BLACKROCK SOLUTIONS®

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BRS Mortgage Model Primer

Executive Summary

This document provides a granular description of the data framework, methodology and model structure of the BlackRock Solutions version 5.2 mortgage model suite. BRS mortgage models are statistically estimated models that project loan performance based on macro-economic variables, government policy, collateral attributes and trends in borrower behavior. At a high level, macro-economic models (used to project unemployment, home price appreciation and existing home sales) and the mortgage rate model (used to compute the appropriate mortgage rate that drives refinancing incentive) interact with the agency and non-agency models, which are estimated separately given the inherent difference in borrower profile, collateral characteristics and treatment of credit risk. Projections are computed for prepayments, delinquency, default and severity. While prepayments are captured for agency and non-agency mortgages, delinquency, default and severity are only projected on non-agency mortgages, given their explicit credit exposure. The model projections are aggregated to provide collateral cash flow projections. In addition, collateral cash flows are then passed through a deal waterfall to calculate a broad array of bond analytics (including both interest rate risk and credit risk metrics).

BRS constantly monitors mortgage model performance using a variety of forecast error reporting as well as by analyzing in-sample and out-of-sample validation data. Model adjustments are made if the model deviates substantially from actual performance.

Home Price Appreciation Model

The BRS agency models utilize FHFA home price indices and the non-agency models utilize Case-Shiller constant-quality home price indices provided by Fiserv in order to construct HPA estimates and mark-to-market loan-to-value ratios. The indices are calculated from data on repeat sales of single-family homes and are produced monthly. Due to the impact of home price appreciation and loan-to-value ratios on many aspects of mortgage performance, granular home price data is used in several components of the BRS mortgage models.

The BRS short-term home price model uses macroeconomic variables such as unemployment, mortgage rates, existing home sales and housing market indicators (distressed property share) when projecting HPI over the next 12 months. It also adds home price momentum and applies adjustments due to seasonal fluctuations. Expectations in timing of the HPA curve trough and the speed and slope of the recovery from the trough are driven by the last four quarters of historical data, affordability metrics and the long term HPA model.

While both the FHFA HPA and Case-Shiller HPA models project home price indices on the state and national level, the Case-Shiller HPA model also projects home price indices separately for the 40 Metropolitan Statistical Areas with the largest balance of securitized non-agency loans in the LoanPerformance data set. The list of 40 MSAs that are now modeled separately is shown in Table 1. This set comprises about 75% of all loans in the LoanPerformance data. In addition to these MSAs the model will continue to project HPA on the state, District of Columbia, and the US aggregate level. Chart 1 shows observed dispersion in HPI dynamics across MSA, even within the same state.

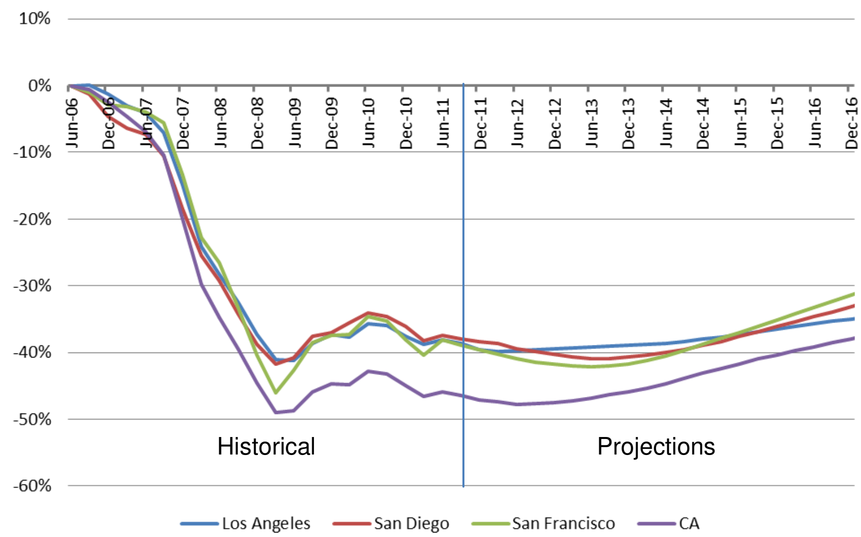
Table 1: List of Modeled MSAs

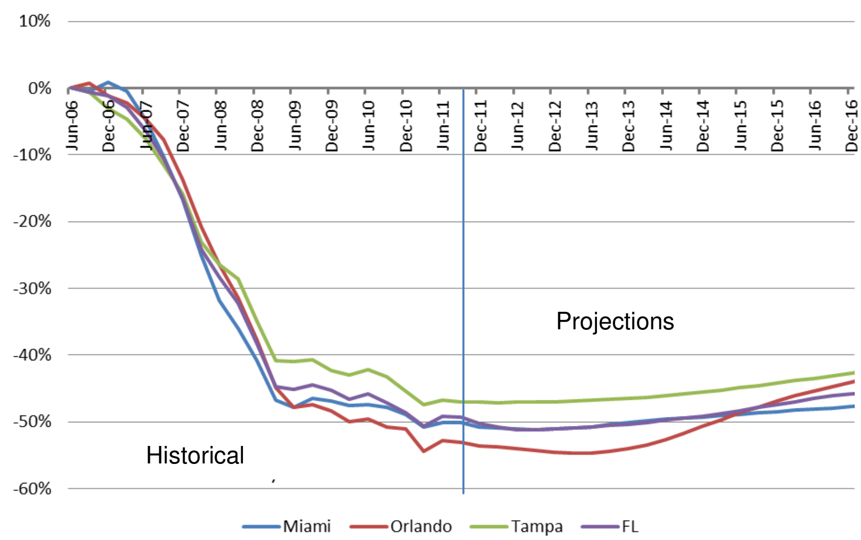
MSA Name	State	MSA Name	State
Phoenix-Mesa-Glendale	AZ	Miami-Fort Lauderdale-Pompano Beach	FL
Los Angeles-Long Beach-Santa Ana	CA	Orlando-Kissimmee-Sanford	FL
Oxnard-Thousand Oaks-Ventura	CA	Tampa-St.Petersburg-Clearwater	FL
Riverside-San Bernardino-Ontario	CA	Atlanta-Sandy Springs-Marietta	GA
Sacramento-Arden-Arcade-Roseville	CA	Honolulu	HI
Salinas	CA	Chicago-Joliet-Naperville	IL
San Diego-Carlsbad-San Marcos	CA	Boston-Cambridge-Quincy	MA
San Francisco-Oakland-Fremont	CA	Providence-New Bedford-Fall River	MA,RI
San Jose-Sunnyvale-Santa Clara	CA	Baltimore-Towson	MD
Santa Barbara-Santa Maria-Goleta	CA	Detroit-Warren-Livonia	MI
Santa Cruz-Watsonville	CA	Minneapolis-St.Paul-Bloomington	MN
Santa Rosa-Petaluma	CA	Charlotte-Gastonia-Rock Hill	NC
Stockton	CA	Wilmington	NC
Vallejo-Fairfield	CA	Virginia Beach-Norfolk-Newport News	NC,VA
Denver-Aurora-Broomfield	CO	Las Vegas-Paradise	NV
Bridgeport-Stamford-Norwalk	CT	New York-Northern New Jersey-Long Island	NY,NJ,PA
Washington-Arlington-Alexandria	DC,MD,VA,WV	Portland-Vancouver-Hillsboro	OR
Philadelphia-Camden-Wilmington	DE,MD,NJ,PA	Dallas-Fort Worth-Arlington	TX
Cape Coral-Fort Myers	FL	Houston-Sugar Land-Baytown	TX
Jacksonville	FL	Seattle-Tacoma-Bellevue	WA

The BRS long-term home price model predicts trends using historical average home prices adjusted by inflation. The model is reviewed on a quarterly basis and adjustments are made in response to structural economic changes as indicated by macro-economic factors such as unemployment, income growth, and mortgage rates.

The transition period between the short term and long term models occur over a specified time frame with the FHFA model fading from the short to long term over 9 quarters and the Case-Shiller model fading over 15 quarters.

Chart 1: Select California and Florida MSA level HPA versus Corresponding State MSA



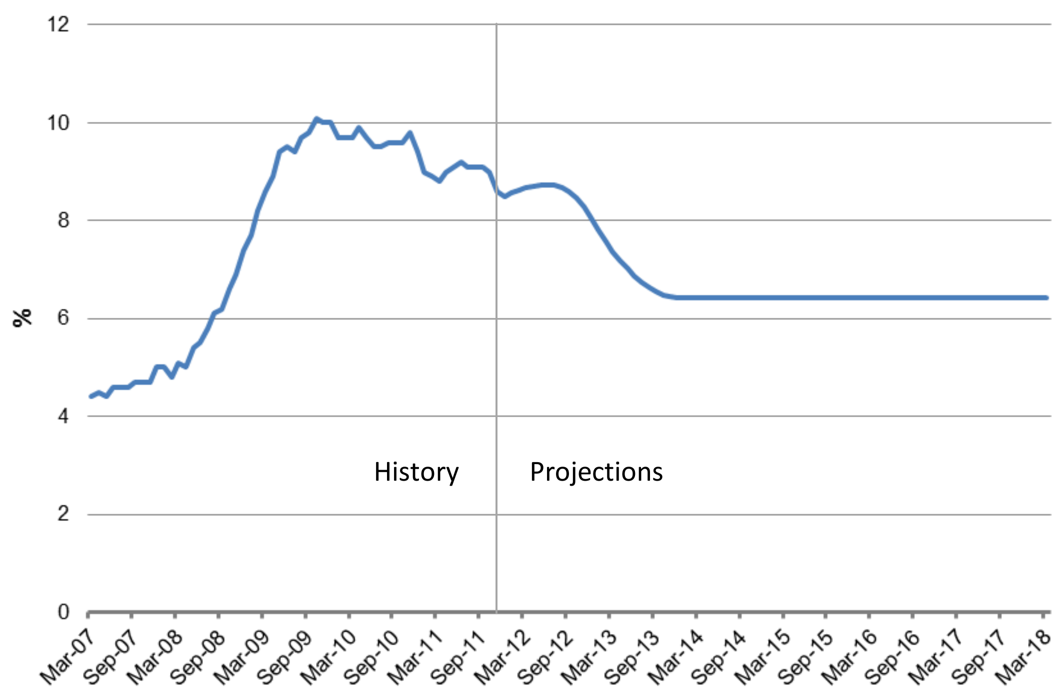


Source: Case-Shiller and BRS

Unemployment Rate Model

Unemployment rates are projected on the state level. Unemployment is projected using both a short term and long term model with a transition period in between. In the short term the unemployment rate is modeled using a regime switching process. We assume that there are two states in the economy, “recession” and “expansion,” and estimate the constant probability of switching between the two regimes. In each state the unemployment rate is a momentum based process with different coefficients and parameters. In the long term we assume the unemployment rate to be equal to the state level long run average. We use the short term model for 9 months with a transition period of 36 months between the short term and long term phases. Chart 2 illustrates our current unemployment projections.

Chart 2: BRS US Unemployment Rate Projections



Source: Bureau of Labor Statistics and BRS

Existing Home Sales Model

The percentage of Existing-Home Sales (EHS) is a key input into the BRS mortgage model, providing a proxy for the overall level of housing turnover. The EHS index is provided monthly by the National Association of Realtors (NAR). Given that EHS and home prices are positive correlated the Home Price Appreciation model is an input into the EHS model. As a result long term home price views are incorporated into EHS projections. The EHS model uses lagged 30-year mortgage rates and lagged moving average of real HPA to form projections of EHS. Lagged 3-month moving average EHS is used to smooth kinks in projections caused by idiosyncratic jumps in EHS. Chart 3 illustrates the current EHS projections.

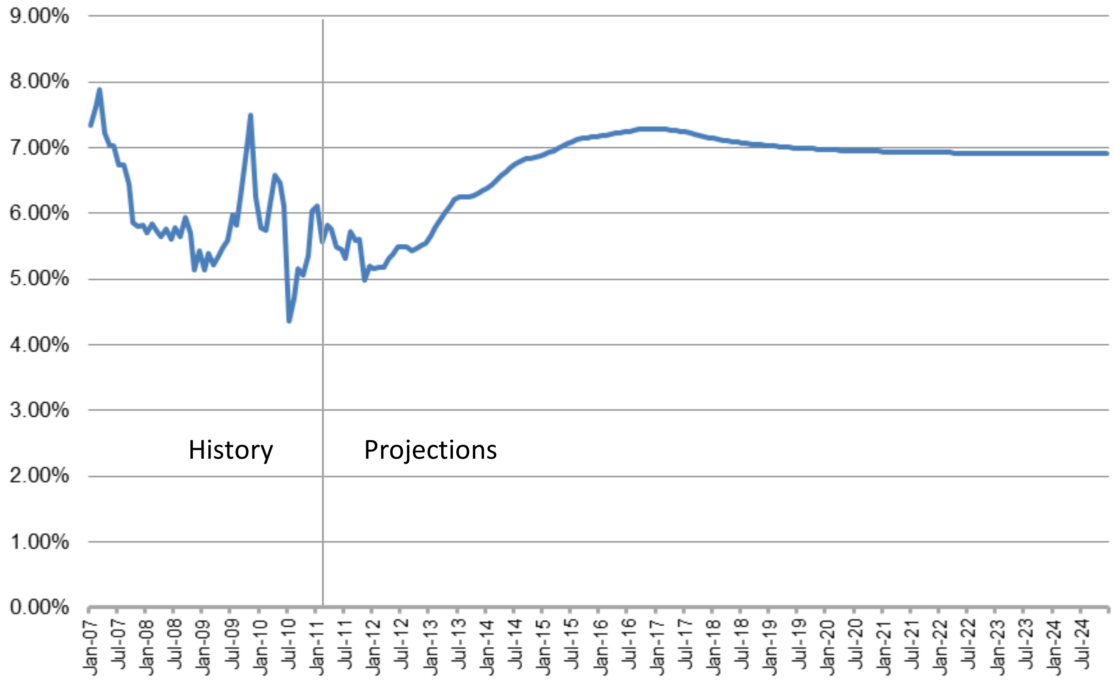
$$EHS(t) = 0.497 - 0.017 * PMMS_{t-2} + 0.3972 * EHS_{t-12} + 1.1251 * HPA\_12MA_{t-3} + \beta$$

Where β is equal to:

$$\beta = 1.2854 * \max(HPA\_12MA_{t-3} - HPA\_Cap, 0) - 0.9798 * \min(HPA\_12MA_{t-3} - HPA\_Flr, 0)$$

PMMS is the 30 year Freddie Mac primary mortgage market survey rate (refer to the Mortgage Rate Model section of the primer for more details) and HPA_12MA is the 12 month moving average of the monthly US Case-Shiller HPI growth rate.

Chart 3: BRS EHS Model Projections



Source: NAR and BRS

Introduction

The ability to project forward primary mortgage rates (estimated via the Primary Mortgage Market Survey (PMMS) rate) is an integral component of MBS valuations. The PMMS rates reflect interest rate payments made by mortgage borrowers and impact the cash flows received by MBS investors. The secondary mortgage rates are determined by the PMMS rates adjusted for servicing, guarantee, and origination fees.

Most of the complexities in valuing MBS arise from the borrowers' options to prepay their mortgage at any time. While prepayments can occur for a number of reasons, the PMMS rate directly affects the borrower's decision to refinance the existing mortgage into a new loan at a lower rate i.e. PMMS is the rate available for eligible borrowers refinance into. The type of rate used to calculate the refinance incentive depends on the mortgage product type held by the borrower.

This section of the primer aims to provide a comprehensive overview of the BRS primary mortgage rate models. After describing BRS's estimation of today's primary mortgage rate for different MBS products, this paper goes on to describe how we project forward PMMS rates into the future.

Primary Mortgage Rate Models

The basic structure of the mortgage rate model is that a spread is added to some underlying rate(s). BRS uses different methodologies to compute the mortgage rate based on the type of mortgage product. Broadly speaking there exist three distinct categories; Conventional 30/15-year mortgages, 1/1 ARMs and Hybrid ARMs. Jumbo and Alt-A mortgages are based on the conventional mortgage rate model of similar product types while Balloons are run using the Hybrid ARM model. For valuation of the 30-year fixed FHA mortgages we construct a mortgage rate based on a spread to the conventional 30-year fixed rate.

Conventional 30Y/15Y Mortgages

Conventional fixed mortgage rates are projected based on the Freddie Mac primary mortgage market survey rate (PMMS). Freddie Mac quotes official PMMS rates on a weekly basis (quoted on Thursday reflecting Monday's data) which represent the average mortgage rates for the past week. The daily primary mortgage rate is obtained by synchronizing the weekly PMMS rate to the dynamics of the secondary mortgage rate (TBA par coupon). This is completed as follows:

- Estimate today's primary market rate implied by the quoted PMMS rate. The change in the PMMS rate from Monday to today is estimated using the change in the observed secondary market rate on both dates

$$Adjusted\ PMMS_{today} = Published\ PMMS_{Monday} + (Par\ Coupon_{today} - Par\ Coupon_{Monday})$$

The primary mortgage rate is projected forward by adding a spread (primary-secondary spread) to the projected secondary mortgage rate (par coupon):

$$Primary\ Rate(t) = Par\ Coupon(t) + spread(t)$$

The par coupon in the primary mortgage rate projection is based on the blended rate and mortgage basis as shown in the below equation.

$$Par\ Coupon(t) = Blended\ Rate(t) + Mortgage\ Basis(t)$$

Mortgage Rate Model

The blended rate is calculated as follows:

- Take the 2Y CMS, 5Y CMS and 10Y CMS Mortgage Bond Equivalent (MBE) rates
- Take the 1x10 ATM normal swaption volatility value
- Compute a ‘blended rate’ as

$$Blended\ Rate = \alpha_1 \times 2Y\ CMS + \alpha_2 \times 5Y\ CMS + \alpha_3 \times 10Y\ CMS + \alpha_4 \times 1x10\ Swaption\ \ Vol$$

- α_1, α_2, α_3 and α_4 are empirically estimated blending coefficients and are currently set to 0.17, 0.35, 0.36 and 0.31 respectively for 15-year MBS and to 0.08, 0.22, 0.55 and 0.47 respectively for 30-year MBS.

The mortgage basis is projected forward based on the spot mortgage basis value and a long term assumption. In general, the mortgage basis is projected according to:

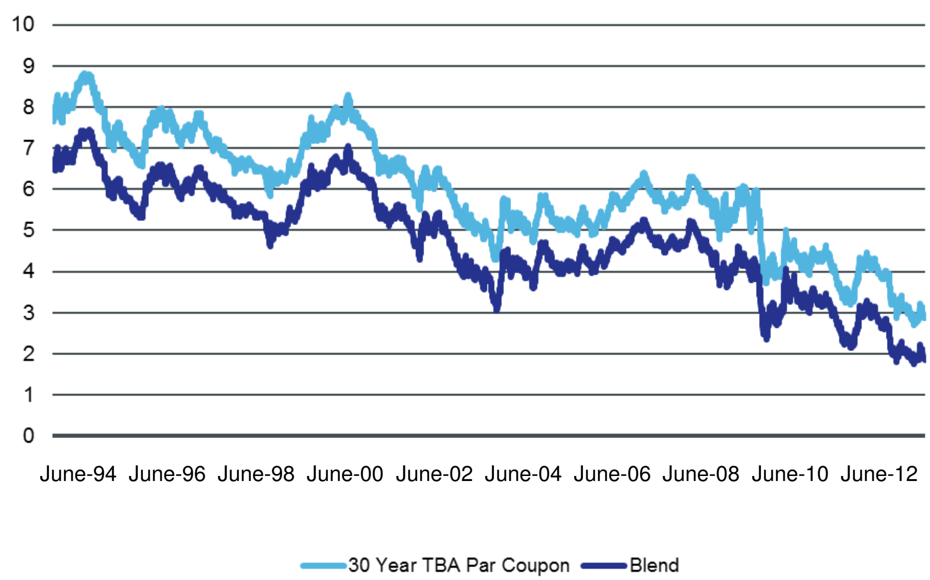
$$Mortgage\ Basis(t) = Long\ Term\ Basis + \beta^t\,(Mortgage\ Basis(0) - Long\ Term\ Basis)$$

Decay speed $\beta < 1$ implies mean reversion in the mortgage basis to the long term basis. Unlike the primary-secondary spread, the default assumption for mortgage basis is $\beta = 1$, i.e., no mean reversion. In this case:

$$Mortgage\ Basis(t) = Mortgage\ Basis(0)$$

However, the model can accommodate various assumptions for the long term mortgage basis and speed of conversion. For instance, users can specify the time length to calculate long term basis as a moving average of historical values based on 1, 2, 3, 4 or 5 years of recent history. Alternatively, users can specify the numerical value for the long term assumption. Separately, users can specify the speed of decay of the basis to the long term basis assumption. See Chart 4 for historical values of 30-year TBA par coupon and corresponding blend values.

Chart 4: 30-Year Par Coupon and Underlying Blend



The spread in the primary mortgage rate equation is projected through the primary-secondary spread model. This model has the flexibility to capture any flat g-fee increase by the GSEs. The primary-secondary spread is projected based on the 12-month history of the par coupon. This captures both the increase in loan applications and capacity constraints of the lenders. During the periods of high and/or increasing rates, the demand for borrowing weakens and lenders cut the work force and decrease the processing capacity. If rates subsequently drop, the demand for borrowing spikes although it takes some time to build up adequate capacity. The primary-secondary spread widens until the capacity is built. The model is able to capture the spikes in primary-secondary spread in the periods of rapid mortgage rate decline (Chart 5). The primary-secondary spread is computed as:

$$spread(t) = 0.946 - 0.793 ParCpn(t-1) - 0.259 Media(t-1) + \lambda^{t} error$$

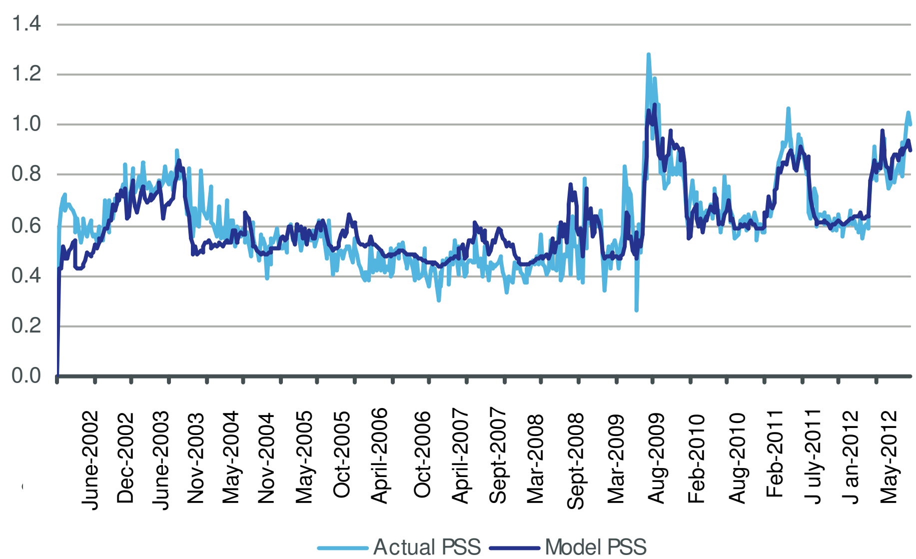
The dynamics of mortgage rates is captured by the media effect, which is the difference between the recent and the 12-month moving average of the par coupon:

$$Media(t-1) = ParCpn(t-1) - \frac{1}{N}\sum_{k=1}^{N} ParCpn(t-1-k)$$

The error term in the primary-secondary spread is the difference between the actual and model primary rates at time 0:

$$error = PSS(t_0) - [0.946 - 0.793 ParCpn(t_0 - 1) - 0.259 Media(t_0 - 1)]$$

Chart 5: BRS Primary-Secondary Mortgage Rate Spread Fit (In-sample)



Source: Freddie Mac, BRS

Hybrid 5/1 ARM and Hybrid Jumbo

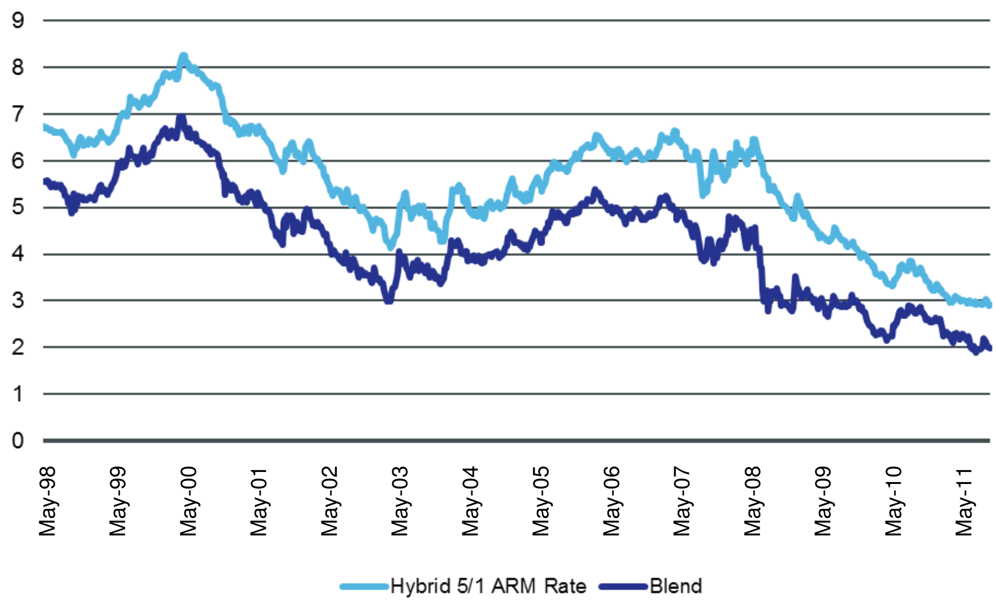
Quotes for hybrid mortgage rates are provided by HSH Associates on a weekly basis. These rates are delivered on Friday night and are aligned mid-week (Wednesday). Hence daily adjustment is required similar to the fixed mortgage rates. The 5/1 conforming hybrid rate projection will affect the conventional fixed-rate speed projection through the mortgage yield curve effect. The 5/1 hybrid conforming mortgage rate is projected as a spread over the primary 30-year fixed mortgage rate adjusted by the LIBOR curve slope as shown in the following equations:

$$Hybrid_{5/1}\ Blend(t) = 30\ Year\ Primary\ Rate(t) - 0.33 * (10YCMS(t) - 2YCMS(t))$$

$$Hybrid_{5/1}\ Rate(t) = Hybrid_{5/1}\ Blend(t) + spread_{5/1}(t)$$

The spread projection starts by truing-up to the current spread level and then exponentially reverting to the long term spread with a 6-month half-life. The long term spread is calculated as a 2-year moving average of historical spreads. The yield slope (the difference between the primary 30-year fixed mortgage rate and the average of 3/1 and 5/1 hybrid rates) is independent of the primary/secondary spread.

Chart 6: Hybrid 5/1 ARM Rate and Underlying Blend



Source: HSH Associates, BRS

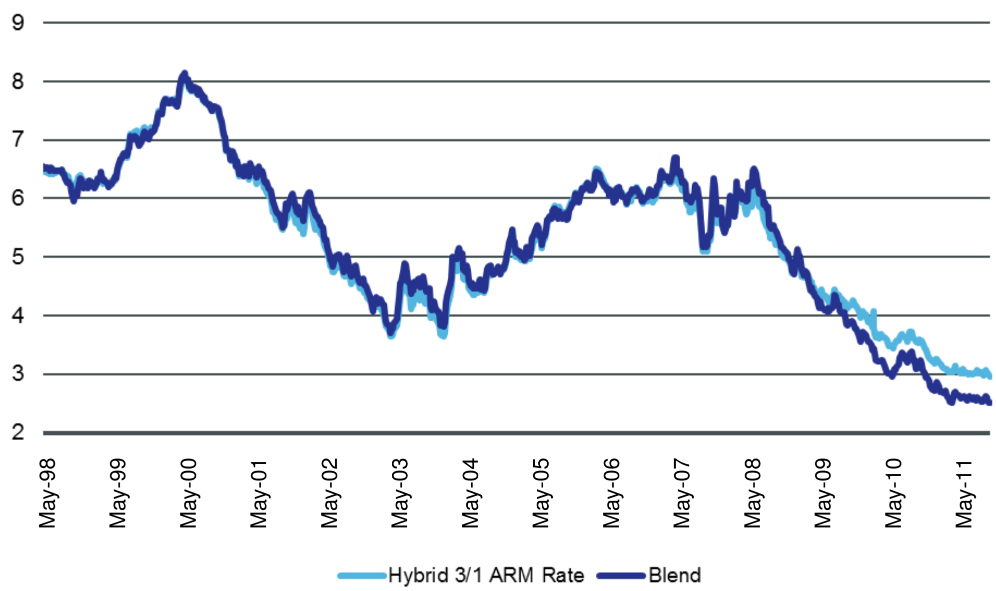
Hybrid 3/1, 7/1 and 10/1 ARM

The 3/1, 7/1 and 10/1 conventional hybrid rates are adjusted and projected using the 30-year fixed mortgage rate and the 5/1 conventional hybrid rate:

$$Hybrid_i\ Blend(t) = 30\ Year\ Primary\ Rate(t) * \alpha_i + Hybrid_{5/1}\ Rate(t) * \beta_i$$

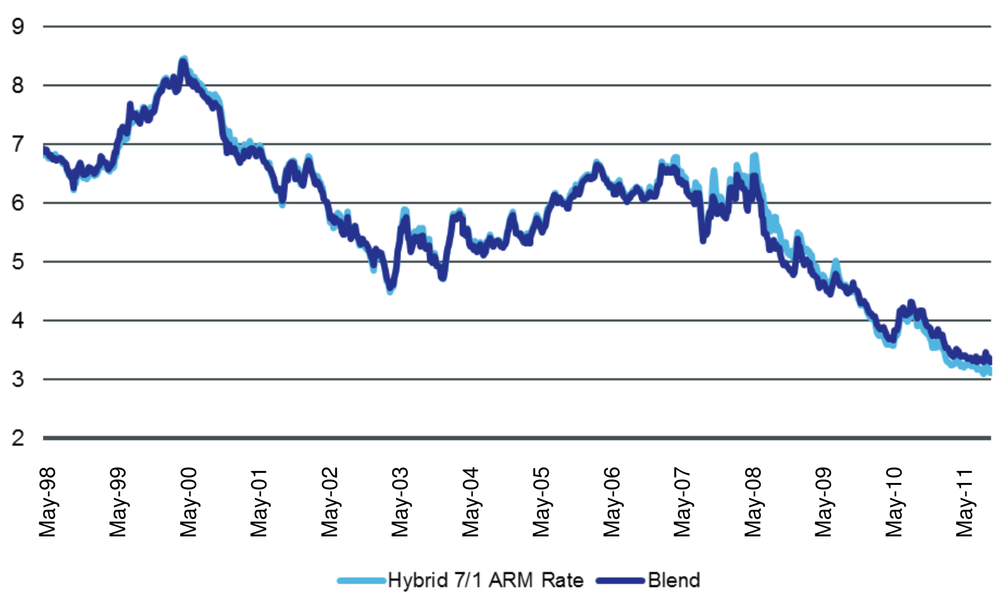
where coefficients are different for 3/1, 7/1 and 10/1 hybrid rates. The coefficients are empirically estimated and are equal to -0.4 and 1.4, 0.4 and 0.6, 0.8 and 0.2 correspondingly. See Charts 7-9 for historical values of HSH hybrid rates and corresponding blends.

Chart 7: Hybrid 3/1 ARM Rate and Underlying Blend



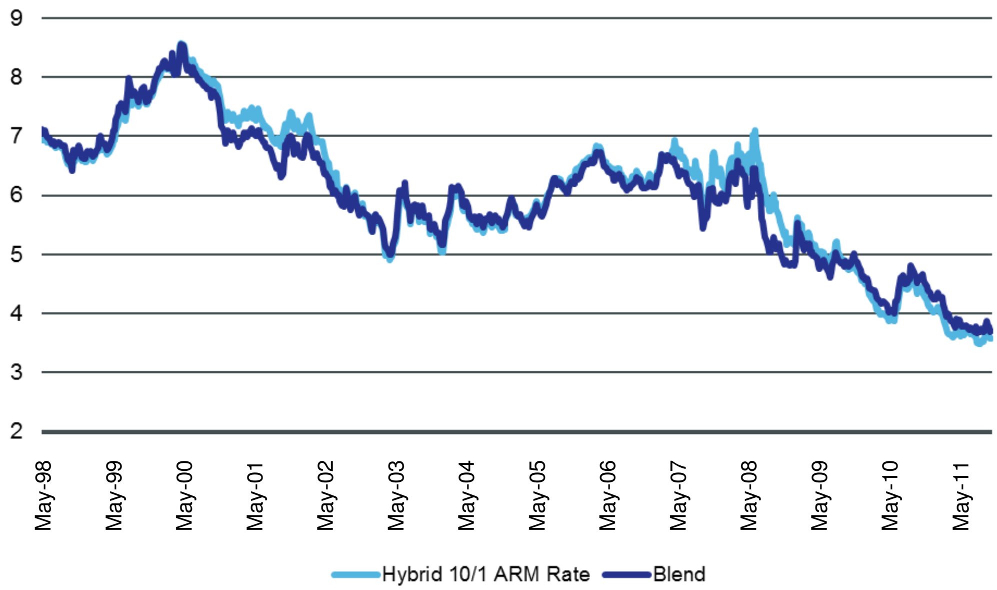
Source: HSH Associates, BRS

Chart 8: Hybrid 7/1 ARM Rate and Underlying Blend



Source: HSH Associates, BRS

Chart 9: Hybrid 10/1 ARM Rate and Underlying Blend



Source: HSH Associates, BRS

Using these blends, we find daily adjusted hybrid rates:

$$Adjusted\ HSH\ Hybrid_i\ Rate_{today} = HSH\ Hybrid_i\ Rate_{Wednesday} + (\ Hybrid_i\ Blend_{today} - Hybrid_i\ Blend_{Wednesday})$$

Forward hybrid rate projections are as follows:

$$Hybrid_i\ Rate(t) = Hybrid_i\ Blend(t) + spread_i(t)$$

Similar to the other mortgage rates, the spread is projected starting from the difference between the daily adjusted rate and corresponding blend on analysis date, converging to the long term assumption with exponential decay of 6 month half life:

$$spread_i(t) = LongTermSpread_i + \lambda^t spread_i(0)$$
$$spread_i(0) = Adjusted\ HSH\ Hybrid_i\ Rate(0) - Hybrid_i\ Blend(0)$$

where $LongTermSpread_i$ is assumed to be a 2 year moving average of corresponding historical spreads. Note that spreads and coefficients in the blends are different across different hybrid rates. Chart 10 shows hybrid rate and 30year primary rate projections.

ARM 1/1

Consistent with BRS's conventional hybrid rate model, the $ARM_{1/1}$ PMMS rate is estimated using 1-year CMS rates and volatilities. The rate is estimated using the 45-day moving average of 1-year CMS rate and the 1x10 ATM normal swaption volatility.

$$ARM_{1/1}\ PMMS\ Rate = \alpha + \beta_1 \times 1Y\ CMS + \beta_1 \times 10Y\ CMS + \beta_3 \times \log(VOL_{1X10})$$

α, β_1, β_2 and β_3 are empirically estimated coefficients and currently set at -2.527, 0.519, 0.363 and 0.480 correspondingly. Daily adjustment is done similar to the hybrid rate adjustment using the above blend. In projections, the spread also starts from the analysis date actual spread and converges to zero with 6 month half life exponential decay.

Alt-A

The primary mortgage rate for Alt-A loans is based off of a spread to the conventional 30Y/15Y model. This spread is a function of collateral type, FICO, LTV, investment property and the average original loan size (AOLS) of the Alt-A loan.

Prime Jumbo

The primary mortgage rate for Prime Jumbo loans is based off of a spread to the conventional 30Y/15Y model. The spread is trued up to the last observed Jumbo to conforming spread and is gradually decayed to a long-term average, linearly over 24 months period. The spread is further adjusted as a function of collateral type, FICO, LTV, investment property and the average original loan size (AOLS) of the Jumbo loan.

