Mortgage Insurance Risk Based Capital

Document 2: Loan Level Cash-Flow Model: Methodology white paper

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Loan Level Cash-Flow Model: Methodology white paper

1. Introduction and background

This document forms an integral part of the proposed risk-based capital ("RBC") framework for US-based mortgage insurers. The proposed framework is covered in two documents:

- Overview of proposed RBC approach: This covers the proposed approach to establishing capital levels for US-based single family mortgage insurance businesses. At the core is a "grids-based" approach to estimating capital for loans based on defined risk characteristics.
- Loan Level cash-flow model methodology white paper (this document): This covers the detailed cash-flow model developed and used to parameterize the aforementioned RBC grids.

The purpose of this document is two-fold.

First, it describes the methods used to parameterize the capital requirements grids in the prosed RBC framework (as described in the separate Overview of the proposed RBC approach document).

Second, the proposed regulatory framework as currently outlined requires firms at a certain capital action levels, as defined in the RBC instructions, to submit a detailed capital plan. Such a capital plan would need to contain more detailed cash-flow forecasting of the exposures of the firm in question; some firms may choose to use the method of developing such forecasts that is outlined in this document.

1.1. Context

In response to the proposed NAIC Model Act, from 2013 to 2016 a project has been undertaken to develop a risk-sensitive framework for estimating capital requirements. This project has involved regular meetings of mortgage insurance participants, regulators, and other interested parties.

At key junctures in the development process, this proposal was reviewed at multiple points with the NAIC, interested State OCI representatives, and also presented in conceptual form in public discussion forums.

1.2. The role of the cash-flow model in the proposed framework

The model outlined in this document is not the proposed regulatory standard for ensuring adequate capitalization. Please see the separate *Overview of proposed RBC approach* document for details of the proposed approach to determining minimum capital requirements.

The proposed RBC capital framework establishes a set of grids to determine major sources and uses of financial resources, under a specific home-price path. The capital requirements determined using the proposed framework are a function of risk factors known at origination on the loan in question (e.g. loan-to-value [“LTV”] of the property, credit score of the borrower [“FICO”], loan purpose). In addition, the market environment in which the loan was originated also impacts capital: the choice of grid reflects the distance of the home price index from a long-term trend (leading to counter-cyclical capital requirements), as well as an aggregate number of risk factors observed in the market – a proxy for underwriting quality.

While the proposal is for the RBC grids to be the primary determinant of capital adequacy, the parametrization of these grids was developed through a more detailed loan-level model of sources and uses of financial resources. This ‘cash-flow’ model was developed using a hazard-rate construct. The model predicts credit losses and prepayment behavior, taking as input a view on future macroeconomic variables (including home prices, unemployment, and interest rates). More simplified approaches to estimating other sources and uses of resources (e.g. investment portfolio incomes) are also covered.

1.3. Structure of this document

The remainder of this document is split into two parts:

- Part A: Model approach. This covers details of the approach used in the cash-flow model. This includes the segmentation approach, loan-level model parameters for default, severity and prepayment, as well as simplified approaches used for other sources and uses. Further, a number of back-testing results are included in the document, demonstrating model fit assuming that the actual realized macroeconomic path had been known

- Part B: Macroeconomic parametrization and translation to grids. This covers how the tool outlined in Part A was used to develop the proposed RBC grids. Key to this is a proposal on the approach to selecting appropriate macroeconomic forecasts used to inform the RBC grids, as well as the approach to developing the grids themselves. Included in this section is a comparison of the simplified RBC-grid capital requirements with the detailed cash-flow model output.

Part A: Model approach

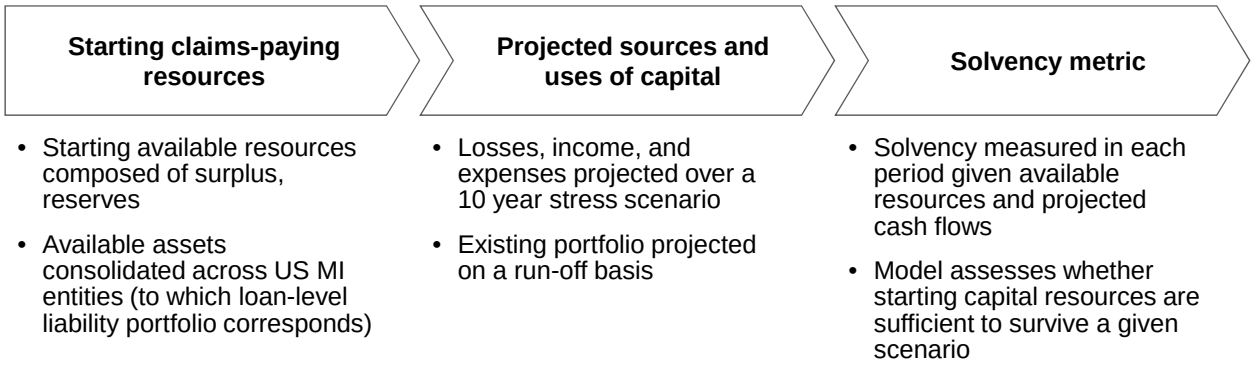
2. Overview of modeling approach

2.1. Sources and uses

The proposed capital framework is designed to measure sources and uses of capital through time, to ensure that sources outweigh uses. As such, the model estimates the amount of starting claims-paying resources necessary to satisfy estimated future liabilities (largely claim losses and expenses). At the core of this analysis is a projection of cash-flows at a certificate (loan) level. In order to simplify the approach the framework assumes a run-off portfolio, and uses a 10 year projection window. Given known sensitivity to macroeconomic variables, as well as other mortgage risk characteristics, the model has been designed to take a 10-year view of (stressed) macroeconomic variables as an input.

The output of the model is a solvency test, defined as available capital resources remaining above zero for the full duration of the projection (i.e. never dipping below zero in the full 10 years). The figure below illustrates the structure of the capital framework at a high level.

Figure 1: Capital framework high level structure



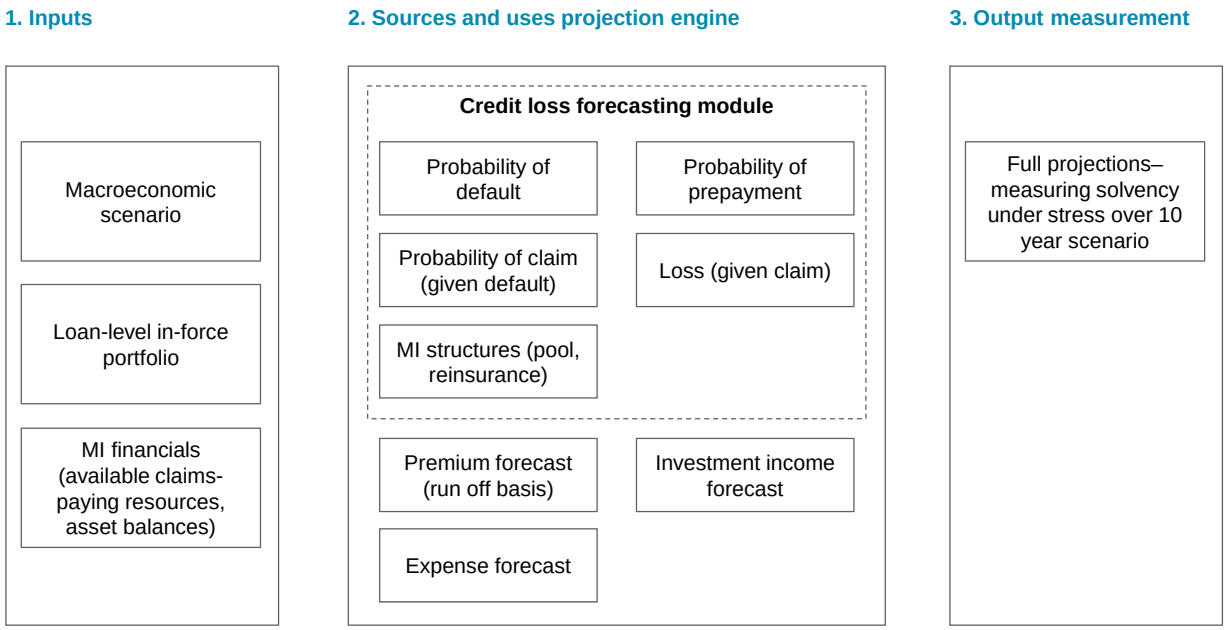
The proposed model can be applied at any level of aggregation; however for the purpose of testing, the proposed approach is applied it at a consolidated basis for each MI's US Mortgage Insurer legal entities covering 1st lien product only. These consolidated entities have other, non-mortgage related assets and liabilities, which have been separately stressed. Investments in other subsidiaries (including US non-MI entities and/or non-US entities) are not consolidated, but rather treated as investment assets, with appropriate haircuts.

The capital model functions by first capturing a set of inputs, which include a macroeconomic stress scenario, a snapshot of the loan-level in-force MI portfolio, and a set of financials capturing available claims-paying and income-generating assets. The inputs are fed through a "sources and uses of capital" projection engine, the key component of which is a credit loss forecasting module, composed of the probability of default ("PD"), prepayment, and claim given default models, as well as estimates for loss given claim and for the impact of loss-mitigating mortgage insurance structures. Other components of the projection engine include a premium forecast for the in-force loan portfolio, an investment income forecast, and an expense forecast.

The output of the projection engine is a set of expected cash flows over 10 years. The minimum capital requirement is the amount of starting claims-paying resources that is sufficient to remain solvent over the projection horizon. A mortgage insurer is expected to be solvent if the starting claims-paying resources exceed the minimum amount.

Figure 2, below illustrates the capital model components at a high level:

Figure 2: Capital model components



2.2. Overview of modeling approach for losses and prepayment

The proposed loan-level methodology is in the family of hazard rate models, in that the model estimates the probability of an outcome (default or prepayment) during a time period of interest, conditional on survival up to the time period of interest.

There is considerable academic literature discussing hazard rate modeling approaches, particularly the proportional hazards approach of Cox (1972)[1]. Such a method has been applied to modeling both default and prepayment for consumer loans, as in Deng, Quigley, and Van Order (2000)[2]. Shumway (2001)[3] proposed a discrete-time hazard model which otherwise closely resembles the Cox approach, and demonstrated that with such a discrete setup, the hazard rate can be estimated with a multi-period logit model in which one of the explanatory variables is a function of the time horizon.

[1] Cox, David R., Regression Models and Life-Tables, Journal of the Royal Statistical Society, Vol. 34, No. 2, 1972

[2] Deng, Yongheng and Quigley, John M. and Van Order, Robert, "Mortgage Terminations, Heterogeneity and the Exercise of Mortgage Options", Econometrica, March 2000, Volume 68, No. 2, pp 275-307

[3] Shumway, T., Forecasting bankruptcy more accurately: A simple hazard model. Journal of Business, 74: 101-124, 2001

For a given in-force loan, PD and prepayment serve as competing hazards – in a given projection period, the mutually exclusive, collectively exhaustive termination outcomes for a loan may include default, prepayment, or survival to the next projection period[4]. Because a loan cannot default and prepay in the same period, the hazards are considered to be "competing". Default and prepayment are correlated, and a number of independent variables are predictive of both default and prepayment (e.g. borrower FICO, current LTV of the loan, HPA). There are also characteristics that are predictive of one outcome, but not of the other (e.g. prepayment incentive driven by decreasing interest rates may suggest increased incidence of prepayment, but does not have an intuitive relationship with default).

The capital model estimates PD and prepayment rates using separate logistic regressions. This approach was selected for two reasons. First, modeling PD and prepayment separately allows correlations between the outcomes to be captured (by capturing independent variables that are predictive of both outcomes), while allowing the specific predictive variable set selected for each outcome to be more closely tailored and parsimonious. Second, the differing segmentation approaches used for PD and prepayment suggest modeling the segments separately and applying relevant models to each loan based on that loan's particular characteristics as of snapshot.

2.3. Modeling data

The model was developed on a broad availability of industry data, cleaned to ensure consistency and centrally aggregated by a third party. Participants included (in alphabetical order): Arch Mortgage Insurance Company, Genworth Mortgage Insurance Corporation, Mortgage Guaranty Insurance Corporation, Radian Group, Inc., and United Guaranty Corp. Further, data was made available from the legacy PMI Mortgage Insurance Co.

The overall credit modeling dataset was used to estimate and test each of the credit model components, and serves as the underlying data for portfolio snapshots whose performance and capital requirements are forecasted by the credit loss projection engine and overall model. The dataset was created by importing data provided by each MI, standardizing the data into a common format, and cleaning the data to account for errors and inconsistencies.

Submitted data included:

- Loan-level origination data for MIs' portfolios through 12/31/2013
- End-of-quarter (where available) and end-of-year loan status and performance snapshots covering 1995-2013 (exact availability varying by MI)
- Modification data mapping pre-modification loan characteristics to post-modification loan characteristics, where applicable
- Structure tables containing contract-level information describing MIs' reinsurance and pool insurance agreements

[4] Scheduled cancellations are another possible outcome for a loan; cancellation incidence is governed largely deterministically by the loan's amortization schedule and origination characteristics. Within the model, cancellation is treated as a "residual" hazard – that is, a loan that is scheduled to cancel in period t is expected to cancel if it neither defaults nor prepays in period t

In total the dataset consisted of over 30 million individual mortgage insurance certificates. This robust dataset allowed construction of a large separate development and testing sub-set. The mortgage data was complemented by a set of macroeconomic data, sourced from public disclosure reports and Moody's ecomomy.com.

