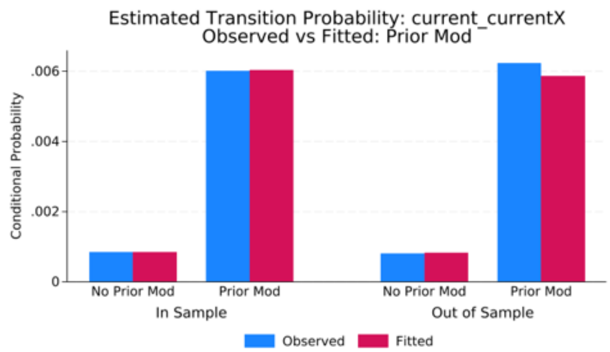


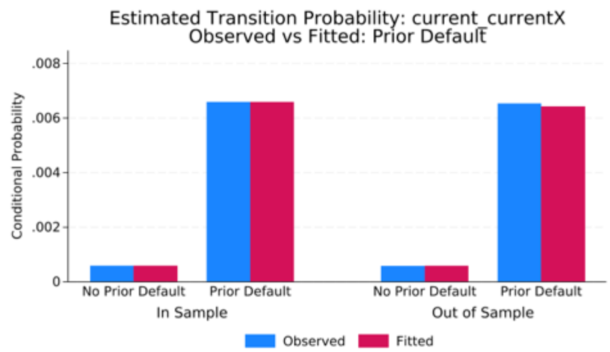
B6. Product 6

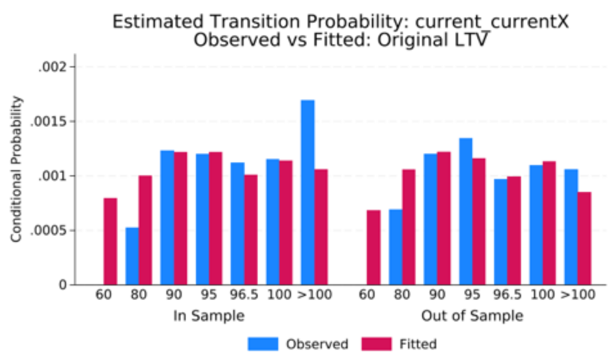
Product 6 - current_currentX

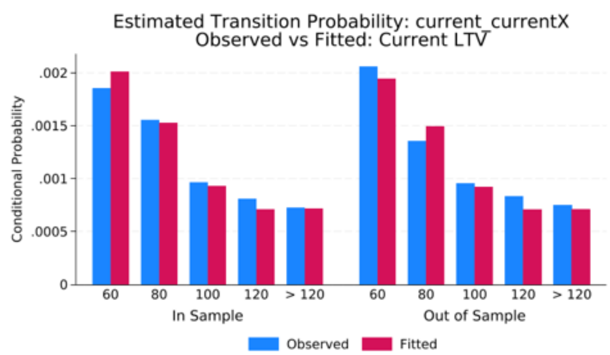


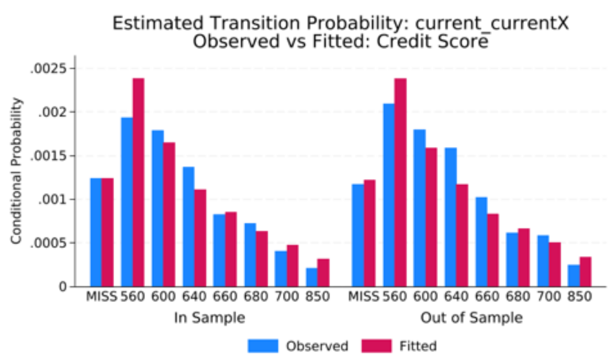


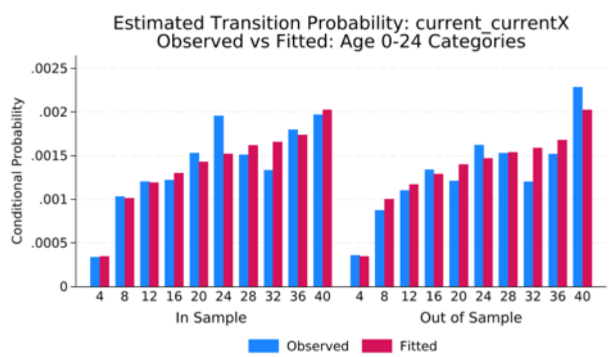




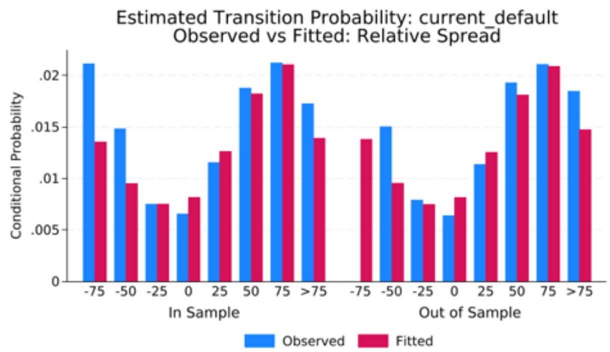


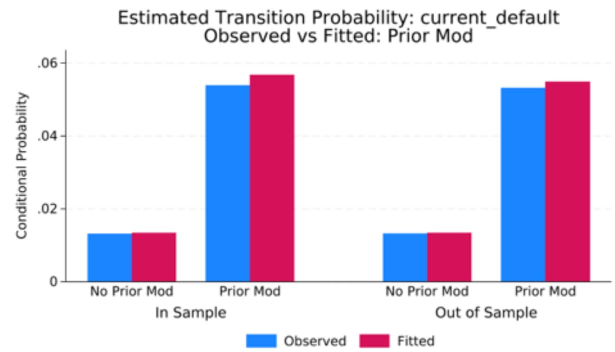


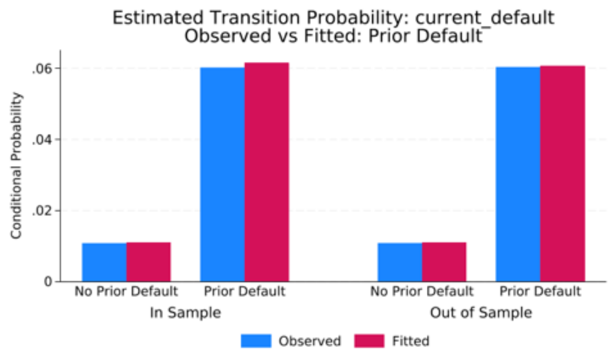


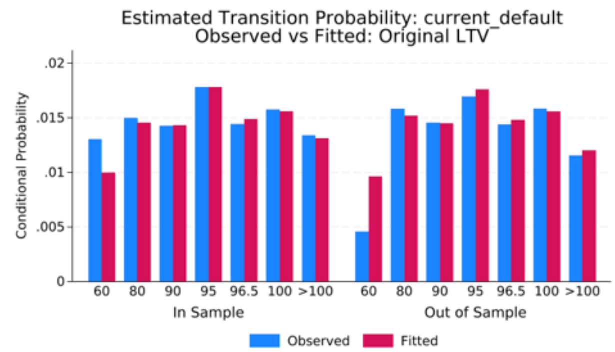


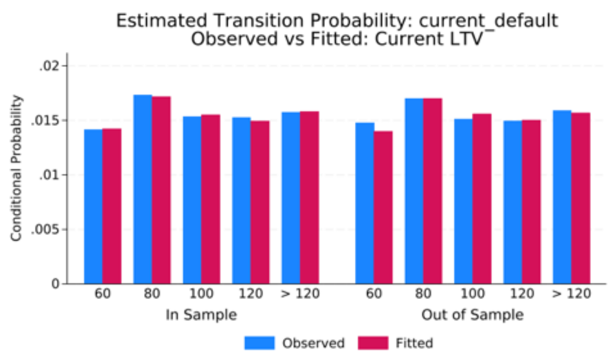
Product 6 - current_default

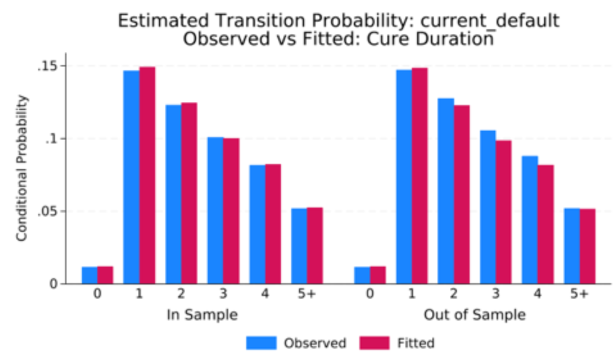


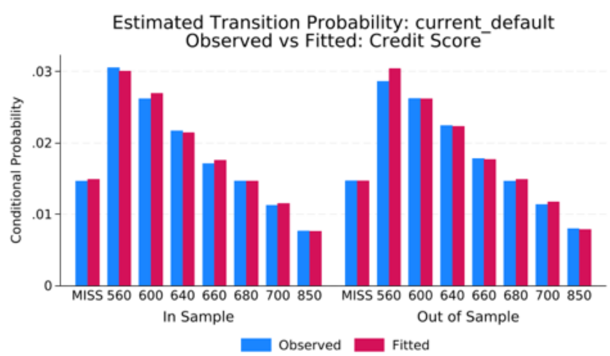


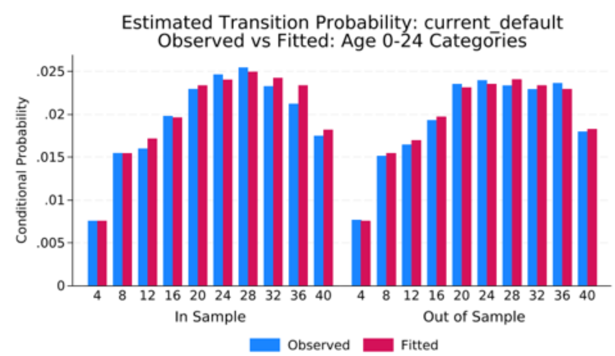




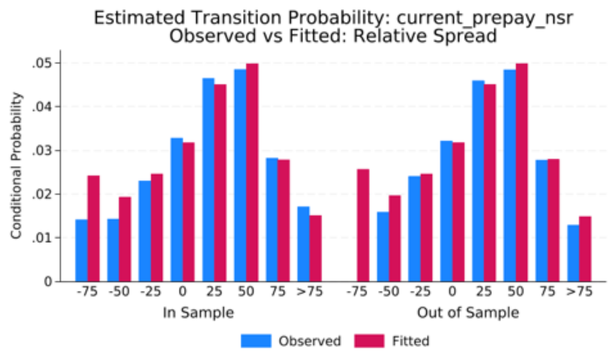


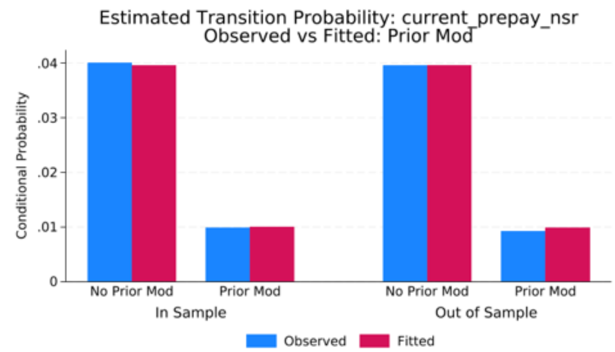


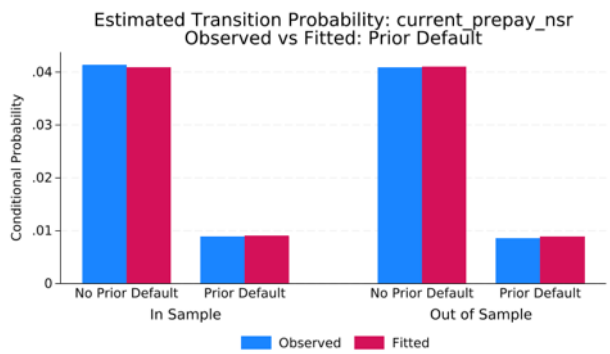


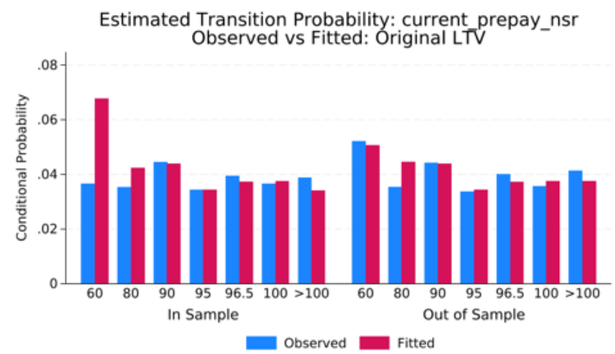


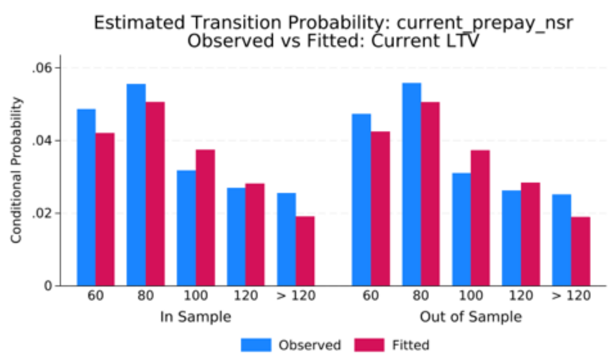
Product 6 - current_prepay_nsr

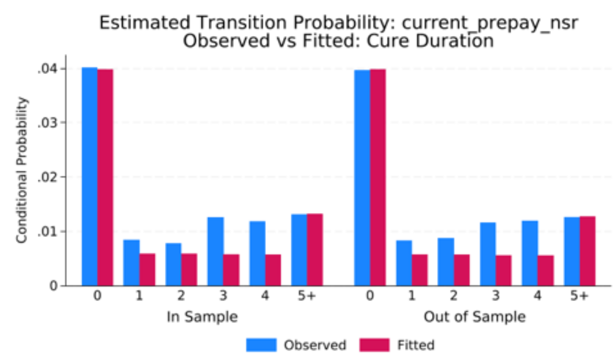


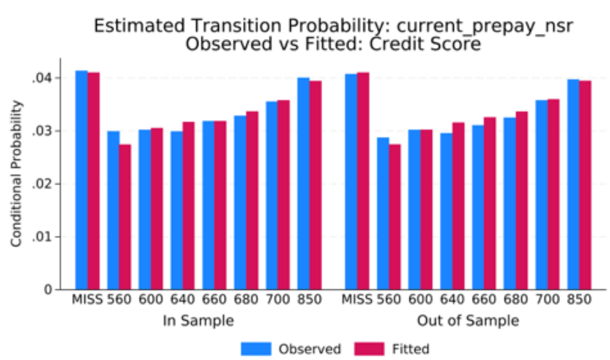


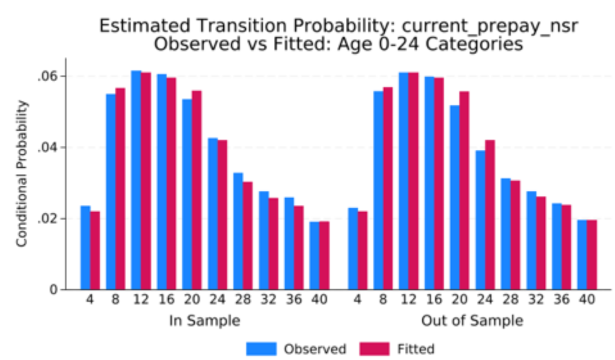




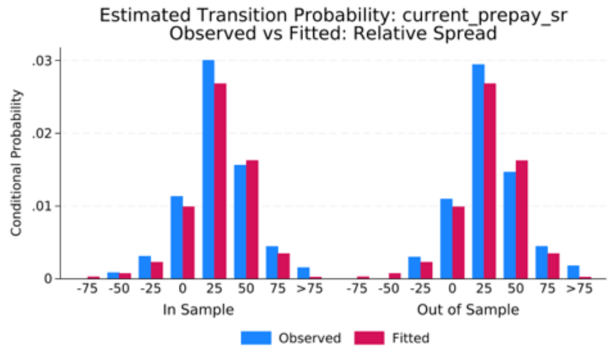


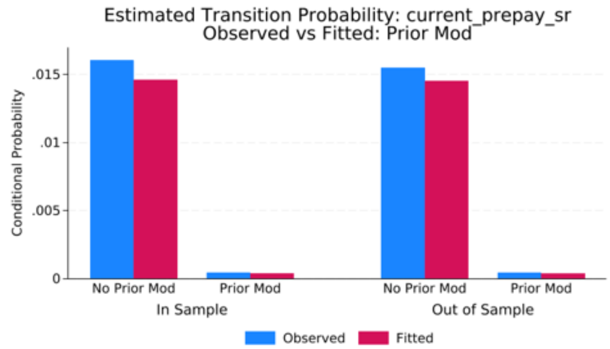


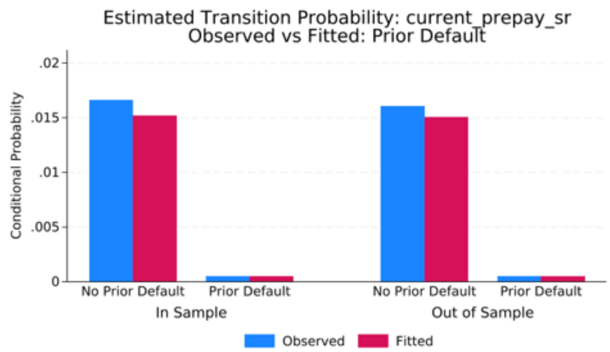


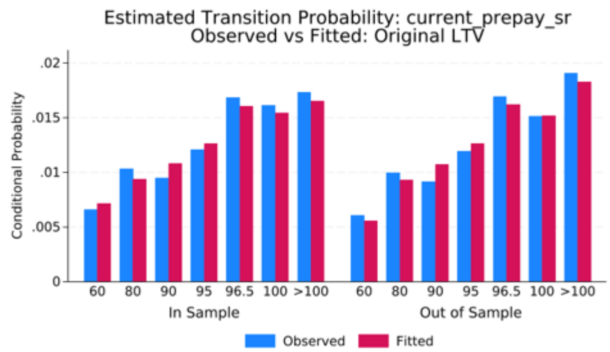


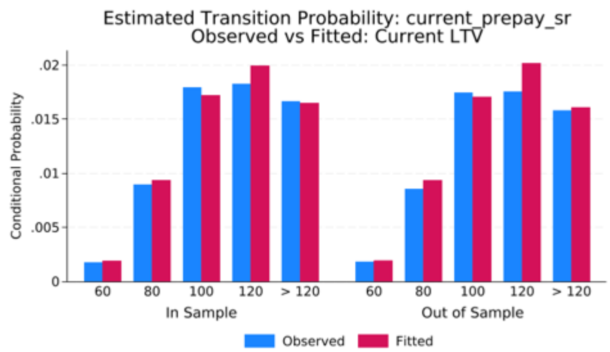
Product 6 - current_prepay_sr

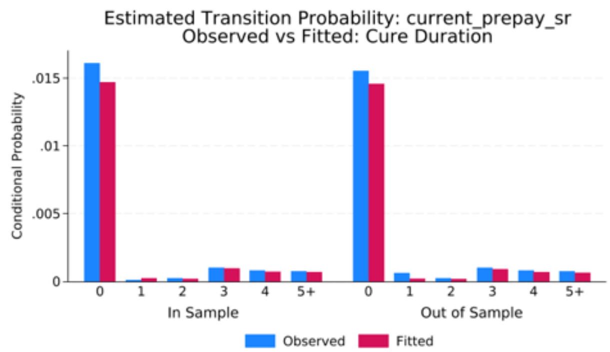


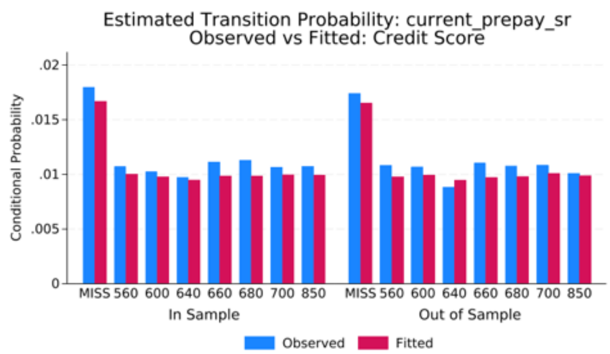


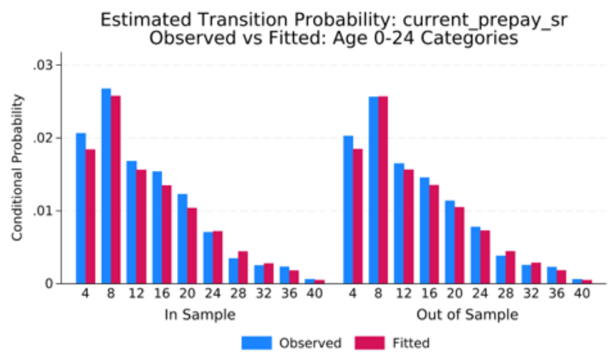




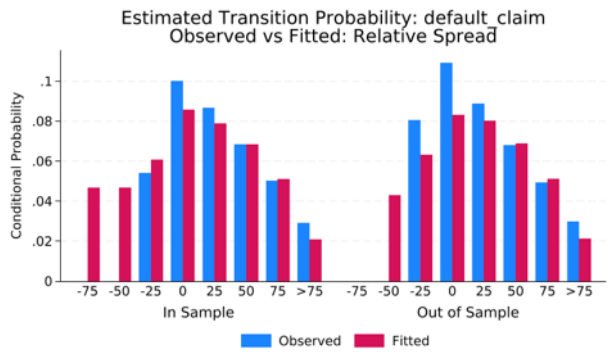


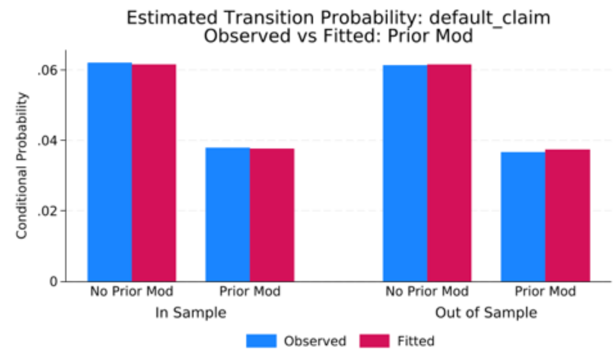


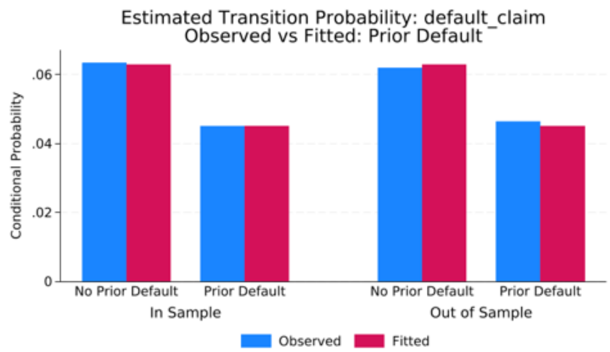


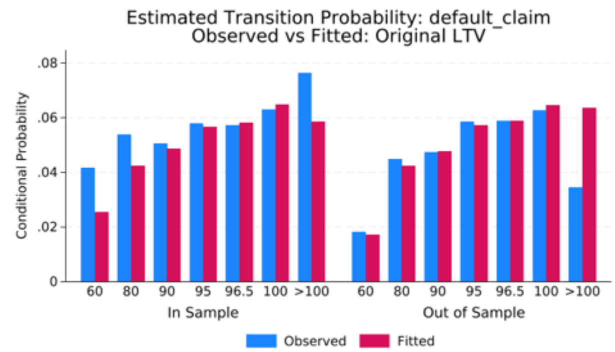


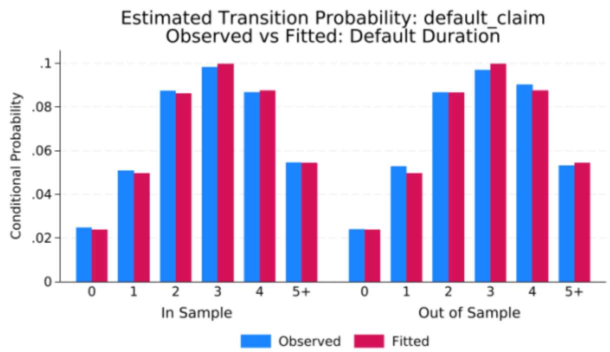
Product 6 - default_claim

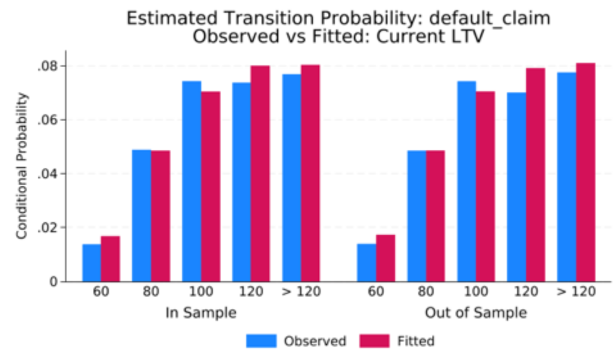