30-year Fixed FHA

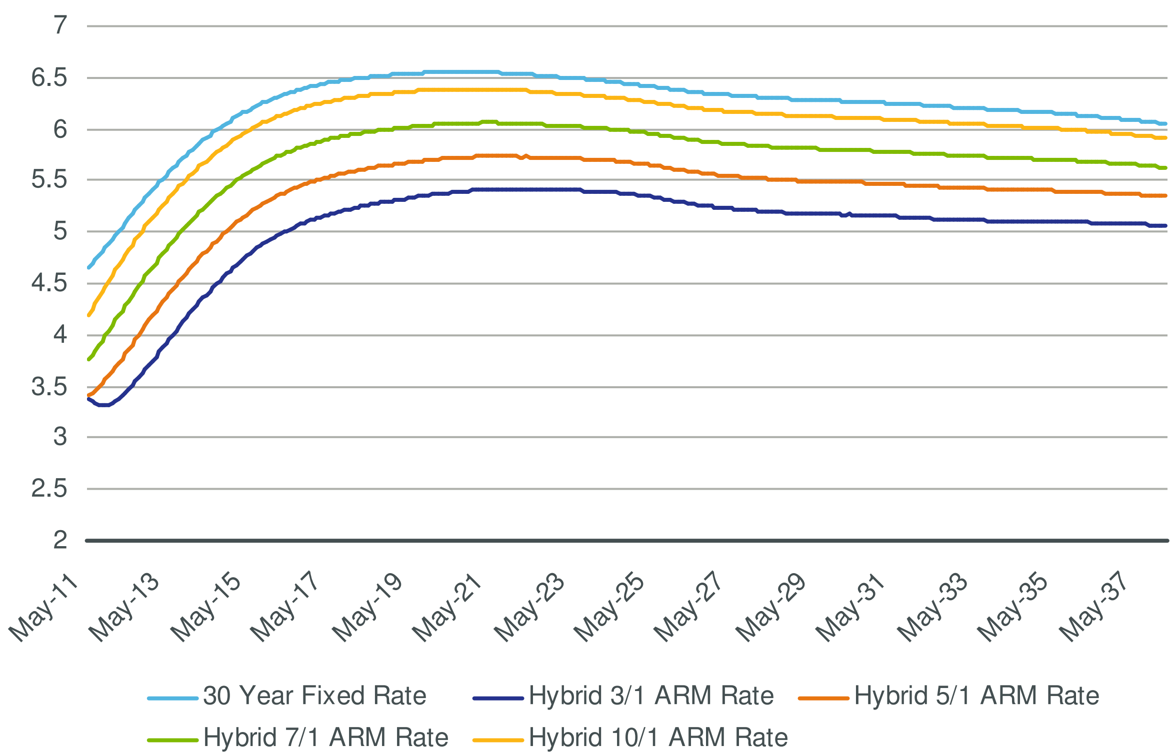
The primary mortgage rate for 30-year fixed FHA loans is obtained by adding a spread to the 30-year fixed conventional rate. The spread is defined as:

$$FHA_{30\,yr}\ Spread = avg(FN\ Current\ Coupon\ TBA\ Yield) - avg(GN\ Current\ Coupon\ TBA\ Yield)$$

where the average is taken over 30 days.

Mortgage Rate Model

Chart 10: BRS Mortgage Rates Projections



Agency Model Estimation and Development

Agency Mortgage Model

Introduction

The agency mortgage prepayment model incorporates much of the new agency disclosures such as the Freddie Mac pool delinquency data, changes in GSE guarantee fees and FHA mortgage insurance premium. It also covers the majority of agency MBS products, including Conventional and GNMA fixed rate 30-year, 20-year (GNMA excluded), 15-year products and hybrid ARM products.

The mortgage landscape has changed dramatically since late 2007 when the financial crisis started. There was significant tightening in underwriting standards by both the agencies and the originators as falling home prices, previously irresponsible loan underwriting practices and a weak economy had driven delinquency rates to unprecedented levels. Borrower refinanceability was greatly reduced by negative equity position in a tight underwriting environment and this prevented many borrowers from taking advantage of historically low mortgage rates. In order to stabilize the collapsing housing market, various government programs were put in place to help borrowers stay in their homes, reduce their mortgage debt burden and ultimately stop them from defaulting on their mortgages. Government intervention in the mortgage market has a profound impact on prepayments, in terms of both refinances and loan modification/delinquency driven buyouts. The model attempts to reflect and account for these distortions to prepayment speeds.

We will primarily focus on the conventional 30-year fixed rate prepayment model in this paper. Conventional 15-year and 20-year models have the same structure and factors as the 30-year model, while their factor sensitivities were estimated and calibrated to their respective collateral performance data. A few product-specific model parameters were also adjusted for various additional conventional collateral types such as 10/20 IO, 40-year, conforming jumbo loan size pools, and high LTV HARP pools.

While the GNMA fixed rate model structure and its estimation methodology are very similar to that of the conventional fixed rate model, a few key differences remain and we will discuss those differences in detail in a separate section for GNMA models.

We will also highlight the model features specific to hybrid ARM collateral.

Data, Model Structure and Modeling Methodology

Agency-provided pool level mortgage data include updated collateral characteristics and factor time series for each pool. Important pool level disclosures include WALA, WAC, average loan size, average FICO, average LTV, loan purpose, occupancy type, property type, and geographic distribution. In addition, quartile statistics are also provided for variables such as WAC, WALA, loan size, FICO and LTV. The model utilizes these data sets to extract relative value between pools in the mortgage market. In order for the model to accurately reflect borrower's prepayment behavior in different economic environments, the estimation sample utilizes a 15-year prepayment history that dates back to 1997, which covers low rate and high rate environments, housing booms and busts, periods when affordable mortgage products gained and then lost popularity, and several economic cycles. Since future prepayments will be more dependent on current GSE underwriting guidelines and originator practices than past behaviors, recent observations are given a heavier weight in the estimation.

The BRS prepayment model consists of three components (Figure 1).

1. **Housing turnover:** Housing turnover is a prepayment event triggered by a home sale. Borrowers sell their properties for a variety of reasons which can include the need to move because of a job-related relocation or a transition to a larger house with improvement in financial situation. Typically housing turnover happens regardless of the levels of prevailing mortgage rate and accounts for the bulk of prepayments on discount mortgages.

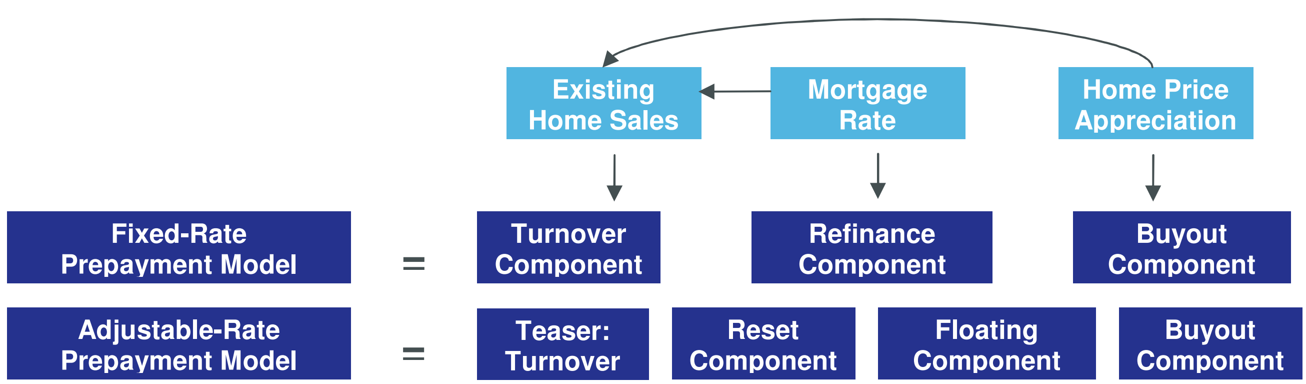
2. **Rate/term refinancing:** When the prevailing mortgage rate is lower than the rate on a borrower's mortgage, the borrower has incentive to refinance at the lower rate to reduce their monthly payment. At a given refinancing incentive, a borrower's refinanceability will be further determined by their collateral attributes. Therefore, a borrower's prepayment response can vary greatly across collateral attributes, generating a rich family of different prepayment levels and trends.

3. **Delinquency-driven buyouts:** Historically, delinquency rates on agency collateral have been very low and defaults were a very small component of pay-downs, accounting for less than 1 CPR. However, delinquency rates have risen significantly since 2007 along with an increase in delinquency-related activities such as loan modifications and buyouts. These events distorted prepayments towards the end of 2009 and throughout the first half of 2010. GSE buyout practices have become more regular and loans are generally bought out once they become 120+ days delinquent. Delinquency buyouts can explain as much as half of total pay-downs in credit-impaired 2007 vintage high-coupon pools.

Though not explicitly modeled as a separate component, cash-out refinancing is an important driver of mortgage prepayments. Cash-out refinancing is less interest rate driven as rate/term refinancing and is more related to the borrower's equity position in the property. When there is significant equity build-up in the property, borrowers can monetize the equity to either pay off existing debt or finance a major expenditure such as an automobile purchase. Intuitively, the level of cash-out refinancing activity is directly linked with cumulative home price appreciation and can take place with or without economic incentive. The model captures cash-out refinancing through home price related variables in both the turnover and rate/term refinance model components.

Figure 1 shows the general model structure of the agency fixed-rate and adjustable rate prepayment models and their interaction with macroeconomic variables. The key factors in each model component are listed in Figure 2.

Figure 1: Prepayment Model Structure



Agency Mortgage Model

The buyout model is estimated using pool level delinquency and buyout data disclosed by Freddie Mac in January 2011. The GSEs announced that they will repurchase any loan that goes more than 120 days delinquent. Consequently it becomes critical to model the less than 120-day to 120+-day delinquent roll rate. The model assumes a one-to-one relationship between 120+day delinquency rate and buyout, although the buyout itself is also dependent on the GSEs' buyout incentive, i.e., the relative coupon of the delinquent loans. The lower the coupon of a delinquent loan compared to the current par coupon yield, the lower the incentive for the GSEs to repurchase the loan.

Figure 2: Fixed-Rate Prepayment Model Components

Prepayment Speed = **Turnover Component** + **Refinance Component** + **Buyout Component**

Prepayment Speed

- PSA
- CPR
- SMM

Turnover Component

- Seasoning
- Lock-in
- State level HPA
- Seasonality
- Existing home sales
- Buy down
- Current LTV
- FICO
- Occupancy
- IO vs Non-IO
- State

Refinance Component

- Refi incentive
- Loan size
- Yield curve
- Yield curve at Origination
- Media effect
- Burnout
- Seasoning
- State level HPA
- FICO
- Current LTV
- SATO
- Property type
- Occupancy
- IO vs Non-IO
- TPO Origination
- State

Buyout Component

- Seasoning
- Current LTV
- SATO
- FICO
- Loan size
- Incentive

Figure 3: Hybrid Prepayment Model Components

Additional Reset Impact	Turnover + Refinance Component
• Month to/since First Reset	• Time Since First Reset
• Cap/Floor structure	• Incentive
• IO vs Non-IO	• Media Effect
• Yield Curve Slope	• Yield Curve Slope
	• Home Price Appreciation
	• Existing Home Sales
	• Seasonality
	• Month to Next Reset

In order to estimate the turnover and refinance components of the prepayment model, we first split involuntary prepayments out from total prepayments using buyout estimates obtained from the buyout component. Buyout activities were very low prior to 2010 but starting from first half of 2010 Freddie Mac and Fannie Mae bought out virtually all 120D or more delinquent loans accumulated in MBS pools. The buyout model projections are adjusted to reflect the spike in prepayments due to these GSE buyout activities. The turnover and refinance model are then estimated on the residual voluntary prepayments after subtracting estimated delinquency buyouts from total prepayments. The turnover model is estimated on observations in periods when refinancing activity is believed to be very low, that is, when borrowers' prepay option is deep out of the money.

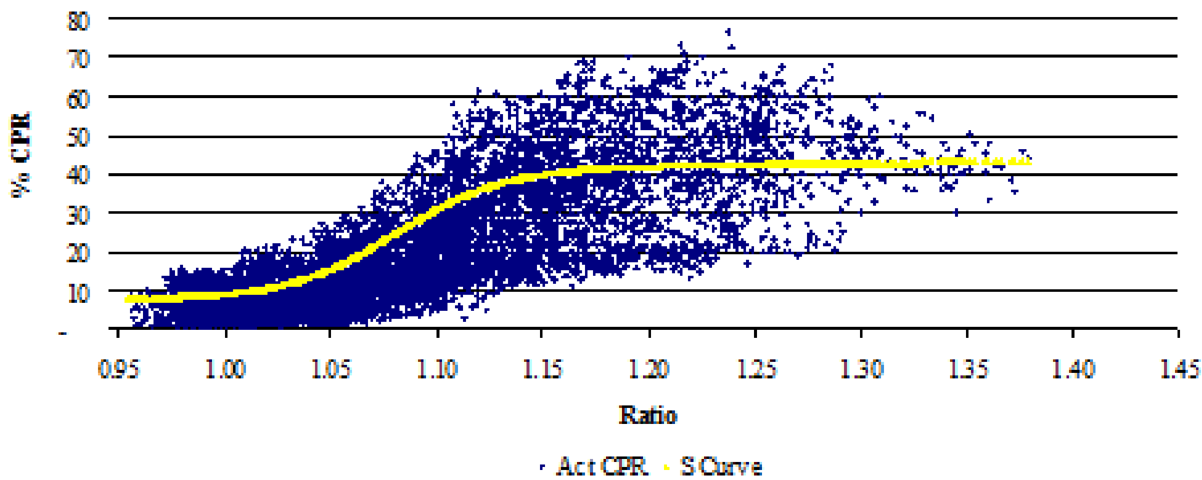
Overall we apply the Generalized Additive Models (GAM) methodology to estimate our models. An additive regression model has the general form:

$$g(\mu) = \sigma + f_1(X_1) + \ldots + f_p(X_p) \quad (1)$$

where g(.) is the link function and mu is the conditional expectation of the dependent variable. We use the logit function to model prepayments because whether a borrower prepays or not is a binary event and the amount of prepayment in a pool for a given month follows a binomial distribution. The x_p's are predictors and the f_p's are their response functions. The response functions tend to be highly non-linear as shown in Chart 11 and the GAM method captures nonlinearity in the prepay data very well since each response function is fitted non-parametrically.[1] We further extend this method within the GAM framework to allow for interactions among predictors.

[1] For detailed introduction on GAM in Splus, please refer W.N. Venables and B.D. Ripley "Modern Applied Statistics with S," Springer, 2002 4th Edition.

Chart 11: Non-Parametric Estimation – Refinancing Incentive



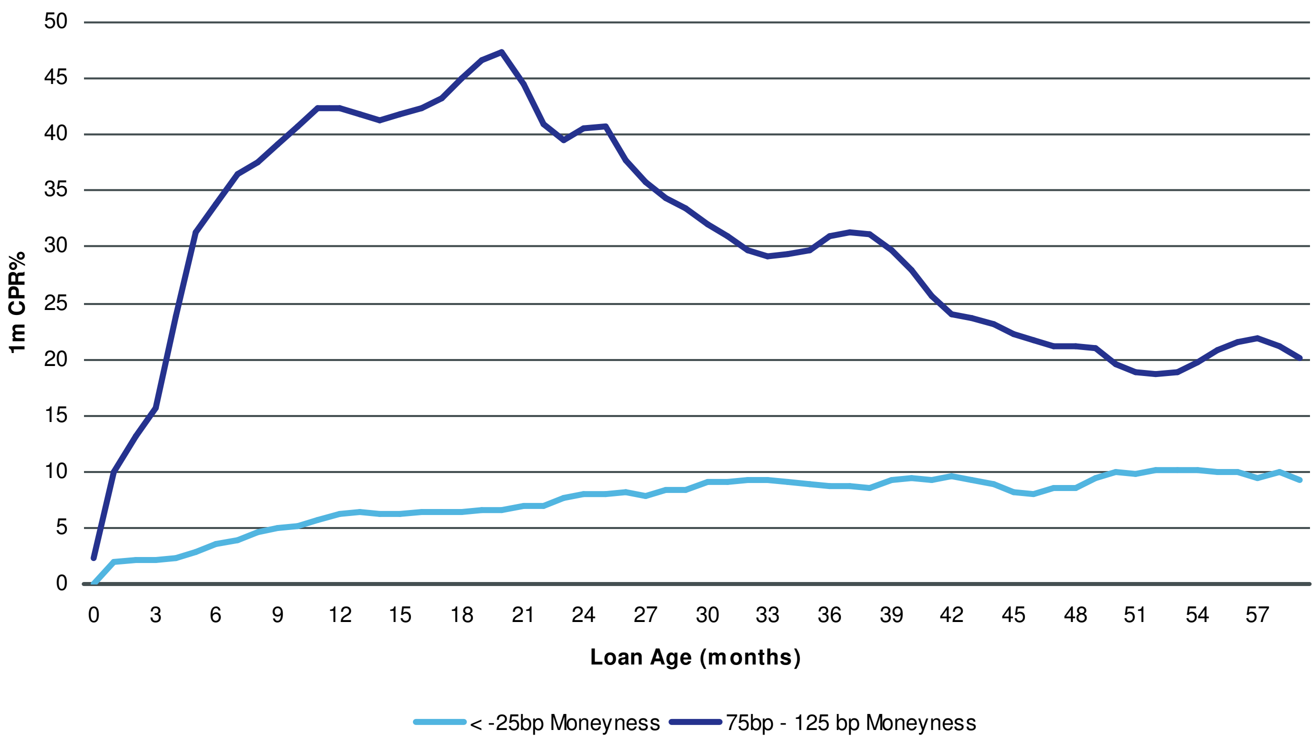
Prepayment Model Key Variables

In this section we will detail each variable in the prepayment model. We will discuss their definitions and how they affect prepayment projections. Note that many variables are common to all three model components, but they may have very different response functions.

Key Variables

Seasoning: Chart 12 shows historical Fannie Mae 30-year fixed-rate prepayment aging curves for different moneyness buckets. The seasoning curve of discount pools has a longer ramp (typically 3-4 years) than that of premium pools (typically 1-1.5 years). As mentioned before, discount speeds are mostly driven by housing turnover and the probability of selling one's home shortly after the initial purchase. As the loan seasons, borrower's mobility increases and likelihood of housing turnover increases. For premium speeds, the initial levels are also low because borrowers are less likely to refinance twice in a few months because of monetary and time costs associated with a refinance transaction. However, the ramp of premium pools is shorter and there is a subsequent slowdown in speeds when the collateral is seasoned. This effect is termed "burnout".

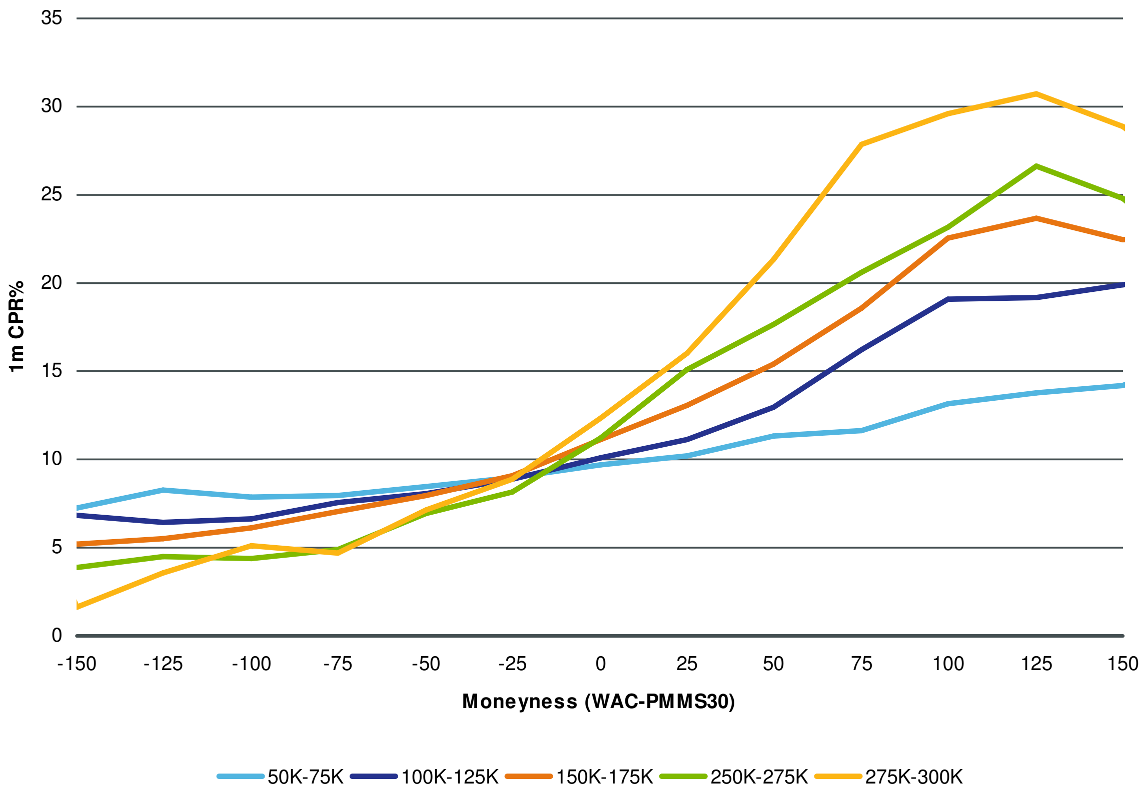
Chart 12: Empirical FN30 Prepayment Speeds on Discount and Premium Pools



Economic incentive: We measure economic incentive as the ratio of a borrower's current monthly mortgage payment to a hypothetical payment assuming the borrower refinances into another loan with similar maturity at the prevailing mortgage rate adjusted for the guarantee fees required by the GSEs, points and origination costs. Economic incentive is also called refinance incentive in the refinance model and lock-in in the turnover model. Intuitively, the higher the economic incentive, the greater one's refinance propensity is. On the other hand, when economic incentive is very low, a borrower may get discouraged to sell their house because he/she will have to pay a much higher rate on the mortgage for a new home.

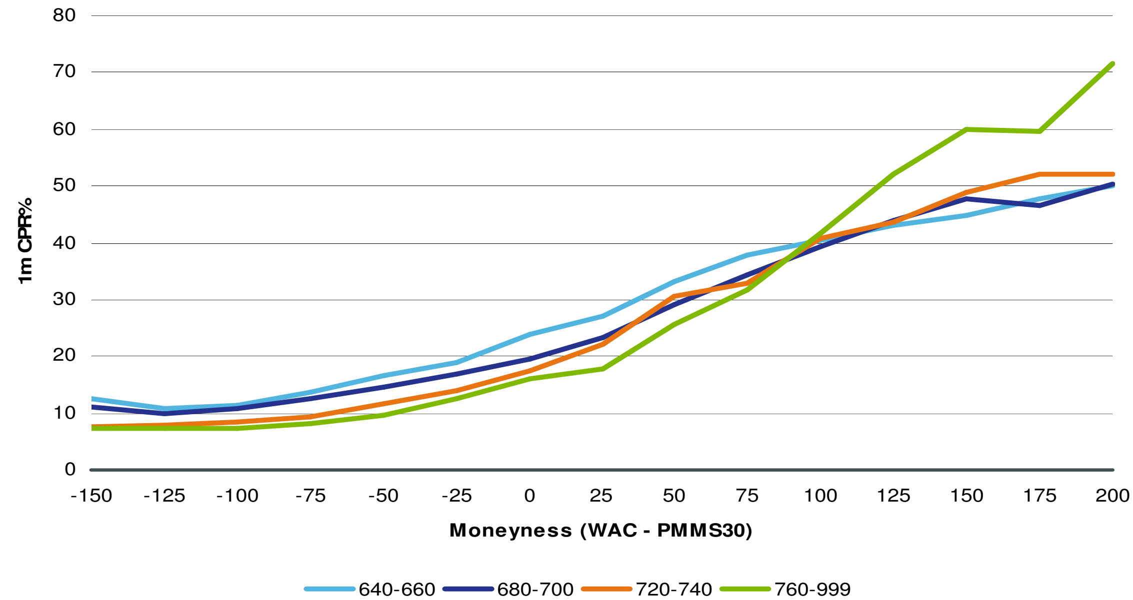
Loan Size: Loan size has a different effect on prepayments in the turnover and refinance models. Smaller loans tend to turn over faster because borrowers "trade-up" as their financial situation improves or a bigger house is needed for the family. In the refinance model however, larger loans tend to prepay faster. This is because for a higher loan balance, the same rate incentive translates into bigger dollar savings; and it takes longer for a borrower with a lower loan balance to recoup the fixed portion of refinancing costs. Chart 13 illustrates the loan size effect on prepayments. Note that we adjust loan size by inflation in the model in order for it to be on a consistent basis across time.

Chart 13: Empirical FN30 S-curves by Loan Size



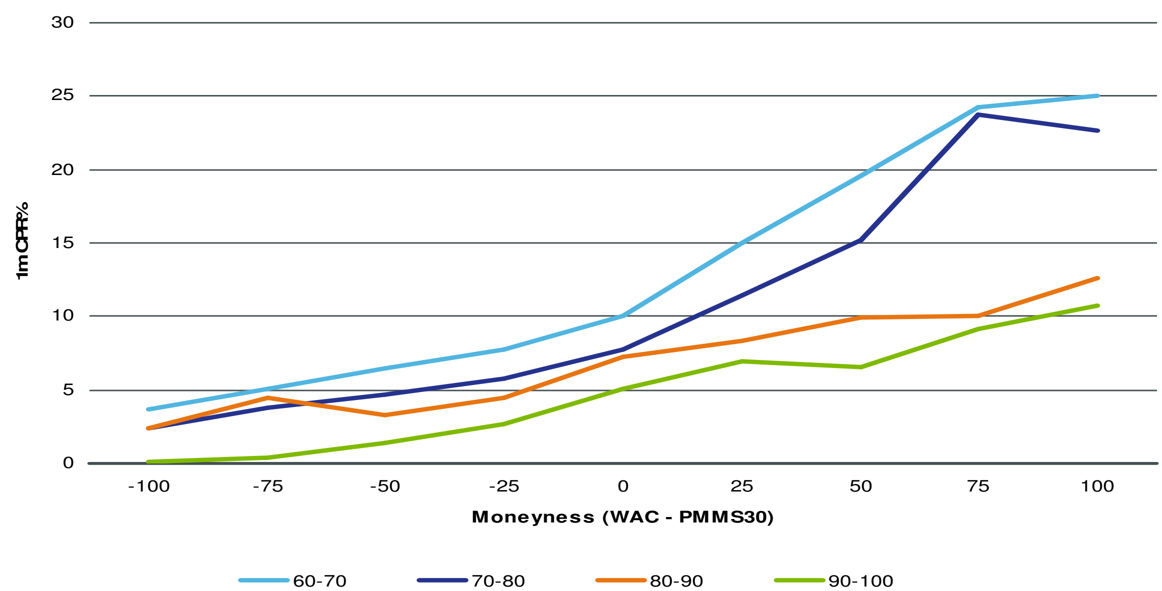
FICO: FICO represents a borrower's credit score and is a variable that has different impacts on prepayments in the turnover and refinance models. In the refinance model, higher FICO score implies better borrower credit quality, which further lends itself to higher prepayments and easier access to loans. In the turnover model on the other hand, lower FICO borrowers exhibit higher turnover speeds for two reasons. First, borrowers can get a lower rate than what they are currently paying as they "cure" their credit and second, lower FICO borrowers tend to be less financially affluent and are more likely to cash-out refinance. The FICO effect is shown in Chart 14.

Chart 14: Empirical FN30 S-curves by FICO



Current Loan-to-value Ratio (CLTV): A borrower's current LTV in a given month is calculated by adjusting the original LTV by amortization on the mortgage and home price appreciation on the property. We use FHFA's state-level all-transaction home price index to calculate home price appreciation. Loans with higher CLTV tend to prepay slower as lack of equity in the property makes it more difficult and more expensive to refinance. Also, it's less likely for borrowers with high LTV to "trade-up" or "cash-out" against their equity position on the property. Chart 15 shows the dampening effect of CLTV on prepayments.

Chart 15: Empirical FN30 S-curves by CLTV



Spread At Origination (SATO): SATO is defined as the spread of a borrower's loan rate over the average loan rate of all loans of the same product type in the same origination month. For 30-year fixed rate mortgages, we approximate the average loan rate in a given month by a weighted average of Freddie Mac's Primary Mortgage Market Survey (PMMS) rates in the two prior months. Intuitively, SATO measures a borrower's credit risk – the greater the credit risk, the higher the lender needs to be compensated for this risk and the higher the SATO. SATO is correlated with FICO and the marginal explanatory power of the SATO variable decreased after the GSEs started disclosing a pool's FICO information in 2003. Nevertheless, SATO is still an important predictor because it captures any "residual" credit risk not reflected by FICO or original LTV. Everything else equal, the higher the SATO the lower the refinanceability.

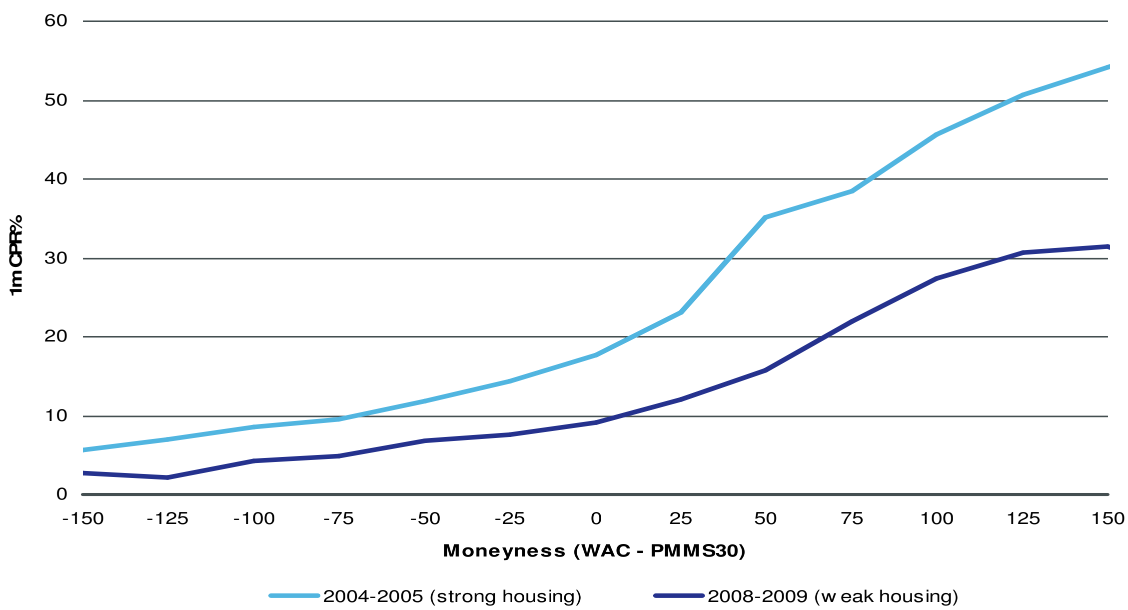
Occupancy: Generally, loans collateralized by owner occupied properties are more refinanceable than investment properties or second homes. However when the housing market is vibrant and home prices are increasing, prepayment speeds tend to be faster on investment properties as owners flip properties to gain from rising home prices.

Property type: Loans collateralized by multi-unit properties have slower refinancing speeds than single family houses as the former exercises the prepay option less efficiently.

Loan Purpose: Purchase loans tend to prepay slower than refinance loans. Typically first-time home buyers are financially less savvy and don't exercise the prepay option as efficiently as those who have refinanced before.

Home Price Appreciation (HPA): The strength of the housing market is one of the most important factors determining prepayment speeds. Higher HPA means greater equity build-up which increases the likelihood of borrowers trading up or cashing out the equity. Furthermore, originators are more willing to lend loans in an upward trending housing market because of lower perceived default risk. Chart 16 illustrates the speeds difference in two time periods when housing market was strong and weak respectively after controlling collateral attributes like WALA, FICO and CLTV.

Chart 16: HPA Impact on FN30 Prepayment Speeds



Yield Curve Slope: For 30-year fixed rate loans we assume that when they refinance they will normally refinance into another 30-year fixed rate loan, so the refinance incentive is calculated by comparing the current loan rate and prevailing 30-year fixed rate. However, when the mortgage yield curve is steep, meaning the hybrid ARM rates are significantly lower than the 30-year fixed rate, borrowers have incentive to refinance into a hybrid ARM when the prevailing 30-year fixed rate is not necessarily lower than their current mortgage rate. Therefore, everything else equal, the steeper the mortgage yield curve, the faster the prepayment speed. The yield curve slope measure is:

$$Yield\ Slope(t) = 30\ Year\ Primary\ Rate(t) - (Hybrid_{3/1}\ Rate(t) + Hybrid_{5/1}\ Rate(t))/2$$

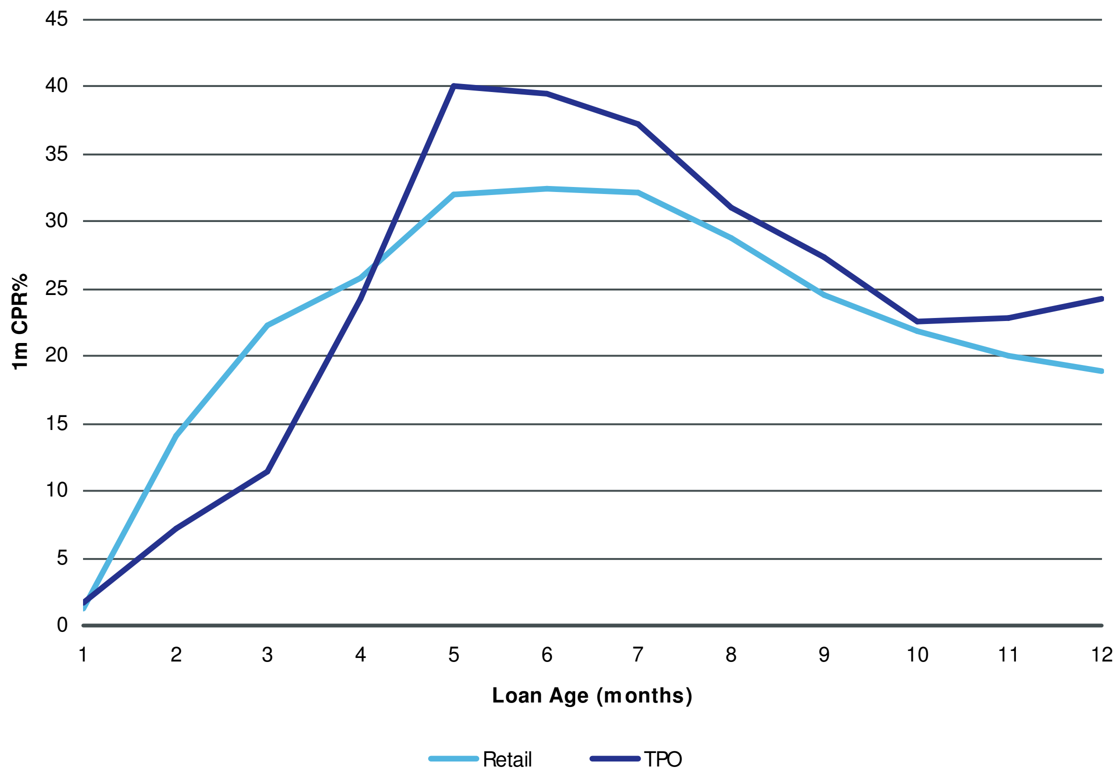
Yield Curve Slope at Origination: Borrowers who chose a fixed rate loan in a steep mortgage yield curve environment tend to have slower prepayment speeds in the future. This is because their "self-selection" into a fixed rate product when they could have had lower monthly payment had they chosen a hybrid ARM mortgage signals their intention to stay in their current mortgage for a longer period of time and greater risk aversion towards hybrid ARM products.