3. Probability of default (PD) models

3.1. Segmentation of PD models

The loan-level cash-flow model uses a seasoned hazard methodology, incorporating both origination characteristics and a loan's performance history since origination. Consistent with mortgage accounting practices, default his defined as 180 days past due.

As confirmed by model specification and testing, a loan's origination characteristics exhibit considerable predictive power, and constitute the primary set of predictors (in addition to macroeconomic and seasoning effects) for loans observed shortly following origination. For seasoned loans, performance history to date constitutes a powerful predictor – knowing that a loan has remained current until the snapshot, or knowing that a loan is delinquent, or that a loan was recently delinquent or defaulted, differentiate both the overall level of risk of a particular loan, and the relevant risk factors. For delinquent and recently-delinquent (blemished) loans in particular, the delinquency serves as a primary indicator of risk, while a number of origination characteristics cease to be significant, relative to unseasoned or performing loans.

Given this behavior, and consistent with mortgage modeling best practices, PD is separately modeled for four segments. When forecasting the performance of a portfolio, each loan in-force as of the snapshot date is assigned uniquely to one segment. Loans are assigned to segments based on their age and performance history as of the snapshot date, per the table below.

Note: the RBC defined using the grids-based approach, as covered in the separate document, fixes capital at origination for performing loans, and thus is essentially a simplification of the unseasoned segment outlined in this section. One major advantage of the more detailed loan-level cash-flow model is that behavioral characteristics can inform future loss expectations; hence the proposal to use more detailed analysis should a capital plan be required.

Table 1: PD model segmentation

Segment	Age as of snapshot	Performance as of snapshot
Unseasoned	<=12 months	Any
Performing	> 12 months	Performing as of snapshot; not delinquent in past five years
Blemished	> 12 months	Performing as of snapshot; delinquent (including defaulted) in past five years
Delinquent	> 12 months	Delinquent as of snapshot (payments past due >0)

Each of the modeling segments uses a different logistic regression equation to forecast the conditional annual default rate. The equation takes the form:

Equation 1: Generalized PD model equation

$$\ln\left(\frac{PD(t)}{1 - PD(t)}\right) = \alpha + \sum \beta_i X_i(0) + \sum \rho_i X_i(t) + \sum \gamma_j Z_j(t)$$

Where:

t:	Projection year, based on calendar date
$PD(t)$:	Probability of defaulting in year *t*, conditional upon having survived to the end of year *t-1*
α:	Intercept
$\sum \beta_i X_i(0)$:	Impact of loan-level origination characteristics
$\sum \rho_i X_i(t)$:	Impact of dynamic loan-level characteristics as of the projection period (e.g. loan age, current LTV)
$\sum \gamma_j Z_j(t)$:	Impact of macroeconomic factors as of projection period *t*

3.2. Key variables tested

Based on working group discussions, a long list of potential PD variables was identified, covering origination characteristics, dynamic loan characteristics, and macroeconomic variables. The long list was driven by data availability across the full set of MIs, as well as by participants' business judgment regarding the variables that have been demonstrated as predictive in previous experience. The tables below contain the long list of independent variables considered across PD segments.

Table 2: Long list of raw loan-level PD variables (origination factors)

Variable
FICO
Origination LTV
Original UPB (inflation adjusted using US national CPI)
DTI back end
Loan amortization term
Loan purpose
Number of borrowers
Mortgage Instrument type
Negative amortization
Interest only
Balloon
Original mortgage rate

Variable
Incomplete docs
Property use
Property type
GSE loan
Lender type
Third party origination
Bulk loan
Pool loan

Table 3: Long list of dynamic loan-level PD variables

Variable
Current LTV
Current UPB (inflation adjusted)
Ever previously delinquent
Ever previously 180 DPD
Years since last delinquency
Months on book
15 year or lower term mortgage
Years with LTV > 100 (LTV burnout)
Underwriting quality proxy
In bankruptcy at snapshot
Foreclosure initiated at snapshot
Modified as of snapshot (including Modification type)

Table 4: Long list of macroeconomic PD variables

Variable
% Change in HPI
% Change in HPI (Lagged)
Unemployment rate
Unemployment rate (Lagged)
% Change in unemployment rate
Absolute change in unemployment rate
% Change in unemployment rate (Lagged)
Absolute change in unemployment rate (Lagged)

Note: For each of these macroeconomic variables, various transformations and lags were tested (e.g. one or two year percentage changes; one or two year lags).

3.3. Modeling underwriting quality

The high magnitude of rescission and denial activity, as well as the overall elevated default rates during the previous crisis, are seen as having been driven in part by weaker underwriting standards in the periods preceding the crisis. Given the treatment of rescissions and denials as defaults within the PD model (see section 5.2, below, for further details), the ability to capture the effect of underwriting quality on a given loan is important for projecting the expected default incidence of that loan. In particular for the pre-crisis vintages observed as being riskier (2004, 2005, 2006, 2007) and characterized by weaker underwriting standards, observed default incidence is likely to be higher than that which would have been experienced with stronger underwriting standards, given the same set of loan-level characteristics and macroeconomic adversity.

The options considered for capturing the effect of underwriting quality for go-forward estimation included specifying vintage dummy variables for inclusion in the model, adding back in PD residuals by vintage, and specifying a proxy variable for industry underwriting quality.

Because underwriting quality is differentiated over time by underwriting vintage, consideration centered around options for capturing predictive signal associated with a loan being underwritten in a particular vintage, which is not otherwise captured by the loan-level or macroeconomic factors included in the model. For go-forward projections, properly calibrating the impact of underwriting quality and setting underwriting quality for particular vintages would then more appropriately reflect the expected behavior of loans in that vintage.

The approach used here is to specify a proxy variable for industry underwriting quality, and include the variable in the model. The proxy variable is specified as a numerical score calculated for each quarter based on the prevalence of non-standard underwriting characteristics in the vintage. The underwriting score for a given quarterly origination vintage is defined as the balance-weighted average of the underwriting scores across all loans in that vintage.

The underwriting score for a given loan is defined as the sum of the following origination characteristics observed in that loan:

- LTV > 90% (+)
- LTV > 95% (+)[5]
- Incomplete documents (+)
- Loan purpose: refinance (+)
- Loan purpose: cash out refinance (+)
- Interest-only loan (+)

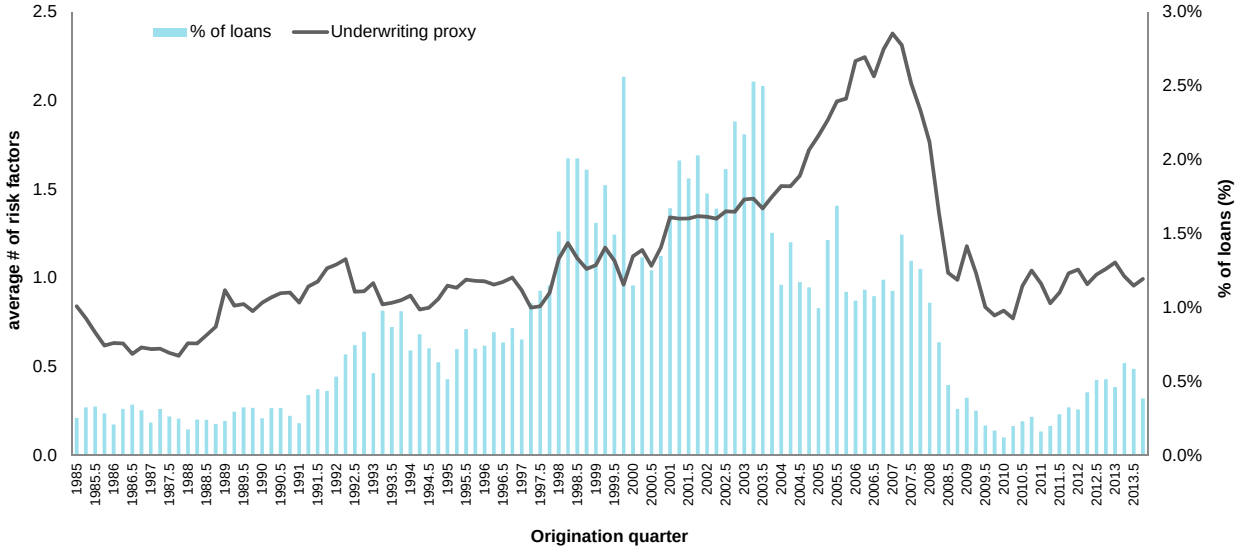
[5] LTV and refinance can cumulatively add up to 2 each to underwriting score for a loan; e.g. if a loan's origination LTV is 98%, it would be recorded as having LTV > 90% and LTV > 95%, and a cash out refi loan would be recorded as both a refinance and a cash out refinance; the cumulative scores are designed to reflect the increasing risk of some origination characteristics, which would not be reflected without additive scoring options

- Negative amortization loan (+)
- Condominium (+)
- Non-primary residence (+)
- Third party origination (+)
- 15 year mortgage (-)[6]

The underwriting score does not include FICO, although low and missing FICO loans were considered to be an intuitive indicator of underwriting risk. Because FICO is not consistently available in loan-level MI data until the early 2000s, including FICO would result in underwriting scores that were not directly comparable across different periods in history. Given the focus on capturing the impact of underwriting quality consistently through the cycle, the working group decided to exclude FICO from the underwriting proxy score.

The chart below illustrates the values of the underwriting proxy by quarterly vintage over time, as well as the number of originated loans corresponding to the vintage, from 1985 through 2013.

Figure 3: Underwriting quality proxy score by origination vintage quarter



3.4. Model specification for each segment

The PD model is specified to predict the probability of an in-force, non-defaulted loan transitioning to default. Default for the purpose of the model, is defined as any of the following:

- Loan is six months (180 days) or more past due
- An insurance claim is paid against the coverage on the loan

[6] Lower term loans are generally less risky, and demonstrated to be so in a statistically significant manner in the PD model, leading to assignment of a negative incremental score

- Insurance coverage on the loan is rescinded
- Insurance claim against the coverage on the loan is denied

Note that these last two states (rescission of coverage or denial of claim) did not result in losses to the Mortgage Insurers. However, given the high volume of rescissions and denials during the crisis, and a view that such activity would be much lower going forwards with new standards in place, the proposed approach treats all rescissions and denials as a default (and loss) to the MI. This is a highly conservative assumption, but is appropriate for a capital metric.

Table 5: Final model specification – Unseasoned PD

Variable	Odds ratio	Coeff.	Std. error	Wald Chi-Sq	Pr>ChiSq
Intercept		-2.836	0.032	8,051	<.0001
Original FICO	0.990	-0.0983	0.000	91,335	<.0001
Original FICO – where LTV is >85%	1.002	0.00208	0.000	3,076	<.0001
Lagged current LTV (0.3-0.9)	22.499	3.114	0.017	34,846	<.0001
Lagged current LTV (0.9-1.2)	5.915	1.778	0.012	22,429	<.0001
Lagged current LTV (where pool or bulk loan)	0.842	-0.172	0.003	3,191	<.0001
Months on book (up to 36)	1.026	0.0260	0.000	26,192	<.0001
Inflation adjusted lagged current UPB	1.000	1.252E-6	3.143 E-8	1,587	<.0001
Loan purpose: property improvement refinance (vs. purchase, unknown, or other)	0.916	-0.0875	0.017	27	<.0001
Loan purpose: cash out refinance (vs. purchase, unknown, or other)	1.079	0.0758	0.003	714	<.0001
Loan purpose: rate/term refinance (vs. purchase, unknown, or other)	1.089	0.0850	0.003	848	<.0001
Multiple borrowers (vs. single borrower)	0.684	-0.380	0.002	32,974	<.0001
Negative amortization – scheduled or potential	1.167	0.154	0.005	1,084	<.0001
Interest only loan	1.309	0.269	0.003	8,404	<.0001
Balloon loan	1.248	0.222	0.011	376	<.0001
Incomplete docs	1.681	0.520	0.003	38,939	<.0001

Variable	Odds ratio	Coeff.	Std. error	Wald Chi-Sq	Pr>ChiSq
Property use: secondary property (vs. primary)	1.040	0.0388	0.005	52	<.0001
Property use: investment (vs. primary)	1.634	0.491	0.004	12,138	<.0001
Lender: credit union (vs. non-credit union, mortgage broker, mortgage banker)	0.477	-0.740	0.008	7,884	<.0001
Lender: mortgage broker (vs. non-mortgage broker, credit union, mortgage banker)	1.147	0.138	0.004	1,098	<.0001
Lender: mortgage banker (vs. non-mortgage banker, credit union, mortgage broker)	1.139	0.130	0.002	3,395	<.0001
Mortgage instrument type: ARM	1.481	0.393	0.005	5550	<.0001
Mortgage instrument type: Hybrid	1.391	0.330	0.003	14,070	<.0001
Fico missing after 2000	1.094	0.0895	0.006	263	<.0001
Lower term loan	0.451	-0.797	0.011	5,133	<.0001
Underwriting proxy (<= 1.4)	5.460	1.698	0.014	14,671	<.0001
Underwriting proxy (> 1.4)	1.494	0.402	0.004	10,633	<.0001
% change in HPI during current year	<0.001	-6.930	0.015	224,984	<.0001
Change in unemployment rate over 2 years	1.100	0.0952	0.000	37,643	<.0001