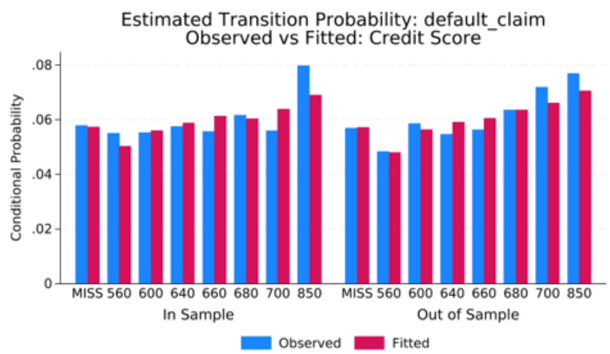


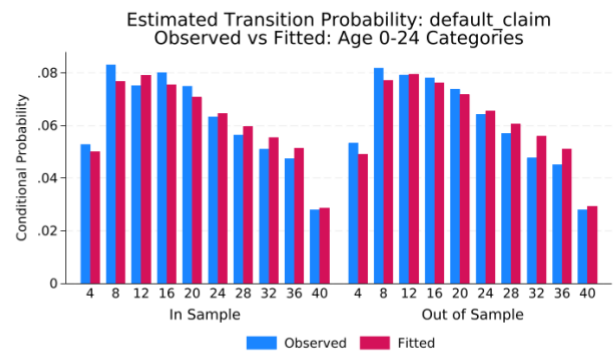




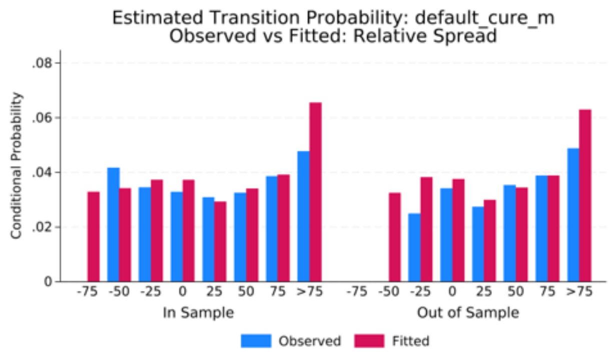


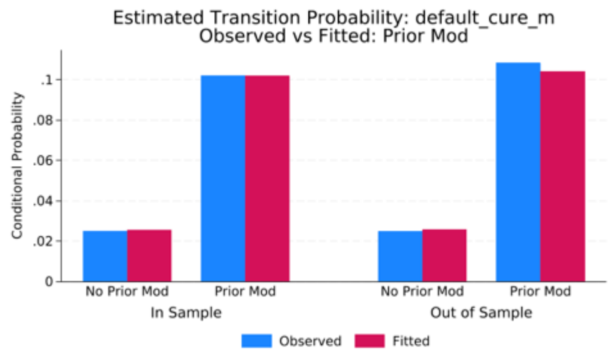


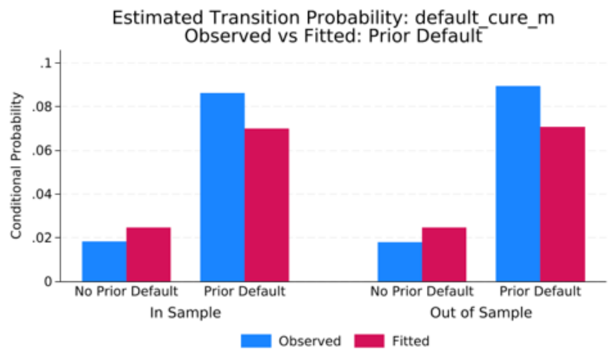


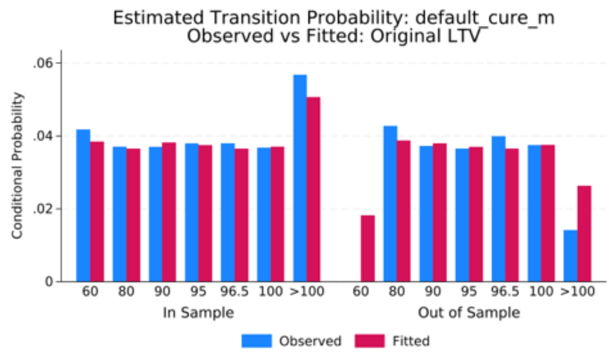


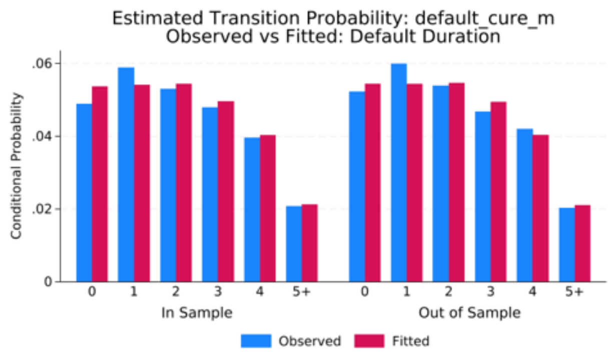
Product 6 - default_cure_m

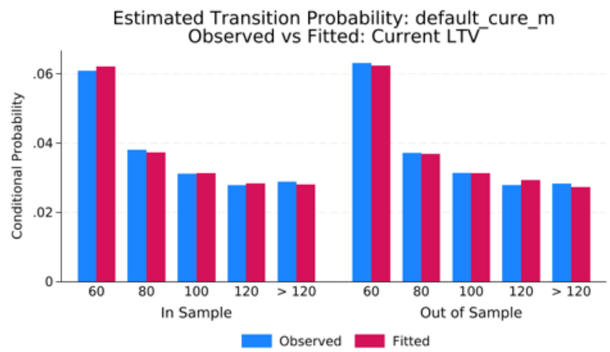


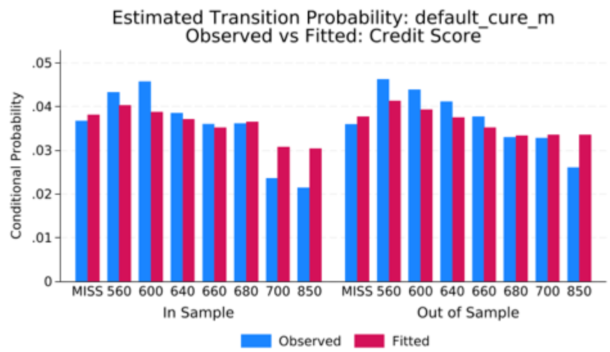


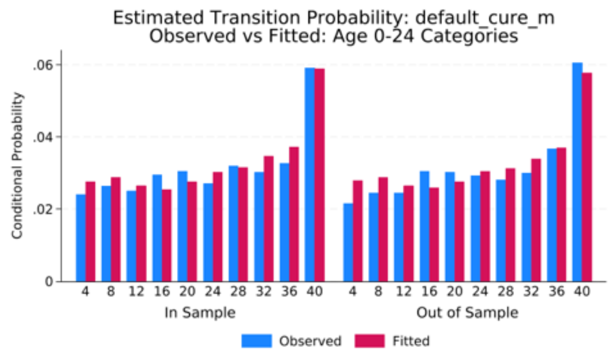




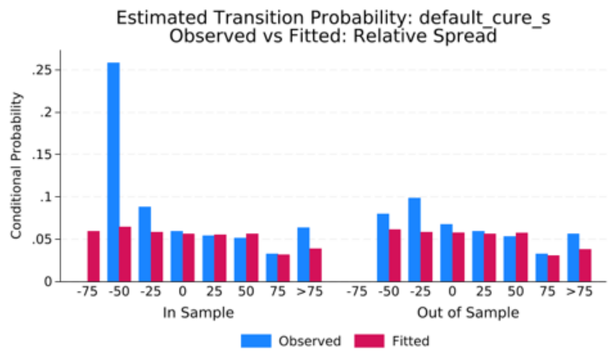


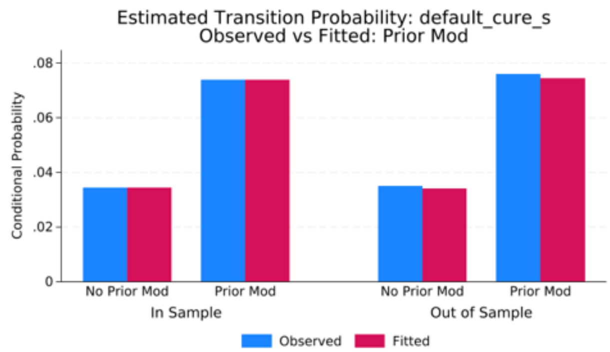


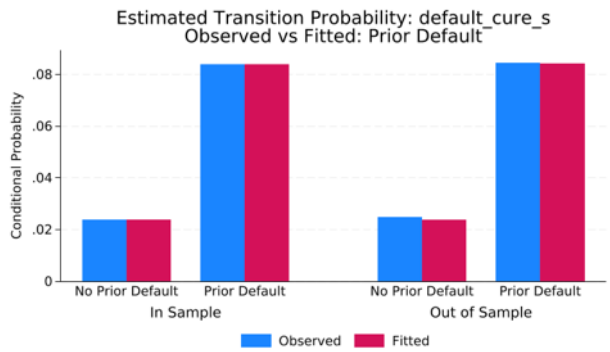


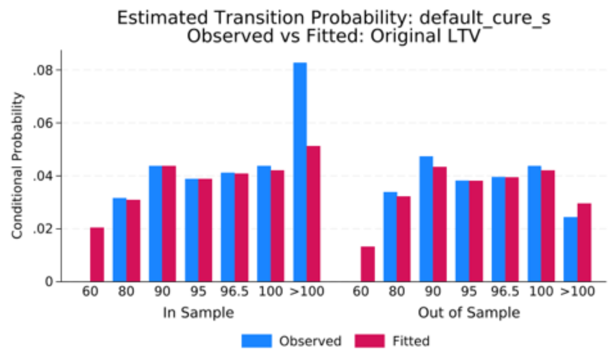


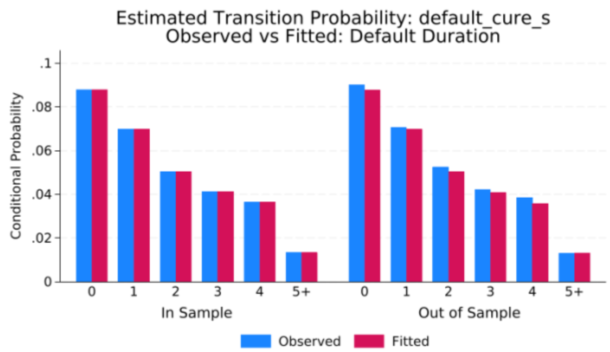
Product 6 - default_cure_s

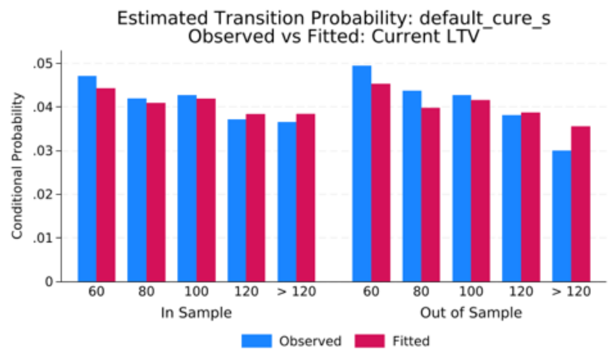


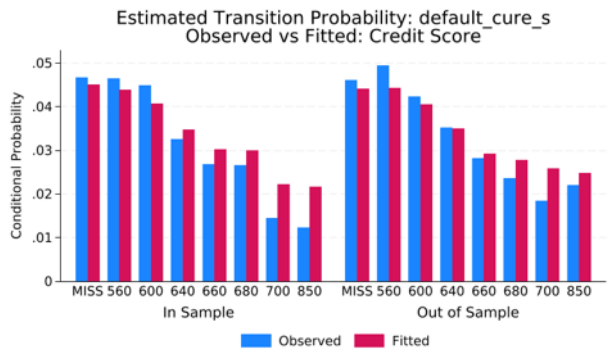


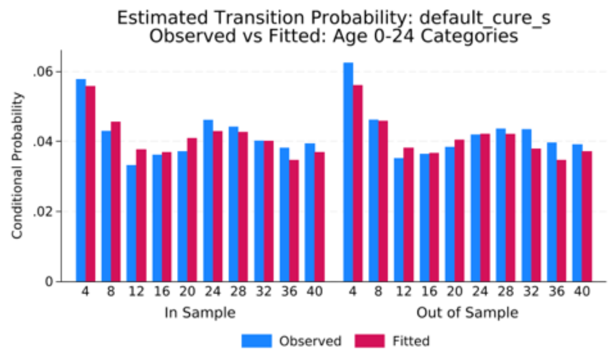




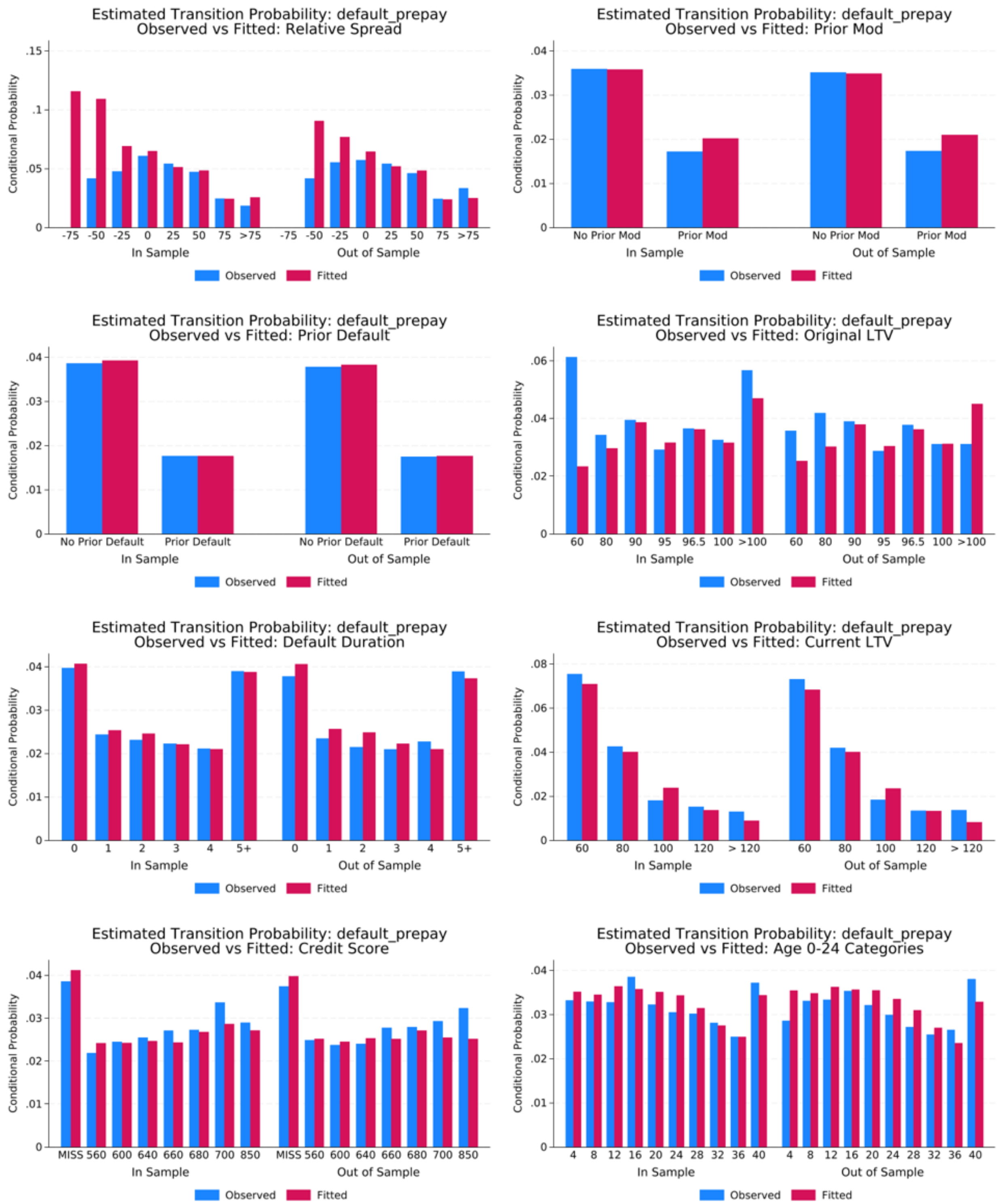








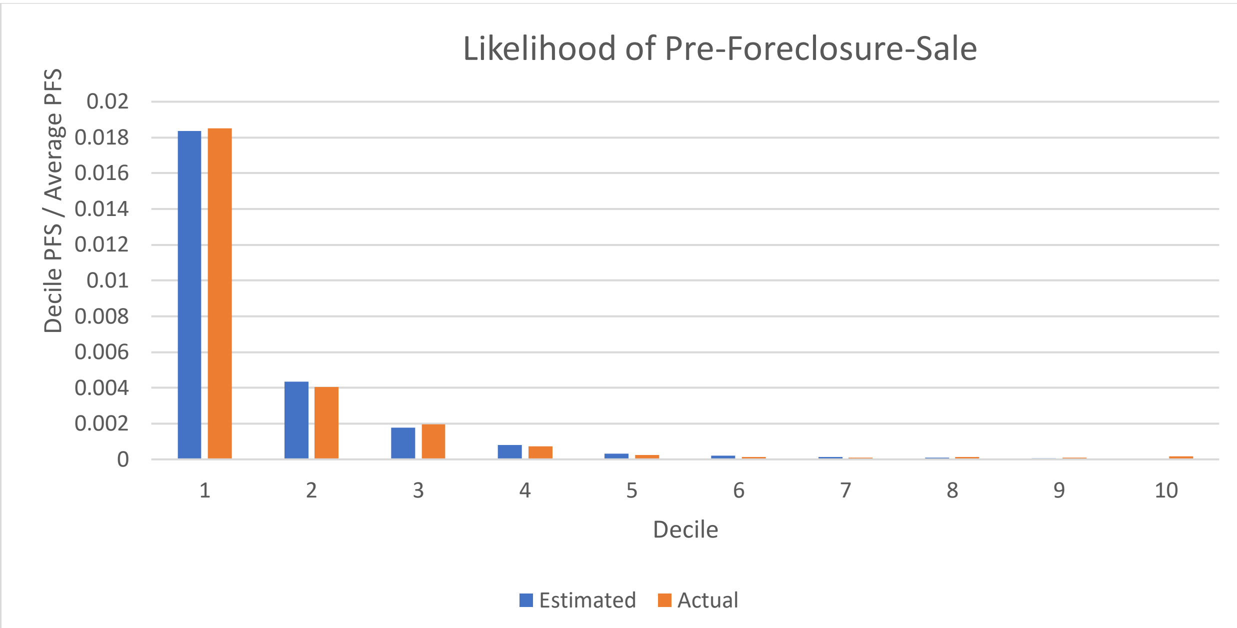
Product 6 - default_prepay



B7. Loss Models

B7.1 Pre-Foreclosure Sale (PFS) Selection Model

A decile chart is created for the Pre-Foreclosure Sale (PFS) selection model using a validation dataset. All records are sorted, or ranked, by the predicted PFS disposition probabilities. Ten equal sized decile groups are created with 10% of the records in each group. The actual result and the predicted result within each decile are calculated for comparison. Based on the validation result below, we confirm that the model outputs reasonably mimic the PFS disposition split in the data.



B7.2 Loss Rate Models