Media effect: Prepayment speeds tend to be faster than can be explained by purely the refinancing incentive when mortgage rates hit multi-year lows. This is because there is greater media attention to mortgage rates and mortgage refinancing when rates are at historical lows and the awareness of such refinancing opportunities for an average borrower is higher. The media effect is defined as the ratio of the long-run (4-year) average of the 30-year fixed mortgage rate to the average 30-year fixed mortgage rate over the most recent 3-month period.

Burnout: As a pool pays down over time, the remaining loans tend to have lower refinancing response for two reasons. One, there is a migration in the average collateral attributes. For example, loans with higher balance prepay faster than those with lower balance and therefore the remaining population will consist of more and more loans with lower balance. Two, even after accounting for migration in the collateral attributes, the remaining loans are becoming less sensitive to rates and this phenomenon is called "burnout". Burnout happens because of survivorship bias – loans that remain in the pool didn't take advantage of past refinancing opportunities – they are either less rate responsive outright or there is some unobservable credit impairment that prevented them from refinancing. Either way, the remaining population will have a flatter prepayment curve. We measure burnout by counting the cumulative refinancing opportunities foregone since origination. The more burnt out a pool, the greater the adjustment on its prepayment response function.

Third Party Origination (TPO): Borrowers can get a loan by going to a bank directly, through a correspondent or a mortgage broker. The latter is called Third Party Origination (TPO). Loans originated through a mortgage broker or correspondent as opposed to a retail channel prepay slower in the first three months since origination and faster in the subsequent six months or so. Chart 17 illustrates this TPO effect.

Chart 17: Empirical FN30 Prepayment Speeds by Origination



Seasonality: We have observed quite consistent seasonal effects in the turnover model – turnover speeds tend to be the fastest in the summer and slowest in the winter due to the scholastic calendar and day count.

Existing Home Sales (EHS): By definition, existing home sales are highly correlated with the level of overall housing turnover. The higher the existing home sales, the faster the turnover speeds.

Interest Only (IO) vs Non-IO: IO loans tend to have slower voluntary prepayment speeds and higher delinquency rates (and hence higher buyouts) compared to non-IO loans. This is because an IO is an affordability product and borrowers who opted for an IO loan tend to be more financially constrained, more leveraged to the housing market and possess greater credit risk.

State multipliers: Different states exhibit different prepayment behavior after controlling for incentive and other collateral attributes like loan size and home price appreciation. For example, New York and Florida are slow states as they have higher mortgage taxes that increase one's refinancing cost. Prepayment behavior differences across states are usually related to differences in state laws and closing costs. We perform a two-stage regression – the core models are estimated at the first stage and we then estimate the state multipliers at second stage based on the residuals from the first regression.

Variable Interactions

Credit variables like FICO and CLTV have much greater differentiating power on prepayments in a weak housing market than in a strong housing market. This is because underwriting standards tend to be looser when home prices are strong and tighter when home prices are weak. Charts 18-21 illustrate the effect of FICO and CLTV on the S-curve in two different periods. This regime shift is captured by the model through interactions between HPA and the credit variables.

Chart 18: Historical FN30 Prepayments by FICO: 2003-2006 Period

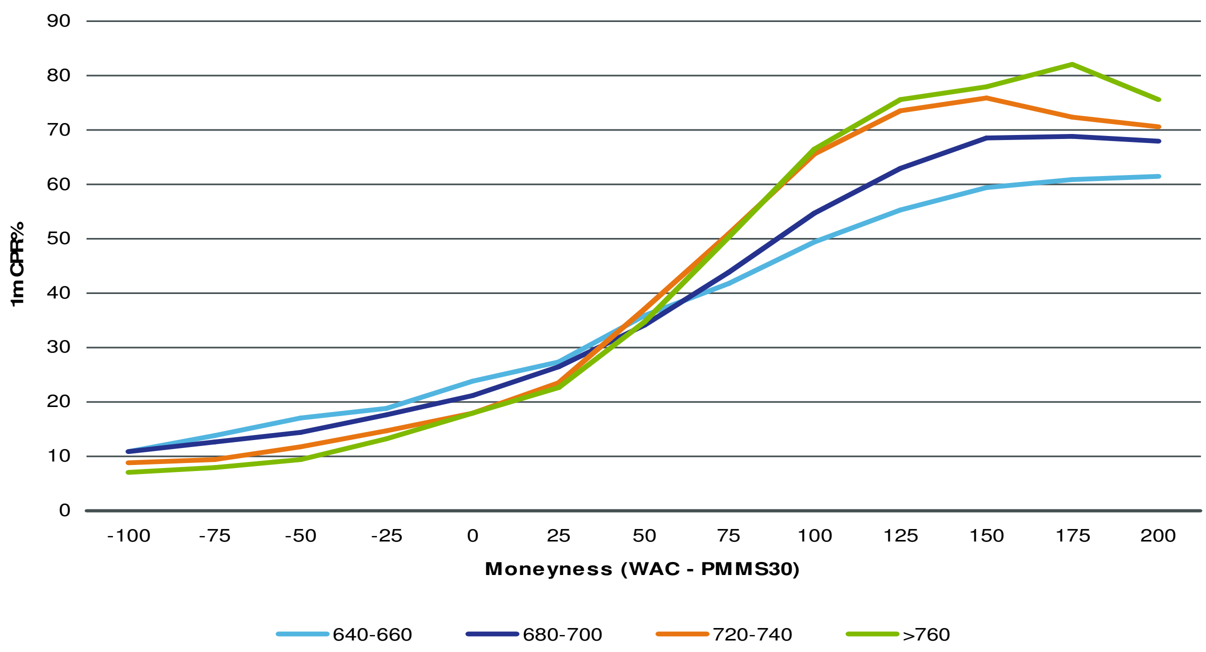


Chart 19: Historical FN30 Prepayments by FICO: 2008-2009 Period

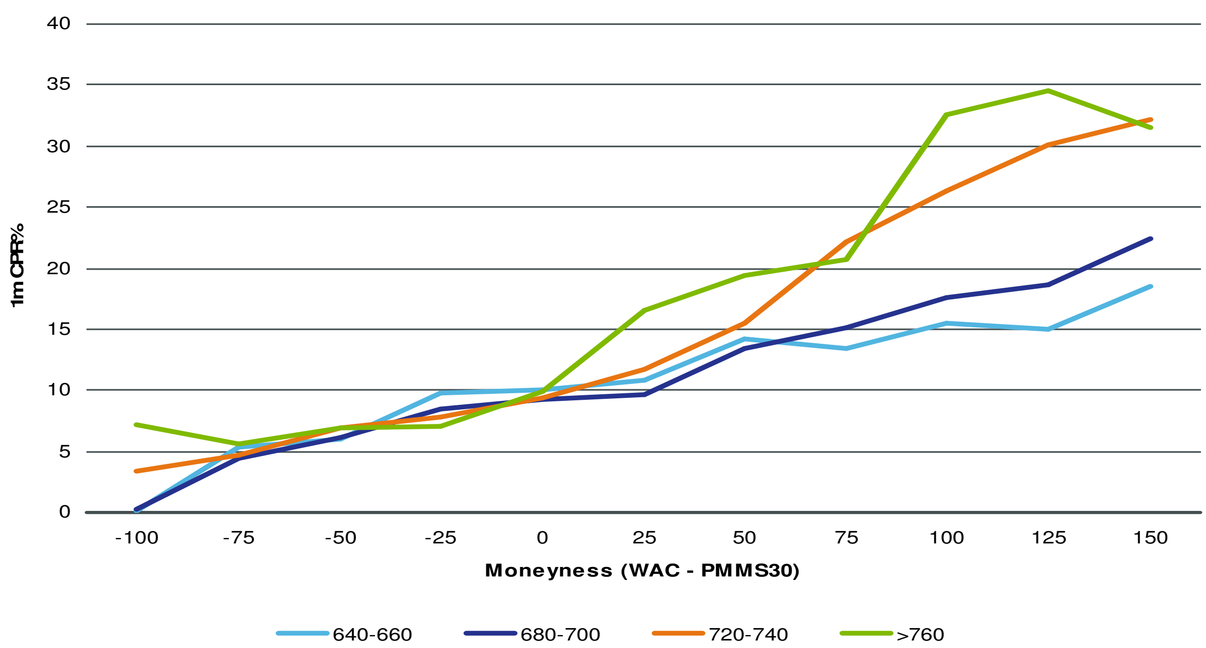


Chart 20: Historical FN30 Prepayments by CLTV: 2003-2006 Period

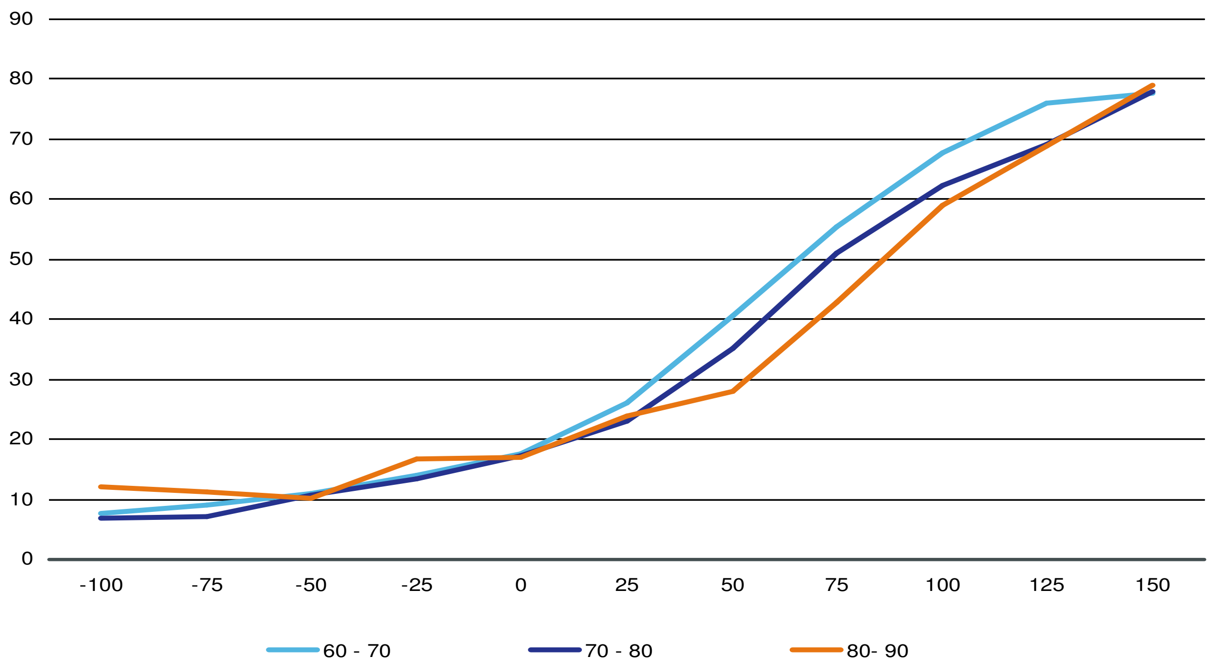
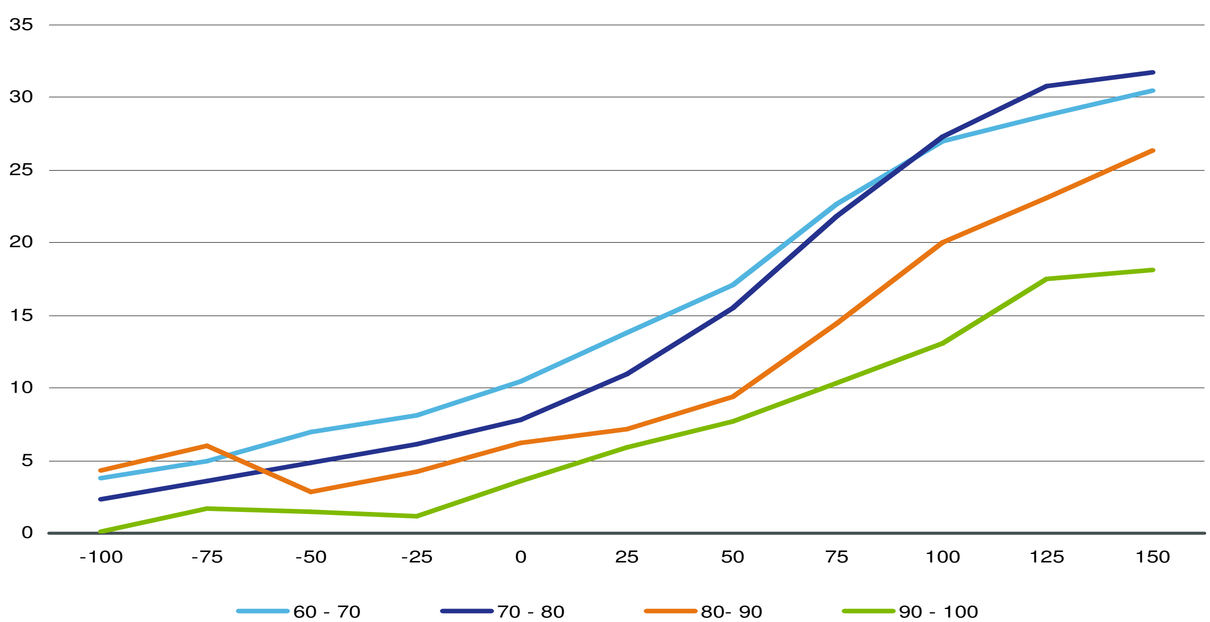


Chart 21: Historical FN30 Prepayments by CLTV: 2008-2009 Period

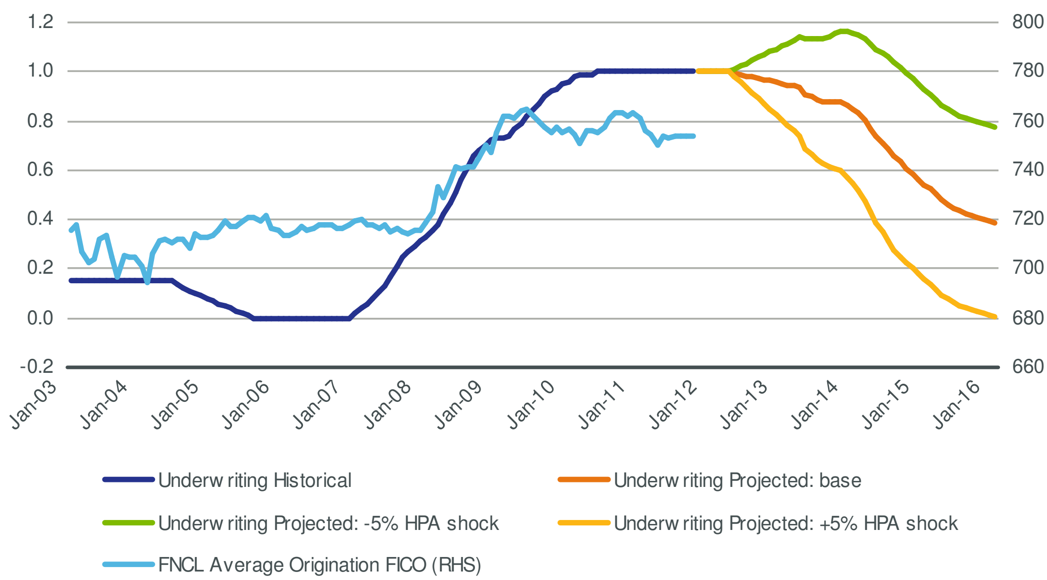


Conventional Mortgage Prepayment Model Feature

Underwriting Variable

The conventional prepayment model contains an underwriting variable to account for the drastically different prepayment behavior in various underwriting regimes. In particular, this variable helps to model the slowdown in voluntary prepayment speeds (even in the cleanest credit cohorts) as underwriting tightens. This variable will better manage the timing of credit renormalization in the mortgage market. The underwriting variable is explicitly defined based on the average origination FICO of the Fannie Mae 30-year universe. A higher average origination FICO corresponds to greater underwriting strictness. Also average origination FICO tends to become higher when the housing market weakens. Historically, a consistent relationship exists between FICO and HPA. In the longer term, the underwriting assumption is driven by HPA. Specifically, the model assumes a looser underwriting environment in the long run if the model HPA projections are optimistic, and vice versa as shown in Chart 22.

Chart 22: Underwriting Barometer



Source: Fannie Mae, BRS

The new underwriting "norm" is based on the conditions experienced in mid-2008, after the GSEs increased loan-level price adjustments (LLPAs) in the spring but before credit further tightened in 2009. The underwriting variable has a smaller impact on the best credit borrowers. With everything else equal, their projected prepayment speeds are slower in a tighter underwriting environment. This variable has a stronger impact on poorer credit cohorts as their speeds are more suppressed than those of good credit cohorts in a tight underwriting environment. Subsequently, speeds for poor credit cohorts will increase when credit loosens. This effect can be seen in Charts 23 and 24. We can see that even though the short-term projections are similar between the old model and the current model, the effect from credit loosening occurs later (sometime in the second half of 2014 as opposed to 2013), and the impact is smaller in the current model. Also note that in the long run (towards the end of 2016) CPR projections converge between the old and current model.

Chart 23: Projected Speeds for FN 2010 4% in the Nominal Scenario, Previous model vs. Current model

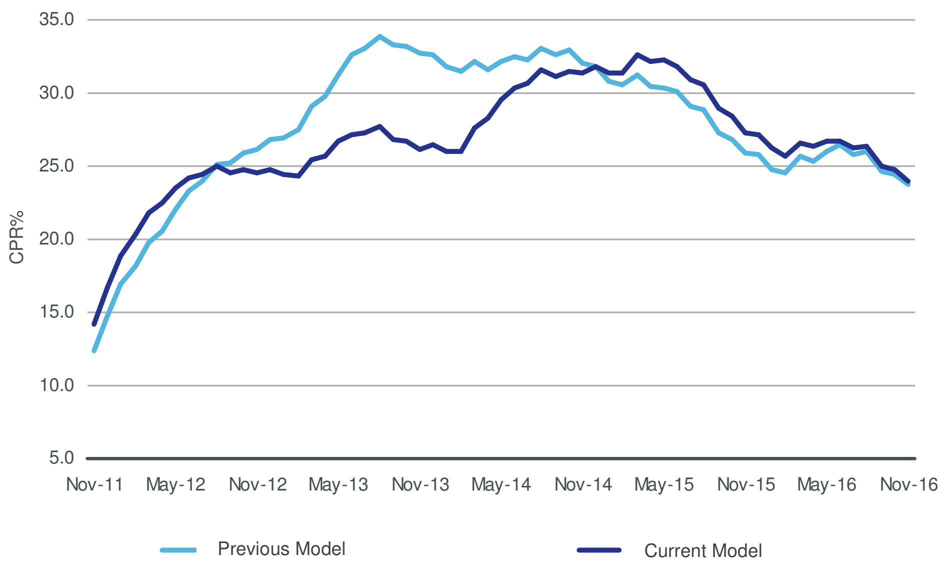
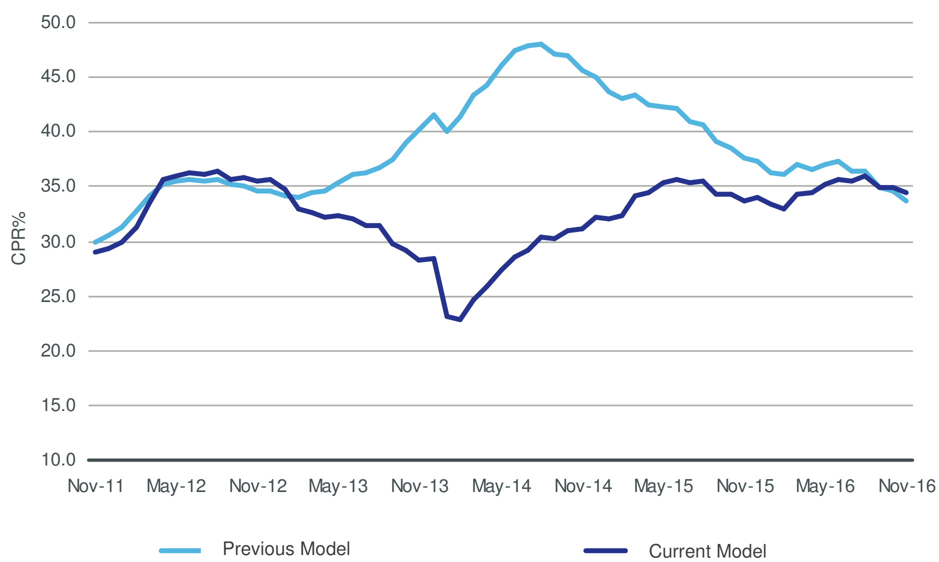


Chart 24: Projected Speeds for FN 2007 6% in the Nominal Scenario, Previous model vs. Current model



HARP

The model captures the CPR impact of HARP 1.0 where flattening in the LTV curve and higher refi efficiency are estimated using actual data. We have built upon this framework following the announcement of the HARP 2.0 program details by further flattening the model LTV sensitivity and increasing refi efficiency. These updates are the result of the rep and warrant relief and increased usage of automated valuation models as part of HARP 2.0. As we can see from Chart 25, the model's LTV sensitivity under HARP 2.0 is flattened dramatically for loans with an LTV greater than 80. We have updated the HARP timeline assumption for the model to account for the fact that it will take originators some time to incorporate and implement the HARP 2.0 changes. As shown in Chart 26, we expect a jump in refinance efficiency in December 2011 immediately following the start of the HARP 2.0 effective date, and a gradual ramping up until April 2012 (for LTV>80 loans). At that point, we assume the HARP 2.0 program will have been fully implemented across originators. Over the next several months until February 2013, servicers will continue to target the loans eligible for HARP 2.0 until they have exhausted the supply of eligible loans. Subsequently, the refi activity will slowly taper off until the end of the HARP 2.0 program in December 2013. At this point we expect a decrease in HARP's effect on refinance activity. Note here that we have provided different refi efficiency multipliers for loans less than and greater than 80 LTV. This is due to the different treatment for <80 and >80 LTV loans in the newly issued guidelines, specifically in terms of the relief on reps and warrants and lender solicitation. Given that the policy change specifically targets borrowers with LTVs greater than 80, there is a higher refi efficiency multiplier for these borrowers. As illustrated in Chart 23, the final model speeds are very similar between the previous model (with the HARP update) and current model during the life of the program.

Chart 25: Reduced Model LTV Sensitivity Under HARP

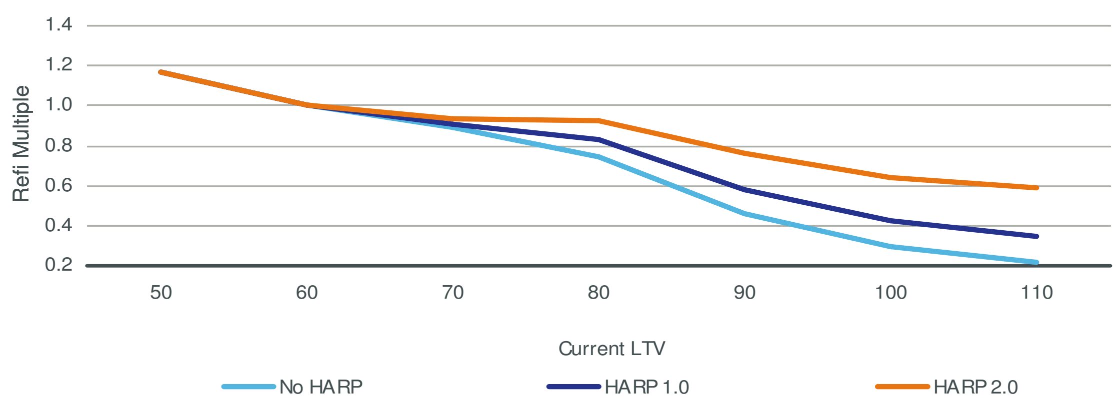
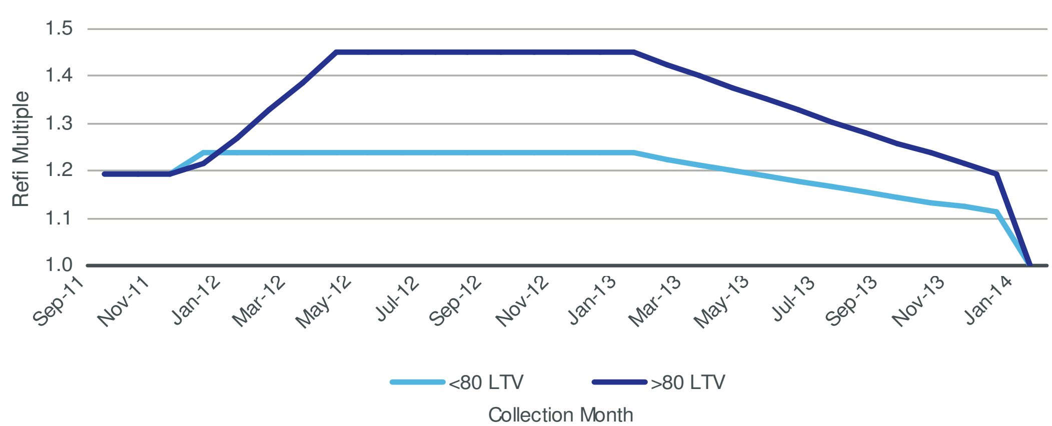


Chart 26: Timeline Assumption of HARP 2.0 Implementation: Greater Refinance Efficiency for 30-Year Fixed Rate HARP Eligible Collateral



Delinquency and Buyout Models

The buyout model framework projected buyouts are driven by a delinquency model. Instead of directly projecting buyout speeds, the model projects delinquencies and then computes buyout speeds based on the buyout incentive given delinquency. The underlying idea is that delinquent loans in deeply discounted coupons are less likely to be bought out at 100%. Unemployment rate and home price momentum variables are also used in the buyout model in order to make the buyout projection more dynamic. Buyout speeds will be significantly slower when housing conditions return to normal and the unemployment rate drops. As we can see from Charts 27 and 28, the more dynamic shape of the buyout curve in the current model can mainly be attributed to fluctuations in these two macroeconomic variables. In particular, the apparent drop in buyout speeds starting from early 2013 can be attributed to the decrease in unemployment and the corresponding rise in home price momentum.

Chart 27: Projected Buyout Speeds for FN 2007 6%, Previous Model vs. Current Model

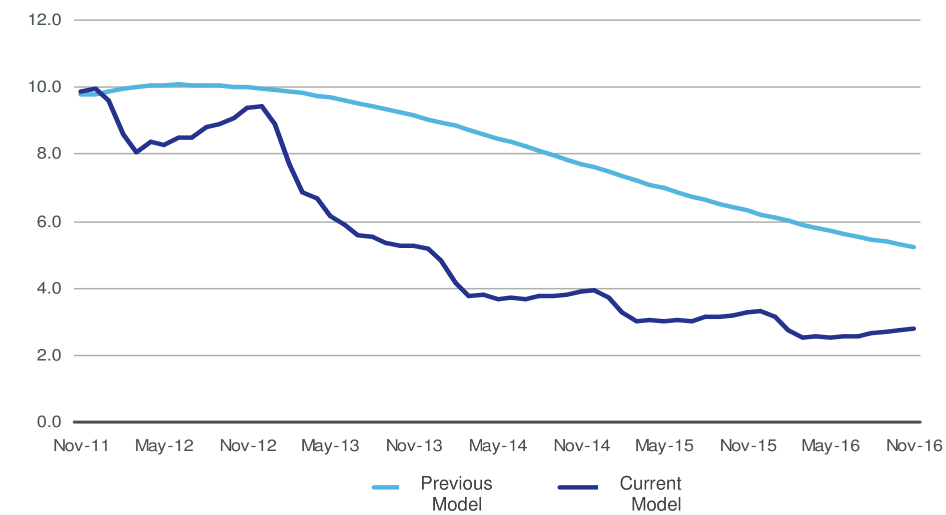
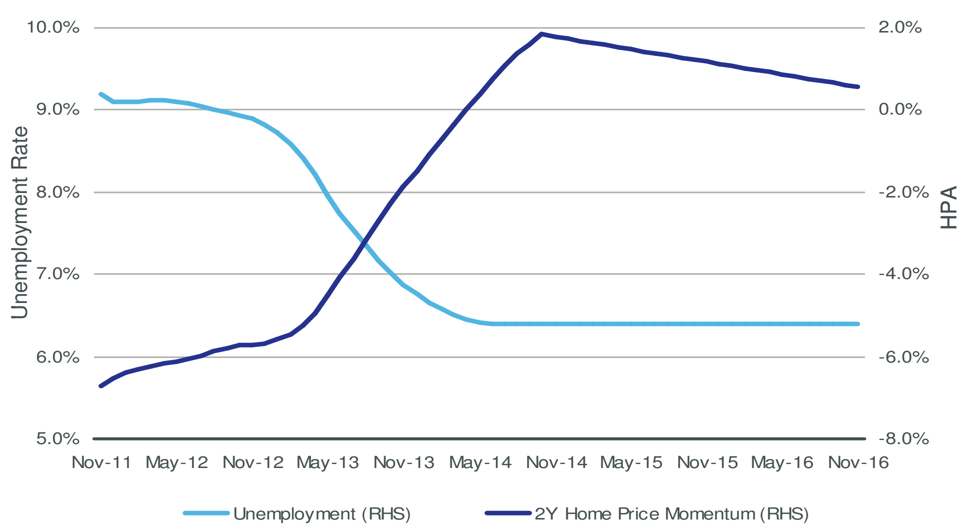


Chart 28: Unemployment and Home Price Momentum Projections



Ginnie Mae Mortgage Prepayment Model Structure

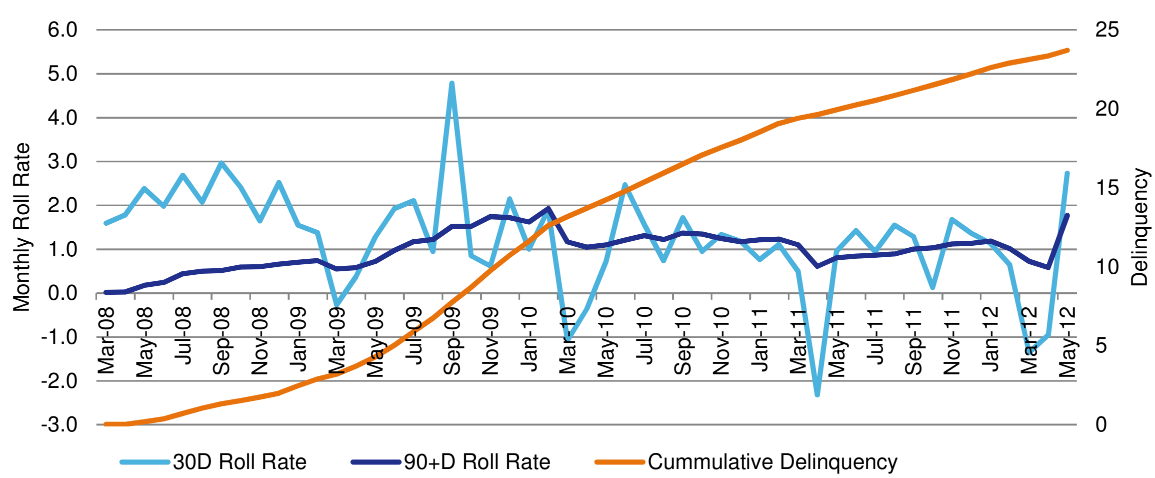
The prepayment behavior of borrowers with loans securitized in Ginnie Mae single-family pools is rather different from that of borrowers underlying GSE pools. As a consequence, we have an entirely separate prepayment model for these (FHA/VA/RHS/PI) pools which takes into account both the different borrower base as well as different Ginnie Mae pool data disclosure. Because the majority of loans in Ginnie Mae pools tend to be insured by the FHA (Federal Housing Administration) and VA (Veteran's Administration) while a much smaller portion comes from the RHS (Rural Housing Service) and PI (Public and Indian Housing), we simply refer to these as FHA/VA loans for convenience.

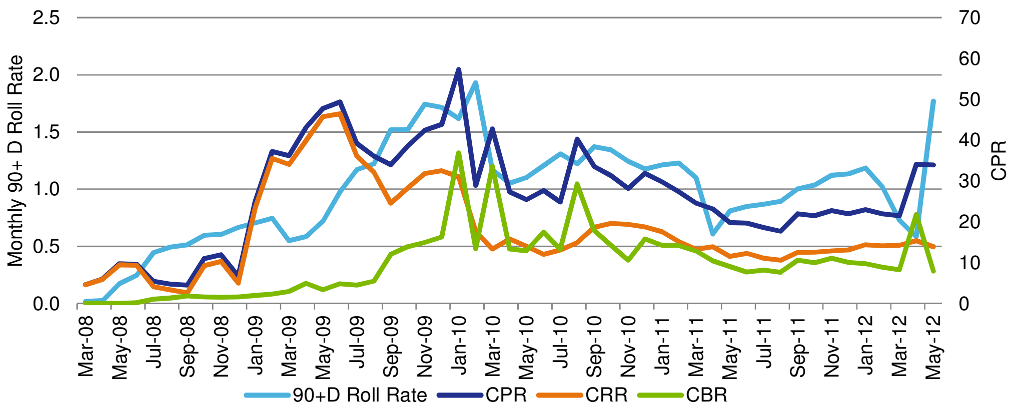
Broadly, the FHA/VA lending programs are designed for borrowers who:

1. are first-time homebuyers
2. have smaller downpayments and hence high original LTV ratios
3. have lower credit or are credit-impaired
4. have low to medium income

The first characteristic means that prepayment speeds tend to ramp up more quickly in a good housing market as first-time homebuyers trade up to larger homes. All four characteristics tend to make borrower credit play a much more prominent role in prepayments (through involuntary prepayments from delinquent loans) compared to conventional pools. Chart 29 illustrates the prepayment speed due to removal of delinquent loans from pools for purposes of loan modification and work out under Ginnie Mae guidelines, which are often dominant contributors to prepayment speed. This is particularly true in a weak housing market.

Chart 29: Ginnie Mae 30-year Fixed Rate 2008 6.0% Delinquency Roll Rates and Prepayment Speeds



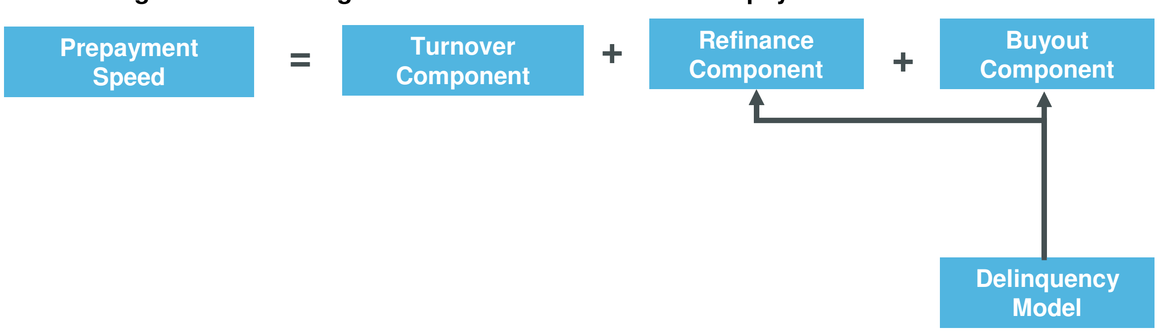


While borrower credit characteristics are critical factors in Ginnie Mae pool prepayment behavior, in some respects Ginnie Mae pool data disclosure of credit information is rather sparse, such as FICO score coverage. Original LTVs are almost uniformly high, but LTV is not a very strong predictor. Consequently SATO is the primary credit measure used in the Ginnie Mae model. Ginnie Mae provided coverage of monthly pool-level delinquency and buyout levels since 2006, making it possible to estimate delinquency and buyout models over a period of housing market stress.

