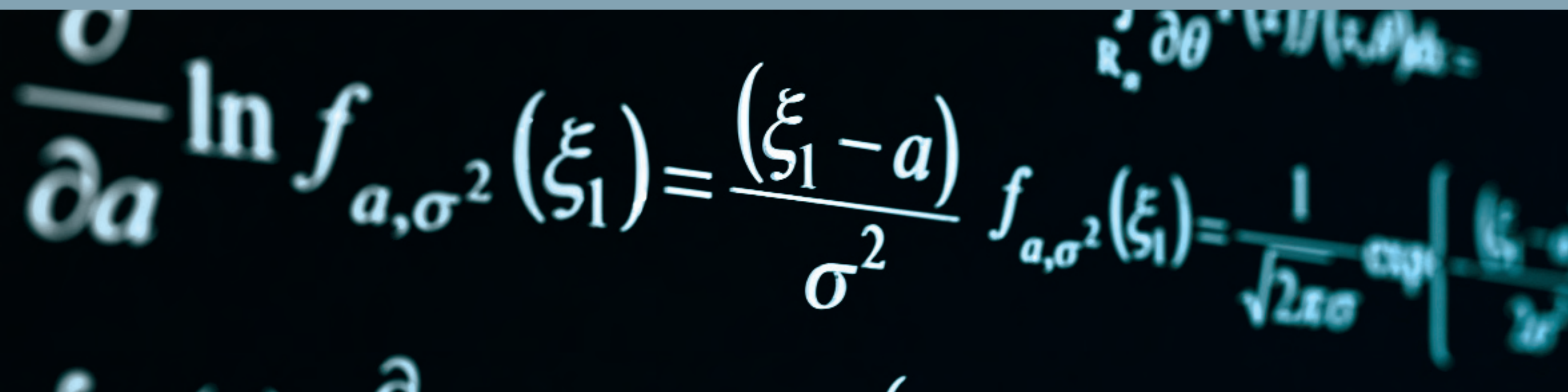
BARCLAYS CAPITAL

SECURITIZATION RESEARCH
March 2011

# INSIDE MORTGAGE VALUATION

## A GUIDE TO MODELS ON BARCLAYS CAPITAL LIVE



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At the close of business on Friday, March 18, 2011, Barclays Capital will introduce a new agency prepayment model, which constitutes a significant enhancement to our agency prepayment model framework. It not only incorporates the effects of important collateral attributes and macroeconomic factors, but also captures major changes in underwriting standards, origination costs, and policy initiatives. In addition, a highly flexible user interface allows clients to edit or override many of these effects. In short, this expanded and highly flexible model structure allows users to respond quickly to changes in the mortgage market, run customized what-if scenarios, quantify risks, or express relative value views contingent on changes to underwriting standards, home prices or policy initiatives.



Barclays Capital Loan Transition Model tracks the progression of mortgages through the entire chain of borrower action and servicer reaction. It is implemented through Monte Carlo simulation at the loan level, which allows it to make full use of the borrower's entire payment history when projecting the level and timing of future defaults. The model can be used to evaluate mortgage pools containing virtually any residential mortgage products.



In tandem with the release of the new prepayment model, we are also upgrading our term structure model. The new framework will be the Libor Market Model (LMM), which captures the entire volatility surface with minimal calibration error. It also produces highly realistic at-the-money (ATM) and out-of-the-money (OTM) skews, resulting in close fits for a wide strike range.



The Barclays Capital Regional Home Price Model provides a methodology for deriving home price projections at the state, CBSA, county, and zip level over a broad range of national home price scenarios. The model explicitly incorporates factors that affect both long-run trends in regional home prices and cyclical deviations from those trends.

# ACKNOWLEDGEMENTS

The term-structure model (Libor Market Model) was developed by the Quantitative Analytics (QA) group within Barclays Capital. We thank Regis Van Steenkiste, Mingyang Xu, and Enping Zhao from the QA group and Zhengao Huang from the structured products research group for adapting the LMM model for mortgage valuation and integrating it into our mortgage analytics framework.

We thank the agency and non-agency trading desks and strategists for their insights throughout the model development process. We would especially like to thank Alex Zirakzadeh for his support and many ideas that helped maximize the usefulness of the analytics.

Finally, none of this would have been possible without the dedicated efforts of our mortgage analytics team, led by Shashidhar Upadhyay, Igor Manuilskiy, Anant Bhatnagar and Mansoor Shaikh. They worked tirelessly to implement the models and enhance the analytics framework on Barclays Capital Live.

*Structured Products Modeling Team*

# BARCLAYS CAPITAL AGENCY FIXED-RATE PREPAYMENT/BUYOUT MODEL

## Introducing a new prepayment model for agency collateral

V.S. Srinivasan
+1 212 412 3854
v.srini@barcap.com

William Sarrett
+1 212 412 1327
William.Sarrett@barcap.com

Steven Bergantino
+1 212 412 2164
steven.bergantino@barcap.com

Derek Chen
+1 212 412 2857
derek.chen@barcap.com

At the close of business on Friday, March 18, 2011, Barclays Capital will introduce a new agency prepayment model. The new model constitutes a significant enhancement to our agency prepayment model framework. It not only incorporates the effects of important collateral attributes and macroeconomic factors, but also captures major changes in underwriting standards, origination costs, and policy initiatives. In addition, a highly flexible user interface allows clients to edit or override many of these effects. In short, this expanded and more flexible model structure will allow users to quickly respond to changes in the mortgage market, run customized what-if scenarios, quantify risks, or express relative value views contingent on changes to underwriting standards, home prices or policy initiatives. Highlights of the new model include the following:

- The new model covers all agency fixed rate products. Independent models were estimated for conventional 30y/15y and GNMA mortgages. These three models form the base for prepayment analytics on all fixed-rate collateral. Product-specific parameters were then estimated to modify individual components of the base model for various additional collateral types such as 10/20 IO, 40y, 20y, expanded eligibility jumbo loan size pools, relocation loans, and high loan-to-value (LTV) HARP pools. These additional parameters are also used to distinguish between Fannie Mae and Freddie Mac mortgage pools and between the GNMA I and GNMA II programs. This leads to a consistent framework being used across products, while still capturing unique differences in prepayment performance.

- The new model explicitly incorporates time varying credit standards. Underwriting requirements have tightened considerably over the past three years. Although there are many different dimensions along which underwriting standards have changed, at origination FICO scores provide the most comprehensive measure of the overall change. The model uses the average FICO score of Freddie Mac purchase originations in any given month as a proxy for overall credit availability in that month. Pools with below average FICO scores are considered to be somewhat credit impaired and have flatter refinancing curves, while pools with above average FICO scores have steeper refinancing profiles. When projecting future prepayments, the model assumes that average FICO scores remain at current levels, and hence that underwriting standards remain unchanged from current practice. However, users can impose their views by inputting their own vector of FICO scores to reflect future changes in GSE origination standards.

- Changes in the equity position of the borrower are a significant driver of projected refinancing rates, delinquency roll rates, and housing turnover. We use CoreLogic distressed excluded, state level home price indices to calculate updated loan-to-value ratios (ULTV) for each pool based on the geographic distribution of the pool. Our forward HPA projections are also at the state level and taken from our regional home price model.

- The refinance model captures the distortions in prepayment performance caused by the HARP program. The base case assumption in the model is that HARP will be extended indefinitely but never expanded to include more recent originations; however, users can change these assumptions to allow for the expiration or expansion of the program.

- The new model takes into account persistent differences in prepayment performance across servicers and geography that cannot be explained by differences in collateral attributes. In addition, users can input additional time varying servicer multipliers to capture more short-lived but potentially pronounced prepayment differences across servicers. For example, over the past several months, HARP eligible loans from the 2008 and 2009 vintages serviced by Wells Fargo and JPMorgan Chase have been prepaying significantly faster than similar loans serviced by Bank of America and Citi.

- We have used the LoanPerformance loan-level mortgage servicing database to estimate a GSE-specific delinquency roll rate model that is used to project buyout driven prepayments on Fannie Mae and Freddie Mac mortgage pools. This roll rate model leverages the extensive work we have done in developing the Barclays Capital Loan Transition Model. The roll rate model for the GNMA program is based on pool level delinquency and buyout information provided by GNMA.

- The economic incentive used to project refinance related prepayments in the model captures the full change in monthly payment resulting from the refinance transaction, including origination costs and delivery fees. In the case of FHA mortgages, we adjust for the up-front mortgage insurance premium (UFMI) net of any refund of previously paid UFMI as well as any changes in annual mortgage insurance premiums since the origination of the borrower's current mortgage. The prepayment response to this incentive is then adjusted for collateral attributes such as loan size, FICO score, updated LTV, Spread at Origination (SATO), property type, historical refinancing opportunities, occupancy, HARP eligibility, servicer and the prevailing underwriting and interest rate environments. Each of these factors can affect either the shape or the level of the refinancing function.

- The model controls for the effect of historical lows in mortgage rates on refinancing activity by calculating a variable that compares current and past mortgage rates and moves continuously in synch with the relative attractiveness of the current mortgage rate environment. The lower current mortgage rates are relative to the past, the steeper is the refinancing response function.

- We have optimized our aggregation criteria to fully leverage the driving factors in the new model while keeping run time to a minimum. As a result, we are able to generate fast OAS calculations without sacrificing pricing precision, even when running CMOs backed by thousands of pools. In contrast, models that run a single representative pool attain their speed advantages at the expense of potentially large losses in pricing precision.

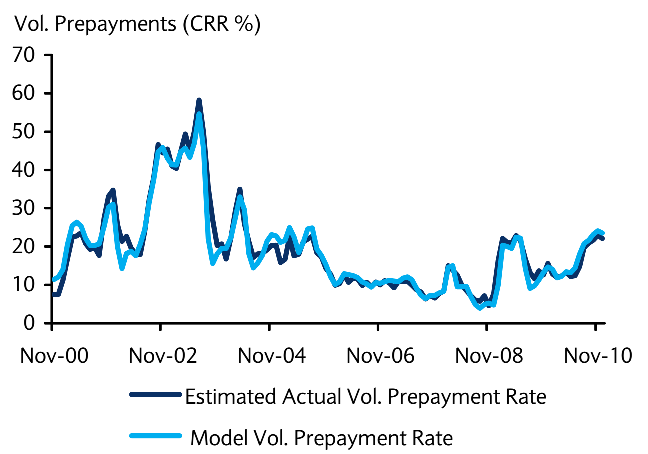
The new prepayment model, along with the new term-structure model will be available in beta mode to investors on March 18, 2011, and will be rolled into production on April 21, 2011. This update includes a significant revamping of the entire analytics infrastructure. This new infrastructure will allow us to better balance the need of some investors for a stable model with the need of others for a model that changes rapidly in response to developments in the mortgage market. We will maintain two separate versions of the model, production, and production-beta. The production model will be updated less frequently (every 12-18 months on average) and will be used for calculating duration on the Barclays Capital mortgage indices. Updates to the production model will also be announced several weeks in advance and will include the re-computation and repopulation of the historical OASs used in our time series analysis tools. Updates to the production-beta model will occur more frequently (every 3 to 6 months or whenever there are material changes to the mortgage market). For example, if the GSEs were to introduce changes to their servicing compensation plan, we would quickly update the production-beta model to reflect our best estimate of the potential implications of the change. However, we would not update the production model until the effect of the change is fully visible in the prepayment data. Because updates to the production-beta model will happen with very little advance notice, we will make the previous version of this model available to users for at least 30 days after an update. This will allow users to transition at their desired pace. Over the next several weeks and months we hope to hear your suggestions on how we can further improve our models and analytics. In order to attain the full potential of our new modeling and analytical framework we need your participation, feedback, and ideas.

## Introduction

The refinancing response to the recent generational low in mortgage rates has been rather underwhelming when measured against historical precedent and has made clear the need for prepayment models that go beyond collateral attributes, interest rates, and home prices when projecting future prepayments. Changes in housing policy, underwriting standards, and refinancing costs now play a very important role in explaining prepayment performance. This new model explicitly incorporates these factors, allowing it to fit the entire history of prepayment performance using a single set of parameters. For example, Figure 1 shows the model's ability to fit the strikingly different prepayment behavior of borrowers during the 2002-03 refinance episode and over the past few months. Both episodes represent periods when 30y mortgage rates were at multi-year lows and the difference between the average WAC of the outstanding 30y universe and prevailing mortgage rates were in excess of 100bp but prepayments were 2-3x higher during the earlier episode.

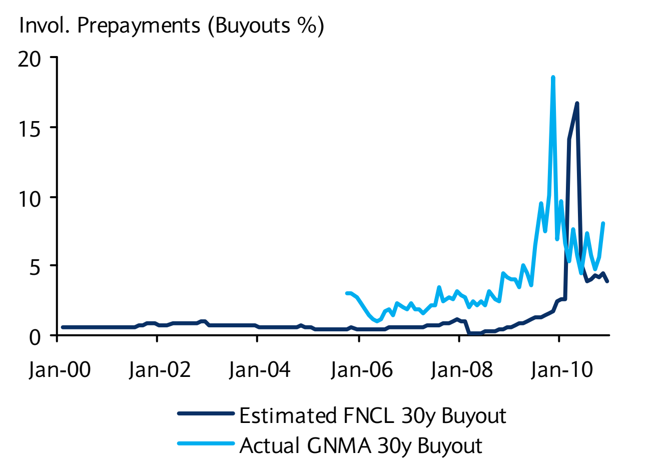
Another significant change in the prepayment landscape is the increased contribution of delinquency buyouts to overall prepayments. This is particularly troublesome in the case of conventional mortgages because, until recently, neither Fannie Mae nor Freddie Mac released pool level delinquency or buyout information[1]. Not only did this limit one's ability to estimate buyout models, but the increased buyouts also corrupted the voluntary prepayment database after 2009.

**Figure 1: Aggregate voluntary prepayments on Fannie Mae 30y collateral – model vs. actual**




Source: Fannie Mae, Barclays Capital

**Figure 2: Aggregate buyout rate on Fannie Mae and GNMA 30y collateral**




Source: CoreLogic, Fannie Mae, GNMA, Barclays Capital

[1] The GSEs started releasing cohort level delinquency information in late 2009. Freddie Mac started releasing pool level delinquency and buyout information in December 2010 and Fannie Mae still does not.

Fortunately, CoreLogic maintains a loan level servicer database that has very detailed information on the actual credit performance of loans backing GSE pools and provides significant insights into how credit performance varies with collateral attributes such as FICO, LTV, Geography, home prices, and SATO. Armed with this delinquency and roll rate data we have estimated historical buyouts based on GSE practices over the past few years (Figure 2). Until late 2007, the GSEs were buying out materially all of the loans that went more than 120 days delinquent (or in the case of Fannie Mae missed four consecutive payments). Between 2008 and early 2010 both GSEs restricted their buyout activity to only those loans that rolled to REO, were permanently modified, or had missed more than 24 payments. Then, during the first half of 2010 the GSEs cleaned out their mushrooming delinquency pipelines by buying out virtually all seriously delinquent loans (this accounts for the large spike in buyouts in Figure 2) and have continued to do so since then. We use this estimated buyout information to split total reported prepayments in our pool database into voluntary and involuntary prepayments. Absent this adjustment we would not be able to use most of the 2009-2010 prepayment performance to estimate voluntary prepayment models.

In contrast to the conventional sector, GNMA provides pool level delinquency and buyout information going back to late 2005. The GNMA buyout model is calibrated to these data.

## Model structure

Total projected prepayments from the model are the sum of rate/term refinancing, housing turnover, cash-out refinancing and delinquency buyouts. [2]

$$SMM = R + T + C + B$$

As described above, for conventional mortgages, the delinquency buyout model was estimated independently using the servicing database and then used to split total reported prepayments in the GSE pool database into voluntary and involuntary prepayments. All three components of the voluntary prepayment model were then estimated simultaneously after subtracting estimated delinquency buyouts from total prepayments.

### Rate/term refinancing

There are two prevalent schools of thought for the structure of the refinancing component of a prepayment model. One approach would argue that given the right economic incentive to refinance, the prepayment response function is very similar across all borrowers. This approach is very attractive, particularly in an environment when almost all borrowers can get a mortgage and can finance the cost of the transaction. In this case, the economic incentive, calculated as the net present value of savings, after accounting for differences in prevailing mortgage rates and closing costs across collateral attributes, provides a reasonable predictor of prepayment propensity.

An alternate approach is to have a very simple definition of economic incentive and estimate a prepayment response function that can vary significantly across incentive ranges and collateral attributes. Both approaches have their merits, but we believe that in the current environment in which some borrowers have no access to financing, the latter approach is more desirable. It is also more in-synch with the way market participants think about refinancing functions. The new agency prepayment model uses this approach.

[2] SMM stands for single monthly mortality and is a measure of the total percent of current outstanding balance that prepays every month.

We measure economic incentive (EI) as the percentage change in monthly payment assuming the borrower refinances into another loan with similar maturity at prevailing mortgage rates. The balance and prevailing rates are adjusted for well-defined factors such as delivery fees, origination costs and, in the case of FHA mortgages, the structure of mortgage insurance premiums.[3] Other factors affect the prepayment response function rather than the economic incentive function.

$$EI = \frac{PMT(WAC, WAM, UPB) + FHA\_MI_{AtOrigination} * UPB}{PMT(MortRate, WAM, NewBalance) + FHA\_MI * NewBalance}$$

The refinancing response function is parameterized as a piece-wise linear function of EI where we allow factors such as SATO, loan size, FICO, and ULTV to multiply the slopes of each section of the spline. This is a highly flexible form that allows collateral attributes, home prices, and other factors to change not only the level, but also the shape of the refinancing function.[4]

### Pure housing turnover

When a borrower sells his house it typically triggers a prepayment event[5]. This accounts for the bulk of prepayments on discount mortgages. Although there are many factors that affect housing turnover, it is safe to assume that most borrowers who take out a new mortgage, be it a purchase or refinance, are signaling an intention to remain in their home over the near term. As a result, housing turnover related prepayments on a mortgage pool tend to be highly correlated with its average loan age for several years after origination. Once a mortgage pool is fully seasoned, its steady state level of housing turnover is primarily a function of interest rates, home prices and borrower demographics. Since available prepayment data do not distinguish between prepayments due to rate/term refinancings or the sale of a property, our estimates of housing turnover and its determinants are dominated by periods when refinancing activity is very low. Fortunately, our prepayment datasets span multiple interest rate cycles containing several such episodes.

### Cash-out refinancing

This function is used to capture any increase in prepayments that can be directly attributed to the borrower's equity position in the property other than the effect of ULTV on rate/term refinancing. Cash-out refinancing primarily falls into two categories

- Borrowers monetizing the equity in their property by trading-up. Most GSE borrowers can easily get 5x leverage on their property. For example, consider a borrower with a $200K home and $160K mortgage. If home prices appreciate by 10% he can sell his current home and use the proceeds for a 20% down payment on a $300K home.

[3] For conventional loans - mortgage rate is adjusted by the delivery fee schedules published by Fannie Mae and Freddie Mac. Balance is adjusted based on our estimate of closing cost. For FHA loans - the balance is adjusted by up front MI and up front MI refund schedule. Prior to 2010, the balance is also adjusted for closing cost. FHA rule changes in late 2009 made it more onerous to finance closing cost. In the model, closing cost now affects the refinancing response function and not the economic incentive function.

[4] Currently, we use eight knot points (0.97,1.00,1.03,1.06,1.09,1.12,1.15,1.20,1.25). Model overrides allow the user to change the slope of the interpolants between each of these knot points. While some factors affect each of the interpolants differently others are constrained to have the same effect across all of them.

[5] Mortgages in the US are not portable, ie, borrowers cannot transfer a mortgage on one property to another. FHA mortgages are assumable i.e. when a borrower sells his house the buyer can assume the mortgage. However, for this to be possible, any difference in the price of the home and the unpaid principal balance on the mortgage has to be made up by cash from either the buyer or seller. Moreover, the seller would have to cover the 5-6% in broker fees out of pocket.

- Borrowers monetizing the equity in their property to either pay-off existing debt or avoid taking out a higher interest rate, non-tax deductible loan to finance a major expenditure such as a car purchase, or home renovation.

Both types of transactions could and did occur even in environments where borrowers had no economic incentive as defined by our economic incentive function. We model cash-out refinances as a function of the weighted cumulative home price appreciation of the pool. We apply a discount factor to home price appreciation such that any appreciation that happened more than three years in the past is significantly less important than recent appreciation. The model also assumes that debt-to-income limits will be significantly more restrictive and, as a result, cash-out refinancing activity will be reduced even more than implied by home prices.

### Delinquency roll rates and buyouts

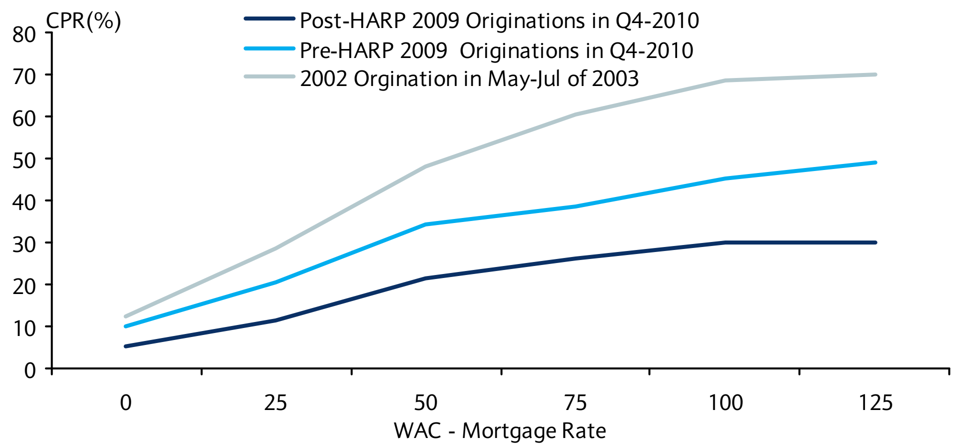
For the conventional sector, we model the roll rate from less than 120 days delinquent to more than 120 days delinquent because the GSEs buy out any loan that goes more than 120 days delinquent. For the GNMA sector, we model the net roll rate from less than 90 days delinquent to more than 90 days delinquent. Unlike the conventional sector, not all 90+ day delinquent loans are bought out by GNMA servicers. While there are many factors that influence the buyout decision, we believe the key systematic factor is the relative coupon of the delinquent loans. If the coupon is below the par coupon, the servicer has limited options to modify the loan without a loss and is therefore less likely to buy it out of the pool. Thus, buyout activity decreases for discount pools and increases for premium pools. In the model, this systematic driver of buyouts is captured by comparing the coupon on the MBS pool to the calculated par coupon. If the coupon on the GNMA pool is significantly higher than the par coupon, buyouts will likely increase. Conversely, buyout activity decreases as the coupon on the pool approaches or declines below the par coupon.

## Rate/term refinancing – Recent prepayment performance

Mortgage valuations, to a large extent, are driven by the efficiency with which borrowers exercise their option to prepay their mortgage and refinance into lower mortgage rates. Over the past few years we have seen significant decreases in the propensity and/or ability of borrowers to exercise this option as characterized by historically low prepayments on mortgages with above market mortgage rates. The prepayment profile from the second and third quarters of 2003 is generally considered the benchmark of peak efficiency in refinancing. In Figure 3 we compare the refinancing curve of 2002 originations in May-July of 2003 with more recent originations in Q4 10. Both sample periods represent historical lows in mortgage rates. There are two obvious observations that can be made. First, the refinancing curve in Q4 10 is significantly flatter than that of 2003. Second, there is a significant difference in prepayments between pre- and post-HARP 2009 originations[6].

[6] Freddie Mac loans originated after May 2009 are not eligible to be refinanced through HARP. For this analysis, we define pre-HARP 2009 originations to include loans originated between October 2008 and May 2009. Post-HARP 2009 includes loans originated between June and December 2009.

**Figure 3: Change in refinancing response function between 2003 and Q4 10**




Source: Freddie Mac, Barclays Capital

There are four key drivers in the model that explain most of this difference in prepayment performance:

- The tightening in underwriting standards.
- The path of home prices and cash-out refinancing.
- The increase in transactions costs and delivery fees.
- Distortions to prepayments caused by the HARP program.

## Underwriting standards

As the real estate and credit crises worsened beginning in 2008, underwriting standards on agency conforming mortgages tightened significantly. Some of this tightening can be attributed to changes in the GSE program, but originators, skittish about put-back risk, exacerbated the tightening. Figure 4 summarizes the distribution and average FICO score of Freddie Mac purchase and refinance originations. Purchase originations, which are not constrained by the credit characteristics of borrowers with above market mortgage rates, are a better proxy for changes in underwriting standards. Between Q4 07 and Q2 09, the average FICO score of purchase originations increased to 760 from 725. More importantly, the percent of loans with FICO scores below 720 declined to the mid–teens from 40%. While we do not necessarily believe that either originators or the GSEs were targeting FICO, the increase in FICO scores signaled a broader tightening in underwriting practices. For example, over the same period, debt-to-income (DTI) ratios declined from 39% to below 32%. In addition, originators started scrutinizing soft underwriting guidelines such as missed payments on non-installment debt much more closely than in the past. These two factors, total indebtedness (a DTI proxy) and payment history account for about 65% of the FICO score calculation. Clearly, this indicated an enormous structural change in underwriting.

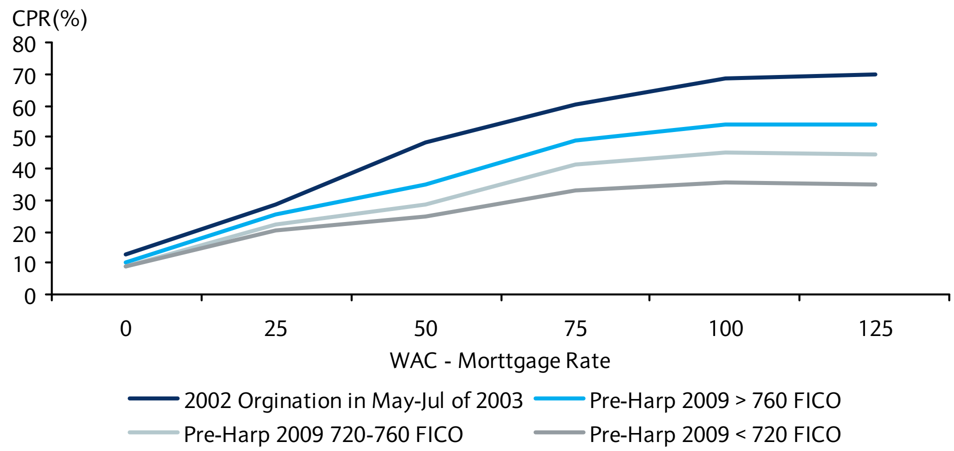
Figure 4: FICO as a proxy for changes in underwriting standards

| | Refinance Loans | | | | Purchase Loans | | | |
|---|---|---|---|---|---|---|---|---|
| Orig. Qtr | <720 | 720-760 | >760 | Average | <720 | 720-760 | >760 | Average |
| 2006-Q1 | 52% | 23% | 25% | 711 | 36% | 25% | 39% | 732 |
| 2006-Q2 | 52% | 23% | 25% | 710 | 35% | 24% | 41% | 732 |
| 2006-Q3 | 52% | 23% | 25% | 708 | 35% | 24% | 41% | 730 |
| 2006-Q4 | 50% | 24% | 27% | 711 | 36% | 24% | 40% | 730 |
| 2007-Q1 | 47% | 24% | 29% | 716 | 37% | 24% | 40% | 731 |
| 2007-Q2 | 49% | 23% | 28% | 715 | 38% | 23% | 39% | 729 |
| 2007-Q3 | 53% | 22% | 25% | 707 | 40% | 22% | 38% | 725 |
| 2007-Q4 | 50% | 23% | 27% | 709 | 40% | 22% | 37% | 726 |
| 2008-Q1 | 36% | 25% | 39% | 730 | 37% | 23% | 39% | 733 |
| 2008-Q2 | 33% | 26% | 41% | 734 | 30% | 24% | 45% | 740 |
| 2008-Q3 | 34% | 26% | 40% | 731 | 25% | 25% | 50% | 743 |
| 2008-Q4 | 29% | 26% | 45% | 735 | 25% | 25% | 50% | 744 |
| 2009-Q1 | 14% | 23% | 63% | 762 | 21% | 25% | 54% | 753 |
| 2009-Q2 | 13% | 23% | 64% | 764 | 16% | 25% | 60% | 760 |
| 2009-Q3 | 18% | 24% | 58% | 758 | 14% | 24% | 62% | 761 |
| 2009-Q4 | 19% | 24% | 57% | 755 | 16% | 24% | 60% | 759 |
| 2010-Q1 | 20% | 23% | 57% | 755 | 16% | 23% | 61% | 760 |
| 2010-Q2 | 22% | 23% | 54% | 752 | 16% | 23% | 61% | 760 |
| 2010-Q3 | 17% | 21% | 62% | 761 | 15% | 22% | 63% | 762 |
| 2010-Q4 | 15% | 20% | 65% | 765 | 14% | 22% | 64% | 764 |

Source: Freddie Mac, Barclays Capital

Once we restrict our sample to borrowers with FICO above 760, the refinancing curve observed in Q4 10 for pre-HARP 2009 originations start to approach the refinancing curve observed in 2003 (Figure 5). The model accounts for this by comparing the FICO of a given pool with the average FICO of all purchase loans originated in a particular month. Consider two pools originated in 2002 with FICO scores of 730 and 770. The model would project very similar prepayments on both these pools through the 2003 sample period when the average FICO of GSE originations averaged about 725. In contrast, the model would project substantially different speeds between these two pools in Q4 10, when the average FICO of GSE originations was 764. The rationale behind this is that a portion of the loans in the 730 FICO pool are locked out of GSE financing and thus have limited refinancing options. Future projections of the model are conditional on the future average FICO of GSE originations. Our base case assumption is that average FICO will remain at 760. However, we allow users to input their own assumptions or views on future GSE underwriting.

**Figure 5: FICO is a significant driver of prepayment performance**




Source: Freddie Mac, Barclays Capital

## The path of home prices

While underwriting standards tightened over the past two years, there were no significant changes in the LTV profile of GSE originations. Historically, the vast majority of GSE loans were under 80 LTV (Figure 6). While the average LTV on purchase loans have always hovered right about 80 in order to avoid the need for mortgage insurance, the LTV of refinanced loans were in the mid- to high 60s, mostly because of the historical path of home prices. As home prices started to decline in 2008, the demand to refinance loans over 80 LTV increased significantly but the overall share of refinanced loans over 80 LTV increased only marginally. This is despite the introduction of HARP, a program with the stated goal of assisting borrowers whose LTV increased over 80 because of home price depreciation.

**Figure 6: LTV profile of GSE origination have remained stable**

| Orig. | Refinance Loans | | | Purchase Loans | | |
|---|---|---|---|---|---|---|
| Qtr | <= 80 | > 80 | Avg | <80 | >80 | Avg |
| 2006-Q1 | 92% | 8% | 66.9 | 81% | 19% | 77.0 |
| 2006-Q2 | 92% | 8% | 66.8 | 81% | 19% | 77.2 |
| 2006-Q3 | 91% | 9% | 67.0 | 80% | 20% | 77.3 |
| 2006-Q4 | 92% | 8% | 67.6 | 79% | 21% | 77.8 |
| 2007-Q1 | 92% | 8% | 67.6 | 77% | 23% | 78.5 |
| 2007-Q2 | 90% | 10% | 68.5 | 72% | 28% | 79.7 |
| 2007-Q3 | 87% | 13% | 69.4 | 63% | 37% | 81.4 |
| 2007-Q4 | 84% | 16% | 69.5 | 57% | 43% | 81.9 |
| 2008-Q1 | 87% | 13% | 68.2 | 58% | 42% | 81.2 |
| 2008-Q2 | 89% | 11% | 66.3 | 66% | 34% | 78.4 |
| 2008-Q3 | 91% | 9% | 65.4 | 70% | 30% | 76.8 |
| 2008-Q4 | 93% | 7% | 65.6 | 72% | 28% | 76.9 |
| 2009-Q1 | 95% | 5% | 64.4 | 74% | 26% | 76.7 |
| 2009-Q2 | 94% | 6% | 63.8 | 77% | 23% | 76.8 |
| 2009-Q3 | 87% | 13% | 65.9 | 81% | 19% | 76.3 |
| 2009-Q4 | 86% | 14% | 66.6 | 82% | 18% | 76.5 |
| 2010-Q1 | 82% | 18% | 67.6 | 85% | 15% | 75.7 |
| 2010-Q2 | 79% | 21% | 68.8 | 83% | 17% | 76.3 |
| 2010-Q3 | 81% | 19% | 68.3 | 82% | 18% | 76.1 |
| 2010-Q4 | 82% | 18% | 67.7 | 82% | 18% | 76.8 |

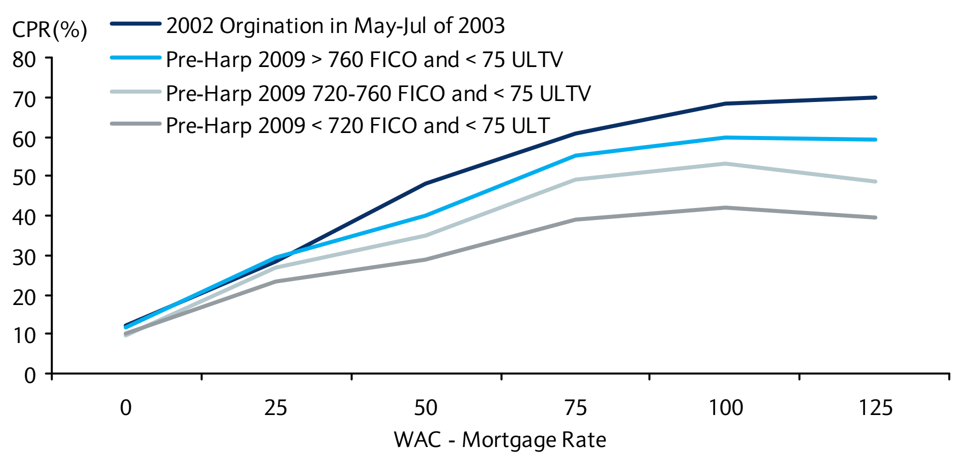
Source: Freddie Mac, Barclays Capital

Thus, LTV has been a significant constraint on refinancing for the many borrowers with loans originated in Q4 08 and early 2009 who saw their equity position deteriorate by Q4 10. In Figure 7, we refresh the refinancing curves controlled not only for FICO but also updated LTV (ie, adjusted for home price appreciation). Now, the difference in the refinancing profile of pre-HARP 2009 originations in Q4 10 and 2002 originations in 2003 decrease significantly.

When comparing these two refinancing curves, we note that mortgage rates rallied 144bp from an average of 6.79% in 2002 to a low of 5.35% in June 2003. In contrast, the average mortgage rate rallied only 100bp between the pre-HARP 2009 origination period and the low in Q4 10. Consequently, many of the pre-HARP 2009 pools with more than 75bp of incentive were originated at above market rates (ie, high SATO). For similar economic incentive, these pools tend to prepay slower relative to pools originated at prevailing mortgage rates. Moreover, cash-out refinancing was significantly subdued in Q4 10. According to quarterly cash-out statistics released by Freddie Mac, 33% of the borrowers increased their loan balance by over 5% in Q2 and Q3 03, compared with just 16% in Q4 10. We believe that these two factors explain virtually all of the remaining difference between the two refinancing profiles.

The model adjusts the refinancing response function based on updated LTV. The model also accounts for differences in SATO and cash-out refinancing. We used CoreLogic distressed excluded state level home price indices to update the LTV of every pool in our database. We have also developed a home price projection model that allows us to project home prices into the future at the state level.

**Figure 7: Controlled for FICO and Updated LTV the prepayment profile is little changed between 2002 originations in 2003 and pre-HARP originations in Q4 10**




Source: Freddie Mac, Barclays Capital

While underwriting changes, the path of home prices, and reductions in cash-out refinancing can explain the prepayment profile of late 2008 and early 2009 originations, we are still left with the mystery of a significantly flatter refinancing profile for post-HARP 2009 originations. After all, these loans were originated to rigorous underwriting standards and have not seen any material decline in home prices. We believe HARP is the culprit.

## Effect of HARP on prepayment performance

As home prices declined throughout 2007 and 2008, a large portion of the 2006-2007 vintage of agency mortgages had their mark-to-market LTV rise above 80. This significantly curtailed their refinancing options. The GSEs could not guarantee loans with LTV in excess of 80 without private mortgage insurance and borrowers trying to refinance were either not able to get mortgage insurance or had to pay prohibitively expensive premiums. Unveiled by the US Treasury in March 2009, HARP was intended to address this problem.

Most of the discussion on HARP has focused on its effect on prepayments of HARP eligible borrowers. We would contend that the biggest effect of HARP has been to suppress prepayments on post-HARP refinance originations. We sliced the data into eight distinct buckets based on origination period (pre-HARP vs. post-HARP), loan purpose (purchase vs. refinance), and original LTV (<=80 and >80). Figure 8 summarizes the collateral attributes for each bucket.

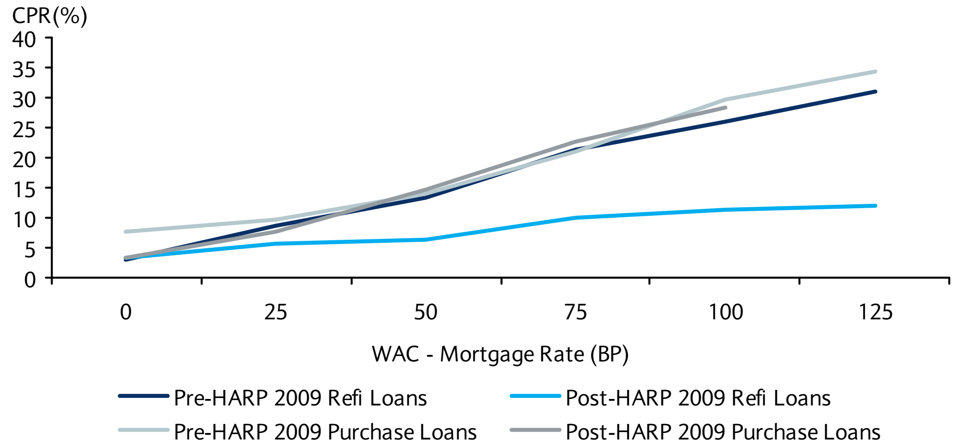
**Figure 8: Collateral attributes of loans based on origination period, LTV and loan purpose**

| Original LTV | Orig Period | Purpose | Balance ($bn) | WAC | WALA | Loan Size | Orig LTV | Orig Comb. LTV | FICO | DTI | Pct MI |
|---|---|---|---|---|---|---|---|---|---|---|---|
| <= 80 LTV | Pre-HARP 2009 | Purchase | 22.3 | 5.35 | 21 | 189,962 | 72.2 | 73.68 | 756 | 36 | 0.1 |
| | Pre-HARP 2009 | Refinance | 122.5 | 4.99 | 20 | 220,218 | 63.5 | 65.48 | 763 | 33 | 0.0 |
| | Post-HARP 2009 | Purchase | 43.8 | 5.10 | 14 | 202,399 | 73.3 | 74.42 | 762 | 35 | 0.0 |
| | Post-HARP 2009 | Refinance | 129.0 | 4.99 | 14 | 216,858 | 63.2 | 65.77 | 760 | 32 | 0.0 |
| > 80 LTV | Pre-HARP 2009 | Purchase | 9.1 | 5.52 | 21 | 194,559 | 91.0 | 91.02 | 746 | 37 | 97.4 |
| | Pre-HARP 2009 | Refinance | 7.5 | 5.11 | 20 | 205,379 | 88.7 | 88.97 | 750 | 35 | 92.5 |
| | Post-HARP 2009 | Purchase | 10.8 | 5.11 | 14 | 195,341 | 91.1 | 91.09 | 757 | 33 | 94.3 |
| | Post-HARP 2009 | Refinance | 23.9 | 5.16 | 14 | 224,867 | 91.5 | 95.77 | 743 | 32 | 25.6 |

Note: Collateral attributes as of October 2010. Source: Freddie Mac, Barclays Capital

Let us consider the prepayment performance for loans with over 80 LTV at origination. Both purchase and refinanced loans originated pre-HARP 2009 have very similar refinancing profiles. (Figure 9) This is reasonable given that they are both eligible for HARP and have similar collateral attributes. The prepayment profile of Post-HARP purchase originations is also very similar to pre-HARP originations. More than 94% of these borrowers have mortgage insurance that was written after the credit crisis. Given that home prices are little changed since the second half of 2009, these borrowers were able to renew their mortgage insurance when refinancing without material changes in premium. However, post-HARP refinanced originations have a much flatter prepayment profile. These loans were originated only because of the HARP program and the vast majority of them do not have mortgage insurance. Absent their eligibility for HARP, they have very few refinancing options. So the overall prepayment profile of greater than 80 LTV post-HARP originations are consistent with pre-HARP originations and can be systematically accounted for in the model. We have stated earlier that the model adjusts the refinancing response function based on updated LTV. This function is significantly more onerous for post-HARP refinanced originations.