The following two graphs (Loss Rate Given Conveyance Model and Loss Rate Given Pre-Foreclosure Sale) represent the average squared error of the loss rate models based on a progression of adding variables and re-estimating the model. The two-graph series represent a training and validation data set that indicate similar error rates occurring throughout the progression. The training data set represents 80% of available data, and conversely, the validation data set represents the remaining 20%. Additionally, these graphs illustrate that the overall error rate declines monotonically as additional variables are utilized in model estimation for both the training and validation datasets.

Exhibit B.7.2.1 Loss Rate Given Conveyance (REO) Model

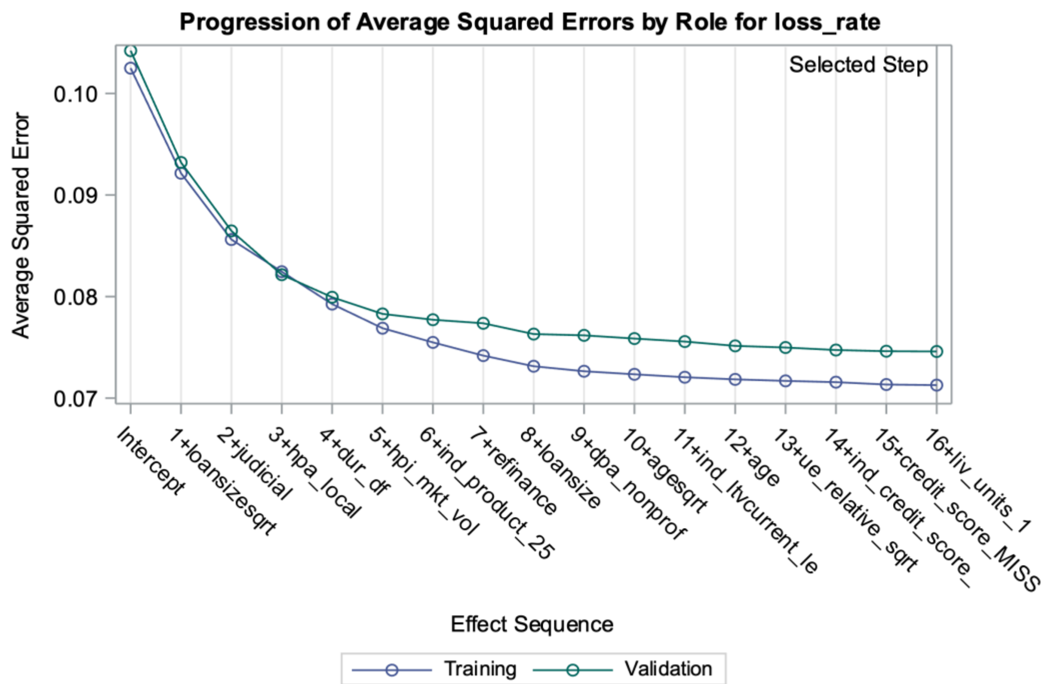
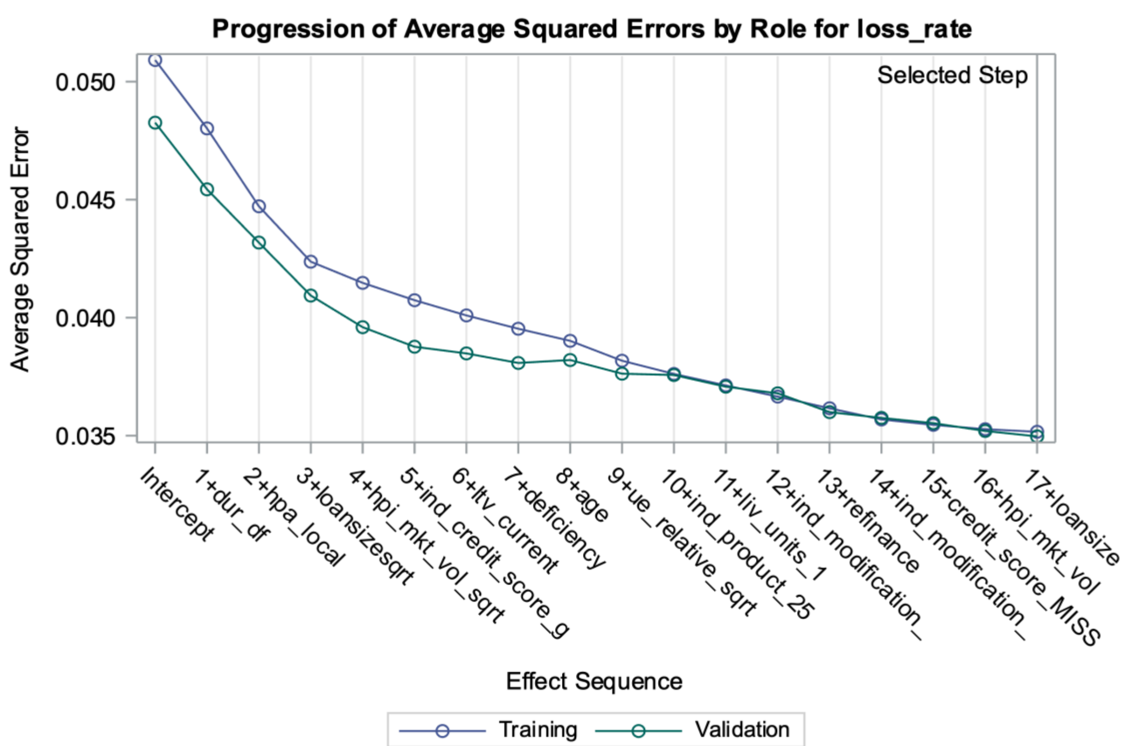


Exhibit B.7.2.2 Loss Rate Given Pre-Foreclosure Sale (PFS) Model



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Appendix C: Estimation, Forecasting, and Actuarial Projections

C1. Estimation

C1.1. Loan Status Transitions Modeled

Econometric models are estimated for the following transitions:

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

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

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

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

We also distinguish two types of prepayment events from current status: prepayments via SR (streamline refinance), and other non-SR prepayments. While the occurrence of these events has similar cash flow implications for the current portfolio (termination of insurance premiums and elimination of future risk of claim), they respond differently to economic factors and vary in their timing, warranting treatment as separate competing risks. We note that prepayments via SR from default status are prohibited under HUD regulations for SR originations.