Delinquency and Buyout Models

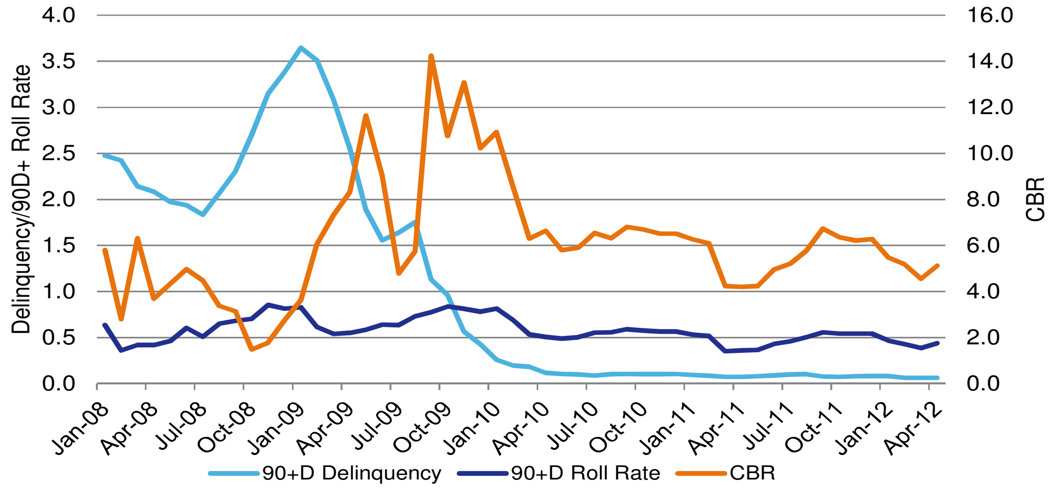
Considerations stemming from the credit and data issues outlined above lead to a prepayment model structure for Ginnie Mae collateral. The approach taken is to use a delinquency model as the driver to the buyout model. As a second order effect, the delinquency model is also a driver to the refinancing model, since lower refinancing is commensurate with higher delinquency. The overall model diagram is shown in Figure 4. The primary factors used in the delinquency model are seasoning, home price appreciation, spread at time of origination (SATO), loan size, and current LTV. There is a seasonality pattern in delinquency such that delinquencies decline in the first quarter of the year and rise through the second and fourth quarters. This seasonality, which is commonly attributed to delinquent borrowers making use of yearly federal tax refunds to become current, is also part of the delinquency model.

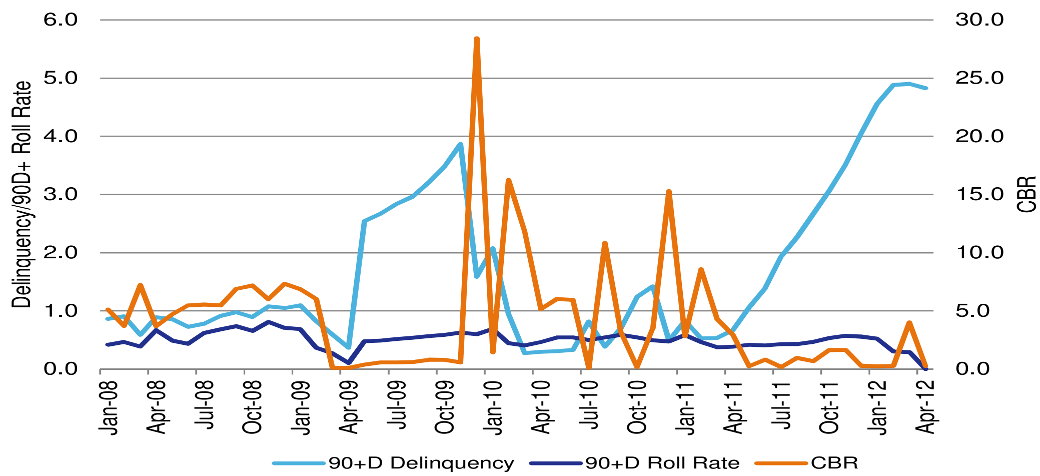
Figure 4: Block Diagram of Ginnie Mae Fixed Rate Prepayment Model Structure



In Ginnie Mae collateral, delinquent loan buyout is determined by the loan issuer and not a behavior of the borrower (Chart 30). The issuer buys out delinquent loans based on overall delinquencies across the issuer's Ginnie Mae portfolio and on economic considerations (financing of the buyout, institutional capitalization, as well as the incentive to buyout the loan at par, modify it, and sell the modified loan usually at some premium). Therefore, the primary factors in the Ginnie Mae buyout model are the delinquency levels generated by the delinquency model and the buyout incentive. Since issuers do not approach buyouts in a uniform manner, the model provides for issuer-specific response to delinquency levels in order to better capture buyout prepayments. In addition to the factors noted above, seasoning, SATO, and current LTV are also factors in the buyout model since issuers may also choose buyout candidates based on these criteria.

Chart 30: Ginnie Mae 30-year FRM 90+D Delinquency, Roll Rate, and Buyout time series for two Ginnie Mae Issuers





Ginnie Mae began to disclose loss mitigation proportions on Ginnie Mae I and II pools in early 2011. The loss mitigation variable represents the proportion of the pool balance that consists of "re-performing loans," that is delinquent loans which have undergone a loan modification and have been re-sold into a Ginnie Mae pool. The disclosure of loss mitigation came at a time when large amounts of re-performing loans were being issued in low-coupon pools. Loss mitigation is a delinquency model variable which helps to better gauge delinquency for low-coupons, where delinquency and buyouts tend to be slow.

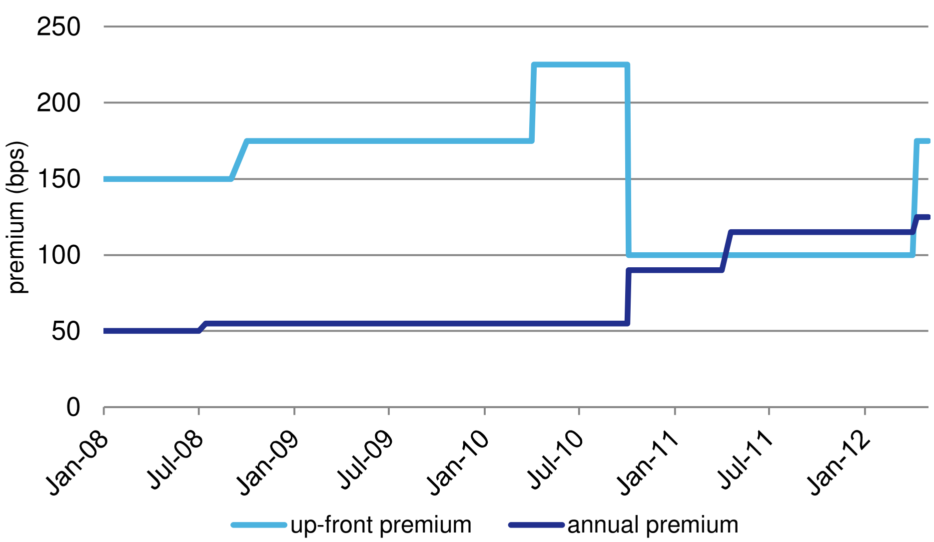
Voluntary Prepayment Model

The Ginnie Mae turnover and refinancing models are similar to their conventional counterparts. As mentioned previously, credit data disclosure is very poor for Ginnie Mae pools compared to what is available for GSE pools. As a result, there are fewer credit variables (SATO and current LTV) in the Ginnie Mae model and these variables are not as strong. The Ginnie Mae streamlined refinance program does not require an appraisal and the FHA will insure a loan without regard to home value. So if the home value has declined, the FHA will still provide insurance on a loan up to the balance of the original balance of the loan being refinanced. Therefore aside from the fact that credit variable disclosure is poor in Ginnie Mae data, FHA streamlined refinance policy itself shows why credit measures play a smaller role.

FHA Insurance Premium

Since 2008, the FHA has made several adjustments to the up-front and annual mortgage insurance premiums which borrowers must pay on newly originated loans. The impact of the mortgage insurance premium can be modeled generally as an elbow shift. However, the fairly frequent changes in insurance premiums by the FHA (Chart 31) mean that the refinancing incentive for a given pool is sensitive to both the FHA premium policy in place at the time that the loans in the pool were originated as well as the policy in effect at the time of refinancing. The mortgage insurance differential between FHA borrowers and subsidized non-FHA (Rural Housing Service, Veteran's Administration, Public and Indian Housing) borrowers as well as FHA insurance refund and cancellation rules all have an adverse effect on the refinanceability of Ginnie Mae collateral. The historical FHA mortgage insurance levels, refund rules and the proportion of FHA borrowers in each pool are all incorporated into the calculation of refinancing incentive at each time step. The explicit inclusion of the up-front and annual mortgage insurance premiums in the incentive calculation provides for a more robust update of the model when the FHA implements policy changes on mortgage insurance.

Chart 31: FHA Up-front and Annual Mortgage Insurance Premiums

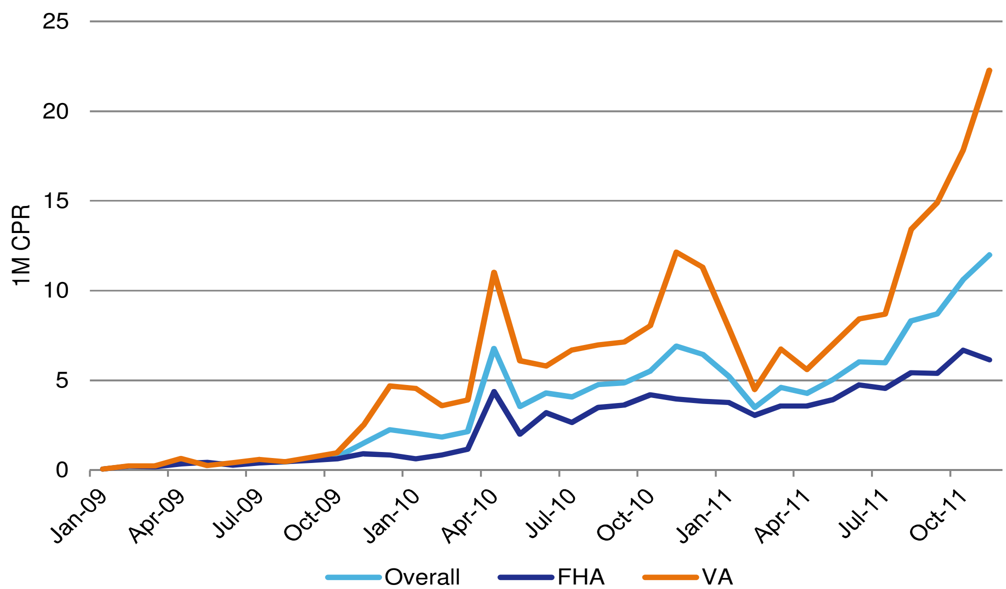


On March 6 2012, the White House and FHA announced new mortgage insurance premiums for FHA loans endorsed prior to June 2009. Refinancing of loans endorsed prior to June 2009 will have an annual mortgage insurance premium of 55 basis points and an up-front premium of 1 basis point when the refinance is endorsed on or after June 11, 2012. This insurance premium structure is part of the Ginnie Mae 30-year model.

VA Prepayments

In the 2010 and 2011 period, FHA borrowers experienced tightening of qualification rules for the FHA streamlined refinancing program as well as higher mortgage insurance premiums. As a result, refinancing speeds of FHA borrowers declined substantially and the responsiveness of FHA borrowers to low rates weakened. During the same period, VA borrowers continued to be very responsive to low mortgage rates as these borrowers have a streamlined refi option, no changes to insurance premiums and relatively better credit characteristics. Consequently, VA and FHA refinancing behavior diverged significantly (Chart 32). The prepayment model uses a separately estimated VA-specific S-curve in the refinancing model which is evaluated for the VA portion of the pool. This feature allows for better calibration of the prepayment model.

Chart 32: FHA, VA and Overall Voluntary Prepayment Speeds in the 2009 4.0% GNSF I Cohort



Ginnie Mae Mortgage Model Mortgage Rate

The 30-year mortgage rate in the Ginnie Mae fixed rate 30-year model is obtained by adding an average Fannie/Ginnie current coupon yield spread to the conventional 30-year rate. Details are given in the BRS mortgage rate model paper entitled “BRS Mortgage Rate Model”.

Agency Hybrid ARM Model Structure

The hybrid ARM prepayment model structure is slightly more complex than the fixed rate models. Hybrid ARM prepayments are also split into buyouts and voluntary prepayments with the buyout model estimated using Freddie's pool delinquency data. For voluntary prepayments, the model structure is time-varying: in the fixed rate period we have turnover and refinance models just like their fixed rate product counterpart; in the floating period we have a unified model that combines the main turnover and refinance model variables; we also have a "reset" model for pools around their first reset month (Figure 5). Chart 33 illustrates the structure of the hybrid ARM prepayment model.

There are two additional key points we would like to note for the hybrid ARM model, both relating to how we compute the economic incentive. First, the benchmark rate is a weighted average of the 30-year fixed rate and the hybrid ARM rate corresponding to the product type. The weights are obtained from Freddie Mac's historical product refinance transition matrix data and are a function of mortgage yield slope and the level of the 30-year fixed rate. Second, the economic incentive has a forward looking component to it around reset as we take the expected rate after reset into consideration rather than using current WAC all the way through.

Hybrid ARMs have increased in popularity because they offer lower rates than typical fixed rate mortgages yet the borrower doesn't bear all the interest rate risk typically associated with ARM products. When taking out a hybrid loan, one pays a fixed payment for an extended period of time, usually 3, 5, 7, or 10 years, after which the loan rate resets and effectively becomes a pure ARM, floating off the one-year Treasury or LIBOR rate. There is also some cap structure associated with the loan to protect the borrower from large rate hikes. In the past, originators came up with other hybrid products such as interest-only (IO) hybrids in order to satisfy increased demand for hybrid affordability products. Interest-only hybrids tend to exhibit unique credit behavior which is also captured by the prepayment model.

On the investor side, hybrids offer shorter duration than their fixed-rate counterparts. In addition, hybrids are associated with higher levels of turnover and somewhat muted refinancing response and thus have somewhat better convexity characteristics.

Prepayment models for 3/1, 5/1, 7/1, and 10/1 ARMs all share the same structure and driving factors. Like most other BRS prepayment models, there are two additive parts: refinancing and turnover components. In addition, there are structural differences for each the fixed, reset, and floating periods.

Chart 33: Hybrid ARM Prepayment Model Structure

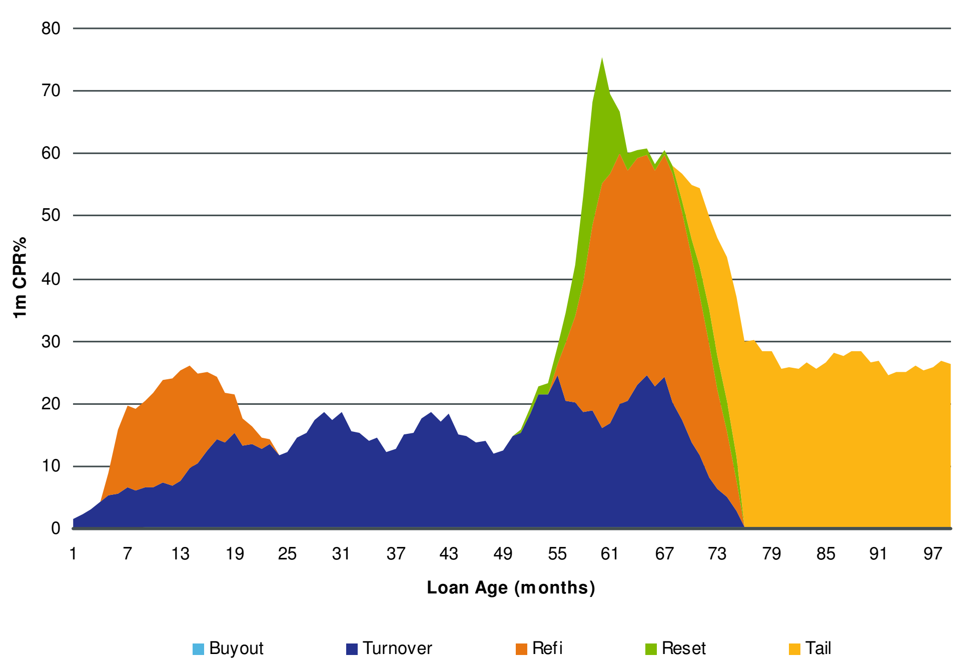


Figure 5: Hybrid ARM Reset Model Variables

Additional Reset Impact	Combined Floating Period Turnover and Refinance
• Month to/since First Reset • Cap/Floor structure • IO vs Non-IO • Yield Curve Spread • CLTV • FICO • Incentive	• Months Since First Reset, months to next reset • Seasoning • Incentive • IO vs. Non-IO • SATO • Yield Curve Spread • Home Price Appreciation • Existing Home Sales • Seasonality

Agency Hybrid Floating (Tail) Period Model

For relative value and hedging purposes, it is desirable to have all hybrids in their floating period reference the same rate to compute the refi incentive. The 1/1 ARM rate is chosen as it better aligns with actual prepayment behavior. Seasonality includes the seasonal turnover changes as well as number-of-business-days impact.

Seasoning/Months to Reset Factor

As the fixed-term of any hybrid ARM approaches its end, prepayment speeds increase dramatically as the more risk-averse borrowers refinance into other products.

Hybrids season faster than their conventional fixed-rate counterparts with 3/1s being the fastest, and 10/1s being the slowest. The self selection process is evident, as many hybrid borrowers keep their homes for shorter periods. Owners that tend to move in a few years select hybrid ARMs for their mortgages.

Compared to fixed rate mortgages, hybrid ARMs normally have fast base-line turnover speeds and less sensitivity to rate changes, therefore less negative convexity. The rate response is more muted when a loan approaches reset. After a couple of resets, the model becomes insensitive to rate changes.

IO vs. non-IO Factor

IOs typically have much larger loan sizes than comparable non-IOs. Hence, IO and non-IO speeds are often not significantly different if loan size is not controlled. However, controlled for loan size, IO becomes a significant factor to be included in the prepayment model.

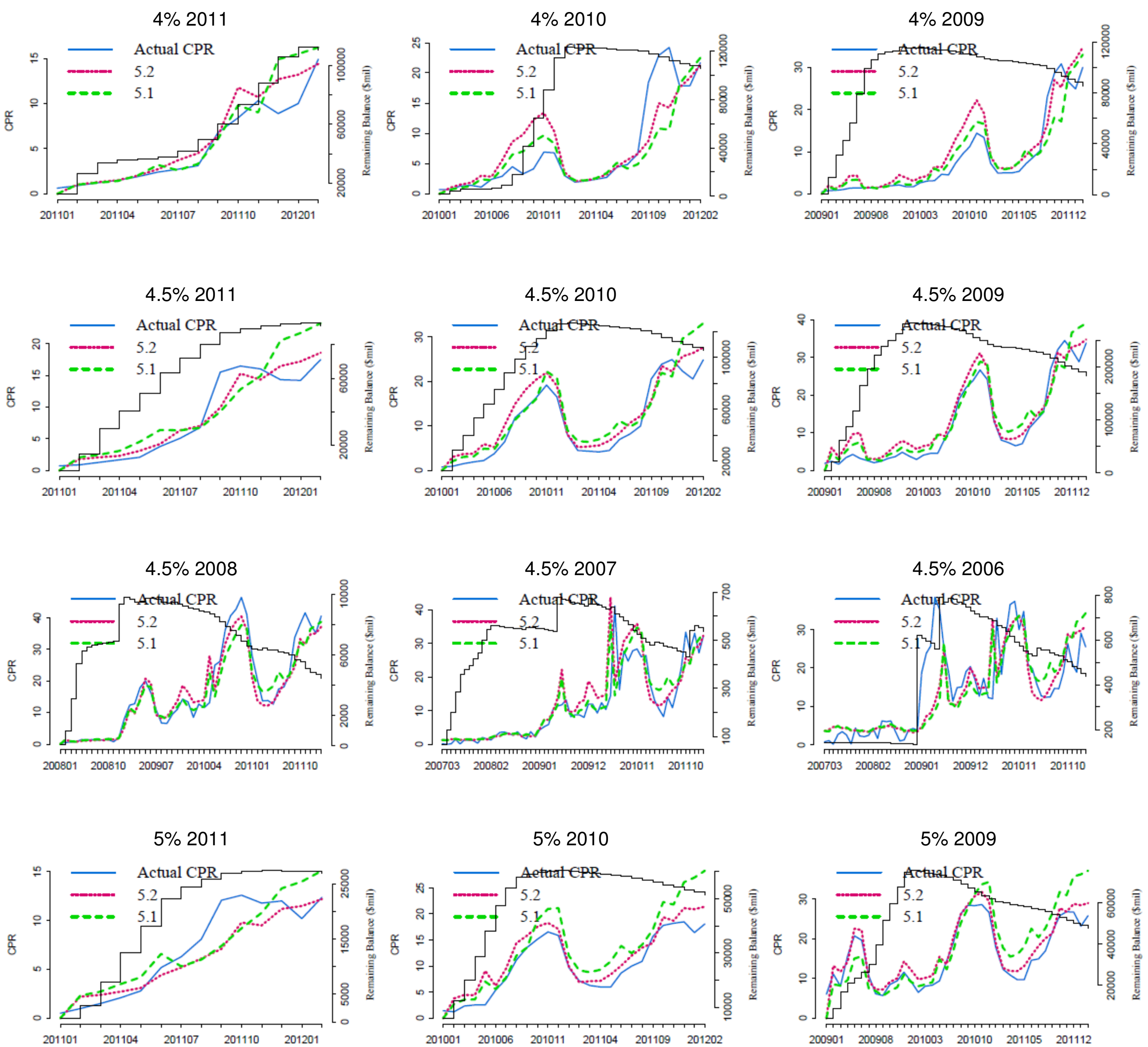
Most agency IOs have a teaser period equal to the IO period, creating low rate incentive. Therefore, IO prepayment speeds are slightly slower in the fixed period than that of non-IOs.

IO speeds pick up and exceed speeds of non-IOs when age approaches first reset. It has slightly reduced response to refinancing incentives. Although data is close to non-existent, we expect the double-shock of rate reset and principal paydown to substantially increase IO speeds near the end of the IO period.

In-sample Validation

As part of model validation, in-sample validation asses how well the model performs relative to actual market disclosures. The graphs below compare the current and previous model prepayment speed projections versus actual prepayments disclosed by the Agencies. Figure 6 shows in-sample validation for FN30 cohorts across different coupons and vintages. Figure 7 shows in-sample validation for GN30 cohorts across different coupons and vintages (5.2 represent the current model and 5.1 represent the previous model projections).

Figure 6: FN30 In-Sample Validation



Agency Mortgage Model

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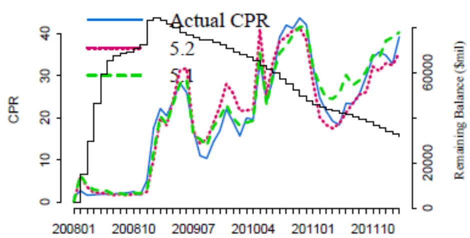

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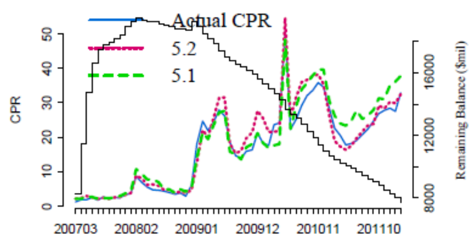

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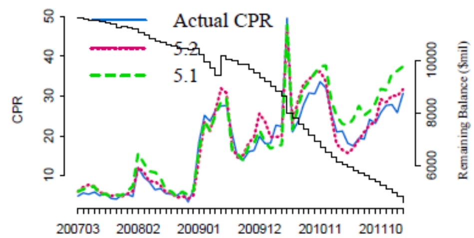

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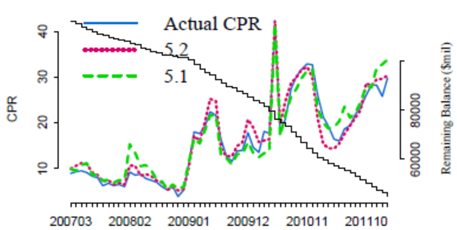
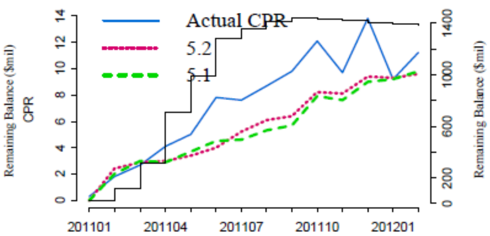


5.5% 2011



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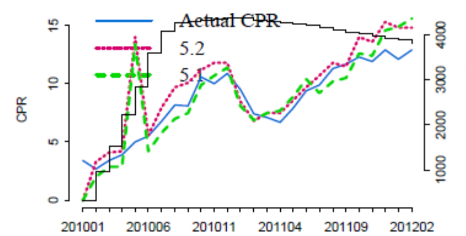

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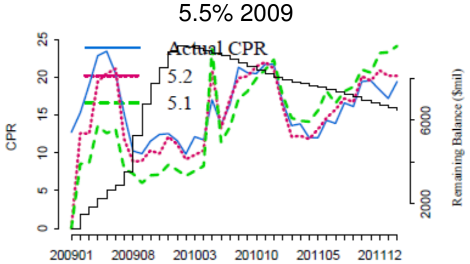

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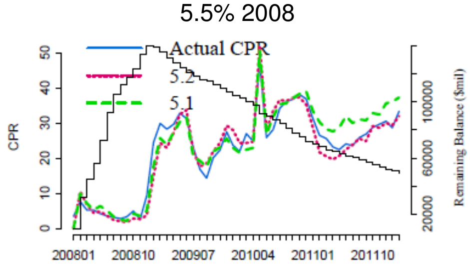

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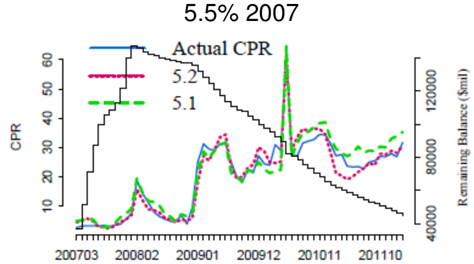

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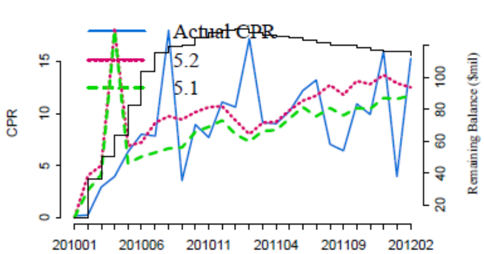

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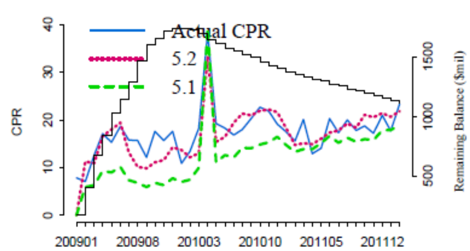

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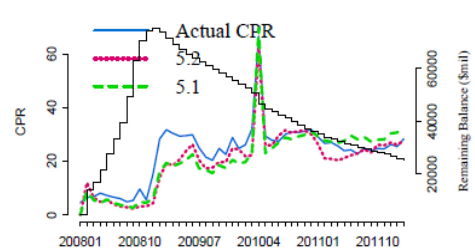

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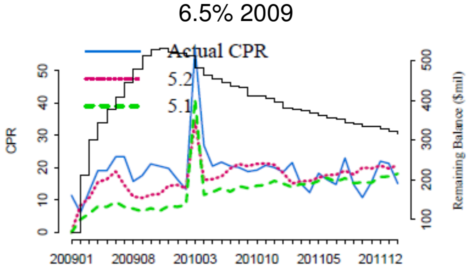

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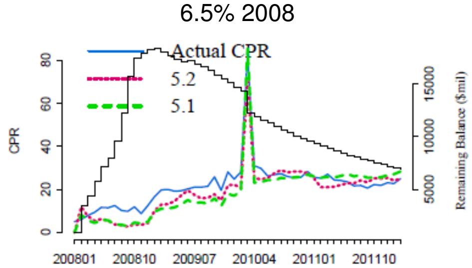

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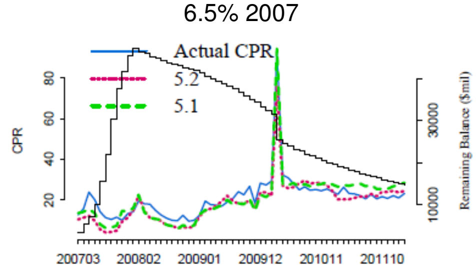


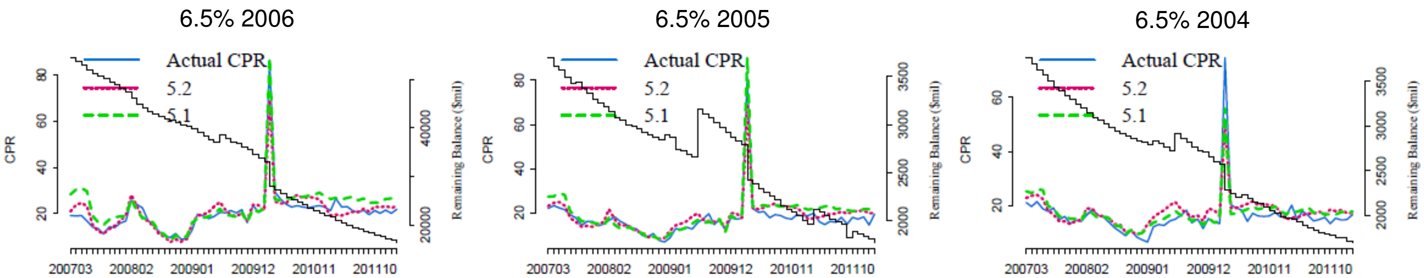
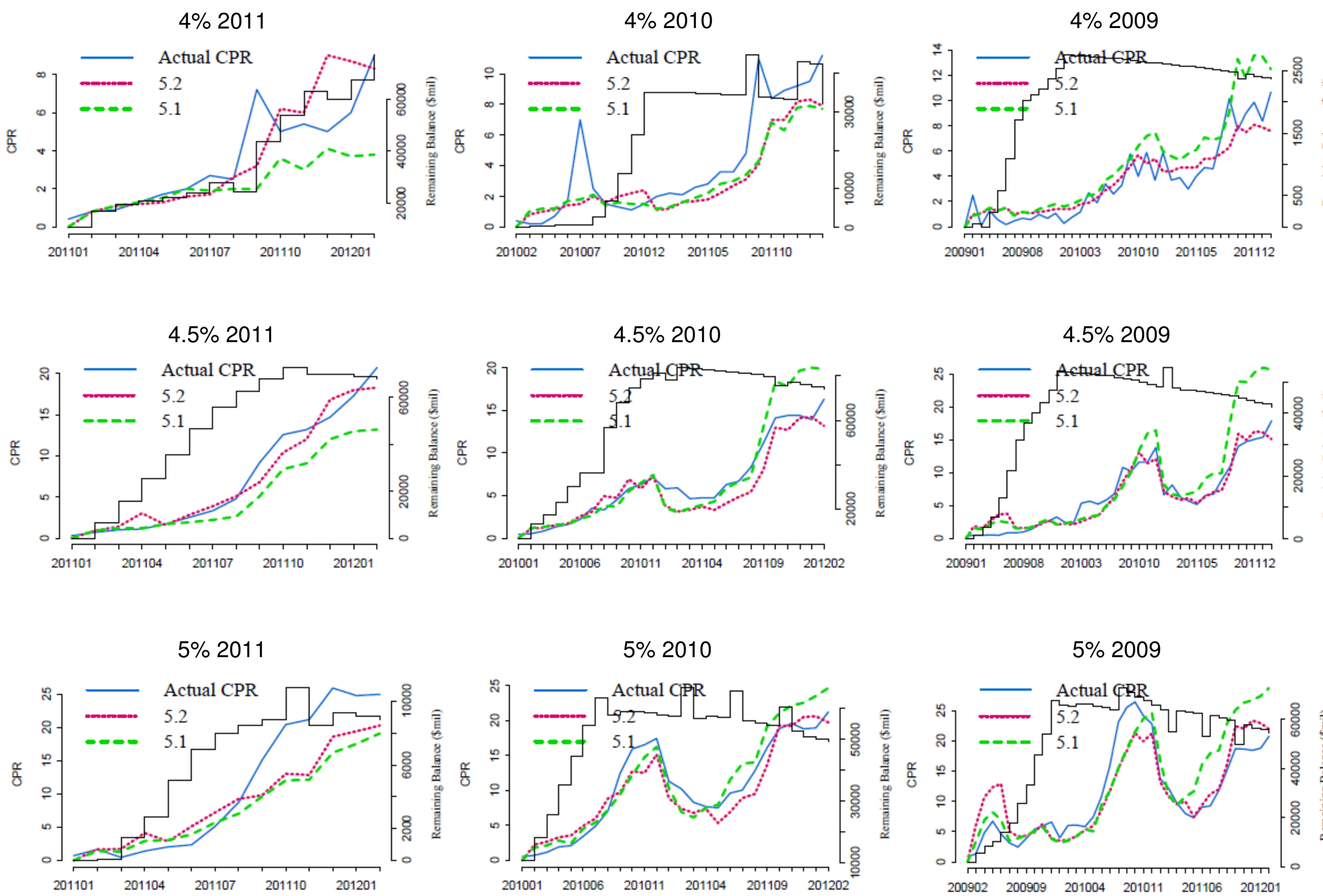


Figure 7: GN30 In-Sample Validation



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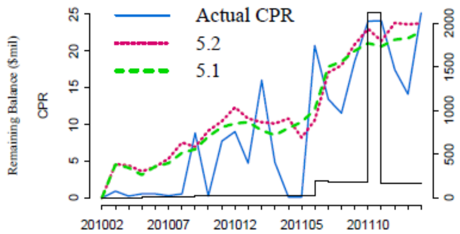

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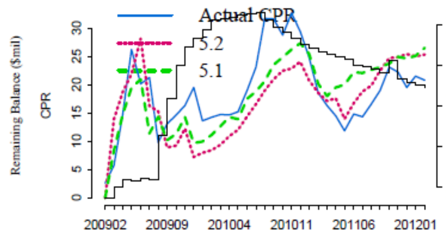

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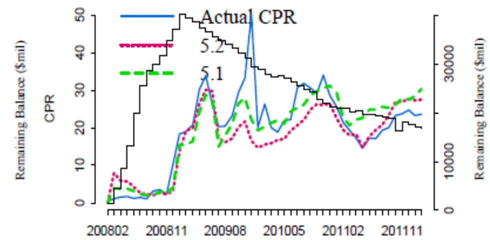

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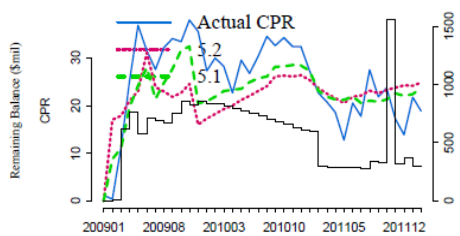

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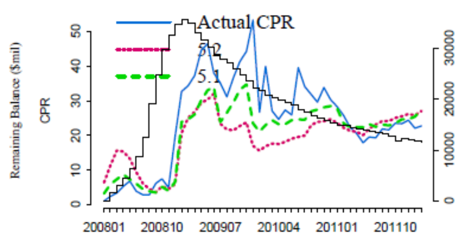

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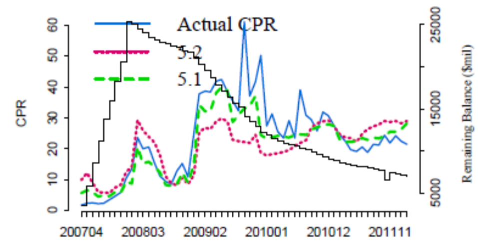


Non-Agency Mortgage Model

Introduction

The BlackRock Solutions non-agency models are non-parametric statistical models of mortgage performance that are used to construct collateral projections, security valuations, and risk metrics. BRS utilizes proprietary statistical estimation methods and detailed loan-level data and TransUnion consumer credit data to calibrate the models. LoanPerformance (LP) mortgage data is used in conjunction with zip-code and MSA level house price data as well as other local economic data.