**Figure 9: Refinancing profile of loans with original LTV > 80**

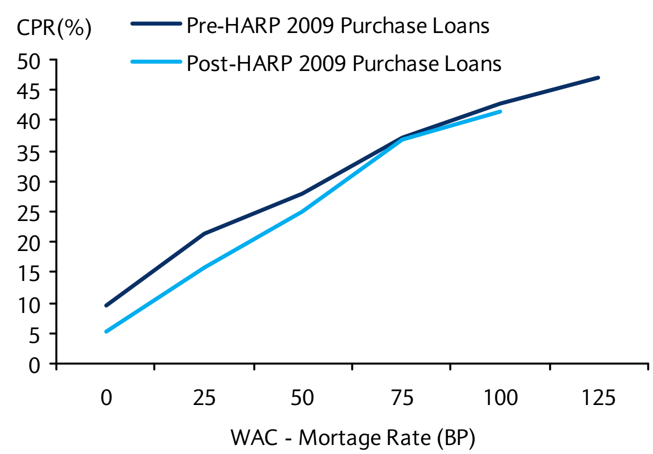



Source: Freddie Mac, Barclays Capital

Now consider loans with less than 80 LTV at origination. Purchase loans originated post-HARP prepay slower than pre-HARP originations for low incentives (less than 50bp), but at similar levels for higher incentive ranges (Figure 10). This is reasonable given that HARP eligible loans have lower transaction cost, delivery fees and can be processed through a streamline refinancing program. We believe this difference in prepayment profile captures the relative advantage of HARP eligibility for less than 80 LTV loans.

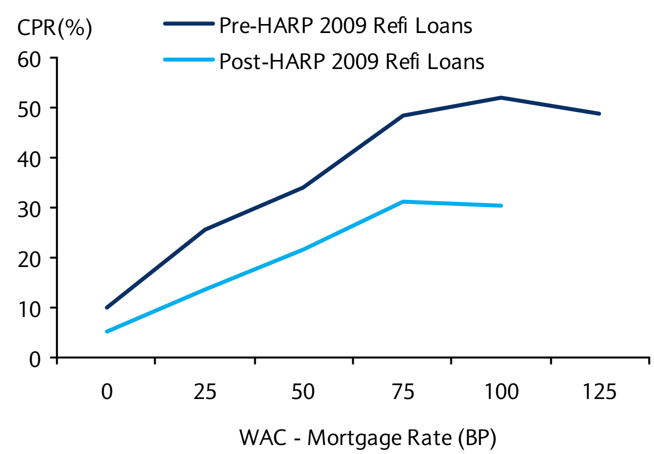
The biggest surprise is the difference in prepayment profile of low LTV refinanced loans. Post-HARP refinanced loans are paying significantly slower than their pre-HARP counterparts despite having very similar collateral attributes (Figure 11). Even more surprisingly, they are paying slower than purchase loans (5 CPR for 75bp and 10 CPR for 100bp of incentive) despite having a 10-point lower LTV, $15K higher loan balance, and 3-point lower DTI. Post-HARP refinanced loans account for more than 40% of all 2009 originations, and their muted refinancing response caused prepayments on this cohort to be significantly below market expectation in Q4 10. Market participants have offered several theories for why post-HARP refinanced loans have been prepaying so slowly.

**Figure 10: Refinancing profile of purchase loans with original LTV<=80**




Source: Freddie Mac, Barclays Capital

**Figure 11: Refinancing profile of refinance loans with original LTV<= 80**




Source: Freddie Mac, Barclays Capital

**Theory #1** – Many borrowers with LTV less than 80 were refinanced through the HARP channel and hence have insufficient documentation to be refinanced through non-HARP channels.

According to FHFA, through the end of 2009, 169,000 Freddie Mac loans were refinanced through the HARP channel of which only 86,000 loans, or 51%, had LTV in excess of 80. It is also true that the documentation requirements for refinancing through the HARP channel are lower. However, we know that greater than 80 LTV loans accounted for less than 15% of all Freddie Mac refinance originations (Figure 6). Hence, at most 17%-18% of the less than 80 LTV loans could have come through the HARP channel in 2009. This is not a large enough percentage to explain observed prepayment differences but does help explain some of the difference.

**Theory #2** – In the current environment appraisals are biased lower. So even though home prices indices do not show declines, appraisals are lower.

This explanation is problematic because it is actually inconsistent with the prepayment differences between Post-HARP purchase loans and Post-HARP refinance loans. Specifically, if appraisals were the real issue, then the 73 LTV post-HARP purchase loans should have been affected much more than the 63 LTV post-HARP refinance loans.

**Theory #3** – Loan officers are less willing to work on post-HARP refinance loans because they don't know if these loans were originated through the HARP channels in the first place.

This hypothesis fits the empirical data. It would explain why all purchase loans and pre-HARP originations, which could not have been originated through the HARP channel, prepay in line with each other but post-HARP refinance loans prepay slower. Unfortunately, even if correct, this explanation provides little insight into future prepayments because it is difficult to determine when loan officers may change their minds.

**Theory #4** – Borrowers who refinanced in the second half of 2009 found the process to be so cumbersome that they were less likely to go through the process again.

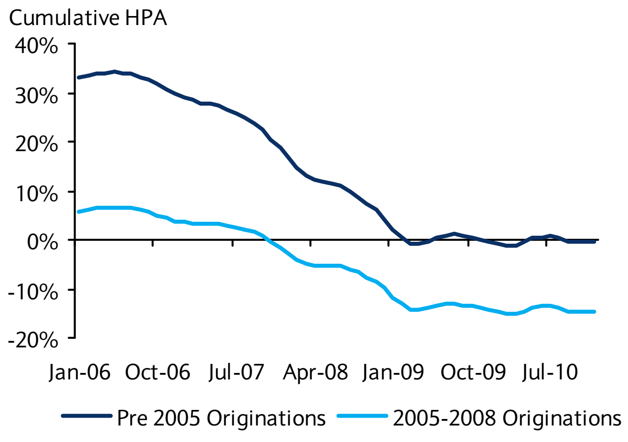
This would fall into the category of increased hassle costs and borrower apathy. Interestingly, the prepayment differences across pre- and post-HARP loans are not confined to just the 30y sector. We see similar differences in the 15y sector. This would be consistent with the notion that it is driven by the borrower since very few 15y mortgages have updated LTV above 80.

Although we cannot fully explain the prepayment performance of post-HARP refinance loans, the data are unambiguous. Consequently, we have added post-HARP refinance percentage as a factor that changes the shape of the refinancing function. This factor affects all Fannie Mae and Freddie Mac originations after June 2009[7]. Users have the option to dial down this effect. We have also assumed that if HARP were ever expanded then this effect disappears.

Overall, changes in underwriting, updated LTV, original LTV, and refinance percentage have all become much more significant drivers of prepayment performance over the past few years. Although the discussion in this section has focused on late 2008 and 2009 originations, these same factors play a prominent role in explaining prepayment performance of more seasoned mortgage pools. For example, many borrowers with loans

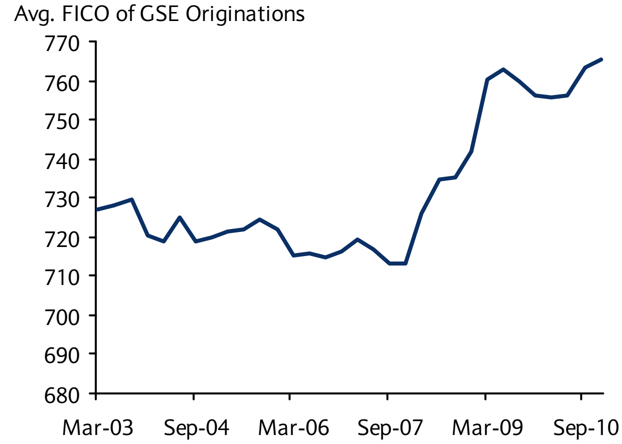
[7] On March 11, 2011, the FHFA announced that the HARP eligibility date for Fannie Mae loans will be expanded to include loans originated before June 2009.

**Figure 12: Cumulative home price change by cohort**




Source: Fannie Mae; CoreLogic, Barclays Capital

**Figure 13: Average FICO of GSE originations over time**




Source: Fannie Mae, Freddie Mac, Barclays Capital

originated between 2005 and 2008 are significantly underwater on their mortgages and have low FICO scores at origination even relative to historical underwriting standards (Figures 12 and 13). Not surprisingly, these cohorts tend to exhibit elevated involuntary prepayments and have a voluntary prepayment profile that is relatively insensitive to changes in the level of mortgage rates. In contrast, most pre-2005 cohorts have higher FICO scores and lower original LTVs than their 2005-2008 counterparts. Moreover, despite large declines in home prices over the past several years, the updated LTVs of pre-2005 cohorts are relatively unchanged from origination. As a result, they tend to prepay faster than comparable 2005-2008 cohorts.

## Changes in GNMA/FHA Prepayment Performance

The GNMA sector has also undergone its share of changes. Unlike the conventional sector most of these changes went into effect in 2010. Furthermore, a lack of good FICO data has robbed market participants of an important proxy for changes in underwriting standards. The key changes to the GNMA program that we address in the model are

- *The ability of borrowers to roll origination costs into refinanced balances*: In late 2009 the FHA revamped their streamline refinancing program. Under the new guidelines, the balance on a loan refinanced through the streamline program was capped at the unpaid principal balance of the current loan plus any upfront mortgage insurance premium. This cap used to be at the *original* balance of the loan plus any upfront mortgage insurance premium. This change implies that most borrowers can roll even less of their refinancing cost into the new loan than previously. The model captures the effect of closing costs for both conventional and GNMA borrowers by adding them into the balance used to calculate the monthly payment on their new mortgage. For GNMA refinances, any closing costs that can't be added into the new balance (which, given the rule change, have increased significantly) are used as an additional factor that affects the shape of the refinance response function.

- *Changes in up-front and annual MI premiums*: The FHA has changed the structure of their mortgage insurance program many times over the years. In just the past year alone they have lowered the UFMI premium paid by borrowers to 1.00% from a high of 2.25% while increasing the annual MI premium to 1.1% from a low of 0.50%. The model controls for changes to annual MI premiums by adding them to the monthly payment used to calculate economic incentive. Changes to UFMI and the UFMI refund schedule affect the balance used to calculate the economic incentive.

## Key factors in the rate/term refinancing sub-model

In the previous section, we highlighted some of the new factors introduced in the model to account for recent changes to the MBS prepayment landscape. In this section, we summarize all of the important variables that contribute to the rate/term refinancing function in the model. To quantify the effect of each of these variables, we present the model projected prepayment performance conditional on rates, assuming all other factors are unchanged[8]. For example, our sensitivities based on FICO assume that the SATO is unchanged across FICO buckets, even though there is a strong correlation between the FICO and SATO of a pool. The goal here is to isolate the effect of each factor.

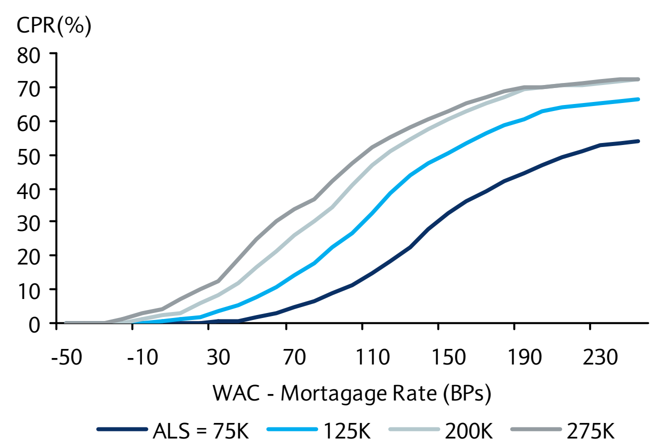
### Current average loan size

Loan size has traditionally been a significant driver of refinancing efficiency. For a given incentive, larger balance loans can generate higher dollar savings by refinancing, allowing them to more easily defray the fixed costs of the transaction. Originators, who have to do the same amount of work irrespective of the loan size, also target higher balance loans. The overall effect of loan size is further exaggerated by other less obvious factors. For example, most homeowners in the US buy as much home as they can afford, making loan size a proxy for borrower income and financial sophistication. Finally, many lower loan balance pools have a truncated loan size distribution since specified pools generally trade in the market with a maximum loan size for every loan in the pool. This further increases the loan size gradient on refinancing efficiency.

The effect of loan size also varies significantly across sectors. In the FHA sector, after recent changes to the streamline refinancing program, closing costs[9] cannot be rolled into the balance of the new loan. This has had a significant effect on the refinancing function of FHA mortgages across all loan sizes, but the largest effects have been on the smaller loan size buckets.

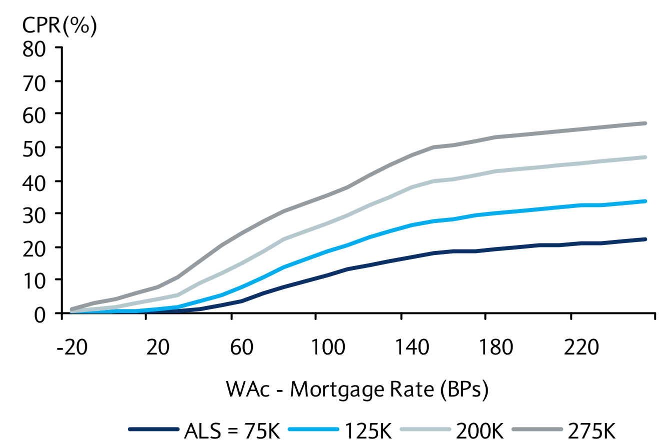
The effect of loan size is estimated based on the current average loan size of the pool. For forward projections, we decay the loan size every month based on amortization and the projected prepayments in the previous month. Figures 14 and 15 show the difference in the

**Figure 14: Effect of loan size – Conventional sector**




Source: Barclays Capital

**Figure 15: Effect of loan size – FHA sector**




Source: Barclays Capital

[8] Unless otherwise stated we assume the following collateral attributes – Pool WAC = 5.5%, Loans Size = 200K, SATO = 0, FICO = 760, Servicer = Other, GEO = Other, Pre HARP originations, Updated Loan-To-Value = 70%, Occupancy = 100% owner occupied, Pool Age = 15, no change in MI for FHA mortgages, low burnout and mortgage rates at historic lows.

[9] We assume that the closing cost currently is $1800 + 30bp of the loan amount for title insurance. In addition to these borrowers faces cost due to upfront MI for FHA and delivery fee for conventional loans.

refinancing response function across loan size buckets for Conventional and FHA loans. While we see significant convergence across loan size buckets as incentive increases in the conventional sector we see less convergence in the FHA sector. Given the very high LTVs in the FHA sector, loan size is more closely correlated with borrower demographics and hence refinancing efficiency. In contrast, for conventional borrowers the economics of the transaction have a more pronounced effect.

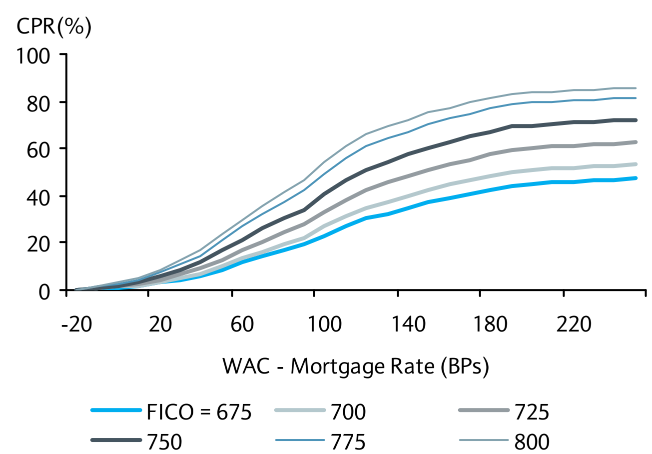
## Pool FICO

Historically, borrowers whose credit profile was adversely affected after loan origination had fewer options to refinance. This contributed to prepayment burnout. More recently, the tightening in GSE underwriting standards has meant that many borrowers who have seen no change to their credit profile suddenly do not qualify for a GSE mortgage. As outlined earlier, we control for this by comparing the average FICO of a given pool to the current FICO of Freddie Mac purchase originations. Figures 16 and 17 show the difference in refinancing curves for pools with similar FICO in two different origination environments. For a 750 FICO pool, model projected peak prepayments are about 15 CPR faster in a 725 FICO environment than a 760 FICO environment. This factor explains much of the difference in prepayment curves across vintages and across sample periods.

## Updated Loan-to-Value Ratio and HARP

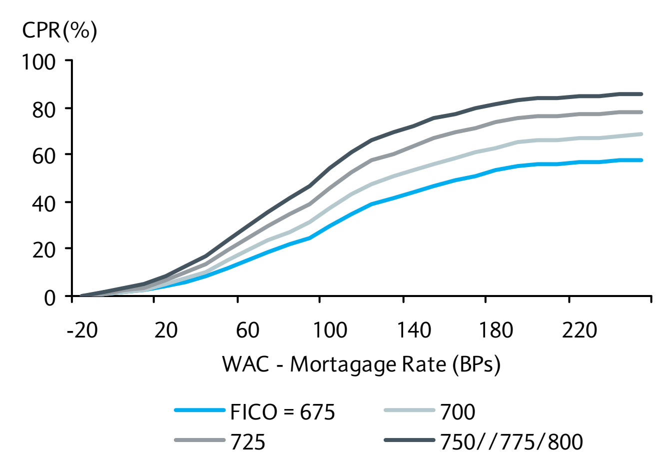
The equity position and HARP eligibility of borrowers substantially alter their prepayment performance. In the conventional model we use a combination of updated LTV, HARP eligibility and loan purpose to duplicate this behaviour. Figure 18 shows the change in refinancing efficiency (ie, refinancing function multiplier) conditional on updated LTV. As we documented in the prior section, post-HARP refinance originations with LTV's in excess of 80 have a very flat refinancing curve (or a refinancing function multiplier significantly below 1). In addition, all post-HARP refinance originations exhibit measurable call protection compared with pre- or post-HARP purchase originations (Figure 19). It is important to note that although the HARP program was introduced in early 2009, there were very few HARP originations until later that year. Moreover, the most significant ramp-up in HARP originations has been in the past six months, signifying that HARP is more effective today than ever before. We capture this in the model by assuming that future prepayment speeds on HARP eligible loans will be elevated relative to early 2010.

**Figure 16: Refinancing profile by FICO in 760 FICO origination environment**



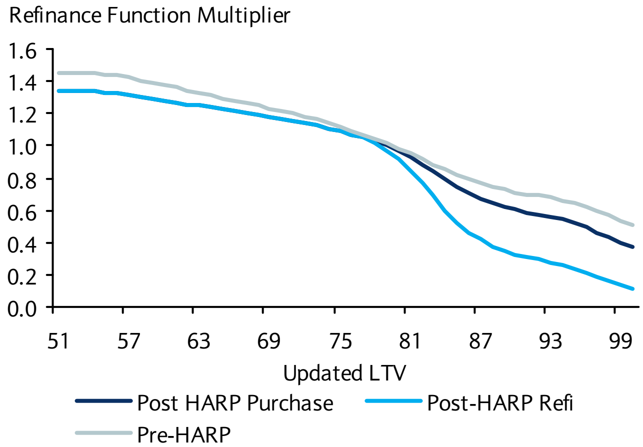

Source: Barclays Capital

**Figure 17: Refinancing profile by FICO in 725 FICO origination environment**



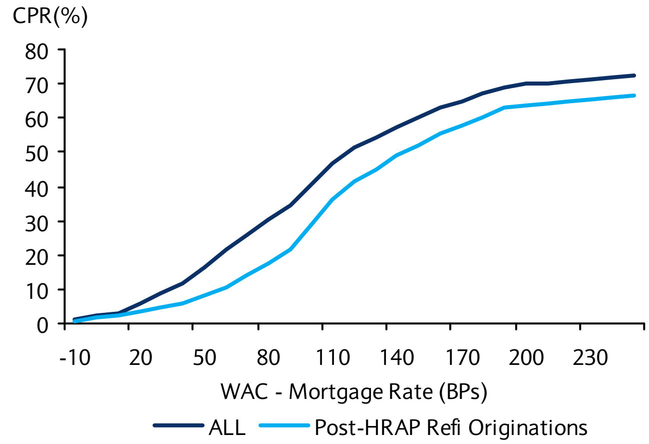

Source: Barclays Capital

**Figure 18: Effect of updated LTV**




Source: Barclays Capital

**Figure 19: Effect of post-HARP refinance originations**




Source: Barclays Capital

For FHA mortgages, changes in home prices since origination serve as a proxy for the borrower's equity position.[10] In this sector, home price declines have had a more muted impact on prepayment performance. HARP was a program targeted for GSE loans and has no effect on the FHA sector.

## Spread at origination (SATO)

We measure SATO as the difference between the WAC of a particular pool and all pools originated in that month. Thus, by construction the average SATO of all pools originated in a given month is zero. Historically, SATO had been the only available metric for the credit quality of a pool. However, in 2003 the GSEs started releasing FICO data. Even after controlling for FICO, we find that SATO is still a good predictor for refinancing efficiency (Figure 20). SATO captures other underwriting requirements beyond FICO, such as the level and type of documentation provided and the stability of a borrower's employment history.

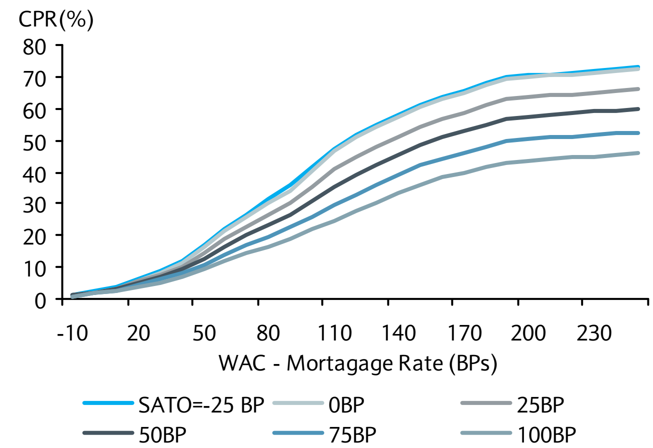
## Occupancy

Mortgages backed by investor properties and second homes tend to have flatter refinancing profiles than those backed by owner occupied homes (Figure 21). However, we find that pools backed by investor properties have a more stable refinancing profile over time and across interest rate cycles when compared with similar pools backed by owner occupied homes. The model incorporates this by assuming a slower rate of burnout for pools backed by investor properties.

Pools backed by investor properties on average have higher FICOs, lower LTVs and are more adversely affected by the Fannie Mae/Freddie Mac delivery fee schedules. Although the model takes into account all of these factors, Figure 21 isolates just the effect of occupancy and ignores differences in delivery fee, FICO, and LTV.

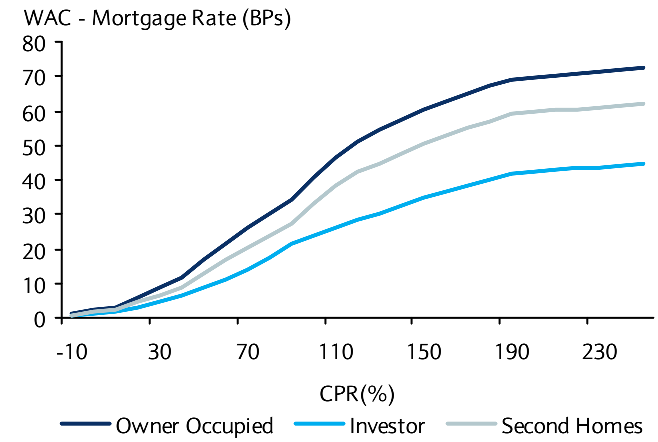
[10] FHA does not require a new appraisal for loans originated through streamline refinancing.

**Figure 20: Effect of SATO**




Source: Barclays Capital

**Figure 21: Effect of occupancy**




Source: Barclays Capital

## Path dependency of prepayment projections

Prepayment performance is very heavily influenced by the historical path of interest rates. The model captures this path dependency using two factors – prior refinancing opportunities and rate attractiveness.

**Prior refinancing opportunities/burnout:** When a borrower passes up an opportunity to refinance he sends a strong signal on either his refinancing threshold or his lack of ability/desire to refinance. In either case it is important information about the borrower's propensity to refinance. In the model, we construct two variables to capture these signals.

One variable sums the prior refinancing opportunities the borrower has had above the current economic incentive. So if a borrower has passed up mortgage rates lower than current rates because they have not met his refinancing threshold, he is less likely to exercise the option at current levels. It would also be reasonable to assume that the more opportunities he has passed up, the less likely he is to refinance.

The second variable sums all prior refinancing opportunities. This becomes a proxy for borrowers' lack of ability or desire to refinance. In both cases, we allow for some regeneration by discounting prior refinancing opportunities such that the effect of each individual refinancing opportunity decays over time. As a result, if a pool goes through an extended period without refinancing opportunities, its total burnout is diminished.

The effects of these two variables, which taken together we refer to as burnout, are estimated by making them factors that affect the refinancing response function. Burnout is a significant driver of both prepayment performance and valuation. For example, on 5.5s of 2002, burnout flattens the refinancing function by about 60%.

**Rate attractiveness**: If there were no transaction costs to refinancing and borrowers kept track of their refinancing opportunities on a daily basis, then refinancing application volume would change smoothly with every basis point change in mortgage rates. In reality, there are significant transaction costs and borrowers try to time the market and refinance at the lowest possible mortgage rate. Moreover, borrowers only pay attention to their refinance opportunities when mortgage rates are at or lower than recent history. As a result, we find that even small declines in mortgage rates can cause large increases in refinancing application volume when these changes push mortgage rates below historical lows.

In the model we capture this with a rate attractiveness variable that is computed by comparing current and past mortgage rates. The value of this variable is dependent on: 1) the current absolute level of mortgage rates; 2) the time that has passed since mortgage rates were last below current levels; and 3) the amount of time mortgage rates were below current levels. When mortgage rates fall below historical lows, the rate attractiveness variable converges to zero and the refinancing function is at maximum efficiency. As we move away from historical lows the value of the rate attractiveness variable increases flattening the refinancing curve.

## Geography

The geographic location of the property backing a loan is a significant determinant of refinancing propensity. States such as Florida and New York have explicit taxes that increase refinancing cost. States such as Texas have rules regarding financing closing costs and caps on loan-to-value ratios, which have added additional friction to the refinancing process. Apart from regulatory differences, title insurance, legal fees, and other closing costs vary across states and even counties within a state. Fortunately, they tend to be fairly stable over time, at least relative to each other.

Isolating the effect of geography also poses some challenges as two key drivers of prepayment performance – loan size and home prices, are both highly correlated with geography. Moreover, most GSE pools have a distribution of balance across states.

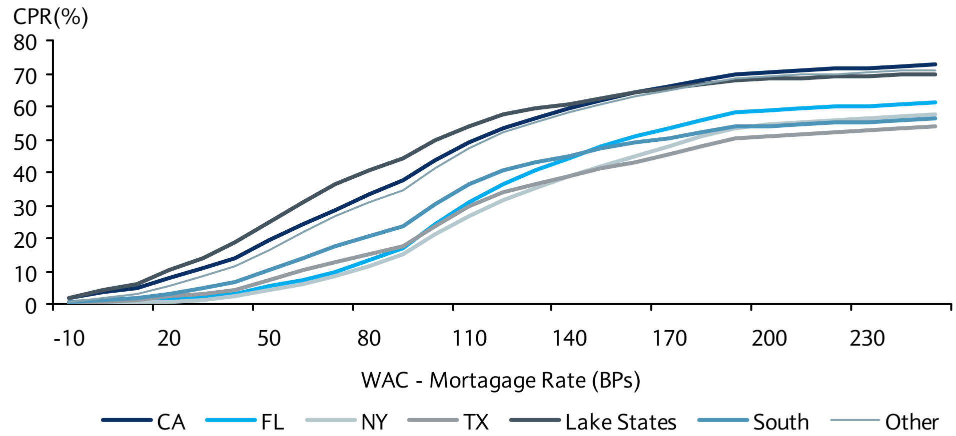
Fortunately, the GSEs update the balance and number of loans in each state for each pool every month. This allows us to create a pool database by state where each pool represents just the fraction of the pool that belongs to a particular state. Since the GSEs also disclose the number of loans in each pool from a particular state our database has the correct loan size. We do, however, have to assume that the WAC, original LTV, and FICO are the same across states for a given pool.

To estimate state specific factors we aggregate the states into eight groups based on historical prepayment performance. We then fix all the parameters of the prepayment model and estimate multipliers to the housing turnover and refinance functions, as well as the updated LTV and, FICO effects within the refinance function. The resulting prepayment profiles are presented in Figure 22. For the FHA sector, we find there is insufficient data to estimate geographic effects.

The state aggregations are:

- *California*: It accounts for roughly 15% of the GSE universe.
- *Florida/New York/Texas/Puerto Rico*: Each of these states has unique prepayment profiles because of differences in taxes and/or regulations. We therefore treat each as a separate geography.
- *Lake States*: This geography includes Illinois, Michigan, Wisconsin, and Minnesota. These states typically have lower closing costs. Even controlled for closing costs they have historically exhibited significantly higher refinancing efficiency.
- *Southern States*: This geography includes Georgia, North Carolina, Tennessee, South Carolina, Alabama, Louisiana, and Mississippi. These states generally have lower loan balances and relatively less volatile home prices. However, even after controlling for these factors they exhibit much lower refinancing efficiency.

Figure 22: Effect of geography on refinancing efficiency




Source: Barclays Capital

- *Other States*: The remaining states, which tend to display less idiosyncratic prepayment profiles, fall into this category.

## Servicer

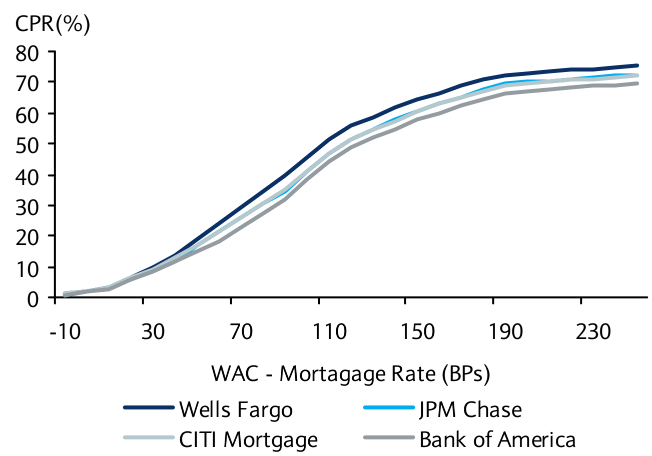
Prepayment performance varies across servicers even after controlling for various collateral attributes. Unfortunately, servicer effects can change very quickly and vary across coupons and vintages. For example, in Q4 10 HARP eligible loans serviced by Wells Fargo and Chase prepaid significantly faster than those serviced by Bank of America or Citi. In contrast, the differences on post-HARP loans were much smaller (Figure 23). The model attempts to tease out just the long-term differences in prepayment performance across servicers (Figure 24). While these differences are relatively small when controlled for all other collateral attributes, users can input additional time varying servicer multipliers to capture more short-lived but potentially pronounced prepayment differences across servicers such as the HARP related differences described above.

Figure 23: Actual Fannie Mae prepayments by servicer

| | | Pre-HARP 2009 Originations | | Post-HARP 2009 Orginations | |
|---|---|---|---|---|---|
| Coupon | Servicer | 3-Mo | 6-Mo | 3-Mo | 6-Mo |
| 4.5 | BOA | 23 | 23 | 18 | 17 |
| | Chase | 30 | 32 | 24 | 25 |
| | Citi | 27 | 27 | 23 | 22 |
| | Wells Fargo | 32 | 33 | 22 | 21 |
| 5 | BOA | 32 | 32 | 23 | 26 |
| | Chase | 52 | 53 | 23 | 28 |
| | Citi | 36 | 36 | 29 | 29 |
| | Wells Fargo | 45 | 49 | 28 | 28 |

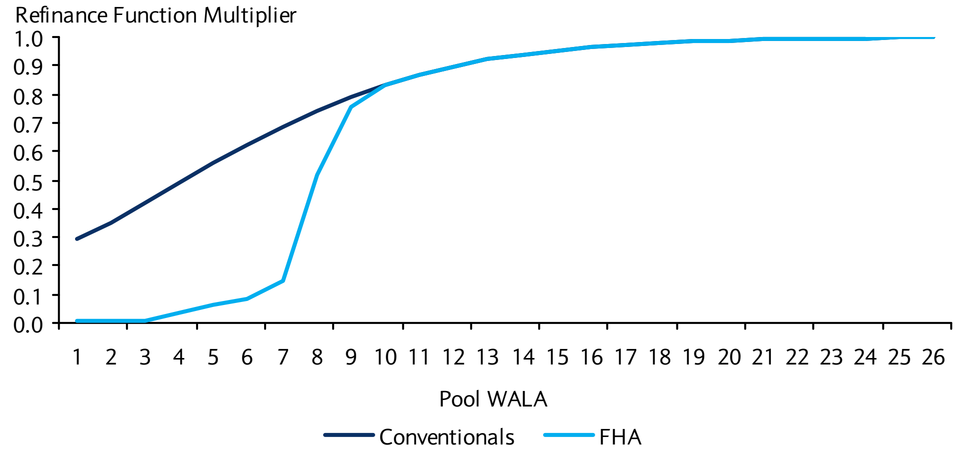
Note: As of January 2011. Source: Fannie Mae, Barclays Capital

Figure 24: Effect of servicer




Source: Barclays Capital

**Figure 25: Refinancing aging ramp**




Source: Barclays Capital

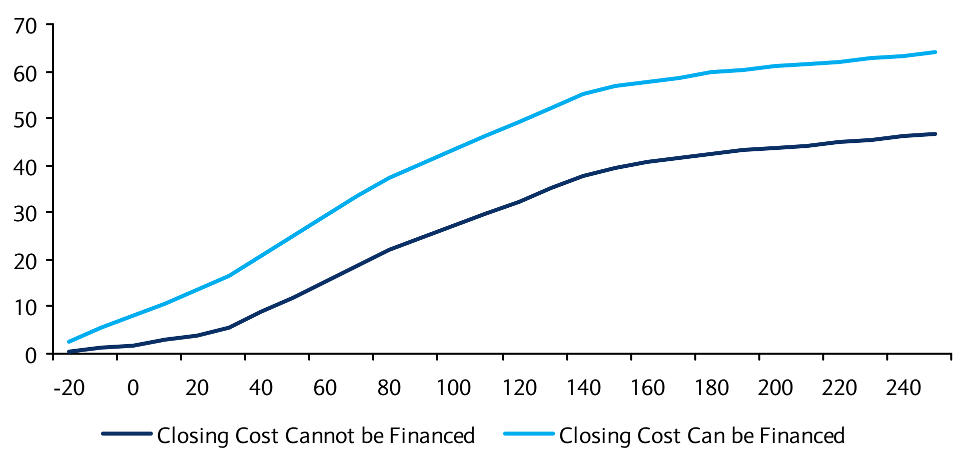
## Refinancing aging ramp

Loans that have been recently originated tend to have a flatter refinancing function than fully seasoned loans. This effect is exacerbated for FHA loans because they require six months of payment history to qualify for streamline refinancing. The effect is incorporated in the model through an estimated refinancing function multiplier that depends on the average loan age of the pool (Figure 25).

## Changes to the FHA program

The model captures the changes in ongoing mortgage insurance in the economic incentive calculation. As noted earlier, the economic incentive is calculated as the percentage change in monthly payment. For FHA loans this payment includes the monthly MI payment. The current payment is calculated based on the WAC, WAM and the required MI by FHA when the loan was originated. The new payment is calculated based on prevailing mortgage rates and the current required MI by FHA. The balance used to calculate the new payment is increased by the required upfront MI and decreased by the upfront MI refund schedule.

**Figure 26: Ability to finance the closing cost is a significant driver of prepayments**




Source: Barclays Capital

Recent changes to the FHA streamline refinancing program make it very onerous for the borrower to roll the closing cost of the refinancing transaction into the balance of the new loan. We believe that this has had a significant effect on the refinancing efficiency of FHA mortgages and accounts for much of the flattening in the refinancing profile that we observed in 2010. In the model, we capture this by converting the closing cost into points (closing cost/loan balance) and allowing it to be another factor that changes the shape of the refinancing function (Figure 26).

The model also accounts for differences between FHA/VA and rural housing programs. Historically, VA loans prepaid only slightly faster than FHA loans but the differences have increased substantially recently. FHA prepayments have been adversely affected by recent changes to mortgage insurance which do not apply to VA loans. Loans originated under the rural housing program exhibit a very flat refinancing function.

## Discount prepayments

Historically, discount prepayments were dominated by housing turnover and cash-out refinancing. Over the past two decades there have been only four distinct periods when the loan rate on the vast majority of the outstanding mortgage universe was below prevailing mortgage rates (Figure 27). Figure 28 compares actual prepayment performance across these four episodes.

At first glance there are some significant differences in prepayment performance. To break down the differences, let us focus on two specific periods 1) July 1996 to June1997 a period of very nominal home price appreciation and an era when cash out refinancing was not popular; and 2) November 2005 to November 2007 a period where borrowers had significant equity in their homes and cash-out refinancing was very popular.

In the models we have three distinct functions, one each for pure housing turnover, cash-out refinancing, and delinquency buyout. This allows us to deconstruct discount prepayments in the November 2005 to November 2007 time period into each component (Figure 29). As we have discussed earlier the vast majority of the prepayments in the mid-1990s came from just housing turnover activity.

**Figure 27: History of mortgage rates**


Source: Freddie Mac, Barclays Capital

**Figure 28: Prepayment performance in a discount environment – 30 to 80 WALA**

| WAC-Mortgage Rate | Jun-1994 to Jun95 | Jul 96 to Jun 97 | Dec 99 to Dec 00 | Nov 05 to Nov 07 |
|---|---|---|---|---|
| 0 | 7.4 | 7.3 | 11.0 | 14.3 |
| -25 | 6.2 | 7.0 | 10.4 | 12.2 |
| -50 | 5.6 | 6.8 | 9.7 | 10.7 |
| -75 | 4.8 | 6.5 | 9.0 | 9.4 |
| -100 | 4.4 | 6.1 | 8.5 | 8.1 |
| -125 | 3.2 | 6.1 | 8.1 | 7.7 |
| -150 | 3.1 | 5.7 | 7.8 | 7.4 |

Source: Fannie Mae, Barclays Capital

Figure 30 makes a strong argument that most of the recent volatility in discount prepayments can be attributed to cash-out refinancing. Pure housing turnover has remained fairly stable across two periods almost 10 years apart that reflect very differing housing market environments.

## Pure housing turnover

Existing home sales are driven by a variety of factors that fall into two broad categories: 1) life altering events; and 2) trade-up activity due to home price appreciation. The first category includes life events such as marriage, the birth of children, children leaving home, job relocation, death, and divorce. For large, seasoned pools of borrowers, the frequency at which these events produce mortgage prepayments is fairly stable over time. It is also relatively unaffected by changes to the macroeconomic environment, with the exception of changes in home prices and/or interest rates that make it harder for borrowers to execute the transaction. In the model we refer to this as pure housing turnover. In contrast, existing home sales resulting from trade-up activity during periods of strong home price appreciation are almost exclusively driven by increases in borrower equity and are captured in the cash-out refinancing component of the model.