Table 6: Final model specification – Seasoned Performing PD

Variable	Odds ratio	Coeff.	Std. error	Wald Chi-Sq	Pr>ChiSq
Intercept		-3.376	0.049	4,677	<.0001
Original FICO	0.993	-0.00736	0.000	31,326	<.0001
Original FICO – where LTV is >85%	1.002	0.00239	0.000	1,967	<.0001
Lagged current LTV (0.3-0.8)	44.202	3.789	0.023	27,744	<.0001
Lagged current LTV (0.8-1.5)	6.483	1.869	0.010	34,506	<.0001
Lagged current LTV	1.256	0.228	0.007	1,197	<.0001

Variable	Odds ratio	Coeff.	Std. error	Wald Chi-Sq	Pr>ChiSq
(where pool or bulk loan, LTV 0.3-0.8)					
Lagged current LTV (where pool or bulk loan, LTV 0.8-1.5)	0.318	-1.144	0.018	4,066	<.0001
Time since snapshot: 2 years	1.519	0.418	0.004	11,808	<.0001
Time since snapshot: >2 years	1.087	0.0835	0.001	4,621	<.0001
Loan purpose: cash out refi (vs. all other but cash out, rate/term)	1.145	0.136	0.004	1,005	<.0001
Loan purpose: rate/term refi (vs. all other but cash out, rate/term)	1.071	0.0682	0.004	241	<.0001
Multiple borrowers (vs. only one borrower)	0.771	-0.260	0.003	7,007	<.0001
Negative amortization – scheduled or potential	1.786	0.580	0.007	6,788	<.0001
Interest only loan	1.327	0.283	0.005	3,513	<.0001
Incomplete docs	1.424	0.353	0.004	7,179	<.0001
Property use: non-primary	1.265	0.235	0.005	2,013	<.0001
Lender: credit union (vs. non-credit union, mortgage broker, mortgage banker)	0.590	-0.528	0.011	2,272	<.0001
Lender: mortgage broker (vs. non-mortgage broker, credit union, mortgage banker)	1.170	0.157	0.007	584	<.0001
Lender: mortgage banker (vs. non-mortgage banker, credit union, mortgage broker)	1.149	0.139	0.003	1,725	<.0001
Mortgage instrument type: ARM	1.250	0.223	0.008	718	<.0001
Mortgage instrument type: Hybrid	1.447	0.369	0.004	7,664	<.0001
Fico missing before 2000	0.931	-0.0712	0.012	38	<.0001
Fico missing after 2000	1.056	0.0547	0.008	45	<.0001
Modified at snapshot: HAMP or other (vs. no mod.)	1.350	0.300	0.023	168	<.0001
Modified at snapshot: HARP (vs. no mod.)	0.588	-0.531	0.034	238	<.0001

Variable	Odds ratio	Coeff.	Std. error	Wald Chi-Sq	Pr>ChiSq
Lower term loan	0.547	-0.603	0.017	1318	<.0001
Underwriting proxy (<= 1.2)	2.300	0.833	0.033	638	<.0001
Underwriting proxy (> 1.2)	1.580	0.458	0.006	6,596	<.0001
% change in HPI during current year	0.001	-6.907	0.026	71,611	<.0001
Change in unemployment rate over 2 years	1.082	0.0791	0.001	11,522	<.0001

Table 7: Final model specification – Seasoned Delinquent PD

Variable	Odds ratio	Coeff.	Std. error	Wald Chi-Sq	Pr>ChiSq
Intercept		-1.713	0.041	1,776	<.0001
Original FICO – where LTV > 85%	1.001	0.00114	0.000	487	<.0001
Lagged current LTV (0.3-0.8)	7.481	2.012	0.032	4,092	<.0001
Lagged current LTV (0.8-1.5)	1.370	0.315	0.013	625	<.0001
Lagged current LTV (where pool or bulk loan)	0.840	-0.174	0.006	943	<.0001
Time since snapshot (2 years)	0.206	-1.581	0.005	113,940	<.0001
Months on book (<=36)	0.972	-0.0285	0.001	909	<.0001
Months on book (>36)	0.998	-0.00207	0.000	403	<.0001
Property type (condo)	1.185	0.170	0.008	512	<.0001
Multiple borrowers (vs. only one borrower)	0.841	-0.174	0.004	1,690	<.0001
Negative amortization – scheduled or potential	1.079	0.0759	0.012	44	<.0001
Interest only loan	1.088	0.0846	0.007	154	<.0001
Property use: second home	1.214	0.194	0.014	197	<.0001
Property use: investment	1.551	0.439	0.011	1,518	<.0001
Mortgage instrument type: ARM	1.252	0.225	0.010	480	<.0001
Mortgage instrument type: Hybrid	1.274	0.243	0.006	1,698	<.0001
Fico missing before 2000	0.878	-0.130	0.011	141	<.0001

Variable	Odds ratio	Coeff.	Std. error	Wald Chi-Sq	Pr>ChiSq
Modded at snapshot: HAMP or other (vs. no mod)	2.380	0.867	0.044	383	<.0001
Modded at snapshot: HARP (vs. no mod)	1.221	0.200	0.010	396	<.0001
Months delinquent as of snapshot	1.253	0.225	0.002	21,186	<.0001
% change in HPI during current year	0.005	-5.249	0.037	20,715	<.0001
Change in unemployment rate over 1 year	1.173	0.159	0.002	8,735	<.0001

Table 8: Final model specification – Seasoned Blemished PD

Variable	Odds ratio	Coeff.	Std. error	Wald Chi-Sq	Pr>ChiSq
Intercept		1.149	0.231	25	<.0001
Original FICO	0.998	-0.00235	0.000	442	<.0001
Original FICO – where LTV > 85%	1.000	0.000499	0.000	10	0.001
Lagged current LTV (0.3-0.8)	10.860	2.385	0.046	2,647	<.0001
Lagged current LTV (0.8-1.5)	2.552	0.937	0.027	1,195	<.0001
Time since snapshot: 2 years	1.448	0.370	0.010	1,476	<.0001
Months on book (up to 36)	0.902	-0.104	0.006	295	<.0001
Inflation adjusted lagged current UPB	1.000	1.328E-6	1.973 E-7	45	<.0001
Multiple borrowers (vs. only one borrower)	0.862	-0.149	0.009	276	<.0001
Property use: non-primary	1.262	0.233	0.023	106	<.0001
Mortgage instrument type: ARM	1.207	0.188	0.021	83	<.0001
Mortgage instrument type: Hybrid	1.165	0.153	0.012	167	<.0001
Previously defaulted as of snapshot	1.370	0.315	0.016	400	<.0001
# years blemished as of snapshot	0.810	-0.211	0.007	890	<.0001
% change in HPI during	0.006	-5.146	0.086	3,627	<.0001

Variable	Odds ratio	Coeff.	Std. error	Wald Chi-Sq	Pr>ChiSq
current year					
Change in unemployment rate over 2 years	1.119	0.112	0.002	2,455	<.0001

4. Prepayment models

The prepayment model estimates the probability that a loan will prepay in year *t*, conditional on having survived to the end of year *t-1*. The model estimates the probability of prepayment based on a set of explanatory variable for each loan, including origination characteristics (e.g. borrower's FICO score, loan purpose, etc.), current loan characteristics (e.g. current LTV, refinancing interest rate incentive), and macroeconomic drivers (home prices and unemployment).

4.1. Segmentation

The prepayment model has three different segments, driven by mortgage type (fixed, hybrid – fixed stage, and floating), using different equations. This segmentation reflects different drivers of prepayment behavior for different loan products. For example, for a fixed-rate loan, incentive to refinance is based on the difference between prevailing mortgage rates as of a given performance period, and rates at origination; for a floating loan, the constant spread of the floating rate makes the appropriate comparison between the current floating rate and an available fixed rate. The broad set of variables in the prepayment model includes both those that capture a borrower's incentive to prepay, as well as the ability to execute a refinance/willingness of lenders to extend credit (e.g. FICO, current LTV).

When forecasting the performance of a portfolio, each loan in-force as of the snapshot date is assigned uniquely to one of the three segments based on their underlying mortgage instrument type and lifecycle phase, per the table below.

Table 9: Prepayment model segmentation

Segment	Loan characteristics
Fixed	- Fixed-rate mortgage instrument type
Hybrid	- Hybrid mortgage instrument type - Loan is within the initial fixed phase of lifecycle, as indicated by months on book elapsed and length of initial period before first reset
Floating	- Hybrid or ARM mortgage instrument type - If hybrid, loan is within the floating phase of lifecycle, as indicated by months on book elapsed and length of initial period before first reset

Each of the modeling segments uses a different logistic regression equation to forecast the conditional annual prepayment rate. The equation takes the form:

Equation 2: Generalized prepayment model equation

$$\ln\left(\frac{\boldsymbol{ProbPrepayment(t)}}{\mathbf{1} - \boldsymbol{ProbPrepayment(t)}}\right) = \boldsymbol{\alpha} + \sum \boldsymbol{\beta_i X_i(0)} + \sum \boldsymbol{\rho_i X_i(t)} + \sum \boldsymbol{\gamma_j Z_j(t)}$$

Where:

$\boldsymbol{t}$:	Projection year, based on calendar date
$\boldsymbol{Prob\_Prepayment(t)}$:	Probability of prepaying in year *t*, conditional upon having survived to the end of year *t-1*
$\boldsymbol{\alpha}$:	Intercept
$\sum \boldsymbol{\beta_i X_i(0)}$:	Impact of loan-level origination characteristics
$\sum \boldsymbol{\rho_i X_i(t)}$:	Impact of dynamic loan-level characteristics as of the projection period (e.g. refinance incentive, current LTV)
$\sum \boldsymbol{\gamma_j Z_j(t)}$:	Impact of macroeconomic factors as of projection period *t*

4.2. Key variables tested

The key variable in prepayment modeling is the prepay incentive. This incentive depends on the current interest rate paid by the borrower and the market rate available at the time to refinance. In the prepayment model segments, this incentive was estimated and included as an independent variable to predict the rate of prepayment. The prepayment incentive for fixed-rate products was calculated as:

$$Prepayment\ Incentive\ =\ Rate\ at\ Origin\ (Ro) - Current\ Market\ Rate\ (Rm)$$

Higher origination rate compared to going market rate results in a larger savings from refinancing, and thus higher incentive for the borrower to refinance. Rate at Origin and Current Market Rate were defined separately for each of the three prepayment segments, because the effective rate paid by the borrower on fixed loans is different from that paid on a floating/hybrid loan.

A borrower who has not refinanced at a certain incentive level for a multiple years is expected to be less likely to refinance at the same incentive level in the future, even if that level of incentive is substantial. This “burnout” effect may be explained by a borrower’s sustained lack of access to refinance options, or the idiosyncratic unwillingness of a particular borrower to proceed with the refinance process at a given level of incentive. Burnout is captured in the model by creating an indicator variable that marks whether a given year in a loan’s history represents the highest level of incentive observed to date, relative to any previous year in the loan’s history. If a borrower is observed at a higher level of incentive than in the past, it is reasonable to expect burnout effects to be inapplicable, whereas continued observation at an incentive level equal to or lower than historically indicates the relative applicability of burnout. The equation below defines the incentive burnout flag:

$$Highest\ Incentive\ so\ Far\ \ =\ 1\ if\ Incentive\ for\ current\ year\ >\ all\ previous\ years$$

In addition to the prepayment incentive driven by interest rates, a further significant driver of prepayment, especially in the pre-crisis era, was the ability to “cash-out refinance”. This effect is where borrowers chose to refinance in order to extract equity from their homes, after material home price appreciation. This is captured through multiple updated LTV variables in the model.