The models are compartmentalized by collateral type and seasoning so that each major collateral type is modeled separately and the models that are applied to new origination are different from those applied to seasoned collateral. This framework provides the modeling flexibility necessary to handle the distinct behavior of different collateral cohorts. In addition to the base model set, modified loan models built using recent loan-level data are incorporated to accommodate the unique characteristics of modified loans.

The estimation process incorporates extensive in-sample validation and out-of-sample validation and monitoring. BRS has developed a set of proprietary tools that enable the validation and monitoring processes to be both efficient and transparent. In order to produce accurate forecasts with optimal run-time efficiency, BRS has also developed a proprietary algorithm to aggregate loan-level data into computationally efficient clusters along with a mapping between Intex and LP data that leverages the Intex cash flow engine for more efficient pool-level projections.

Mortgage Market Developments Influencing the Non-Agency Models

Stress in credit markets and weakness in the broader economy that began to emerge in 2007 have led to a variety of new issues for the modeling of mortgage behavior. The BRS non-agency modeling approach handles each of these developments by first relying on statistical analysis to expose historical relationships and then carefully fine-tuning the models to accommodate economic conditions that are not well-represented in the historical data.

Higher Delinquency and Credit Burnout: Residential mortgage performance began to deteriorate in 2007 as house prices started to fall and concerns over collateral performance caused significant credit market stress. As difficulties in the financial markets precipitated weakness in the larger macro-economy, unemployment rates increased and consumer credit performance continued to deteriorate. As shown in Chart 34, the share of delinquent outstanding loans increased from around 5% to over 35% and unemployment also rose quickly.

Chart 34: Delinquent Share of Outstanding Mortgages and the National Unemployment Rate

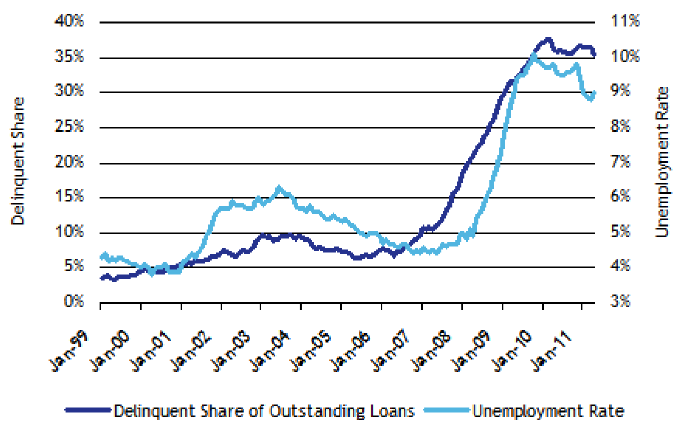
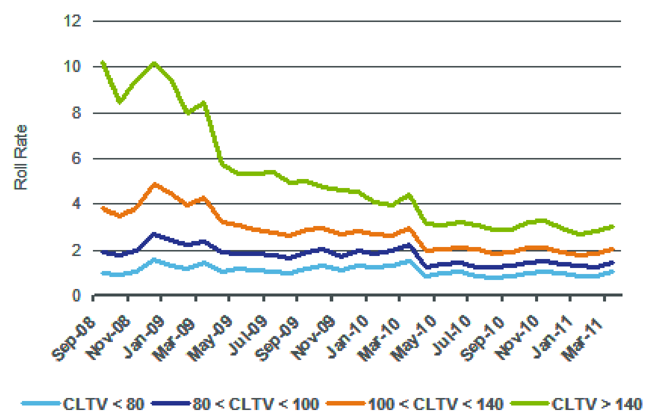


Chart 35: Current to 30 Days Past Due Roll Rate by Current LTV - Alt-A

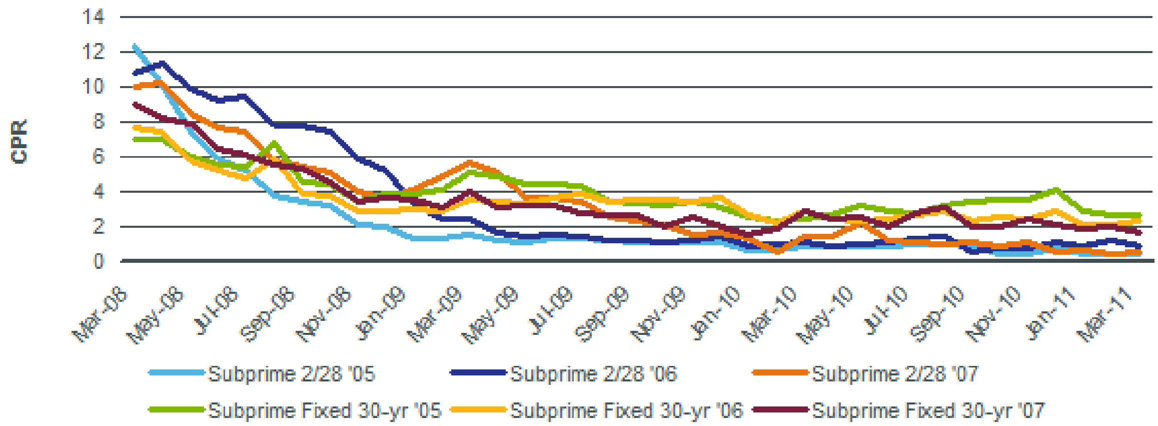


Those loans that survived this period have shown evidence of a weaker response to LTV than the loans that defaulted initially. Chart 35 shows the rate at which borrowers who are current become delinquent by month for a sample of Alt-A collateral. Loans with high mark-to-market loan-to-value (LTV) ratios became delinquent at high rates in 2008 but those that did not default and remained in the pool have had much lower delinquency rates.

The delinquency response to LTV that was observed in 2008 and 2009 is therefore likely to overestimate the future response of the remaining loans so the historical relationship must be adjusted when used to construct projections. The extent to which this relationship should be fine-tuned to accurately predict future behavior is a modeling challenge that continues to receive significant attention and analysis.

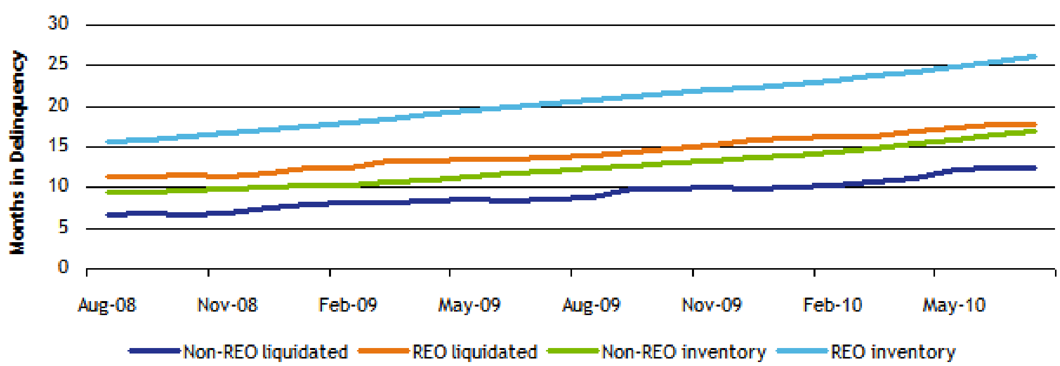
Constrained Credit: Concerns over the performance of mortgage-backed securities caused new issuance of mortgage-backed securities to stop almost completely and constrained access to refinancing opportunities for borrowers with weaker credit or nonconforming loans. As a result, prepayment rates have ground to very low levels for collateral with poor credit quality. Chart 36 shows that prepayment rates for Sub-Prime collateral have fallen close to zero since the credit crisis began. Low prepayment rates are not challenging to model in the short term but the regime change in underwriting standards has caused the historical relationship between the prepayment rate and refinancing incentive to weaken so the models must be re-calibrated to accommodate the change. In addition, constructing long-term forecasts has become more challenging since it is difficult to determine when credit constraints may loosen and the extent to which seasoned loan prepayment rates will respond at that point.

Chart 36: Historical Prepayment Rates for Sub-Prime Collateral



Foreclosure Timeline Extension*:* As a result of increased liquidation volume and foreclosure documentation issues, foreclosure timelines have extended significantly, creating uncertainty about the timing of cash flows and higher loss severity. Chart 37 shows the average number of months since the last payment as a measure of months-in-delinquency for loans already liquidated and loans that are in the pipeline. Non-REO liquidations can be assumed to be short sales. The months-in-delinquency for liquidated loans has been steadily increasing over the past two years. In addition, loans in inventory today have a much longer timeline than loans that were already liquidated, which implies that the future REO liquidation timeline may increase further.

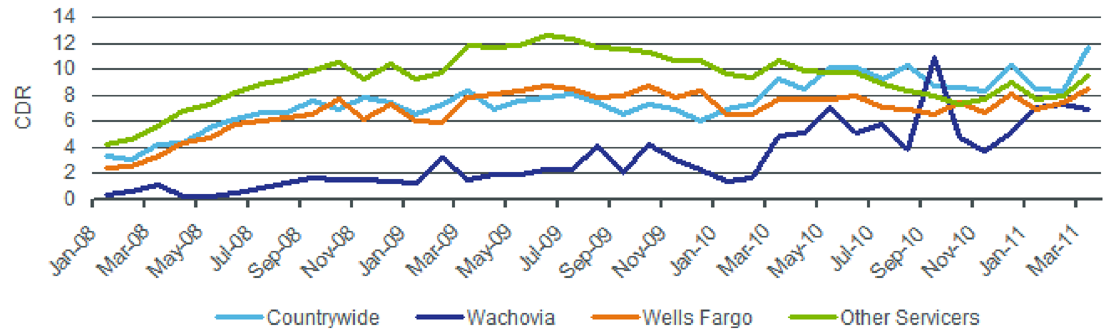
Chart 37: Months in Delinquency by Status



We explicitly model this timeline extension using recent historical data as a guide, but predicting the extent to which timelines will extend further or the point at which they will begin to contract requires ongoing attention. Policy changes are difficult to predict and new developments in the foreclosure process have been emerging frequently.

Servicer Behavior Differences: A closely related issue to the extension in foreclosure timelines is variation in servicer performance in the handling of distressed loans. As the volume of distressed loans has increased, significant servicer variation has emerged in the handling and liquidation of distressed properties. While some servicers have been relatively aggressive in liquidating properties, others have built up large delinquency pipelines. In addition, some servicers have themselves faced financial issues that complicated their ability to actively expand their capacity. Chart 38 shows the average aggregate default rate for non-agency collateral over time for several large servicers. The default rate can vary significantly depending upon servicer performance and policy, and it can vary over time as servicers ramp up liquidation processing or enact temporary foreclosure moratoria.

Chart 38: CDR by Servicer



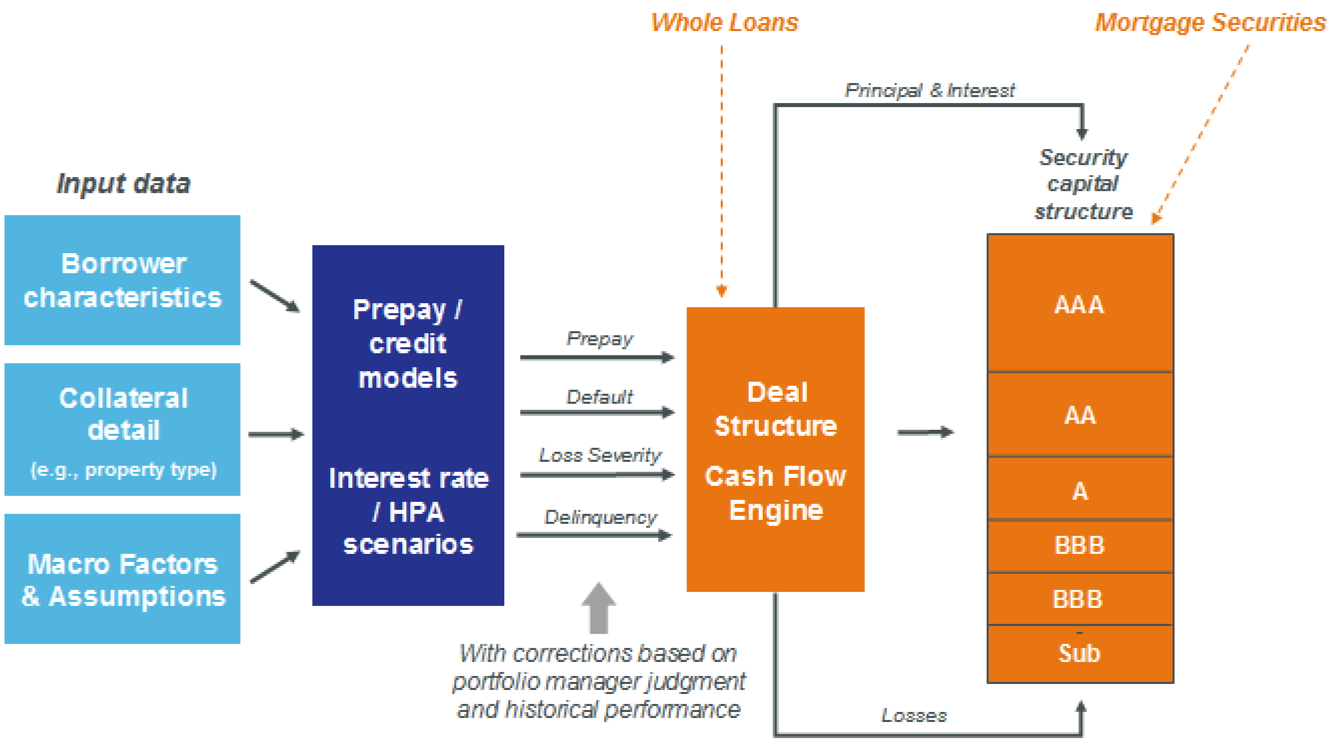
Servicer behavior is incorporated in our default models based on servicers' recent historical performance. Because servicer behavior can change quickly, the BRS models are built to allow the servicer adjustments to be easily turned off or modified, and these components of our models are constantly monitored so that adjustments can be made quickly when conditions change.

Non-Agency Mortgage Model

Data Framework

The BRS non-agency models are non-parametric statistical models estimated using loan-level data on mortgage characteristics and performance supplemented by local economic indicators and house price data. Figure 8 illustrates the operational structure of the forecasting process. Loan-level mortgage and TransUnion Consumer Credit data and various macroeconomic factors provide the inputs to the BRS model suite which forecast the performance of mortgage pools. The Intex cash flow engine is used to transform these pool-level projections into security-level cash flow projections for valuation and risk management. Below we describe the underlying data, econometric approach and model structure in greater detail.

Figure 8: Non-Agency Data and Model Structure



Loan-level Data: Loan-level mortgage data including both static and dynamic information on each loan are provided by LoanPerformance (LP). The static dataset includes borrower attributes (FICO, DTI, documentation, etc.) as well as loan characteristics (loan size, origination date, LTV, purpose, occupancy, penalty term, product type, etc.). The dynamic dataset provides borrowers' monthly payment and delinquency history. Significant due-diligence is applied to the loan-level data in order to prepare it for use in model estimation. The level of detail provided by the data creates tremendous opportunity to build attribute-sensitive models where each model factor can be estimated and used to predict prepayment and credit events.

LP provides loan level details on approximately 90% of all outstanding non-agency origination. Table 2 provides sample characteristics by collateral type and vintage for the bulk of the loans used in model estimation. Additional data covering older vintages, second liens, and modified loans are also utilized. A proprietary mapping between LP and Intex has been engineered into the BRS platform to leverage both sources of data for more accurate projections. The clustering of loan-level data from LP, in conjunction with Intex data, improves both model accuracy and run-time efficiency. The LP data is also used to create cohort averages to provide additional details for deals with missing pool information.

Table 2: Aggregate Loan Sample Characteristics

Collateral Type	Vintage	Aggregate Balance ($Bill)	OWAC	Combined LTV	Average Loan Size	FICO	Full Doc	Judicial State
Prime	2000	43.9	7.90	74.2	360,879	598	75%	28%
Prime	2001	126.4	6.95	68.5	438,802	687	75%	24%
Prime	2002	166.8	6.00	65.6	463,785	717	69%	25%
Prime	2003	218.4	5.06	66.2	462,723	705	67%	26%
Prime	2004	179.0	4.89	71.5	429,318	727	60%	25%
Prime	2005	160.8	5.62	72.9	506,096	729	53%	27%
Prime	2006	116.9	6.38	74.6	568,510	734	46%	28%
Prime	2007	97.4	6.39	76.3	603,205	742	43%	30%
Alt-A	2000	14.0	9.12	80.0	193,065	689	37%	29%
Alt-A	2001	34.2	7.77	77.7	252,921	679	36%	27%
Alt-A	2002	55.3	6.97	76.3	243,039	705	37%	27%
Alt-A	2003	97.0	6.02	75.5	226,273	706	35%	27%
Alt-A	2004	196.3	5.76	80.4	239,829	697	36%	27%
Alt-A	2005	290.2	6.21	81.1	258,989	708	31%	30%
Alt-A	2006	283.9	6.90	83.0	293,259	705	21%	31%
Alt-A	2007	127.5	6.48	80.3	362,633	715	20%	28%
Option ARM	2000	3.0	4.07	70.1	515,505	720	29%	15%
Option ARM	2001	2.2	4.07	68.0	492,292	719	32%	14%
Option ARM	2002	3.7	3.54	69.2	490,552	718	33%	17%
Option ARM	2003	2.9	1.97	71.8	296,666	700	31%	19%
Option ARM	2004	50.0	1.36	73.2	368,368	703	26%	20%
Option ARM	2005	134.9	1.29	77.3	373,658	693	18%	19%
Option ARM	2006	140.2	1.98	79.1	378,951	707	10%	23%
Option ARM	2007	33.7	2.54	79.0	388,021	709	11%	26%
Sub-Prime	2000	47.4	10.24	78.5	103,390	554	77%	37%
Sub-Prime	2001	68.2	9.25	80.2	125,342	574	73%	35%
Sub-Prime	2002	114.5	8.23	80.8	145,073	607	68%	35%
Sub-Prime	2003	210.5	7.37	82.5	164,153	623	64%	35%
Sub-Prime	2004	349.9	7.04	84.0	179,434	620	62%	35%
Sub-Prime	2005	457.0	7.28	85.4	199,350	627	58%	38%
Sub-Prime	2006	379.8	8.21	86.4	211,662	624	56%	41%
Sub-Prime	2007	74.1	8.35	83.8	218,251	620	61%	43%

The details of the definitions of prepayment, default and delinquency are important to make explicit. Two standards exist for the calculation of delinquency status, the Office of Thrift Supervision (OTS) calculation method and Mortgage Bankers Association (MBA) calculation method. The difference between the two is the cut-off date for declaring a loan delinquent.[4] The industry convention is to use the more lenient OTS standard for Sub-Prime and Alt-A mortgages and the stricter MBA standard for prime

[4] Under the Mortgage Bankers' Association (MBA) standard, a loan is considered delinquent if the payment is not received on the end of business day before the next due date. On the contract, under OTS standard, a loan is only considered delinquent if the payment is not received by the close of business on the next payment due date. A loan can miss one payment and still be "current" under the OTS standard whereas the same loan would be 30 days late using the MBA standard.

mortgages. Following this convention, we define delinquency as OTS 60-day or more past due, including foreclosure and REO, plus bankruptcy.

Distinguishing default from prepayment in the loan-level data is more challenging since LP data does not provide information on the types of mortgage termination. We use the following two criteria to define a default. First we define default as a mortgage termination event, i.e. default occurs only when the loan balance is reported as 0. Second, the loan must be non-performing in the previous month. Non-performing loans include loans 150+ days past due, foreclosure, REO, and loans that made 1 or less payments in last 3 months or 3 or less payments in last 6 months. Once defaults are determined, the remaining terminations, excluding servicing release and clean-up calls, are classified as prepayments.

TransUnion Consumer Credit Data: Many important loan-level variables are provided only at origination and quickly become stale as a loan seasons or its borrower's financial circumstances change. The integration of updated consumer credit information with loan-level mortgage data therefore provides a valuable opportunity to improve estimates of credit and prepayment risk by differentiating borrowers whose credit quality has deteriorated from those whose credit quality has improved since origination.

TransUnion matches borrowers' credit files with loans in LoanPerformance using loan attributes such as origination date, size, interest rate and zip code. Version 2.0 of the TransUnion data has an active loan match rate with LoanPerformance of 93% and a false positive rate of 1.0% according to TransUnion.[5] The false positive rate is estimated using a sub-sample of loan in LoanPerformance for which TransUnion has a known credit file match. The active loan match rate varies moderately by collateral type.

The consumer credit data provides information that is incorporated into various components of the non-agency models. Among the most important variables constructed using the consumer credit dataare the following:

- Updated credit score – significant in the credit and prepayment models, updated credit scores allow the models to better differentiate borrowers whose credit has deteriorated since origination from those who have cured
- Updated mark-to-market LTV – the consumer credit data provides the account balances for other real estate loans on each borrower's credit file, allowing us to create a more accurate LTV estimate that takes into account silent seconds and second liens that have closed since origination of the first lien
- Credit account inquiries – when a borrower applies for a new line of credit, a credit account inquiry is recorded, providing a useful short-term predictor of refinancing activity
- Revolving account utilization – utilization on revolving accounts such as HELOCs, credit cards, and consumer loans provides a measure of financial distress useful in both credit and prepayment models
- Co-borrower – TransUnion provides credit account information for all borrowers matched to a particular loan, and we observe empirically that loans with more than one borrower tend to have lower credit risk, possibly due to a diversification of financial risk
- DTI estimator – using a proprietary income estimator and debt information from consumers' credit files, TransUnion has created an estimator for updated DTI
- Oldest trade age – measuring the time since a consumer opened his/her first credit account, this variable captures credit file length and has proven useful in the credit models

These variables are discussed in greater detail in the context of their incorporation into specific non-agency credit and prepayment models in subsequent sections of this document.

House Prices: The non-agency models utilize Case-Shiller constant-quality home price indices provided by Fiserv in order to construct HPA estimates and mark-to-market loan-to-value ratios. The indices are calculated from data on repeat sales of single-family homes and are produced monthly at the zip code level. Due to the impact of home price appreciation and loan-to-value ratios on many aspects of mortgage performance, granular home price data are used to create several important components of the BRS non-agency models.

Unemployment: Each month the Bureau of Labor and Statistics (BLS) releases seasonally-adjusted state-level unemployment data. This data is incorporated into many of the non-agency credit models in order to capture variation in economic activity both in the time series and across geographic regions.

[5] See "Non-Agency RMBS Product 2.0 Migration Overview" by TransUnion, June 21, 2011.

Existing Home Sales: The percentage of existing home sales (EHS) is an important variable in the BRS prepayment models because it captures the level of housing market activity. Quarterly state-level existing home sales data from the National Association of Realtors (NAR) and housing stock data from the US Census Bureau are used to compute the EHS time series.

Model Structure

The BRS models utilize the Generalized Additive Model (GAM) framework to estimate the highly non-linear relationships that occur in prepayment and credit models. Each predictor is estimated non-parametrically, and all predictors are linked together in the regression form in (1).

$$g(\mu) = \beta_0 + f_1(X_1) + \ldots + f_m(X_m) \qquad (1)$$

The function $g(\cdot)$ is the link function and μ is the conditional expectation of the dependent variable. Each of the X_i are predictors and the f_i are functions of the predictors. In most BRS models, the link function $g(\cdot)$ is the logit function. We assume the model errors follow a Bernoulli distribution. Then the expectation, μ, of the dependent variable, Y, as given by (2) is linked to the predictors via (3). The function log(μ/(1- μ)) is called the "logit" link function.

$$\mu = P(Y = 1 \mid X_1, \ldots, X_m) \qquad (2)$$

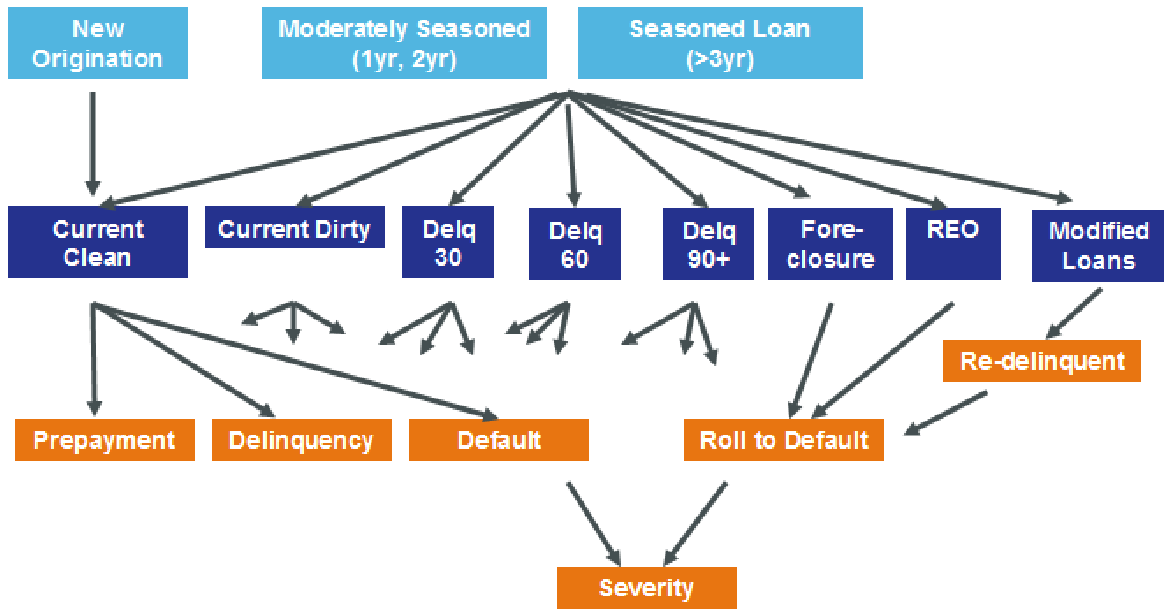
$$\log\left(\frac{\mu}{1-\mu}\right) = \beta_0 + f_1(X_1) + \ldots + f_m(X_m) \qquad (3)$$

A back-fitting algorithm is used to numerically solve for the optimized curves. Since each predictor's function is fitted non-parametrically, this method captures nonlinear relationships very well.[6] BRS has further extended the method to include more flexibility to handle predictor interactions.

Since loans that belong to different collateral types and seasoning groups can behave very differently, we separately construct prepayment, delinquency, and default models for each major collateral type and for several seasoning buckets as part of the BRS seasoned loan framework. This framework is illustrated in Figure 9. Alt-A hybrid loans are modeled separately from Alt-A fixed and jumbo hybrid loans, and within each collateral type, seasoned loans that are three years old are modeled separately from those that were originated two years ago. Loans are further distinguished by their payment status because loans that are already delinquent or in foreclosure have different relationships with input variables than loans that have remained current. This structure provides the flexibility necessary to accommodate the variation in loan behavior that occurs across collateral cohorts.

[6] For detailed introduction on GAM in Splus, please refer W.N. Venables and B.D. Ripley "Modern Applied Statistics with S," Springer, 2002 4th Edition.

Figure 9: BRS Seasoned Loan Framework



In order to produce accurate forecasts with optimal run-time efficiency, BRS has also developed a proprietary algorithm to aggregate loan-level data into computationally efficient clusters. Clusters are created by grouping loans with similar characteristics in order to minimize any impact on forecast accuracy, and projections are created by applying the model at the cluster level rather than at the loan level in order to improve processing time. BRS has also developed a proprietary mapping between Intex and LP data so that the LP data can be used to provide the inputs necessary to generate cash flow projections and the Intex cash flow engine is used to construct security-level performance projections. In practice, projections must be produced quickly because they are a necessary component of standard monitoring procedures, and this process allows projections to be run much more efficiently.

In addition, the BRS models incorporate proprietary logic to handle collateral with missing attributes. While key characteristics including WAC, WAL and LTV are always populated, some variables are not reported for all loans. Also, model users may create custom generic bonds without completely specifying all collateral characteristics. In these cases where collateral information is incomplete, cohort-level averages are used where a loan's cohort is defined by characteristics including collateral type, vintage, and WAC. Cohort averages are re-calculated each month to account for changes in collateral characteristics. This process ensures that the BRS models are robust to situations where collateral information is not specified completely.

Prepayment Model Structure and Key Variables

Borrowers pay off their mortgages ahead of schedule for a variety of reasons. Among the most important are the following:

- *Housing turnover.* Significant life events such as marriage and job-related relocation might cause a borrower to pay off their mortgage as part of the process of selling their property.
- *Rate refinancing.* Borrowers may refinance in order to acquire a loan with a lower interest rate.
- *Cash-out refinancing.* In order to consolidate loans or resolve financial constraints, some borrowers may refinance into a larger loan. This type of refinancing is particularly prevalent among Sub-Prime borrowers, and in some years, more than half of all Sub-Prime loans have been cash-out loans.

The BRS models treat turnover and refinancing separately in an additive framework. In contrast to the data available for modeling agency mortgages, the non-agency loan-level data provides payment status information that identifies mortgage defaults so default rates do not need to be estimated as buyouts are estimated for agency collateral. A refinancing remains indistinguishable from turnover-related prepayment, however, therefore out-of-the money loans are segregated into a dataset that is used to estimate turnover. We assume that prepayments in this pool are purely the result of turnover and not economic incentives. The turnover model is then used to construct a turnover estimate for the in-the-money loans and any excess prepayments are assumed to be the result of economic incentives and are used to estimate the refinance models. We do not construct a cash-out refinancing model directly since cash-out refinancing is mainly the result of home equity buildup which is already included in the turnover and refinancing components.

Due to self-selection, different products exhibit unique prepayment behaviors and we individually model most product types. For ARM products, prepayment behavior in the fixed period is different from that in the floating period, so the prepayment speed is estimated separately in each period.

This section provides additional details about the most important variables in the BRS prepayment models. The prepayment rate is often reported as a conditional prepayment rate (CPR) that is equal to the proportion of the collateral pool that is prepaid each month.

Seasoning: The aging curve describes the average prepayment rate by loan age in months and it may be considered a base projection that is adjusted by the incorporation of additional static and dynamic variables. Charts 39 and 40 illustrate historical prepayment aging curves by product type and vintage. A typical aging curve includes an initial 12-month ramp-up because borrowers who have recently obtained loans are less likely to pay off or refinance since they have just invested the fixed costs involved in moving and obtaining a loan. Prepayment curves for hybrid loans will include spikes at 1-year increments as prepayments rise substantially upon the expiration of the fixed-rate period and the expiration of a prepayment penalty.

Chart 39: CPR by Collateral Type

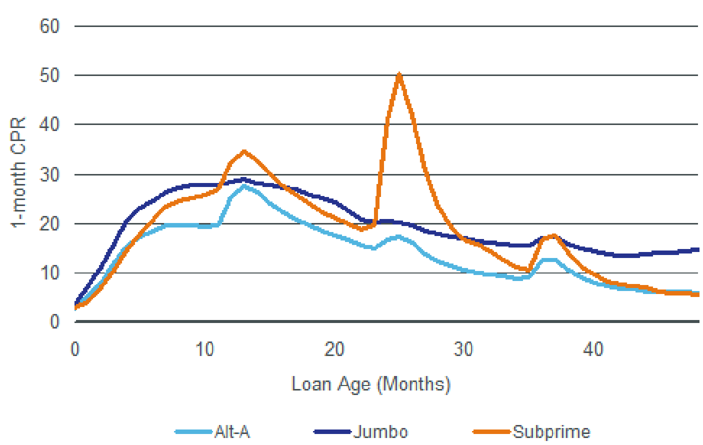
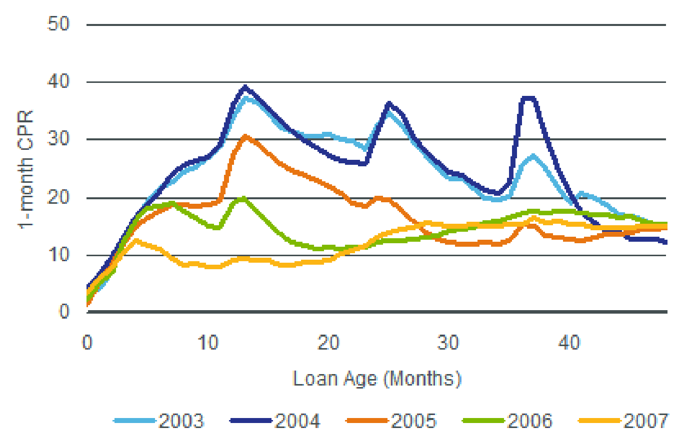
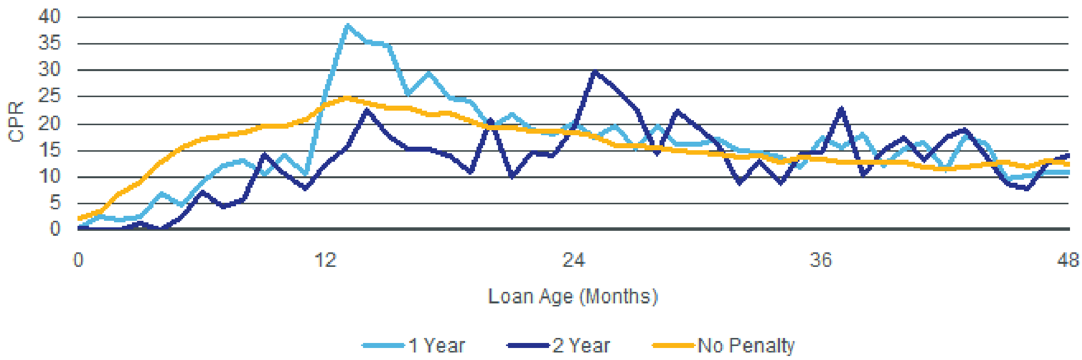


Chart 40: CPR by Vintage - Alt-A



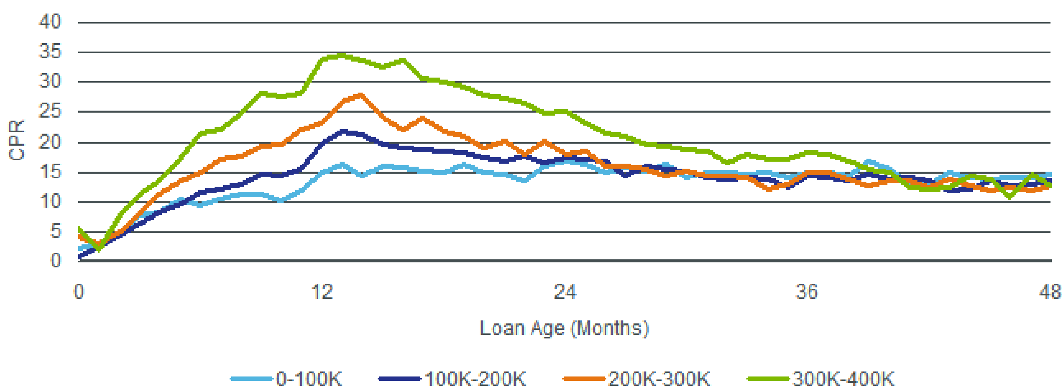
Fixed-rate loans without a prepayment penalty do not exhibit the same peaks in CPR. As illustrated in Chart 41, when a 1-year penalty expires, prepayment speeds jump from about 20% in the no penalty case to 38% in the 1-year penalty case. Prior to penalty expiration, the speed is slower than in the no-penalty case as borrowers who would otherwise pay off their loan delay their prepayment. After the penalty expires, the prepayment speed gradually slows and almost flattens out. When an ARM reaches the end of its fixed period, prepayments may also spike if interest rates are low since borrowers will attempt to refinance into a new loan with a lower rate than their current ARM.