## Pure housing turnover sub-model

When borrowers take out a new mortgage (be it a purchase or refinance) they are clearly signaling that they do not plan to move in the near term. Consequently, pure housing turnover is positively correlated with a mortgage pool's loan age for the first few years after origination. This period of positive correlation is generally referred to as the seasoning ramp. In the longer term, steady state levels are driven mostly by demographic factors that can be altered by the path of home prices and interest rates. In the model, pure housing turnover is a function of loan age and sensitive to the following factors:

## Mortgage rates/lock-in

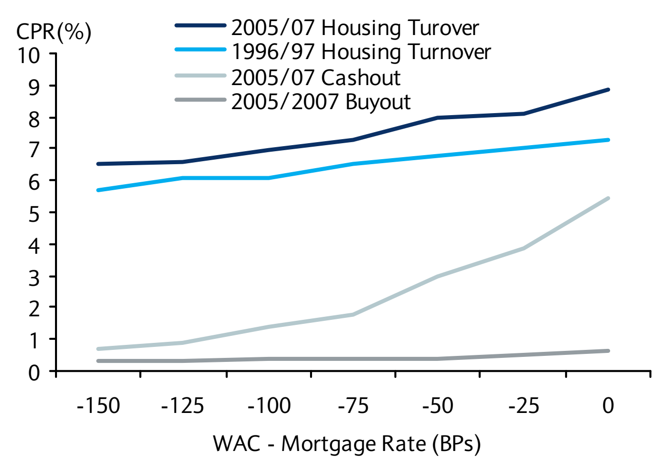
If borrowers have a below market mortgage rate, their option to move is limited by the increase in monthly payment that result from taking out a new mortgage at the prevailing mortgage rate. This is typically referred to as the lock-in effect of an increase in mortgage

**Figure 29: Deconstructing 2005-07 discount prepayments**

| Wac - Mortgage Rate | Actual | Model | | | |
|---|---|---|---|---|---|
| | CPR | CPR | Pure HT | Cashout | Buyout |
| 0 | 14.3 | 14.5 | 8.88 | 5.47 | 0.65 |
| -25 | 12.2 | 12.1 | 8.11 | 3.89 | 0.49 |
| -50 | 10.7 | 11.1 | 7.97 | 2.96 | 0.41 |
| -75 | 9.4 | 9.3 | 7.30 | 1.77 | 0.39 |
| -100 | 8.1 | 8.6 | 6.98 | 1.37 | 0.35 |
| -125 | 7.7 | 7.7 | 6.57 | 0.87 | 0.33 |
| -150 | 7.4 | 7.5 | 6.55 | 0.71 | 0.30 |

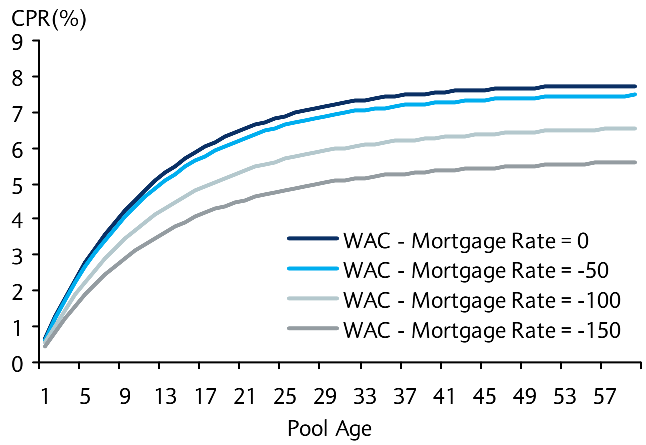
Source: Fannie Mae, Barclays Capital

**Figure 30: Change in pure housing turnover prepayments since the mid 1990s**



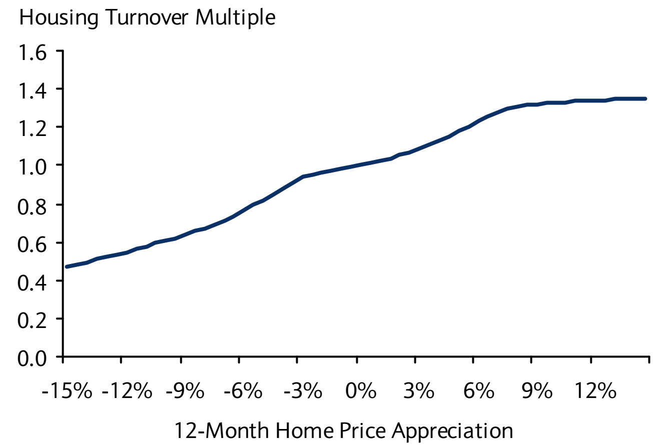

Source: Fannie Mae, Barclays Capital

**Figure 31: Effect of interest rates on housing turnover**




Source: Barclays Capital

**Figure 32: Effect of recent home price appreciation on housing turnover**




Source: Barclays Capital

rates because borrowers—and, in particular, borrowers with fixed mortgage rates—become locked into their current homes by their desire to avoid giving up a below market mortgage rate. Consider, for example, a borrower with a 5.5% loan rate. If prevailing mortgage rates are at 6.5% his monthly payment will increase by 11% even if he were to buy a home priced the same as his current home. With DTI becoming a more important driver of underwriting, we expect interest rate lock-in to have a more pronounced effect in the future than it has in the recent past (Figure 31).

## Recent home price changes

In periods when home prices decline sharply, there can be a wide gap between the seller's asking price and the bid price of potential buyers. This price discovery process leads to a delay and temporary decline in pure housing turnover transactions. Conversely, in periods of rapid home price appreciation buyers are more motivated to close the transaction as quickly as possible leading to a temporary increase in housing turnover. In the model we use trailing 12-month home price appreciation as a proxy for recent home price changes. This effect accounts for much of the difference in pure housing turnover levels between the mid-1990s and 2005-07 (Figure 32). It is important to note, however, that this effect does not alter the steady state level of housing turnover and so has a limited effect on model valuations.

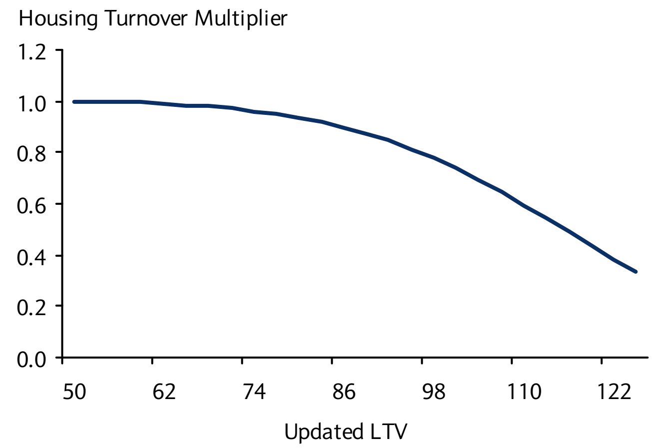
## Updated LTV

Borrowers who are underwater on their mortgages cannot sell their home without dipping into savings to make up the difference between the sale price and their outstanding mortgage balance. Naturally, this significantly reduces housing turnover levels (Figure 33). This is also a key factor in explaining differences in housing turnover speeds across sectors. For example, FHA loans, which generally start at high original LTV, are much more susceptible to declines in home prices.

## Seasonality

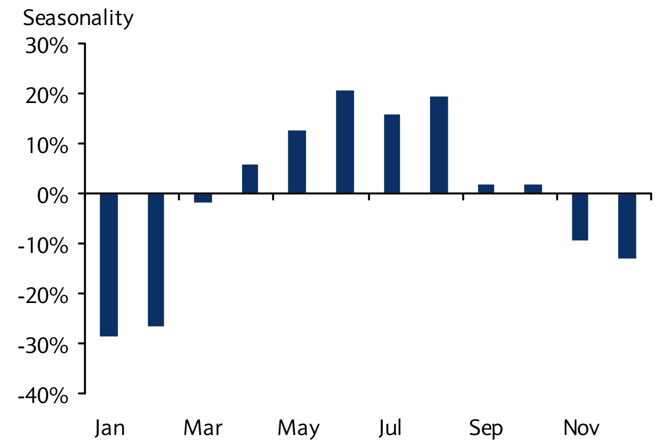
Housing turnover activity in the US varies across calendar months. Most homeowners prefer to move in the summer months when schools are on vacation and it is easier to inspect the exterior of the property. While seasonality is important for capturing m/m changes in prepayments it is not a significant driver of steady state turnover or valuations.

**Figure 33: Effect of Updated LTV**




Source: Barclays Capital

**Figure 34: Seasonality**

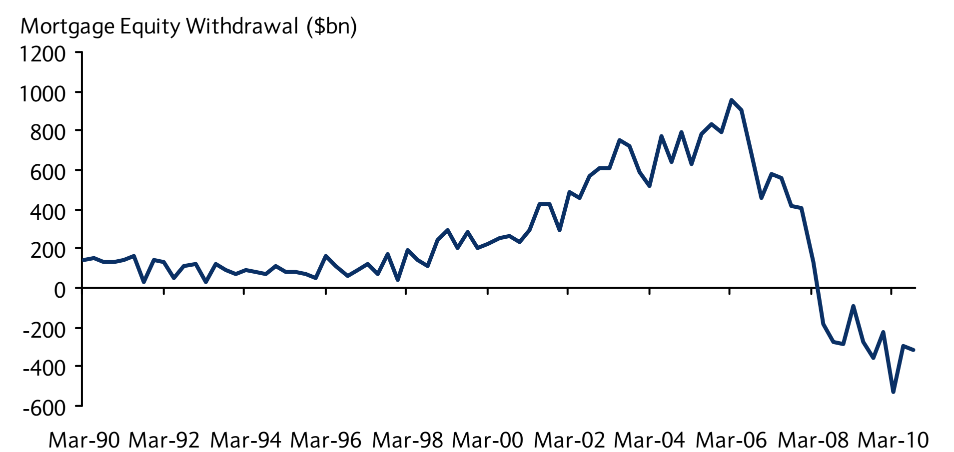



Source: Barclays Capital

## Cash-out refinancing

Cash-out refinancing encompasses all prepayment transactions where the motivation of borrowers is to tap the equity locked in their property. This is generally achieved by either using the equity in the property to trade-up or by refinancing the existing mortgage to a higher LTV loan. The aggregate amount of cash-out refinancing, or more precisely, mortgage equity withdrawal (MEW), can be easily quantified by looking at changes in the total outstanding balance of mortgages less that portion of the change due to mortgages used to purchase newly constructed homes. A combination of sharp increases in home prices, lower mortgage rates, and loose underwriting caused cash-out refinancing activity to rise to more than $750bn per year during the 2005-06 mortgage boom (from $100bn per year in 2000). Since then we have seen a sharp decline in cash-out refinancing activity (Figure 35).[11] Given the current tightness in underwriting standards and the weak housing market environment, we expect cash-out refinancing activity to remain muted for the foreseeable future. Nonetheless, it is important to have a robust cash-out refinancing model to ensure that estimates of the refinancing and housing turnover functions are not biased.

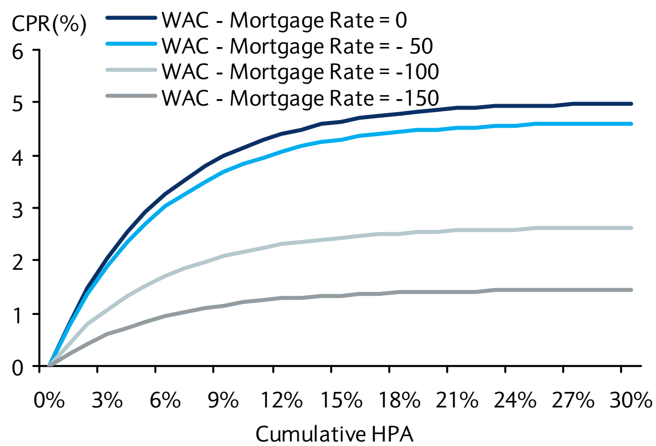
**Figure 35: Aggregate cash-out refinancing (SAAR $bn)**




Source: Haver Analytics

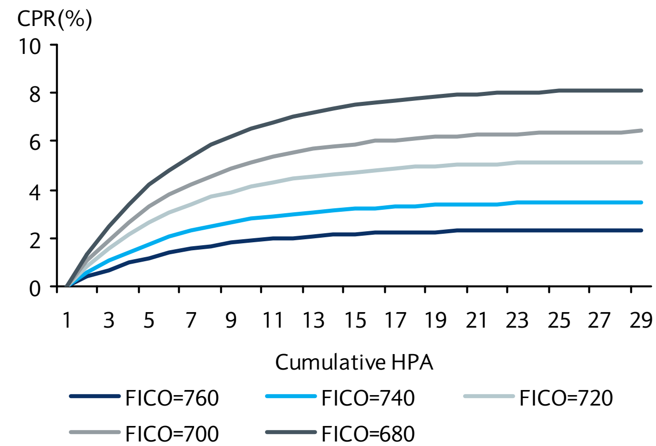
[11] If the decrease in mortgage debt is due to defaults and curtailments exceed cash-out refinancing, the mortgage equity withdrawal is negative.

**Figure 36: Effect of relative coupon on cash-out refinancing**




Source: Barclays Capital

**Figure 37: Weaker credit borrowers are more likely to tap the equity in their property**




Source: Barclays Capital

We model cash-out refinances as a function of the weighted cumulative home price appreciation of the pool. We apply a discount factor to positive cumulative home price appreciation such that any appreciation that happened more than 3-years in the past is significantly less important than recent appreciation.[12] For a given level of appreciation the propensity to cash-out depends on the level of mortgage rates and the credit quality of the borrower (Figures 36 and 37). Not surprisingly, weaker credit borrowers are much more likely to tap the equity in their homes. These borrowers typically have other outstanding high interest rate debt which can be consolidated into their mortgage debt as home prices increase. However, the economics of this transaction is significantly diminished if the borrower has a below market rate on the mortgage.

## Delinquency roll rate and buyout model[13]

The severe deterioration in credit performance over the past few years has substantially increased the contribution of buyouts to overall prepayments. Until recently, neither Fannie Mae nor Freddie Mac released pool level delinquency or buyout information.[14] Fortunately, the loan level servicer database from Core Logic provides us with very detailed information on the actual credit performance of loans backing GSE pools.

There are, however, some challenges in using these data to build a pool level roll rate model. First, a model estimated at the loan level cannot be applied at the pool level using weighted average collateral characteristics. The sensitivities to collateral attributes at the loan level are significantly different than at the pool level. Second, while the database has more than 50%-60% of all GSE loans, the sample is biased to certain servicers and hence does not have the same distribution of collateral characteristics as the GSE universe. Moreover, it does not distinguish between loans delivered to Fannie Mae or Freddie Mac.

[12] The resulting home price change would be very similar to MAX(0,MIN(Cumulative Home Price change, Home price change over the past 36 months)) The rationale is that: 1) home price appreciation is a necessary condition for cash-out refinancing; and 2) if borrowers have had equity in their property for more than three years they are less likely to tap it.
[13] This model was introduced in Barclays Capital Live as part of the September 2010 model update. In the interest of completeness, we present the key factors of this model as part of this write-up.
[14] The GSE started releasing cohort level delinquency information in late 2009. Freddie Mac started releasing pool level delinquency and buyout information in December 2010 and Fannie Mae still does not.

To address these issues we created synthetic mortgage pools from the loan-level servicing data by aggregating the loans in the database into origination date, WAC, FICO, and LTV buckets and then mapped each mortgage pool from our GSE pool database to one or more of the synthetic pools. The mapping was done using both the weighted average collateral characteristics of the MBS pools and their quartile data. We tested and refined the synthetic pool creation and mapping processes by using the mapped delinquency and roll rate data to generate cohort level credit statistics within the pool database and comparing these statistics with the cohort level information provided by each of the GSEs. We used the mapped roll rate data to estimate a conventional roll rate model. Since the GSEs now buyout virtually all loans that miss four payments there is no need for a separate buyout model.

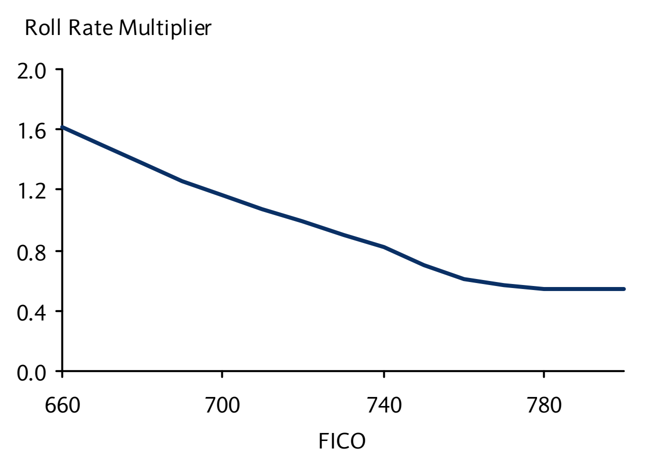
In contrast to the conventional sector, GNMA provides us with delinquency and buyout information at the pool level going back to late 2005. The GNMA buyout and prepayment models are calibrated to these data.

## Summary of key factors in the delinquency roll rate model

The extensive work done in developing the Barclays Capital Loan Transition Model provides us with an excellent framework for the conventional and GNMA roll rate models. Borrowers suffer financial hardships for a variety of reasons such as job loss or income reduction, unanticipated medical costs, and divorce. In most surveys, job loss and income reduction are quoted as the most common reasons for missing payments. So it is no coincidence that the severe deterioration in credit performance beginning in 2007 coincided with sharp declines in home prices and large increases in unemployment. The unemployment rate is an important driver of default probabilities in the model. The original credit quality of a borrower is another as it provides a measure of his ability to withstand any financial shocks. Finally, a borrower's equity position in his property can provide an additional resource he can access to overcome temporary financial stresses.

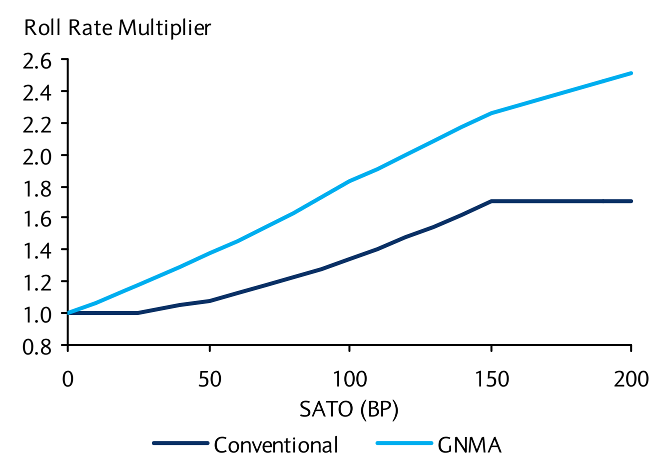
**Original credit quality**: In the conventional sector we use a combination of FICO and SATO to proxy for original credit quality. While FICO captures the borrower's payment history and debt levels at origination, SATO provides additional information about the borrower's credit quality such as the extent of income verification provided, past stability of employment and income, and net worth. Figures 38 and 39 display model estimated changes in default probabilities for different values of FICO and SATO. In the GNMA sector, where we have

**Figure 38: Effect of FICO on roll rates**




Source: Barclays Capital

**Figure 39: Effect of SATO on roll rates**




Source: Barclays Capital

limited FICO data, SATO serves as the only metric for credit quality. Absent FICO, SATO has a more pronounced effect.

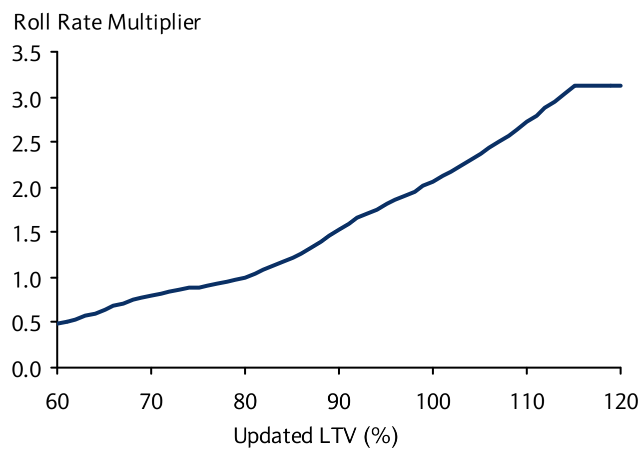
**Home prices:** As discussed earlier, we have updated LTV for all conventional pools and our delinquency roll rate model uses this as a measure of the borrower's equity position. In the GNMA sector the quality of LTV data leaves much to be desired. Consequently, we use the change in home prices since origination to proxy for the borrower's equity position. Not surprisingly, we find that home prices are a very significant driver of credit performance (Figures 40 and 41).

**Unemployment:** There are a number of different ways in which unemployment can be introduced in the credit model. We find that the change in unemployment since origination provides the best fit. A high unemployment rate signals a weak economic environment. So borrowers underwritten in such an environment tend to be better credits and to have a more stable employment outlook. Our estimates show that every 1% increase in the unemployment rate since origination increases default probability by 15%.

**Adverse selection stemming from voluntary prepayments:** In our prepayment section we repeatedly highlighted the increased prepayment propensity of clean credits with low LTV. A consequence of this is that the remaining pool has weaker credit and higher LTV. We control for this in the model by using the burnout factor defined in the prepayment model in our delinquency roll rate model. The more burnout a pool experiences, the higher the default probability.

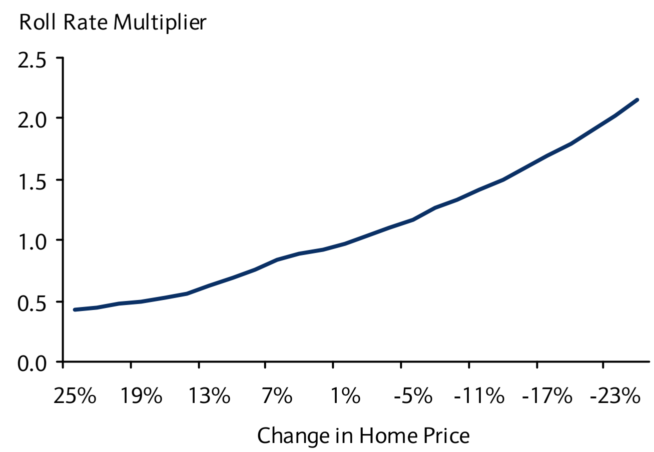
**Loss mitigation loans:** These are loans that were previously bought out from GNMA pools, cured and then redelivered into new GNMA pools. Our experience in the non-agency sector suggests that the credit performance of these loans is initially 10 times worse than for regular loans[15]. Over time the credit performance improves, but we still expect 70% of these loans to go delinquent. Where information on the contribution of loss mitigation loans in a pool is available the model adjusts projected roll rates to account for the weaker credit performance of these loans.

**Figure 40: Effect of updated LTV on conventional roll rates**




Source: Barclays Capital

**Figure 41: Effect of change in home prices on GNMA roll rates**




Source: Barclays Capital

[15] For further discussion of this topic, please refer to the performance of dirty current loans in the Barclays Capital Loan Transition Model.

**Refinanced loans:** Historically, GNMA refinanced loans were adversely selected. Borrowers who saw improvement in their credit or equity position refinanced into the conventional sector leaving the weakest borrowers to refinance through the GNMA streamline program. Consequently, the default probability of refinance loans is 45% higher than their purchase counterparts. This effect is smaller for more recent vintages as the tightening of underwriting standards in the conventional sector has made it significantly harder for GNMA borrowers to refinance into a conventional mortgage.

**Credit burnout**: Just as adverse selection as a result of voluntary prepayments weakens the credit quality of the underlying pool, high involuntary prepayments improves the quality of the pool. However, this is much more nuanced. We can say with some certainty that 100% of the borrowers who refinance are good credits. Defaults, however, are more distributed across the credits in a pool because the default function is a combination of the borrower's credit, home price changes (which unlike mortgage rate changes can vary significantly across loans) and financial hardship. The agency sector does not have enough historical data to account for this evolution of credit performance. Fortunately, we have a loan-level non-agency model that is designed to capture compositional changes and credit burnout. Our forward projections of roll rates impose this outlook derived from the non-agency model.

**Seasonality**: Delinquency roll rates exhibit a strong seasonal pattern. They peak in the winter months (Nov, Dec, Jan) and then decline through spring. For the GNMA sector, roll rates peak in November and bottom in April. Conventional roll rates peak a little later but also bottom in April.

## Model inputs and implementation

Over the past few sections we have highlighted the many factors that drive model projections. For the estimation of the model we carefully construct datasets that have all the required inputs. However, to get forward projections that are consistent with the model the implementation of the model has to provide the same set of inputs. Broadly, they fall into two categories 1) collateral attributes and 2) mortgage rates.

### Collateral attributes

The estimation of the model is done at the pool level to provide as much variability of collateral attributes as possible for model calibration. In an ideal world, we would also run the models at the pool level. Unfortunately, this computation is prohibitively expensive. A given CMO can be backed by thousands of pools and run-time for an OAS calculation would escalate to unacceptable levels. We could simply aggregate all the pools into a single representative pool and this would run very quickly, but would miss all the dispersion in collateral attributes. For example, even after controlling for coupon there is significant WAC dispersion across pools. More importantly, the higher WAC pools within a coupon tend to have lower FICO and lower loan sizes. Ignoring these correlations between WAC and other collateral attributes can cause significant variations in model projected prepayments. To achieve maximum precision of model projections and minimum runtime, we have implemented an aggregation scheme that is most sensitive to the key factors driving model projections.

### Summary of key factors in aggregation

- Pool code – Most CMOs are backed by pools originated under one program (or pool code). However, there is a small fraction of deals that mix collateral types (such as 15y and 20y collateral). Since we have different model factors by pool code, we aggregate each pool code separately.

- Origination Date – For the conventional sector there are two buckets, pools originated before and after the HARP eligibility end date. For the GNMA sector there are three buckets, one each for pools with 50/55bp of MI, 80/85bp of MI and in the future 105/110bp of MI.
- Pool WAC in 25bp buckets.
- Pool WALA (0 to 6, 6 to 12, 12 to 24, 24 to 48, 48 to 72 and greater than 72).
- Loan Size (LLB, MLB, HLB, 150 to 250K and greater than 250K).
- SATO (<-12.5 bp, -12.5 to 12.5, 12.5 to 37.5 and greater than 37.5).
- FICO (< 690, 690 to 720, 720 to 750, 750 to 780 and greater than 780).
- LTV buckets (< 70, 70-77.5, 77.5 to 82.5, > 82.5).

At every stage of the aggregation, if any bucket has less that 1% of the outstanding collateral balance we roll the bucket into the neighboring bucket with the lowest balance. This ensures that no CMO will have more than 100 representative pools. The only exception is re-remics. We do not aggregate pools across remics as we have to project prepayment vectors by remic. Consequently, a CMO with 5 re-remics could have as many as 500 representative pools that are run through the model.

### Mortgage rates

Mortgage rates are clearly the single most important driver of prepayment performance. While the term-structure model gives us the distribution of swap rates consistent with the forward curve and volatility surface, the prepayment model needs a distribution of mortgage rates to project cash flows. We model the mortgage rate as the sum of the par coupon and a primary secondary spread.

Par coupon is defined as the coupon required on a mortgage pass-through that would be priced at par in the secondary market. The spread between the mortgage rates available to borrowers and the par coupon implied by secondary market TBA prices is referred to as the primary-secondary spread.

### Par coupon model[16]

Par coupon is calculated by pricing to par a stream of cash flows generated along the forward curve (as implied by the yield curve at each node of the Monte Carlo simulation) and discounted at the appropriate rate. This requires both a base case prepayment assumption (similar to a PSA curve) and a discount rate.

The prepayment assumption used in the par coupon model is a deterministic function of the slope of the yield curve at each node of the Monte Carlo simulation. If the yield curve is steep at a given node, then forward mortgage rates are expected to increase, implying a lower lifetime prepayment rate on that node's par coupon. Conversely, a flatter yield curve implies lower forward mortgage rates and hence a higher lifetime prepayment rate on that node's par coupon.

The discount rate used in the model is the sum of forward Libor plus a spread that can be broken into two sources: 1) that which can be explained by increased option cost due to the

[16] This par coupon model presented here has been used for several years with minor changes.

shape of the yield curve and the volatility of rates and; 2) a risk premium that is determined by market pricing.

When the yield curve is flat option cost increases because today's par coupon remains cuspy along the forwards. When the curve is steep today's par coupon quickly becomes a deep discount and has very little sensitivity to changes in rates decreasing the option cost. In reality the volatility of rates also has a significant effect on option cost. However, in the simulation, volatility is assumed to be deterministic given rates. Consequently, we model option cost as a function of the level of 2y and 10y swap rates.

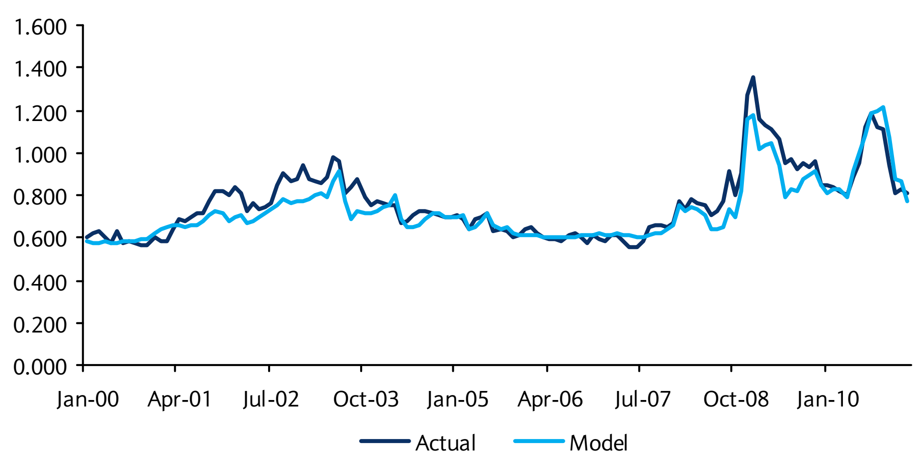
We use the methodology described above to calculate the par coupon on the pricing date assuming risk premium. The difference between this par coupon and the one calculated by interpolating actual TBA prices is assumed to be the risk premium and is held constant across all nodes of the simulation.

### Primary-secondary spread model[17]

We define the primary secondary spread as the difference between the Monday-Thursday average of the par coupon implied by TBA prices and the no point primary mortgage rate based on the HSH survey. Historically, the primary secondary spread has been driven by two factors.

- Over the near term, this spread is driven by supply/demand dynamics. When mortgage rates hit historical lows there is a sharp increase in the demand for refinancing and originators take some time to ramp-up. Invariably, this causes the primary secondary spread to widen. In the model we use the rate attractiveness variable described earlier to capture these dynamics.
- Over the medium to longer term, this spread is driven by the cost of hedging the origination pipeline. Typically this cost increases as the level of rates decrease (mostly because the volatility and level of rates are correlated).

**Figure 42: Model vs. actual primary-secondary spread**




Source: HSH, Barclays Capital

The primary-secondary spread in the model is a function of the level of 2y and 10y swap rates and rate attractiveness. Figure 42 shows that this fits the actual spread very well over long periods.

[17] The primary-secondary spread model was introduced in 2009.

## Conclusion

Before 2007, the vast majority of mortgage data reflected an environment of increasing home prices and credit availability. In contrast, the past three years provide valuable insights into mortgage performance in an environment of falling home prices and tightening credit standards. This model represents our best effort to incorporate this new information into a model framework.

Over the coming months, many of the factors and assumptions in the model will be challenged by the constantly changing dynamics of the mortgage market. But the flexible structure of this model should allow us to respond quickly to these changes.

## Model Results

Figures 43-45 display the combined valuation effect of changes to the term structure and prepayment models. In the conventional sector, OAS on high premiums (6.0s and 6.5s) have increased significantly, and the effect of HARP eligibility on the 2008 and early 2009 vintages is more pronounced.[18] In the GNMA sector, increases in FHA mortgage insurance have reduced the option cost, resulting in wider OAS across the board.

Figures 46-48 show one- and three-year voluntary and involuntary prepayment projections for most major cohorts and across several mortgage rate scenarios.

The last set of figures shows model fits for a large number of benchmark cohorts. Figures 49-51 display model fits for the most recent 1, 3 and 6 months. Figures 52-69 show longer-term model fits. For the conventional sector, we only have actual data on total prepayments, whereas GNMA provides voluntary prepayments. For this reason, the comparisons in Figures 49 and 50 are total CPR,[19] while in Figure 51 we display model fits for CRR.

[18] On March 11, 2011, the FHFA announced that the HARP eligibility date for Fannie Mae loans will be expanded to include loans originated on or before June 2009. These valuations include the change. Although the FHFA extended the HARP program only for 12 months, we assume that they are permanent. Users have the option to choose any expiry date.

[19] We eliminate the distortion to total prepayments caused by the spike in buyouts in the 1st half of 2010.

Figure 43: Effect of model changes on Fannie Mae pass-through valuation

| | | | New Prepayment and Term-Structure model | | | | | | Online Model | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Vintage | Cpn | Price | Yield | Avg Life | OAS | ZV | OAD | OAC | Yield | Avg Life | OAS | ZV | OAD | OAC |
| TBA | 4.0 | $ 98.45 | 4.23 | 8.49 | 36 | 61 | 6.9 | -0.07 | 4.26 | 7.13 | 33 | 58 | 6.78 | -0.60 |
| 2010 | | $ 98.47 | 4.23 | 8.69 | 39 | 59 | 7.1 | -0.10 | 4.25 | 7.65 | 36 | 58 | 6.94 | -0.42 |
| 2009 | | $ 98.55 | 4.23 | 8.08 | 42 | 64 | 6.7 | -0.10 | 4.25 | 6.86 | 39 | 62 | 6.60 | -0.68 |
| TBA | 4.5 | $ 101.92 | 4.12 | 6.62 | 36 | 70 | 6.0 | -1.25 | 4.09 | 6.15 | 30 | 71 | 5.60 | -1.56 |
| 2010 | | $ 101.92 | 4.16 | 7.46 | 36 | 68 | 6.3 | -0.87 | 4.11 | 6.41 | 32 | 70 | 5.87 | -1.35 |
| 2009 | | $ 101.95 | 4.13 | 6.93 | 38 | 70 | 6.1 | -1.04 | 4.09 | 6.18 | 32 | 71 | 5.65 | -1.44 |
| 2008 | | $ 102.00 | 3.96 | 4.76 | 29 | 75 | 4.9 | -2.04 | 4.03 | 5.46 | 33 | 77 | 5.16 | -1.64 |
| TBA | 5.0 | $ 104.83 | 3.44 | 3.69 | 20 | 76 | 3.6 | -2.46 | 3.73 | 4.63 | 27 | 83 | 4.09 | -2.01 |
| 2009 | | $ 104.83 | 4.05 | 6.50 | 43 | 80 | 5.5 | -0.96 | 3.86 | 5.29 | 28 | 81 | 4.60 | -2.08 |
| 2008 | | $ 104.83 | 3.51 | 3.91 | 23 | 78 | 3.7 | -2.35 | 3.74 | 4.68 | 29 | 83 | 4.15 | -1.96 |
| 2007 | | $ 104.83 | 3.63 | 4.29 | 34 | 81 | 4.2 | -1.53 | 3.75 | 4.75 | 38 | 84 | 4.35 | -1.41 |
| 2006 | | $ 105.08 | 3.62 | 4.48 | 31 | 77 | 4.2 | -1.71 | 3.71 | 4.81 | 37 | 81 | 4.34 | -1.38 |
| 2005 | | $ 105.27 | 3.65 | 4.77 | 32 | 76 | 4.3 | -1.75 | 3.72 | 5.04 | 39 | 78 | 4.48 | -1.28 |
| TBA | 5.5 | $ 107.08 | 3.16 | 3.52 | 19 | 79 | 3.1 | -1.91 | 3.33 | 3.84 | 23 | 86 | 3.21 | -2.23 |
| 2009 | | $ 107.08 | 4.12 | 6.58 | 64 | 97 | 5.5 | -0.67 | 3.63 | 4.60 | 32 | 90 | 3.89 | -1.94 |
| 2008 | | $ 107.08 | 3.32 | 3.82 | 27 | 83 | 3.4 | -1.82 | 3.47 | 4.16 | 30 | 89 | 3.54 | -1.96 |
| 2007 | | $ 107.08 | 3.46 | 4.12 | 39 | 85 | 3.8 | -1.20 | 3.47 | 4.16 | 37 | 87 | 3.65 | -1.47 |
| 2006 | | $ 107.33 | 3.43 | 4.21 | 35 | 82 | 3.8 | -1.28 | 3.42 | 4.19 | 34 | 82 | 3.64 | -1.49 |
| 2005 | | $ 107.55 | 3.70 | 5.11 | 45 | 83 | 4.2 | -1.24 | 3.62 | 4.84 | 44 | 82 | 4.10 | -1.12 |
| TBA | 6.0 | $ 108.91 | 2.97 | 3.37 | 30 | 85 | 3.1 | -1.10 | 2.73 | 3.11 | 14 | 75 | 2.44 | -1.67 |
| 2008 | | $ 108.97 | 3.23 | 3.77 | 41 | 90 | 3.4 | -1.02 | 3.03 | 3.52 | 26 | 82 | 2.85 | -1.59 |
| 2007 | | $ 108.91 | 3.40 | 4.05 | 52 | 91 | 3.6 | -0.70 | 3.20 | 3.72 | 39 | 84 | 3.16 | -1.08 |
| 2006 | | $ 109.31 | 3.38 | 4.21 | 47 | 87 | 3.7 | -0.84 | 3.23 | 3.95 | 37 | 80 | 3.28 | -1.15 |
| 2005 | | $ 109.63 | 3.76 | 5.26 | 63 | 92 | 4.5 | -0.48 | 3.38 | 4.36 | 43 | 80 | 3.64 | -0.87 |
| 2004 | | $ 110.09 | 3.70 | 5.33 | 55 | 87 | 4.4 | -0.82 | 3.31 | 4.44 | 34 | 76 | 3.42 | -1.38 |
| TBA | 6.5 | $ 111.86 | 3.15 | 4.13 | 36 | 72 | 3.6 | -0.46 | 1.95 | 2.87 | -27 | 10 | 2.28 | -0.50 |
| 2008 | | $ 111.86 | 3.20 | 4.22 | 38 | 72 | 3.6 | -0.49 | 2.41 | 3.27 | -3 | 46 | 2.44 | -0.96 |
| 2007 | | $ 111.86 | 3.37 | 4.51 | 47 | 72 | 3.9 | -0.15 | 2.50 | 3.35 | 2 | 39 | 2.73 | -0.61 |
| 2006 | | $ 112.27 | 3.40 | 4.73 | 46 | 73 | 4.0 | -0.28 | 2.71 | 3.71 | 8 | 45 | 2.89 | -0.75 |

Note: As of Friday, March 11, 2010. Source: Barclays Capital

Figure 44: Effect of model changes on IOS valuation

| | | | New Prepayment & Term-Structure model | | | | | | Online Model | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Vintage | Cpn | Price | Yield | Avg Life | OAS | ZV | OAD | OAC | Yield | Avg Life | OAS | ZV | OAD | OAC |
| IOS 10 | 3.5 | $ 24.36 | 4.41 | 9.28 | 208 | 302 | -1.5 | -6.11 | 3.63 | 8.73 | 174 | 349 | -3.32 | -8.60 |
| IOS 10 | 4.0 | $ 25.20 | 5.25 | 8.68 | 314 | 445 | -4.6 | -8.19 | 3.44 | 7.68 | 250 | 473 | -7.99 | -11.98 |
| IOS 09 | | $ 23.66 | 5.23 | 8.02 | 281 | 462 | -8.8 | -12.98 | 3.00 | 6.97 | 254 | 488 | -10.83 | -12.50 |
| IOS 10 | 4.5 | $ 25.06 | 4.43 | 7.10 | 403 | 591 | -10.4 | -15.49 | 2.79 | 6.46 | 283 | 544 | -15.10 | -16.92 |
| IOS 09 | | $ 23.88 | 3.75 | 6.46 | 360 | 611 | -15.5 | -22.54 | 3.07 | 6.22 | 319 | 568 | -15.36 | -15.83 |
| IOS 10 | 5.0 | $ 24.50 | 5.87 | 6.64 | 574 | 720 | -9.3 | -8.74 | 1.92 | 5.39 | 306 | 561 | -19.94 | -16.46 |
| IOS 09 | | $ 22.89 | 5.85 | 6.13 | 617 | 791 | -12.4 | -10.51 | 3.29 | 5.36 | 427 | 664 | -19.07 | -16.18 |
| IOS 08 | 5.5 | $ 19.69 | 1.72 | 3.83 | 544 | 764 | -19.0 | -6.93 | 4.07 | 4.22 | 675 | 858 | -19.62 | -12.49 |
| IOS 08 | 6.0 | $ 19.11 | 4.97 | 3.82 | 825 | 942 | -12.1 | -2.53 | 3.31 | 3.63 | 686 | 775 | -18.04 | -3.92 |