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

Appendix H and Exhibits H-1 to H-6 present the 48 binomial logit models that were estimated to obtain the parameters needed to compute the multinomial logit probabilities for the competing-risk status-transition probability models.

C2. Forecasting

Once the logit probability models have been estimated on historical data, the forecast programs rebuild the data used in estimation and extend the data into the future periods for each loan, generating new values of the explanatory variables based on the forecasted values of the same economic factors used in estimation (FHFA house price indices, BLS household unemployment rates, FHLMC mortgage rates, Census median home prices, Treasury rates, and yields). The historical series is obtained from Moody's' Economy.com. The baseline scenario utilized is the FY 2025 Mid-Session Review of the President's Economic Assumptions (PEA). We also apply four alternative scenarios based on stochastic simulation models to illustrate the sensitivity of the model to other possible outcomes. The stochastic model development is described in Appendix F.

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

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

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

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

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

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

In practice this is achieved by the following steps:

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

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

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

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

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

C4. Actuarial Projections

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

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

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

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

C4.2. Survivorship Probabilities

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

pr_cur_def_N	no duration dependence, no prior default, no prior mod
pr_cur0_def_S	duration cure 0, prior default, no prior mod
pr_cur0_def_M	duration cure 0, prior default, prior mod
pr_cur1_def_S	duration cure 1, prior default, no prior mod
pr_cur1_def_M	duration cure 1, prior default, prior mod

¦

pr_curC_def_S	duration cure C, prior default, no prior mod
pr_curC_def_M	duration cure C, prior default, prior mod

current-to-prepay (non-SR)

pr_cur_pre_nsr_N

pr_cur0_ pre_nsr_S

pr_cur0_ pre_nsr _M

pr_cur1_ pre_nsr_S

pr_cur1_ pre_nsr_M

¦

pr_curC_ pre_nsr_S

pr_curC_ pre_nsr_M

current-to-prepay (SR)

pr_cur_pre_sr_N

pr_cur0_ pre_sr_S

pr_cur0_ pre_sr _M

pr_cur1_ pre_sr_S

pr_cur1_ pre_sr_M

¦

pr_curC_ pre_sr_S

pr_curC_ pre_sr_M

current-to-currentX

pr_cur_curX_N

pr_cur0_curX_S

pr_cur0_curX_M

pr_cur1 curX_S

pr_cur1_curX_M

⋮

pr_curC_curX_S

pr_curC_curX_M

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

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

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

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

pr_defD_cur_m_M duration default D, prior default and prior modification, mod-cure

<u>default-to-prepay</u>

pr_def0_pre_N

pr_def0_pre_S

pr_def0_pre_M

pr_def1_pre_N

pr_def1_pre_S

pr_def1_pre _M

⋮

pr_defD_pre_N

pr_defD_pre_S

pr_defD_pre_M

<u>default-to-claim</u>

pr_def0_clm_N

pr_def0_clm_S

pr_def0_clm_M

pr_def1_clm_N

pr_def1_clm_S

pr_def1_clm_M

⋮

pr_defD_clm_N

pr_defD_pre_S

pr_defD_pre_M

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

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

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

We expand the categories of loans to be projected to include initial status, duration, prior default, and mod history according to the same mnemonics used above for the probabilities. For example, default3_S would measure total loans in a current default episode of duration 3 that have a prior default that self-cured and would be multiplied by probability pr_def3_def_S to obtain default4_S, the corresponding total for duration 4. Of course, the updating is proportional based on the probability and some of the loans in default3_S would proceed to current status (with probability pr_def3_cure_s_S for self-cure and probability pr_def3_cur_m_S for mod-cure), to claim (with probability pr_def3_clm_S), or to prepay (with probability pr_def3_pre_S). For loans transitioning back to status, the loan categories to be incremented are current0_S or current0_M, for self-cure or mod-cure, respectively.

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

current0 – current status never defaulted

current0_S to current5_S – current status with prior default and self-cure by duration of cure

current0_M to current5_M – current status with prior default and mod-cure by duration of default

default0 – default status with no prior self-cure or mod-cure

default0_S to default5_S – default status with prior default and self-cure by duration of default

default0_M to default5_M – default status with prior default and mod-cure by duration of default

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

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

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

Appendix D: Loss Severity and Cash Flow Analysis

D1. Introduction

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

The evaluation of the Fund's economic net worth at a point in time (e.g. FY 2024) requires the addition of the value of net assets and the expected present value of future cash flows. The latter comprises future revenue and expenses. The actuarial model uses projections from econometric models as discussed in Appendices A-E.

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

We estimated an econometric model of loss severity rates (Appendix D). The loss rate model distinguishes between pre-foreclosure sales, conveyance, and third-party sales. We estimated future FHA mortgage volumes for purchase, refinance, and streamlining refinance mortgages that vary with alternative house prices, unemployment rates, and interest rate paths. Based on the mortgage termination rates projected by the econometric models, individual components of cash flows are projected into the future. These cash flows are discounted to the present time based on the MMI Single Effective Rate discount factors provided by FHA. The relevant cash flow components are itemized in Exhibit D-1.

Exhibit D-1. Cash Flow Components

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

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

D2. Background Information

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

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

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

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

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

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

Unpaid Principal Balance (UPB) Factor: the principal balance outstanding at a given time divided by the original mortgage amount. The UPB factor is calculated based only on amortization, given the original 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 loan, which is updated according to the contractual rate adjustment rule. In our model, the contract interest rates of ARM loans are updated by using changes in the 1-year Treasury rate as an approximation for changes in the underlying index, subject to limits implied by FHA annual and lifetime rate adjustment caps.

D3. Cash Flow Components

D3.1. Premiums

D3.1.1. Premium Structure

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

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

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

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

- On October 1, 1992, the upfront premium for 30-year mortgages was reduced from 3.80 percent to 3.00 percent. The annual premium for 30-year mortgages was extended for a longer time, while for 15-year mortgages it was lowered to 0.25 percent for a shorter time or completely waived if the initial LTV ratio was less than 90 percent.
- As of April 17, 1994, FHA lowered the upfront premium rate on 30-year mortgages from 3.00 percent to 2.25 percent. To align this change with fiscal quarters, we started applying this policy change on April 1, 1994.
- Starting from October 1, 1996, FHA lowered the upfront premium rate on 30-year mortgages for first-time homebuyers who receive homeowner counseling from 2.25 percent to 2.00 percent. This rate was further reduced to 1.75 percent for mortgages executed on or after September 22, 1997. This favorable treatment for borrowers with homeownership counseling was terminated shortly thereafter.
- Effective January 1, 2001, FHA lowered the upfront premium rate for all mortgages to 1.50 percent. The annual premium would stop as soon as the current LTV ratio of the loan was below 78 percent according to the home price as of the loan origination date. The annual premium was required to be paid for a minimum of five years for 30-year mortgages.
- Effective October 1, 2008, FHA charged an upfront premium rate of 1.75 percent for purchase money mortgages and full-credit qualifying refinances; and 1.50 percent for all types of streamline refinance loans. A varying annual premium, remitted monthly, was charged based on the initial loan-to-value ratio and maturity of the mortgage.
- Effective April 1, 2010, FHA changed the upfront premium to 2.25 percent for all mortgages executed after April 1, 2010.

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

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

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

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

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

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

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

- Effective March 20, 2023, Mortgagee Letter 2023-05, an annual premium rate reduction of 30 basis points was issued for all mortgages except streamline refinance and simple refinance mortgages on previous FHA endorsed mortgages on or before May 31, 2009 along with Hawaiian Home Lands (HHL). The impact from this MIP reduction is forecasted to be a decrease of $4.4 billion in annual premium collection, resulting in a 16.4 percent reduction in the cash flow NPV.

- Effective January 1, 2024, the threshold for one-unit loans in high-cost areas was increased from $1,089,300 to $1,149,825 pursuant to Mortgage Letter 2023-01.

D3.1.2. Upfront Premium

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

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

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

D3.1.3. Annual Premium

The annual premium is calculated as follows:

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

The premium is collected monthly. The above formula models the premium as being collected at the beginning of each quarter for purposes of our analysis. In addition, the termination rate will have an impact on future premium flows. All potential future premium income would no longer be paid when a particular mortgage loan is prepaid or claimed. The annual premium is not assessed on the amount of the financed upfront premium.

D3.2. Losses Associated with Claims

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

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

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

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

$$ClaimLoss_t = UPB_t * LossRate_t$$

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

The loss rate is usually referred to as the loss-given default (LGD) or "severity" in the banking industry. It measures the amount of principal not recovered from property sale and expenses incurred in property acquisition, holding, and sales. This amount is divided by the unpaid principal balance at the time of claim. The portfolio-level loss rate is predicted as the weighted average loss rates among conveyance, pre-foreclosure sales, and the implemented policy of third-party sales, where the weights reflect the probability that a claim is associated with the individual types of claims. Note that since the beginning of FY2018, there have been no Single Family Forward note sales per the data provided by FHA and per the disclosure of note sales provided publicly by FHA's Office of Asset Sales. This disposition type currently is excluded from disposition modeling due to no historical activity since FY2018. However, this disposition type may be modeled in future studies based on potential future policy changes that trigger new Single Family Forward note sales. The loss rate formulation is as follows:

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

To model the probability of pre-foreclosure sale, a binary logistic regression model was deployed to estimate the likelihood that a property would undergo a pre-foreclosure sale transaction for loan claim *k* using explanatory variables defined in Appendix A.

$$P(PFS) = \frac{e^{(\beta_0+\beta_1 x_{1_k}+\cdots+\beta_n x_{n_k})}}{1+\ e^{(\beta_0+\beta_1 x_{1_k}+\cdots+\beta_n x_{n_k})}}$$

The probability of a third-party sale was calculated by first taking the average annual ratio from 2014 to 2024 of Third Party Sale (TPS) dispositions divided by the sum of Real Estate Owned (REO) and TPS dispositions. This average was calculated to be 69.48% and was subsequently multiplied by the difference of 1 minus the probability of a pre-foreclosure sale.

$$P(TPS) = (1 - (P(PFS)\ ) \times (TPS\ Annualized\ Ratio)$$

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

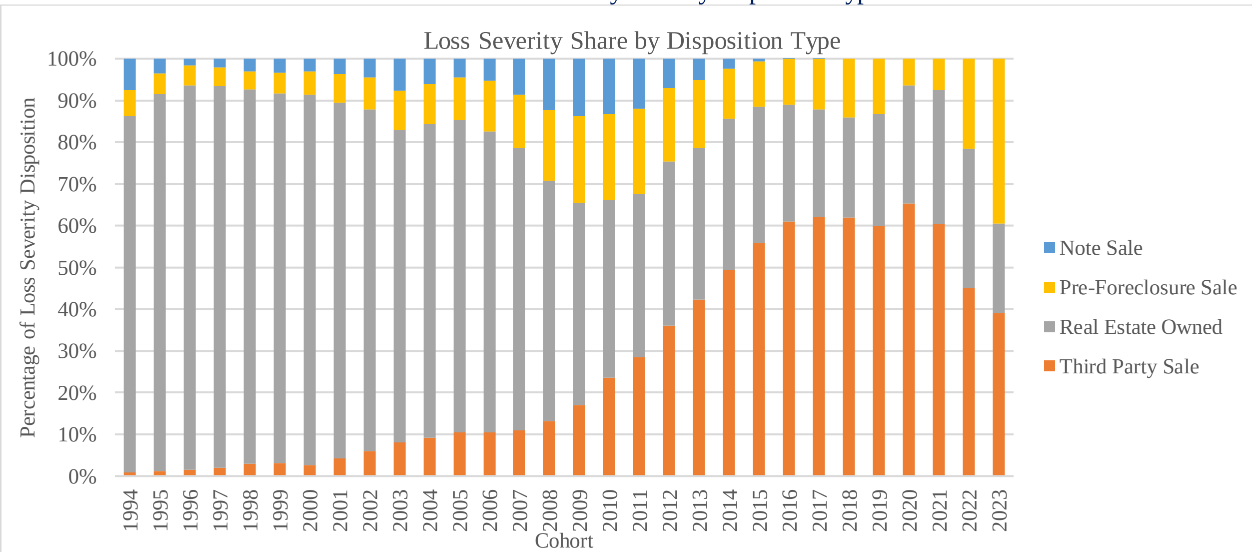
$$P(REO) = (1 - (P(PFS)\ ) - (P(TPS))$$

Following the estimation of the disposition probabilities, we calculate the loss rates of each of the dispositions. Generalized least-squares regression was deployed to estimate the PFS and REO loss rate dispositions with the explanatory variables described in Appendix A and historical loss rate data from the SFDW as the independent variable. The TPS loss rate was calculated by taking a historical proportion of the REO loss rate.

$$LossRate_{TPS} = (LossRate_{REO} \times (1 - TPS\ reduction))$$

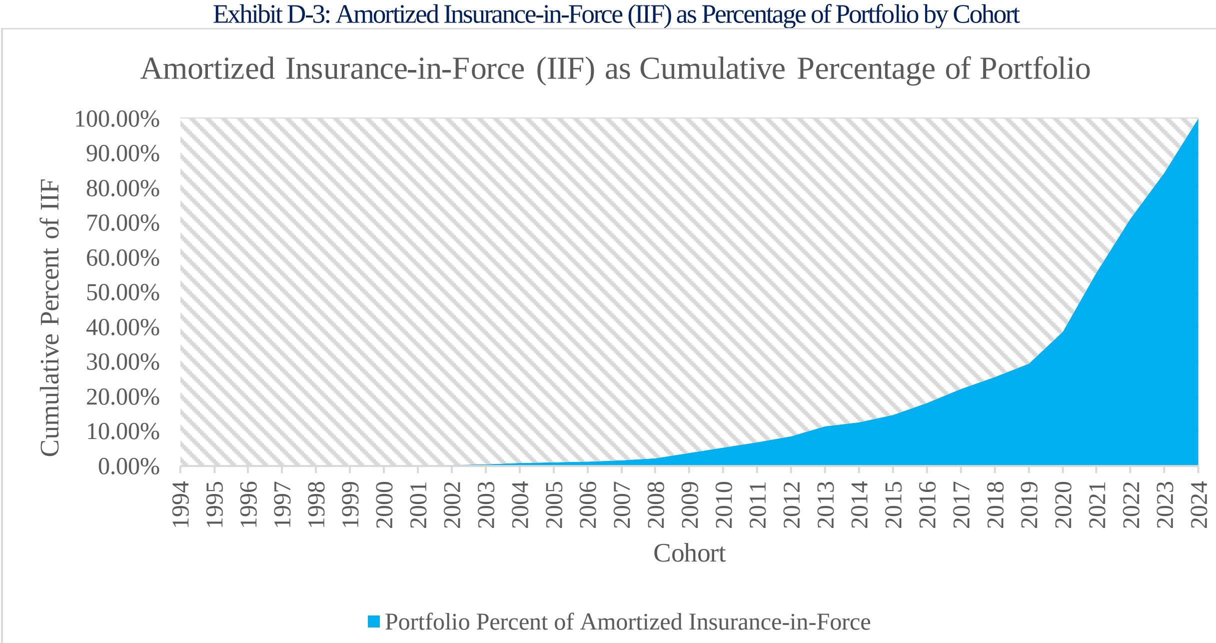
The computed average loss rates across 2009 to 2024 were 39.8% for TPS and 51.4% for REO. This difference translates into a 29.29% reduction in the REO loss rate to get a resulting TPS loss rate. The historical temporal period was adjusted for the historical loan composition to be more comparable with the current loan population as displayed in Exhibit D-2, Exhibit D-3, and Exhibit D-4.