4.3. Final prepayment model specification for each segment

Table 10: Final model specification – Fixed prepayment

Variable	Odds ratio	Coeff.	Std. error	Wald Chi-Sq	Pr>ChiSq
Intercept		-1.327	0.012	11,452	<.0001
Original FICO	1.001	0.00132	0.000	10,923	<.0001
FICO missing: originated in 2000 or prior	0.960	-0.0411	0.002	476	<.0001
Lagged current LTV (0.6-1.2)	0.100	-2.302	0.007	113,706	<.0001
Lagged current LTV (1.2-1.5)	0.107	-2.234	0.043	2,693	<.0001
Inflation adjusted current UPB	1.000	6.693E-6	2.94E-8	51,841	<.0001
Months on book (0-36)	1.005	0.00482	0.000	1,179	<.0001
Months on book (36+)	0.994	-0.00598	0.000	29,874	<.0001
Loan purpose: property improvement refinance (vs. purchase, unknown, or other)	0.979	-0.0216	0.005	20	<.0001
Loan purpose: cash out refinance (vs. purchase, unknown, or other)	0.866	-0.144	0.002	3,879	<.0001
Loan purpose: rate/term refinance (vs. purchase, unknown, or other)	0.896	-0.110	0.002	4,464	<.0001
Multiple borrowers (vs. single)	1.141	0.132	0.001	10,188	<.0001
Interest only loan	0.729	-0.317	0.005	3,867	<.0001
Balloon flag	1.522	0.420	0.006	4,812	<.0001
Incomplete docs (HPI is decreasing)	1.114	0.108	0.004	798	<.0001
Property use: non-primary (HPI is decreasing)	0.943	-0.0585	0.005	139	<.0001
Property type: condo	0.964	-0.0370	0.003	213	<.0001
Previously delinquent as of snapshot date	0.686	-0.378	0.004	8,693	<.0001
Refinance incentive: (-1-0.75%) LTV < 85%	1.782	0.578	0.002	56,026	<.0001
Refinance incentive: (0.75-1%) LTV < 85%	1.726	0.546	0.010	2,899	<.0001
Refinance incentive: (1-2%) LTV < 85%	1.045	0.0440	0.003	227	<.0001

Variable	Odds ratio	Coeff.	Std. error	Wald Chi-Sq	Pr>ChiSq
Refinance incentive: (2%+) LTV < 85%	1.134	0.126	0.002	2,707	<.0001
Refinance incentive: (-1-0.75%) LTV 85- 100%	1.740	0.554	0.006	9,522	<.0001
Refinance incentive: (1-1%) LTV 85-100%	0.853	-0.159	0.022	55	<.0001
Refinance incentive: (1%+) LTV 85-100%	0.884	-0.123	0.004	1,209	<.0001
Highest incentive so far	1.072	0.0697	0.001	2,253	<.0001
Modified as of snapshot: HARP (vs. no mod)	0.702	-0.355	0.010	1,191.	<.0001
Modified as of snapshot: HAMP or other (vs. no mod)	0.541	-0.615	0.012	2,603	<.0001
% change in HPI during current year (<0.1%)	>999.999	8.186	0.016	280,661	<.0001
% change in HPI during current year (>0.1%)	4.056	1.400	0.025	3,113	<.0001

Table 11: Prepayment model specification – Hybrid segment

Variable	Odds ratio	Coeff.	Std. error	Wald Chi-Sq	Pr>ChiSq
Intercept		-1.259	0.047	714	<.0001
Original FICO	1.001	0.00106	0.000	442	<.0001
Lagged current LTV (0.6-1.2)	0.792	-2.111	0.009	733	<.0001
Lagged current LTV (1.2-1.5)	0.947	-0.521	0.011	26	<.0001
Inflation adjusted lagged current UPB	0.121	7.137E-6	0.029	5,196	<.0001
Months on book (0-36)	0.594	0.0177	0.095	30	<.0001
Months on book (36+)	1.000	-0.0102	9.107 E-8	6,141	<.0001
Loan purpose: property improvement refinance (vs. purchase, unknown, or other)	1.018	0.0955	0.000	1,640	<.0001
Loan purpose: cash out refinance (vs. purchase, unknown, or other)	0.990	0.129	0.000	1,698	<.0001
Loan purpose: rate/term refinance (vs. purchase,	1.100	-0.0827	0.022	18	<.0001

Variable	Odds ratio	Coeff.	Std. error	Wald Chi-Sq	Pr>ChiSq
unknown, or other)					
Multiple borrowers (vs. single)	1.138	0.0759	0.009	197	<.0001
Negative amortization loan	0.921	-0.481	0.007	123	<.0001
Interest only loan	1.079	-0.623	0.005	212	<.0001
Previously delinquent as of snapshot date	0.618	-0.244	0.030	262	<.0001
FICO missing: originated in 2000 or prior	0.536	-0.233	0.010	3,584	<.0001
FICO missing: post-2000 origination	0.784	-0.0550	0.023	117	<.0001
Refinance incentive: (-1-1.5%) LTV < 85%	1.271	0.239	0.005	2,532	<.0001
Refinance incentive: (1.5-2%) LTV < 85%	1.433	0.360	0.031	134	<.0001
Refinance incentive: (>2%) LTV < 85%	1.279	0.246	0.024	105	<.0001
Refinance incentive: (-1-0.75%) LTV 85-100%	1.089	0.0853	0.006	212	<.0001
Highest incentive so far	1.133	0.125	0.007	290	<.0001
Modified as of snapshot: HARP (vs. no mod)	0.372	-0.989	0.134	55	<.0001
Modified as of snapshot: HAMP or other (vs. no mod)	0.739	-0.303	0.053	32.	<.0001
% change in HPI during current year (<0.1%)	>999.999	9.429	0.063	22,514	<.0001
% change in HPI during current year (>0.1%)	35.978	3.583	0.081	1,959	<.0001

Table 12: Final model specification – Floating prepayment

Variable	Odds ratio	Coeff.	Std. error	Wald Chi-Sq	Pr>ChiSq
Intercept		-1.204	0.029	1,757	<.0001
Original FICO	1.001	0.000581	0.000	275	<.0001
FICO missing: originated in 2000 and prior	1.062	0.0605	0.006	114	<.0001
Current LTV (0.6-1.2)	0.258	-1.357	0.011	15,972	<.0001
Inflation adjusted lagged current UPB	1.000	5.006E-6	5.417 E-8	8,543	<.0001

Variable	Odds ratio	Coeff.	Std. error	Wald Chi-Sq	Pr>ChiSq
Months on book (0-36)	1.021	0.0205	0.000	2382	<.0001
Months on book (36+)	0.995	-0.00550	0.000	8,392	<.0001
Loan purpose: rate/term refinance (vs. purchase, unknown, property improvement, or other)	0.902	-0.104	0.006	331	<.0001
Loan purpose: cash out refinance (vs. purchase, unknown, property improvement, or other)	1.164	0.152	0.005	798	<.0001
Negative amortization loan (HPI is decreasing)	0.841	-0.173	0.010	309	<.0001
Interest only loan	0.801	-0.222	0.007	980	<.0001
Incomplete docs (HPI is decreasing)	1.194	0.177	0.008	480	<.0001
Property use: secondary (HPI is increasing)	0.870	-0.140	0.010	199	<.0001
Property type: condo	0.912	-0.0917	0.006	223	<.0001
Previously delinquent as of snapshot date	0.761	-0.273	0.009	955	<.0001
Refinance incentive: (-1-2%) LTV 85-100%	1.326	0.282	0.006	1,953	<.0001
Highest incentive so far	1.090	0.0862	0.005	311	<.0001
Previously defaulted as of snapshot date	0.831	-0.185	0.036	26	<.0001
Modified as of snapshot: HARP (vs. no mod)	0.478	-0.739	0.065	128	<.0001
Modified as of snapshot: HAMP or other (vs. no mod)	0.636	-0.453	0.019	589	<.0001
% change in HPI during current year (<0.1%)	157.406	5.059	0.039	17,118	<.0001
% change in HPI during current year (>0.1%)	28.030	3.333	0.066	2,545	<.0001

5. Severity model

5.1. Potential severity paths

Loss given default is estimated in two stages. First, a defaulting loan is scored using a model that estimates the probability of the loan transitioning to one of several post-default outcomes over time, including “cure”, “cancel”, or “claim made”. Outcomes are modeled using a multinomial logistic regression, starting with a panel dataset that captures loans’ performance starting from the point of default through a final outcome. Outcomes are modeled through five years following default. Expected unresolved balances after five years are pushed to claim, due to the small percentage of balances remaining unresolved.

Second, for expected balances corresponding to “claim made”, the corresponding credit losses are modeled. For coverages under 40%, losses are estimated as a fixed multiplier of expected risk in force at the time of default. For deeper coverages, including 100% coverages, losses are estimated as a function of borrower obligation at default and expected recoveries given LTV at the time of default.

Due to the time element to incidence of claims and other outcomes, as well as the distinct timing of each (e.g. claims can occur immediately upon defaulting, cancellations may occur starting one year after, and cures can occur starting two years after), a hazard panel approach is considered appropriate.

The dependent variables in the LGD model included the possible set of outcomes a loan can undergo following default. For a given loan as of a given year, there are four possible outcomes:

- No final outcome (i.e. loan remains in-force, in default to the next period
- Cure (loan returns to current after defaulting, and remains current at least two years)
- Cancel (coverage cancels following default, without a paid MI claim
- Claim made (claim is paid, claim is denied, or coverage is rescinded)

The LGD model estimates the probability that a loan defaulted in year *t* experiences one of the possible post-default outcomes in years *t+1, t+2, t+3, t+4, t+5, t+6* (i.e. through six years following default). For the projected claim volume in each year, the model then projects a loss rate that estimates the total payment. In the context of the model, losses are projected through the 10-year overall projection horizon only, e.g. a loan that defaults in year 9 of the projection will only have one year of losses calculated (in year 10). However, this is not a material portion of losses, given the run-off assumption embedded in the forecast, and the average life of mortgage insurance (which is limited by the Homeowners Protection Act of 1998, which requires mortgage servicers to initiate MI cancellation after 22% equity is achieved).

5.2. Treatment of rescissions

One key methodological decision affecting PD modeling is determining an appropriate treatment of policy rescissions and denials, historically and going forward. During the last crisis, MIs were able to rescind or deny a material percentage of policies, both prior to and after claims related to the loans. The rescission/denial rate materially exceeded historical levels, and as a result provided considerable capital relief to MIs, lowering aggregate claim losses during the

downturn. Elevated rescission/denial rates are seen to have been driven by lax underwriting standards during the pre-crisis run-up and bubble in home prices.

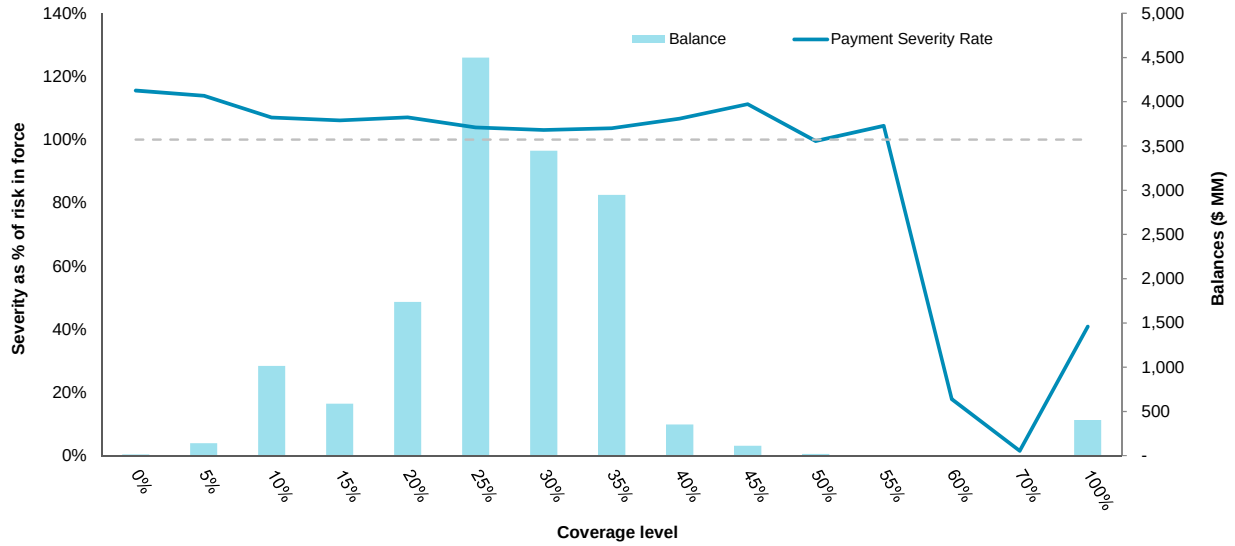
Going forward, MIs expect to be unable to rescind coverage in volumes observed during the crisis, primarily as a result of restrictions imposed by new master policy documents developed by the MIs in conjunction with the FHFA and GSEs. The policies limit MIs' ability to rescind coverage due to loans' failures to meet certain MI eligibility criteria, after a given point in the lifetime of a performing loan. As a result, both because crisis-period rescission/denial activity was historically unprecedented, and because going forward, rescission/denial activity is expected to be curtailed, the MI coalition determined that the model should not project loss relief/capital benefit from rescissions/denials when estimating capital requirements.

The selected treatment of rescissions and denials in the PD model consists in treating rescissions/denials as defaults (i.e. triggering default in addition to 180 days past due and paid claims), while including in the model a variable measuring, for each origination vintage, the prevalence of risky origination characteristics for that vintage across the industry.

5.3. Modeling approach

Based on analysis of historical loan-level data, MI coverage levels typically do not exceed 40%, except for a material share of loans with 100% coverage (primarily loans under a single pool coverage contract). For loans with coverage levels in the typical material range, loss as a percentage of risk in force was found to be relatively constant across coverage levels, slightly exceeding 100% at the time of default. This observation was intuitive given that at lower coverage levels, typical foreclosures are expected to result in losses that exhaust standard coverage, along with capitalized interest and costs increasing the extent of losses above 100% of risk in force.