As of Friday, March 11, 2010. Source: Barclays Capital

Figure 45: Effect of model changes on GNMA I pass-through valuation

| | | | New Prepayment & Term-Structure model | | | | | | Online Model | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Vintage | Cpn | Price | Yield | Avg Life | OAS | ZV | OAD | OAC | Yield | Avg Life | OAS | ZV | OAD | OAC |
| TBA | 4.0 | $ 99.94 | 4.02 | 8.40 | 40 | 50 | 6.7 | 0.42 | 4.02 | 7.90 | 17 | 40 | 6.83 | -0.09 |
| 2010 | | $ 99.94 | 4.02 | 8.54 | 39 | 48 | 6.8 | 0.50 | 4.02 | 7.68 | 22 | 44 | 6.76 | -0.01 |
| 2009 | | $ 99.94 | 4.02 | 7.98 | 43 | 53 | 6.5 | 0.38 | 4.02 | 7.54 | 23 | 44 | 6.61 | 0.02 |
| TBA | 4.5 | $ 103.30 | 3.95 | 7.50 | 39 | 55 | 5.9 | -0.13 | 3.83 | 6.00 | 20 | 57 | 5.51 | -0.83 |
| 2010 | | $ 103.30 | 3.98 | 8.00 | 36 | 52 | 6.3 | -0.02 | 3.87 | 6.49 | 18 | 55 | 5.81 | -0.81 |
| 2009 | | $ 103.30 | 3.95 | 7.50 | 40 | 55 | 6.0 | -0.03 | 3.83 | 6.05 | 22 | 57 | 5.54 | -0.74 |
| TBA | 5.0 | $ 106.20 | 3.76 | 6.18 | 35 | 60 | 4.7 | -0.72 | 3.30 | 4.27 | 13 | 58 | 3.83 | -1.44 |
| 2010 | | $ 106.20 | 3.90 | 7.14 | 37 | 60 | 5.5 | -0.48 | 3.55 | 5.12 | 21 | 62 | 4.53 | -1.23 |
| 2009 | | $ 106.20 | 3.81 | 6.46 | 38 | 60 | 5.0 | -0.48 | 3.39 | 4.53 | 18 | 59 | 4.08 | -1.21 |
| 2008 | | $ 106.20 | 3.74 | 6.01 | 36 | 61 | 4.6 | -0.76 | 3.49 | 4.88 | 16 | 56 | 4.12 | -1.37 |
| TBA | 5.5 | $ 108.38 | 3.49 | 4.95 | 33 | 65 | 3.8 | -1.08 | 3.10 | 4.04 | 6 | 49 | 3.14 | -1.44 |
| 2009 | | $ 108.38 | 3.66 | 5.52 | 45 | 67 | 4.5 | -0.35 | 2.70 | 3.35 | 4 | 38 | 2.89 | -0.88 |
| 2008 | | $ 108.38 | 3.53 | 5.08 | 35 | 66 | 3.9 | -1.01 | 3.14 | 4.13 | 9 | 51 | 3.24 | -1.37 |
| 2007 | | $ 108.41 | 3.43 | 4.80 | 35 | 64 | 3.7 | -0.95 | 3.19 | 4.25 | 17 | 49 | 3.52 | -0.91 |
| TBA | 6.0 | $ 110.06 | 3.30 | 4.34 | 42 | 69 | 3.5 | -0.69 | 2.88 | 3.69 | 9 | 40 | 2.90 | -0.90 |
| 2008 | | $ 110.06 | 3.35 | 4.46 | 41 | 71 | 3.5 | -0.84 | 2.60 | 3.32 | -9 | 28 | 2.36 | -1.22 |
| 2007 | | $ 110.06 | 3.37 | 4.49 | 46 | 71 | 3.6 | -0.60 | 2.94 | 3.77 | 12 | 42 | 2.98 | -0.87 |
| 2006 | | $ 110.19 | 3.48 | 4.78 | 49 | 75 | 3.8 | -0.67 | 3.19 | 4.21 | 23 | 54 | 3.36 | -0.85 |
| TBA | 6.5 | $ 112.80 | 2.72 | 3.82 | 9 | 29 | 3.1 | -0.19 | 1.55 | 2.78 | -76 | -56 | 1.99 | -0.61 |
| 2008 | | $ 112.80 | 2.93 | 4.10 | 17 | 40 | 3.3 | -0.21 | 1.12 | 2.51 | -101 | -77 | 1.53 | -0.72 |
| 2007 | | $ 112.86 | 2.89 | 4.06 | 18 | 36 | 3.3 | -0.11 | 1.73 | 2.92 | -65 | -45 | 2.15 | -0.61 |
| 2006 | | $ 112.95 | 3.11 | 4.41 | 29 | 49 | 3.6 | -0.15 | 2.24 | 3.37 | -33 | -12 | 2.56 | -0.63 |

As of Friday, March 11, 2010. Source: Barclays Capital

Figure 46: Model projections for Fannie Mae cohorts

| | | 1y Total CPR Projections | | | | | | | 3y Total CPR Projections | | | | | | | CBR Proj. | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Coupon | Vintage | Dn. 150 | Dn. 100 | Dn. 50 | Base | Up 50 | Up 100 | Up 150 | Dn. 150 | Dn. 100 | Dn. 50 | Base | Up 50 | Up 100 | Up 150 | 1y | 3y |
| 4.0 | 2010 | 46.6 | 24.0 | 8.8 | 4.3 | 3.7 | 3.3 | 3.1 | 36.3 | 22.0 | 11.3 | 6.4 | 5.4 | 4.7 | 4.3 | 0.5 | 0.5 |
| | 2009 | 66.7 | 42.5 | 16.3 | 6.7 | 5.8 | 5.2 | 4.8 | 50.7 | 34.6 | 17.1 | 7.8 | 6.6 | 5.8 | 5.3 | 0.7 | 0.6 |
| 4.5 | 2010 | 55.4 | 38.3 | 17.1 | 6.9 | 5.2 | 4.5 | 4.0 | 41.2 | 29.9 | 16.7 | 8.8 | 6.8 | 5.8 | 5.1 | 0.8 | 0.7 |
| | 2009 | 63.3 | 47.9 | 25.4 | 9.8 | 6.8 | 6.1 | 5.5 | 47.2 | 36.9 | 22.8 | 11.0 | 7.6 | 6.6 | 5.8 | 0.9 | 0.8 |
| | 2008 | 65.7 | 56.3 | 37.1 | 17.1 | 10.1 | 9.1 | 8.4 | 50.9 | 44.5 | 32.0 | 17.1 | 9.9 | 8.7 | 7.8 | 2.8 | 2.4 |
| 5.0 | 2010 | 40.3 | 32.4 | 18.8 | 9.9 | 6.8 | 6.2 | 5.5 | 31.4 | 26.1 | 17.3 | 11.2 | 8.1 | 7.3 | 6.4 | 1.8 | 1.5 |
| | 2009 | 40.5 | 33.8 | 22.1 | 12.5 | 8.6 | 7.6 | 7.0 | 32.0 | 27.3 | 19.6 | 13.1 | 9.3 | 8.0 | 7.1 | 1.8 | 1.6 |
| | 2008 | 51.3 | 46.6 | 37.7 | 23.6 | 15.1 | 12.6 | 11.8 | 42.9 | 38.9 | 32.5 | 22.1 | 14.5 | 11.4 | 10.4 | 5.2 | 4.3 |
| | 2007 | 42.6 | 39.1 | 32.6 | 22.3 | 15.7 | 13.2 | 12.4 | 36.7 | 33.5 | 28.7 | 20.9 | 15.0 | 11.9 | 11.0 | 6.0 | 5.0 |
| | 2006 | 43.9 | 39.6 | 32.0 | 21.1 | 14.6 | 12.2 | 11.4 | 37.3 | 33.5 | 27.9 | 19.7 | 14.0 | 11.2 | 10.3 | 4.7 | 3.9 |
| | 2005 | 47.7 | 41.7 | 31.0 | 18.8 | 12.4 | 10.9 | 10.1 | 38.6 | 34.2 | 26.8 | 18.0 | 12.3 | 10.4 | 9.4 | 3.4 | 3.0 |
| 5.5 | 2009 | 22.8 | 20.6 | 16.5 | 12.1 | 10.0 | 9.1 | 8.6 | 20.8 | 19.0 | 15.9 | 12.5 | 10.6 | 9.5 | 8.9 | 3.2 | 2.8 |
| | 2008 | 40.2 | 38.4 | 33.3 | 24.4 | 17.9 | 14.9 | 13.9 | 36.1 | 34.3 | 30.1 | 22.7 | 16.9 | 13.4 | 12.2 | 6.6 | 5.9 |
| | 2007 | 34.2 | 32.9 | 29.2 | 23.0 | 18.2 | 15.6 | 14.6 | 31.1 | 29.9 | 26.8 | 21.5 | 17.0 | 14.1 | 12.9 | 8.2 | 6.6 |
| | 2006 | 34.4 | 32.9 | 28.8 | 22.2 | 17.1 | 14.5 | 13.6 | 31.5 | 29.9 | 26.5 | 20.8 | 16.2 | 13.3 | 12.1 | 6.7 | 5.5 |
| | 2005 | 33.3 | 30.2 | 25.1 | 17.7 | 13.6 | 12.0 | 11.4 | 29.3 | 26.5 | 22.6 | 16.9 | 13.3 | 11.4 | 10.7 | 4.8 | 4.0 |
| 6.0 | 2008 | 31.9 | 31.0 | 29.0 | 24.4 | 20.2 | 17.8 | 16.5 | 29.6 | 28.8 | 26.9 | 23.1 | 19.0 | 16.2 | 14.6 | 9.0 | 8.1 |
| | 2007 | 28.3 | 27.7 | 26.1 | 22.7 | 19.5 | 17.7 | 16.7 | 26.3 | 25.7 | 24.2 | 21.4 | 18.3 | 16.2 | 15.0 | 10.8 | 8.9 |
| | 2006 | 28.0 | 27.3 | 25.2 | 21.4 | 18.0 | 16.1 | 15.1 | 26.1 | 25.4 | 23.5 | 20.3 | 16.9 | 14.8 | 13.6 | 8.6 | 6.9 |
| | 2005 | 23.8 | 23.0 | 20.9 | 17.8 | 15.5 | 14.3 | 13.8 | 22.5 | 21.6 | 19.8 | 17.0 | 14.8 | 13.4 | 12.7 | 7.5 | 6.1 |
| | 2004 | 26.1 | 24.6 | 21.3 | 16.6 | 13.6 | 12.1 | 11.5 | 24.0 | 22.5 | 20.0 | 16.1 | 13.4 | 11.8 | 11.0 | 4.3 | 3.6 |
| 6.5 | 2008 | 28.1 | 27.6 | 26.7 | 24.2 | 22.0 | 20.3 | 19.3 | 26.0 | 25.5 | 24.7 | 22.5 | 20.3 | 18.4 | 17.1 | 13.4 | 10.7 |
| | 2007 | 25.1 | 24.8 | 24.3 | 22.8 | 21.4 | 20.4 | 19.7 | 23.3 | 23.0 | 22.5 | 21.1 | 19.8 | 18.6 | 17.7 | 14.5 | 12.0 |
| | 2006 | 24.1 | 23.7 | 22.9 | 21.0 | 19.2 | 18.0 | 17.2 | 22.4 | 22.1 | 21.3 | 19.6 | 17.9 | 16.5 | 15.5 | 11.2 | 9.1 |

Note: As of Friday, March 11, 2010. Source: Barclays Capital

Figure 47: Model projections for IOS

| | | 1y Total CPR Projections | | | | | | | 3y Total CPR Projections | | | | | | | CBR Proj | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Vintage | Cpn | Down 150 | Down 100 | Down 50 | Base | Up 50 | Up 100 | Up 150 | Down 150 | Down 100 | Down 50 | Base | Up 50 | Up 100 | Up 150 | 1y | 3y |
| IOS 10 | 3.5 | 36.6 | 15.2 | 4.8 | 3.6 | 3.2 | 2.9 | 2.7 | 30.9 | 16.7 | 7.2 | 5.5 | 4.7 | 4.3 | 4.0 | 0.4 | 0.4 |
| IOS 10 | 4.0 | 46.6 | 24.0 | 9.1 | 4.2 | 3.6 | 3.2 | 3.0 | 36.3 | 22.1 | 11.7 | 6.4 | 5.4 | 4.7 | 4.3 | 0.5 | 0.5 |
| IOS 09 | | 69.8 | 45.2 | 16.7 | 6.6 | 5.7 | 5.1 | 4.7 | 53.0 | 36.4 | 17.6 | 7.7 | 6.5 | 5.7 | 5.2 | 0.6 | 0.5 |
| IOS 10 | 4.5 | 50.9 | 36.6 | 18.1 | 7.4 | 5.2 | 4.6 | 4.1 | 37.8 | 28.9 | 17.6 | 9.5 | 6.8 | 5.8 | 5.1 | 0.8 | 0.7 |
| IOS 09 | | 66.7 | 51.0 | 27.1 | 9.8 | 6.7 | 6.0 | 5.4 | 49.6 | 39.0 | 24.1 | 11.1 | 7.6 | 6.5 | 5.8 | 0.9 | 0.7 |
| IOS 10 | 5.0 | 35.3 | 28.6 | 17.4 | 9.7 | 6.9 | 6.3 | 5.7 | 28.7 | 24.2 | 16.8 | 11.3 | 8.3 | 7.4 | 6.5 | 1.8 | 1.7 |
| IOS 09 | | 42.1 | 35.2 | 23.0 | 12.7 | 8.6 | 7.5 | 6.8 | 33.0 | 28.2 | 20.2 | 13.2 | 9.3 | 8.0 | 7.0 | 1.7 | 1.4 |
| IOS 08 | 5.5 | 41.6 | 39.6 | 34.3 | 24.8 | 17.9 | 14.7 | 13.7 | 37.2 | 35.3 | 31.0 | 23.0 | 16.9 | 13.2 | 12.0 | 6.8 | 5.6 |
| IOS 08 | 6.0 | 32.1 | 31.2 | 29.1 | 24.3 | 19.8 | 17.2 | 15.9 | 29.8 | 29.0 | 27.0 | 23.1 | 18.7 | 15.8 | 14.1 | 9.2 | 7.5 |
| IOS 6/7 | 6.5 | 24.5 | 24.2 | 23.6 | 21.9 | 20.3 | 19.2 | 18.5 | 22.8 | 22.5 | 21.9 | 20.4 | 18.9 | 17.6 | 16.6 | 12.9 | 10.5 |

Note: As of Friday, March 11, 2010. Source: Barclays Capital

### Figure 48: Model projections for GNMA I cohorts

| | | 1y Total CPR Projections | | | | | | | 3y Total CPR Projections | | | | | | | CBR Proj | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Coupon | Vintage | Down 150 | Down 100 | Down 50 | Base | Up 50 | Up 100 | Up 150 | Down 150 | Down 100 | Down 50 | Base | Up 50 | Up 100 | Up 150 | 1y | 3y |
| 4.0 | 2010 | 22.3 | 9.5 | 7.0 | 6.5 | 6.2 | 5.9 | 5.8 | 20.4 | 10.6 | 8.5 | 7.7 | 7.2 | 6.9 | 6.7 | 4.0 | 3.9 |
| | 2009 | 24.7 | 11.5 | 8.6 | 7.9 | 7.5 | 7.2 | 7.0 | 23.3 | 11.9 | 9.3 | 8.4 | 7.8 | 7.4 | 7.2 | 4.2 | 3.7 |
| 4.5 | 2010 | 33.4 | 20 | 9.6 | 7.6 | 7.1 | 6.7 | 6.4 | 27.9 | 18.1 | 10.3 | 8.6 | 7.8 | 7.3 | 7 | 4.2 | 3.8 |
| | 2009 | 32.8 | 20.3 | 11.0 | 8.9 | 8.4 | 8.0 | 7.7 | 28.8 | 19.1 | 11.5 | 9.6 | 8.8 | 8.3 | 7.9 | 4.8 | 4.5 |
| 5.0 | 2010 | 32.7 | 24 | 15.5 | 10.5 | 9.6 | 9.1 | 8.7 | 26.4 | 21 | 15 | 11.1 | 10.1 | 9.4 | 9 | 6.4 | 5.8 |
| | 2009 | 34.1 | 26.4 | 18.0 | 13.1 | 12.0 | 11.4 | 11.0 | 28.6 | 24.0 | 17.2 | 13.1 | 11.9 | 11.2 | 10.7 | 8.0 | 7.2 |
| | 2008 | 40.5 | 31.6 | 20.4 | 14.1 | 12.8 | 12.3 | 11.9 | 33.6 | 28.2 | 19.6 | 13.9 | 12.6 | 11.9 | 11.5 | 8.9 | 8.1 |
| 5.5 | 2009 | 28.3 | 25.7 | 21.3 | 17.5 | 15.8 | 15.1 | 14.6 | 25.3 | 22.9 | 20.0 | 16.8 | 15.2 | 14.5 | 13.8 | 11.2 | 10.2 |
| | 2008 | 36.2 | 31.5 | 25.3 | 18.4 | 15.9 | 15.1 | 14.6 | 31.6 | 27.7 | 23.4 | 17.7 | 15.2 | 14.4 | 13.8 | 11.0 | 10.3 |
| | 2007 | 32.7 | 29.5 | 24.2 | 18.4 | 15.9 | 15.2 | 14.7 | 28.8 | 26.3 | 22.6 | 17.8 | 15.2 | 14.5 | 13.9 | 11.3 | 10.6 |
| 6.0 | 2008 | 31.8 | 30.5 | 26.5 | 22.1 | 19.1 | 18.0 | 17.3 | 29.2 | 28.1 | 24.7 | 21.2 | 18.2 | 16.9 | 16.2 | 13.4 | 12.4 |
| | 2007 | 27.9 | 26.9 | 24.1 | 20.8 | 18.6 | 17.7 | 17.2 | 26.1 | 25.3 | 22.9 | 20.2 | 17.9 | 16.8 | 16.3 | 13.6 | 12.7 |
| | 2006 | 26.8 | 25.7 | 22.7 | 19.1 | 16.5 | 15.4 | 14.9 | 24.9 | 24.0 | 21.4 | 18.5 | 16.0 | 14.8 | 14.2 | 10.3 | 9.6 |
| 6.5 | 2008 | 29.2 | 28.6 | 27.7 | 24.7 | 22.9 | 21.5 | 21.0 | 27.0 | 26.6 | 25.9 | 23.4 | 21.7 | 20.2 | 19.6 | 16.8 | 15.5 |
| | 2007 | 26.3 | 25.8 | 25.0 | 23.0 | 21.7 | 20.8 | 20.3 | 24.8 | 24.4 | 23.9 | 22.2 | 20.9 | 19.8 | 19.3 | 17.0 | 15.8 |
| | 2006 | 24.2 | 23.7 | 22.9 | 20.6 | 19.2 | 18.1 | 17.7 | 22.9 | 22.5 | 21.9 | 20.0 | 18.7 | 17.5 | 16.9 | 13.6 | 12.7 |

Note: As of Friday, March 11, 2010. Source: Barclays Capital

### Figure 49: Model vs. actual – Fannie Mae 30y collateral

| | | | | | | LTV | | Actual Total CPR | | | Model Total CPR | | | Model CBR | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Coupon | Vintage | WAC | WALA | SATO | FICO | Orig | Curr | 1Mo | 3-Mo | 6-Mo | 1Mo | 3-Mo | 6-Mo | 1Mo | 3-Mo | 6-Mo |
| 4.0 | ALL | 4.53 | 13 | -23 | 768 | 68 | 69 | 3.2 | 6.8 | 10.3 | 3.2 | 6.3 | 10.1 | 0.4 | 0.5 | 0.7 |
| | 2010 | 4.50 | 5 | -12 | 767 | 70 | 70 | 1.9 | 4.0 | 6.5 | 1.7 | 3.2 | 5.9 | 0.1 | 0.1 | 0.2 |
| | 2009 | 4.58 | 22 | -35 | 768 | 65 | 66 | 4.9 | 8.6 | 10.2 | 5.0 | 8.9 | 10.8 | 0.8 | 0.8 | 0.7 |
| 4.5 | ALL | 4.96 | 22 | -7 | 759 | 70 | 71 | 7.8 | 14.8 | 19.8 | 8.3 | 15.5 | 19.9 | 1.0 | 1.0 | 0.9 |
| | 2010 | 4.94 | 9 | -1 | 759 | 72 | 73 | 4.5 | 10.2 | 15.4 | 5.7 | 11.2 | 15.1 | 0.5 | 0.4 | 0.3 |
| | 2009 | 4.94 | 21 | -3 | 762 | 69 | 71 | 8.1 | 15.4 | 19.9 | 8.7 | 16.2 | 20.1 | 1.1 | 1.1 | 0.9 |
| | 2003 | 5.06 | 91 | -50 | 736 | 68 | 62 | 15.4 | 22.9 | 26.7 | 12.6 | 21.6 | 26.5 | 1.1 | 1.1 | 0.9 |
| 5.0 | ALL | 5.52 | 51 | -7 | 735 | 73 | 76 | 17.8 | 24.4 | 28.0 | 18.5 | 26.2 | 31.4 | 2.9 | 2.8 | 2.3 |
| | 2010 | 5.35 | 10 | 30 | 739 | 78 | 79 | 7.2 | 11.1 | 13.8 | 7.9 | 12.6 | 15.5 | 1.4 | 1.1 | 0.8 |
| | 2009 | 5.43 | 20 | 34 | 745 | 74 | 76 | 12.3 | 19.1 | 23.9 | 13.2 | 20.0 | 24.7 | 2.1 | 2.0 | 1.7 |
| | 2008 | 5.65 | 34 | -35 | 742 | 73 | 84 | 24.7 | 33.3 | 38.0 | 27.1 | 35.4 | 41.4 | 4.5 | 3.8 | 3.6 |
| | 2005 | 5.63 | 68 | -21 | 730 | 71 | 82 | 21.3 | 26.9 | 29.3 | 21.4 | 28.8 | 33.6 | 4.1 | 3.9 | 3.3 |
| | 2004 | 5.53 | 82 | -26 | 728 | 70 | 71 | 20.5 | 27.4 | 30.0 | 20.6 | 29.3 | 34.8 | 2.5 | 2.3 | 1.9 |
| | 2003 | 5.48 | 91 | -23 | 727 | 70 | 64 | 20.6 | 27.8 | 30.7 | 19.2 | 28.1 | 33.8 | 1.7 | 1.6 | 1.3 |
| 5.5 | ALL | 6.01 | 63 | -4 | 724 | 73 | 80 | 23.8 | 28.0 | 29.4 | 23.4 | 28.8 | 33.0 | 5.5 | 5.2 | 4.4 |
| | 2008 | 6.03 | 34 | -5 | 734 | 76 | 87 | 26.4 | 31.6 | 34.3 | 27.6 | 32.4 | 36.1 | 6.5 | 6.1 | 5.5 |
| | 2007 | 6.13 | 45 | -25 | 725 | 74 | 91 | 27.1 | 31.0 | 32.0 | 26.1 | 30.0 | 33.5 | 8.6 | 8.2 | 6.9 |
| | 2006 | 6.14 | 56 | -30 | 724 | 72 | 90 | 26.4 | 29.6 | 30.7 | 25.6 | 29.8 | 33.5 | 7.3 | 6.9 | 5.9 |
| | 2005 | 5.98 | 68 | 9 | 717 | 73 | 86 | 19.7 | 23.3 | 24.1 | 19.4 | 24.0 | 27.4 | 5.9 | 5.7 | 5.0 |

| | | | | | | LTV | | Actual Total CPR | | | Model Total CPR | | | Model CBR | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Coupon | Vintage | WAC | WALA | SATO | FICO | Orig | Curr | 1Mo | 3-Mo | 6-Mo | 1Mo | 3-Mo | 6-Mo | 1Mo | 3-Mo | 6-Mo |
| | 2004 | 5.92 | 80 | 1 | 717 | 73 | 75 | 20.6 | 24.1 | 25.4 | 20.6 | 26.7 | 31.0 | 3.5 | 3.4 | 2.9 |
| | 2003 | 5.92 | 93 | 2 | 721 | 71 | 65 | 23.4 | 27.9 | 28.8 | 21.4 | 28.2 | 32.9 | 2.2 | 2.1 | 1.7 |
| | 2002 | 6.00 | 100 | -26 | 728 | 71 | 61 | 25.9 | 32.1 | 33.5 | 24.6 | 32.3 | 37.5 | 1.7 | 1.6 | 1.3 |
| 6.0 | ALL | 6.53 | 59 | 15 | 713 | 77 | 87 | 23.6 | 25.7 | 26.2 | 23.0 | 25.2 | 27.0 | 9.3 | 9.1 | 8.1 |
| | 2008 | 6.52 | 33 | 32 | 720 | 80 | 91 | 26.6 | 29.2 | 30.1 | 26.8 | 29.1 | 31.3 | 9.2 | 9.1 | 8.5 |
| | 2007 | 6.56 | 43 | 5 | 712 | 78 | 95 | 25.0 | 27.1 | 27.6 | 24.7 | 26.4 | 27.9 | 12.1 | 11.8 | 10.5 |
| | 2006 | 6.55 | 56 | 3 | 714 | 75 | 93 | 24.2 | 26.2 | 26.6 | 23.3 | 25.2 | 26.9 | 9.8 | 9.5 | 8.4 |
| | 2005 | 6.49 | 67 | 55 | 704 | 78 | 91 | 18.3 | 19.8 | 19.8 | 18.5 | 20.1 | 21.3 | 9.7 | 9.5 | 8.6 |
| | 2004 | 6.42 | 80 | 39 | 703 | 78 | 79 | 18.4 | 20.3 | 20.7 | 18.0 | 20.6 | 22.8 | 5.5 | 5.4 | 4.8 |
| | 2003 | 6.44 | 93 | 47 | 708 | 74 | 68 | 20.1 | 21.9 | 21.6 | 17.3 | 20.1 | 22.5 | 3.6 | 3.5 | 3.1 |
| | 2002 | 6.49 | 103 | -6 | 716 | 73 | 63 | 22.8 | 25.3 | 25.6 | 22.4 | 25.7 | 28.4 | 2.3 | 2.2 | 1.9 |
| 6.5 | ALL | 7.01 | 67 | 42 | 700 | 79 | 86 | 21.3 | 22.4 | 22.4 | 22.4 | 23.4 | 24.0 | 11.8 | 11.7 | 10.7 |
| | 2008 | 6.98 | 33 | 74 | 702 | 80 | 91 | 25.2 | 26.3 | 26.0 | 25.9 | 26.9 | 27.4 | 14.1 | 13.9 | 12.6 |
| | 2007 | 7.05 | 43 | 49 | 695 | 82 | 99 | 22.7 | 23.9 | 24.3 | 24.5 | 25.3 | 25.5 | 16.7 | 16.6 | 15.5 |
| | 2006 | 7.00 | 56 | 42 | 701 | 79 | 96 | 21.5 | 22.7 | 22.8 | 22.3 | 23.2 | 23.7 | 13.2 | 13.0 | 12.0 |
| | 2002 | 6.96 | 106 | 11 | 704 | 76 | 63 | 20.1 | 20.1 | 19.9 | 21.2 | 22.9 | 24.3 | 2.9 | 2.8 | 2.5 |
| | 2001 | 7.00 | 115 | -7 | 705 | 76 | 61 | 17.8 | 19.5 | 19.4 | 20.0 | 21.5 | 22.8 | 2.7 | 2.6 | 2.4 |

Note: As of February prepayments – March factor. Source: Barclays Capital

**Figure 50: Model vs. actual – Fannie Mae 15y collateral**

| | | | | | | LTV | | Actual Total CPR | | | Model Total CPR | | | Model CBR | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Coupon | Vintage | WAC | WALA | SATO | FICO | Orig | Curr | 1Mo | 3-Mo | 6-Mo | 1Mo | 3-Mo | 6-Mo | 1Mo | 3-Mo | 6-Mo |
| 3.5 | ALL | 3.92 | 5 | -9 | 771 | 61 | 61 | 2.6 | 4.2 | 7.7 | 2.6 | 5.1 | 7.9 | 0.0 | 0.0 | 0.0 |
| 3.5 | 2010 | 3.93 | 5 | -9 | 772 | 61 | 61 | 2.7 | 4.1 | 7.5 | 2.7 | 5.0 | 7.6 | 0.0 | 0.0 | 0.0 |
| 4 | ALL | 4.46 | 24 | -10 | 761 | 60 | 61 | 9.9 | 17.4 | 21.3 | 10.5 | 18.4 | 21.5 | 0.2 | 0.2 | 0.1 |
| 4 | 2010 | 4.41 | 9 | 3 | 763 | 62 | 62 | 6.9 | 13.4 | 17.7 | 8.9 | 16.8 | 20.0 | 0.1 | 0.1 | 0.1 |
| 4 | 2009 | 4.49 | 20 | -13 | 765 | 60 | 61 | 11.1 | 19.7 | 23.5 | 12.3 | 20.6 | 23.6 | 0.2 | 0.2 | 0.2 |
| 4 | 2003 | 4.55 | 91 | -38 | 743 | 59 | 54 | 14.7 | 19.1 | 20.1 | 9.4 | 13.6 | 15.4 | 0.2 | 0.2 | 0.2 |
| 4.5 | ALL | 4.95 | 58 | 0 | 744 | 61 | 60 | 18.4 | 24.3 | 26.5 | 17.3 | 24.3 | 27.4 | 0.4 | 0.3 | 0.3 |
| 4.5 | 2009 | 4.89 | 20 | 24 | 754 | 62 | 63 | 16.7 | 24.9 | 28.3 | 16.6 | 23.9 | 27.1 | 0.3 | 0.3 | 0.3 |
| 4.5 | 2008 | 5.06 | 35 | -24 | 750 | 62 | 70 | 30.1 | 40.1 | 44.9 | 32.1 | 43.5 | 47.9 | 0.9 | 0.8 | 0.6 |
| 4.5 | 2004 | 4.96 | 82 | -10 | 735 | 59 | 59 | 18.3 | 22.2 | 23.0 | 15.6 | 21.4 | 23.8 | 0.3 | 0.3 | 0.2 |
| 4.5 | 2003 | 4.96 | 92 | -8 | 738 | 59 | 54 | 17.2 | 21.1 | 21.7 | 13.5 | 18.6 | 20.9 | 0.2 | 0.2 | 0.2 |
| 5 | ALL | 5.48 | 77 | 8 | 734 | 61 | 60 | 20.9 | 25.0 | 25.5 | 19.5 | 25.0 | 28.0 | 0.5 | 0.5 | 0.4 |
| 5 | 2008 | 5.56 | 33 | 6 | 741 | 63 | 70 | 29.7 | 36.6 | 39.0 | 30.6 | 38.2 | 42.5 | 1.1 | 1.0 | 0.8 |
| 5 | 2005 | 5.49 | 68 | 7 | 732 | 60 | 68 | 20.4 | 23.9 | 24.2 | 20.0 | 25.4 | 28.2 | 0.5 | 0.5 | 0.4 |
| 5 | 2004 | 5.42 | 80 | 15 | 725 | 61 | 62 | 16.9 | 20.1 | 20.2 | 16.7 | 21.3 | 23.8 | 0.4 | 0.4 | 0.3 |
| 5 | 2003 | 5.43 | 94 | 20 | 732 | 60 | 54 | 18.1 | 21.0 | 20.9 | 14.9 | 19.3 | 21.9 | 0.3 | 0.3 | 0.2 |
| 5 | 2002 | 5.50 | 101 | -15 | 741 | 61 | 52 | 19.6 | 23.6 | 23.7 | 17.3 | 23.2 | 26.2 | 0.3 | 0.3 | 0.2 |

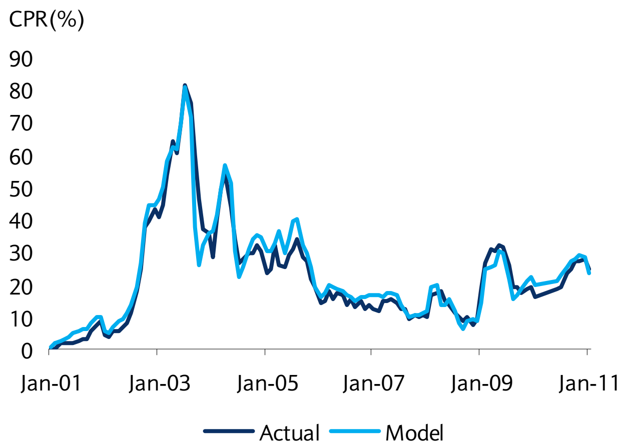
Note: As of February prepayments – March factor. Source: Barclays Capital

**Figure51: Model vs. actual – GNMA I 30y collateral**

| | | | | | Cum. | Actual CRR | | | Model CRR | | | Annualized Model Roll Rate | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Coupon | Vintage | WAC | WALA | SATO | HPA | 1Mo | 3-Mo | 6-Mo | 1Mo | 3-Mo | 6-Mo | 1Mo | 3-Mo | 6-Mo |
| 4.0 | ALL | 4.48 | 9 | -27 | -1% | 2.4 | 3.1 | 3.2 | 2.1 | 3.4 | 4.6 | 2.7 | 4.1 | 5.4 |
| | 2010 | 4.46 | 4 | -20 | 0% | 1.3 | 1.4 | 1.5 | 1.3 | 1.7 | 3.3 | 1.3 | 1.8 | 3.6 |
| | 2009 | 4.50 | 19 | -41 | -1% | 4.6 | 4.3 | 3.4 | 3.8 | 4.7 | 4.7 | 5.5 | 5.7 | 5.5 |
| 4.5 | ALL | 5.00 | 16 | -2 | -1% | 8.5 | 11.5 | 10.6 | 7.5 | 10.9 | 10.8 | 4.3 | 4.4 | 4.3 |
| | 2010 | 4.99 | 8 | -5 | 0% | 6.0 | 7.3 | 7.4 | 5.7 | 7.1 | 7.7 | 3.1 | 3.1 | 3.0 |
| | 2009 | 5.00 | 19 | 3 | -2% | 9.7 | 13.5 | 11.5 | 8.4 | 12.8 | 11.7 | 4.8 | 4.9 | 4.6 |
| 5.0 | ALL | 5.50 | 29 | 21 | -2% | 16.1 | 20.4 | 19.5 | 16.5 | 21.0 | 20.2 | 7.4 | 7.3 | 6.7 |
| | 2010 | 5.49 | 9 | 40 | 0% | 10.5 | 12.6 | 12.8 | 12.6 | 13.5 | 13.5 | 5.4 | 5.2 | 4.9 |
| | 2009 | 5.50 | 19 | 43 | -2% | 16.6 | 22.4 | 21.1 | 17.8 | 23.0 | 21.7 | 8.0 | 7.9 | 7.0 |
| | 2008 | 5.50 | 31 | -53 | -11% | 21.1 | 24.7 | 22.8 | 20.0 | 26.2 | 24.2 | 9.8 | 9.6 | 8.6 |
| | 2005 | 5.50 | 66 | -33 | -4% | 16.8 | 16.1 | 14.7 | 13.0 | 16.3 | 15.3 | 6.3 | 6.3 | 5.8 |
| | 2004 | 5.50 | 79 | -28 | 5% | 14.6 | 14.9 | 13.4 | 11.3 | 14.4 | 13.9 | 4.6 | 4.6 | 4.3 |
| | 2003 | 5.50 | 90 | -16 | 10% | 15.3 | 15.2 | 13.6 | 11.7 | 14.2 | 13.8 | 3.8 | 3.8 | 3.5 |
| 5.5 | ALL | 6.00 | 50 | 5 | -4% | 19.2 | 20.2 | 18.8 | 19.2 | 22.1 | 21.6 | 9.4 | 9.4 | 8.6 |
| | 2008 | 6.00 | 30 | -10 | -10% | 21.8 | 23.6 | 22.0 | 23.4 | 26.6 | 25.7 | 11.5 | 11.3 | 10.2 |
| | 2007 | 6.00 | 43 | -40 | -15% | 21.2 | 20.4 | 19.2 | 19.8 | 23.1 | 22.0 | 12.2 | 12.1 | 11.1 |
| | 2006 | 6.00 | 55 | -44 | -11% | 20.9 | 20.8 | 18.9 | 20.6 | 23.8 | 22.7 | 9.8 | 9.7 | 8.9 |
| | 2005 | 6.00 | 66 | 11 | -7% | 14.3 | 14.1 | 13.2 | 14.4 | 16.6 | 16.3 | 8.9 | 9.0 | 8.5 |
| | 2004 | 6.00 | 79 | 8 | 3% | 13.2 | 13.1 | 12.1 | 14.7 | 16.9 | 16.6 | 6.2 | 6.3 | 5.9 |
| | 2003 | 6.00 | 91 | 10 | 11% | 16.7 | 16.4 | 14.5 | 15.5 | 17.6 | 17.2 | 4.9 | 5.0 | 4.6 |
| | 2002 | 6.00 | 98 | -26 | 14% | 19.7 | 20.2 | 18.4 | 18.7 | 20.8 | 19.9 | 3.4 | 3.4 | 3.1 |
| 6.0 | ALL | 6.50 | 53 | 21 | -4% | 16.4 | 16.5 | 15.7 | 19.1 | 19.8 | 19.9 | 12.0 | 12.0 | 11.2 |
| | 2009 | 6.50 | 22 | 121 | -4% | 17.6 | 17.5 | 18.0 | 18.0 | 20.2 | 20.4 | 16.8 | 16.7 | 15.5 |
| | 2008 | 6.50 | 29 | 27 | -10% | 17.8 | 18.9 | 18.1 | 21.1 | 24.3 | 24.4 | 14.6 | 14.4 | 13.1 |
| | 2007 | 6.50 | 42 | -1 | -15% | 17.3 | 15.9 | 15.2 | 17.0 | 19.4 | 19.3 | 15.0 | 15.1 | 14.2 |
| | 2006 | 6.50 | 54 | -5 | -13% | 17.4 | 17.4 | 16.1 | 18.9 | 21.5 | 21.3 | 11.3 | 11.3 | 10.6 |
| 6.5 | ALL | 7.00 | 86 | 30 | 8% | 12.4 | 11.6 | 11.3 | 13.6 | 14.6 | 15.1 | 11.6 | 11.7 | 11.4 |
| | 2007 | 7.00 | 41 | 43 | -16% | 13.8 | 10.4 | 9.5 | 11.1 | 11.9 | 12.2 | 19.4 | 19.8 | 19.3 |
| | 2006 | 7.00 | 53 | 35 | -15% | 12.7 | 12.0 | 11.4 | 12.3 | 13.2 | 13.4 | 15.6 | 16.0 | 15.5 |

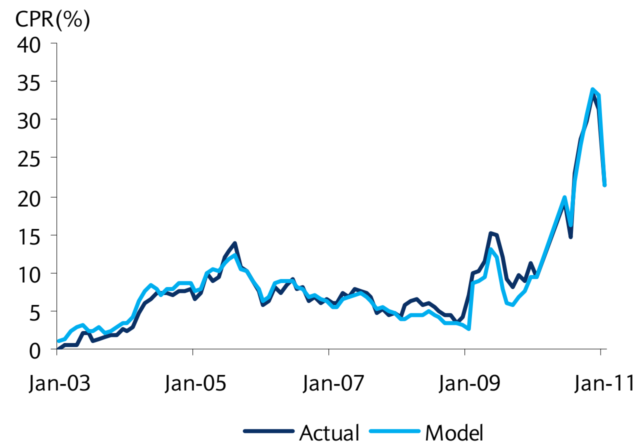
Note: As of December prepayments – January factor. The recent change in FHA mortgage insurance that went into effect on October 19, 2010, has caused some volatility in GNMA voluntary prepayments in January 2011 (February 2011 factor date). We therefore show model fits through December 2010 (January 2011 factor date). Source: Barclays Capital