Exhibit D-2: Loss Severity Share by Disposition Type



As illustrated in Exhibit D-2, loans in cohorts 2012 and earlier leaned more towards the Real Estate Owned (REO) property disposition. From 1994 through 2012, REO made up most of the HUD's recovery on claimed assets. However, since 2012, Third Party Sales (TPS) have overtaken REO as the most utilized disposition method. Examining this historical trend in loss severity dispositions, we determined that recent cohort disposition splits are more in line with the current state of claim recoveries. By shifting the temporal periods forward for both the disposition split along with the computed average loss rates, the model more accurately forecasts the loss severity and loss share of REO and TPS.

Exhibit D-3: Amortized Insurance-in-Force (IIF) as Percentage of Portfolio by Cohort



The historical frame of reference to compute the average loss rates was determined by the Historic Loss Severity Share by Cohort, Exhibit D-2, and Amortized Insurance-In-Force (IIF) of the active portfolio, Exhibit D-3. Cohorts 2009-2024 were selected to train the loss severity and loss rate models based on their (1) current composition as 96% of the IIF and (2) loss severity share trends beginning with Cohort 2009 that are more reflective of the recent trends of the active portfolio in comparison with prior Cohorts.

Exhibit D-4: Amortized Insurance-in-Force (IIF) as Percentage of Portfolio by Cohort

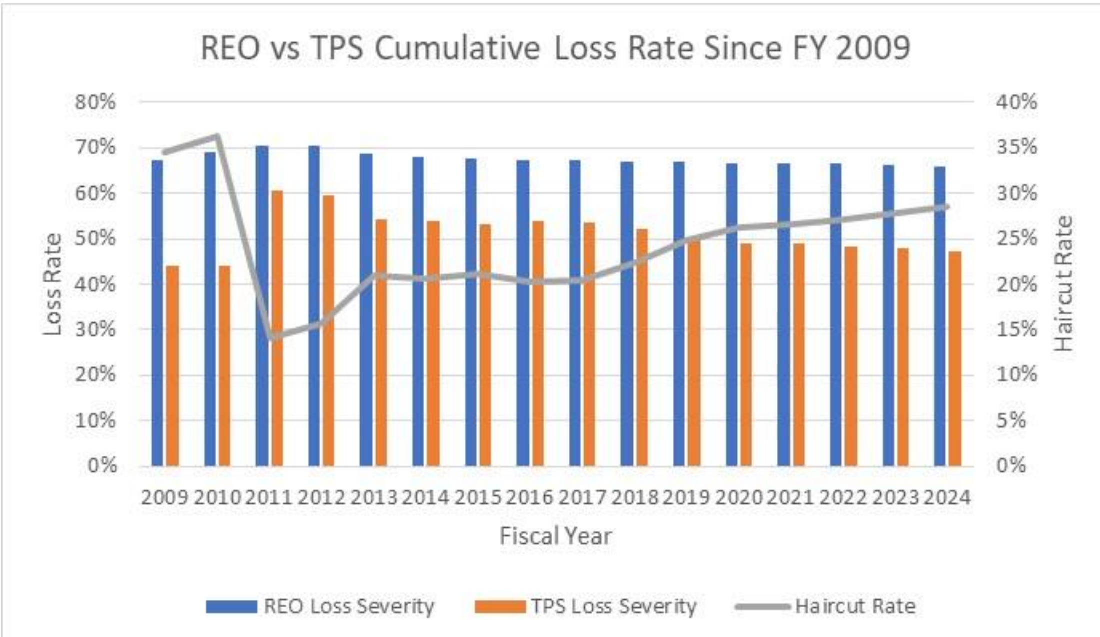


Exhibit D-4 illustrates the cumulative loss rates for REO and TPS since FY 2009. Throughout this temporal period the cumulative loss rate for TPS has been consistently lower than REO. The haircut rate (in grey) represents the percent reduction that is applied to the REO loss rate to calculate the TPS loss rate. The data for TPS is relatively sparse for fiscal years 2009 though 2012, with only a handful of data points during this period. Looking into FY 2013 and beyond, the data is much more plentiful and stable when comparing TPS with REO. Tracking the haircut rate across the cumulative loss rates from 2009 through 2024 results in the 29.29% assumption for the reduction in REO loss rate to calculate the TPS loss rate.

The estimation of the loss severity model utilized loan-level data from the FHA single-family data warehouse for conveyance, pre-foreclosure, and third-party sale claims from 2009 to 2024.

The final sample used for estimation included 152,412 loans claimed over the timeframe. The following tables include the model parameters for the 3 models, including the coefficients, Chi-square, and t-statistics confirming the sufficiency of the model specification.

Exhibit D-5: PFS Selection Model Parameters

Parameter Estimates			
Variable Name	Coefficient	WaldChiSq	ProbChiSq
Intercept	-9.1751	18949.02	<.0001
ind_ltvcurrent_le_100	-0.5489	1078.38	<.0001
ind_loansize_le_100	-0.8002	1224.65	<.0001
ind_loansize_100_160	-0.3418	235.09	<.0001
ind_modification_age_le_20	0.0548	5.27	0.0217
hpa_local	-8.7813	12014.01	<.0001
ind_loanage_le_20	4.6286	7839.74	<.0001
ind_loanage_20_32	3.3871	3636.33	<.0001
refinance	1.1357	3259.45	<.0001
ind_dur_df_le_5	1.1469	3798.68	<.0001
credit_score_MISSING	0.0732	3.77	0.0523
ind_credit_score_ge_620	-0.0776	15.42	<.0001
ind_product_25	-2.0641	3744.42	<.0001
judicial	-0.0466	8.54	0.0035
deficiency	0.102	22.01	<.0001
Model Fit Statistics			
Description			Value
Chi-Square Statistic			1008.967

The model and results from Exhibit D-5 are used to determine the probability of the Pre-Foreclosure Sale (PFS) disposition split. A positive coefficient indicates a tendency towards the PFS disposition whereas a negative coefficient indicates a tendency towards alternative disposition types. The shift in the coefficient signs when compared with the 2023 PFS parameter estimates reflect the adjusted temporal period adjustment made for the REO and TPS disposition calculations.

Exhibit D-6: Loss Rate Given Conveyance (REO) Model Parameters

Parameter Estimates			
Variable Name	Estimate	t Value	Pr > |t|
Intercept	0.8129	13.88	<.0001
ind_ltvcurrent_le_90	-0.0318	-6.66	<.0001
age	-0.0089	-8.86	<.0001
agesqrt	0.1109	11.64	<.0001
loansizesqrt	-0.1757	-23.81	<.0001
ind_modification_age_20_40	-0.0355	-2.48	0.013
dur_df	0.0222	18.06	<.0001
liv_units_1	-0.0645	-3.57	0.0004
hpa_local	-0.9519	-30.95	<.0001
hpi_mkt_vol	6.8156	21.09	<.0001
refinance	0.0784	17.31	<.0001
judicial	0.1474	34.75	<.0001
ind_credit_score_ge_580	-0.0518	-9.25	<.0001
credit_score_MISSING	-0.0697	-7.54	<.0001
ind_product_25	0.1053	17.65	<.0001
dpa_nonprof	0.0529	8.09	<.0001
loansize	0.0062	17.18	<.0001
ue_relative_sqrt	0.1176	5.7	<.0001
Model Fit Statistics			
Description			Value
R-Square			0.300891

Exhibit D-7: Loss Rate Given PFS Model Parameters

Parameter Estimates			
Variable Name	Estimate	t Value	Pr > |t|
Intercept	-6.2364	-6.12	<.0001
ltv_current	0.0006	10.18	<.0001
age	0.0074	15.57	<.0001
loansize	0.0021	4.75	<.0001
loansizesqrt	-0.0740	-7.27	<.0001
ue_relative	-0.2970	-3.36	0.0008
ue_relative_sqrt	0.8689	4.59	<.0001
hpa_local	-0.5312	-18.81	<.0001
hpi_mkt_vol	-79.8783	-5.8	<.0001
hpi_mkt_vol_sqrt	45.8219	6.11	<.0001
dur_df	0.0258	18.06	<.0001
liv_units_1	-0.1249	-9.51	<.0001
ind_credit_score_ge_620	-0.0394	-6.43	<.0001
credit_score_MISSING	0.0624	5.3	<.0001
refinance	0.0526	8.36	<.0001
deficiency	0.0525	7.15	<.0001
ind_modification_flag	-0.2499	-9.43	<.0001
ind_modification_age_le_20	0.1958	7.37	<.0001
ind_product_25	0.0912	7.93	<.0001
Model Fit Statistics			
Description			Value
R-Square			0.304999

D3.3. Loss Mitigation Expenses

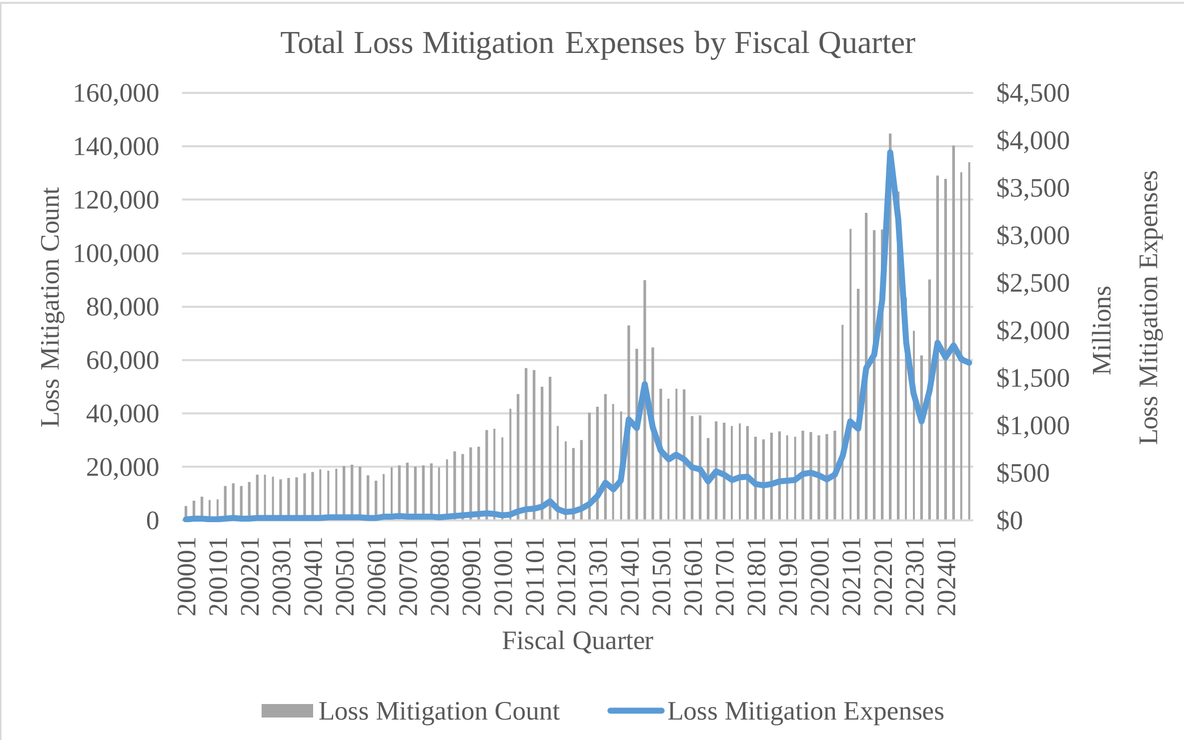
HUD initiated a loss mitigation program in 1996 to provide opportunities for borrowers in financial difficulties to retain homeownership. Loss mitigation also reduces foreclosure costs. In the standard process, mortgages provide default counseling for borrowers who are behind in their payments and offer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

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

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

Exhibit D-8 shows the historical loss mitigation expenses by fiscal quarter.

Exhibit D-8: Loss Mitigation Expenses



Loss mitigation expenses are estimated using a GLM model with a gamma distribution. The expected value of loss mitigation is as follows:

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

The estimation of loss mitigation expenses utilized loan-level data of historical mitigations from the FHA single-family data warehouse from 1997 to 2024. The sample used for estimation included 22,449 loans with associated loss mitigation over the timeframe. The following table includes the model parameters for the loss mitigation expense estimates, including the coefficients, standard error, and Chi-square statistics.

Exhibit D-9: Loss Mitigation Expense Model Parameters

Parameter Estimates				
Variable Name	Estimate	Standard Error	WaldChiSq	ProbChiSq
Intercept	6.2962	0.039	26519	<.0001
sqrt_orig_mrtg_amt	0.0067	1E-04	9147.1	<.0001
ue_relative	-0.68	0.02	1138.9	<.0001

Parameter Estimates				
Variable Name	Estimate	Standard Error	WaldChiSq	ProbChiSq
ind_product_456	0.3015	0.022	187.12	<.0001
judicial	0.1648	0.014	143.58	<.0001
hpa_local	1.1568	0.059	379.81	<.0001
dti_front_end	0.0095	7E-04	184.06	<.0001
dpa_nonprof	-0.05	0.023	4.79	0.0287
covid_lossmit	0.348	0.018	368.39	<.0001

D3.4. Refunded Premiums

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

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

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

D4. Economic Net Worth

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

D4.1. Discount Factors

The discount factors applied in computing the present value of cash flows are the Single Effective Rates (SER). Our simulations aggregated each future year's cash flows, which are treated as being received at the end of the year. The single effective rates applied for discounting are listed in Exhibit D-10.

Exhibit D-10: Single Effective Rate

Cohort Year	Single Effective Rate
1992	0.0736
1993	0.0668
1994	0.0686
1995	0.0722
1996	0.068
1997	0.0659
1998	0.0593
1999	0.0593
2000	0.062
2001	0.0612
2002	0.0548
2003	0.0476
2004	0.0371
2005	0.0233
2006	0.0455
2007	0.0461
2008	0.0488
2009	0.0447
2010	0.0167
2011	0.0372
2012	0.0204
2013	0.0241
2014	0.0298
2015	0.023
2016	0.0243
2017	0.0265
2018	0.0281
2019	0.0268
2020	0.014
2021	0.0142
2022	0.0236
2023	0.0261
2024	0.0436

D4.2. Calculating the Economic Net Worth

The economic net worth of the Fund as of the end of FY 2024 was calculated first by determining the present value of the future cash flows for all surviving loans as of September 30, 2024. This figure was then added to the capital resources of the Fund, estimated as of the same date.

Appendix E: Tables of Historical and Projected Termination Rates

Note: The relevant files are provided as separate attachments to this document.

Instructions to View PDF Attachments

1. **Open the PDF**:
   - Use a PDF reader application, such as Adobe Acrobat Reader or a similar program.
2. **Locate the Attachments Panel**:
   - In **Adobe Acrobat Reader**:
     - Open the PDF file.
     - Look for the **paperclip icon** in the left-hand navigation pane. This icon represents attachments.
     - If you don't see the icon, click on the **View** menu at the top, then go to **Show/Hide** > **Navigation Panes** > **Attachments**.
3. **View the List of Attachments**:
   - Click on the paperclip icon or the attachments option in the navigation pane.
   - A list of all attached files will appear in a panel.
4. **Open an Attachment**:
   - Double-click the attachment you want to view.

Appendix F: Stochastic Simulation Models

This Appendix describes the stochastic models used to generate the economic variables used in the Monte Carlo simulations of the FHA Single-Family Forward Mortgage Actuarial Review 2024. Based on the best fitted stochastic model, we use Monte Carlo simulation technique to simulate 1000 paths of future economic variables and obtain the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentiles of the simulated paths.