Figure 4: Loss as percentage of risk in force by coverage level

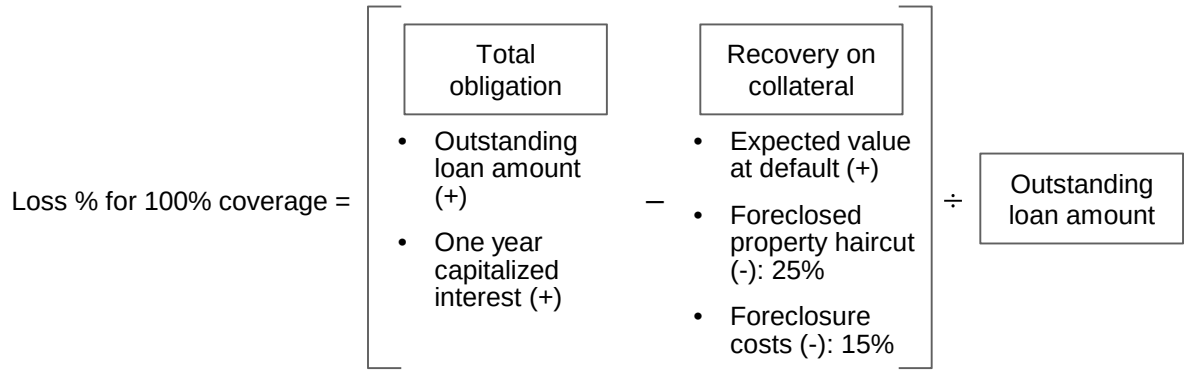


The final loss amount is a function of a loan's LTV at the time of default, because the value of the property at the time of default drives recovery amounts subtracted from the borrower's outstanding obligation. Given the relative stability for loss severity across the largest LTV

buckets, the average observed loss percentage was taken for standard coverages, estimated at 106% of risk in force at default.

For loans with deeper coverage, given the lack of data available, a formulaic approach to determining loss given claim is proposed. This is shown in figure 5 below.

Figure 5: Factors considered in loss estimate for 100% coverage loans



Impact of modifications and re-defaults

Given the uncertainty around the go-forward impact of modifications, the working group made the decision to exclude post-default modifications from the model, and to assume no modifications going forward. Due to the higher cumulative claim rates observed for unmodified loans relative to modified, this assumption was viewed as appropriately conservative given the challenges in estimating future modification incidence and impact.

The model accounts for re-default by applying a multiplier to the projected cures in each period for loans that are projected based on historical experience to re-default and lead to claim. A loan that cures may subsequently re-default at a later date, and may eventually trigger an MI claim.

The timing curve associated with historical post-default claims indicates that almost 60% of ultimate re-default claims occur by the end of the third year following the initial cure; over 90% occur by the end of the sixth year.

5.4. Variables tested in severity model

An initial list of variables was generated based on intuitive relationship with post-default outcomes and timing. Variables initially tested include time since default, estimated current LTV, current UPB, percent change in HPI, percent change in unemployment, age of the loan at default, FICO score, negative amortization, and non-standard underwriting (interest only loans, low documentation). Additional variables tested include judicial vs. non-judicial foreclosure regimes in a given loan's state (affecting overall timing of outcomes) and market subprime origination volumes at the time of default (reflecting potential ease of refinancing out of default into a subprime loan). In addition to the raw variables, interactions with LTV were tested in select cases (to reflect likelihood that a borrower would be less likely to refinance, even in a favorable origination climate, when underwater or having limited equity in the home.

The following variables from the data spec were discussed to have potential significance in the LGD model: origination FICO, negative amortization, documentation type, interest only, mortgage instrument type, and lender type. However, none of the loan-level variables were significant enough to be included in the final model.

The following loan-level derived variables were developed for the LGD model:

Table 13: LGD model candidate loan-level variables

Variable	Description
Default counter	Number of years elapsed since default
Current UPB	Current UPB based on the loans simple status and number of delinquent months currently associated with the loan
Current LTV	Current loan to value of the mortgage
Months on book at default	The age of the loan in months at the time of default
Sub-par loan flag	A flag that combines negative amortization loans, interest only loans, and non-full doc loans into a single variable
FICO	Indicative of a borrower's overall credit worthiness; potentially significant with respect to claim vs. cancel vs. cure outcome

The following US macroeconomic variables were considered for the LGD model:

Table 14: LGD model candidate macroeconomic variables

Variable	Description
Percent change in HPI	% change in annual HPI over one year
Percent change in unemployment	% change in unemployment rate over one year
Sub-prime originations ratio	Ratio of subprime originations in a given year using the year 2000 as a reference year
Sub-prime originations flag	A flag that is 1 during the years 2001-2006, which was the peak of sub-prime originations
Judicial flag	A flag that represents foreclosure regimes in a given loan's state

5.5. Model parametrization

The table below contains the regression specifications for the final post-default outcome model equation.

Table 15: LGD model final specification

Variable	Outcome	Odds ratio	Coeff.	Std. error	Wald Chi-Sq	Pr>ChiSq
Intercept	Cure		-20.179	21.705	1	0.353
Intercept	Cancel		-14.279	9.632	2	0.138
Intercept	Claim		-2.719	0.024	12,730	<.0001

Variable	Outcome	Odds ratio	Coeff.	Std. error	Wald Chi-Sq	Pr>ChiSq
	made					
Current LTV (0.4-1)	Cure	0.300	-1.203	0.057	440	<.0001
Current LTV (0.4-1)	Cancel	0.005	-5.318	0.043	15,476	<.0001
Current LTV (0.4-1)	Claim made	2.022	0.704	0.019	1,409	<.0001
Current LTV (1-2.5)	Cure	0.504	-0.685	0.035	389	<.0001
Current LTV (1-2.5)	Cancel	0.480	-0.733	0.032	515	<.0001
Current LTV (1-2.5)	Claim made	1.091	0.0875	0.008	7	<.0001
Subprime origination interaction with LTV	Cure	1.609	0.475	0.043	121	<.0001
Subprime origination interaction with LTV	Cancel	1.749	0.559	0.025	494	<.0001
Subprime origination interaction with LTV	Claim made	0.731	-0.313	0.013	615	<.0001
Sub-prime origination ratio	Cure	1.001	0.00144	0.007	0.048	0.827
Sub-prime origination ratio	Cancel	1.016	0.0162	0.004	21	<.0001
Sub-prime origination ratio	Claim made	1.108	0.103	0.002	2,717	<.0001
Unknown sub-prime origination ratio flag	Cure	1.767	0.569	0.024	555	<.0001
Unknown sub-prime origination ratio flag	Cancel	1.326	0.282	0.018	236	<.0001
Unknown sub-prime origination ratio flag	Claim made	1.095	0.091	0.008	133	<.0001
Sub-par loan flag (LTV 0-1)	Cure	0.802	-0.220	0.019	138	<.0001
Sub-par loan flag (LTV 0-1)	Cancel	1.603	0.472	0.012	1,647	<.0001
Sub-par loan flag (LTV 0-1)	Claim made	1.415	0.347	0.004	6,156	<.0001

Variable	Outcome	Odds ratio	Coeff.	Std. error	Wald Chi-Sq	Pr>ChiSq
Sub-par loan flag (LTV > 1)	Cure	0.627	-0.467	0.017	747	<.0001
Sub-par loan flag (LTV > 1)	Cancel	2.247	0.809	0.015	2,994	<.0001
Sub-par loan flag (LTV > 1)	Claim made	1.006	0.00550	0.004	1.913	0.167
Non-judicial state	Cure	2.233	0.804	0.011	5,275	<.0001
Non-judicial state	Cancel	1.802	0.589	0.008	5,024	<.0001
Non-judicial state	Claim made	2.145	0.763	0.003	61,391	<.0001
Years since default (0-1)	Cure	1.374	0.318	34.727	0	0.993
Years since default (0-1)	Cancel	>999.999[7]	15.789	9.632	2.7	0.101
Years since default (0-1)	Claim made	2.714	0.998	0.004	76,666	<.0001
Years since default (2)	Cure	>999.999[8]	17.492	27.108	0.4	0.519
Years since default (2)	Cancel	1.271	0.240	0.010	551	<.0001
Years since default (2)	Claim made	0.925	-0.0781	0.005	288	<.0001
Years since default (3)	Cure	0.522	-0.650	0.015	1,929	<.0001
Years since default (3)	Cancel	0.820	-0.198	0.015	188	<.0001
Years since default (3)	Claim made	0.828	-0.188	0.007	800	<.0001
Years since default (4)	Cure	1.041	0.0397	0.022	3	0.064
Years since default (4)	Cancel	0.885	-0.123	0.020	36	<.0001
Years since default (4)	Claim made	0.852	-0.160	0.010	256	<.0001
Years since default (5-6)	Cure	1.005	0.00455	0.017	0.070	0.791
Years since default (5-6)	Cancel	0.821	-0.197	0.016	152	<.0001
Years since default (5-6)	Claim made	0.627	-0.467	0.012	1,579	<.0001

[7] High odds ratio due to cancellations first occurring 1 year from default

[8] High odds ratio due to cures first occurring 2 years from default

Variable	Outcome	Odds ratio	Coeff.	Std. error	Wald Chi-Sq	Pr>ChiSq
Percent change in HPI (<= 0)	Cure	39.089	3.666	0.235	243	<.0001
Percent change in HPI (<= 0)	Cancel	0.240	-1.427	0.130	121	<.0001
Percent change in HPI (<= 0)	Claim made	0.285	-1.254	0.033	1,483	<.0001
Percent change in HPI (> 0)	Cure	2.918	1.071	0.165	42	<.0001
Percent change in HPI (> 0)	Cancel	285.267	5.653	0.096	3,462	<.0001
Percent change in HPI (> 0)	Claim made	0.562	-0.576	0.059	97	<.0001
Percent change in unemployment	Cure	0.581	-0.543	0.046	138	<.0001
Percent change in unemployment	Cancel	1.199	0.181	0.024	59	<.0001
Percent change in unemployment	Claim made	0.583	-0.540	0.008	4,757	<.0001
Months on book (0-24)	Cure	1.051	0.0502	0.003	339	<.0001
Months on book (0-24)	Cancel	0.995	-0.00463	0.002	9	0.003
Months on book (0-24)	Claim made	1.013	0.0125	0.001	361	<.0001
Months on book (25-36)	Cure	1.023	0.0227	0.002	127	<.0001
Months on book (25-36)	Cancel	1.013	0.0127	0.001	74	<.0001
Months on book (25-36)	Claim made	1.008	0.00821	0.001	237	<.0001
Months on book (37-48)	Cure	0.995	-0.00508	0.002	9	0.002
Months on book (37-48)	Cancel	0.972	-0.0285	0.001	463	<.0001
Months on book (37-48)	Claim made	0.997	-0.00302	0.000	42	<.0001
Months on book (48+)	Cure	0.995	-0.00492	0.000	147	<.0001
Months on book (48+)	Cancel	0.994	-0.00583	0.000	475	<.0001
Months on book (48+)	Claim made	0.995	-0.00515	0.000	1,439	<.0001

5.6. Application of models to generate loan-level cash-flows

For each loan, the models outlined above are used to determine the 10-year cash-flows, as follows:

1. Loans in the portfolio on which capital is to be calculated are aggregated, with all required origination and behavioral characteristics to execute the model
2. The required macroeconomic data is sourced
3. A number of loan-specific parameters are estimated, including estimated current loan-to-value (based on the home-price path) as well as estimated UPB (based on the loan terms and conditions)
4. The models are run, to create a 10-year vector of delinquencies and prepayments for each loan
5. For the portion of the loan estimated to be delinquent, the likelihood of claim and loss-given-claim models are applied
6. In addition, an overlay of the rules regarding termination of mortgage insurance based on the Homeowners Protection Act rules is applied. These cancellations are reduced by 36% to match observed cancellations as a percentage of expected. This increases capital requirements.
7. For the balance of loans not delinquent or prepaid, the premium cash-flow is calculated, as per section 5.7 below

5.7. Premium calculation

Premium dollars are calculated based on average balances over the course of the year (in the case of amortizing renewal premiums). Premiums are calculated based on the average of the loan's survival probability between the beginning and end of the year – reflecting the possibility that a loan terminates at some point over the course of the year, and ceases paying premiums

- For single, refundable premiums:
  - Calculate the premium paid as: $\text{premium rate} * \text{original UPB}$
  - If the loan prepays, calculate the refund as: $\text{probability of survival to current period} * \text{probability of prepayment} * \text{premium paid} * \text{percent refund}$
  - If the loan is scheduled to cancel, calculate the refund as: $\text{probability of survival to current period} * \text{probability } of\ not\ defaulting * premium\ paid * percent\ refund$
- Calculate the probability of survival to the next period as: $\text{probability of survival to current period} * (1 - \text{probability of default} - \text{probability of prepayment})$
- Calculate the average probability of survival over the course of the year as: $\frac{(probability\ of\ survival\ to\ next\ period + probability\ of\ survival\ to\ current\ period)}{2}$

- If the loan is a single premium type, the premium is 0
- For non-single premium type loans:
  - If the loan has a constant renewal, calculate the premium as: $\text{premium rate} * \text{original UPB} * \text{probability of survivial to the middle of the period}$
  - Otherwise, the loan is considered to be an amortizing renewal, so calculate the premium as:
    $\text{premium rate} * \text{average UPB for the year} * \text{probability of survival to the middle of the period}$
  - If the loan is reinsured, calculate the final premium as the portion not ceded

6. Other modeled components of capital

In addition to the loan-level cash-flows modeled using the methodology covered above, other sources and uses of capital needed to be considered when assessing the overall future solvency of the mortgage insurance firms. As per the forecast of loans, these estimates were developed assuming a run-off book (rather than ongoing originations).