**Figure 52: FNCL (Fannie Mae 30y) 6.0s of 2002 – Total CPR**



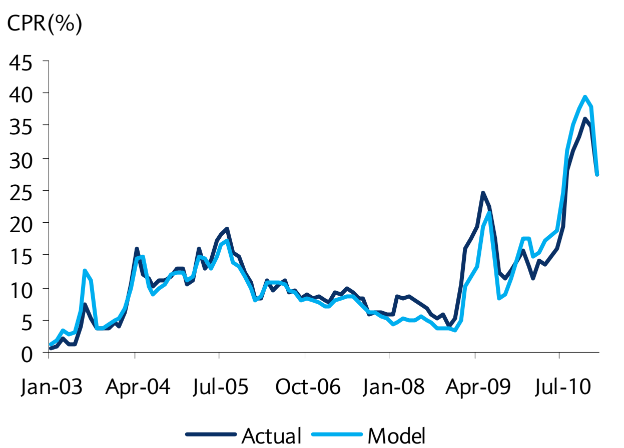

Source: Fannie Mae, Barclays Capital

**Figure 53: FNCL (Fannie Mae 30y) 4.5s of 2003 – Total CPR**



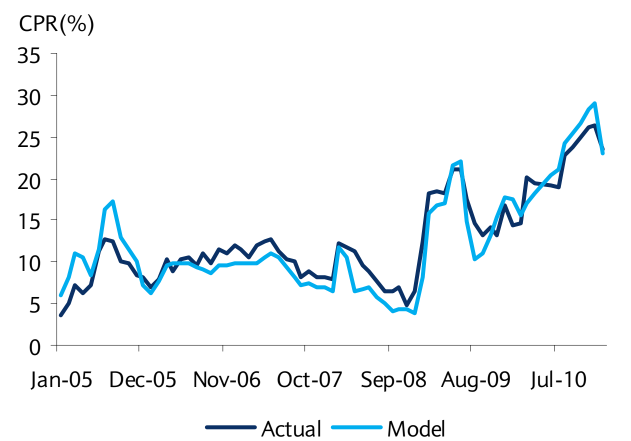

Source: Fannie Mae, Barclays Capital

**Figure 54: FNCL (Fannie Mae 30y) 5.0s 2003 – Total CPR**



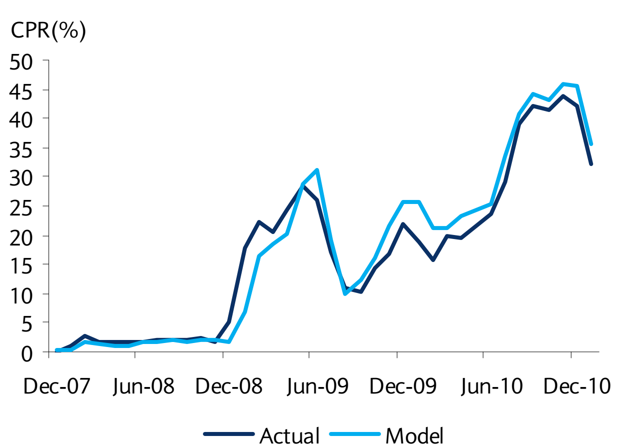

Source: Fannie Mae, Barclays Capital

**Figure 55: FNCL (Fannie Mae 30y) 5.5s 2005 – Total CPR**



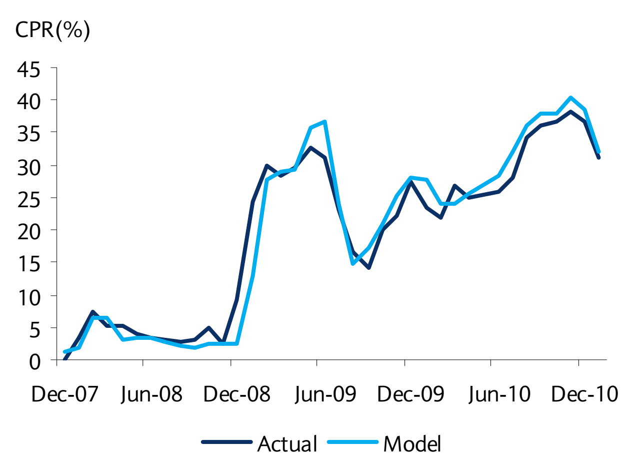

Source: Fannie Mae Barclays Capital

**Figure 56: FNCL (Fannie Mae 30y) 5.0s 2008 – Total CPR**



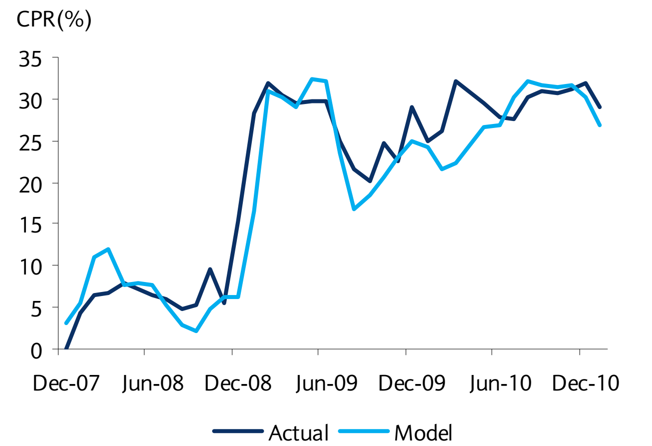

Source: Fannie Mae, Barclays Capital

**Figure 57: FNCL (Fannie Mae 30y) 5.5s 2008 – Total CPR**



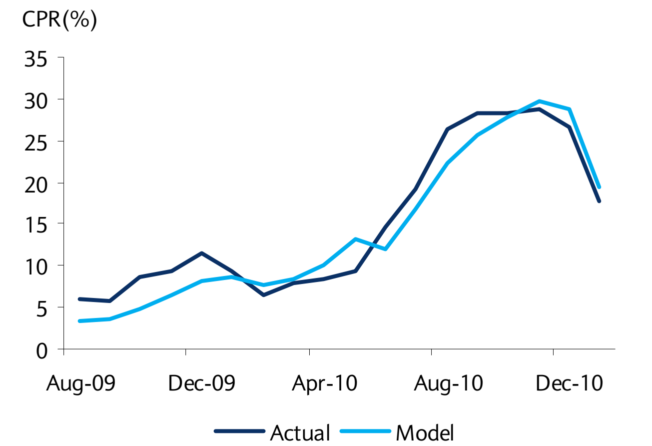

Source: Fannie Mae, Barclays Capital

Figure 58: FNCL (Fannie Mae 30y) 6.0s 2008 – Total CPR



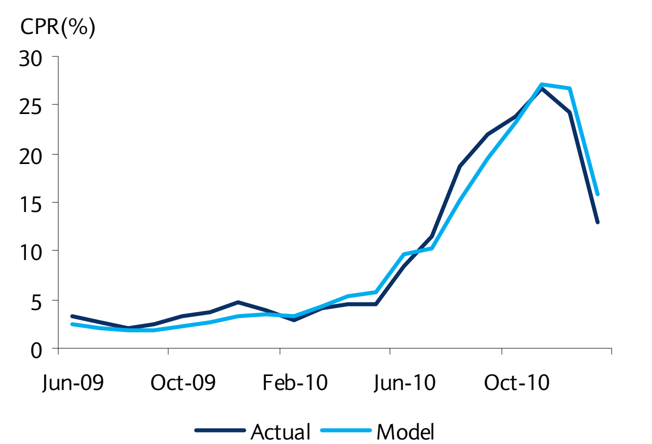

Source: Fannie Mae, Barclays Capital

Figure 59: FNCL (Fannie Mae 30y) 4.5s 2009 – Total CPR



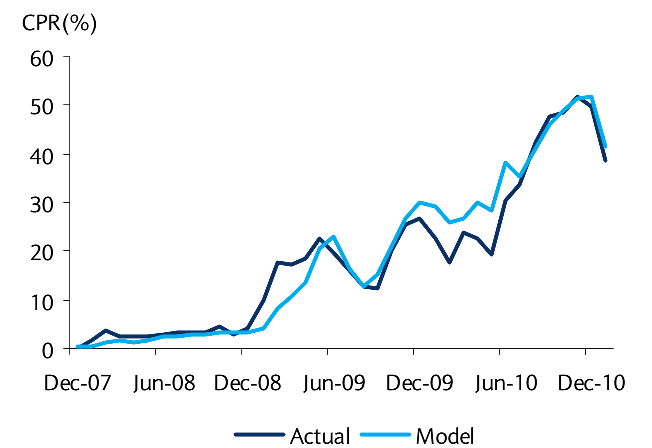

Source: Fannie Mae, Barclays Capital

Figure 60: FNCL (Fannie Mae 30y) 5.0s 2009 – Total CPR



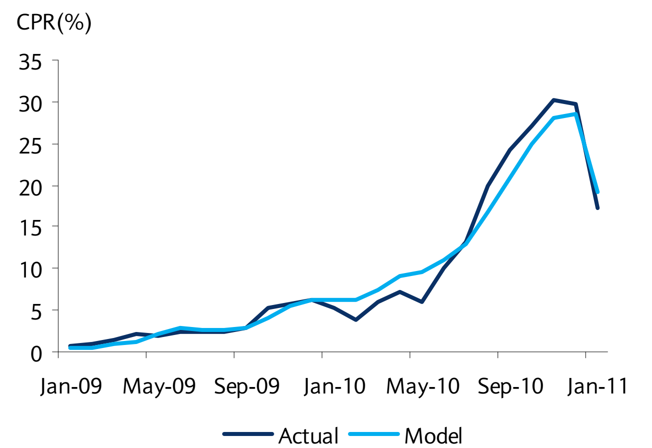

Source: Fannie Mae, Barclays Capital

Figure 61: FNCI (Fannie Mae 15y) 4.5s 2008– Total CPR



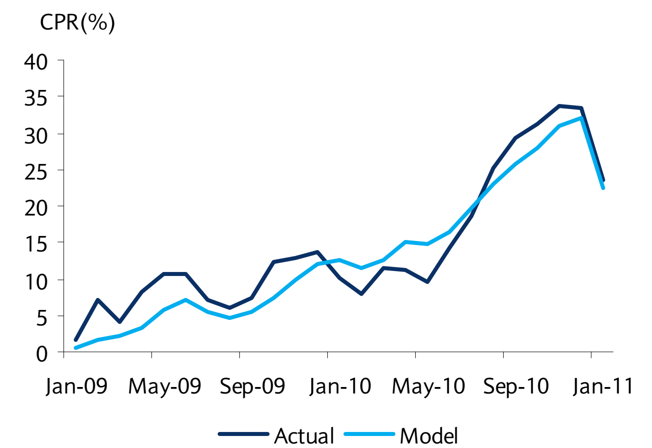

Source: Fannie Mae, Barclays Capital

Figure 62: FNCI (Fannie Mae 15y) 4.0s 2009 – Total CPR



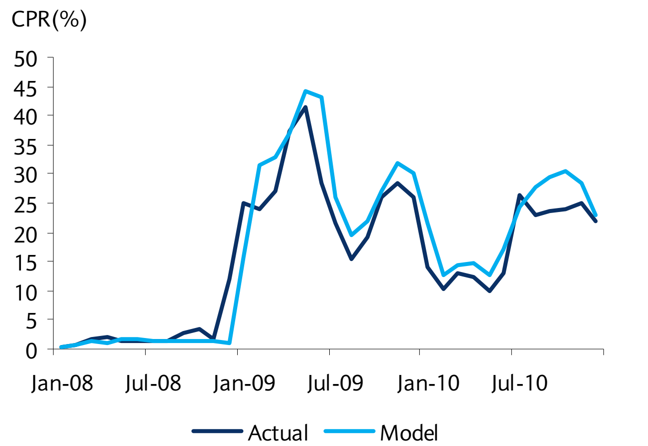

Source: Fannie Mae, Barclays Capital

Figure 63: FNCI (Fannie Mae 15y) 4.5s 2009– Total CPR



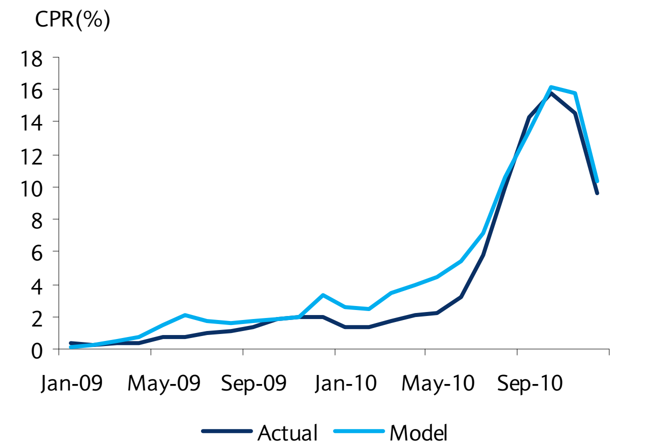

Source: Fannie Mae, Barclays Capital

**Figure 64: GNMA I 5.5s 2008 – Voluntary prepayments**



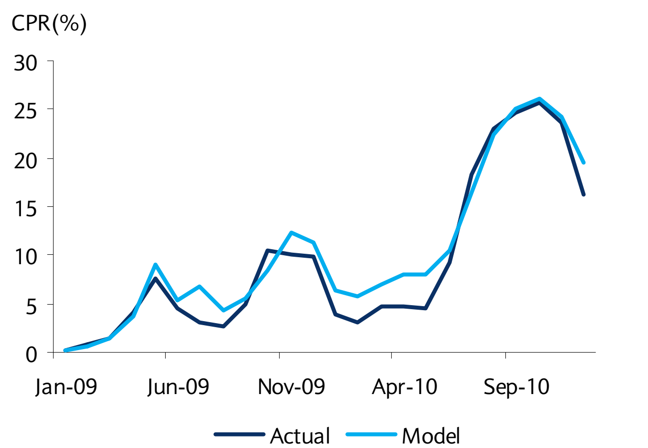

Source: GNMA, Barclays Capital

**Figure 65: GNMA I 5.0s 2009 – Voluntary prepayments**



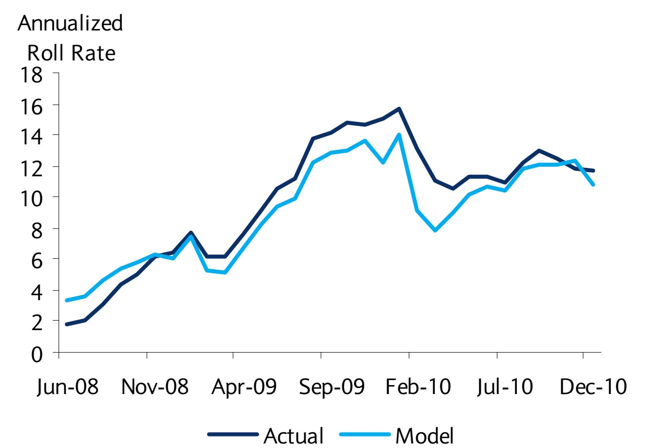

Source: GNMA, Barclays Capital

**Figure 66: GNMA I 4.5s 2009 – Voluntary prepayments**



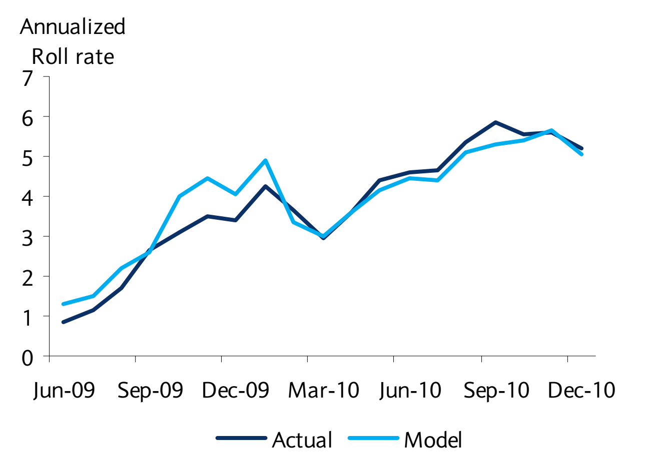

Source: GNMA, Barclays Capital

**Figure 67: GNMA 1 5.5s 2008 – Annualized roll rate**



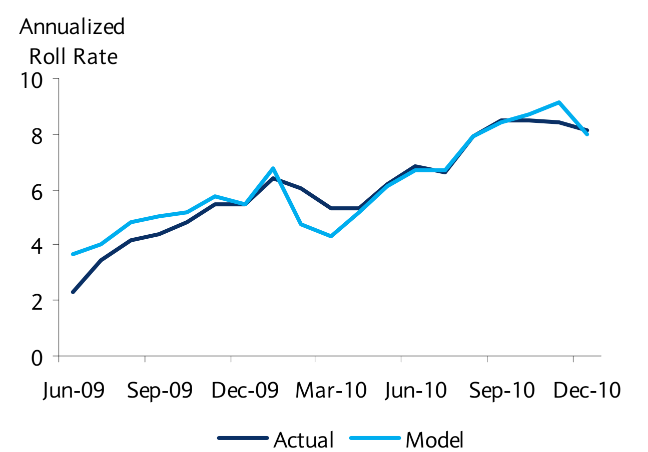

Source: GNMA, Barclays Capital

**Figure 68: GNMA I 5s 2009 – Annualized Roll Rate**




Source: GNMA, Barclays Capital

**Figure 69: GNMA I 4.5s 2009 - – Annualized Roll Rate**




Source: GNMA, Barclays Capital

# BARCLAYS CAPITAL LOAN TRANSITION MODEL

## Introducing a new Residential Mortgage Credit Model

Steven Bergantino
+1 212 412 2164
steven.bergantino@barcap.com

Chun Li
+1 212 412 7944
chun.li@barcap.com

This is an updated version of *Barclays Capital Loan Transition Model*, November 30, 2010.

On Friday, December 3, 2010, Barclays Capital introduced a new residential mortgage credit model to Barclays Capital Live. Highlights include:

- It is a loan-level transition model that tracks the progression of mortgages through the entire chain of borrower actions and servicer reactions. It is implemented through Monte Carlo simulation at the loan level, which allows it to make full use of a borrower's entire payment history when projecting the level and timing of future prepayments and defaults.

- The model can be used to evaluate mortgage pools containing virtually any residential mortgage products whether prime, AltA, subprime, or second lien; fixed or adjustable rate; amortizing, interest only or negatively amortizing; 15y, 30y, or 40y amortization terms. It also distinguishes between second lien mortgages securitized into stand-alone deals and other second liens. This feature is particularly important when modelling transitions from 60+ to liquidation versus 60+ to foreclosure since the vast majority of second-lien securitizations require that loans be charged off once they become more than 180 days delinquent.

- We use the OTS method to classify borrowers as either current or delinquent and make a sharp distinction between those who have never been delinquent and those who are up-to-date on their payments but have been delinquent at some point in the past. This distinction is especially important for pools in which large numbers of borrowers have been cured back to a non-delinquent status through loan modification.

- Loan modifications are explicitly included as a form of curing separate from non-modification related cures, allowing us to make full use of this important information when projecting future delinquencies and cures. We also model the rate and/or principal reductions resulting from the modification and incorporate these mortgage contract changes into projections of post modification cash flows.

- LTVs are marked-to-market using zip code level home price indices provided by Core Logic. This improves the accuracy of LTV calculations over using state or MSA level home prices. The model uses y/y trends in zip code level home prices to track the strength or weakness of local housing markets. It also uses MSA-level unemployment information to measure improvements or deterioration in the local economy since loan origination.

- In modelling transitions for severely delinquent borrowers, the new model uses months delinquent, months in state and recent payment behaviour. This allows us to better distinguish consistently non-cash flowing, delinquent borrowers who are likely to transition through the foreclosure process to liquidation from those delinquent but cash flowing borrowers (e.g., borrowers in trial modifications) who are likely to cure or be modified back to a non-delinquent payment status.

- Foreclosure to REO transitions incorporate state-level differences in foreclosure laws and timelines to more accurately project the timing of transitions from foreclosure to REO. The model also incorporates the effect of the nationwide slowdown in foreclosures on the rate at which severely delinquent borrowers transition through the foreclosure process.

- Our loss severity model distinguishes between REO and non-REO liquidations and incorporates projected principal and interest advances into the calculation of loan-level losses. As a result, factors that slow down the foreclosure process or discourage non-REO liquidations automatically increase advances and projected severities.

- The prepayment model incorporates the dampening effect of tighter underwriting guidelines on the ability of borrowers with past delinquencies, high LTVs or nonconforming mortgage balances to refinance their mortgages, while at the same time allowing for the "prepayment curing" of borrowers who maintain clean payment profiles for several years.

- We include a range of scenarios on Barclays Capital Live for use with the new model. The national home price forecasts that define each scenario are distributed to state, MSA, county, and zip code levels using the Barclays Capital Regional Home Price Model.

## Beyond borrower collateral characteristics

The severe deterioration in mortgage performance over the past several years has made clear the need to go beyond credit models that use only borrower collateral characteristics and changes in the economic environment when projecting defaults and losses on individual pools of mortgages. This need is especially pronounced in the non-agency MBS sector, where the time and credit tranching of traded securities makes them particularly sensitive to the prepayment, default and recovery assumptions applied to the underlying mortgages.

Compared with the early stages of the housing crisis, the percentage of non-agency borrowers who are behind on their mortgages has increased markedly, with delinquencies on Jumbo ARMs approaching levels seen on Subprime mortgages just three years ago (Figure 1). A quick examination of defaulted loans also reveals that the number of missed payments between initial delinquency and ultimate liquidation has almost doubled, from an average of 9 months in 2007 to 16 months for recent liquidations. Finally, notice that, due to the systematic modification of delinquent loans, the share of borrowers classified as up-to-date on their mortgage payments but delinquent at some point in the past has increased significantly, from just 7% of all subprime borrowers in June 2007 to 23% today.

Figure 1: Changes in borrower delinquency profiles over time, OTS delinquencies

| | %Current, Never Delinquent | % Current, Previously Delinquent | % 30+, FLC & REO | Months Delinquent at Liquidation |
|---|---|---|---|---|
| | | June 2010 | | |
| Jumbo Fixed | 88.9 | 3.1 | 8.1 | 14 |
| Jumbo ARM | 84.4 | 3.5 | 12.1 | 15 |
| AltA Fixed | 69.1 | 8.0 | 22.9 | 17 |
| AlA ARM | 57.1 | 9.5 | 33.5 | 17 |
| NegAm | 44.7 | 9.5 | 45.8 | 17 |
| Subprime | 30.3 | 22.9 | 46.9 | 17 |
| | | June 2007 | | |
| Jumbo Fixed | 99.2 | 0.5 | 0.3 | 8 |
| Jumbo ARM | 98.9 | 0.6 | 0.5 | 7 |
| AltA Fixed | 95.9 | 1.7 | 2.5 | 11 |
| AltA ARM | 93.0 | 1.9 | 5.1 | 8 |
| NegAm | 95.8 | 1.5 | 2.6 | 6 |
| Subprime | 76.9 | 6.9 | 16.3 | 12 |

Source: LoanPerformance, Barclays Capital

Other things equal, the likelihood of becoming delinquent is higher for someone who has missed payments in the past than for a borrower who has never missed a payment. Similarly, a property that has passed through the foreclosure process and is now real-estate owned (REO) is much more likely to be liquidated over the next several months—bringing to an end any interest advances on the associated mortgage—than one that is still passing through the foreclosure process. In short, knowing a borrower's current delinquency status and pay history is extremely important in estimating his likelihood of default and the loss that will be suffered if and when a default occurs. It is not surprising, therefore, that most non-agency investors now employ some form of transition model (also known as roll rate models) when evaluating non-agency MBS.

While transition models vary in complexity, all share a common structure in which loans are classified into one of several delinquency buckets, and then the probability of transitioning from one bucket to another or to prepayment/default is modelled. The simplest transition models classify mortgages into a small number of delinquency buckets and use recently observed transition rates to project future behaviour. Enhancements typically involve using separate transition matrices for each collateral type and vintage of interest, increasing the number of delinquency buckets, or replacing empirical transition rates with transition functions estimated using historical data. The most sophisticated and computationally intensive transition models tend to be implemented through Monte Carlo simulation because this allows them to factor a borrower's full payment history, not just his current delinquency status, into projections of future borrower (and servicer) behaviour.

The Barclays Capital Loan Transition Model is a simulated loan-level transition model that includes a number of enhancements relative to standard transition models. In the remainder of this article we will discuss in greater detail the model's basic structure and implementation, the primary factors affecting borrower delinquency and curing behaviour, servicer responses to borrower delinquencies, and loss severities on liquidated properties. We will also discuss the treatment of prepayments within the model as well as the home price assumptions used in the economic scenarios available on Barclays Capital Live.

# Model structure and implementation

## Model structure

As stated in the introduction, the Barclays Capital Loan Transition Model is a Monte Carlo simulated, loan-level, transition model. The transition matrix in Figure 2 provides a useful visual representation of the model. At each point in time along a given simulation path, every loan with nonzero remaining balance is classified into one of the six delinquency categories in the left-most column of the matrix. The nonzero cells to the right of each starting delinquency category represent the possible ending delinquency states for a loan. The names displayed within each of these cells signify transition probability functions that take values between 0 and 1 and together determine the relative likelihood of each ending delinquency status. The transition functions displayed in Figure 2 represent a combination of borrower and servicer actions. Borrowers primarily choose whether or not to make payments (DQ functions), cure delinquencies (CC, C3, and C6 functions), or prepay their mortgages (PP functions). Servicers primarily choose whether to modify delinquent borrowers (M and MC functions) or pursue foreclosure (CFC and CREO functions). Involuntary payoffs (DD functions) can be the result of borrower actions (e.g., the sale of a property and full payoff of the mortgage), servicer actions (e.g., a foreclosure sale or REO liquidation) or the joint effort of both the borrower and servicer (e.g., a short sale). Since the columns to the right of a starting delinquency category constitute all possible one-period-ahead transitions, the probabilities in each row must sum to one. The named cells in each row signify those transition probabilities that we explicitly model. These functions were estimated using loan-level data from the LoanPerformance MBS/ABS securities database. The cells marked with an X represent no change in delinquency category and are calculated as the residual of the other transition probabilities, as indicated by the formulas listed below the matrix.

**Figure 2: Structure of Barclays Capital Loan Transition Model**

| From \ To | ACUR | DCUR | 30D | 60+ | FCL | REO | Prepay | Default |
|---|---|---|---|---|---|---|---|---|
| ACUR | $X_{AC}$ , $M_{AC}$ | 0 | $DQ_{AC}$ | 0 | 0 | 0 | $PP_{AC}$ | 0 |
| DCUR | 0 | $X_{DC}$ , $M_{DC}$ | $DQ_{DC}$ | 0 | 0 | 0 | $PP_{DC}$ | 0 |
| 30D | 0 | $MC_{30D} + CC_{30D}$ | $X_{30D}$ | $DQ_{30D}$ | 0 | 0 | $PP_{30D}$ | 0 |
| 60P | 0 | $MC_{60P} + CC_{60P}$ | $C3_{60P}$ | $X_{60P}$ | $DQ_{60P}*CFC_{60P}$ | 0 | 0 | $DD_{60P}$ , SEV |
| FCL | 0 | $MC_{FCL} + CC_{FCL}$ | 0 | $C6_{FCL}$ | $X_{FCL}$ | $DQ_{FCL}*CREO_{FCL}$ | 0 | $DD_{FCL}$ , SEV |
| REO | 0 | 0 | 0 | 0 | 0 | $X_{REO}$ | 0 | $DD_{REO}$ , SEV |

Note: Delinquencies are calculated using OTS method (i.e., 30D implies two missed payments). ACUR signifies always current. DCUR signifies dirty current (i.e., current but previously delinquent). DQ functions represent probability of missing next payment. CC, C3, and C6 functions represent probability of borrower self curing to current, 30D OTS, and 60+ OTS, respectively. M functions represent probability that an OTS current borrower is modified. MC functions represent probability of a delinquent borrower being modified back to current. Prepayment is defined as any payoff out of a current or 30D OTS state (PP functions), while default is defined as any payoff out of OTS 60+, foreclosure or REO (DD functions). In the event of a default, losses are calculated using the severity function SEV. Xs represent the residual of other transition probabilities and are given by:

$X_{AC} = 1 - DQ_{AC} - PP_{AC}$
$X_{DC} = 1 - DQ_{DC} - PP_{DC}$
$X_{30D} = 1 - MC_{30D} - CC_{30D} - DQ_{30D} - PP_{30D}$
$X_{60P} = 1 - MC_{60P} - CC_{60P} - C3_{60P} - DQ_{60P}*CFC_{60P} - DD_{60P}$
$X_{FCL} = 1 - MC_{FCL} - CC_{FCL} - C6_{FCL} - DQ_{FCL}*CREO_{FCL} - DD_{FCL}$
$X_{REO} = 1 - DD_{REO}$

Source: Barclays Capital

### *OTS versus MBA delinquencies*

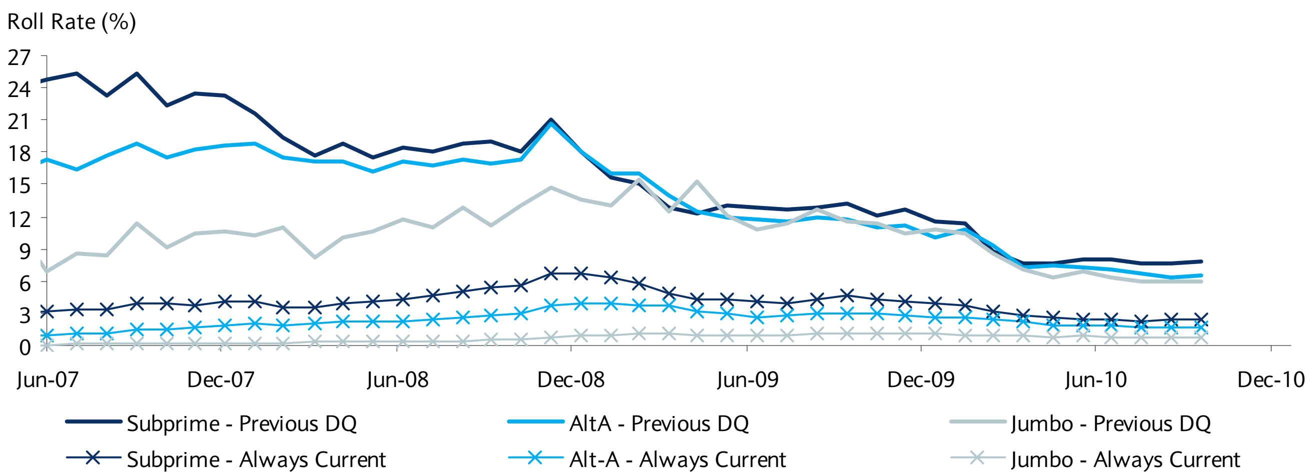
The delinquency classifications used within the model are based on the OTS (Office of Thrift Supervision) method for determining delinquencies, as opposed to the MBA (Mortgage Bankers Association) method. This is true for all mortgage products covered by the model.

The difference between the two methods is that, under the OTS method, a borrower is considered current until he becomes two months delinquent. Thus, a borrower who is "30 days" delinquent under the OTS method would be considered "60 days" delinquent under the MBA method and vice versa.[1] We have found the transition from OTS always current to OTS 30 days delinquent to be a much more reliable and powerful signal of changes in borrower credit quality than the transition from MBA always current to MBA 30 days delinquent. For this reason, we use OTS delinquencies to distinguish always current borrowers from other borrowers within our model.[2]

### *Always current versus dirty current and delinquent*

One very important feature of the model is its distinction between borrowers who have never been delinquent (i.e., OTS 30-days delinquent or worse) and borrowers who are considered current on their payments but have been delinquent in the past. We refer to the former as clean current or always current (ACUR) and the latter as delinquent current or dirty current (DCUR). It is difficult to understate the disparity in performance between always current and dirty current borrowers. The difference is not just that dirty current borrowers are much more likely to become delinquent than borrowers who have never been delinquent (Figure 3), but also that their credit performance is much less correlated with the primary drivers of always current to delinquent transitions – factors such as original FICO score and Updated Combined LTV (UCLTV) (Figure 4). In addition, cross sector differences in current to delinquent transition rates are much less pronounced for dirty current borrowers than for always current borrowers. In fact, we have found that while it is best to have separate always current to delinquent transition functions for each non-agency sector (Jumbo, AltA,

**Figure 3: OTS current-to-delinquent roll rates, 2006 originations**




Source: LoanPerformance, Barclays Capital

[1] The convention within the non-agency sector has traditionally been to report MBA delinquencies in the remittance reports of Jumbo securitizations and OTS delinquencies in the remittance reports of subprime securitizations. For AltA securitizations, the choice between OTS and MBA methods varies across deals.

[2] Servicing transfers, clerical errors, and life events that distract a borrower from his normal routine can all lead to a one-time MBA 30-day delinquency that contains little or no information about the borrower's ability to continue making payments. Since these issues tend to be cleared up before they result in a second missed payment, they are much less likely to result in an OTS 30-day delinquency. This noisiness in always current to 30-day MBA transitions was especially pronounced for prime mortgages during the pre-crisis period when delinquencies on prime collateral were extremely low and consequently erroneous transitions constituted a larger share of all current to delinquent transitions.

NegAm Subprime), it is not necessary for transitions out of dirty current or worse delinquency states. This finding has allowed us to sharply reduce the number of functions estimated for the new model. In particular, outside of the always current bucket, our model uses a single set of transition functions for all first lien mortgages.

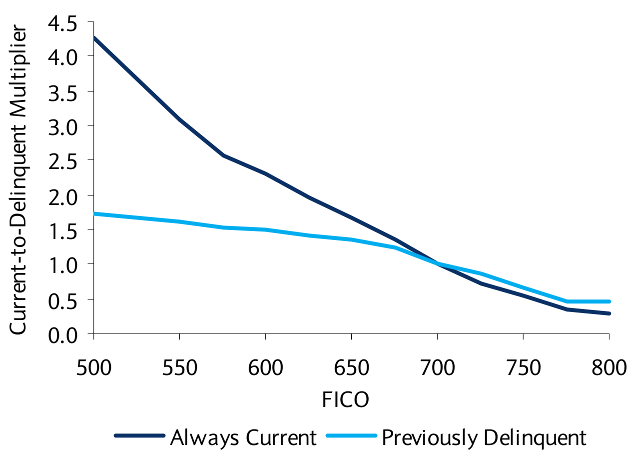
## Implementation using Monte Carlo simulation

There is nothing in our description of the model's structure so far that requires that it be implemented through Monte Carlo simulation. If the only borrower payment information used by the transition probability functions were the starting delinquency categories on the left-hand side of Figure 2, then simulation would be unnecessary. However, information about a borrower's past and recent payment behaviour is enormously helpful in improving our estimates of future behaviour. For example, the probability that a recently delinquent borrower becomes delinquent again is much more dependent on how many continuous payments they have made since being modified than on their credit score at origination. Similarly, the speed with which non cash flowing borrowers transition from foreclosure to REO depends on how long they have been in foreclosure relative to the typical time to foreclose in the state where the mortgaged property is located. In order to use information like this to project future delinquency transitions, we must calculate and keep track of it as part of our projection. And we can only accomplish this by simulating each loan's behaviour forward from our last observed month until the point at which it is prepaid, liquidated or fully amortized. The appendix contains an example of the simulation process for interested readers.

Figure 5 contains a list of the factors affecting the various components of the model. In the sections that follow we will discuss the most important factors.

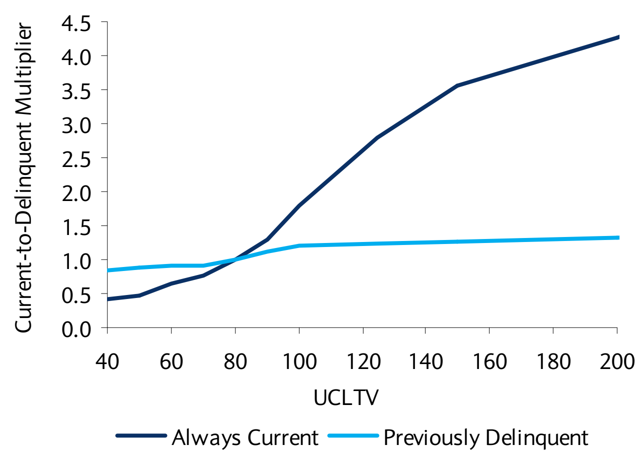
**Figure 4: Estimated sensitivity of current-to-delinquent roll rates to FICO and UCLTV by pay history**

a. FICO




Roll rates are shown as multiples of the case where FICO=700
Source: Barclays Capital

b. UCLTV




Roll rates are shown as multiples of the case where UCLTV=80
Source: Barclays Capital

**Figure 5: Primary factors affecting delinquency transitions in the Barclays Loan Transition Model**

| | Borrower Delinquencies & Cures | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Delinquencies | | | Cures | Servicer Reactions To Delinquency | | | | |
| **Model Variables** | **ACUR** | **DCUR** | **30/60+/FC** | **30/60+/FC** | **Foreclosure** | **Short Sale** | **Modification** | **Loss Severity** | **Prepayments** |
| **Static Factors** | | | | | | | | | |
| Sector: Jumbo, AltA, Subprime , 2nd Lien | x | x | | | | | x | x | x |
| Product Choice: ARM vs. Fixed | x | x | x | x | | | x | | x |
| Product Choice: 15y, 40y, IO, NegAm vs. 30y | x | x | x | x | | | x | | x |
| Original FICO Score | x | x | x | x | | | x | | x |
| Documentation | x | x | x | x | | | x | | x |
| Occupancy | x | x | x | x | x | x | x | x | x |
| Loan Purpose | x | x | | | | | | x | |
| Property Type | x | x | x | x | | | | x | |
| Prepayment Penalties | | | | | | | | | x |
| Spread at Origination (SATO) | x | | | | | | | | |
| Month of Year | x | x | x | x | | | | | x |
| Judicial vs. Non Judicial Foreclosure | | | x | x | x | x | | x | |
| State Specific Foreclosure Timeline | | | | | x | | | | |
| Borrower / Lender Paid Mortgage Insurance | | | | | | | | x | |
| **Time Varying Factors** | | | | | | | | | |
| Delinquency Status | | | | | | | x | | x |
| Loan Age | x | | | | | | | x | x |
| Updated Combined LTV (UCLTV) | x | x | x | x | x | x | | | x |
| Updated LTV (ULTV) | | | | | | | x | x | |
| Payment Reset Shocks | x | x | x | x | | | | | x |
| Cumulative Payment Change Since Origination | x | x | x | x | | | | | |
| Year-Over-Year HPA | x | x | x | x | x | x | | | |
| Change in Unemployment Rate Since Orig | x | x | | | | | | | |
| Loan Size | x | x | x | x | | | x | x | x |
| Refinance Incentive / Lockin | | | | | | | | | x |
| **Path Dependent Factors** | | | | | | | | | |
| Previous Delinquency Status | | x | x | x | x | x | | x | |
| Number of Missed Payments | | | x | x | x | x | | x | |
| Months in State (i.e., months in dq bucket) | | x | x | x | x | x | | | x |
| Recent Payment Behavior | | | x | x | x | x | | | |
| Modification History | | x | x | x | | | x | | x |
| Advanced Principal and Interest | | | | | | | | x | |

Source: Barclays Capital

## Borrower delinquencies and cures

### Always current-to-delinquent Roll Rates

The always current to delinquent transition can be thought of as giving the rate at which good borrowers go bad. Once borrowers become OTS 30 days delinquent for the first time, their likelihood of ultimate default increases markedly even if, in the near term, they manage to cure back to current. For this reason, the always current to delinquent roll rate is by far the most important borrower-driven delinquency transition in determining the overall level of defaults for a mortgage pool. It is also the one place in the model where we use separate transition functions for different collateral types. Specifically, the model contains separate always current to delinquent transition functions for each non-agency sector and product type (i.e., Jumbo Fixed, Jumbo ARM, AltA Fixed, AltA ARM, NegAm, Subprime Fixed, and Subprime ARM). This increases our ability to capture the full range of credit performance across non-agency mortgages.

The most important drivers of always current to delinquent roll rates for prime, AltA, and subprime borrowers alike, are their credit score at origination, the amount of equity they have in the property, the level of income and asset verification they provided at the time of origination, any mortgage product choices they made that suggest a weaker or stronger credit profile than normal (e.g. 15y, 40y, IO, NegAm), and whether or not the mortgaged property is their primary residence.