This year's review uses the same simulation method as the 2023 Review to obtain percentile paths. For each time point, the desired percentiles across all simulation paths are obtained and used as the percentile reference paths. This method focuses on the volatilities in the simulated variables at each time point.

In our Monte Carlo simulation, the simulated paths are centered on the baseline economic assumptions, this is, the 50^{th} percentile of the simulated path is closest to the baseline PEA forecast and replaced by the PEA. The estimated simulation models are identical for the Single-Family Forward and HECM with respect to Treasury rates and national and regional HPIs. Additional forecast models are developed for 30-year mortgage rates and unemployment rates to be applied to Single-Family Forward mortgages, while a forecast model of the SOFR is for application to HECM loans.

The economic variables modeled herein as a stochastic process are comprised of the following:

- 1-year Treasury rates,
- 10-year Treasury rates,
- FHFA national-level Purchase Only house price appreciation rate
- 30-year fixed mortgage commitment rates
- National household unemployment rate

The simulated economic scenarios of the U.S. economy and the components of the forecast include:

- 1-year CMT rate
- 10-year CMT rate
- 30-year fixed mortgage rate
- HPI at the MSA, state, regional and national levels
- Unemployment rate

The stochastic models are estimated using historic data and are chosen based on standard criteria such as likelihood, AIC, and BIC values. Since all status transition probabilities are estimated and projected using the historically observed interest rates and house price appreciation for the same series, the model estimates and forecasting are internally consistent. This approach is appropriate for the Actuarial Review as we are computing the present value of projected future cash flows for liability valuation.

F1. Historical Data

F1.1. Interest Rates

With the high inflation rate caused by the global oil crisis in the late 1970's, interest rates rose to a historically high level in the early 1980's. Then the Federal Reserve shifted its monetary policy from managing interest rates to managing the money supply, at least until inflation, and consequently interest rates, receded. Exhibit F-1 shows historical interest rates from 1970Q1 to 2024 Q2[67]. The one- year Treasury rate (CMT1) fluctuated around 6% in the early 1970s and increased steadily to its peak of 16.31% in CY 1981 Q3. After that, it followed a decreasing trend and reached an all-time low around 1.2% in 2004. From then on, interest rates started a slow upward trend until the 2007 financial crisis and rates started a sharp downward trend reaching a historic low of 0.06% in CY 2021 Q2. Inflation turned up dramatically because of the COVID-19 pandemic. Monetary policy aimed to overturn the post-pandemic inflation, and we saw the beginning of the Federal Reserve tightening where the one-year rate increased to the highest 5.39% in 2023 Q3 and slightly overturned afterward. The 1-year CMT rate is 5.14% in 2024 Q2.

Also shown in Exhibit F-1 are historical 1-year CMT rates, 10-year CMT rates, and 30-year fixed mortgage rates. Mortgage rates are available since 1971Q2. The data is used for estimating the ARMA-GARCH models for 1-year CMT rate and interest rate spreads.

Exhibit F-1 Historical Interest Rates and Mortgage Rates (%)

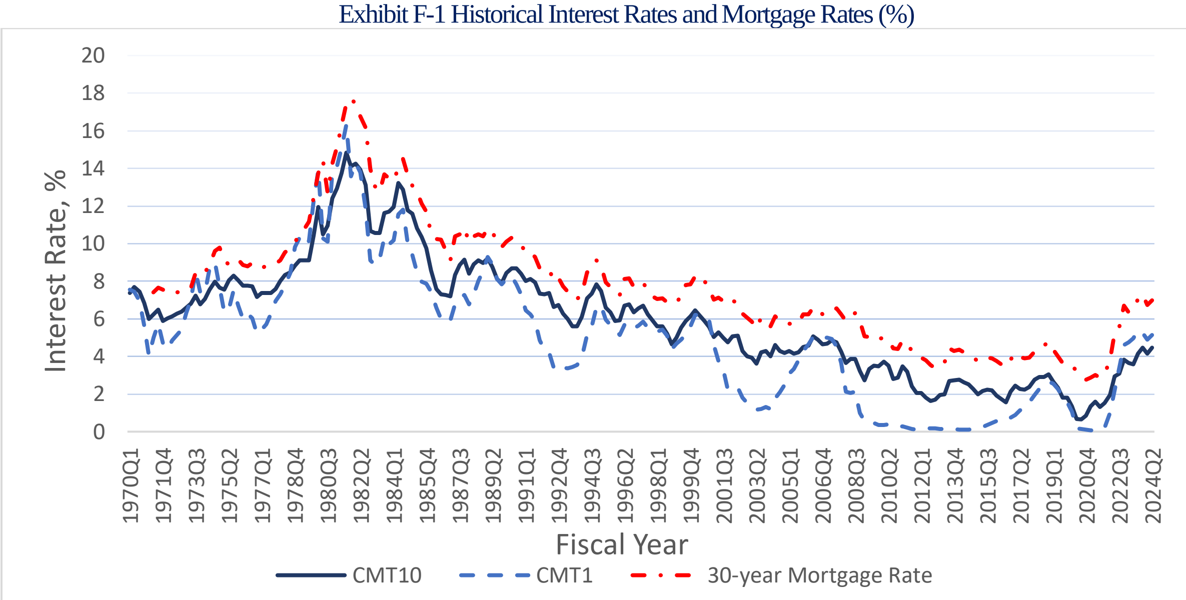
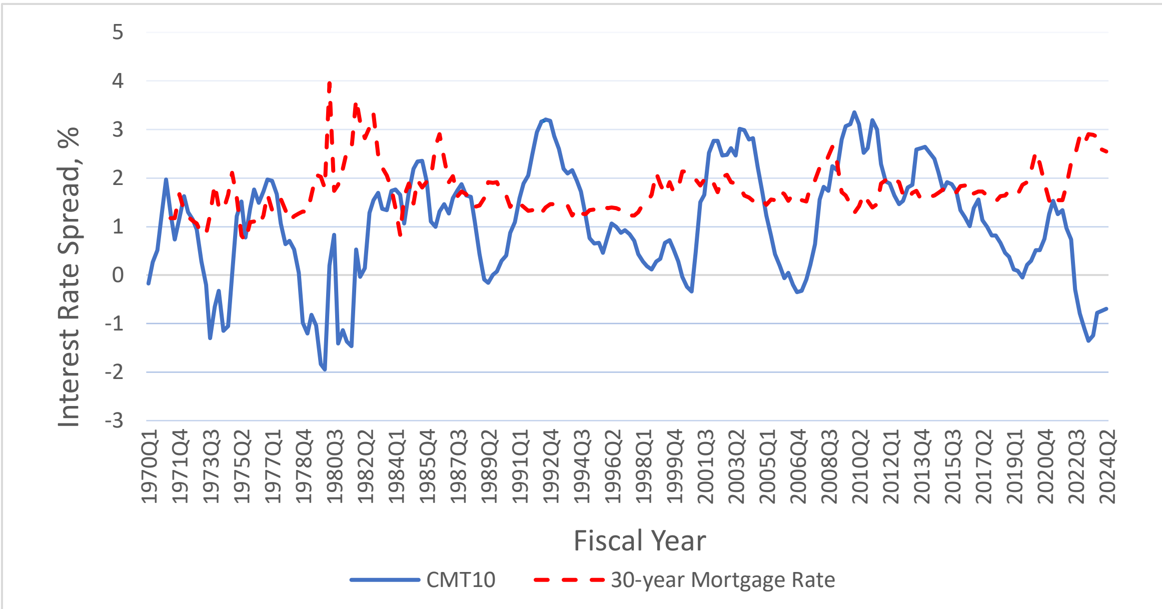


Exhibit F-2 shows historical interest rate spreads, including the spread between the 10-year CMT rate and the 1-year CMT rate and the spread between the 30-year fixed mortgage rate and the 1-

[67] Historic data up to 2024 Q2 was available when stochastic models were estimated

year CMT rate. The spread between the 10-year and 1-year Treasury rates appears to have long cycles and high volatilities. The 30-year mortgage rates quite closely follow 10-year CMT rates, which presents less volatile fluctuations in the spread between the 30-year fixed mortgage rate and the 1-year CMT rate.

Exhibit F-2 Historical Interest Rate Spread (%)



F1.2. House Price Appreciation Rates

The national house price appreciation rate (HPA) is derived from the FHFA repeat sales seasonally adjusted purchase-only (PO) house price indices (HPIs). The HPA at time t is defined as:

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

Exhibit F-3 shows the \ national HPI and annualized HPA from CY 1991 Q1 to CY 2024 Q2. The long-term average quarterly HPA is around 1.085% (4.41% annual rate). The long-term average quarterly HPA is around 1.085% (4.41% annual rate). The HPI increased steadily before 2004 with an annual appreciation rate of about 4.64%. Then house prices rose sharply starting in 2004. The house price appreciation rate was around 10% annually during the subprime mortgage expansion period from 2004 to 2005 and reached its peak at the annual rate of 11% in CY 2005 Q3. The house price appreciation slowed down in 2006. The overturn started in 2007 Q2 and the average growth rate of house prices became negative till 2011. Since then, house prices have been stably appreciated for 10 years. During COVID-19 pandemic period of 2021 to 2022, house prices went up at a much higher appreciation rate due to the economy stimulation policy and then slowed down after the pandemic is over. Exhibit F-4 shows the annualized average HPA by selected historical time periods.

Exhibit F-3 Historical National HPI and Quarterly HPA

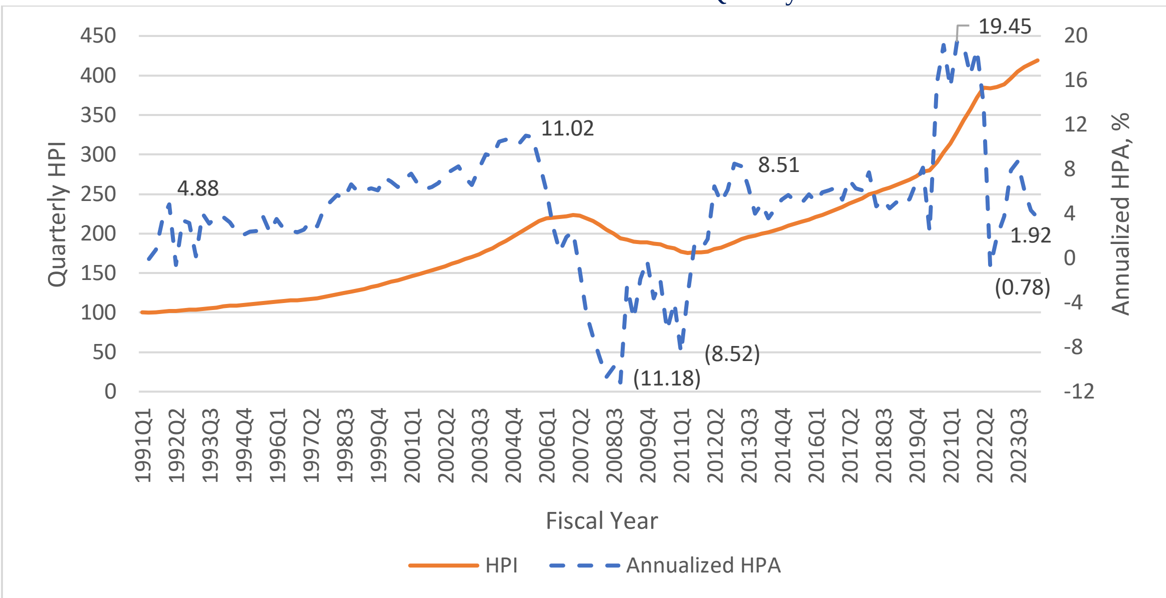


Exhibit F-4 Average Quarterly HPA by Time Span

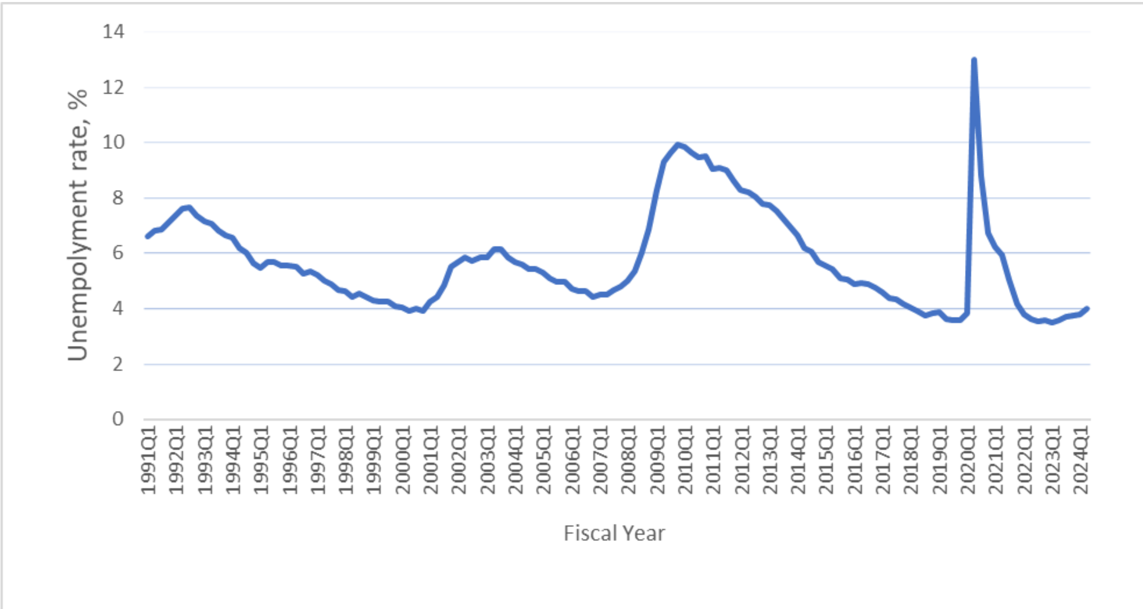
Period	Average Annual HPA
1991 – 2003	4.64%
2004 – 2006	7.69%
2007 – 2011	-4.87%
2011 – 2020	5.26%
2020 – 2022	14.75%
2022 – 2024Q2	4.43%

F1.3. Unemployment Rates

Unemployment rates typically increase during economic downturns and decrease during economic growth periods. Government policies also significantly impact employment. Exhibit F-5 displays historical national unemployment rates since 1991Q1.

We can see a high unemployment rate during the 2007-2008 financial crisis due to the widespread economic instability during that time. The unemployment rate rose sharply, reaching almost 10% in 2009 Q4. The high unemployment rate during the Covid-19 pandemic was unprecedented in its speed and scale, rising from 3.8 in 2020 Q1 to 13% in 2020Q2, as the enforced lockdowns led to widespread business closures and disruptions. The Coronavirus Aid, Relief, and Economic Security Act (CARES Act) in response to the economic fallout from the pandemic provided the largest economic stimulus in the U.S. history and brought down the unemployment rates to between 3.5% to 4% since 2022Q1.

Exhibit F-5 Historical National Unemployment Rates



F2. 1-Year Treasury Rate

Several Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are tested using historical 1-year CMT rates from fiscal year 1991 Q1 to CY 2024 Q2. Based on the AIC, BIC, and Likelihood values, the best fitted model is an AR (2)- GARCH (1,1) with student's t-distribution innovations and external regressor for conditional volatility.