Chart 41: CPR Aging Curves by Prepayment Penalty Period - Alt-A



Loan Size: In general, larger loans tend to prepay more quickly both in terms of turnover speed and refinance rate. Larger loans tend to be associated with more settled, older households who tend to relocate less often than younger households. They also tend to be more responsive to interest rate incentives and prepay more quickly as interest rates fall. This is because a borrower with a larger loan can save more in total dollar terms even with the same rate incentive since fixed refinancing costs reduce the savings by a smaller relative amount. Chart 42 shows CPR aging curves by origination loan size and illustrates that at their peak CPR one year after origination, loans with an original size below $100k have a CPR of 15 while those with a loan size between $300,000 and $400,000 have a CPR more than twice as high.

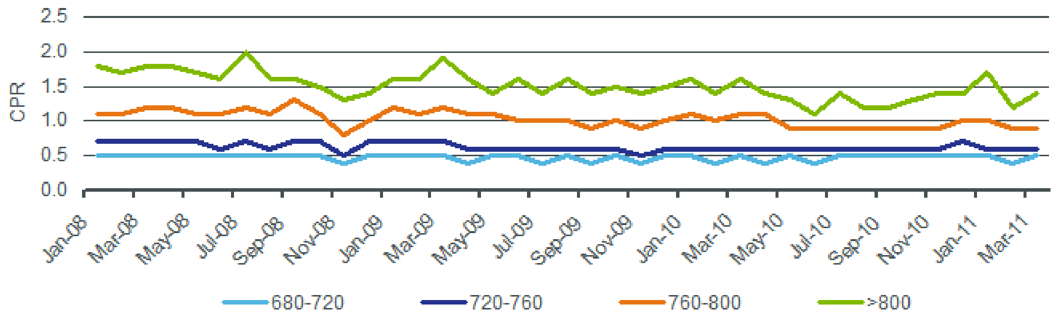
Chart 42: CPR Aging Curves by Origination Loan Size - Alt-A



It should be noted that borrowers with very large loans may have trouble refinancing when credit markets are under stress. It is currently difficult for borrowers with large non-conforming loans to refinance, particularly into hybrid products, because of the collapse of the non-agency market and the lack of alternative sources of financing.

Credit Score: Borrowers with better credit tend to prepay more quickly since they are less likely to be constrained by their credit when an incentive to move or refinance arises. Higher credit scores as measured by FICO therefore generally imply higher prepayment speeds. Chart 43 shows CPR over time for loans that have never been delinquent by FICO at origination. Loans with an average FICO at origination between 680 and 720 prepay at roughly half the rate of borrowers with a FICO above 800.

Chart 43: CPR by Origination FICO (Current Loans)



For some product types the FICO score may have opposite effects in the turnover and refinance models. Since it is easier for borrowers with high FICO scores to refinance, they tend to prepay faster in general. On the other hand, borrowers with low scores may prepay relatively quickly because if they do not become delinquent, their credit scores will improve and they will acquire access to credit with better terms. This behavior is called credit curing and is noticeable for 2005-2007 Sub-Prime collateral. Also, low FICO borrowers have historically been more likely to engage in cash-out refinancing when it has been available which increases their refinance rates. These effects are likely to be less significant in the foreseeable future, however, since tighter underwriting standards have increased minimum down payment requirements and restricted access to credit for borrowers with weak credit.

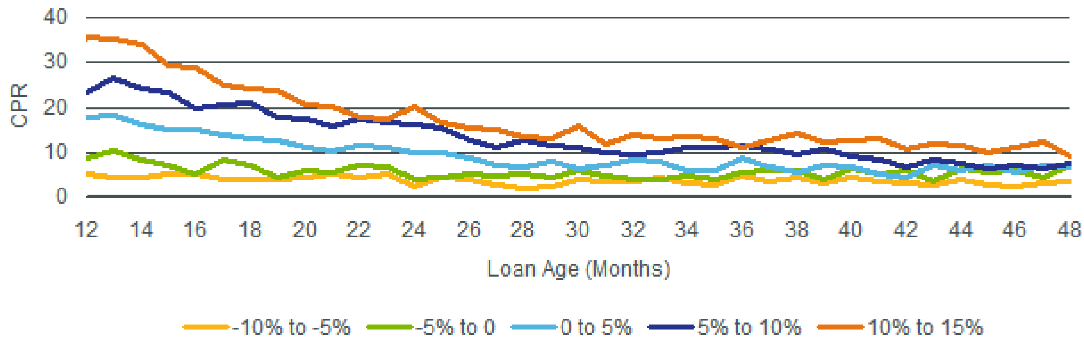
In addition to FICO at origination, the BRS non-agency models also incorporate updated credit score information derived from consumer credit data. Updated credit scores allow the models to better differentiate borrowers whose credit has deteriorated since origination from those who have improved, particularly for borrowers who have remained current on their mortgage. The variation in credit quality across borrowers is significant, even for always-performing non-agency collateral. Table 3 provides the fraction of borrowers with current updated credit score in several FICO buckets by their score at origination for loans that have been current for the previous twelve months. TransUnion provides a Vantage Score which we translate here into an “implied FICO” for ease of comparison with the origination data. The models are estimated and run using the Vantage Score directly in order to avoid potentially introducing noise through score translation.

Table 3: Updated Implied FICO by Origination FICO – Alt-A Fixed as of Dec. 2011

		Updated Implied FICO					
		<660	680	700	720	740	>740
Origination FICO	<660	32%	13%	14%	11%	10%	19%
	680	25%	11%	12%	12%	11%	28%
	700	21%	10%	11%	11%	11%	35%
	720	17%	8%	10%	10%	12%	43%
	740	13%	7%	8%	10%	12%	50%
	>740	7%	4%	5%	6%	9%	69%

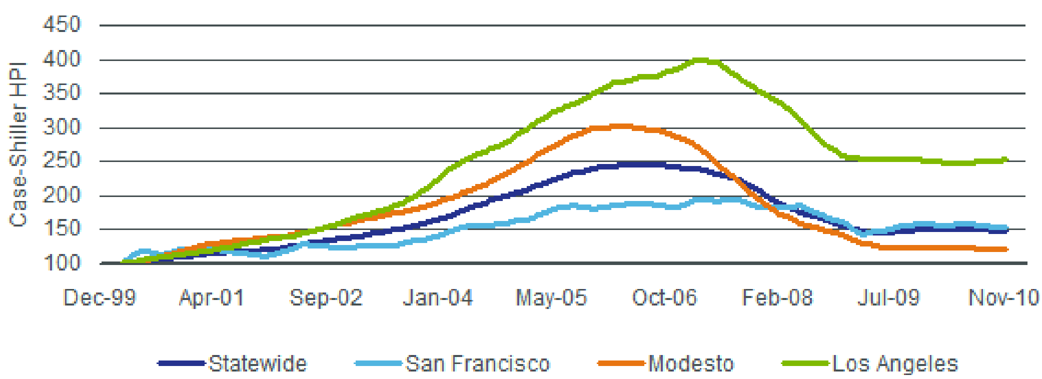
HPA: The condition of the housing market is clearly one of the most important factors driving prepayment rates. When house prices are rising, home equity is accumulated and borrowers are more likely to cash out the equity and consolidate their loans. In addition, a strong housing market tends to imply a strong economy or low interest rates, both of which increase prepayment speeds. When house prices fall, the opposite is true and homeowners are reluctant to sell and potentially realize a loss on their investment. Chart 44 shows aggregate prepayment rate by loan age for Alt-A fixed-rate collateral within 5 HPA buckets. Prepayment rates are significantly higher following high HPA.

Chart 44: CPR by HPA – Alt-A



Our prepayment models have held up well during the housing market slowdown to some extent because we use state-level HPA data which has enabled us to capture the impact of HPA changes at high level of granularity. While the differences in HPA among states are well-known, HPA within a single state can vary significantly as well. Chart 45 illustrates the difference in cumulative HPA between several large zip codes and the aggregate state level in California.

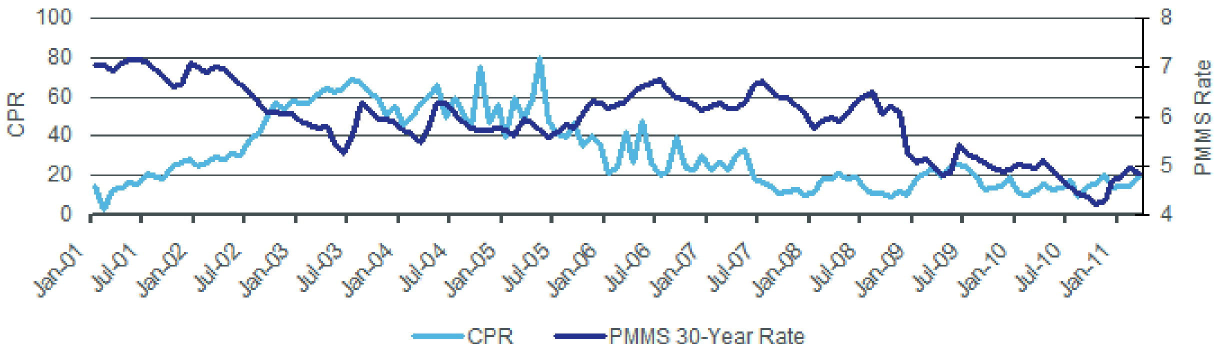
Chart 45: Case-Shiller Home Price Index by California Zip Code



Saving Incentive: A borrower's financial incentive to refinance is captured by a variable called the saving incentive, defined as the ratio of a borrower's current mortgage payment divided by his or her hypothetical payment after refinancing. If rates drop, borrowers can reduce their mortgage payments by refinancing into new loans, and the incentive increases.

Chart 46 shows the prepayment rate for Alt-A 30-year fixed-rate loans originated in 2001 and the 30-year Primary Mortgage Market Survey (PMMS) rate. As rates declined in 2002 and 2003, prepayment rates increased as borrowers refinanced into lower-rate loans, and as rates increased in late 2005, prepays fell as the financial incentive to refinance disappeared. As a pool of collateral seasons, it becomes less responsive to the refinance incentive since the remaining borrowers may not be able to refinance due to poor credit or they may be less willing to go through the refinancing process. As rates decreased in 2009, prepayment rates in this cohort showed a very weak response to the large drop in rates.

Chart 46: PMMS Rate and CPR for Alt-A 30-year 2001 Collateral



The saving incentive depends critically on the hypothetical refinancing rate and the construction of this rate involves a number of technical challenges since a market mortgage rate must be projected, a spread must be constructed to account for variation in borrower credit quality, and assumptions must be made about which product the borrower is most likely to choose when refinancing.

First, a set of rate models must be built to project the path of future loan rates available to borrowers. The details of these models are described in the BRS Mortgage Rate Model section. The models are estimated via the PMMS rates and constructed separately for conventional fixed-rate mortgages, ARMs and hybrid ARMs.

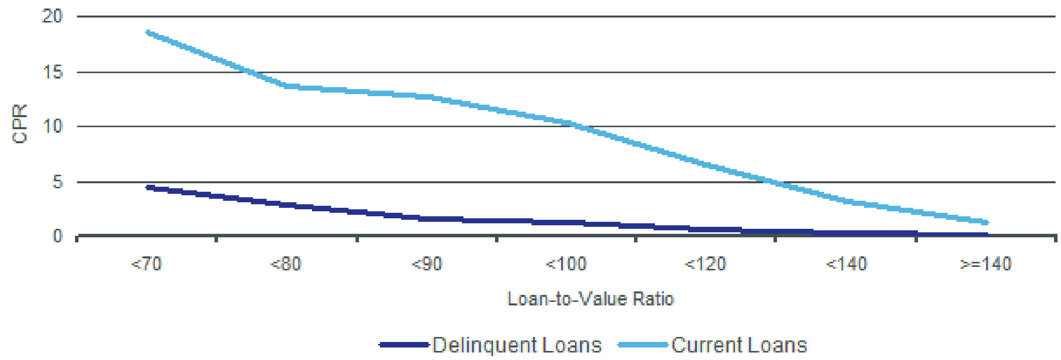
Second, originators price loan risk by charging higher rates for more risky loans. An interest rate spread model is therefore built to adjust the refinancing rate for the additional interest that each borrower may be forced to pay depending upon their credit risk profile. The spread model is calibrated using historical data and then used to estimate a refinancing spread that is added to the benchmark rate. The most important inputs to the spread model are listed below:

- *FICO* - Since the spread is intended to compensate investors and originators for credit risk, FICO is a very important indicator of the spread a borrower is likely to bear when refinancing.
- *LTV* - Borrowers who refinance are not likely to reduce their LTV unless it is required by the lender. A borrower's current LTV is therefore a good indication of future LTV and borrowers with higher leverage are charged a higher spread.
- *FICO-LTV interaction* - There is a strong interaction between LTV and FICO in the creation of the spread. Borrowers with better credit can receive the same spread for a higher LTV loan but borrowers with poor credit may be charged significantly more for a higher LTV.
- *Documentation* - When income is partially documented or not documented at all, a borrower is likely to be of higher credit risk.
- *Loan Size* - Jumbo loans require an extra spread to compensate for financing constraints.

Finally, adjustments must be made for refinancing costs. Some loans include a prepayment penalty that requires the borrower to pay an additional fee (generally six months of interest) if the borrower prepays the mortgage before a certain date (generally 1-3 years after origination). Prior to prepayment penalty expiration, a rate drop has a smaller impact on prepayment speed because of this additional refinancing cost. The saving incentive is therefore adjusted to take into account the prepayment penalty if it exists and other fixed refinancing costs.

Loan-to-Value Ratio: Borrowers with high LTV loans tend to prepay more slowly since they have less home equity to extract towards the down payment of a better quality property or alternatively to cash out. Also, high LTV loans tend to have higher rates which may reduce the saving incentive. Chart 47 shows the prepayment rate by current combined LTV for delinquent and current loans separately. As LTV increases, the prepayment rate decreases for both delinquent and current loans. Tt may be more difficult for delinquent borrowers to refinance, therefore the absolute magnitude of the effect is smaller for delinquent loans.

Chart 47: CPR by CLTV Bucket - Alt-A Fixed



The LTV used in the non-agency models is adjusted for amortization and house price appreciation. In addition, consumer credit data is used to identify second liens and HELOCs originated after the first-lien that are not observed in the LoanPerformance origination data. This leverage information is used to update the LTV to create a combined LTV that takes into account the “silent” seconds.

Credit Account Inquiries: When a borrower applies for a new line of credit, a credit account inquiry is recorded on the consumer’s credit file, providing a useful short-term predictor of refinancing activity. This information is obtained from consumer credit data and is primarily used to improve the accuracy of the near-term (1-6 month) prepayment projections.

Revolving Account Utilization: Utilization on revolving accounts such as HELOCs, credit cards, and consumer loans provides a useful measure of financial distress.

IO: Interest-only loans tend to prepay more slowly because they are self-selecting for borrowers with affordability constraints.

Loan Purpose: Loans originated during the process of purchasing a property often prepay more slowly than refinance loans. Many first-time home buyers have financial constraints so they tend to move and refinance less frequently. Also, cash-out fixed-rate refinance loans tend to prepay more slowly because of a self-selection bias: borrowers who refinance into fixed-rate loans instead of ARMs signal their intention to remain in their current houses longer.

Seasonality: Due to weather, the number of business days, and the scholastic calendar, prepayment speeds vary by calendar month with prepayments occurring more frequently during the summer.

Existing Home Sales: A strong housing market and high existing home sales result in faster turnover speeds. We utilize the EHS time series published by the National Association of Realtors to enhance our estimate of the base level of turnover.

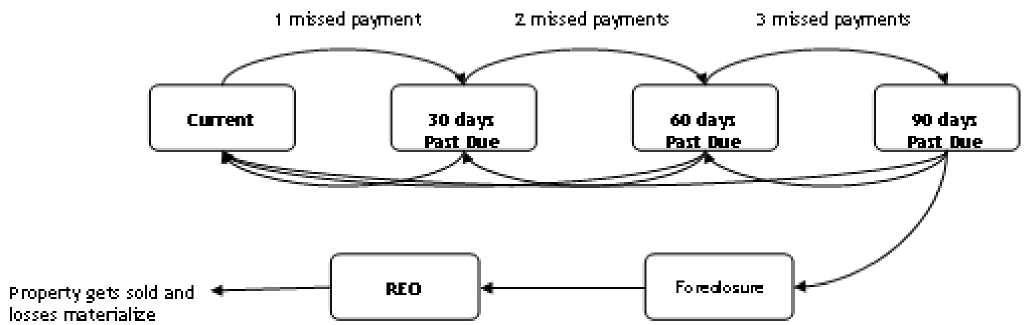
Media Effect: As mortgage rates hit new lows, speeds on relatively new mortgage products accelerate because borrowers who are considering a refinance may become apprehensive that rates will begin to rise, and lenders tend to approach borrowers more actively during this period. We measure the media effect by comparing recent benchmark rates to longer term averages.

Delinquency and Default Model Structure and Key Variables

When a default and foreclosure occurs, a non-agency investor may not recover the total outstanding principal balance from the liquidation value of the collateral. Credit risk is therefore a primary concern for holders of non-agency securities because unlike agency investors, they bear that risk directly. Forecasting defaults is therefore crucial to projecting deal performance.

The schematic diagram in Figure 10 illustrates the steps involved in a typical mortgage default which may vary by state and servicer. In general by the time the borrower has missed several payments, the servicer will attempt to contact the borrower and discuss alternatives, including loan modification. If the borrower continues to miss payments, the lender will begin the foreclosure process, eventually taking ownership in the REO (Real Estate Owned) stage before liquidating the property.

Figure 10: Typical Mortgage Default Process



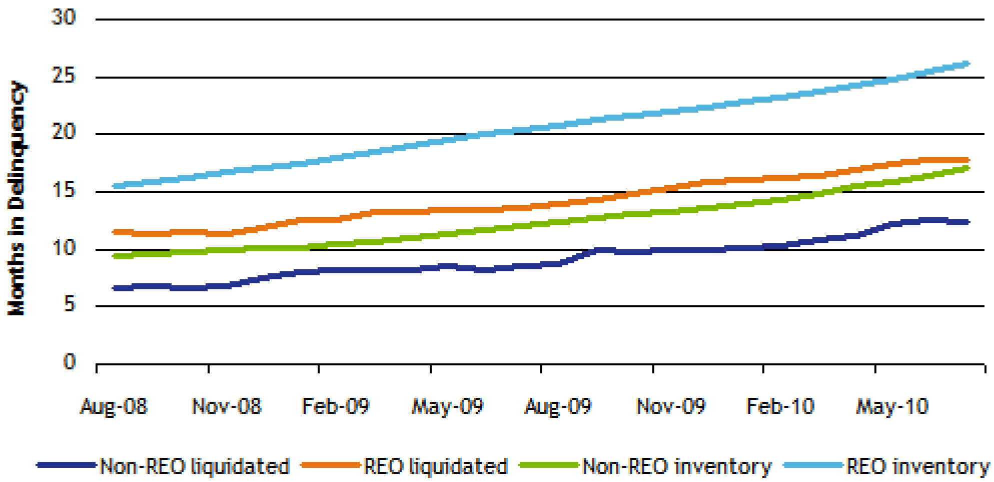
Delinquencies do not impact performance directly because the servicer typically continues to make the interest and principal payments on delinquent loans until the delinquency is resolved, however, delinquencies are a key component in determining the credit performance of a non-agency deal for several reasons:

1. Delinquencies are the best predictors of future defaults and losses.
2. Step-down triggers are based on delinquencies and cumulative losses. Forecasting delinquencies makes it possible to measure the risk inherent in subordinate bonds.
3. The residual holders and other subordinate tranches of the deal are directly impacted by delinquencies because of the triggers.
4. Losses on loans that default after a prolonged period in delinquency tend to be higher relative to defaulted loans that spent less time in delinquency.
5. Interest and principal advances are only made by the servicer to the extent that the servicer deems them recoverable and therefore may not always occur.

We therefore model delinquencies as well as defaults and refer to them jointly as “credit” models because they are so closely related and share many of the same driving factors.

Recently, the foreclosure timeline has extended due to mortgage documentation issues, servicer behavior, and the large volume of loans in the pipeline. Chart 48 shows the average number of months since the last payment as a measure of months-in-delinquency for liquidated loans and loans that are in the pipeline. Non-REO liquidations can be assumed to be short sales. The months-in-delinquency for liquidated loans has been steadily increasing over the past two years. In addition, loans in inventory today have a much longer timeline than loans that were already liquidated, which implies that the future REO liquidation timeline may increase further. We explicitly model this extension through the servicer-level aging curves in our default models described below.

Chart 48: Months in Delinquency by Status



The BRS delinquency and default models incorporate a broad range of variables that each capture some component of credit risk but the most salient model inputs are the following:

- The models are estimated based on loan-level borrower attributes such as seasoning, FICO, current combined loan-to-value ratio (CCLTV), documentation level, occupancy type, property type, loan purpose (cash-out, purchase or refinance) and debt-to-income (DTI) ratio.
- Local home price appreciation data is used to construct a current combined loan-to-value ratio (CCLTV) which is a key variable in our delinquency and default models because it captures the level of borrowers' remaining home equity.
- Foreclosure timelines vary by state and servicer so our models take into account the geographic location of the property and the recent historical performance of its servicer.
- Although rates are currently low, ARM borrowers can experience a sudden increase in mortgage payments when their rate resets. BRS has incorporated a payment shock variable in its delinquency and default models to capture this factor.
- As borrowers prepay and leave the pool, the proportion of borrowers that might default increases. Our models capture this adverse selection process.

This section provides additional details about the most important variables in the BRS delinquency and default models. The default rate is often reported as a constant default rate (CDR), defined as the proportion of outstanding loans that default each month expressed as an annualized rate.

Seasoning: As in the prepayment model suite, the aging curve describes the average delinquency or default rate by loan age in months. It may be considered a base projection that is adjusted by the incorporation of additional variables. Charts 49 and 50 illustrate average delinquency and default rates by months since origination and collateral type for a sample of loans originated between 2000 and 2010. Defaults and delinquencies are highest for Sub-Prime and lowest for prime due to various differences in credit quality and origination characteristics.

Chart 49: Delinquency Aging Curves by Collateral Type

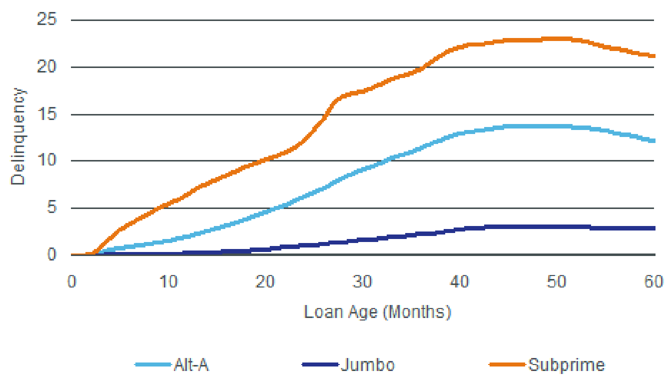
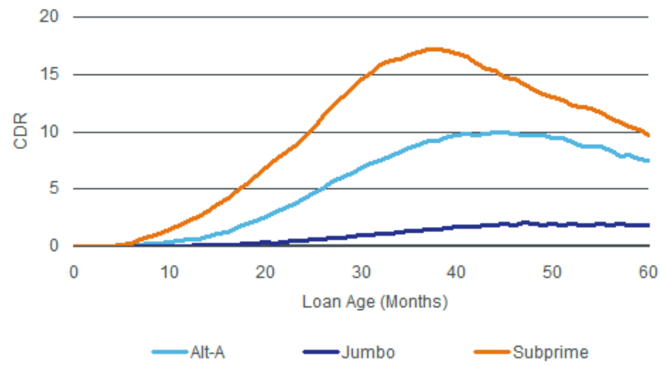


Chart 50: CDR Aging Curves by Collateral Type



Charts 51 and 52 provide delinquency and default rates by vintage for Alt-A collateral. Substantial performance variation exists by vintage, primarily due to differences in origination standards and LTVs. Loans in older vintages were originated during a period of tighter underwriting and tend to have lower current LTVs due to loan amortization and property appreciation.

Chart 51: Delinquency Aging Curves by Vintage

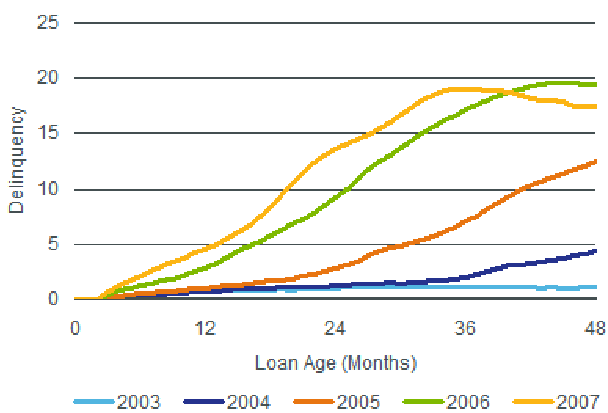
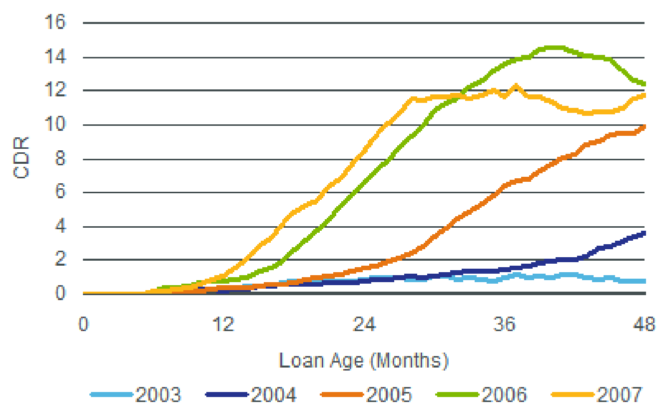


Chart 52: CDR Aging Curves by Vintage



Judicial State: Foreclosure practices vary significantly by state and a principal difference is defined by whether a state requires foreclosures to be processed through the courts or without court intervention. A judicial foreclosure requires significantly more time and provides the court with the opportunity to review foreclosure documentation so judicial states typically have extended foreclosure timelines. Chart 53 shows the average months in delinquency for delinquent loans, a proxy for the length of the liquidation period, and judicial states maintain a consistently longer liquidation timeline. Therefore within each default model and cohort, we estimate distinct aging curves for loans in judicial states and those in non-judicial states. Chart 54 shows CDR aging curves comparing collateral in judicial and non-judicial states, illustrating the aging curve adjustment necessary to compensate for slower defaults in judicial states.

Chart 53: Months in Delinquency by Judicial State

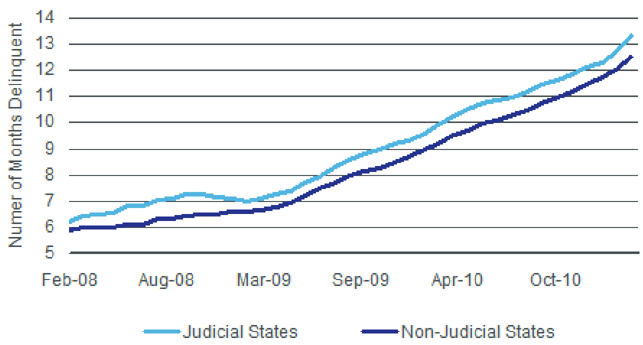
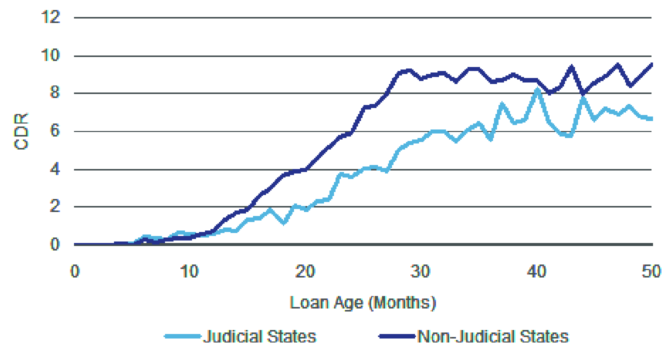
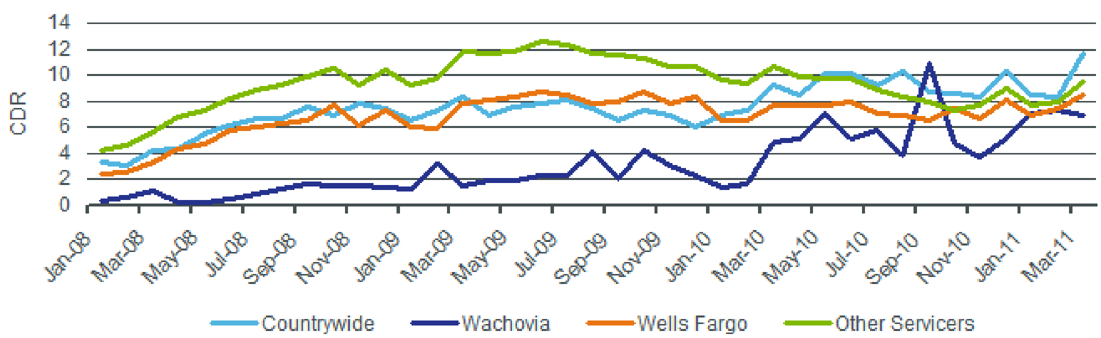


Chart 54: CDR Aging Curves by Judicial State



Servicer: As the volume of distressed loans has increased, significant servicer variation has emerged in the handling and liquidation of distressed properties. While some servicers have been relatively aggressive in liquidating properties, others have built up large delinquency pipelines. In addition, some servicers have financial issues that complicate their ability to actively expand their capacity. Chart 55 shows the average aggregate default rate for non-agency collateral over time for several large servicers. The default rate can vary significantly depending upon servicer performance and policy, and it can vary over time as servicers ramp up liquidation processing or enact temporary foreclosure moratoria.

Chart 55: CDR by Servicer

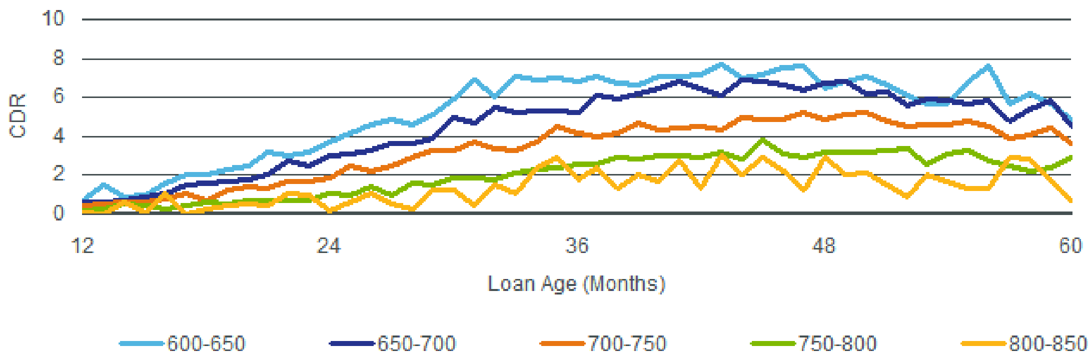


In order to capture this variation, we construct distinct default aging curves for several large servicers. Because it is difficult to predict when a servicer's performance or policy will change, these curves are actively monitored and adjusted as new developments arise.[7]

Credit Score: The most important static loan characteristic is the borrower's credit score, captured in our data by FICO. Chart 56 shows the Alt-A fixed-rate 30-year historical default rate by seasoning for different FICO buckets after controlling for LTV. The higher the FICO score, the lower the default and delinquency rate. After three years of seasoning, the average default rate for a borrower with a FICO score of 625 is about three times higher than that of a borrower with a FICO score of 775. High FICO borrowers are less cash-constrained compared to lower FICO borrowers, and a high FICO borrower has a higher opportunity cost of default compared to low FICO borrowers.

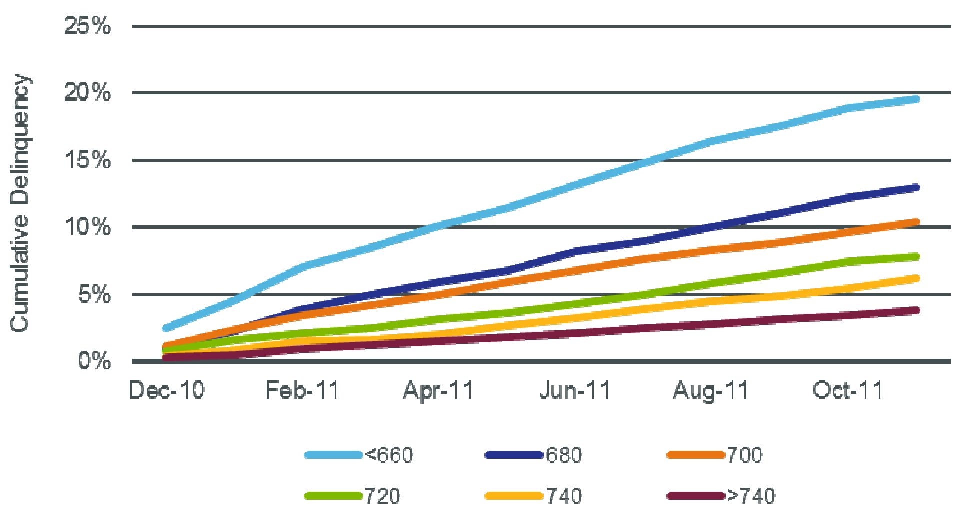
[7] Servicers also vary with respect to the loan quality and geography of the collateral they process, and these variations can cause differences in liquidation timelines that in turn result in shifts in the composition of the collateral. This is an additional reason for actively monitoring the servicer adjustments.

Chart 56: CDR Aging Curves by Origination FICO Score – Alt-A



In addition to FICO at origination, the BRS non-agency credit models also incorporate updated credit score information derived from consumer credit data. Due to significant credit score migration, updated scores have a very significant impact on delinquency and default projections. Chart 57 provides cumulative delinquency rates by updated implied FICO (as of November 2010) for a pool of Alt-A fixed-rate collateral that was current for 12 consecutive months ending in November 2010 and controls for other observable loan characteristics including origination FICO (700-740) and mark-to-market CLTV (60-80).[8] Chart 57 illustrates that the updated scores are a highly informative predictor of delinquency even after controlling for other observable loan attributes.

Chart 57: Cumulative Delinquency by Updated Credit Score – Alt-A Fixed Collateral

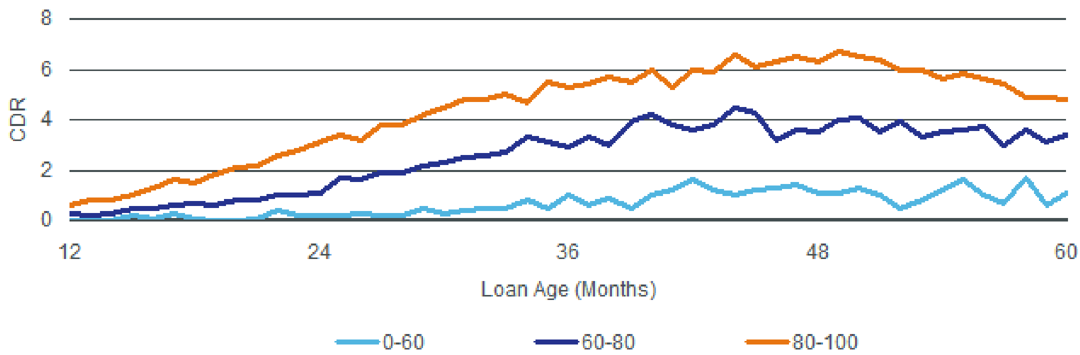


Current Combined LTV: Chart 58 shows historical default seasoning curves for Alt-A fixed-rate 30-year loans by origination LTV after controlling for FICO. Borrowers with more home equity (lower LTV) are less likely to default since they can avoid foreclosure costs and credit impairment by selling their property themselves. The LTV used in the BRS credit models is the current combined loan-to-value ratio (CCLTV), the ratio of loan amount to the appraised value of the house after updating the property value using average local property appreciation since origination. In addition, consumer credit data is used to identify second liens and HELOCs originated after the first-lien that are not observed in the LoanPerformance origination data. This leverage information is used to update the LTV to create a combined LTV that takes into account the additional leverage. CCLTV is

[8] TransUnion provides a Vantage Score which we translate here into an "implied FICO" for ease of comparison with the origination data. The models are estimated and run using the Vantage Score directly in order to avoid potentially introducing noise through score translation.

useful in the credit models because in the event of a job loss, divorce, or illness, borrowers who made higher down payments (lower CCLTV) are likely to sell the house to avoid the financial costs of default and potential negative impact to credit history.