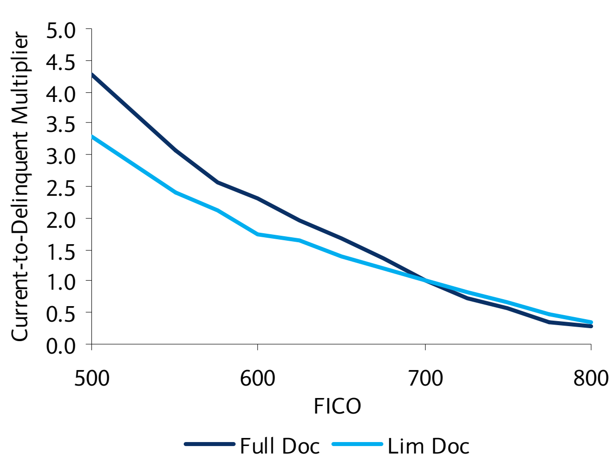
- **FICO score at origination**: While a borrower's credit quality is far from static (if it were, we would not need credit models), it tends to be sticky, especially for always current borrowers. As a result, knowing a borrower's FICO score at origination provides useful information for predicting future delinquencies (Figure 6a). Assuming all other characteristics are the same, always current borrowers with subprime FICO scores (FICO<=600) are 2.5-3.5 times more likely to become delinquent than high quality jumbo borrowers (FICO>=750).

- **Updated combined LTV (UCLTV)**: One of the most important factors in any credit model is the borrower's equity position in the property, adjusted for changes in home prices and (possibly negative) amortization of the mortgage (Figure 6b). Borrowers with UCLTV>100 have an incentive to strategically default on their mortgage. High UCLTVs resulting from property price declines can also signal a weak local economy and therefore a reduced ability to continue paying one's mortgage. Both of these effects create a strong correlation between borrower equity and roll rates from always current to delinquent. Model estimates displayed in Figure 6b indicate that always current borrowers with a 20% equity deficit in their property (UCLTV=120) are 2.5-3.5 times more likely to become delinquent than borrowers with a 20% equity cushion (UCLTV=80).

- **Documentation**: Borrowers who willingly accept a higher mortgage rate (often significantly higher) in return for not verifying their income and assets reveal themselves to be riskier credits than their FICO scores might suggest. It is not surprising, therefore,

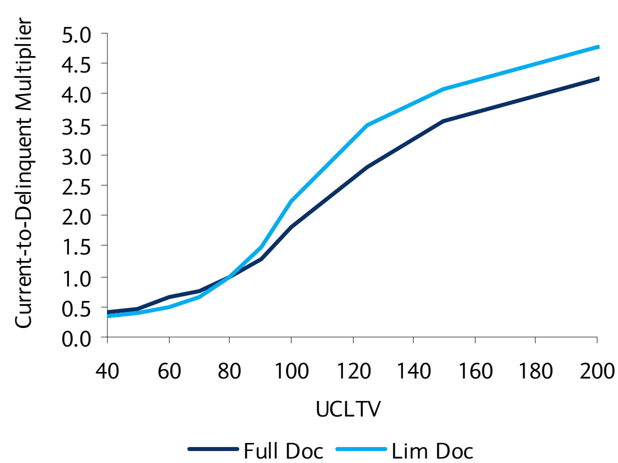
**Figure 6: Estimated sensitivity of always current-to-delinquent roll rates to FICO and UCLTV by documentation type**

a. FICO




Roll rates are shown as multiples of the case where FICO=700.
Source: Barclays Capital

b. UCLTV



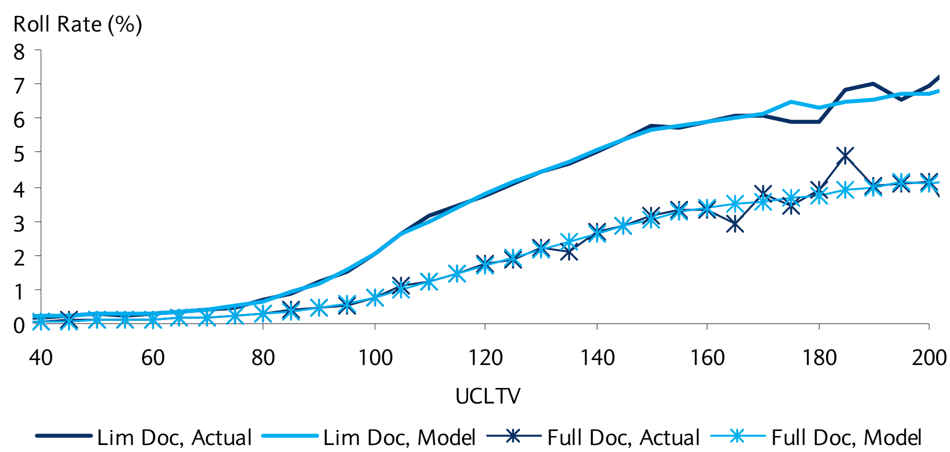

Roll rates are shown as multiples of the case where UCLTV=80.
Source: Barclays Capital

that limited documentation mortgages perform significantly worse than full-documentation mortgages with similar FICO and UCLTV (Figure 7). This difference is captured in our model, as is a slightly more subtle effect of limited documentation displayed in Figures 6a and 6b. Specifically, while FICO is an important predictor of credit quality for all borrowers, it is less informative for borrowers who failed to verify their income and assets at origination (Figure 6a). In contrast, UCLTV becomes an even more important predictor of future delinquency for these borrowers since, in many cases, they overstated their income in order to purchase a larger home or extract more equity from an existing home than might otherwise have been allowed.

- **Product selection**: Another way in which borrowers reveal themselves to be better or worse credits than suggested by their other collateral characteristics is through the mortgage products they select. Borrowers who opt for mortgages with extended amortization schedules (e.g., 40-year mortgages) or low initial monthly payments (e.g., interest-only mortgages, negatively amortizing mortgages and adjustable rate mortgages with short fixed rate periods) tend to become delinquent at higher rates than borrowers with 30-year fixed rate amortizing mortgages. In many cases, the weaker performance occurs even before their initial payment resets higher (Figure 8). Once the reset occurs, credit performance can deteriorate rapidly (Figure 9). Conversely, borrowers who select mortgages with shorter amortization schedules (e.g., 15-year mortgages) tend to perform better despite the higher monthly payments required.

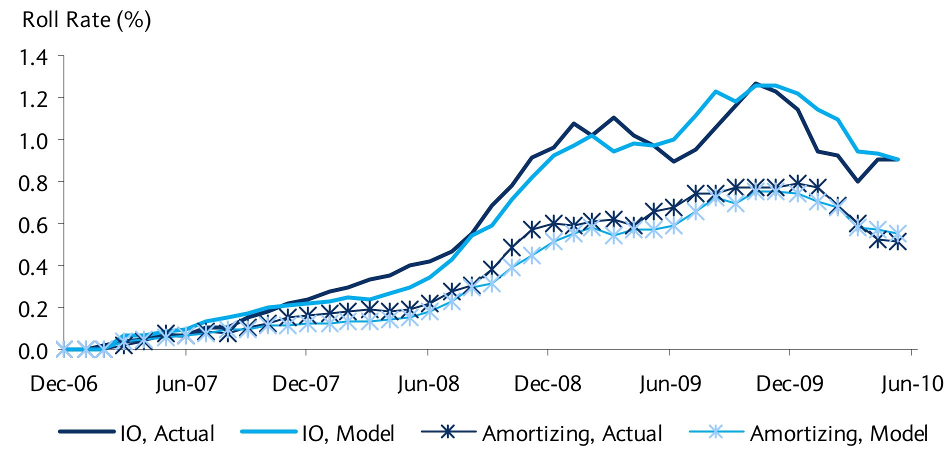
- **Occupancy**: Most home owners become anchored to their communities through the schools their children attend and the friends they make. As a result, defaulting on the mortgage backing one's primary residence can be a jarring experience, one that most people would choose to avoid. By contrast, an investment property primarily represents a stream of income or speculative opportunity, making the decision to default more one of dollars and cents than of a major life change. As a result, all else being equal, borrowers are less likely to default on a mortgage backed by their primary residence than on one backed by an investment property.

**Figure 7: Always current-to-delinquent roll rates by UCLTV and documentation type, Alt-A hybrid**



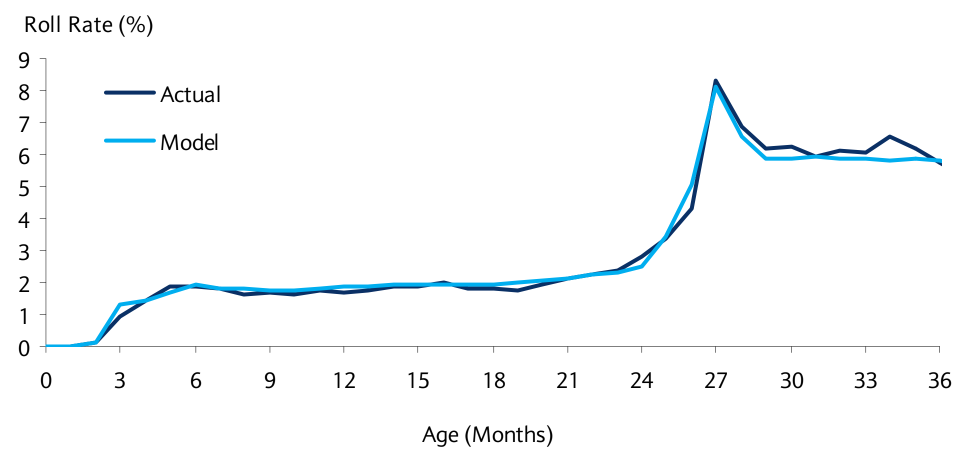

Source: LoanPerformance, Barclays Capital

**Figure 8: Always current–to-delinquent roll rates by amortization type, jumbo fixed rate, 2007 originations**




Source: LoanPerformance, Barclays Capital

**Figure 9: Effect of payment shocks on always current-to-delinquent roll rates, subprime 2/28 ARM, 2005 originations**




Source: LoanPerformance, Barclays Capital

- **Spread at origination (SATO)**: Just as borrowers reveal their credit quality via their product choices, originators reveal some of the information taken in on the mortgage application but not included in the published loan data via the rates they charge borrowers. Specifically, borrowers who receive mortgage rates significantly above or below that which a standard prime borrower with similar loan size would have received for the same mortgage product tend to perform worse or better, respectively, than other observable indicators of performance would indicate. For example, even though borrowers with interest only mortgages (IOs) tend to perform worse than borrowers with amortizing mortgages, a borrower with an IO who paid no premium over the prevailing prime mortgage rate is likely to be a better credit than an otherwise identical borrower with a 30-year amortizing mortgage who paid a 75bp premium over the prime mortgage rate.[3]

[3] Mortgages with initial interest-only periods or 40-year amortization schedules typically cost the borrower an additional 25bp in rate. Thus, a borrower with an IO who receives the standard prime rate has a 100bp better SATO than a borrower with a 30-year amortizing mortgage who paid a 75bp premium at origination.

- **Payment shocks/payment changes**: Changes in monthly payments enter the model in two ways. The initial payment shock associated with a resetting ARM or recasting option ARM produces a short-lived spike in always current to delinquent roll rates, while the longer-term effect of the payment increase is captured in the model through a factor that measures the cumulative change in payment since origination. This treatment of payment changes allows us to more effectively capture both the large spike in delinquency rates that immediately follows a sudden increase in monthly payment as well as the long-run effect of the payment increase (Figure 9).

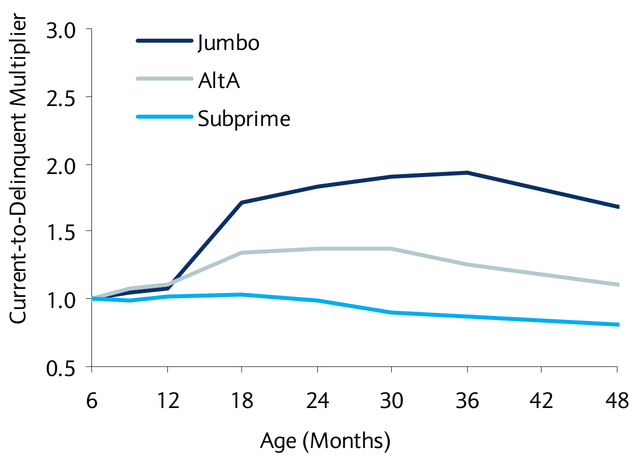
- **Recent home price appreciation**: In addition to their effect on UCLTV, home prices enter the model directly as well. In particular, y/y trends in zip code level home prices are used as an indicator of the strength or weakness of local housing markets. Even after adjusting for changes in UCLTV, periods of rapid home price appreciation are associated with improved credit performance, while periods of home price decline tend to exacerbate already-high delinquency rates.

- **Unemployment rates**: The model also uses the cumulative change since origination in the MSA-level unemployment rate to proxy for changes in a borrower's ability to continue making payments on his mortgage. This differs significantly from using the absolute level of the unemployment rate because it implies that underwriting standards are pro-cyclical and therefore that borrowers originated during a recession will tend to perform better during a recession than borrowers underwritten during a boom. Not surprisingly, the data appear to support this approach.

- **Consecutive payments made**: For an always current borrower, loan age is synonymous with the number of consecutive payments made since origination. The seasoning curve for an always current borrower can therefore be interpreted as measuring the extent to which maintaining a clean pay history improves a borrower's performance relative to his original credit score.  The curves in Figure 10 display the probability of transitioning from always current to delinquent at each age (i.e., number of consecutive payments made) relative to the half year mark after origination. For subprime borrowers, the curves quickly start to decline, suggesting that for borrowers with low original FICO scores, making two or more years of consecutive payments is indicative of improving credit quality and hence higher current FICO scores. Prime borrowers, in contrast, often

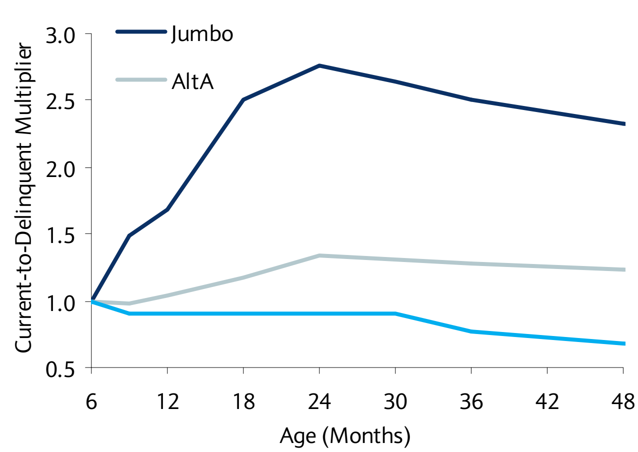
**Figure 10: Positive self-selection among always current borrowers by non-agency sector**

a. Fixed Rate




Roll rates are shown as multiples of the case where loan age = 6 months
Source: Barclays Capital

b. ARM




Roll rates are shown as multiples of the case where loan age = 6 months
Source: Barclays Capital

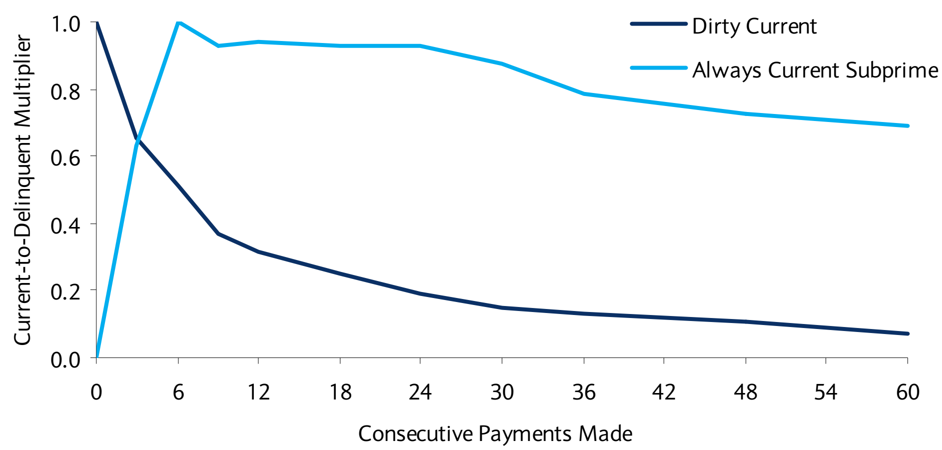
have FICO scores of 740 or higher at origination. Thus, while making even several years of payments is unlikely to materially increase their FICO scores, the passage of time increases the possibility of income shocks that could lower them.

## Later stage delinquencies and cures

### *Dirty current to delinquent roll rates*

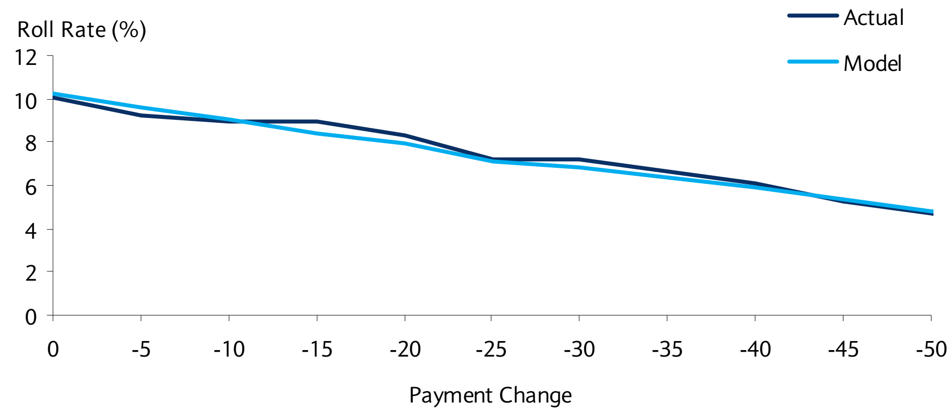
As Figure 3 illustrates, borrowers who are up to date on their payments but have checkered pay histories are much more likely to become delinquent than borrowers with similar collateral characteristics who have never been delinquent. The negative signal contained in the previous delinquency manifests itself not just in a higher base case delinquency rate but also in a significantly reduced sensitivity to the primary drivers of always current to delinquent roll rates. This point is illustrated in Figures 4a and 4b, which compare the effects of FICO and UCLTV on the current to delinquent roll rates of always current and dirty current borrowers. The positive signal of providing full documentation at origination is also reduced once a borrower has gone OTS 30-days delinquent for the first time. What matters most in the case of dirty current borrowers is precisely the factor that seemed to be least predictive for always current borrowers, namely the number of consecutive payments made since becoming current (Figure 11). Future delinquencies are also reduced by the magnitude of any payment reductions resulting from loan modifications (Figure 12).

**Figure 11: Pay history and positive self-selection, always current versus dirty current**




Note: DCUR-to-DQ roll rates are shown as multiples of the case where consecutive payments made = 0
ACUR-to-DQ roll rates are shown as multiples of the case where consecutive payments made = 6
Source: Barclays Capital

**Figure 12: Effect of payment reductions on dirty current to delinquent roll rates, all non-agency**



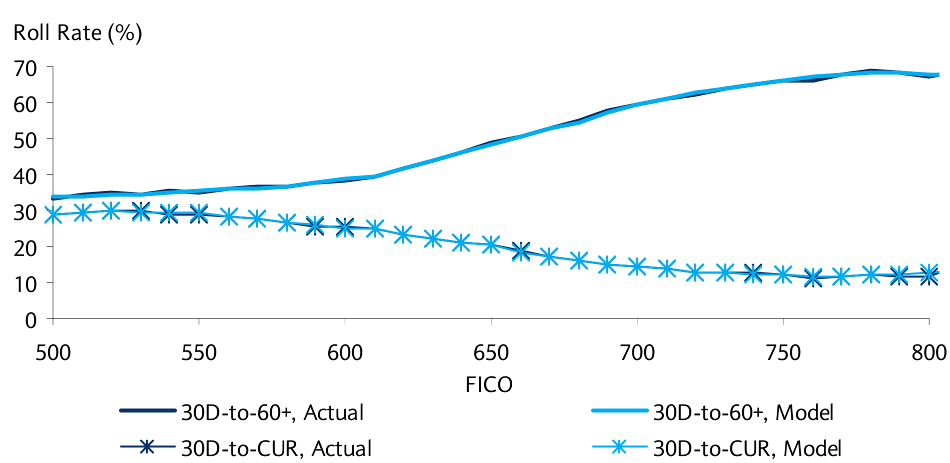

Source: LoanPerformance, Barclays Capital

*Delinquencies and cures from 30D, 60+ and foreclosure*

For delinquent borrowers, the usual correlation between credit performance and FICO score at origination becomes inverted and borrowers with large loan sizes struggle under the weight of their outsized monthly payments. UCLTV and recent payment behaviour are the most important drivers of future performance for delinquent borrowers.

- **FICO Reversal**: One of the more striking observations about the performance of delinquent borrowers is that borrowers with high FICO scores at origination are less likely to cure themselves back to a non-delinquent state than borrowers with lower FICO scores at origination (Figure 13). The reason for this is that borrowers with low FICO scores, such as subprime borrowers, have a history of cycling in and out of delinquency depending on their immediate income and employment situation and most likely received a mortgage sized to their more volatile incomes and smaller savings. In contrast, high FICO borrowers who become severely delinquent are likely to have suffered a more significant reduction in income and wealth and are therefore less likely to recover.

**Figure 13: Transitions out of OTS 30-days delinquent by FICO score, excluding modifications, all non-agency**

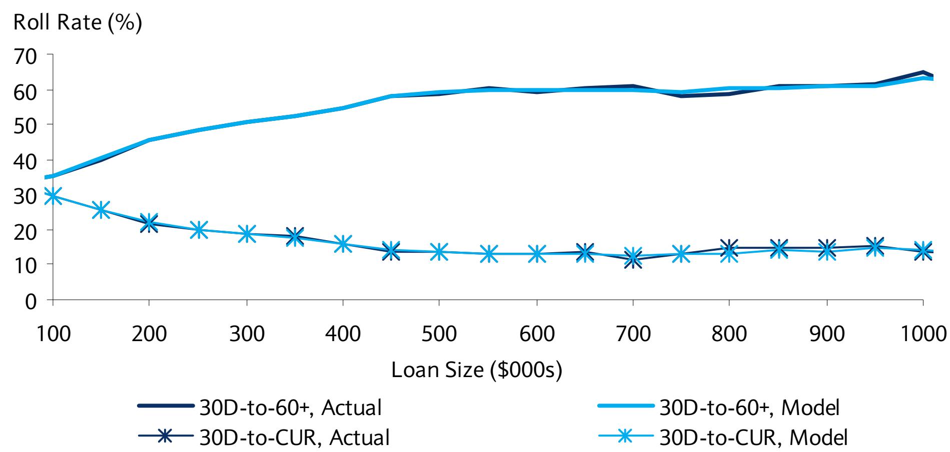



Source: LoanPerformance, Barclays Capital

- **Loan size**: Similar to the case of FICO scores, borrowers with large mortgages, and therefore high monthly mortgage payments, are less likely to cure than borrowers with smaller mortgages (Figure 14). Once again, the issue is that borrowers with large loan sizes are more likely to have suffered an income loss that makes their current mortgage burden unsustainable.

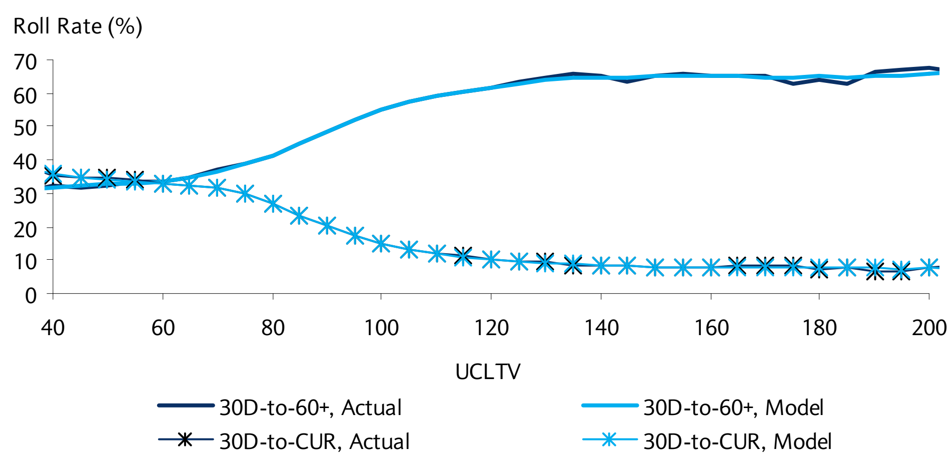
- **UCLTV**: The effect of borrower equity, while muted relative to its effect on initial delinquency remains intact once borrowers become delinquent (Figure 15). Specifically, borrowers with little or no equity in their properties (UCLTV>=100) are much less likely to cure their delinquency than borrowers with a substantial equity stake.

**Figure 14: Transitions out of OTS 30-days delinquent by loan size, excluding modifications, all non-agency**




Source: LoanPerformance, Barclays Capital

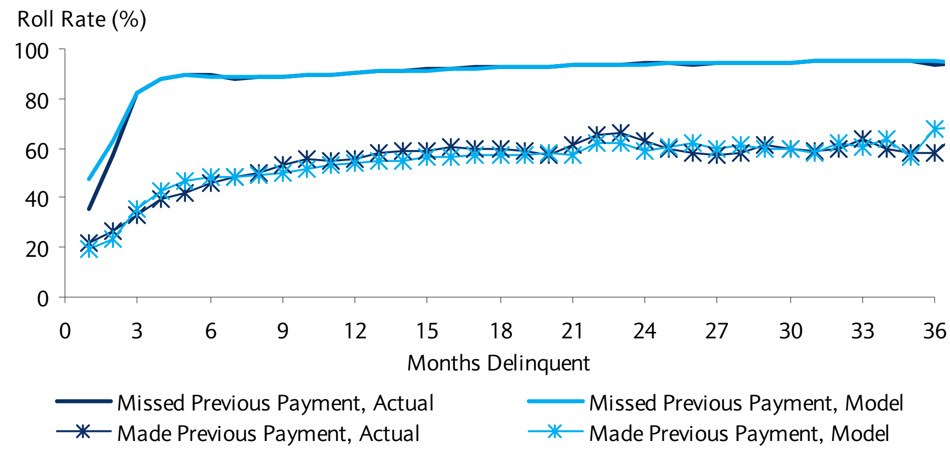
**Figure 15: Transitions out of OTS 30-days delinquent by UCLTV, excluding modifications, all non-agency**




Source: Loan Performance, Barclays Capital

**Months delinquent and recent pay history**: One of the most important pieces of information for determining whether a borrower is likely to cure his delinquency or pass through the foreclosure process is the number of payments missed and recent payment behaviour (Figure 16). Borrowers who have made payments recently are much less likely to miss their next payment than borrowers who have not been cash flowing. This is true even in cases where the borrower is many months (or even years) behind on his payments.

**Figure 16: Delinquency performance of mortgages in foreclosure by months delinquent and recent pay history, all non-agency**




Roll rate measures the likelihood of missing an additional payment while in foreclosure.
Source: LoanPerformance, Barclays Capital

## Servicer responses to borrower delinquencies

Once a borrower is delinquent, the three main options available to servicers are: 1) trying to "cure" the borrower back to a non-delinquent status, most likely via a loan modification; 2) facilitating a short sale in which the borrower sells the property and the servicer agrees to accept the net sale proceeds as payment on the outstanding mortgage, relieving the borrower of the responsibility of making up any shortfall;[4] or 3) initiating a foreclosure proceeding.

### Modification

The implementation of the Home Affordable Modification Program (HAMP) since mid-2009 means that virtually all delinquent mortgages are screened for modification as an alternative to foreclosure. To qualify for a HAMP modification, borrowers must use the mortgaged property as their primary residence and be able to document a loss of income as the cause of the delinquency. The modification must also pass an NPV test as the most profitable alternative from the standpoint of the mortgage holder, although in practice this does not seem to be a particularly onerous hurdle. While HAMP does not limit the ability of servicers to modify non-HAMP-eligible mortgages, HAMP guidelines provide some indication of the types of mortgages that tend to get modified.

[4] The servicer could also accept deed to the property, absolving the borrower of any further obligation, and then sell the property without any borrower participation. This is referred to as a deed-in lieu of foreclosure.

Figure 17: Modification rates by occupancy, documentation and delinquency status, ULTV>100

| | Owner Occupied | | Non Owner Occupied | |
|---|---|---|---|---|
| Starting Delinquency Status | Full Doc | Lim Doc | Full Doc | Lim Doc |
| Always Current, Never Modified | 0.09 | 0.10 | 0.05 | 0.06 |
| Dirty Current, Never Modified | 1.70 | 1.54 | 0.67 | 0.65 |
| OTS 30D | 1.64 | 1.21 | 0.49 | 0.25 |
| OTS 60+ | 2.58 | 1.79 | 0.75 | 0.71 |
| Foreclosure | 0.55 | 0.45 | 0.06 | 0.08 |

Source: LoanPerformance, Barclays Capital

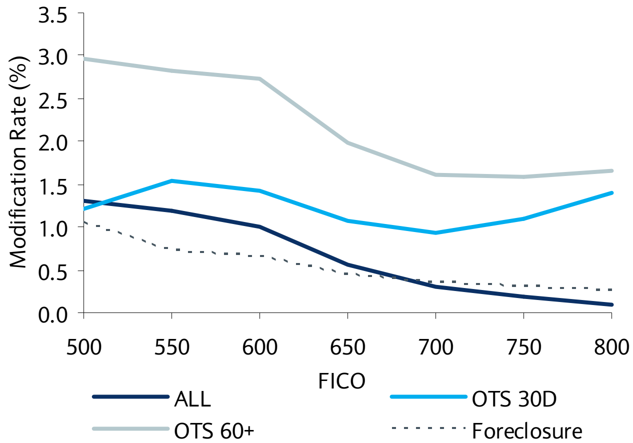
For example, modification rates are much higher for owner-occupied properties than for investment properties and are higher for full-documentation loans than for limited-documentation loans (Figure 17). This latter effect may reflect the fact that many limited-documentation borrowers significantly overstated their incomes at origination and so would require much larger payment reductions than full-documentation borrowers to make their homes affordable. Moreover, occupancy fraud is probably more pronounced in limited documentation mortgages. We control for occupancy and documentation type in our modification model. Modification rates also appear to be correlated with ULTV and FICO at origination, but a significant portion of this correlation is driven by the fact that the vast majority of modifications are for delinquent borrowers (as would be expected) and delinquency status is highly correlated with ULTV and original FICO (Figure 18). That said, modification rates are higher for low-FICO borrowers, even after adjusting for delinquency status, but much of this is probably because low-FICO borrowers tend to have much lower loan sizes than average, making the fixed costs of liquidation particularly onerous. Similarly, even after controlling for delinquency status, modification rates are lower for borrowers with ULTVs that are low enough to make a property sale a viable option. For those loans that are modified, payment reductions average 30-40%, with most of this coming from mortgage rate reductions (Figure 19). Balance forgiveness/forbearance seems to be much less prevalent, except in cases where the modified borrower's pre-modification mortgage rate is already very low, as is currently the case for most option ARMs .

## Short sale

In cases where a loan modification is deemed unfeasible because the payment reduction required to keep the borrower in the house would entail a greater loss than an REO liquidation, the next most preferred outcome from the standpoint of the mortgage holder would be a short sale. Short sales take less time than REO liquidations, have lower associated costs, and require that the borrower maintain the property in good condition until a sale is completed. However, they can be less attractive than foreclosure for those borrowers who have given up on keeping their homes. This is because a drawn-out foreclosure process can leave the borrower living rent-free for many months, or even years.

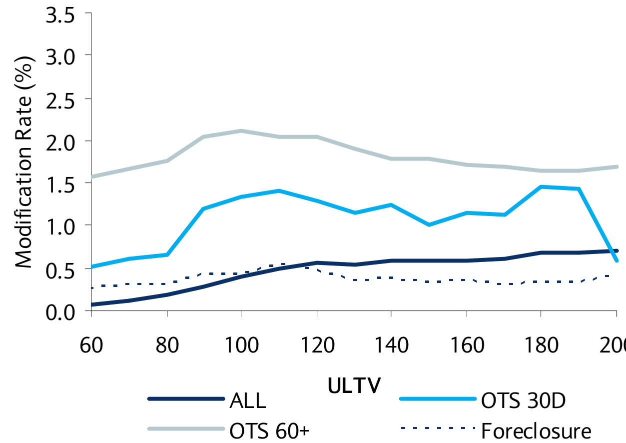
**Figure 18: Modification rates by FICO and ULTV, July 2009-August 2010, all non-agency**

a. FICO




Source: LoanPerformance, Barclays Capital

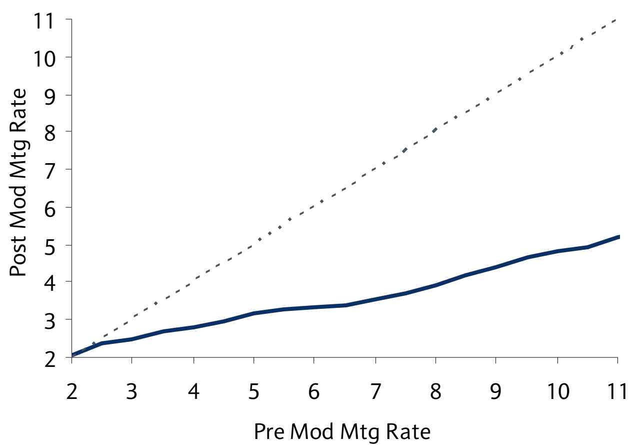
b. ULTV




Source: LoanPerformance, Barclays Capital

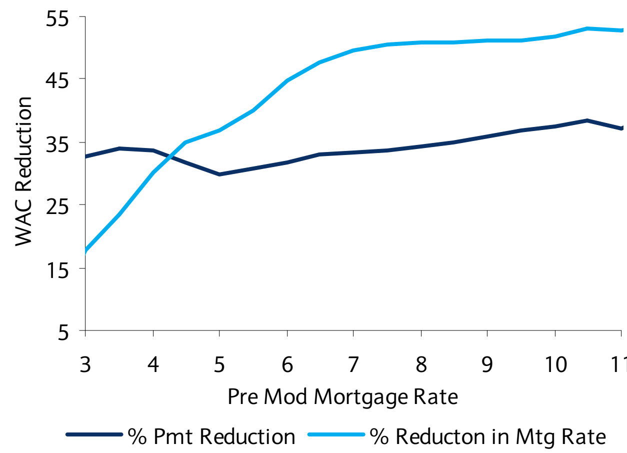
**Figure 19: Effect of modification on mortgage rates and monthly payments, July 2009-August 2010, all non-agency**

a. Post-Mod Mortgage Rate vs. Pre-Mod Mortgage Rate




Source: LoanPerformance, Barclays Capital

b. Percent Reduction in Payment and Mortgage Rate vs. Pre-Mod Mortgage Rate




Source: LoanPerformance, Barclays Capital

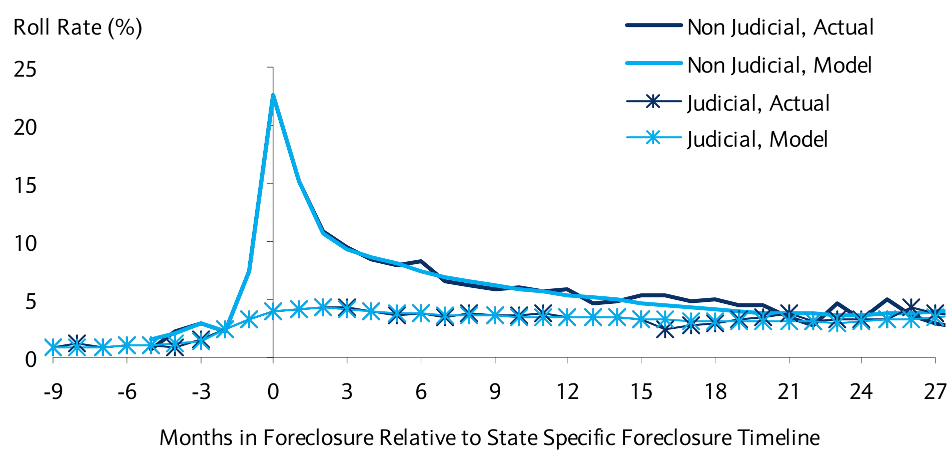
## Foreclosure

Even with recent increases in the use of loan modifications and short sales, the majority of borrowers who become seriously delinquent end up in foreclosure. While this removes much of the uncertainty about the ultimate outcome, the rate at which mortgages pass from initial delinquency through foreclosure to liquidation and the costs incurred by servicers along the way can vary widely. The primary source for much of the variation is due to differences in the time required to foreclose on properties located in states with judicial versus non-judicial foreclosure laws. In states where non-judicial foreclosures are the norm, servicers can complete a foreclosure quickly and with few legal hurdles. By comparison, in states where foreclosure proceedings are conducted in the courts and are more likely to face legal challenges from borrowers, the time to foreclose on a property is typically much longer and more open ended. We capture this by modelling the foreclosure to REO transition for non-cash-flowing borrowers as a function of the amount of time that the borrower has been in foreclosure relative to the typical time to foreclose in the state where the foreclosed property is located. In addition, we estimated separate timing curves for judicial and non-judicial states to allow for the more open ended timelines in judicial states (Figure 20). The model also incorporates the effect of the nationwide slowdown in foreclosures on the rate at which severely delinquent borrowers transition through the foreclosure process (Figure 21).

## Second lien charge-off policy

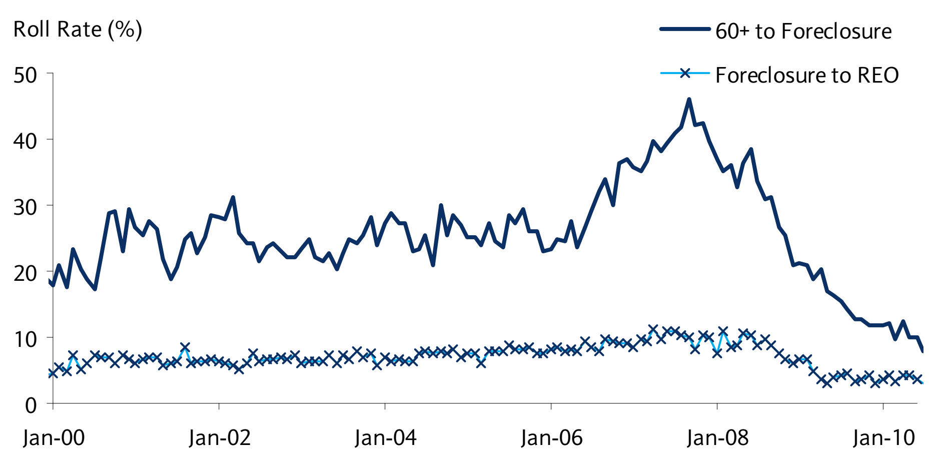
Most second-lien securitizations issued during the mortgage boom require servicers to charge off loans that become more than 180 days delinquent. As a result, very few second liens securitized into standalone deals transition from 60+ to foreclosure. To model this correctly, we estimated separate 60+ to liquidation (DD60P) and 60+ to foreclosure (CFC60P) transition functions for second lien mortgages included in standalone deals relative to other second liens. This allows us to capture the large spike in liquidations out of 60+ when the former pass the 180 day delinquent threshold while still managing to fit the more muted liquidation profile of second lien mortgages included in subprime securitizations (Figure 22).