6.1. Expenses

MI expenses over the projection period are modeled as two components, which together encompass the full MI expense base:

- Loss adjustment expense (LAE)
- Expenses other than loss adjustment (EOLA)

LAE, which is driven by losses incurred by an MI, is forecast as a function of projected credit losses. EOLA, which is dependent on the overall size of the MI's business, is forecast as a ratio of projected premiums

6.1.1. Loss adjustment expense

The equations below describe the logic for forecasting LAE used in the model, as well as the historical average industry LAE ratio that the logic is based on. LAE is estimated based on losses incurred (as opposed to paid) by MIs.

$$LAE_t = Average(Loss_{t-1}, Loss_t) * Historical\ Industry\ LAE\ ratio$$

$$Historical\ Industry\ LAE\ ratio = \frac{\sum_{2003}^{2012} Average(Loss_{t-1}, Loss_t) * \ LAE_t}{\sum_{2003}^{2012} Average(Loss_{t-1}, Loss_t)}$$

Given the relative stability of LAE as a percentage of losses, the model estimates LAE as a constant ratio of losses projected by the model. The model forecasts LAE as a ratio of the previous two years' loss experience. As-of year-end 2013 the ratio of LAE to two-year losses calibrated based on industry experience, which is used to project LAE in the model, is **3.81%**.

6.1.2. Expense other than loss adjustment

Expense other than loss adjustment (EOLA) includes the “Other Underwriting Expense” and the “Investment Expense” line items captured by MIs’ statutory financial statements. Investment-related expenses are included with other expenses because of their immaterial size (historically averaging approximately 2% of expenses unrelated to losses).

In the model, ELOA is projected as a constant function of projected premiums for the MI loan book. An MI’s non-loss expense is broadly reflective of the size of the firm’s business, as well as its particular expense structure. It is expected, therefore, that when projecting an MI’s portfolio on a runoff basis, the gradual reduction in the size of the in-force portfolio will be reflected in a reduction of the MI’s expense requirements, but at a slower rate. . For the purpose of testing the combined portfolio, the industry’s 2011-2012 average non-loss expense ratio of **23%** was utilized.

6.2. Investment income

The capital model estimates the investment income earned by the MI over the projection period as a function of the overall starting level of claims-paying assets, portfolio mix, and estimated future yields. Investment income on MI assets is calculated using simplified yield projections, consistently with the starting level of claims-paying resources, as well as the cash flows (losses, premiums/refunds, and expenses) over the course of the 10-year projection period.

The investment income projection estimates future income for the following four asset classes of unaffiliated investments held by an MI:

- Long term bonds
- Cash and short term investments
- Equity investments
- Other invested assets (e.g. partnerships, private equity)

An MI’s portfolio mix between different asset classes is assumed to remain constant over time. The actual asset mix at the time of the portfolio snapshot used for projection governs the way that balances are distributed over the full projection period.

The total yield is defined as the average income from four different portfolios, with bond yield playing the key role.

6.2.1. Investment asset balance calculation

Asset balances are calculated for each annual projection period, starting from the initial balances specified as a model input. Asset balances evolve over time to reflect projected cash flows, including sources (premium income), and uses (paid claims, premium refunds, and expenses) of assets. Asset balances for a year-end of a given projection year t are described by the equation below.

Equation 3: Asset balance calculation

$$Asset\ Balance_t(YearEnd) =$$
$$=Asset\ Balance_{t-1}(YearEnd) + Premiums_t - Losses_t - Expenses_t + InvestmentIncome_t$$

6.2.2. Long term bond income

Income on MIs' long term bond portfolios is calculated by assuming reinvestment of maturing balances at a constant spread, given an underlying portfolio maturity profile and a projected interest rate path (consistent with the interest rate path used for credit loss forecasting).

Equation 4: Long-term bond income calculation

$$Income_t = Average(Bond\ Balance_{t-1}, Bond\ Balance_t) * Yield_t$$

Equation 5: Long term bond balance calculation

$$Bond\ Balance_t = Asset\ Balance_t * \left(\frac{Bond\ Balance_{t-1}}{Asset\ Balance_{t-1}}\right)$$

Equation 6: Long term bond yield calculation

$$Yield_t = Yield_{t-1} * \{1 - [1/(2 * m)]\} + [1/(2 * m)] * (r + s))$$

6.2.3. Cash and short-term investment income

Income on cash and short-term investments is calculated by projecting short-term investment balances (as a constant share of the overall investment balances projected as described in **Equation 3**), and estimating a yield based on the three month treasury reference rate.

Equation 7: Short-term income calculation

$$Income_t = Average(ShortTerm\ Balance_{t-1}, ShortTerm\ Balance_t) * Yield_t$$

Equation 8: Short-term yield calculation

$$Yield_t = 3 - month\ treasury\ rate_t$$

6.2.4. Equity income

Income on unaffiliated equity investments is calculated by projecting equity balances (as a constant share of the overall investment balances projected as described in **Equation 3**), and estimating a yield based on the MI's historical yields on equity assets, except in outlier years.

Equation 9: Equity income calculation

$$Income_t = Average(EquityBalance_{t-1}, EquityBalance_t) * Yield_t$$

Equation 10: Equity yield calculation

$$Yield_t = Average\ yield\ on\ equities, 2004 - 2013; excluding\ outlier\ years$$

6.2.5. Other invested assets income

Income on other invested assets is calculated by projecting balances in other invested assets (as a constant share of the overall investment balances projected as described in **Equation 3**), and estimating a yield based on the MI's historical yields on other invested assets, except in outlier years.

Equation 11: Other invested assets income calculation

$$Income_t = Average(OtherAsetsBalance_{t-1}, OtherAssetsBalance_t) * Yield_t$$

Equation 12: Other invested assets yield calculation

$$Yield_t = Average\ yield\ on\ equities, 2004 - 2013; excluding\ outlier\ years$$

7. Approach to determining minimum capital

The minimum capital requirement is the amount of starting claims-paying resources that is sufficient to remain solvent over the projection horizon. A mortgage insurer is expected to be solvent if the starting claims-paying resources exceed the minimum amount. Within the RBC approach, proposed firm-level floors to capital requirements are in place.

Within the model, the cash-flow components, outlined above, are applied for each year in the forecast to the starting capital position, to determine the year-end available resources.

Available capital resources are composed of MI surplus, with loss, contingency, and unearned premium reserves added in (as losses for defaulted loans and expected premium refunds are estimated by the loan-level credit loss forecasting model). The available starting claims-paying resources also take into account legally bound contingent capital that may be available to the

MI, as well as investments in unconsolidated subsidiaries (subject to a haircut). The table below lists the components in additional detail.

Table 16: calculation of starting capital position

Starting capital component		Comments
+	Surplus as regards policyholders	Source: annual statement, P3, L37, C1
+	Loss reserve	Source: annual statement, P3, L1, C1
+	Statutory contingency reserve	Source: annual statement, P3, L2501, C1
+	Unearned premium reserve	Source: annual statement, P3, L9, C1
+	Legally binding contingent capital	As specified by MI
-	Haircut to investments in subsidiaries	Unconsolidated affiliates (i.e. US non-MI entities or non-US entities), are treated as investments in the model, and subject to a haircut when calculating starting available capital resources
=	Total available capital resources	

8. Summary of back-testing results

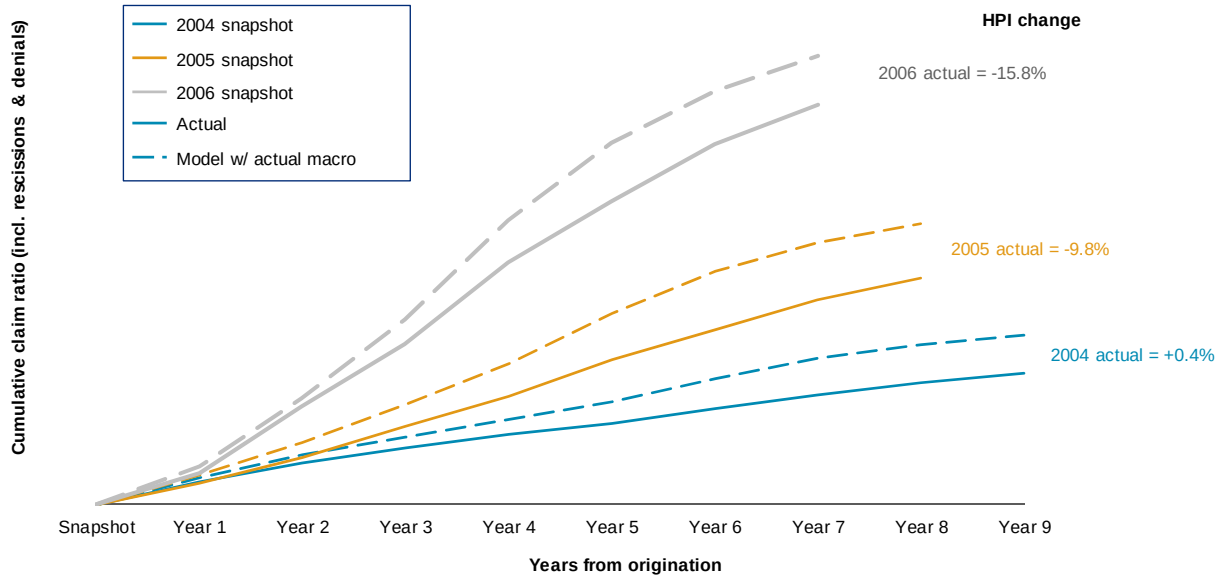
In addition to back-testing individual model components, back-testing was performed on the aggregated credit loss projection engine. Back-testing was run on both the in-sample and 20% holdout sample reserved from model fitting. The projection engine was run starting from a given snapshot date, and projected subsequent loan performance through 2013. For example, for a 12/31/05 snapshot, 2006-2013 would be projected.

The engine was set to project each loan-level model, including defaults, prepayments, claim outcomes, and losses, under the actual observed local (MSA or state) HPI paths and national unemployment path observed during the projection period. Projection results were compared with actual loan-level behavior over the projection period, both per period and cumulatively. Back-testing was performed on all snapshots from 2003 through 2010.

8.1. Delinquency model back-test

The model back-tests relatively well. As shown below, during the crisis period, the model predicts slightly higher claims-rates than actual for each portfolio (snapshot) held through the crisis years, if actual realized macroeconomic paths are used.

Figure 6: Cumulative claims ratios by snapshot year



Cumulative claim ratio is defined as % of starting insurance in force as of snapshot date projected to transition to claim (or transitioning to claim, rescission, or denial) through 12/31/2013
HPI drop for actual macro path measured from snapshot through post-crisis trough HPI level

8.2. Loss given default back-test and adjustment to the claims rate for delinquent and defaulted loans

The initial back-test results showed that the model was over-predicting claims for loans that were defaulted or delinquent as of the snapshot. Therefore, the actual and predicted claims were compared for the three snapshots with the highest stress over the actual performance window. The table below provides the actual and predicted claim rates for defaulted loans using the actual MSA-level HPI path.

Table 17: Defaulted to claim rate for 2007-2009

	2007	2008	2009
Historical actuals (A)	70%	71%	63%
Actual macro path (B)	80%	78%	78%
Scaling ratio (A/B)	87%	91%	81%

While the results from the model projection based on the actual macro path are fairly stable across the snapshots, the historic actuals are consistently lower than predicted claim rates with an average over-prediction of 17% from 2007 to 2009.

For loans that are delinquent as of the snapshot, the model under-predicts claims in 2007 but over-predicts claims for the 2008 and 2009 snapshots. The table below gives the actual and predicted claims scaling ratios for loans that are delinquent as of the snapshot date from 2007 to 2009.

Table 18: Delinquent to claim rate for 2007-2009

	2007	2008	2009	Scale (07-09)
1 month (non-defaulted)	120%	98%	61%	93%
2 month (non-defaulted)	114%	91%	60%	88%
3 month (non-defaulted)	122%	98%	64%	95%
4 month (non-defaulted)	120%	95%	66%	94%
5 month (non-defaulted)	116%	101%	71%	96%
6+ month and defaulted	87%	91%	81%	86%

Based on this analysis, the claims rate is adjusted downward by 13.7% and 7.1% for defaulted and delinquent loans respectively as of the snapshot to more closely match the actual claim rates.