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

$$r_{1,t} = a_{1,0} + a_{1,1}r_{1,t-1} + a_{1,2}r_{1,t-2} + \varepsilon_t$$

where $\varepsilon_t = \sigma_t z_t$. $z_t = \sqrt{\frac{v-2}{v}}T_v$, where T_v follows a student's distribution with degrees of freedom $v > 2$, and variance ${\sigma_t}^2$ follows a GARCH (1, 1) model,

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

The estimated results are presented in Exhibit F-6

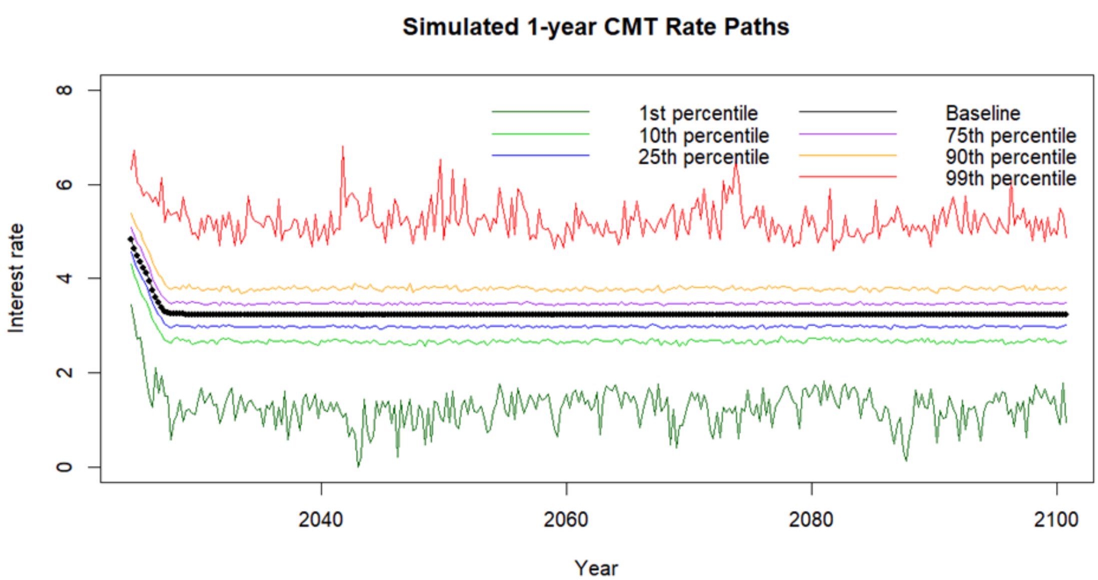
Exhibit F-6 Estimation Results for 1-Year Rate Model

Parameter	Estimate	Std. Error	t value	Pr(>|t|)
$a_{1,0}$	7.50578	0.339384	22.1159	0
$a_{1,1}$	1.51016	0.001989	759.3553	0
$a_{1,2}$	-0.51184	0.001422	-359.904	0

Parameter	Estimate	Std. Error	t value	Pr(>|t|)
α	0.50762	0.23931	2.1212	0.033906
β	0.45819	0.138717	3.3031	0.000956
γ	0.01706	0.010871	1.5693	0.116589
υ	3.53623	1.050907	3.3649	0.000766

The model based on these parameters is used to simulate the 1-year Treasury rates for the forecast period starting in FY 2024 Q3. When the simulation is implemented, the conditional mean is replaced by the PEA baseline forecast. This simulation method is to ensure the stochastic path of future 1-year Treasury rate is centered on the PEA baseline forecast. We applied the same procedure for the conditional mean in the 10-year Treasure rate, SOFR rate and HPA rate.

1000 paths of the future 75 years[68] of 1-year Treasury rates are simulated. The 1st, 10th, 25th, 75th, 90th , and 99th percentiles paths are displayed. The 50th percentile path is close to the baseline forecast and replaced by the PEA baseline assumption. The resulting forecasts for the 1-year Treasury rates are shown in the following chart for the baseline PEA and the four alternative stochastic percentile paths.



F3. 10-Year Treasury Rate

The 10-year Treasury rate is modeled by adding a stochastic spread term to the simulated 1-year Treasure rate. We estimate the dynamics of the spread between the 10-year Treasury rate and 1-year Treasury rate from historical data. Based on the AIC, BIC, and Likelihood values, the best fitted GARCH model assumes the spread term depends on the 1-year CMT rate, the lagged values

[68] The required number of projection years.

of the spread term and a random component. Let $s_{10,t}$ be the spread between the 10-year and 1-year Treasury rates at time t. Mathematically, the model for $s_{10,t}$ is as follows.

$$s_{10,t} = a_{10,0} + a_{10,1}s_{10,t-1} + a_{10,2}s_{10,t-2} + \gamma r_{1,t} + \varepsilon_t,$$

where ε_t is a normal innovation with mean 0 and variance ${\sigma_t}^2$ following a GARCH (1, 1) model,

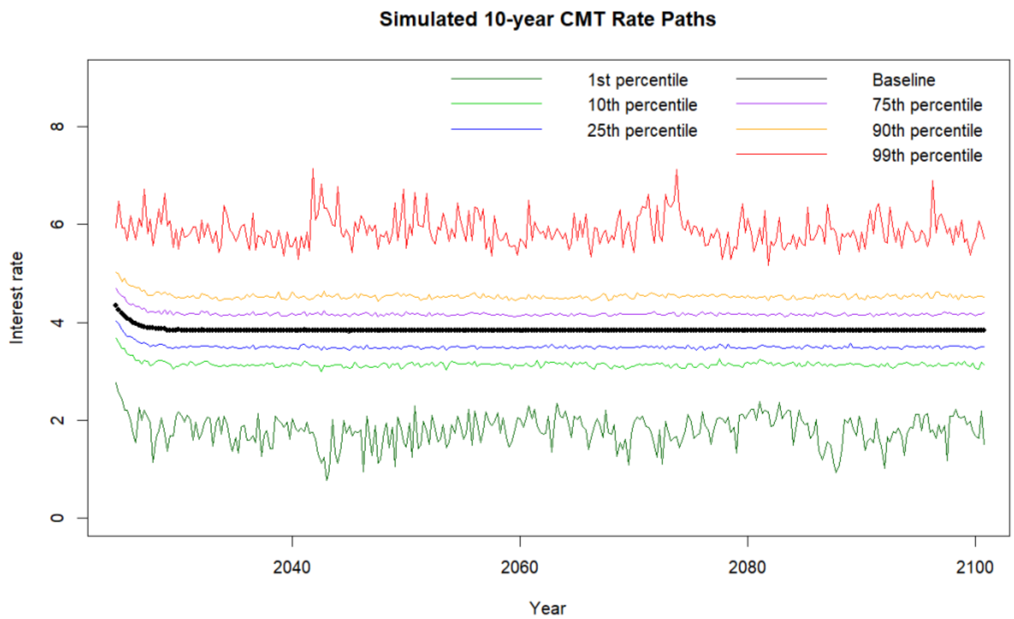
$${\sigma_t}^2 = \omega + \alpha{\varepsilon_{t-1}}^2 + \beta{\sigma_{t-1}}^2$$

The model is estimated based on historic spread data from CY 1970 Q1 to CY 2024Q2. parameters are shown in the following Exhibit F-7.

Exhibit F-7 Estimation Results for 10-Year Rate Spread Model

	Estimate	Std. Error	t value	Pr(>|t|)
$a_{10,0}$	3.526985	0.298636	11.8103	0
$a_{10,1}$	1.211568	0.067686	17.8997	0
$a_{10,2}$	-0.23911	0.068513	-3.49	0.000483
γ	-0.46752	0.030336	-15.4116	0
ω	0.007685	0.004931	1.5585	0.119118
α	0.086025	0.047364	1.8162	0.069332
β	0.825331	0.078667	10.4915	0

We used the estimated parameters to simulate the spread between the 10-year and 1-year Treasury rates with the conditional mean equal to the PEA baseline forecast, such that the 1000 simulated paths are centered on the baseline estimation. The simulated spread percentile paths are added to the corresponding 1-year CMT percentile paths. Percentile paths are obtained therein. The 1st, 10th, 25th, 75th, 90th , and 99th percentiles paths, together with the PEA baseline assumption for the ten-year Treasury rates are shown in the following chart.



F4. 30-year Fixed Mortgage Rate

The 30-year fixed mortgage rate closely follows the 10-year CMT rates and is modeled by simulating a spread added to the simulated 10-year CMT rate. We estimate the dynamics of the spread between 30-year fixed mortgage rate and the 10-year CMT rate from historic data. The best fitted model is

$$s_{m,t} = a_{m,0} + a_{m,1}s_{m,t-1} + a_{m,2}r_{1,t} + a_{m,3}s_{10,t} + \varepsilon_{t,}$$

where $r_{1,t}$ is 1-year CMT rates, $s_{10,t}$ is the spread between 10-year CMT rate and 1-year CMT rate, and $\varepsilon_{m,t}$ is a skewed t-distributed innovation with variance ${\sigma_t}^2$ following a GARCH (1, 1) model,

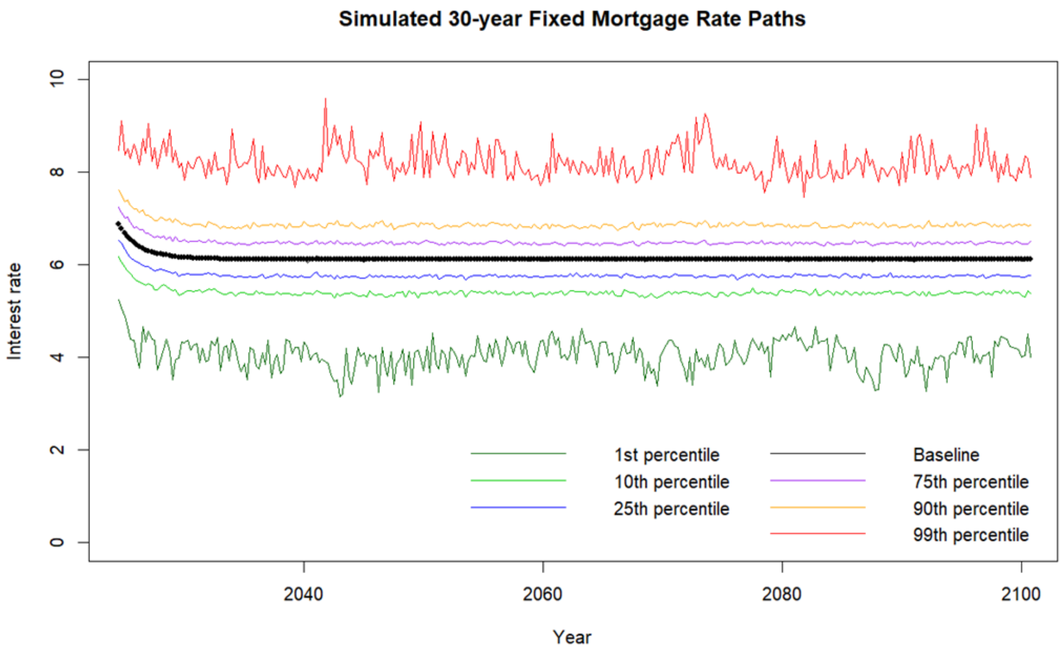
$${\sigma_t}^2 = \omega + \alpha {\varepsilon_{t-1}}^2 + \beta {\sigma_{t-1}}^2$$

Using historic data from CY 1991Q1 to CY 2024Q2, the estimated parameters are shown in Exhibit F-8.

Exhibit F-8 Estimation Results for the Mortgage Rate Model

	Estimate	Std. Error	t value	Pr(>|t|)
$a_{m,0}$	2.325708	0.1401	16.6003	0
$a_{m,1}$	0.877885	0.029703	29.5552	0
$a_{m,2}$	-0.08571	0.019821	-4.324	0.000015
ω	-0.22426	0.040391	-5.5522	0
α	0.0069	0.003593	1.9203	0.054822
β	0.438059	0.211394	2.0722	0.038243
v	0.335195	0.250267	1.3393	0.180458

We used the estimated parameters to simulate the 30-year fixed spread rate with the conditional mean equal to the baseline spread. The simulated spread paths are added to the simulated 10-year CMT paths. The mortgage rate percentile paths are obtained therein as shown in the following chart.



F5 House Price Appreciation Rate (HPA)

F5.1. National HPA

Several GARCH model with different external regressors are fitted to the historical house appreciation rates. Based on the AIC, BIC, and Likelihood values, the best fitted GARCH model for the national HPA takes the following form:

$$HPA_t = a_{h,0} + a_{h,1}HPA_{t-1} + a_{h,2}HPA_{t-2} + \gamma r_{m,t-1} + \varepsilon_t$$

Where $r_{m,t-1}$ is the fixed 30-year mortgage rate at time $t-1$, ε_t is a skewed t-distributed innovation with variance ${\sigma_t}^2$ following a GARCH (1, 1) model,

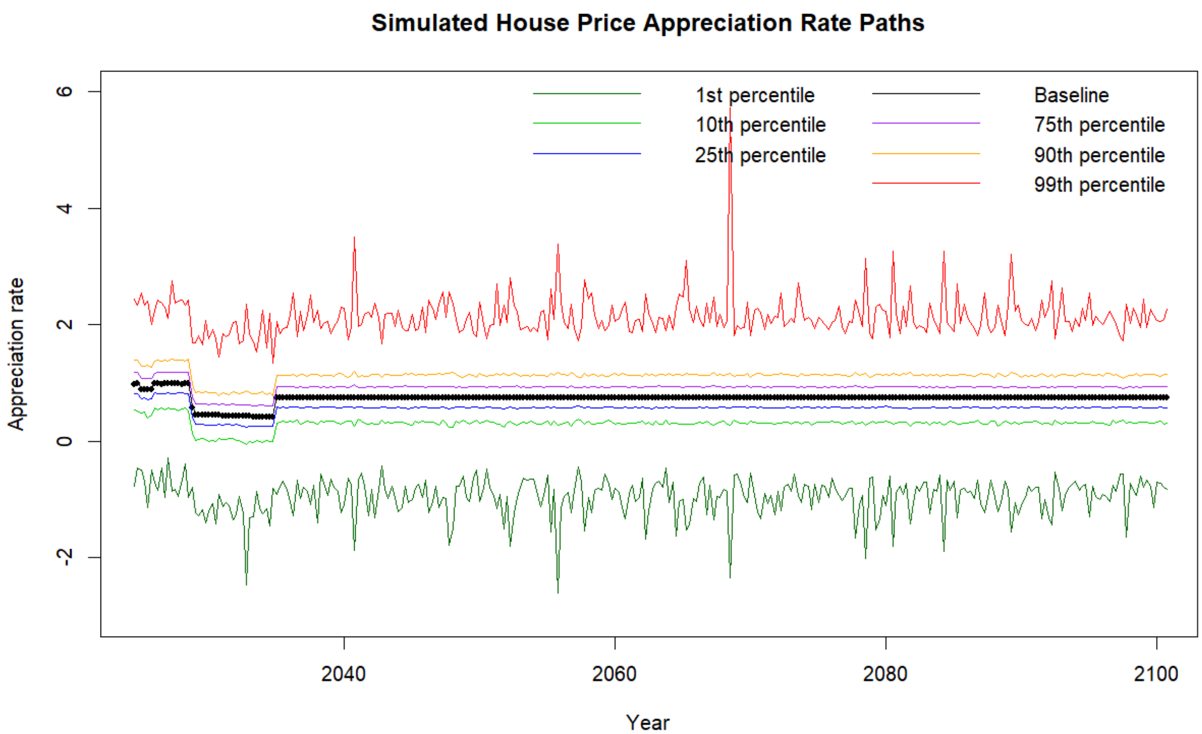
$${\sigma_t}^2 = \omega + \alpha{\varepsilon_{t-1}}^2 + \beta{\sigma_{t-1}}^2$$

In this model, the conditional mean of HPA_t depends on its own lags and the 30-year fixed mortgage rate in the previous quarter. The GARCH (1,1) model with skewed t-distributed innovations performs much better than the one with normal innovations in this model. Using the historic data from 1991Q1 to 2024Q2, we estimate the model and have the results as shown in Exhibit F-9.

Exhibit F-9 Estimation Results for the National HPA Model

	Estimate	Std. Error	t value	Pr(>|t|)
$a_{h,0}$	1.845205	0.741154	2.4896	0.012787
$a_{h,1}$	0.757953	0.094409	8.0284	0
$a_{h,2}$	0.227165	0.099659	2.2794	0.022642
γ	-0.2015	0.064804	-3.1094	0.001875
ω	0.021436	0.012113	1.7697	0.076785
α	0.451986	0.191091	2.3653	0.018016
β	0.547014	0.134978	4.0526	0.000051
skew	0.8267	0.089068	9.2817	0
shape	3.722303	1.023533	3.6367	0.000276

We used the best fitted model to simulate 1000 future HPA paths starting from 2024 Q3, with the conditional mean equal to the PEA baseline forecast and obtain the 1st, 10th, 25th, 75th, 90th, and 99th percentile paths of the future HPA rates, as shown in the following chart.



F6.1. Geographic Dispersion

Regional forecasts are derived by applying dispersion factors calculated using Moody's baseline all-transaction AT HPI forecasts at the national, census division, state, and MSA levels to the national-level GARCH simulations estimated using the PO series. The FHFA AT HPI retains significantly broader regional coverage than the PO HPI as discussed in Section A of this report.