**Figure 20: Foreclosure to REO transitions by months in state minus state-specific foreclosure timeline, judicial vs. non-judicial states, all non-agency**



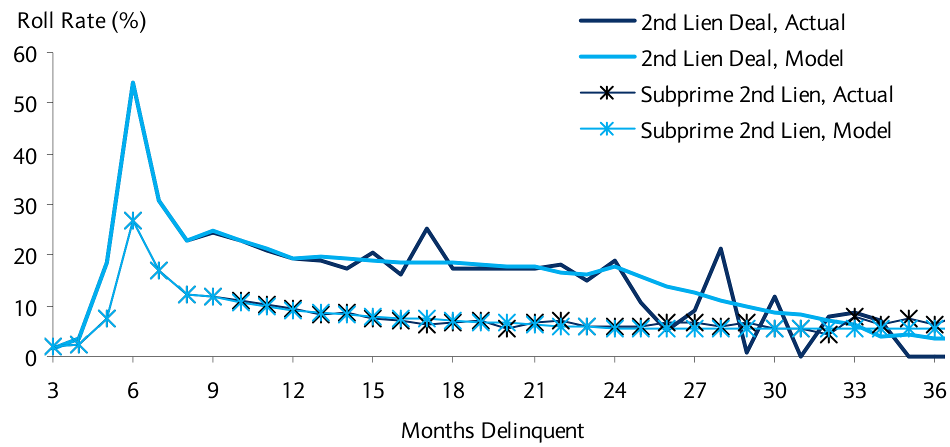

Source: LoanPerformance, Barclays Capital

**Figure 21: Changes in OTS 60+ to foreclosure and foreclosure to REO transition rates, excluding modifications, non-cash flowing mortgages**




Source: Loan Performance, Barclays Capital

Figure 22: OTS 60+ to liquidation transition rates for second liens




Source: LoanPerformance, Barclays Capital

## Loss severity

The dollar loss suffered by non-agency MBS investors when a delinquent mortgage is liquidated is equal to the unpaid principal balance on the mortgage (B) plus any reimbursements due the servicer (PI + TIM + FCOST) minus the net proceeds received from the sale of the property (H) along with any payouts received from mortgage insurance policies taken out at origination (MI). The primary expenses for which servicers need to be reimbursed include all principal and interest advanced to the trust prior to liquidation of the property (PI), property taxes, hazard insurance premiums and maintenance costs paid by the servicer (TIM), and legal fees and other administrative expenses incurred by the servicer during the foreclosure process (FCOST). It follows that the associated loss severity (S) can be represented in equation form as follows:

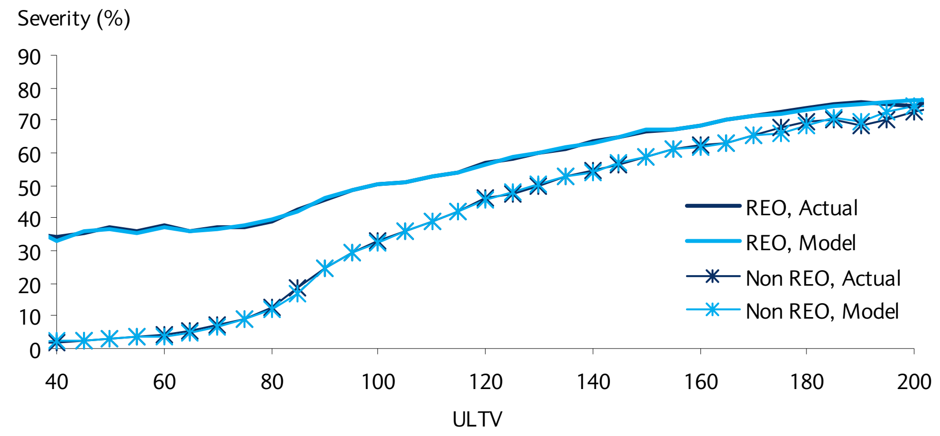
$$S = \frac{B + PI + TIM + FCOST - H - MI}{B}$$

The Barclays Capital Loan Transition Model takes each of these items into consideration along with several additional factors when calculating loss severities.

- **Updated LTV (ULTV)**: The most important determinant of loss severity for a first lien mortgage is the liquidated value of the property relative to the unpaid balance on the mortgage. This is given in the above equation by the H/B term which, in turn, is just 1 /ULTV. The ULTV used in the calculation of severity employs the same zip code level home price indices drawn on elsewhere in the model. For REO liquidations, a calculated ULTV below 100 suggests that the home price index used is overstating the liquidation value of the property (otherwise the borrower would have sold the house, paid off the mortgage and kept the profit). A calculated ULTV well above 100, in contrast, signifies a sharp fall in local home prices consistent with mass foreclosures. In these situations, home price indices are less likely to overstate the true value of REO liquidations.[5] Consequently, observed severities on REO liquidations tend to be much higher than implied by standard home price indices when ULTV<<100 and more in line with home

[5] To the contrary, REO liquidations may actually represent a significant portion of the transactions used to construct the index in these situations.

Figure 23: Sensitivity of loss severity to ULTV, REO vs. non-REO liquidations, all non-agency




ULTV is the updated LTV (not combined LTV) Source: LoanPerformance, Barclays Capital

price index implied severities when ULTV >>100. To address this issue, we estimated separate LTV functions for REO and non-REO liquidations. This allows us to capture both the flatter ULTV profile of REO liquidations and the convergence in severity between REO and non-REO liquidations for extremely high values of ULTV (Figure 23).

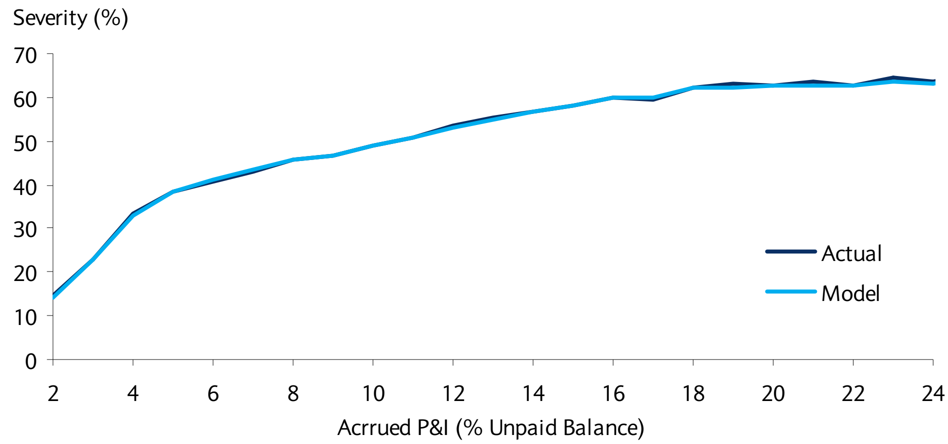
- **Servicer advances**: The severity model incorporates projected principal and interest advances into the calculation of loan-level losses. As a result, factors that slow down the foreclosure process – such as the longer foreclosure timelines in judicial states – or discourage non-REO liquidations – such as a lack of borrower equity in the property – automatically increase total principal and interest advances and resulting severities. For loans where accrued principal and interest reaches extremely high levels, the effect on severities starts to diminish both in the data and in our model, reflecting a potential reduction in servicer advances (Figure 24). The model also takes into account other advances such as property taxes, hazard insurance, and maintenance fees (TIM/B in the above equation), which tend to be proportional to original property value rather than mortgage size.

- **Loan size**: Because many of the legal fees and other administrative costs incurred by servicers during the foreclosure process are unrelated to the size of the underlying mortgage, they increase severities much more for small loans than for larger loans (FCOST/B). We capture this effect by including loan size as a factor in our severity model.

- **Mortgage insurance**: With mortgage insurance companies struggling under the weight of existing policies, rescission rates have increased markedly. We estimate that higher rescission rates have increased severities by 7-14 percentage points on mortgages with MI and incorporate this into our severity projections.

- **Occupancy and loan purpose**: Non-owner occupied properties, and in particular investment properties, tend to produce higher severities than owner occupied properties. This occurs because the borrower's decision to not sell the property prior to liquidation is more revealing about the resale value of the property than when it is the primary residence of the delinquent borrower. Similarly, since the original LTVs of refinanced properties are the result of appraisals rather than arms-length transactions, they tend to overstate the initial value of a property, leading to higher severities in the event of default.

Figure 24: Sensitivity of loss severity to accrued principal and interest, all non-agency




Source: LoanPerformance, Barclays Capital

## Prepayments

The notable tightening of mortgage underwriting guidelines in terms of restrictions on borrower DTI, FICO and LTV, along with significantly more onerous documentation requirements and higher out-of-pocket costs, have significantly dampened prepayment rates on even the most refinanceable borrowers. This observation is made abundantly clear in Figure 25, which compares the recent refinancing response of high quality non-agency borrowers with that of similar borrowers during the refinancing episode of 2002-2003. During the earlier episode, fixed rate borrowers with clean pay histories, original FICO>=760, UCLTV<=70 and mortgage rates 100bp or more above prevailing mortgage rates prepaid at speeds greater than 80 CPR. In contrast, the current low mortgage rate environment has generated prepayment rates of only 30-40 CPR for borrowers with similarly pristine characteristics and large rate incentives. Just as striking is the fact that even minor deviations in FICO and UCLTV significantly reduce the already depressed prepayment rates observed for the highest quality borrowers – for example, fixed rate borrowers with clean pay histories, FICO at origination between 720 and 760, UCLTV between 70 and 80 and 150bp of rate incentive have prepaid at less than 20 CPR over the past year and a half.

Our prepayment model incorporates today's tighter underwriting guidelines into its projections of future prepayments. In addition to FICO at origination, UCLTV, documentation type and occupancy type, the prepayment model utilizes information on borrower pay history, modification history and GSE loan size limits in its projections.

- **FICO at origination and UCLTV**: Consistent with the tighter underwriting guidelines that have replaced the go-go years of the housing boom, deviations in any direction from a high FICO, low UCLTV profile significantly reduce rate-term and cash-out refinancing in the prepayment model. UCLTV also significantly reduces projected turnover related prepayments for borrowers with little or no equity in their property.
- **Loan size**: Borrowers with mortgage balances that exceed county-level GSE loan size limits are assumed to face much higher mortgage rates than borrowers with GSE eligible loan sizes. This effect is gradually reduced over time in model projections in anticipation of an eventual return of jumbo-conforming mortgage rate spreads to levels more consistent with a normally functioning mortgage market.

- **Pay history**: Borrowers with recent delinquencies are assumed to have little to no ability to refinance in the near term but can "cure" themselves by maintaining a clean payment profile for several years.
- **Occupancy and documentation type**: Mortgages on investment properties and mortgages where the borrower provided less than full documentation of income and assets are assumed to have much more muted refinancing profiles than full documentation mortgages on owner-occupied properties.

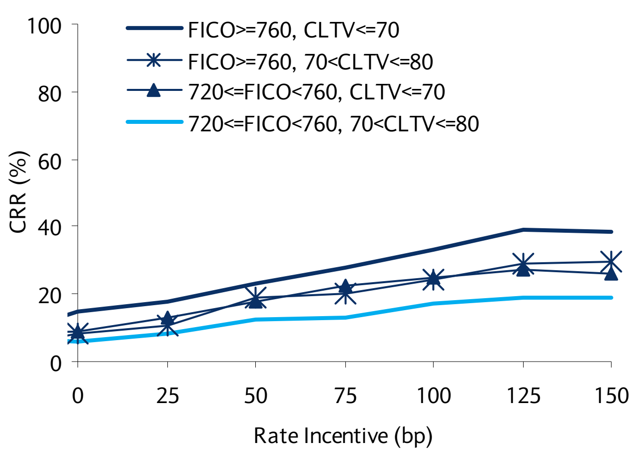
## Home prices

### Zip code versus state- and MSA-level home price indices

LTVs are marked-to-market in the model using zip code level home price indices provided by Core Logic. The model also uses y/y trends in zip code level home prices to track the strength or weakness of local housing markets. Using zip code level prices improves the accuracy of the calculations over using state or MSA level home prices. This is demonstrated in Figure 26, which compares average home price declines for 2006 originated non-agency mortgages calculated using state, MSA and zip code level home price indices. When measured at the zip code level, the home prices of jumbo fixed rate borrowers in California fell 10.7 percentage points less than for California subprime borrowers (-31.6% vs. -42.3%). This compares with a 7.1 percentage point smaller decline when measured using MSA level home prices (-33.6% vs. -40.1%) and no difference when measured using state level home prices (-35.9% for both). Even more telling than differences in average declines is the within-MSA variation displayed in the right-hand side of Figure 26, which shows that the home price declines of the top and bottom 10% of zip codes within an MSA typically differed by 13-15 percentage points. Given the importance allocated to home prices within most credit models, differences of this magnitude are too large to ignore.

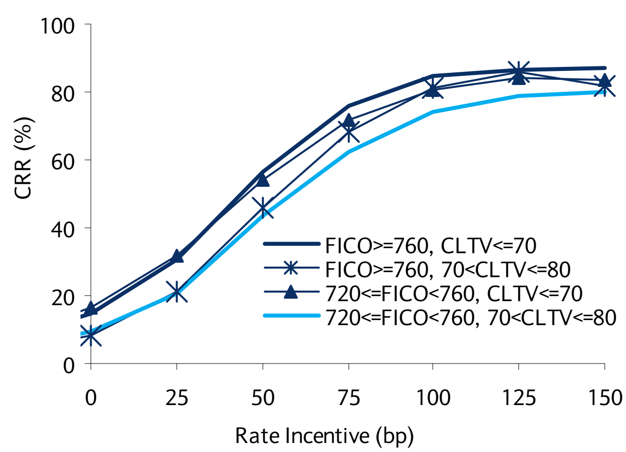
**Figure 25: Sensitivity of prepayments to credit characteristics, always current, fixed-rate mortgages with current loan size $417K-$729K**

2009-2010




Source: LoanPerformance, Barclays Capital

2002-2003




Source: LoanPerformance, Barclays Capital

**Figure 26: Comparison of zip code vs. state- and MSA-level home price indices, 2006 originations**

| | Cum HPA, Jan 2007 - Sep 2010 | | | Zip Code Level Variation within MSAs | | |
|---|---|---|---|---|---|---|
| | | | | | Diff from MSA Cum HPA | |
| Region | State | MSA | Zip | Std. Dev | 10th Pctl | 90th Pctl |
| US | | | | | | |
| Jumbo Fixed | -27.4 | -26.8 | -25.1 | 9.9 | -6.4 | 6.5 |
| Jumbo Hybrid | -30.7 | -28.9 | -26.9 | 10.3 | -6.7 | 6.6 |
| AltA Fixed | -26.2 | -26.5 | -27.3 | 7.0 | -8.5 | 6.1 |
| AltA Hybrid | -31.4 | -31.9 | -32.6 | 7.2 | -8.3 | 6.1 |
| AltA NegAm | -34.1 | -34.8 | -35.8 | 6.9 | -8.6 | 6.1 |
| Subprime | -27.8 | -28.9 | -30.8 | 5.6 | -9.3 | 5.9 |
| CA | | | | | | |
| Jumbo Fixed | -35.9 | -33.6 | -31.6 | 10.4 | -6.6 | 6.8 |
| Jumbo Hybrid | -35.9 | -32.0 | -29.9 | 11.0 | -7.4 | 7.1 |
| AltA Fixed | -35.9 | -37.4 | -38.0 | 7.6 | -8.8 | 6.6 |
| AltA Hybrid | -35.9 | -36.5 | -37.0 | 8.2 | -8.4 | 6.6 |
| AltA NegAm | -35.9 | -36.8 | -37.9 | 7.4 | -9.2 | 6.5 |
| Subprime | -35.9 | -40.1 | -42.3 | 5.1 | -10.3 | 6.1 |

Source: LoanPerformance, Barclays Capital

## Projected defaults and losses across US HPA scenarios

Figure 27 displays state-level HPA projections for key states across a range of national HPA scenarios. These were calculated using the Barclays Capital Regional Home Price Model under the assumption that US home prices evolve as shown in each of the five scenarios displayed in the figure. The base case assumes that home prices fall another 2.5% nationally over the next year before stabilizing and eventually growing at a long-run rate of approximately 3.5% per year after 2015. Home prices in the boom-bust states of California, Arizona, and Florida are expected to fall by more than the national average in the stress scenarios and increase by more than the national average in the recovery scenarios. In contrast, home prices in Texas, which was less affected by the housing market boom and bust, are expected to continue to display less sensitivity to national home price cycles, falling by less than the average in the stress scenarios and rising less than the average in the recovery scenarios. Figure 28 displays how these differences in home price appreciation rates across the various scenarios affect projected cumulative defaults and losses across the non-agency sector. Not surprisingly, defaults are lowest on the cleanest collateral types and most seasoned vintages, which have the highest percentages of always current borrowers and the lowest updated LTVs. These same cohorts are also the ones that are the most adversely affected in the stress scenarios. For example, between the base case and severe stress scenarios, Jumbo prime loans originated in 2007 see cumulative defaults increase by 43% (from 28.8% to 41.2%). In contrast, subprime loans originated in 2007 see cumulative defaults increase by just 7% (from 73.4% to 78.7%). Conversely, the recovery scenarios help the credit performance of cleaner credits more as well.

Figure 27: State-level home prices across US HPA scenarios

| | Annualized Home Price Appreciation | | | | | | | | Cumulative Home Price Appreciation[1] | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | US | AZ | CA | FL | MI | NV | NY | TX | US | AZ | CA | FL | MI | NV | NY | TX |
| **History** | | | | | | | | | | | | | | | | |
| Jan 2000 - Jun 2006 | 11.3 | 13.5 | 15.8 | 15.9 | 3.1 | 13.7 | 12.2 | 5.2 | 99.2 | 125.0 | 156.7 | 157.3 | 21.7 | 128.5 | 109.3 | 38.1 |
| Jun 2006 - Dec 2010 | -7.8 | -14.3 | -10.7 | -13.6 | -11.6 | -16.1 | -3.3 | -1.8 | -30.5 | -50.0 | -39.9 | -48.2 | -42.7 | -54.7 | -13.9 | -7.8 |
| **Strong Recovery** | | | | | | | | | | | | | | | | |
| 2011 | 5.6 | 9.2 | 8.8 | 8.8 | 7.3 | 10.4 | 4.8 | 2.8 | 5.6 | 9.2 | 8.8 | 8.8 | 7.3 | 10.4 | 4.8 | 2.8 |
| 2012 | 6.7 | 8.1 | 8.0 | 10.4 | 9.3 | 11.1 | 6.1 | 3.6 | 12.6 | 18.1 | 17.5 | 20.2 | 17.3 | 22.7 | 11.3 | 6.5 |
| 2013 | 4.8 | 5.0 | 3.8 | 6.2 | 9.5 | 8.2 | 3.6 | 3.4 | 18.0 | 24.0 | 21.9 | 27.6 | 28.4 | 32.7 | 15.2 | 10.1 |
| 2014 | 4.3 | 4.2 | 3.4 | 5.4 | 7.7 | 5.5 | 3.3 | 2.9 | 23.1 | 29.3 | 26.1 | 34.5 | 38.2 | 40.0 | 19.0 | 13.3 |
| 2015 | 4.1 | 3.6 | 3.3 | 4.8 | 6.4 | 3.8 | 3.5 | 3.2 | 28.2 | 33.9 | 30.2 | 41.0 | 47.1 | 45.3 | 23.2 | 17.0 |
| 2016-2020 | 3.5 | 3.2 | 3.6 | 4.0 | 3.9 | 3.1 | 3.8 | 3.2 | 52.2 | 56.8 | 55.1 | 71.1 | 78.0 | 68.9 | 48.7 | 36.9 |
| **Recovery** | | | | | | | | | | | | | | | | |
| 2011 | 2.6 | 4.8 | 4.0 | 4.5 | 5.4 | 6.4 | 1.9 | 1.2 | 2.6 | 4.8 | 4.0 | 4.5 | 5.4 | 6.4 | 1.9 | 1.2 |
| 2012 | 3.6 | 4.2 | 3.5 | 6.3 | 7.6 | 7.2 | 3.0 | 2.0 | 6.3 | 9.1 | 7.6 | 11.1 | 13.5 | 14.0 | 4.9 | 3.2 |
| 2013 | 4.8 | 5.0 | 4.0 | 6.2 | 9.3 | 8.2 | 3.8 | 3.1 | 11.4 | 14.6 | 11.8 | 18.0 | 24.1 | 23.4 | 8.9 | 6.5 |
| 2014 | 4.3 | 4.0 | 3.2 | 5.2 | 8.1 | 5.4 | 3.4 | 3.1 | 16.2 | 19.1 | 15.4 | 24.1 | 34.2 | 30.0 | 12.5 | 9.7 |
| 2015 | 4.1 | 3.5 | 3.1 | 4.7 | 6.6 | 3.8 | 3.5 | 3.3 | 20.9 | 23.3 | 19.0 | 29.9 | 43.1 | 34.9 | 16.5 | 13.3 |
| 2016-2020 | 3.5 | 3.2 | 3.5 | 3.9 | 3.9 | 3.0 | 3.8 | 3.2 | 43.5 | 44.2 | 41.6 | 57.6 | 73.1 | 56.7 | 40.5 | 32.5 |
| **Base Case** | | | | | | | | | | | | | | | | |
| 2011 | -2.5 | -2.5 | -4.1 | -2.5 | 2.3 | -0.3 | -3.2 | -1.5 | -2.5 | -2.5 | -4.1 | -2.5 | 2.3 | -0.3 | -3.2 | -1.5 |
| 2012 | 1.6 | 1.8 | 0.4 | 3.4 | 6.6 | 4.5 | 0.8 | 0.9 | -0.9 | -0.8 | -3.7 | 0.8 | 9.0 | 4.2 | -2.4 | -0.6 |
| 2013 | 3.8 | 4.1 | 2.8 | 5.1 | 8.2 | 6.9 | 2.8 | 2.3 | 2.8 | 3.2 | -0.9 | 6.0 | 17.9 | 11.4 | 0.3 | 1.6 |
| 2014 | 4.3 | 3.8 | 3.1 | 5.0 | 8.6 | 5.3 | 3.4 | 3.1 | 7.3 | 7.2 | 2.1 | 11.2 | 28.0 | 17.3 | 3.8 | 4.8 |
| 2015 | 4.1 | 3.5 | 3.0 | 4.6 | 7.0 | 3.8 | 3.5 | 3.3 | 11.7 | 10.9 | 5.1 | 16.3 | 36.9 | 21.8 | 7.4 | 8.2 |
| 2016-2020 | 3.5 | 3.2 | 3.5 | 3.9 | 3.9 | 3.0 | 3.8 | 3.2 | 32.4 | 29.6 | 25.0 | 41.0 | 65.6 | 41.4 | 29.4 | 26.5 |
| **Stress** | | | | | | | | | | | | | | | | |
| 2011 | -7.0 | -8.0 | -11.2 | -8.6 | -1.0 | -6.1 | -8.1 | -4.1 | -7.0 | -8.0 | -11.2 | -8.6 | -1.0 | -6.1 | -8.1 | -4.1 |
| 2012 | -1.9 | -3.1 | -5.0 | -1.5 | 4.3 | -0.3 | -2.8 | -1.2 | -8.8 | -10.8 | -15.7 | -10.0 | 3.2 | -6.3 | -10.7 | -5.3 |
| 2013 | 2.2 | 2.6 | 1.4 | 3.6 | 6.2 | 5.5 | 1.2 | 1.0 | -6.7 | -8.5 | -14.5 | -6.7 | 9.6 | -1.2 | -9.6 | -4.3 |
| 2014 | 3.8 | 3.5 | 2.9 | 4.6 | 7.8 | 4.9 | 3.0 | 2.5 | -3.2 | -5.4 | -12.0 | -2.5 | 18.2 | 3.6 | -6.9 | -1.9 |
| 2015 | 4.1 | 3.5 | 3.2 | 4.6 | 7.1 | 3.8 | 3.5 | 3.1 | 0.8 | -2.1 | -9.2 | 2.0 | 26.7 | 7.6 | -3.6 | 1.1 |
| 2016-2020 | 3.4 | 3.1 | 3.4 | 3.8 | 3.9 | 2.9 | 3.7 | 3.2 | 19.2 | 13.9 | 7.3 | 23.0 | 53.3 | 24.3 | 15.8 | 18.2 |
| **Severe Stress** | | | | | | | | | | | | | | | | |
| 2011 | -9.5 | -11.0 | -15.1 | -11.7 | -3.4 | -9.1 | -10.9 | -5.7 | -9.5 | -11.0 | -15.1 | -11.7 | -3.4 | -9.1 | -10.9 | -5.7 |
| 2012 | -6.9 | -9.6 | -12.7 | -8.4 | 0.6 | -6.5 | -8.1 | -4.2 | -15.8 | -19.6 | -25.8 | -19.2 | -2.9 | -15.1 | -18.1 | -9.7 |
| 2013 | 0.7 | 0.8 | -0.7 | 1.6 | 5.2 | 3.6 | -0.2 | 0.0 | -15.2 | -19.0 | -26.3 | -17.8 | 2.1 | -12.1 | -18.3 | -9.6 |
| 2014 | 2.8 | 2.6 | 2.1 | 3.6 | 6.5 | 3.8 | 2.0 | 1.5 | -12.8 | -16.9 | -24.8 | -14.9 | 8.7 | -8.7 | -16.6 | -8.3 |
| 2015 | 4.1 | 3.6 | 3.5 | 4.6 | 7.3 | 3.7 | 3.6 | 3.0 | -9.2 | -13.9 | -22.1 | -10.9 | 16.7 | -5.3 | -13.6 | -5.6 |
| 2016-2020 | 3.3 | 2.9 | 3.2 | 3.7 | 3.9 | 2.8 | 3.6 | 3.1 | 6.9 | -0.5 | -8.7 | 6.6 | 41.3 | 8.8 | 3.3 | 10.2 |

Note: [1]For 2011 and beyond, scenario specific values of cumulative home price appreciation are calculated from Dec 2010.
Source: LoanPerformance, Barclays Capital

## Figure 28: Projected cumulative defaults and losses[1]

| | | | | OTS Delinquency Dist | | | Projected Future Defaults & Losses by HPA Scenario, % of Current Balance | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | % Always | %Dirty | % DQ incl | Severe Stress | | | Stress | | | Base Case | | | Recovery | | | Strong Recovery | | | Timing of Projected Future Base Case Losses[2] | | | | | |
| Sector | Issue Yr | Factor | UCLTV | Current | Current | FC/ REO | Default | Loss | Severity | Default | Loss | Severity | Default | Loss | Severity | Default | Loss | Severity | Default | Loss | Severity | Year 1 | Year 2 | Year 3 | Year 4 | Year 5 | Year 10 |
| Jumbo Fixed 30Y | 2004 | 0.31 | 70 | 92.4 | 3.2 | 4.4 | 12.5 | 4.8 | 38 | 9.2 | 2.9 | 32 | 7.1 | 1.8 | 26 | 6.2 | 1.3 | 21 | 5.8 | 1.1 | 18 | 0.2 | 0.6 | 1.1 | 1.4 | 1.6 | 1.8 |
| | 2005 | 0.51 | 95 | 86.6 | 4.3 | 9.1 | 27.9 | 14.3 | 51 | 22.0 | 10.2 | 46 | 17.5 | 7.1 | 41 | 15.2 | 5.4 | 36 | 14.0 | 4.5 | 32 | 0.9 | 2.2 | 3.8 | 5.0 | 5.7 | 6.9 |
| | 2006 | 0.48 | 109 | 79.6 | 7.1 | 13.3 | 38.5 | 21.8 | 57 | 32.1 | 16.6 | 52 | 26.7 | 12.5 | 47 | 23.5 | 9.9 | 42 | 21.9 | 8.5 | 39 | 1.6 | 3.8 | 6.6 | 8.6 | 9.9 | 12.1 |
| | 2007 | 0.59 | 110 | 79.4 | 7.1 | 13.5 | 41.2 | 22.5 | 55 | 34.5 | 17.2 | 50 | 28.8 | 12.9 | 45 | 25.5 | 10.3 | 40 | 23.6 | 8.7 | 37 | 1.6 | 3.8 | 6.7 | 8.8 | 10.1 | 12.5 |
| Jumbo Hybrid | 2004 | 0.27 | 79 | 86.9 | 4.3 | 8.7 | 26.4 | 10.4 | 39 | 20.6 | 6.9 | 34 | 16.5 | 4.6 | 28 | 14.5 | 3.4 | 24 | 13.4 | 2.8 | 21 | 0.7 | 1.6 | 2.6 | 3.3 | 3.8 | 4.6 |
| | 2005 | 0.45 | 100 | 83.2 | 4.6 | 12.2 | 42.5 | 21.2 | 50 | 34.9 | 15.5 | 44 | 28.5 | 11.1 | 39 | 24.5 | 8.3 | 34 | 22.2 | 6.8 | 31 | 1.4 | 3.2 | 5.4 | 7.0 | 8.1 | 10.7 |
| | 2006 | 0.48 | 113 | 75.5 | 7.0 | 17.5 | 54.8 | 30.7 | 56 | 47.8 | 24.2 | 51 | 40.6 | 18.4 | 45 | 35.7 | 14.5 | 41 | 32.8 | 12.2 | 37 | 2.5 | 5.4 | 9.2 | 11.9 | 13.6 | 17.7 |
| | 2007 | 0.58 | 110 | 70.8 | 7.1 | 22.1 | 59.2 | 33.4 | 56 | 52.6 | 26.9 | 51 | 45.6 | 20.9 | 46 | 40.6 | 16.7 | 41 | 37.5 | 14.1 | 38 | 2.8 | 6.3 | 10.9 | 14.1 | 16.1 | 20.1 |
| AltA Fixed | 2004 | 0.34 | 79 | 80.1 | 8.4 | 11.6 | 32.6 | 15.8 | 48 | 27.4 | 11.6 | 42 | 23.3 | 8.4 | 36 | 21.1 | 6.6 | 31 | 19.9 | 5.6 | 28 | 1.2 | 2.7 | 4.7 | 6.1 | 6.9 | 8.2 |
| | 2005 | 0.52 | 103 | 72.6 | 9.0 | 18.3 | 49.0 | 28.5 | 58 | 43.1 | 22.7 | 53 | 37.8 | 17.7 | 47 | 34.4 | 14.6 | 42 | 32.6 | 12.6 | 39 | 2.4 | 5.6 | 9.5 | 12.2 | 13.9 | 17.2 |
| | 2006 | 0.53 | 118 | 56.3 | 12.7 | 31.0 | 65.1 | 43.2 | 66 | 60.2 | 37.0 | 62 | 55.3 | 31.2 | 56 | 51.9 | 27.0 | 52 | 49.9 | 24.3 | 49 | 5.2 | 11.1 | 18.0 | 22.6 | 25.5 | 30.3 |
| | 2007 | 0.65 | 115 | 56.3 | 14.0 | 29.8 | 66.0 | 41.9 | 63 | 60.9 | 35.6 | 58 | 55.8 | 29.6 | 53 | 52.1 | 25.3 | 48 | 50.1 | 22.6 | 45 | 4.5 | 9.8 | 16.3 | 20.9 | 23.7 | 28.5 |
| AltA Hybrid | 2004 | 0.21 | 95 | 73.8 | 10.3 | 15.9 | 46.8 | 22.0 | 47 | 41.2 | 16.9 | 41 | 36.2 | 12.5 | 35 | 32.7 | 9.7 | 30 | 30.6 | 8.1 | 26 | 1.8 | 3.8 | 6.2 | 7.9 | 9.1 | 12.1 |
| | 2005 | 0.41 | 119 | 63.9 | 11.5 | 24.6 | 64.6 | 37.7 | 58 | 59.7 | 31.6 | 53 | 54.7 | 25.9 | 47 | 50.5 | 21.4 | 42 | 47.6 | 18.5 | 39 | 3.8 | 8.0 | 12.9 | 16.3 | 18.7 | 24.9 |
| | 2006 | 0.46 | 134 | 46.4 | 14.4 | 39.2 | 75.8 | 50.6 | 67 | 72.4 | 44.8 | 62 | 68.4 | 38.8 | 57 | 65.1 | 33.9 | 52 | 62.6 | 30.5 | 49 | 7.0 | 14.5 | 22.6 | 27.7 | 30.9 | 37.5 |
| | 2007 | 0.57 | 128 | 45.2 | 14.2 | 40.6 | 78.3 | 51.9 | 66 | 74.8 | 46.0 | 61 | 70.6 | 39.7 | 56 | 67.2 | 34.6 | 52 | 64.7 | 31.1 | 48 | 7.1 | 14.8 | 23.3 | 28.9 | 32.2 | 38.5 |
| AltA NegAm | 2004 | 0.13 | 98 | 57.3 | 14.5 | 28.2 | 62.6 | 34.6 | 55 | 56.5 | 28.0 | 49 | 50.9 | 22.0 | 43 | 46.5 | 17.7 | 38 | 44.0 | 15.0 | 34 | 3.2 | 7.0 | 11.8 | 15.3 | 17.5 | 21.4 |
| | 2005 | 0.31 | 125 | 44.3 | 12.2 | 43.5 | 78.5 | 53.8 | 69 | 74.6 | 47.3 | 63 | 70.1 | 40.6 | 58 | 66.3 | 35.1 | 53 | 63.7 | 31.3 | 49 | 6.4 | 14.2 | 23.2 | 29.2 | 32.9 | 39.6 |
| | 2006 | 0.52 | 143 | 37.5 | 13.7 | 48.8 | 85.5 | 62.4 | 73 | 83.0 | 56.7 | 68 | 79.9 | 50.4 | 63 | 77.0 | 45.0 | 58 | 74.8 | 41.1 | 55 | 8.3 | 18.0 | 29.2 | 36.5 | 41.0 | 48.9 |
| | 2007 | 0.69 | 137 | 41.5 | 12.4 | 46.2 | 87.0 | 61.4 | 71 | 84.4 | 55.4 | 66 | 81.0 | 49.0 | 61 | 78.0 | 43.5 | 56 | 75.7 | 39.5 | 52 | 7.6 | 16.6 | 27.9 | 35.5 | 40.0 | 47.6 |
| Subprime | 2004 | 0.11 | 91 | 43.2 | 23.9 | 32.9 | 56.4 | 36.8 | 65 | 52.1 | 31.1 | 60 | 48.2 | 26.1 | 54 | 45.6 | 22.6 | 50 | 44.1 | 20.5 | 47 | 3.9 | 8.4 | 14.0 | 18.1 | 20.8 | 25.2 |
| | 2005 | 0.22 | 117 | 28.9 | 26.0 | 45.1 | 72.2 | 55.2 | 76 | 69.0 | 49.3 | 71 | 65.6 | 43.5 | 66 | 63.4 | 39.0 | 62 | 61.8 | 36.0 | 58 | 7.5 | 15.2 | 24.4 | 31.0 | 35.1 | 42.2 |
| | 2006 | 0.37 | 134 | 22.0 | 27.0 | 50.9 | 79.0 | 66.1 | 84 | 76.4 | 60.6 | 79 | 73.7 | 54.9 | 74 | 71.7 | 50.5 | 70 | 70.2 | 47.3 | 67 | 10.5 | 20.6 | 31.9 | 39.7 | 44.5 | 53.1 |
| | 2007 | 0.56 | 130 | 21.2 | 27.6 | 51.2 | 78.7 | 64.6 | 82 | 76.2 | 59.0 | 77 | 73.4 | 53.2 | 73 | 71.2 | 48.6 | 68 | 69.7 | 45.4 | 65 | 9.5 | 18.9 | 29.8 | 37.5 | 42.4 | 51.2 |
| Second Lien | 2004 | 0.06 | 97 | 76.0 | 15.3 | 8.8 | 47.4 | 47.4 | 100 | 43.0 | 43.0 | 100 | 38.4 | 38.4 | 100 | 35.3 | 35.3 | 100 | 33.0 | 33.0 | 100 | 11.8 | 20.7 | 26.4 | 30.3 | 32.9 | 38.0 |
| | 2005 | 0.11 | 118 | 69.9 | 16.9 | 13.2 | 63.6 | 63.6 | 100 | 59.7 | 59.7 | 100 | 55.4 | 55.4 | 100 | 51.5 | 51.5 | 100 | 48.8 | 48.8 | 100 | 18.0 | 30.7 | 38.5 | 43.7 | 47.4 | 54.5 |
| | 2006 | 0.22 | 126 | 73.9 | 12.2 | 13.9 | 66.9 | 66.9 | 100 | 63.1 | 63.1 | 100 | 58.7 | 58.7 | 100 | 54.8 | 54.8 | 100 | 52.1 | 52.1 | 100 | 19.5 | 32.5 | 40.5 | 46.0 | 49.7 | 57.8 |
| | 2007 | 0.29 | 129 | 74.4 | 13.5 | 12.1 | 67.2 | 67.2 | 100 | 63.4 | 63.4 | 100 | 58.9 | 58.9 | 100 | 55.1 | 55.1 | 100 | 52.2 | 52.2 | 100 | 18.7 | 32.1 | 40.4 | 45.8 | 49.6 | 57.8 |

Note: [1]Projections are as of February 2011 remittance reports for a sample of loans taken from each sector and issue year. [2] Cumulative projected base case loss realized as of end of period.
Source: LoanPerformance, Barclays Capital

## Appendix – Monte Carlo simulation

To give an example of how the simulation works, consider a borrower who has just entered OTS 60+, is three months delinquent, has not made any payments in the past two months and has a UCLTV of 105. Given this information, the borrower is likely to miss another payment. Moreover, because the borrower is severely delinquent and has negative equity in the property, the only sales that are likely to occur are short sales, in which the servicer agrees to accept less than what is owed by the borrower. According to Figure 2 the possible outcomes for the next period are for the borrower to miss another payment and remain in OTS 60+ (DQ60P*(1-CFC60P)), miss another payment and be foreclosed on (DQ60P*CFC60P), sell the property (DD60P), be modified back to current (MC60P), self cure back to current (CC60P), self cure back to OTS 30-day (C360P) or make a single payment and remain in OTS 60+ (1 – DQ60P – MC60P – CC60P – C360P). If we assign numbers to these probabilities then it might look something like the following:

1. Miss another payment and remain OTS 60+ = DQ60P*(1-CFC60P) = 0.90*0.50 = 0.45
2. Miss another payment and be foreclosed on = DQ60P*CFC60P = 0.90*0.50 = 0.45
3. Sell the property = DD60P = 0.01, loss severity = SEV = 0.20
4. Be modified back to current = MC60P = 0.04
5. Self cure back to OTS current = CC60P = 0.02
6. Self cure back to OTS 30-day = C360P = 0.02 or
7. Make payment, remain OTS 60+ = 1 – 0.45 - 0.45 – 0.01 – 0.04 - 0.02 – 0.02 = 0.01.

While we have assigned probabilities for this example, in the actual simulation they would be calculated using the model's probability transition functions (which would make use of the fact that the borrower has just entered OTS 60+ and has not made any payments in several months). The next step in the simulation is to draw a random number between 0 and 1 and compare it to the above probabilities. If the number is less than or equal to 0.45 then the borrower misses a payment and enters foreclosure, if it is greater than 0.45 but less than or equal to 0.90 then the borrower misses a payment and remains in OTS 60+, if it is greater than 0.90 but less than or equal to 0.91 then the property is sold, producing a loss of 20% of the outstanding balance, and so on. Once the borrower's new delinquency status is determined and payment history updated, the process is repeated until the mortgage is either paid off or liquidated. One complete sequence of draws leading to payoff or liquidation represents a single path. We simulate 200 paths per loan and then average across paths and loans.

# BARCLAYS CAPITAL TERM STRUCTURE MODEL

## Libor Market Model for Mortgage Valuation[1]

Derek Chen
+1 212 412 2857
derek.chen@barcap.com

V.S. Srinivasan
+1 212 412 3854
v.srini@barcap.com

**In tandem with the release of the new prepayment model, we are also upgrading our term structure model. The new framework will be the Libor Market Model (LMM), implemented with improved variance reduction methods. Compared with the current Futures-Heath-Jarrow-Morton (FHJM) model, the new one represents several improvements:**

- The new model better captures the entire volatility surface, with much smaller calibration error and reduced calibration time. It also produces more realistic at-the-money (ATM) and out-of-the-money (OTM) skews, resulting in closer fits for a wide strike range. The drop in calibration errors improves the valuation accuracy for mortgages.
- The new model lowers the probability of negative rates being generated. This effectively reduces volatility when rates are low (flatter skews), which tends to decrease the value of OTM prepayment options, leading to a better fit for prices of discount coupons and POs.
- The new model allows more flexible correlation structures among forward rates. This affects the slope of the yield curve along the forward paths and tends to improve the OAS of premiums and IOs.
- We use several variance reduction techniques such as antithetic sampling, the Sobol random number sequence, and control variates to reduce the number of sample paths required to generate precise OAS results.
- The net effect of the new model is to increase the OAS of premiums and IOs marginally but slightly reduce that of POs. Also, the flatter skews result in slightly longer durations for most pass-throughs.