Part B: Macroeconomic parametrization and translation to grids

9. Summary of parametrization required to determine capital

The forecasting models described in Part A of this document enable an interested party to determine the full anticipated cash-flows for a specific book of loans, and have been applied in this case at the consolidated US Mortgage MI level, on a firm-by-firm basis. However, in addition to loan-level and asset information, the model requires a specification of future macroeconomics in order to develop a forecast of losses, prepayments, and investment income.

The proposed RBC grids were developed with a specific proposed parameterization of future macroeconomic variables. The adverse nature of this future scenario is what defines the confidence interval of the proposed capital. Given the business activities of the Mortgage Insurance segment, the most sensitive macroeconomic assumption is future home price development. As currently proposed, the parameterization is 'counter-cyclical', in that the size of the home-price shock applied is a function of where the current home price index is relative to a pre-established long-term trend.

Specific data series used for the macroeconomic parameters are:

- House price index – FHFA All Transactions index, available from FHFA 1975-present[9]. This can be applied at various levels of granularity, down to the MSA-level. Critically, this is used to estimate mark-to-market loan to value of mortgages through time, at the loan level.
- US unemployment rate (spot and natural) at the national level – available from Federal Reserve Economic Data (FRED).
- US interest rates (US Treasuries and 30 year mortgage rates) – also available from FRED.

The remainder of this document outlines the proposed macroeconomic scenario input in the model to develop the forecasts of required capital used in the parameterization of the RBC grids.

10. Approach to forecasting home prices

10.1. Key dimensions for consideration

Given the countercyclical nature of the model, a number of key decisions are required when projecting future home prices:

a) *Establishing a long-term trend:* This is required to determine the size of the home price drop applied in the capital model, by providing a comparison point for the latest value of the home price index.

[9] http://www.fhfa.gov/Default.aspx?Page=87

b) *Determining a trough relative to that trend*: Given this is a capital metric – rather than an expected value – a trough relative to the trend is required. This reflects the fact that US home prices have been observed to 'over-correct', and dip below trend.

c) *Establishing a path over the 10-year forecast:* The correction in home prices, from latest observed index levels, to trough, and then a return to trend will not occur instantly. Decisions as to the path of this evolution are therefore needed.

d) *Granularity and potential dispersion multiplier:* Losses – and hence capital – are non-linear with respect to home prices. As a result, dispersion in shocks will increase required capital. The model was developed on MSA-level home price observations, however developing forecasts at that level is a challenge and hence decisions on granularity are required.

10.2. Establishing a trend with PCI

The proposed approach specifies a conditional scenario with a severity level calibrated by comparing the starting level of HPI to the long run trend in HPI. The methodology for specifying a home price path is based on a 2012 FHFA publication discussing the design of a counter-cyclical capital regime[10]. While the proposed approach is related to that proposed by Smith and Weiher, the proposed approach is not identical. Specifically, the proposed approach uses the full home price series to determine the trend, to prevent subjective decisions on when the pre-crisis real estate bubble started. In order to not over-state the trend, however, the HPI projection is forecast as a function of per-capita income (PCI). This is aligned with an intuitive macroeconomic relationship expected between income levels and housing prices over the long-term.

The proposed approach to determining the trend is shown below, and is the output of a simple regression between the HPI index and PCI.

Equation 13: PCI relationship to HPI

$$\ln(HPI) = a + b * \ln(PCI)$$

This methodology incorporates a rolling regression for the trend so that each trend point is estimated based on the previous historical values only. Therefore, the relationship between HPI and PCI is defined as

Equation 14: Long-run nominal HPI trend equation

$$HPI_t = \exp(a_t + b_t * \ln(PCI_t))$$

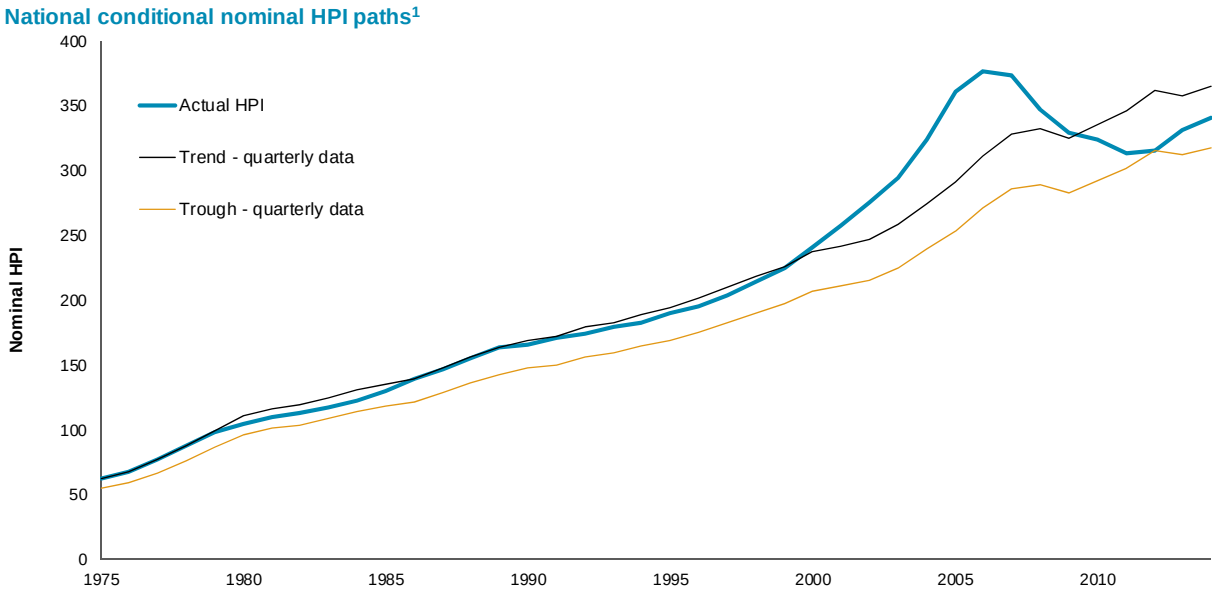
Where a_t and b_t are coefficients for time t estimated on historical values from time 1 to t.

.

[10] Scott Smith and Jesse Weiher, "Countercyclical Capital Regime: A Proposed Design and Empirical Evaluation", FHFA Working Paper, April 2012

This methodology may be impacted by differences between PCI and HPI, which may be significant in the shorter term. However, this methodology was chosen because it employs the most up-to-date PCI data, which allows for an accurate reflection of changing trends.

Figure 7: Illustrative Home Price forecast approach



10.3. Trough definition

The HPI shock is calibrated by leveraging the observed HPI fluctuations above and below trend. In a downturn, as HPI corrects from an elevated level, it tends to decrease below the trend (i.e. over-correct), before subsequently recovering toward the trend level. The extent of over-correction has varied in different downturns. The proposed approach captures the lowest historical level of HPI relative to the long-run trend as a “historical trough”.

The size of this tough is 12.9% below trend. This was the largest observed national deviation from trend, since 1975 (when data became available). While certain regions had larger observed deviations below trend, the national trough is applicable given the diversified nature of the current MI portfolios. While non-diverse portfolios may be envisaged in the future, this is addressed in the proposed capital framework through an on-top multiplier for overly concentrated portfolios (see RBC Instructions for further details).

In addition, in unlikely cases where the actual regional index is below the estimated trough, the model has been set such that there is no home price appreciation during the stress (i.e. home prices stay flat).

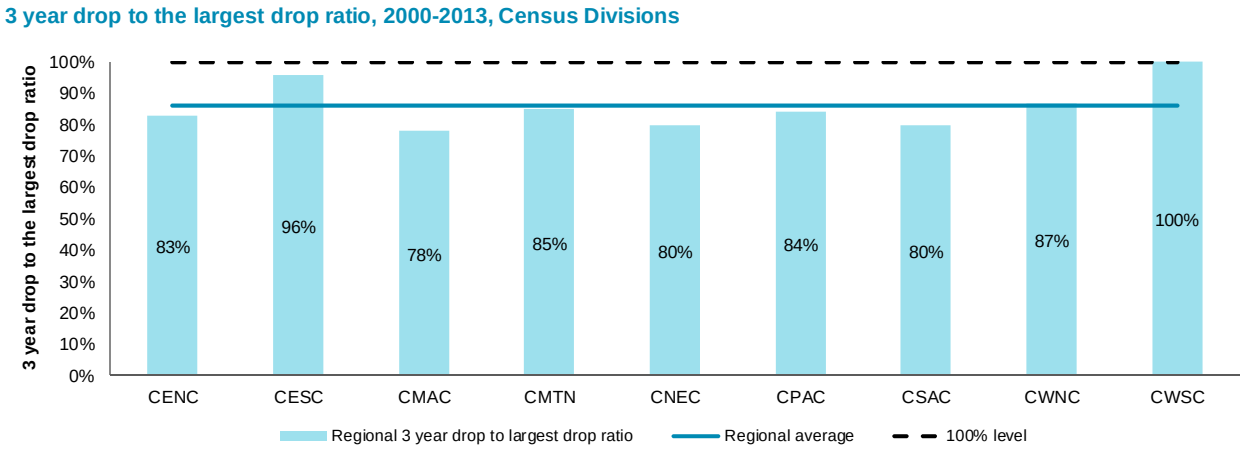
10.4. Path over 10-year projection

The proposed 10-year HPI path follows a 3-4-3 year timing pattern. Projection years 1-3 are the period where HPI declines from the starting level to the historical trough target. In projection years 4-7, HPI remains at the trough level. Finally, in years 8-10, HPI recovers from the trough level to the long-run trend level projected for that year based on continued real HPI growth and the inflation forecast.

This path is actually quicker than the observed decline in home prices during the 2008 crisis, when home prices declined over a four-year timeframe. However, this may have been impacted by the first time homebuyer tax credit (2009 – 2010), which may have supported home prices for a period of time during the declines.

Figure 8: Observed regional HPA peak-to-trough magnitude and time-lines

	CENC	CESC	CMAC	CMTN	CNEC	CPAC	CSAC	CWNC	CWSC	Reg.avg.	US
Most severe peak to trough	-16%	-8%	-13%	-30%	-16%	-35%	-26%	-9%	-4%	-17%	-18%
Time from peak to trough (years)	5.25	3.25	5.25	4	6.25	5.25	5.25	3.25	2.25	4.4	5.25
Most severe 3 year peak to trough	-14%	-8%	-10%	-25%	-13%	-29%	-21%	-8%	-4%	-15%	-15%
3 year drop to the largest drop	83%	96%	78%	85%	80%	84%	80%	87%	100%	86%	83%



10.5. Granularity and dispersion multiplier

Home prices forecasts are modeled at a US census division level, as this appropriately balances capturing nuances beyond the national level with pragmatism. Strong correlation in home prices is observed at these census levels, as their core macroeconomics are similar.

However, the parametrization of the model outlined in Part A uses MSA-level mark-to-market LTV in specification of the parameters using historical observations. Given the non-linear relationship between LTV use of less granular mark-to-market forecasts will miss the impact of home price path dispersion. In order to address this, based on testing of differences in loss forecasts between MSA and census level home prices, a dispersion multiplier of 12% is added to the model for all non-defaulted loans.

11. Approach to other macroeconomic forecasts

11.1. Unemployment

The proposed approach for specifying the unemployment rate path is a fixed target level of unemployment, with a minimum absolute increase from the unemployment rate as of a given snapshot date. The table below illustrates the parameters of the unemployment path.

Table 19: Parameters included in unemployment rate scenario specification

Component	Specification
Unemployment series used	US unemployment rate, annual average
Target unemployment rate level	10%
Annual rate of increase to target	3% (absolute)
Minimum increase in unemployment rate	3.5% (absolute)
Annual rate of decrease after target	0.7% (absolute)
Minimum unemployment rate following recovery	Projected natural rate of unemployment

The approach to specifying an unemployment path was chosen to be consistent with the intended goal of counter-cyclicality in the capital framework. Using a fixed 10% target promotes counter-cyclicality as the path is expected to be more adverse (greater annual increases in unemployment) when projecting from a benign economic environment.

11.2. Rates

Consistently with monetary policy undertaken by the Federal Reserve in recent downturns, rates in a stress scenario are expected to decline and to remain low for the bulk of the scenario. Given the comparable severity of the specified scenario path to the recent crisis, as well as the highly accommodative monetary policy pursued by the Federal Reserve through 2013, interest rate levels in 2009-2013 are an appropriate proxy for the level of rates that may be expected in a stress scenario. Therefore, in a stress scenario, rates at each maturity are expected to decline to the average level for that maturity observed in 2009-2013. If projection begins in a very low rate environment (e.g. projecting 2014-2023 as of the end of 2013), where current rates are lower than the 2009-2013 average, rates will be projected to remain at that lower level, rather than increase to the 2009-2013 average.