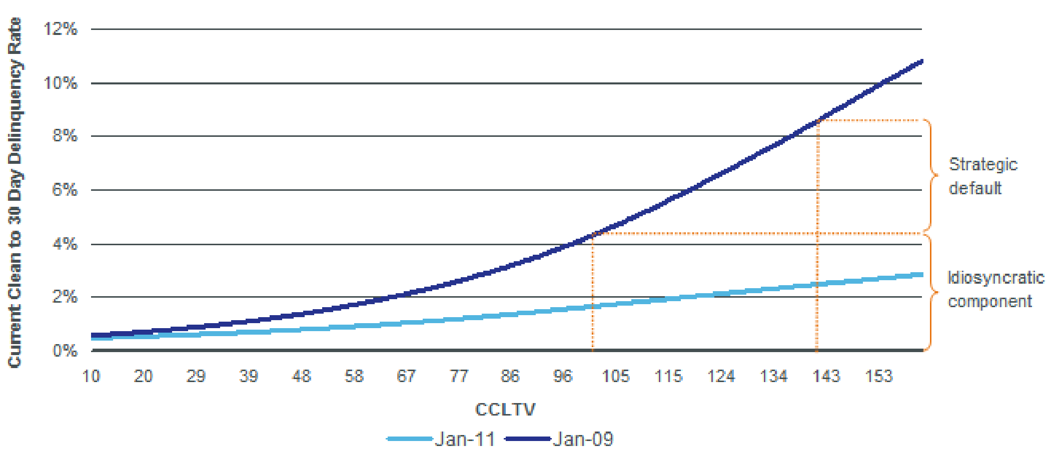
Chart 58: CDR Aging Curves by Origination LTV – Alt-A



CCLTV is also informative because domestic mortgages are generally non-recourse.[9] If a home is worth significantly less than the outstanding loan amount and expected home price appreciation is low or negative, a borrower has a financial incentive to walk away from the property instead of continuing to make payments. When a borrower takes this step and stops making payments on a loan despite having the ability to do so, this action is called “strategic default.” The principal deterrent of strategic default is the restricted access to credit that will result from a tarnished credit history.

The ability to default can be viewed as a put option embedded in a mortgage that allows a borrower to sell the mortgaged property to the lender in exchange for the outstanding mortgage balance. When the option is out-of-the money, defaults are mainly driven by idiosyncratic shocks, such as underwriting fraud, unemployment, illness, divorces etc. When the option is in-the-money, the default rate is composed of the same idiosyncratic component in addition to a second component consisting of loans for which the put option is exercised. The idiosyncratic component can be estimated as the default rate when the CLTV is near 100, and the increase in the default rate that occurs as the CLTV increases past 100 can be attributed to the default option being exercised. Chart 59 shows the roll rate from current clean to 30 days delinquent by CCLTV for two different periods. Examining the January 2009 line, the roll rate at CCLTV 100 is approximately 4% and the roll rate at CCLTV 140 is approximately 8%. Therefore for loans with a CCLTV of 140, we would expect 4% to be delinquent for idiosyncratic reasons while the remaining 4% may be strategically delinquent.

Chart 59: Delinquency Rate by Period for Borrowers with FICO = 720



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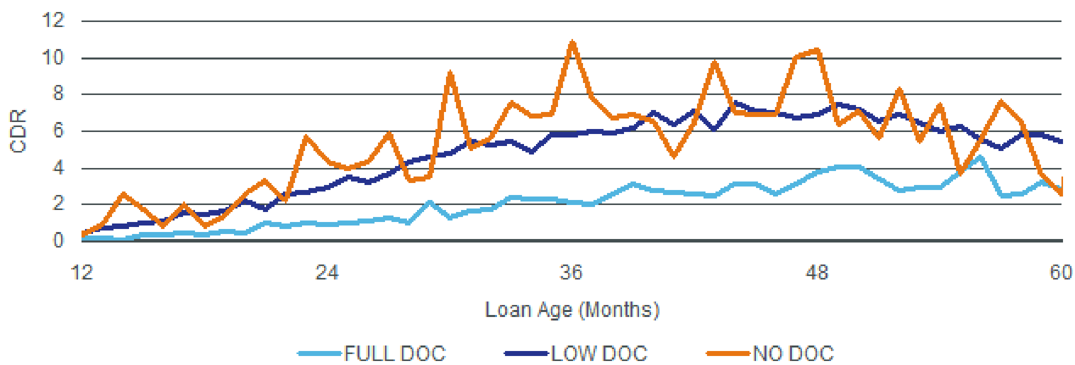
[9] In some states, labeled “recourse states,” the lender may pursue a borrower who defaults for the principal balance that remains unpaid if the proceeds from property liquidation are insufficient to cover the loan balance, however in practice recourse claims are pursued very infrequently.

The January 2011 curve in Chart 59 is considerably less steep than the January 2009 curve, indicating that the influence of CCLTV on delinquency may be less significant currently than it was two years ago. Since those borrowers who are likely to default strategically are more likely to do so soon after their loan goes underwater, high CCLTV loans that have had negative equity for a longer period may be less likely to become delinquent than those that are newly underwater. This "credit burnout" may result in overestimation of the CCLTV impact for seasoned loans. However, it is difficult to disentangle vintage and burnout effects in the data so the evidence for significant credit burnout is not yet conclusive and we remain conservative when taking into account credit burnout in our estimation process.

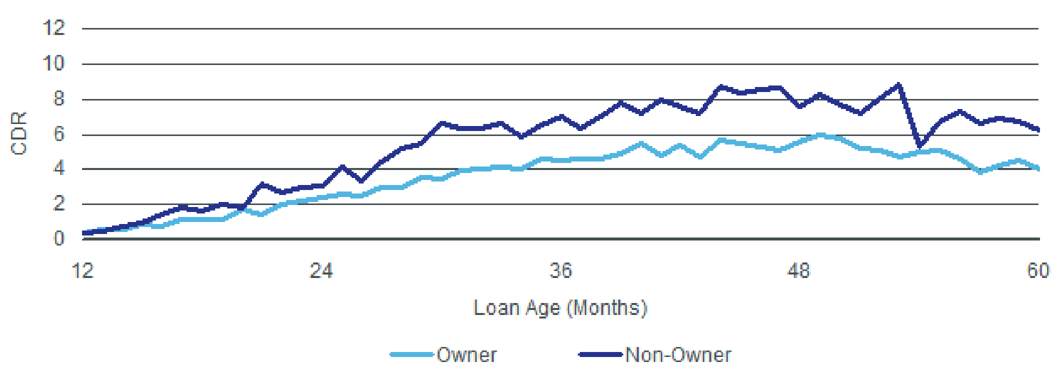
Documentation: The extent to which an originator is thorough in collecting income and employment information from borrowers varies significantly by loan, particularly among Sub-Prime and Alt-A collateral. Our loan level data includes a variable that indicates whether a loan was fully documented during origination and this is another important indicator of credit risk because it indicates weak underwriting and questionable credit quality. This can be seen from Chart 60 which shows CDR by documentation level and seasoning for Alt-A fixed-rate 30-year loans. Full doc loans have a default rate that is less than half the rate for loans with low or no documentation. Interestingly, loans with low documentation perform no better and often worse than loans with no documentation.

Chart 60: CDR Aging Curves by Documentation – Alt-A



Occupancy: Borrowers who occupy their property tend to have a lower likelihood of default than those who finance their property to rent it to a third party. This can be seen from Chart 61 which shows CDR by seasoning and occupancy type for Alt-A fixed-rate 30-year loans. Borrowers who occupy their property are significantly less likely to default across the life of the loan than investors.

Chart 61: CDR Aging Curves by Occupancy Type – Alt-A

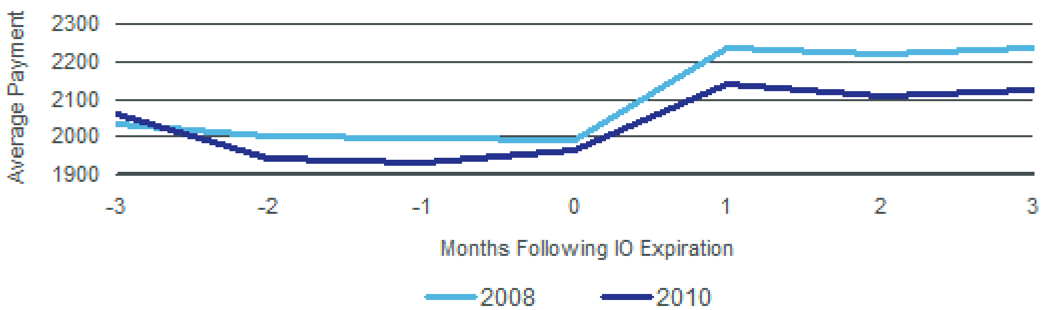


There are several potential explanations for this effect. First, a borrower who defaults on a rental property does not bear the costs associated with moving and finding a new residence. In addition, such borrowers may be less cash constrained and better able to deal with a lower credit score than the average homeowner who is unlikely to be able to afford to invest in an additional property.

Finally, the borrower may be more likely to default strategically when his/her LTV is high because he/she views the property purely as an investment.

Interest-Only: Borrowers with adjustable-rate products face annual payment adjustments that can significantly impact performance if the adjustment is large. This is particularly important for interest-only (IO) borrowers since the first reset can be very steep. As illustrated in Chart 62 the average monthly payment for IO borrowers whose IO period expired in 2008 increased from about $2,000 to $2,200. The impact of these payment jumps is modeled through a payment shock variable that captures the percentage change in monthly payment.

Chart 62: Average Monthly Payment by Months around IO Expiration



Revolving Account Utilization: Utilization on revolving accounts such as HELOCs, credit cards, and consumer loans provides a measure of financial distress that is useful in the non-agency delinquency and default models. Because updated credit scores are incorporated into the non-agency credit models and the scores are based on credit account data such as revolving utilization, the impact of utilization is muted by the inclusion of the credit score variable. However, we include revolving utilization in addition to a borrower's credit score because utilization captures mortgage credit risk that is not completely captured by the credit score.

Co-borrower: TransUnion provides credit account information for all borrowers matched to a particular loan, and we observe empirically that loans with more than one borrower tend to have lower credit risk, possibly due to a diversification of financial risk. We therefore incorporate a variable representing the fraction of a loan cluster where more than one borrower is linked to the loan.

DTI Estimator: Using a proprietary income estimator and debt information from consumers' credit files, TransUnion has created an estimator for updated DTI. This updated DTI information represents a scaled measure of debt that we have found to be empirically informative in projecting credit performance.

Oldest Trade Age: Measuring the time since a consumer opened his/her first credit account, this variable captures credit file length and has proven useful in the credit models. As a consumer's credit file extends, credit risk decreases towards a minimum near approximately 250 months after which it slowly increases.

Prepayment Rate: The default and delinquency behavior of a pool also interacts with its historical prepayment experience. If a pool has experienced a high level of prepayments then the remaining borrowers in the pool are those that did not respond to prepayment incentives. They may simply not be aggressive in optimizing their mortgage payments, but in younger pools it is more likely that they are not able to refinance due to credit or income issues. This adverse selection implies that the pool should have worse credit performance going forward. Our credit models therefore include a prepayment factor indicating the historical degree of prepayments the pool has experienced. As a pool seasons, the effect of prepayments becomes muted due to burnout.

Loss Severity Model Structure and Key Variables

Loss, cumulative loss, and loss severity are the three primary loss metrics used to describe mortgage performance.

- *Loss* is computed as the loss amount divided by the total unpaid loan balance.
- *Cumulative loss* is defined as the cumulative loss amount over the original balance.
- *Loss severity* is the total loss balance divided by the defaulted balance (i.e. it is the loss rate conditional upon default). If the pool includes only one loan, then the loss is equal to the loss severity.

Conditional on a default occurring, the relationship between loss, default and loss severity can be summarized as:

$$Loss = DefaultBalance \cdot LossSeverity$$

Loss values are important for constructing cash flows, and the cumulative loss is also an important deal trigger. If performance triggers fail, principal that would otherwise have gone to increase over-collateralization or to pay down mezzanine and subordinate bonds, are instead redirected to pay senior bonds. When losses occur, they are primarily the result of these factors:

- *Foreclosure discount.* Properties sold in a foreclosure auction often sell at discounts of 10-20% and sometimes at dramatic discounts of 40–50% or more. This discount is partly the result of the poor or uncertain condition of foreclosed properties since they are often poorly maintained or damaged. In addition, areas with many foreclosures are likely to experience continued home price declines and investors require a premium to compensate for further expected declines. Also, foreclosure auctions tend to attract a smaller and more sophisticated pool of buyers than a normal property sale, partly because the auction typically requires full payment in cash at the close of the auction.
- *Interest loss.* When a borrower stops making loan payments, the servicer typically advances principal and interest until it deems further advances to be unrecoverable. However, the servicer will eventually be reimbursed for these advances from the liquidation proceeds so unpaid interest will contribute to the final loss severity. The longer the period between the last payment and liquidation, the higher the eventual loss severity.
- *Foreclosure costs.* The servicer will charge the trust various fees for handling the foreclosure process. These include collection fees, legal fees, sales commissions, marketing fees, taxes, etc.
- *Modification loss.* Modification losses arise when there is principal forgiveness or when servicers recapture advances they have made to the trust during the modification process.
- Revisions. Revisions occur when an adjustment to recovery is required several months after the default has taken place. They represent a relatively small fraction of loss.

Chart 63 shows loss severity by collateral type and month of liquidation. Loss severities increased substantially in 2008 primarily due to housing price declines and have since leveled off somewhat but continue to edge upwards.[10] Products with better credit quality tend to have lower loss severities due partly to larger loan size and more favorable geographic distributions. Due to their subordinate claim on the underlying property, loss severities on 2nd liens tend to be very high relative to 1st liens. BRS constructs separate loss severity models for each product type since performance of loss severities is very different across different products.

[10] There is a significant positive correlation between default and loss severity which has created significant implications for risk management because it results in a fat-tailed loss distribution.

Chart 63: Loss Severity by Collateral Type

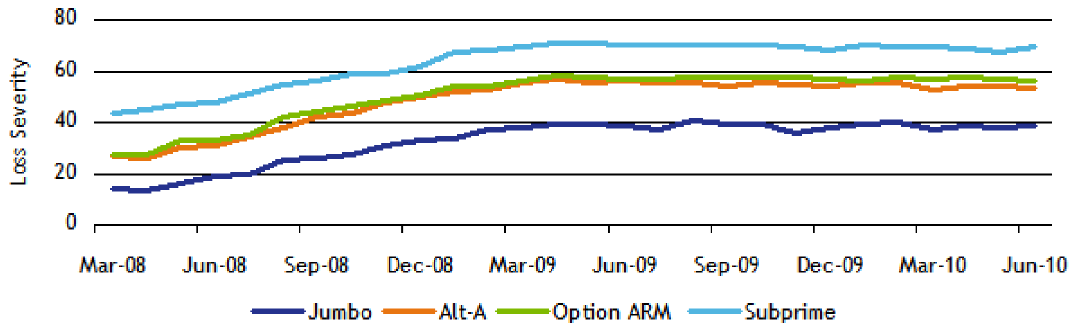
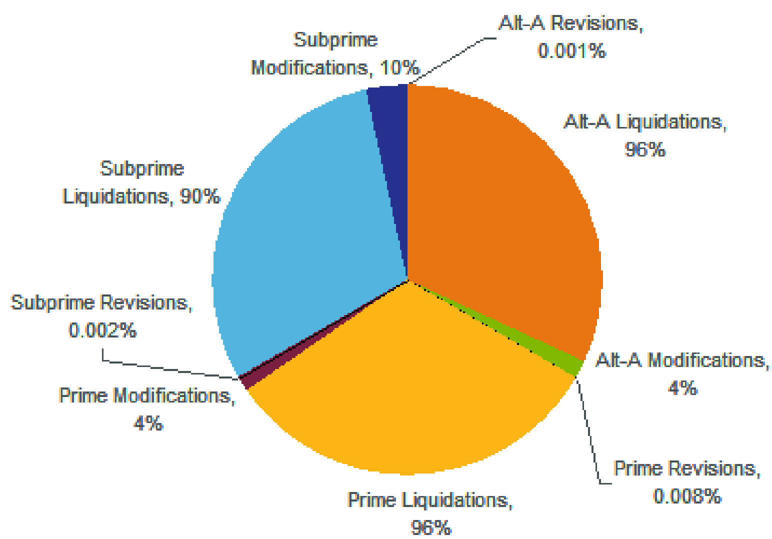


Figure 11 breaks out modification-related losses and loss revisions from trustee reports for active non-agency loans. Modification losses are measured as losses from loans that are still active divided by the balance of those loans in the period prior to the loss. This is a proxy for principal forgiveness but also includes other elements such as servicer recapture. While modification-related losses have increased, they still represent a relatively small fraction of losses overall. Recently, Alt-A and Sub-Prime deals have seen a significant amount of principal forgiveness and this has spurred increases in loss severity in those collateral types.

Figure 11: Non-Agency Losses; Sept. 2010 – Feb. 2011

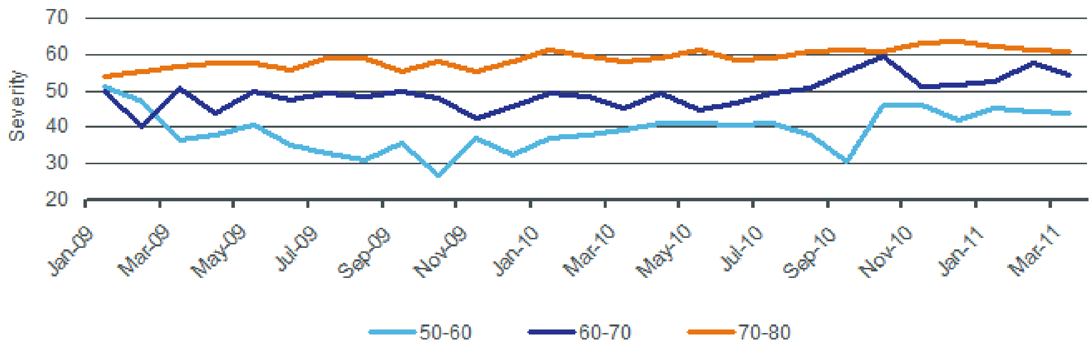


There is substantial variation in loss severity behavior across servicers. Much of this variation can be attributed to differences in the composition of loans that are liquidated, modified or remain in the pipeline. In terms of loan size, CLTV, occupancy, and other important loan characteristics, the composition of loans liquidated is often very different from the composition of loans that remain in the pipeline which implies that loss severities may shift as loans work through the pipeline. Modifications have also created reporting issues in some deals since some servicers may be reporting losses several months after modification. This can have a negative impact on bond cash flows due to disruptions in credit enhancement and excess spread.

This section provides additional details about the most important variables in the BRS severity models.[11]

Loan-to-value Ratio: The most important factor in the projection of loss severity is the updated loan-to-value ratio since it has a direct impact on the fraction of the outstanding loan balance the investor is likely to receive upon liquidation. Chart 64 shows loss severity rates for 2006 Alt-A fixed-rate collateral by LTV at origination. As the LTV increases, the fraction of the loan balance that can be recovered through liquidation decreases and severity rises.

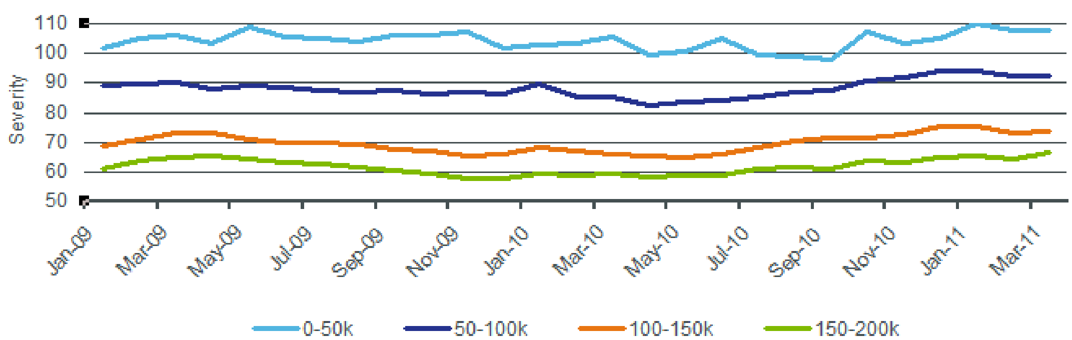
Chart 64: Loss Severity by OLTV – Alt-A Fixed 2006



Incorporating updated LTV into the BRS severity models also indirectly takes into account cumulative HPA since we mark the LTV to market based on Case-Shiller house price appreciation data. Loss severity in high growth real estate markets is lower than loss severity in low growth areas due to the direct impact of HPA on liquidation values.

Loan Size: Smaller loans generally have higher loss severity, as illustrated in Chart 65 for non-agency first liens with a mark-to-market LTV near 100.[12] The fixed costs of foreclosure including legal fees and commissions will consume a higher percentage of the principal balance for smaller-sized loans. Also, servicers may allocate more resources to handling larger loans because their fees are often defined in terms of a percentage of the loan balance. This can result in shorter carrying times for larger loans and more favorable liquidation prices due to better preparation, maintenance and marketing on the part of servicers.

Chart 65: Loss Severity by Current Loan Size (First Liens with CCLTV 90-110)



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[11] Similar to the other model types, BRS loss severity models are estimated in the GAM framework, however to explicitly incorporate the log linear relationship between default and loss (loss = default * loss severity implies log[loss] = log[default] + log[loss severity]), we must force the coefficient of log defaults to be one. BRS has designed a Possion non-canonical GAM estimation method to handle this issue.

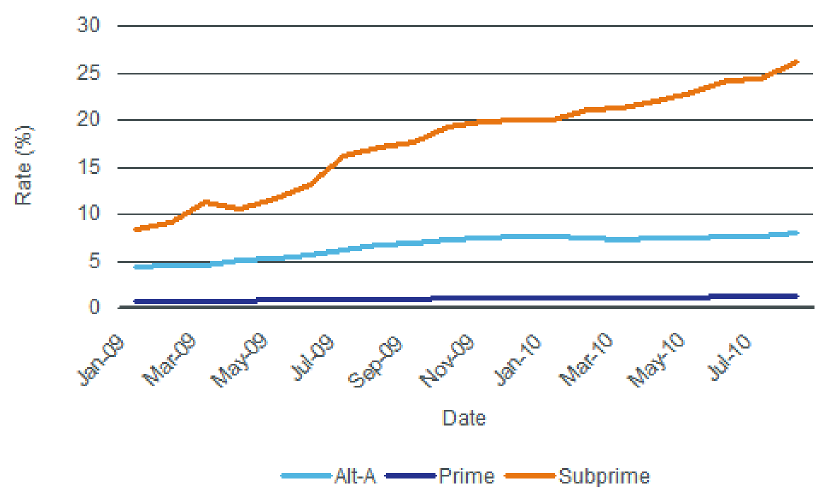
[12] The mean severity for small first liens in Chart 65 is often above 100 percent and this can occur if the proceeds from liquidation are insufficient to cover servicer advances and fees that accumulate during the foreclosure process.

Servicer Advances: In most non-agency deals, the servicer is required to advance delinquent principal and interest to the trustee to the extent that it is deemed recoverable.[13] Recent high delinquency rates and increased foreclosure timelines are creating liquidity issues for many servicers that are advancing into RMBS. Recoveries on servicing advances can take several years and the interest cost to carry relative to the servicer's credit facility can become a serious financial burden. In addition, the cost of servicing a delinquent loan has been increasing and in some cases a servicer may not be able to recover all of its costs from the liquidation proceeds. Consequently, servicers have been more likely to stop advancing earlier in the foreclosure process.

We do not observe stop advances directly, but we use LoanPerformance data to indirectly identify servicer stop-advances through the reported investor balance. For a non-performing loan, if the investor balance continues to decline, it must be a result of servicer advances. For a non-IO loan or a loan beyond its IO period, we identify a stop-advance if the investor balance of the loan stops amortizing.[14]

Chart 66 illustrates how quickly stop-advance rates have increased, particularly for Sub-Prime collateral where at least 25% of delinquent loans are not advancing. For Alt-A collateral, the stop-advance rate is still relatively low in delinquent loans, but is much higher for defaulted loans.

Chart 66: Stop-Advance Rates on All Delinquent Loans



When advances are stopped, loss severity is reduced through savings on advanced payments. The earlier the servicer stops advancing, the fewer payments will be deducted from liquidation proceeds and therefore the lower the eventual loss severity (all else equal).[15] Our severity models therefore include a variable that captures advances as a fraction of the outstanding balance.

Servicer Stop-Advance Functionality: Servicer stop-advance rates have climbed steadily over the past two years and can have a significant impact on bond cash flows. Accounting for rising stop-advance rates in model projections is complicated due to shortcomings in the loan-level data. Stop-advances are not directly observed in the data, but instead must be inferred from loan balance information. It is therefore impossible to detect stop-advancing for some types of loans (eg. interest-only loans).

The BRS stop-advance adjustments assume that servicers continue to advance interest on interest-only loans before IO expiration. To assume that the advancing behavior of interest-only loans before IO expiration is same as that of the amortizing loans, we compute a new stop-advance rate as the BRS stop-advance rate divided by stop-advance coverage.

[13] Servicers are also expected to make escrow advances for delinquent taxes, insurance and reasonable "out-of-pocket" corporate expenses in the performance of its servicing obligation.
[14] A caveat of this method is that we have to exclude all IO loans, so our numbers will under-estimate the magnitude of stop-advances.
[15] Because stop-advance is mostly likely caused by higher severity in the first place, one would find from an uncontrolled empirical data study that loans with stop-advance actually have a higher severity.

We are somewhat more confident about the stop-advance data quality for loans that are amortizing at origination or interest-only after IO expiration. However, other issues complicate the stop-advance calculation for these loans. For example, we find that some servicers may convert delinquent amortizing loans into IO loans in which case the servicer will continue to advance interest but not principal. The current stop-advance rate does not capture this phenomenon.

The most significant component of the stop-advance functionality is an adjustment to severity. In order to construct the adjustment, we assume that advancing will continue at each deal's current rate (for non-IO pools). We then adjust the severity to incorporate the total value of the advanced interest payments that will eventually be extracted from liquidation proceeds by the servicer. Default and delinquency projections are also adjusted to account for the difference in principal balance that occurs as a result of advancing. Accounting for faster stop-advancing will in general reduce severity at liquidation and may have a significant impact on bond cash flows depending upon deal characteristics. Table 4 provides a sample yield comparison for a bond with stop-advance rate of 49% where turning off the stop-advance functionality in the model increases the yield by 130 basis points.

Table 4: Yield Comparison CWABS 2005-AB1 A3 (126673XR8); Price 77.61; 49% Stop Adv.

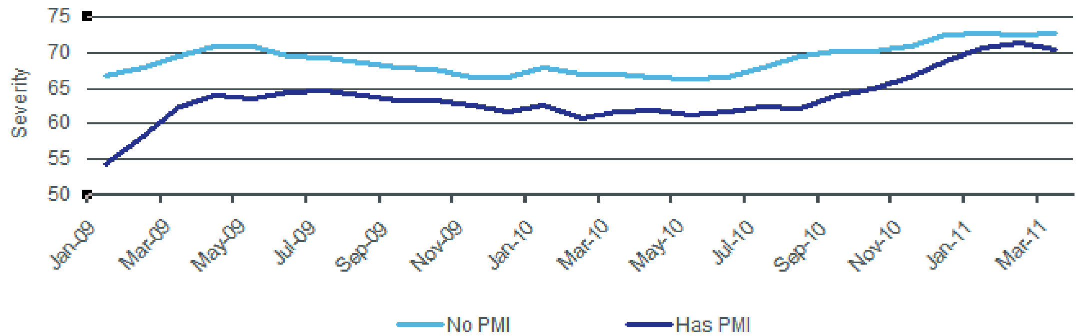
	Without Stop Adv Adjustment	With Stop Adv Adjustment
Yield	12.37	11.07
WAL	2.41	2.72
Cum Loss	16.56	16.24
Rem Loss	60.07	58.02
3M CPR	1.42	1.42
3M CDR	15.1	14.84
3M SEV	82.37	79.28
LT CPR	3.19	3.29
LT CDR	23.87	22.93
LT SEV	76.87	73.15

Source: BRS

Mortgage Insurance: Private mortgage insurance (PMI) is generally used in cases where the borrower makes a down payment that is less than 20% of the value of the property. The policy is intended to partially compensate the lender for the risk involved in making a loan with a high loan-to-value (LTV) ratio. PMI is not tax-deductible for the borrower if paid directly and approximately 46% of PMI policies are lender-paid where the lender passes the premium on to the borrower in the form of a higher mortgage rate.

If an insured loan is foreclosed upon, the lender files a claim with the insurance provider for an amount which includes foreclosure expenses and any unpaid principal and interest. Pools with a higher percentage of insured loans tend to have lower loss severity, as shown in Chart 67. The BRS loss severity models therefore include a variable indicating whether mortgage insurance is present.

Chart 67: Loss Severity by PMI



If the insurer determines the mortgage to be fraudulent, lacking documentation, or otherwise misrepresented, it may then deny or rescind the insurance, and there is evidence that this has been occurring more frequently as insurers face a growing volume of claims. The decrease in the severity gap between the loans with and without PMI is decreasing over time partly because of the increased rescission rate. Only about 4% of existing loans are covered by PMI, but PMI is concentrated in products with relatively high rates of delinquency where losses may be significant when PMI is rescinded.

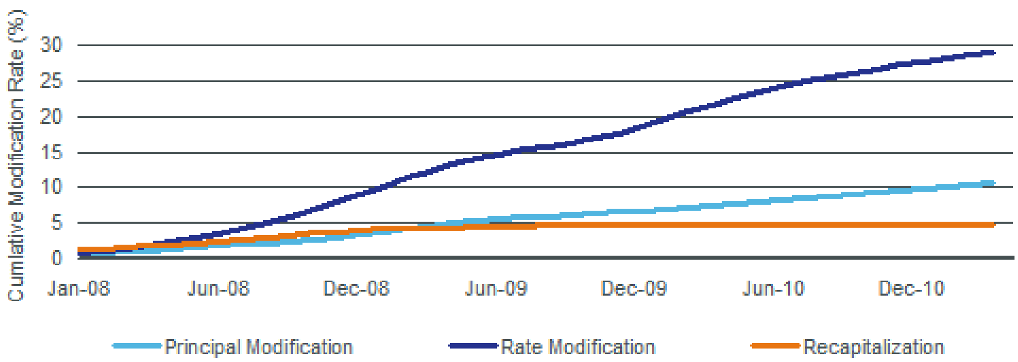
Occupancy Type: Another important factor is the occupancy type. Investor properties have a higher loss severity rate than owner-occupied homes. There are two possible explanations. First, owners may take better care of their properties than renters so their homes may obtain higher liquidation values. Second, investor properties tend to be associated with inflated appraisals more frequently. They therefore tend to have higher actual or mark-to-market LTVs than the average owner-occupied property.

Judicial State: As in the credit models, state laws regulating the foreclosure process have a significant impact on loss severity. Judicial foreclosures involve the state court system, and in general, foreclosures in judicial states take much longer than those in non-judicial states. The length of time a property spends in the foreclosure process directly affects losses since unpaid interest and fees continue to accumulate.

Modified Loan Model Structure and Key Variables

Loan modification activity has increased substantially since the mortgage performance deterioration that began in 2007. Chart 68 illustrates that the cumulative modification rate since January 2008 is nearly 45% for Sub-Prime collateral. New modification activity is currently slow but steady although cumulative modifications can be high in certain deals, and future policy changes could result in jumps in modification activity.

Chart 68: Sub-Prime Cumulative Modification Rate



Modified loans perform differently from similar non-modified loans for a number of reasons. The modification process creates an extra layer of due diligence that identifies borrowers who are likely to be able to afford their modified loan and adjusts a variety of loan characteristics. BRS has therefore constructed a separate set of credit models to project delinquencies and defaults for modified loans. The modified loan models are turned on by default for Sub-Prime and Alt-A collateral.

The modified loan model structure adheres to the same GAM framework as the rest of the BRS models. Two sets of models for handling modifications are currently in place:

- **Modified Loan Model:** A model for projecting delinquency and default rates of previously modified loans
- **Projected Modifications Model:** A model that will project future modifications

The first model is only applied to modified clusters and the TransUnion variable dynamics will be present through the non-modified clusters. In the model, loans that have been modified in the past but are now in foreclosure or REO will run through the standard model, not the modified loan model. Projections for all pay status return to the standard model after 60 months.

The second model contains general assumptions to determine what portion of non-modified clusters may be modified in the near term, and the existing modified loan model is used to determine the performance of this portion of the cluster. There is a twelve month horizon over which future modifications are computed. Re-modifications are included in projections of future modification allowing a portion of projected modification to come from previously modified clusters. In addition, the model contains servicer variation. Ocwen-owned servicing as well as the five servicers affected by the recent Attorney General's settlement, including Ally, Bank of America, Citi, JPMorganChase and Wells Fargo, will be projected to modify loans at a higher rate than other servicers. Default and loss severity are adjusted at the time of modification to account for the degree of principal forgiveness. WAC deterioration and recapitalization are accounted for through Intex functionality. The result is that cash flows are adjusted for both past and future modifications. The focus of the second model is on cash flow projection rather than estimating eligibility.

The modified loan models include many of the most important factors incorporated into the standard BRS credit models discussed in the previous section on the BRS delinquency and default models, as well as a few additional variables unique to modified loans.

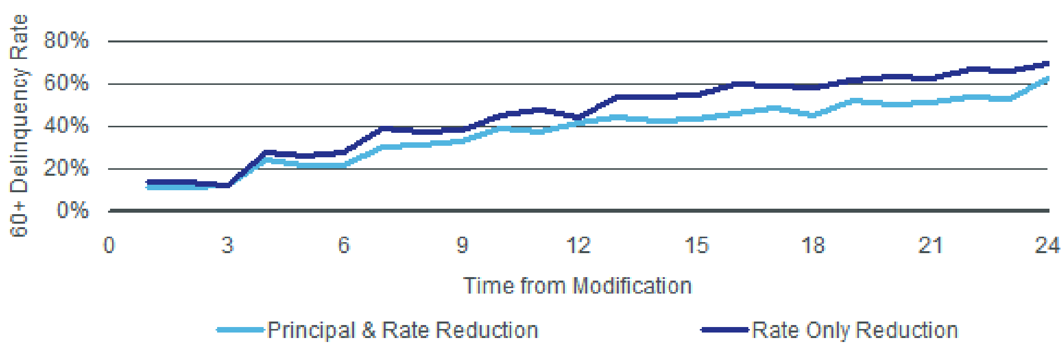
Time since Modification: Similar to other loan types, modified loans behave differently as they age. Delinquency rates are fairly low immediately after a modification as loan status is reset to current but ramp up over the months following modification.

Modification Type: Modifications can be divided into three categories:

- *Recapitalization.* Fees and interest that have accrued since a borrower has become delinquent are added to the outstanding loan balance and the loan status is reset to current.
- *Rate reduction.* The loan's interest rate is reduced with the goal of making the scheduled loan payment affordable by the borrower. The rate caps for adjustable loans may also be adjusted with the rate reduction.
- *Principal reduction.* A portion of the outstanding principal balance may be forgiven. This type of modification is rare because lenders are reluctant to create the potential for moral hazard, servicers may not have the authority to forgive principal, and servicers may not have an incentive to forgive principal since their income is often based on outstanding loan balance.

The type of modification has a significant impact on subsequent delinquency rates since principal and rate reductions tend to improve performance more than a simple recapitalization. Chart 69 shows delinquency rate after modification by modification type. Loans with only a principal reduction are consistently less likely to become delinquent after modification.