Specifically, at each time t, there is a dispersion of HPAs between the ith region and the national forecast:

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

This dispersion forecast under Moody's baseline estimates was preserved for all local house price forecasts under individual future economic paths. That is, for economic path j, the HPA of the ith region at time t was computed as:

$$HPA_{i,t}^{j} = (HPA_{i,t}^{j} - DISP_{i,t}^{Base})$$

This approach retains the relative current housing market cycle among different geographic locations, and it allows us to capture the geographical concentration of FHA's current endorsement portfolio. This approach is also consistent with Moody's logic in creating local market HPI and HPA forecasts relative to the national HPI/HPA forecast under alternative economic scenario forecasts. We understand this approach is equivalent to assuming perfect correlation of dispersions among different locations across simulated national HPA paths, which creates systematic house price decreases during economic downturns and vice versa during booms. Due to Jensen's Inequality, this tends to generate a more conservative estimate of claim losses.

At the national level, the HPA derived from the FHFA PO HPI exhibits a correlation of 97.5 percent with the AT-derived HPA over the 1991 Q1 through 2024 Q2 period while exhibiting greater seasonal variation that we wish to capture in the GARCH simulation model.

The apparent inconsistency between the PO HPI utilized in developing the HPA GARCH model and the AT HPI utilized for purposes of simulating regional dispersion is a consequence of judgments that (i) seasonal variation HPI/HPA captured in the PO series should be retained; and (ii) dispersion between national and regional HPA is better captured in the AT series as discussed in Section A. By combining these two series as described above we incorporate the best features of each for our purposes.

F6. Unemployment Rate (UE)

The Covid-19 pandemic disproportionately impacted service-based industries where work was typically in-person. The high unemployment rate was unprecedented in its speed and scale, leading to 13% in 2022Q2, the highest rate since the Great Depression. In the model estimation. Therefore, this one-time jump in the unemployment rate was treated as an outline and smoothed out using the moving average of the data. The best fitted model is the following.

$$ue_t = a_{u,0} + a_{u,1}ue_{t-1} + a_{u,2}ue_{t-2} + a_{u,3}r_{1,t} + a_{u,4}r_{m,t} + \varepsilon_t,$$

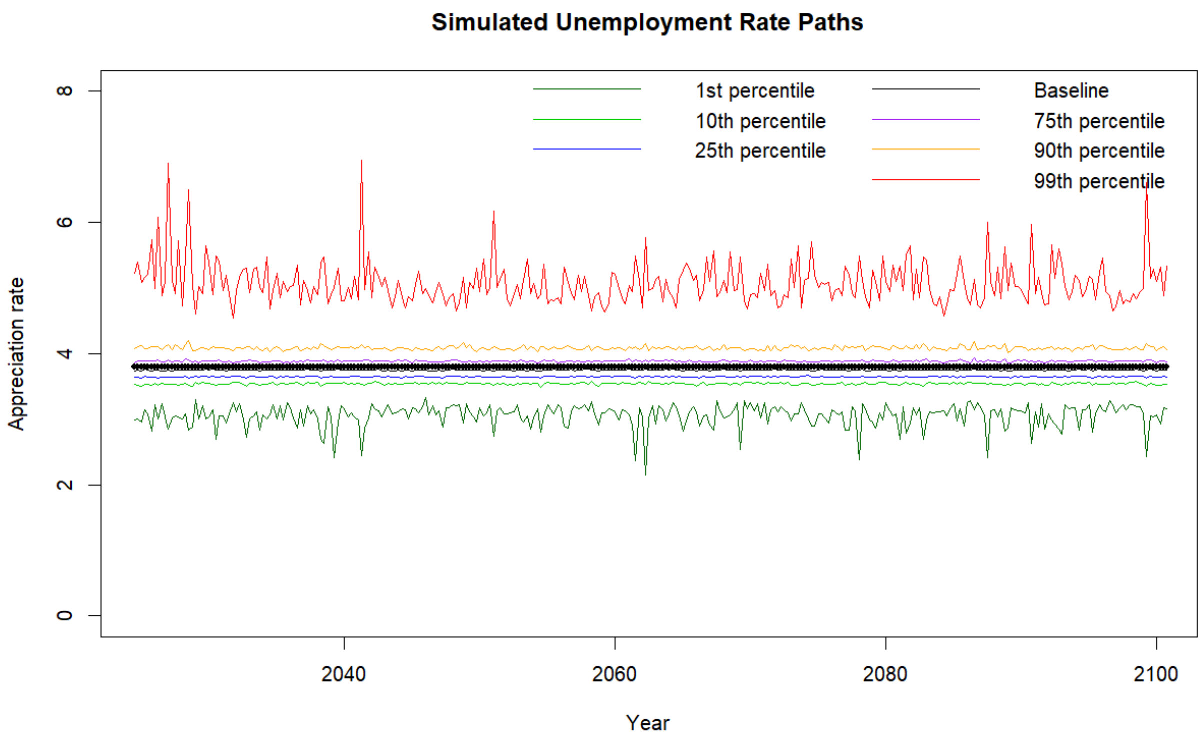
where ue_t is the unemployment rate in quarter t , $r_{1,t}$ is 1-year CMT rates, $r_{m,t}$ is the 30-year fixed mortgage rate in quarter t, and $\varepsilon_{m,t}$ is a t-distributed innovation with variance ${\sigma_t}^2$ following a GARCH (0, 1) model,

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

Using the historic data from 1991Q1 to 2024Q2, we estimate the model and have the results as shown in Exhibit F-10. The unemployment rate percentile paths are obtained as shown in the following chart.

Exhibit F-10 Estimation Results for the National Unemployment Rate Model

	Estimate	Std. Error	t value	Pr(>|t|)
$a_{u,0}$	7.217023	0.092508	78.01471	0
$a_{u,1}$	1.336735	0.044725	29.88797	0
$a_{u,2}$	-0.34812	0.041993	-8.28992	0
$a_{u,3}$	-0.24402	0.106853	-2.28371	0.022389
ω	0.115689	0.078835	1.46748	0.142245
α	0.061971	0.076424	0.81088	0.417433
β	0.549265	0.464145	1.18339	0.236655
skew	0.449735	0.162579	2.76626	0.00567
shape	1.407751	0.174551	8.06497	0



F7. COVID-19 Pandemic Consideration

The impact from the COVID-19 pandemic is noticeable and dramatic when analyzing these economic indicators, causing higher volatility in these economic variables. Abrupt changes in the recent historic data of these economic measures present additional challenges when fitting stochastic models. Because of the historic nature of this event and the changing economic environment before and after the pandemic, it is difficult to ascertain which impacts might be attributed solely to the pandemic, and whether these changes will persist into the future or conditions or revert to pre-pandemic conditions. Rather than apply different models including and excluding the pandemic period to interpret COVID-19 impacts, we use customized GARCH models for the individual economic variables to capture the high volatility of the COVID-19 period and subsequent economic changes in the data and to develop the simulated diversions from the PEA baseline assumptions.

With 2024 economic data, the best fitted GARCH models have similar structures to the corresponding models used in 2023 Review, with slightly changed parameters. This evidences that GARCH models can capture the volatilities in various economic variables, including the impact of COVID-19. Therefore, we continue to use this approach for the FY 2024 review.

Appendix G: Logistic Model Estimation Results

Note: The detailed results are provided as separate file attachment to this document.

Instructions to View PDF Attachments

1. **Open the PDF**:
    - Use a PDF reader application, such as Adobe Acrobat Reader or a similar program.
2. **Locate the Attachments Panel**:
    - In **Adobe Acrobat Reader**:
        - Open the PDF file.
        - Look for the **paperclip icon** in the left-hand navigation pane. This icon represents attachments.
        - If you don’t see the icon, click on the **View** menu at the top, then go to **Show/Hide** > **Navigation Panes** > **Attachments**.
3. **View the List of Attachments**:
    - Click on the paperclip icon or the attachments option in the navigation pane.
    - A list of all attached files will appear in a panel.
4. **Open an Attachment**:
    - Double-click the attachment you want to view.

Appendix H: Data – Sources, Processing and Reconciliation

H1. Data Sources

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

From FHA, we have received the following data:

1. Claims_601_Case_Data: used for the cash entry from note sales
2. IDB: core case data; this table is derived based on fields from IDB_1, IDB_2, IDB_3 and the Decision_FICO_Score (one file each for 1975 – 2024)
3. Lossmit_Costs: derived table based on the Loss Mitigation table and IDB_1, used to obtain mitigation claim amounts
4. Sams_case_record: used to determine the status of the conveyances, the capital income/expense amounts, the sales and REO expenses, and sales proceeds to FHA, where applicable
5. SFDW_Default_History: used to create period information related to default histories
6. Fannie_FICO_pre2004: used for supplemental credit data
7. Current_Status: table displaying the current status of each loan

From OMB, we have received the Economic Assumptions for the FY 2025 Mid-Session Review of the President's Economic Assumptions (PEA). The economic data that is included in the analysis is shown below:

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

H2. Data Processing – Mortgage Level Modeling

Starting with the raw data, ITDC developed datasets for the mortgage level transition and loss severity models. The first step in preparing the data for analysis was the processing of the economic data. Historical economic data 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 2024, if the mortgage remained active.

H3. Data Reconciliation

Data reconciliation is a very important step to ensure the accuracy of the model and the estimation results. To reconcile the data processed with the data provided by FHA, we compared summaries of key data elements with the summaries provided by FHA. The summaries for the number of active mortgages, IIF, number of 90-day delinquencies, and the number of claims to date are shown in the following tables, Exhibit H-1 through H-4. Most of the data processed matches the FHA data totals, with differences centered on early years. The reconciliation tables are based on data as of September 30, 2024.

Exhibit H-1 Data Reconciliation for Number of Active Loans

Credit Subsidy Cohort	Federal Housing Administration (Data as of September 2024)	Independent Actuary	Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
1994	2,985	2,985	0	0.00%
1995	6,298	6,298	0	0.00%
1996	12,791	12,791	0	0.00%
1997	15,202	15,202	0	0.00%
1998	24,048	24,048	0	0.00%
1999	31,375	31,375	0	0.00%
2000	18,695	18,695	0	0.00%
2001	31,942	31,942	0	0.00%
2002	45,738	45,738	0	0.00%
2003	63,351	63,351	0	0.00%
2004	79,531	79,531	0	0.00%
2005	58,374	58,374	0	0.00%
2006	47,349	47,349	0	0.00%
2007	45,885	45,885	0	0.00%
2008	102,879	102,879	0	0.00%
2009	203,897	203,897	0	0.00%
2010	247,415	247,415	0	0.00%
2011	199,088	199,088	0	0.00%
2012	256,422	256,422	0	0.00%
2013	364,259	364,259	0	0.00%
2014	153,129	153,129	0	0.00%
2015	257,538	257,538	0	0.00%
2016	362,499	362,499	0	0.00%
2017	399,330	399,330	0	0.00%
2018	322,752	322,752	0	0.00%
2019	325,011	325,011	0	0.00%
2020	658,749	658,749	0	0.00%
2021	1,112,702	1,112,702	0	0.00%
2022	889,710	889,710	0	0.00%
2023	683,467	683,467	0	0.00%
2024	736,965	752,143	15,178	2.06%
Total	7,759,376	7,774,554	15,178	0.20%

Exhibit H-2 Data Reconciliation for Insurance in Force

Credit Subsidy Cohort	Federal Housing Administration (Data as of September 2024)	Independent Actuary	Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
1994	204,160,052	204,160,052	0	0.00%
1995	413,520,518	413,520,518	0	0.00%
1996	862,139,516	862,139,516	0	0.00%
1997	1,040,575,310	1,040,575,310	0	0.00%
1998	1,779,346,718	1,779,346,718	0	0.00%
1999	2,428,018,676	2,428,018,676	0	0.00%
2000	1,426,871,144	1,426,871,144	0	0.00%
2001	2,746,784,693	2,746,784,693	0	0.00%
2002	4,262,234,806	4,262,234,806	0	0.00%
2003	6,666,061,639	6,666,061,639	0	0.00%
2004	8,387,492,193	8,387,492,193	0	0.00%
2005	6,286,951,823	6,286,951,823	0	0.00%
2006	5,368,376,567	5,368,376,567	0	0.00%
2007	5,609,680,329	5,609,680,329	0	0.00%
2008	14,409,613,958	14,409,613,958	0	0.00%
2009	30,886,215,407	30,886,215,407	0	0.00%
2010	36,001,727,762	36,001,727,762	0	0.00%
2011	29,485,343,968	29,485,343,968	0	0.00%
2012	39,214,523,125	39,214,523,125	0	0.00%
2013	57,564,411,072	57,564,411,072	0	0.00%
2014	20,515,368,503	20,515,368,503	0	0.00%
2015	40,235,732,405	40,235,732,405	0	0.00%
2016	60,755,413,920	60,755,413,920	0	0.00%
2017	70,348,394,866	70,348,394,866	0	0.00%
2018	57,640,114,562	57,640,114,562	0	0.00%
2019	61,252,227,972	61,252,227,972	0	0.00%
2020	143,920,651,612	143,920,651,612	0	0.00%
2021	266,305,325,972	266,305,325,972	0	0.00%
2022	234,003,930,228	234,003,930,228	0	0.00%
2023	195,343,949,136	195,343,949,136	0	0.00%
2024	222,148,192,617	226,798,752,857	4,650,560,240	2.09%
Total	1,627,513,351,069	1,632,163,911,309	4,650,560,240	0.29%

Exhibit H-3 Data Reconciliation for Number of 90 Day Delinquencies

Credit Subsidy Cohort	Federal Housing Administration (Data as of September 2024)	Independent Actuary	Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
1994	223	241	18	8.07%
1995	359	375	16	4.46%
1996	612	622	10	1.63%
1997	672	686	14	2.08%
1998	976	993	17	1.74%
1999	1,321	1,335	14	1.06%
2000	982	996	14	1.43%
2001	1,543	1,569	26	1.69%
2002	1,948	1,969	21	1.08%
2003	2,319	2,356	37	1.60%
2004	3,306	3,352	46	1.39%
2005	2,772	2,813	41	1.48%
2006	2,539	2,570	31	1.22%
2007	2,822	2,872	50	1.77%
2008	6,264	6,365	101	1.61%
2009	8,731	8,868	137	1.57%
2010	8,315	8,472	157	1.89%
2011	5,913	6,024	111	1.88%
2012	6,110	6,225	115	1.88%
2013	7,103	7,210	107	1.51%
2014	6,129	6,232	103	1.68%
2015	10,123	10,309	186	1.84%
2016	14,164	14,476	312	2.20%
2017	17,393	17,777	384	2.21%
2018	19,221	19,781	560	2.91%
2019	21,573	22,157	584	2.71%
2020	26,844	27,679	835	3.11%
2021	39,515	40,785	1,270	3.21%
2022	43,833	45,132	1,299	2.96%
2023	29,324	29,767	443	1.51%
2024	7,864	7,962	98	1.25%
Total	300,813	307,970	7,157	2.38%

Exhibit H-4 Data Reconciliation for Number of Claims to Date

Credit Subsidy Cohort	Federal Housing Administration (Data as of September 2024)	Independent Actuary	Difference (Actuary - FHA)	Percent Difference (Actuary - FHA) / FHA
1994	66,012	66,012	0	0.00%
1995	44,743	44,743	0	0.00%
1996	63,600	63,600	0	0.00%
1997	60,050	60,050	0	0.00%
1998	67,776	67,776	0	0.00%
1999	84,630	84,630	0	0.00%
2000	71,641	71,641	0	0.00%
2001	85,846	85,846	0	0.00%
2002	91,142	91,142	0	0.00%
2003	91,957	91,957	0	0.00%
2004	116,951	116,951	0	0.00%
2005	93,099	93,099	0	0.00%
2006	95,428	95,428	0	0.00%
2007	107,721	107,721	0	0.00%
2008	227,102	227,102	0	0.00%
2009	230,163	230,163	0	0.00%
2010	118,813	118,813	0	0.00%
2011	49,468	49,468	0	0.00%
2012	31,326	31,326	0	0.00%
2013	29,637	29,637	0	0.00%
2014	17,748	17,748	0	0.00%
2015	18,240	18,240	0	0.00%
2016	16,740	16,740	0	0.00%
2017	13,539	13,539	0	0.00%
2018	9,325	9,325	0	0.00%
2019	5,334	5,334	0	0.00%
2020	2,920	2,920	0	0.00%
2021	2,487	2,487	0	0.00%
2022	2,001	2,001	0	0.00%
2023	471	471	0	0.00%
2024	8	8	0	0.00%
Total	1,915,918	1,915,918	0	0.00%