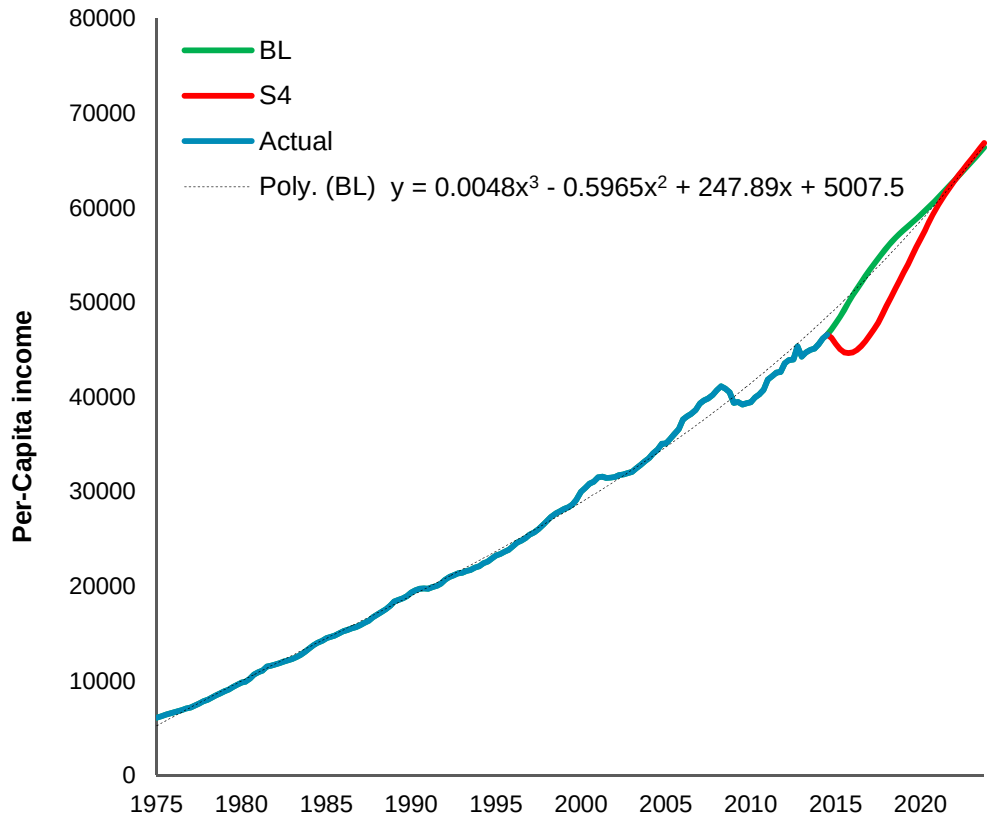
Consistently with the timing of the HPI shock path, years 1-7 of projection reflect a downturn environment, while years 8-10 reflect recovery. Therefore, rates are projected to remain at low levels through year 7. In years 8-10, rates are projected to revert, in a straight line fashion, to forward rates for the given maturity, as forecast for 10 years out as of the snapshot date.[11]

[11] Kamakura Corporation forward interest rate forecasts used to specify target rate levels in recovery

11.3. PCI

An adverse PCI forecast is required in order to fully capture the anticipated home price path, given the specified relationship between the two outlined above. The proposed approach is to use Moody's Economy.com "S4 severely adverse" scenario. The figure below portrays the per-capita income forecasts for the Moody's base and S4 scenarios.

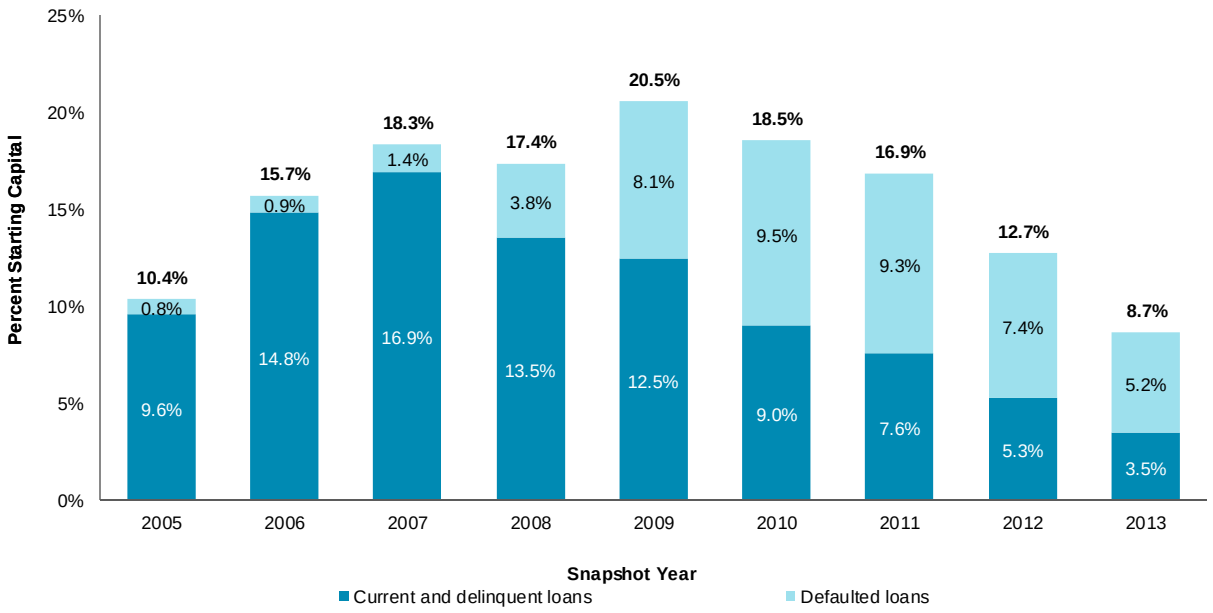
Figure 9: Moody's per-capita income forecasts



12. Capital output using proposed macro scenarios

As expected, the model produces a counter-cyclical capital requirement for the industry as a whole, with materially higher capital requirements in the run-up to the crisis. Following the crisis, capital on performing loans reduces, as the portfolio composition becomes less risky with higher quality originations, and the size of the home price shock reduces to reflect actual regional HPI indices getting closer to long-term trend. Material resources continue to be required for defaulted loans, prior to claims being resolved. The majority of this would be covered by reserves.

Figure 10: Estimate of required resources by year-end portfolio



13. Translation of cash-flow model into RBC grids

The loan-level cash-flow model detailed in sections above is not the primary approach proposed to determine capitalization – the RBC grids proposed will form the key test of capital. The specification and instructions for use of these grids is included in separate documentation. However, the grids themselves were parameterized using the loan-level cash-flow model. The remainder of this document covers the approach used to do so.

13.1. Overview of RBC principles

The RBC grids are a simplification of the loan-level model. At the core, the proposed construct is similar to the Private Mortgage Insurer Eligibility Requirements (“PMIERs”) developed by the GSEs and issued by the FHFA. This is by design, to where possible allow comparability between the two approaches.

At the core, the RBC approach seeks to replicate the dynamics of the loan-level model, albeit at a simplified level of detail. Nonetheless, proposed grids calculate the losses, premiums and other elements of the capital stack for each loan. The main grids, as in PMIERs, are defined by the origination LTV of the loan, and origination FICO of the borrower. A number of additional risk factors are included to capture the most significant drivers of risk observed in the detailed cash-flow model. A trade-off between parsimony and fully capturing all risk factors was made to arrive at the final proposed list. In addition, the risk factors multipliers in the RBC grids are applied in log-space, which is aligned with the application of the logarithmic regression methodology used in the cash-flow model.

In addition, the proposal has RBC capital fixed at origination – rather than evolving through time – for all loans except those that are observed to be delinquent (in which case they have much higher capital from a separate grid).

13.2. Approach to counter-cyclicality

Each grid developed reflects a specific loss or premium path observed in the model given a defined home price path. Given the desired development of a counter-cyclical approach to capital, five distinct sets of grids have been developed, representing different magnitudes of home price shock. These were created though the application of such shocks to a synthetic portfolio of loans, created from a sample of the full dataset originated over the past 10 years.

The selection of which grid to use is based on the distance of the quarterly actual home price index from the trend, as per the loan-level model. The minimum home price drop was selected at 10%. For specific rules, see the RBC instructions document.

13.3. Construction of synthetic portfolios

A set of stylized portfolios is used to calibrate the grid values; these stylized portfolios contain a subset of the full loan dataset with specific characteristics. A synthetic dataset, rather than the historical dataset, was used to remove ‘normalize’ the data and enable the impact of individual risk characteristics to be isolated and quantified. Additionally, various risk factors are correlated, especially when considering the effects of multiple risk multipliers for a single loan. Creating a synthetic dataset prevents these unwanted correlations from being present in the calibrations. This synthetic dataset creates a monotonic risk portfolio that is therefore unbiased by multiple risk factors being present for the same loan.

A new synthetic dataset is created for each grid to be calibrated. Each dataset is created such that there is a loan for every type of bucket, risk factor, origination, etc. used in the calibration grids. Therefore, there is a loan for every possible risk permutation that could exist for a specific grid. For portfolios with bucketed variables (e.g. FICO score), those buckets contain the balance weighted average of the loans that fall within that bucket.

13.4. Estimation of additional risk factors

If a loan is performing, then the claim risk is calculated using the result of the claim incidence grids plus the compilation in the log-odds space of a series of different risk-factors – underwriting risk, negative amortization, incomplete documentation, single lender, credit union origination, non-primary residence, and low-term loan—associated with the loan. These risk factors are captured through multipliers on the claim incidence grids, and were calibrated based on the impact of these risk factors on the loss estimates in the loan-level cash-flow model.

When defining the original grid, all loans that contained other risk factors were excluded from the calibration.

For example, the calibration to determine the risk factor for non-full documentation did not include other loans with additional risk factors (e.g. not fully amortizing). This prevents a biased

risk factor calculation for each loan characteristic. All loan-level multiplier grids are determined by calculating the claims percentage of all loans when the given risk factor is null vs. not null. Additional risk factors are always equal to zero for delinquent and defaulted loans.

Once a loan is assigned a claim incidence rate and a series of risk factor variables, the RBC model generates a performing loan claims risk value in two steps.

1. The model converts the claim incidence rate to log-odds to match the additional risk factor variables and sums all applicable risk factor values:

$$Log\ odd\ adjusted\ claim\ rate = \ln\left(\frac{claim\ incidence\ rate}{1-claim\ incidence\ rate}\right) + applicable\ risk\ factor\ values$$

2. The model converts the sum back to a probability:

$$Claim\ rate = \frac{\exp(\log odd\ adjusted\ claim\ rate)}{1+\exp(\log odd\ adjusted\ claim\ rate)}$$

By this approach, for example, a loan with a 12.4% claim incidence rate, with an UW log-odds risk factor of 0.63, an incomplete documentation log-odds risk factor of 0.50, and a credit union log-odds risk factor of -0.78 would have a claim rate of 16.7%.

Although ultimately selecting a log-odds approach for combining the claim incidence rate with the applicable individual risk factor variables, a multiplicative as well as an additive approach were also considered. The reason that log-odds are proposed is twofold:

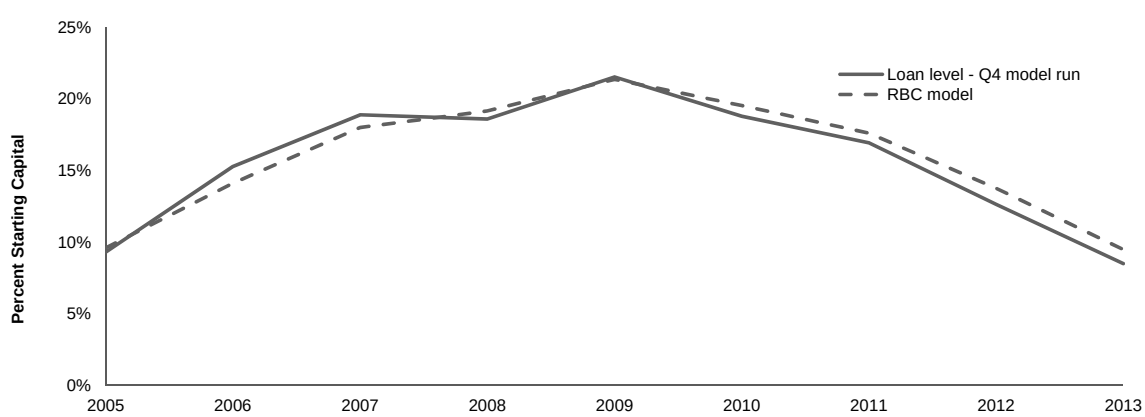
1. The log-odds approach is best able to capture the nuances of multiple layered risk-factors, without under or overstating the relevance of variables

2. The log-odds approach appropriately matches the mathematics of logistic regression used by the loan-level model (for more information, see the loan level model documentation description of the PD model)

14. Comparison of RBC approach capital with loan-level

Overall, RBC model outputs align well with loan level outputs, as per the figure below.

Figure 11: Capital requirements by snapshot, all vintages, full portfolio



For the full portfolio aggregate data sample shown above, the RBC model is closely aligned with the loan level model when the loan level model is run as of Q4 of each snapshot year. In the early snapshot years, loan level model capital slightly exceeds RBC model capital, but in the later years, RBC model capital is slightly above the loan level outputs.