Chart 69: Delinquency Rate by Modification Type

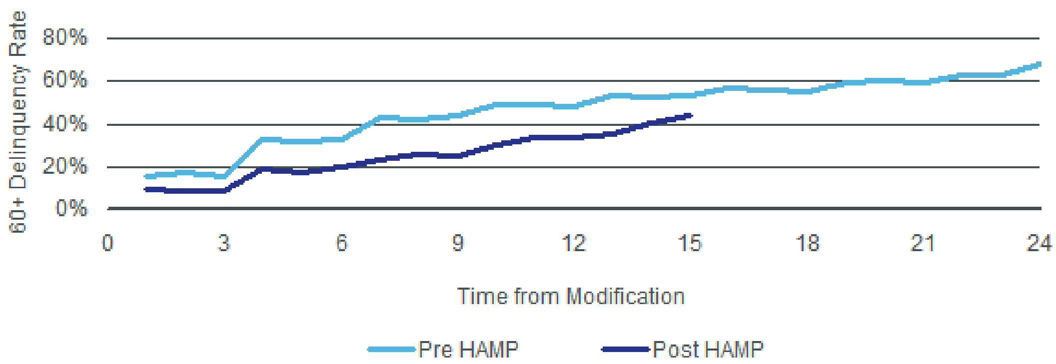


Pre-HAMP/Post-HAMP: In mid-2009, the US government introduced the Home Affordable Modification Program (HAMP) to provide servicers with incentives to perform modifications. The goal of the program was to reduce the volume of foreclosures because the foreclosure process imposes significant costs on homeowners and because a high volume of liquidations would further depress home prices. The program provided monetary incentives for servicers to perform modifications and effectively created a standardized set of rules for modification eligibility. In January 2010, the program was expanded to include additional incentives for principal modification.

The incentives and procedural requirements created by the HAMP program resulted in servicers implementing modifications with delinquency rates that are lower than those implemented before the program.[16] Chart 70 shows the delinquency rate by HAMP regime and while this chart does not control for other loan characteristics, those loans modified after the start of the HAMP program show a significantly lower delinquency rate post modification. The modified loan models therefore include a variable that captures this performance difference.

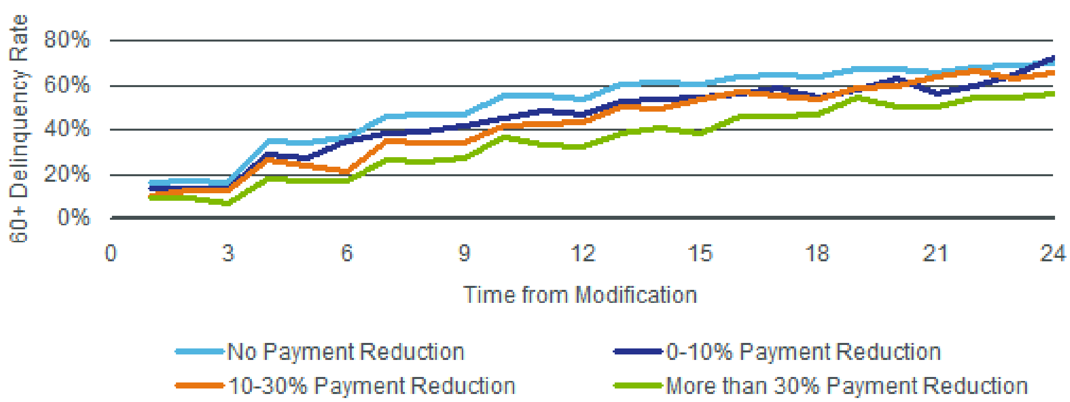
[16] The HAMP program includes a three-month trial period during which the borrower must remain current for the modification to be completed. Since a loan does not complete modification until after the trial period, delinquencies during this period are not counted towards the delinquency rate of HAMP modifications.

Chart 70: Delinquency Rate by HAMP Regime



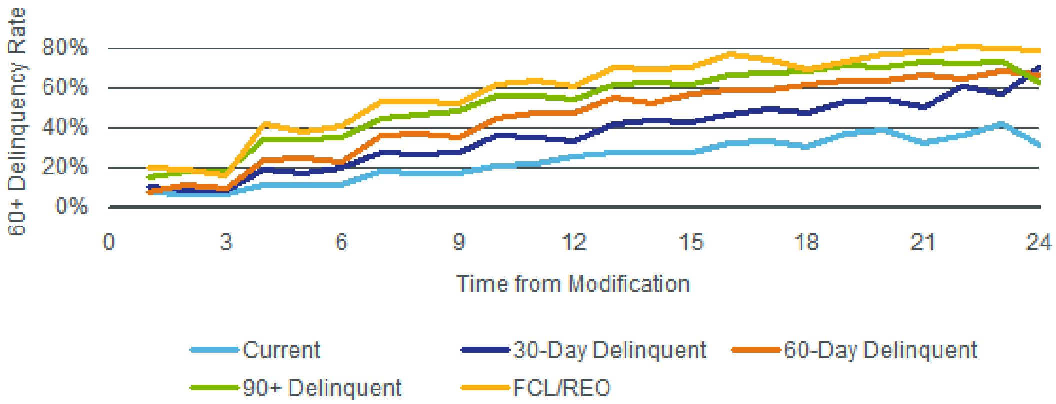
Payment Reduction Amount: When the modification results in a larger reduction in the scheduled payment amount, the loan is more affordable so the borrower is more likely to be able to make payments and may be more eager to hold on to the favorable terms. 59 shows the post-modification delinquency rate by payment reduction amount, and borrowers with larger reductions show lower post-modification delinquency rates. Chart 71 may understate the impact of the payment reduction amount since those borrowers who acquire larger reductions are able to do so because their original rate is high or because their income is low so they may have higher credit risk than borrowers who receive a smaller reduction.

Chart 71: Delinquency Rate by Payment Reduction Amount



Delinquency Status Prior to Modification: Loans that were further along in the foreclosure process at the time of modification tend to become delinquent more quickly since the borrowers may have been under more significant stress or may have taken a larger hit to their credit scores, constraining their access to credit. Chart 72 shows the post-modification delinquency rate by payment status prior to modification. Loans that remained current have significantly lower delinquency rates than loans that were already seriously delinquent when the modification was completed.

Chart 72: Delinquency Rate by Status Prior to Modification



In-Sample Validation

Prepayment Models

As a part of model validation, in-sample validation examines model residuals and assesses how well the model fits the input data set. When grouped by different factors, it could confirm the covariate effect found during the data study and uncover factors not yet identified.

In-sample charts also provide a method to check the inputs of the model and to ensure that data is of sufficient quality for estimation.

However, the model error from in sample validation is biased toward optimistic performance and it should be supplemented by rigorous out-of-sample validation.

Figure 12: Alt-A In-Sample Validation

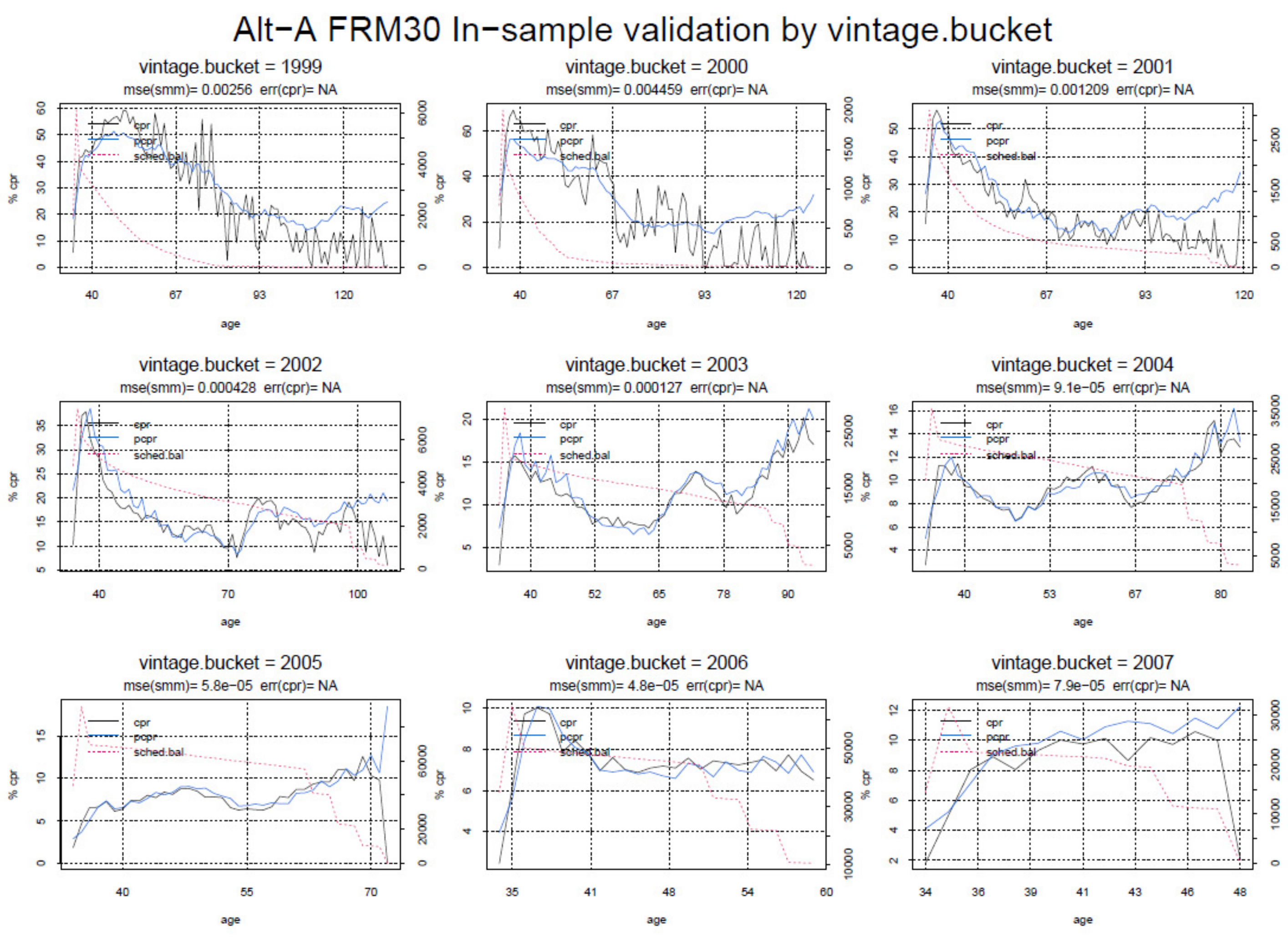
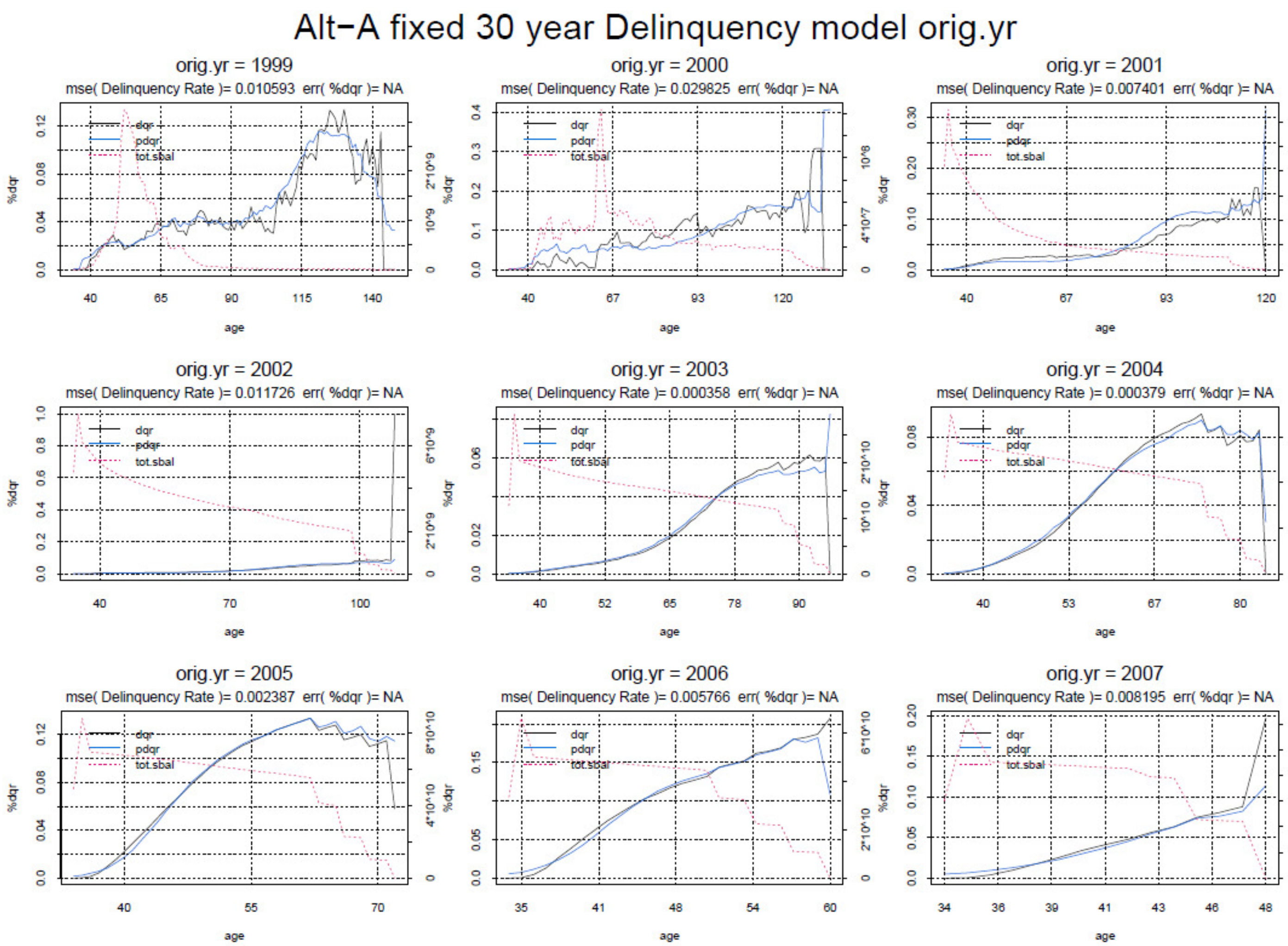


Figure 12 provides an in-sample chart grouped by vintages for the Alt-A 30-year fixed rate model. Vintage is an important factor and prepayment behavior varies a lot across vintages due to different attributes such as LTV, seasoning and prepayment penalty in vintage cohorts. We can see that the model predicts the prepayment ramp-up very well at prepayment penalty expiration period. The different aging curves for seasoned loans and non-seasoned loans were also captured by the model.

Credit Models

Figure 13 provides an in-sample chart by vintage for the Alt-A 30-year fixed rate delinquency model. The chart shows that the model captures delinquency performance across different seasoning vintages quite well. Model projections are very close to the actuals. Our models also perform very well across different vintages and different collateral attributes.

Figure 13: Alt-A In-Sample Validation



Out-of-Sample Validation and Monitoring

Prepayment Models

In order to avoid embedding unwanted sample dependency, our models are also validated using an out-of-sample approach. Historical data for building a model is chosen up till early 2011 and out-of-sample validation data is selected from the most recent 6-month period.

A forecast error report is generated using the most recent 6-month period. Loans are first clustered by a proprietary BRS algorithm to produce clusters, which are subsequently used in the forecasting. Model projections for each cluster are then balance weighted to estimate aggregated speeds for various cohorts.

Two objective measures are introduced to compare the performance of prepayment models to actual prepayment speeds: 6-month Error and 6-month Error Ratio. 6 month error is calculated as the difference between projected cumulative prepayment speeds and actual cumulative prepayment speeds over 6 months. 6 month error ratio is the ratio of projected cumulative speeds to actual cumulative speeds. These are measures that gauge the predictive accuracy of the model.

Forecast error is constructed with out-of- sample data and it could help verify whether the relationship in the model has stayed stable over time. If changes in the housing market and macro economy lead to a change in the prepayment pattern, forecast error would quickly detect this trend.

Forecast error also serves as a guide when models are adjusted and dialed. In order to produce reliable short-term and long-term forecasts, the forecast error should fall within an acceptable range of error.

The forecast error report (Figure 14) shows that the Alt-A prepayment model is performing well and 6-month error is within 2 CPR of actual prepayment speeds for most cohorts.

Figure 14: Alt-A Prepayment Forecast Error Report

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v5.2 Alt-A FRM Forecast Error as of 02/01/2012 - Prepayments

Collateral Characteristics	Projections			Actual vs. Projection												Forecast Error	
Collateral Type/Vintage	Apr '12 Proj	Mar '12 Proj	Feb '12 Proj	Jan '12 Act	Jan '12 Proj	Dec '11 Act	Dec '11 Proj	Nov '11 Act	Nov '11 Proj	Oct '11 Act	Oct '11 Proj	Sep '11 Act	Sep '11 Proj	Aug '11 Act	Aug '11 Proj	6 Month Error	6 Month Error Ratio
2006	7.13	6.07	6.18	8.31	6.32	8.39	7.42	9.06	7.75	8.25	8.01	8.49	7.94	9.11	7.28	-1.15	0.87
2005	8.7	7.31	7.55	7.82	7.67	9.78	9	8.46	9.2	10.29	9.73	8.29	9.67	8.69	8.21	0.02	1
2004	9.37	7.73	8.3	10.4	8.4	11.56	9.81	10.02	9.85	9.31	10.46	9.21	10.17	9.94	8.55	-0.53	0.95
2003	10.97	9.02	9.54	11.24	9.61	10.48	11.02	8.87	10.88	12.12	11.72	9.34	11.31	10.3	9.6	0.3	1.03
2002	11.87	10.24	10.31	11.31	10.29	6.91	12.08	12.62	12.17	10.62	13.35	7.43	13.27	8.57	11.1	2.45	1.26
2001	9.59	7.98	7.81	7.96	7.8	11.13	9.74	16.97	10.22	4.42	10.78	3.58	10.95	2.22	9.58	1.99	1.25
Alt-A 30 Year FRM	3.96	3.59	3.56	4.77	3.55	4.86	4.24	4.92	4.44	4.61	4.59	4.53	4.49	4.34	4.21	-0.42	0.91
2007	2.83	2.56	2.52	3.12	2.5	3.39	2.97	3.19	3.12	2.98	3.2	3.19	3.03	2.89	2.98	-0.16	0.95
2006	2.74	2.48	2.42	3.17	2.4	3.29	2.88	3.13	3.01	3.07	3.1	3.16	3.01	3.4	2.93	-0.32	0.9
2005	4.57	4.16	4.23	5.32	4.22	5.51	5.07	5.91	5.37	5.34	5.6	5.3	5.58	4.71	5.1	-0.19	0.96
2004	5.75	5.2	5.13	7.84	5.14	7.6	6.07	7.53	6.33	7.45	6.5	6.57	6.39	6.27	5.92	-1.15	0.84
2003	7.48	6.78	6.76	10.26	6.75	9.89	7.88	10.06	8.06	9.49	8.37	8.34	8.15	8.47	7.36	-1.66	0.82
2002	6.42	5.71	5.36	6.97	5.33	6.51	6.19	6.34	6.44	6.34	6.67	7.29	6.64	6.69	6.47	-0.4	0.94
2001	5.98	5.31	4.91	3.81	4.94	7.32	5.92	14.04	6.04	2.91	6.26	9.77	6.31	6.29	6.11	-1.5	0.8
2000	5.11	4.57	4.18	4.74	4.25	1.7	4.83	4.58	5.09	9.49	5.41	5.56	5.53	4.39	5.24	-0.04	0.99
1999	6.5	5.78	5.32	4.81	5.45	1.61	6.21	7.57	6.3	0.29	6.46	4.67	6.44	4.8	6.56	2.25	1.56
Alt-A Jumbo 15 Year FRM	16.98	15.83	15.12	19.79	15.27	23.28	17.65	16.5	17.52	18.52	19.03	17.57	18.66	14.97	14.87	-1.3	0.93
2007	11.91	11.1	11.7	21.79	12.03	4.14	13.67	11.06	13.91	16.22	14.71	25.52	13.96	15.07	13	-2.37	0.85
2006	9.41	8.7	8.79	21.7	9.27	29.91	11.04	14.91	11.2	13.43	11.96	15.51	11.92	10.95	10.29	-7.04	0.61
2005	15.89	14.88	14.51	15.86	14.56	25.85	16.88	17.13	17.06	23.53	18.97	20.15	18.88	17.12	14.91	-3.13	0.84
2004	18.18	16.91	15.9	20.67	16.03	21.64	18.6	17.16	18.42	12.57	19.69	17.24	19.57	19.25	15.36	-0.18	0.99
2003	25.51	23.9	21.85	20.45	21.77	23.49	24.71	19.38	23.75	22.01	25.92	12.57	24.91	12.35	18.67	4.84	1.26
2002	22.27	19.22	17.78	29.28	18.48	19.79	21.65	10.02	21.71	25.55	22.55	14.17	22.46	2.79	19.86	3.71	1.21
Alt-A Jumbo 30 Year FRM	5.7	5.45	5.56	9.17	5.6	9.88	6.69	9.56	7	8.56	7.26	9.15	7.26	8.76	6.79	-2.41	0.74
2007	4.74	4.59	4.77	6.95	4.8	7.84	5.83	6.5	6.1	6.52	6.28	7.2	6.08	7.5	6.03	-1.23	0.83
2006	4.29	4.1	4.17	7.25	4.25	7.04	5.08	6.96	5.31	5.68	5.53	6.89	5.47	6.12	5.3	-1.5	0.77
2005	6.05	5.79	5.99	9.33	6.03	10.32	7.21	10.81	7.61	9.05	7.95	9.82	8.15	9.71	7.39	-2.45	0.75
2004	8.02	7.61	7.51	13.31	7.47	14.27	8.77	14.82	9.16	13.83	9.4	13.57	9.52	11.3	8.52	-4.72	0.65
2003	10.4	9.93	9.78	19.2	9.75	21.16	11.31	17.84	11.65	18.88	12.11	16.34	12.06	16.41	10.43	-7.1	0.61
2002	9.71	9.19	8.83	16.18	8.77	17.28	10.34	20.43	10.75	13.65	10.74	17.69	11.08	13.41	10.66	-6.08	0.63
2001	8.12	7.55	7.13	7.33	6.84	3.99	8	30.64	8.34	5.69	9.42	8.01	9.23	0.08	9.4	-1.36	0.86
2000	10.26	9.84	9.39	9.35	8.43	20.62	10.33	9.82	10.42	8.83	10.89	1.55	11.67	41.31	9.74	-6.13	0.63

Monitoring

Forecast error reports provide a tool to monitor prepayment model performance on a monthly basis. The model is refitted using up-to-date economic inputs to predict the prepayment speeds of each cluster and aggregated cohorts. Model outputs are compared with actuals and if deviations from actuals are observed for a substantial period of time, BRS will recommend dial sets to clients and update the model in the next release.

Delinquency and Default Models

Figure 15 shows out-of-sample predictions for Alt-A 30-year fixed rate delinquency rates. The BRS Alt-A fixed delinquency model projections are right on top of actuals with errors within 1 point for all cohorts.

Figure 15: Alt-A Delinquency Forecast Error Report

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v5.2 Alt-A FRM Forecast Error as of 02/01/2012 - Delinquency

Collateral Characteristics	Projections			Actual vs. Projection												Forecast Error	
Collateral Type/Vintage	Apr '12 Proj	Mar '12 Proj	Feb '12 Proj	Jan '12 Act	Jan '12 Proj	Dec '11 Act	Dec '11 Proj	Nov '11 Act	Nov '11 Proj	Oct '11 Act	Oct '11 Proj	Sep '11 Act	Sep '11 Proj	Aug '11 Act	Aug '11 Proj	6 Month Error	6 Month Error Ratio
Alt-A 15 Year FRM	10.59	10.45	10.33	10.21	10.04	10.21	9.99	10.15	9.94	9.94	9.72	9.78	9.66	9.51	9.63	-0.14	0.99
2007	16.53	16.49	16.49	16.49	16.49	16.01	17	17.31	16.23	16.28	15.47	14.91	15.44	14.79	15.2	0.01	1
2006	19.39	19.23	19.1	18.35	18.26	18.74	18.4	18.55	18.46	17.95	17.83	17.58	17.65	17.33	17.84	-0.01	1
2005	12.75	12.56	12.4	11.8	11.71	11.58	11.6	11.52	11.59	11.32	11.48	11.49	11.46	11.09	11.25	0.05	1
2004	7.23	7.09	6.97	7.34	7.16	7.38	6.82	7.22	6.92	7.33	6.89	7.31	6.83	6.98	6.96	-0.33	0.95
2003	4.58	4.46	4.37	4.54	4.26	4.52	4.25	4.4	4.17	4.36	4.11	4.27	4.13	4.24	4.17	-0.2	0.95
2002	10.47	10.23	10.01	10.28	9.6	10.25	10.08	9.85	9.8	9.68	9.27	9.59	9.69	9.65	9.52	-0.22	0.98
2001	12.69	12.46	12.24	12.75	13.46	11.58	11.96	11.91	11.14	10.42	10.6	9.51	10.57	9.28	10.65	0.49	1.04
Alt-A 30 Year FRM	26.77	26.61	26.5	26.81	26.6	26.91	26.55	26.71	26.39	26.64	26.45	26.53	26.34	26.49	26.54	-0.2	0.99
2007	33.3	33.19	33.13	33.57	33.34	33.85	33.5	33.58	33.26	33.47	33.32	33.24	32.96	33.33	33.46	-0.2	0.99
2006	34.16	34	33.89	34.28	34.03	34.43	34.03	34.27	33.97	34.12	33.98	34.07	33.97	34.04	34.17	-0.17	0.99
2005	22.44	22.25	22.12	22.29	22.25	21.98	22.01	22.05	21.83	21.86	21.73	21.7	21.59	21.54	21.64	-0.06	1
2004	15.27	15.06	14.9	15.13	14.83	15.46	14.68	14.87	14.34	14.89	14.52	15.06	14.63	14.95	14.69	-0.44	0.97
2003	9.52	9.34	9.2	9.57	9.15	9.54	9.05	9.6	9.16	9.63	9.19	9.4	9.05	9.36	9.09	-0.4	0.96
2002	13.47	13.21	12.98	13.23	12.85	13.45	12.86	13.14	12.66	12.71	12.55	12.4	12.33	12.61	12.57	-0.29	0.98
2001	19.14	18.69	18.28	17.93	17.41	18.24	17.46	17.34	16.54	17.15	16.35	17.1	16.54	16.85	16.06	-0.71	0.96
2000	14.35	14.08	13.85	15.86	13.72	15.05	14.32	16.88	14.61	15.55	15.21	13.38	12.03	11.66	12.05	-1.08	0.93
1999	18.69	18.33	17.99	17.59	18.03	20.61	18.95	17.64	16.08	16.36	16.47	19.13	18.8	14.6	15.86	-0.29	0.98
Alt-A Jumbo 15 Year FRM	10.49	10.36	10.25	10.95	10.48	10.62	10.22	10.17	9.93	10.23	9.73	9.99	9.61	10.01	9.89	-0.35	0.97
2007	13.28	13.17	13.08	12.63	12.49	13.59	13.15	13.64	13.39	13.96	13.53	13.88	13.56	14.25	13.35	-0.41	0.97
2006	18.99	18.9	18.85	19.69	19.57	18.64	18.63	17.61	18.03	18.17	17.59	18.35	17.82	18.71	19.07	-0.08	1
2005	8.94	8.84	8.77	9.93	9.39	9.66	9.06	8.77	8.6	8.73	8.39	8.41	8.22	8.38	8.44	-0.3	0.97
2004	8.65	8.56	8.48	9.21	8.54	8.69	8.23	8.51	7.95	7.8	7.54	7.58	7.21	7.34	7.46	-0.37	0.96
2003	5.13	4.98	4.84	5.29	4.64	5.2	4.81	5.23	4.75	5.48	4.79	5.01	4.47	4.83	4.42	-0.52	0.9
2002	8.39	7.86	7.35	8.95	7.26	7.68	6.66	9.53	7.61	10.31	7.94	9.99	8.54	10.63	8.35	-1.79	0.81
Alt-A Jumbo 30 Year FRM	20.9	20.7	20.54	20.74	20.34	20.66	20.31	20.54	20.21	20.53	20.25	20.41	20.11	20.19	20.12	-0.29	0.99
2007	26.33	26.18	26.08	26.45	26	26.13	25.77	26.05	25.7	26.14	26.01	26.05	25.81	25.79	25.82	-0.25	0.99
2006	24.61	24.4	24.24	24.28	23.89	24.28	24.06	24.34	24.08	24.32	23.96	24.25	23.9	23.95	24.02	-0.25	0.99
2005	17.17	16.92	16.72	16.77	16.55	16.76	16.54	16.76	16.56	16.48	16.29	16.44	16.37	16.45	16.38	-0.16	0.99
2004	12.64	12.43	12.25	12.63	12.04	12.6	12.04	11.92	11.49	12.24	11.89	11.9	11.15	11.6	11.42	-0.48	0.96
2003	10.31	10.17	10.04	10.48	9.93	10.5	9.86	10.26	9.52	10	9.51	9.98	9.45	9.71	9.16	-0.58	0.94
2002	13.05	12.84	12.65	13.09	12.47	13.52	12.25	13.34	12.48	13.71	12.48	13.39	12.33	12.8	12.01	-0.97	0.93
2001	18.62	18.41	18.21	21.38	19.82	20.16	20.22	19.86	19.71	19.36	19.66	20.59	19.75	19.35	17.95	-0.6	0.97

Loss and Loss Severity Models

Figure 16 shows out-of-sample predictions for Alt-A 30-year fixed-rate severity rates.

The model has been built on the conservative side and tends to over-project loss severity since it only accounts for loss given default but did not adjust for modification loss. Over the last year, Alt-A, Sub-Prime and other collateral have seen a significant increase in modification activities and rising modification losses rise. As a result, the actuals are catching up with model projected rates.

Figure 16: Alt-A Severity Forecast Error Report

Green Package

v5.2 Alt-A FRM Forecast Error as of 02/01/2012 - Severity

Collateral Characteristics	Projections			Actual vs. Projection												Forecast Error	
Collateral Type/Vintage	Apr '12 Proj	Mar '12 Proj	Feb '12 Proj	Jan '12 Act	Jan '12 Proj	Dec '11 Act	Dec '11 Proj	Nov '11 Act	Nov '11 Proj	Oct '11 Act	Oct '11 Proj	Sep '11 Act	Sep '11 Proj	Aug '11 Act	Aug '11 Proj	6 Month Error	6 Month Error Ratio
2007	63.24	63.8	64.32	82.29	64.5	60.99	62.78	73.21	63.43	72.29	62.48	50.1	62.23	63.75	60.28	-4.49	0.93
2006	65.52	66.13	66.66	77.13	66.59	60.13	66.45	48.73	65.95	73.02	67.05	67.22	66.46	74.76	66.69	-0.3	1
2005	57.64	58.37	59.04	50.24	59.72	52.5	59.71	49.9	59.96	39.76	58.8	46.54	58.25	70.91	57.72	7.39	1.14
2004	54.3	55.35	56.37	62.91	55.55	58.83	55.01	64.72	55.51	24.81	54.52	53.16	55.72	47.64	54.93	3.2	1.06
2003	49.43	50.64	51.82	31.85	51.21	34.56	51.49	61.7	51.71	32.66	51.38	31.14	50.18	40.19	48.94	12.14	1.31
2002	50.9	51.27	51.39	0	50.86	92.24	50.58	81.4	53.61	79.68	52.1	32.08	50.63	56.98	49.48	-5.85	0.9
2001	51.03	51.86	52.56	8.93	50.22	104.8	50.01	0	51.07	0	63.85	0	50.49	0	49.64	33.59	2.77
Alt-A 30 Year FRM	64.66	65.42	66.02	63.18	66.2	64.9	66.21	63.32	66.11	63.21	65.56	64.81	64.5	62.75	63.57	1.66	1.03
2007	65.43	66.13	66.66	61.36	66.72	64.44	66.65	64.95	66.43	63.83	65.84	66.52	64.81	63.52	63.87	1.61	1.03
2006	67.91	68.64	69.21	66.71	69.49	66.99	69.35	65.76	69.37	66.3	68.81	67.35	67.72	65.73	66.71	2.1	1.03
2005	61.84	62.6	63.2	61.08	63.2	62.5	63.38	60.96	63.11	59.85	62.52	61.61	61.47	60.83	60.62	1.24	1.02
2004	54.45	55.32	56.04	54.37	55.99	58.08	56.1	52.02	56	53.02	55.44	51.42	53.64	47.2	52.83	2.32	1.04
2003	46.22	47.25	48.11	47.47	48.93	58.38	48.45	38.12	48.05	51.14	47.35	50.04	46.9	46.15	45.72	-0.98	0.98
2002	51.21	52.29	53.07	63.34	53.34	72.43	53.65	72.38	52.63	60.17	52.78	46.32	50.64	53.51	50.34	-9.13	0.85
2001	40.07	40.97	41.64	53.65	44.29	97.68	45.27	65.36	45.47	26.62	44.48	63.92	42.66	73.44	43.17	-19.22	0.7
2000	43.09	44.61	46.12	105.9	47.98	90.79	40.35	52.67	44.73	109.52	41.53	0	42.73	106.11	40.5	-34.53	0.55
1999	38.01	38.19	38.28	0	36.53	94.31	41.02	0	40.46	0	40.03	166.79	37.29	0	34.6	-5.2	0.88
Alt-A Jumbo 15 Year FRM	47.9	48.81	49.7	49.81	50.74	28.94	49.92	42	49.9	45.85	49.85	66.89	49.54	38.3	48.5	4.44	1.1
2007	46.47	47.33	48.25	73.16	50.88	33.36	51.11	54.34	51.02	88.89	51.45	81.34	45.93	0	45.15	-5.92	0.89
2006	58.29	59.01	59.63	53.89	59.4	54.22	58.8	50.26	58.67	0	57.5	76.11	58.62	46.77	56.87	11.43	1.24
2005	44.91	45.39	45.78	41.82	48.56	19.1	47.33	0	46.85	37.87	47.58	53.93	46.2	43.99	46.82	14.44	1.44
2004	36.37	37.26	38.23	0	39.02	0	39.85	45.69	40.24	57.42	42.93	0	42.54	0	41.05	23.75	2.38
2003	25.64	26.22	26.86	1.72	26.82	0	26.36	0.09	26.85	0	26.58	0	26.6	0	26.29	26.28	88.33
2002	22.66	23.36	24.19	0	26.59	0	24.4	0	26.75	0	25.01	0	23.86	0	22.41	24.84	
Alt-A Jumbo 30 Year FRM	55.37	56.14	56.72	54.49	56.9	54.54	56.55	52.52	56.2	52.36	56.09	52.22	55.22	52.95	54.18	2.68	1.05
2007	57.56	58.18	58.63	57.91	59.05	58.87	58.83	56.48	58.53	54.79	58.28	55.51	57.57	57.35	56.3	1.28	1.02
2006	59.11	59.8	60.27	57.05	60.18	60.14	59.99	56.31	59.41	54.71	59.56	49.33	58.41	56.41	57.45	3.51	1.06
2005	51.86	52.66	53.31	46.1	53.68	45.01	53.06	47.95	52.9	50.52	52.77	52.35	52.15	47.39	51.07	4.38	1.09
2004	41.51	42.41	43.18	44.61	43.55	45.56	42.23	39.41	42.58	42.48	42	43.43	40.63	23.26	39.59	1.97	1.05
2003	33.37	34.33	35.13	31.99	34.71	22	34.78	9.12	33.33	15.68	33.43	56.17	32.87	17.26	31.89	8.13	1.32
2002	36.76	38.36	39.68	76.64	40.35	0	39.43	22.03	37.28	23.86	36.02	0	34.6	0	33.21	16.39	1.8
2001	31.14	32.56	33.89	43.31	34.02	0	32.61	0	33.69	45.83	38.54	43.98	37.43	0	35.16	13.05	1.59
2000	15.93	16.17	16.48	0	18.61	0	19.03	0	18.58	0	20.76	0	15.34	0	13.26	17.6	