### The Libor Market Model

The LMM, also known as the BGM model (referring to Brace, Gatarek, and Musiela, who developed it), has emerged as the standard term structure model for valuing mortgages in recent years. It is called a Libor market model because the basic quantities being modeled are the forward Libor rates that are directly observable in the market. FHJM models use instantaneous future rates, whereas LMM uses Libor rates, which are traded using instruments such as swaptions and caplets. As a result, the LMM is more intuitive and can be calibrated more easily and closely to the market. The basic formulation of LMM is as follows:

At any future time $t$ for a given set of reset times $0 = T_0 < T_1 < T_2 < \cdots < T_N$, the Libor rate between $T_i$ and $T_{i+1}$, denoted by $L_i^t$, is governed by:

$\frac{dL_i^t}{f_i(L_i^t)} = \mu_i^t dt + \sum_j \sigma_i^{jt} dW_j^t$, where $W_j^t,\ j = 1, \cdots, N$ is a vector of independent Brownian motions. The volatility function $\sigma_i^{jt}$ is defined as $\sigma_i^{jt} = \bar{\sigma}_i^t e_i^{jt}$ where $e_i^{jt}$ is the $j$-th eigenvector of the covariance matrix among the forward Libor rates. The drift terms,

[1] The authors would like to acknowledge the significant contribution from Regis Van Steenkiste, Zhengao Huang, Mingyang Xu, and Enping Zhao in preparing this document.

$\mu_i^t$, need not be estimated separately because they are a function of the volatility term structure $\sigma_i^{jt}$ based on no-arbitrage conditions. The remaining item, the functional form of $f_i(L_i^t)$, is chosen by the user to reflect a certain view on the fundamental distribution of forward rates. For example, if $f_i(L_i^t)$=1, then rates are assumed to be normal distributed. On the other hand, a choice of $f_i(L_i^t) = L_i^t$ would correspond to a lognormal distribution. In our implementation, we select $f_i(L_i^t) = \beta_i^t L_i^t + \left(1 - \beta_i^t\right)L_i^0$, where $\beta_i^t$ controls the skew while preserving $\sigma_i^{jt}$ as being lognormally scaled. This functional form allows us to have far more control over the skew. Because swap rates are simply combinations of forward Libor rates, once the model parameters are set, the user can easily obtain the entire forward swap curve(s) and volatility surface at any future time from the model.

Compared with the FHJM model, the LMM offers a number of advantages (some of the main differences are summarized in Figure 1). It provides much more flexibility in fitting the volatility surface, which naturally leads to smaller calibration error and more accurate valuation of MBS. We will see numerical examples of this in the next few sections. In addition, the LMM allows better control of the correlations among forward rates, which affects the slope of the forward curves and valuation of MBS, especially mortgage derivatives.

**Figure 1: Major differences between the LMM and FHJM models**

| LMM | FHJM |
|---|---|
| Models evolution of forward Libor (string of 1m or 3m Libor rates)<br>■ Directly observable in market<br>■ Easy translation to swap rates<br>■ Easy interpretation | Models instantaneous futures rates<br>■ Not observable in market<br>■ Hard to interpret |
| Starting point is the yield curve; perfectly calibrated to yield curve by design | Needs to be calibrated to the yield curve |
| ■ Calibration to volatility surface via closed form approximations using a wider range of swaptions/caps<br>■ Fast calibration and reduced calibration errors<br>■ More flexibility and better fit of the entire volatility surface<br>■ Less prone to local minima during calibration<br>■ More realistic ATM and OTM skews | Calibration done by pricing swaptions/caps on a lattice/tree<br>■ Slow calibration<br>■ More prone to local minima and pricing noise coming from binomial trees<br>■ Difficulty in modeling ATM and OTM skews |
| Relatively easy to specify correlations among forward rates<br>■ Correlations can be controlled independent of the volatility surface calibration<br>■ More realistic slopes for forward curves, which could help IO valuation. | Limited flexibility in modeling correlations<br>■ Correlations cannot be controlled independent of the volatility surface calibration<br>■ Tendency toward a flatter curve, which hurts IO-like MBS |
| Ability to prevent negative rates while preserving accuracy of close form solution<br>■ Control over occurrence of negative rates | Allows for negative rates<br>■ Affects IIO by giving too much value to zero strike floor |
| Paths are not re-combining, and therefore can only be implemented as Monte Carlo simulation<br>■ Not a problem for MBS because valuation of prepayment options is path dependent | Can be implemented either as a Monte Carlo simulation or a lattice/tree |

Source: Barclays Capital

## Performance of calibration to volatilities

### *Calibrating to the volatility surface*

The LMM model is calibrated to the entire volatility surface using a basket of swaptions and interest rate caps. Figure 2 shows the average calibration errors (expressed in percentage volatility) for three swaptions and an interest rate cap from June 2010 to February 2011. For comparison, we also show the same errors for the FHJM model. The bottom row in Figure 2 shows the daily volatility changes during this period, to provide context when assessing the significance of the errors.

On average, the LMM produces smaller calibration errors for ATM, ITM and OTM options. Furthermore, the calibration errors are reasonably small compared with daily market changes. Clearly, LMM is superior to the FHJM model in fitting to the volatility surface, The better fit naturally leads to more accurate valuation of the MBS call option and less day-to-day noise in the valuation.

### *ATM and ITM/OTM skews*

While the volatility surface captures two dimensions of volatilities – term and tenor – two other dimensions are reflected by the skews. Specifically, the ATM skew describes how the percentage volatility (Black volatility) changes with the level of rates, and the ITM/OTM skew describes how percentage volatility changes with moneyness. Because these have a significant effect on MBS valuation, it is important to examine how well the model fits skews.

Skews have long been recognized and traded by the market. Figure 3 plots the percentage volatility against the level of the 1y forward 5y swap rate from January 2005 to February 2011. It is clear that the volatility is strongly correlated with the level of rates, increasing when rates are lower and decreasing when they are higher. The bias toward using a higher (percentage) volatility in the Black formula when valuing ATM options struck at a lower rate level is called the ATM skew.

When interest rates are lognormal, the volatility of rates is proportional to their level. Normalized volatility (bp volatility) increases with higher rates, but percentage volatility stays constant. Clearly, this assumption can be inconsistent with how rates actually move. In real life, the rates distribution is somewhere between normal and lognormal but closer to normal, with normalized volatility mostly independent of the level of rates. To accommodate this, the lognormal Black formula has to be adjusted.

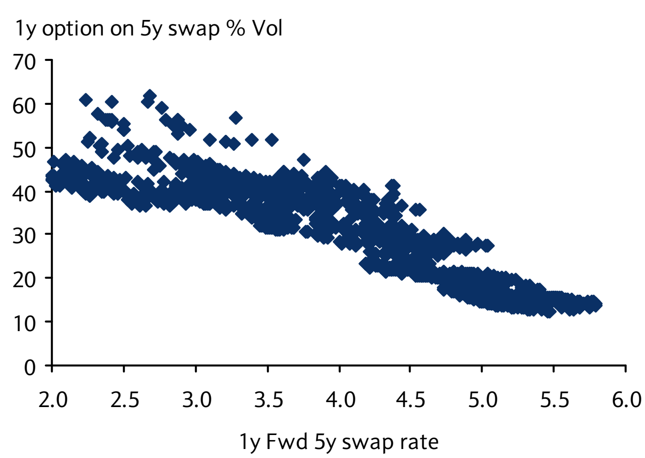
The ATM skew increases the value of ATM options with lower strike, which affects the valuation of MBS. A steeper skew should decrease the current coupon OAS when the current coupon is low and increase it when current coupon is high. The ATM skew also affects MBS hedging; when rates move lower, volatility increases, leading to a smaller price appreciation, and when rates sell off, volatility decreases, resulting in a smaller price

**Figure 2: Volatility calibration error of the LMM**

| | Absolute error in percentage Volatility by ITM-ness (%) | | | | | | | | | 6.85% 5y cap |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1Y10Y | | | 5Y10Y | | | 10Y10Y | | | |
| | -100 | ATM | +100 | -100 | ATM | 100 | -100 | ATM | +100 | |
| LMM | 1.2 | 0.1 | 0.7 | 1.0 | 0.2 | 0.4 | 1.3 | 0.2 | 0.2 | 0.4 |
| HJM | 0.9 | 0.4 | 0.6 | 1.7 | 0.3 | 0.2 | 2.3 | 0.7 | 0.6 | 1.0 |
| Mkt Daily Chg | 0.6 | 0.7 | 0.6 | 0.6 | 0.5 | 0.5 | 0.5 | 0.5 | 0.4 | 0.9 |

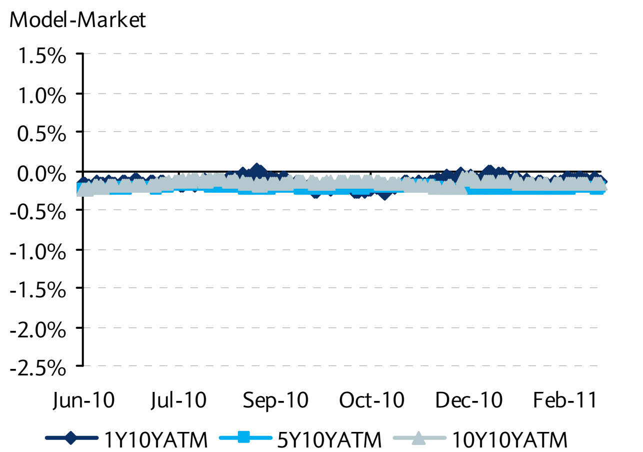
Note: Model fits from June 2010 to February 2011. Source: Barclays Capital

**Figure 3: Historical ATM skew**



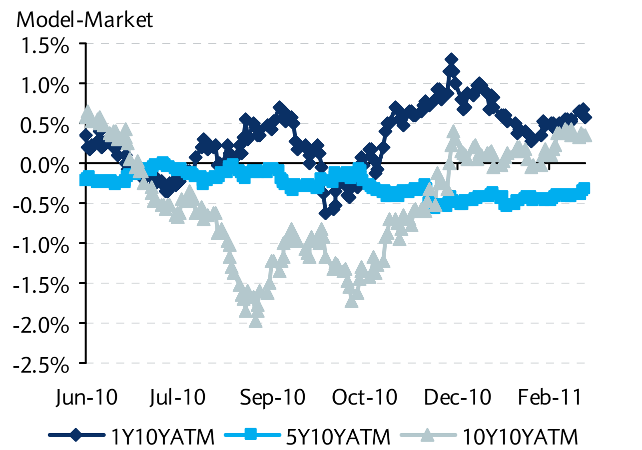

Note: January 5-February 11, 2011. Source: Barclays Capital

**Figure 4: LMM calibration error for ATM swaptions**




Source: Barclays Capital

**Figure 5: FHJM calibration error for ATM swaptions**




Source: Barclays Capital

drop. The net effect is a shorter duration, and the effect becomes bigger as the skew becomes steeper.

The OTM skew exists for the same reason as the ATM skew: a lognormal distribution underestimates volatility for OTM strikes and overestimates it for ITM strikes. Hence, users of the Black formula have to adjust the percentage volatility higher for OTM strikes and lower for ITM options, leading to a volatility skew. This tends to reduce the OAS of discount-coupon MBS while increasing that for premium bonds.

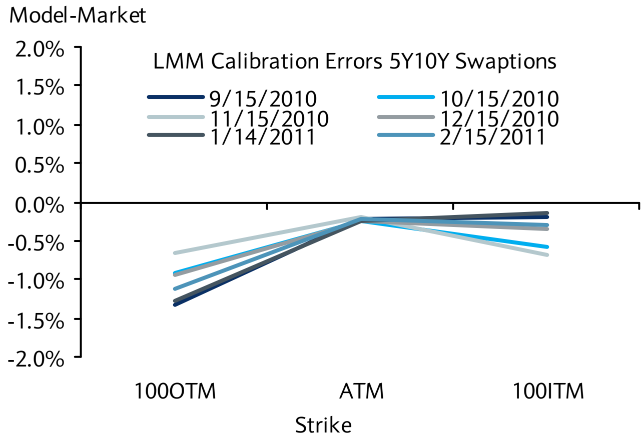
Figures 4 and 5 compare the LMM and FHJM model fits for ATM swaptions over time. They show that the LMM does a much better job in the fit, leading to nearly zero calibration errors over time. Generally, our implementation of the LMM model has resulted in a slightly flatter ATM skew but significantly less deviation from the market.

A similar story can be told for OTM skews. Figures 6 and 7 compare OTM skew calibration errors for the LMM and FHJM models. The new model produces much less noise than the production model. The significantly improved accuracy in fitting the skews should improve the accuracy of MBS valuations. Also, because the model significantly lowers the chance of negative rates, it effectively reduces the volatility for low rate scenarios, leading to a slightly flatter OTM skew.

## Modeling correlations among forward rates

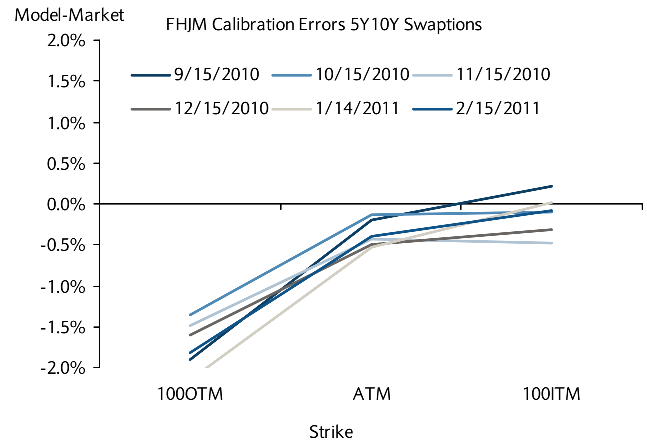
A major appeal of the LMM is better control of the correlations among forward rates. All else equal, lower correlations between the shorter and longer ends of the yield curve increase the model value of premium-priced MBS and IOs, but decrease that of discount coupons and POs. This is intuitive since IOs are natural yield-curve steepners and POs are natural flatteners. Structurally, LMM provides control for correlations while maintaining the ability to fit swaptions and caps accurately. This is more difficult to achieve with the FHJM model.

## Figure 6: OTM skew errors for the LMM




Note: September 2010 to February 2010. Source: Barclays Capital

## Figure 7: OTM skew errors for the FHJM model




Note: September 2010 to February 2010.Source: Barclays Capital

Figure 8 and Figure 9 illustrate this point. The α shown in these tables is a model parameter that controls correlations among forward rates and is estimated from market prices. It remains relatively stable day to day, and a larger value leads to greater correlations among forward rates. Figure 8 shows that for a large range of values for α on any given day, the model is able to achieve an equally good fit for the volatility surface. This flexibility allows it to fit much more closely to the market-implied correlations than the FHJM model (Figure 9).

Figure 10 and Figure 11 show the pricing effect on MBS. As one can imagine, greater correlations (a bigger α) would increase the OAS (at fixed price) and prices (at fixed OAS) of discount pass-throughs but decrease those of premium bonds. The effect is bigger on IOs and POs and is largest on inverse IOs because they have the most exposure to the slope of the curve.

## Figure 8: Correlations can be controlled independent of the volatility surface

| ATM Swaption Implied Vol - Market | | | |
|---|---|---|---|
| | LMM Corr Param | | |
| | α = -0.6 | α = -0.35 | α = 0.26 |
| 1Y10Y | -0.2% | -0.2% | -0.2% |
| 5Y10Y | -0.2% | -0.2% | -0.2% |
| 10Y10Y | -0.2% | -0.2% | -0.2% |

| 5y Cap Implied Vol - Market | | | |
|---|---|---|---|
| | LMM Corr Param | | |
| Strike | α = -0.6 | α = -0.35 | α = 0.26 |
| 6.35% | -0.1% | 0.0% | 0.1% |
| 6.85% | -0.7% | -0.6% | -0.5% |
| 7.35% | -1.2% | -1.2% | -1.1% |

Note: As of March 9, 2010.Source: Barclays Capital

## Figure 9: Adjusting correlations among forward rates

| 3M vs 10Y Terminal Correlation | | | | | |
|---|---|---|---|---|---|
| | LMM Corr Param | | | | |
| Term | α = -0.6 | α = -0.35 | α = 0.26 | Market | FHJM |
| 3M | -51% | -21% | 40% | 24% | |
| 1Y | -25% | 0% | 49% | 40% | -21% |
| 2Y | 1% | 19% | 56% | 58% | 13% |
| 3Y | 30% | 40% | 66% | 69% | 28% |
| 4Y | 51% | 56% | 72% | 77% | 45% |
| 5Y | 58% | 63% | 76% | | 63% |
| 6Y | 76% | 80% | 88% | | 63% |
| 7Y | 80% | 83% | 89% | | 71% |
| 8Y | 82% | 84% | 91% | | 72% |
| 9Y | 83% | 86% | 91% | | 70% |
| 10Y | 83% | 86% | 92% | | 76% |

Note: As of March 9, 2010.Source: Barclays Capital

Figure 10: Effect of correlations on TBA valuation

| TBA | $Px | OAS Diff. (LMM - FHJM) α =-0.6 | α =-0.3 | α =0.26 | $px Diff. (LMM -FHJM) α =-0.6 | α =-0.3 | α =0.26 |
|---|---|---|---|---|---|---|---|
| FNCL 4 | 98-16+ | -2 | -2 | -4 | -0.12 | -0.12 | -0.23 |
| FNCL 4.5 | 101-26 | -1 | -1 | -4 | -0.07 | -0.08 | -0.23 |
| FNCL 5 | 104-20 | 0 | -1 | -4 | -0.01 | -0.05 | -0.19 |
| FNCL 5.5 | 106-25+ | 0 | -1 | -4 | 0.02 | -0.02 | -0.18 |
| FNCL 6 | 108-19+ | 1 | 0 | -4 | 0.02 | -0.02 | -0.16 |
| FNCL 6.5 | 111-18 | 0 | 0 | -3 | 0.01 | -0.01 | -0.09 |

Note: Pricing as of February 25, 2011. Source: Barclays Capital

Figure 11: Effect of correlations on derivative valuation

| | Security | $Px | OAS Diff. (LMM - FHJM) α =-0.6 | α =-0.3 | α =0.26 | $px Diff. (LMM -FHJM) α =-0.6 | α =-0.3 | α =0.26 |
|---|---|---|---|---|---|---|---|---|
| Trust PO | FNT-399 | 87-24+ | -9 | -7 | -4 | -0.36 | -0.28 | -0.14 |
| | FNT-400 | 77-20 | -11 | -8 | -4 | -0.50 | -0.38 | -0.17 |
| | FNT-405 | 73-02 | -10 | -7 | -3 | -0.49 | -0.36 | -0.16 |
| Trust IO | FNT-399 | 19-01 | 44 | 26 | -10 | 0.30 | 0.18 | -0.07 |
| | FNT-400 | 24-10 | 34 | 22 | -7 | 0.39 | 0.25 | -0.08 |
| | FNT-405 | 25-20+ | 26 | 16 | -6 | 0.35 | 0.22 | -0.08 |

Note: Pricing as of February 25, 2011. Source: Barclays Capital

Generally, correlations produced by the new model can be aligned more easily with the market and are slightly lower than the production model. This should improve the accuracy of MBS valuation while marginally reducing the OAS of discount coupons and increasing those of premiums and IOs.

## Variance reduction methods

By design, the OAS framework is a Monte Carlo process, meaning that the OAS, OAD, OAC are all random numbers obtained from one sampling of interest rate paths. Although the standard errors of these measures decrease with a greater number of paths, one needs an extremely large number of paths to bring down the errors to acceptable levels. To speed up the process and improve computational efficiency, we employ three variance reduction methods in the new model:

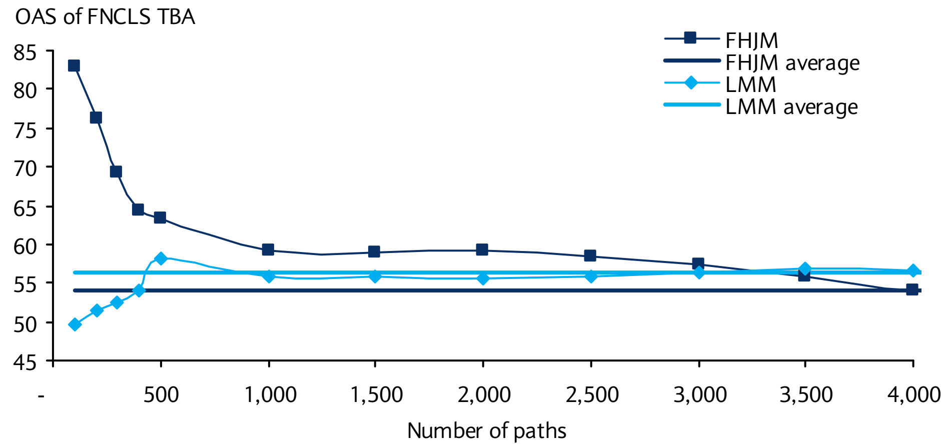
- **Antithetic variates.** For each random sample generated, its mirror image within the sample space is also used as a sample. Because these two antithetic paths are the opposite of each other, they help "fill up" the entire sample space, thereby reducing the standard error of the simulation.

- **Sobol sequence.** This method attempts to generate sample paths in such a way that they tend to spread evenly across the sample space, thereby reducing the "randomness" and standard errors.

- **Control variates.** In theory, an infinite number of paths would eliminate the error and give the true value of the security. Although we cannot do this for every bond, we can do so for some benchmark securities and estimate the errors resulting from running a smaller number of sample paths on these securities. For any other bond, we first run the valuation based on the smaller sample and then adjust the results using the errors obtained for the benchmark securities. The magnitude of adjustment also depends on the correlations between the prices of the subject bond and the benchmark securities.

Figure 12 shows how the OAS of a pass-through changes with an increasing number of sample paths. Comparison between the two models is done here without the use of control variates to show more clearly the improvement brought by switching to the LMM. It is evident that the new model (LMM+antithetic+Sobol) does a much better job than the production model (FHJM+antithetic), achieving near convergence with only 500 paths, compared with 4000 paths required by the old model. With the additional improvement from control variates, our tests have shown that the new model generally gives reasonably precise OAS, OAD, and OAC for MBS pass-throughs with only 200 sample paths.

Figure 12: Rate of convergence for the LMM and FHJM models




Note: Pricing as of February 25, 2011. Source: Barclays Capital

## Overall effect on MBS valuation

The biggest achievement of the new model is improved accuracy. Because the LMM gives a perfectly calibrated yield curve, much better fitted volatility surface and skews, and more realistic correlation structures, the prepayment options and coupons (on floaters and IIOs, for example) can be valued more correctly. As we mentioned earlier, the control of negative interest rates in the new model effectively leads to a slightly flatter skew. Although this could in theory hurt the prices of premium coupons and IOs, this effect is overwhelmed by an overall reduction in calibration errors. Meanwhile, the more flexible correlation structures tend to increase the valuation of premium MBS and IOs and decrease that of discounts and POs.

Figure 13 compares the OAS, OAD, and OAC on representative TBA, IOs, and POs using the two models. On an even OAS basis, the new model tends to increase the price of most TBA coupons but the effect is more pronounced in higher premiums, as one would expect from a more flexible correlation structure. This also explains why the pricing effect is positive for IOs but negative for POs.

Finally, the new model gives a slightly longer OAD for most pass-throughs. This pattern is consistent with the flatter ATM/OTM skew in the new model, which is symptomatic of reduced occurrence of negative rates in the LMM compared with FHJM. In calculating OAD, the interest rate curve is shifted up and then down. In the down shift, lower volatility associated with flatter skew results in a greater price gain and, thus, a longer duration. The effect is more pronounced for cuspy coupons because they are the most sensitive to rate changes.

**Figure 13: Overall effect of the term-structure model change on MBS valuation (even OAS)**

| | FHJM Model | | | LMM Model | | | LMM - FHJM | | |
|---|---|---|---|---|---|---|---|---|---|
| CUSIP | $ Price | LOAD | LOAC | $ Price | LOAD | LOAC | $ Price | LOAD | LOAC |
| FNCL 3.5 TBA | 94.13 | 7.6 | 0.2 | 94.11 | 7.6 | 0.2 | -0.02 | -0.01 | 0.05 |
| FNCL 4 TBA | 98.62 | 6.9 | -0.5 | 98.64 | 7.0 | -0.4 | 0.02 | 0.04 | 0.15 |
| FNCL 4.5 TBA | 102.20 | 5.9 | -1.2 | 102.27 | 5.9 | -1.2 | 0.07 | 0.08 | 0.03 |
| FNCL 5 TBA | 104.35 | 3.6 | -2.1 | 104.46 | 3.7 | -2.3 | 0.11 | 0.05 | -0.16 |
| FNCL 5.5 TBA | 106.81 | 3.1 | -1.7 | 106.94 | 3.1 | -1.8 | 0.13 | 0.02 | -0.10 |
| FNCL 6 TBA | 109.49 | 3.0 | -1.1 | 109.61 | 3.0 | -1.2 | 0.12 | 0.01 | -0.04 |
| FNCL 6.5 TBA | 114.66 | 3.4 | -0.5 | 114.78 | 3.4 | -0.5 | 0.12 | -0.01 | -0.07 |
| IOS FN-4009 IO | 23.59 | -9.8 | -15.6 | 23.85 | -9.0 | -15.1 | 0.26 | 0.79 | 0.48 |
| IOS FN-4509 IO | 23.83 | -16.2 | -18.2 | 24.13 | -15.7 | -19.3 | 0.30 | 0.52 | -1.10 |
| IOS FN-5009 IO | 24.47 | -12.6 | -10.4 | 24.68 | -12.4 | -10.7 | 0.21 | 0.12 | -0.32 |
| IOS FN-5508 IO | 18.51 | -18.5 | -6.7 | 18.66 | -18.6 | -7.1 | 0.15 | -0.15 | -0.33 |
| IOS FN-6008 IO | 19.76 | -12.2 | -2.5 | 19.89 | -12.3 | -2.7 | 0.13 | -0.13 | -0.26 |
| IOS FN-4009 PO | 63.55 | 14.5 | 7.5 | 63.17 | 14.3 | 7.6 | -0.38 | -0.21 | 0.14 |
| IOS FN-4509 PO | 64.01 | 17.3 | 8.6 | 63.59 | 17.4 | 9.5 | -0.42 | 0.08 | 0.96 |
| IOS FN-5009 PO | 62.23 | 15.8 | 5.0 | 61.92 | 16.0 | 5.4 | -0.31 | 0.17 | 0.34 |
| IOS FN-5508 PO | 67.18 | 14.7 | 2.0 | 66.91 | 15.0 | 2.1 | -0.27 | 0.28 | 0.12 |
| IOS FN-6008 PO | 67.91 | 11.2 | 0.2 | 67.70 | 11.4 | 0.3 | -0.21 | 0.19 | 0.10 |

Note: pricing as of March 11, 2011. Source: Barclays Capital

# BARCLAYS CAPITAL REGIONAL HOME PRICE MODEL

## Introducing a new Regional Home Price Model

Robert Tayon
+1 212 412 2512
robert.tayon@barcap.com

Steven Bergantino
+1 212 412 2164
steven.bergantino@barcap.com

V.S. Srinivasan
+1 212 412 3854
v.srini@barcap.com

**At the close of business on Friday, March 18, 2011, Barclays Capital will be introducing a new regional home price model on Barclays Capital Live. At that time, state-level projections for CoreLogic Aggregate and Distressed Excluded HPI will be available on Barclays Capital Live via the keyword HPA. The model provides a methodology for deriving home price projections at the state, CBSA, county, and zip level over a broad range of national home price scenarios. Highlights include:**

- The model explicitly incorporates factors that affect long-run trends in regional home prices and cyclical deviations from those trends. Over the long run, projected home prices are driven by trends in per capita disposable income. They can, and do, however, deviate from these trends for significant periods in response to national boom/bust cycles or large local swings in unemployment, foreclosure inventory, or population growth/decline. The model accounts for each of these factors, and incorporates momentum and mean reversion effects that determine the duration of deviations from long run equilibrium relationships. With this framework, we are able to distribute a wide array of national home price scenarios to the state, CBSA, county, and zip levels.
- The model projects home price appreciation at each regional level for both the aggregate and distressed excluded Core Logic home price indices. Over the long run, as the proportion of distressed transactions in a region reverts to its historical average, projections of aggregate and distressed excluded home prices converge.
- Cyclical swings in national home prices arise from changes in factors such as the availability of credit, mortgage rates, and wage expectations. We estimate the degree to which each region's HPA amplifies national swings in home prices, and use this sensitivity as the primary driver of risk in stress and recovery scenarios.
- Our estimates of the effect of foreclosure supply on voluntary transactions, which suggest that foreclosure externalities suppress nondistressed home prices by approximately 0.7% for each 1% rise in foreclosure and REO stock, are consistent with academic studies on the effect of foreclosures on local housing markets. Foreclosure externalities have suppressed nondistressed home price indices by 2.8% nationally. However, our estimate of the combined effect of distressed sales and foreclosure externalities on the aggregate home prices indices is 13.6%.
- The regional projections produced by the home price model are used by the Barclays Capital Agency Prepayment Model and Barclays Capital Loan Transition Model for projecting the prepayment and default performance of agency and non-agency mortgages across home price scenarios.

### Introduction

The housing market has experienced a wild roller-coaster ride over the past decade. Nationally, home prices virtually doubled between January 2000 and June 2006, only to give back almost two-thirds of that gain by early 2009. Home prices have remained relatively unchanged since then but the outlook for the housing market seems every bit as uncertain as before. Indeed, the current state of the housing market presents an interesting dilemma for analysts who hope to forecast home price movements in 2011 and beyond.

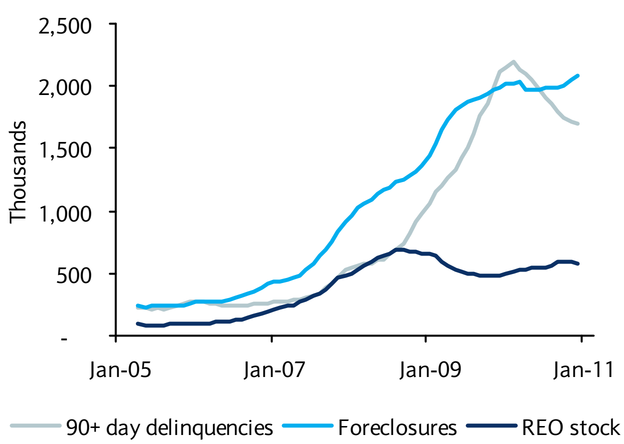
Specifically, the buildup in distressed supply following the bursting of the housing bubble has created a large shadow inventory in many regional housing markets that make further home price declines seem inevitable (Figure 1). At the same time, however, measures of housing market froth, such as price/income ratios, suggest that home prices are in line with historical averages, or even relatively cheap to historical levels when financing costs are considered (Figure 2). With buyers and sellers reluctant to trade, factors such as market sentiment, consumer confidence and expectations of future home price appreciation could turn out to be more important drivers of near-term home price movements than traditional economic fundamentals. This, in turn, makes forecasting near-term movements in national home prices more of an art than a science. Nonetheless, even while these intangible factors make near-term forecasting of national home prices a unique challenge, the historical data suggest that explaining regional variation in home prices conditional on movements in national home prices is a more tractable modelling problem. We attempt to leverage this observation in our model framework by using national home prices relative to income growth as an exogenous input into a regional home price model. Our analysis of the historical data strongly suggests:

1. Over long periods, home prices – at the national and regional levels – track income growth. This provides us with a long-term link between national and regional home prices.

2. Over shorter periods, deviations of national home price appreciation away from the pace of income growth tend to get amplified in regions of the country where land comprises a large fraction of the typical home's value. These regional differences are generally stable over time and are incorporated in our model framework through state specific sensitivities to national home price cycles.

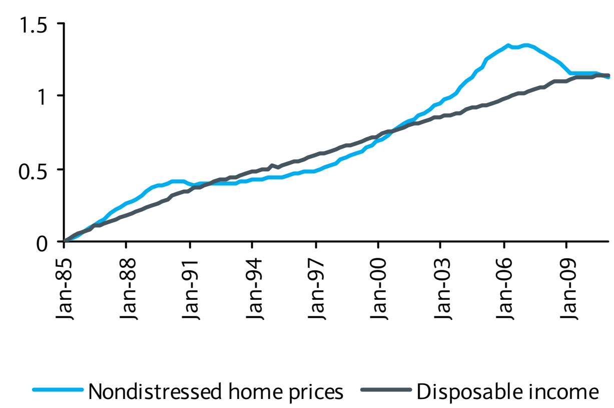
3. Foreclosures have a significant effect on national and regional home price indices. This effect can be classified into two sources: a) the direct effect of foreclosed properties included in these indices selling at a discount to voluntary transactions (ie, the distressed sales effect) and b) the indirect effect that an increase in foreclosures has in depressing the prices of all homes in the same area (ie, the foreclosure externalities effect). Fortunately, we have a significant amount of information on regional foreclosure trends from our loan level mortgage database. Our analysis of this data, which yields

**Figure 1: Distressed supply elevated, delinquencies falling**




Source: CoreLogic LoanPerformance, GSE investor reports, HUD, Fed Flow of Funds, MBA, Barclays Capital

**Figure 2: Home prices are back in line with incomes**




Note: Log scale normalized to zero in January 1985. Disposable income is the three-year average per capita. Source: CoreLogic LoanPerformance, BLS, Barclays Capital results consistent with the academic literature, suggests that the distressed sales effect is a much more significant driver of recent declines in home price indices than are foreclosure externalities.

4. After adjusting for the effects of foreclosures and swings in national home prices, regional economic factors, such as population changes and the unemployment rate, add only incrementally to our ability to explain variation in regional home prices. Unemployment rates tend to be correlated with income growth and foreclosures, while most population changes are slow moving and therefore have difficulty explaining shorter term movements in home prices.

Over the next few sections, we describe in detail the empirical evidence for the above assertions and how they are factored into our regional home price model.

## Selecting a home price index

Core Logic produces not only Aggregate Home Price Indices (HPI), which include voluntary and distressed transactions (ie, REO sales and short sales), but also Distressed Excluded Home Price Indices (DX HPI), which include only nondistressed transactions. We forecast both indices, adjusting for the effect of distressed transactions in creating divergences between the two.

### *Distressed discount*

One of the key assumptions behind most home price indices is the notion of constant quality of the housing units used to construct the index. In the case of distressed transactions, this assumption is typically violated as foreclosed properties often fall into a state of disrepair and/or are stripped of some of their value by their former owners. In addition, the sellers of distressed properties, typically foreclosing banks, do not occupy the properties, so are more motivated to accept a below market price to avoid continued property tax, insurance, and maintenance costs. As a result, distressed sales typically sell at a discount to voluntary sales, independent of underlying trends in home prices. This difference is referred to as the **distressed discount**.

### *Distressed gap and distressed share*

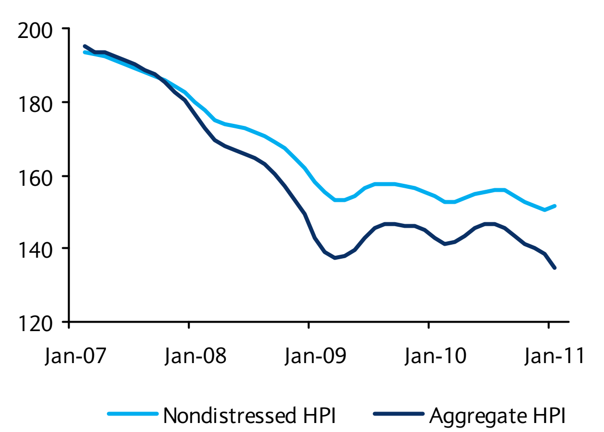
Because of this discount, changes in the share of distressed transactions in total home sales can cause aggregate home price indices to change simply due to compositional variation. As Figure 3 demonstrates, this is not just a hypothetical concern. For the past several years, the rising share of distressed sales has suppressed aggregate relative to nondistressed home price indices. As of the most recent print for January 2011, aggregate HPI was 11.1% below nondistressed HPI, the widest gap in the 35-year history of the index. This coincides with a spike in distressed share following the expiration of the homebuyer tax credits, exacerbated by weak winter seasonal demand.

We define the **distressed gap** as the percentage difference between aggregate and nondistressed HPI. Specifically,

$$\text{Aggregate HPI} = \text{DX HPI} * (1 + \text{Distressed Gap})$$

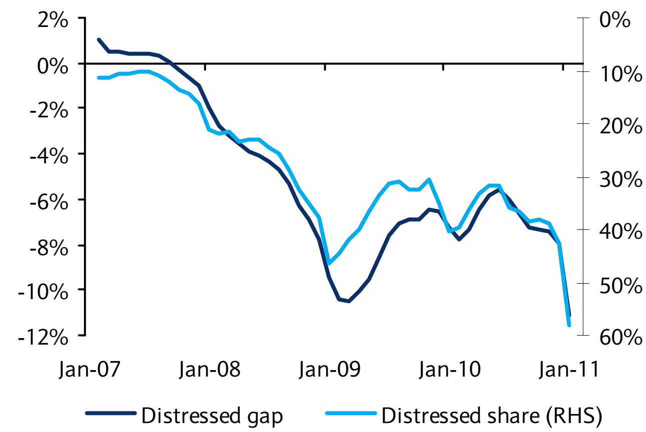
Figure 4 shows that the distressed gap is largely explained by the **distressed share**, that is, the share of distressed transactions in total housing sales. The distressed share of transactions can be inferred from the number of repeat sales used to calculate the aggregate and distressed excluded CoreLogic home price indices. CoreLogic calculates

**Figure 3: Gap between aggregate and nondistressed HPI**




Source: CoreLogic LoanPerformance, Barclays Capital

**Figure 4: Distressed share explains the distressed gap**




Source: CoreLogic LoanPerformance, Barclays Capital

home price indices at the national, state, CBSA, county, and zip levels. We observe a similar pattern of rising distressed share and widening distressed gap at each level of aggregation.

In our projections, we model the gap between aggregate and distressed excluded HPI as depending on the share of distressed transactions in total home sales and the discount associated with those transactions:

Distressed Gap = Distressed Discount*(Distressed Share - LR Avg. Distressed Share)

Consequently, in our model, aggregate HPI reverts to DX HPI as distressed share converges to its long run average. This is consistent with recent research by John Campbell and others, which analyzed transactions in Massachusetts over the past 20 years and found that the distressed discount – estimated at 27% for foreclosure-related sales – did not persist beyond the distressed sale.[1]

## Decomposing HPA into income growth and excess appreciation

We make use of the observation that home prices track income in the long run, but that each state's HPA varies considerably in its volatility around this trend. In Figure 5, for example, Ohio HPI followed per capita disposable income (PCDI) from 1987 to 2006, before falling under the weight of rising foreclosures and unemployment. California HPI, on the other hand, is shown in Figure 6 as having diverged considerably from income growth. We can explain much of the recent divergence of Ohio home prices from income by rising foreclosure inventory and deteriorating economic conditions.

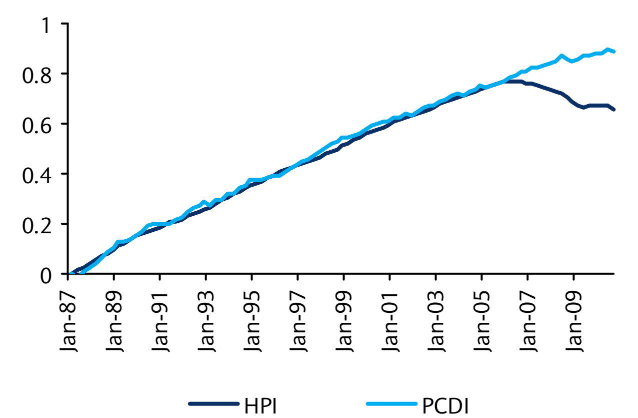
[1] Campbell, John Y.; Giglio, Stefano and Pathak, Parag A. Forthcoming, 2011. "Forced Sales and House Prices," *American Economic Review* . Our national average estimate of distressed discount is 26%, very close to the 27% estimated of Campbell et al.

We prefer PCDI as a measure of income over alternatives such as median household income and per capita income. While median household income growth may shed insight into the median home buyer, home price indices such as CoreLogic and Case-Shiller are valuation weighted. Such a value-weighted index is more akin to measuring the price growth of the mean home, not the median. PCDI is also preferred to per capita income because it accounts for regional differences in tax policy.

When decomposing HPA into **income growth** and **excess appreciation**, we define income growth as the change in the three-year moving average of per capita disposable income and the difference between HPA and income growth as excess appreciation. Using changes in the three-year moving average of disposable personal income reduces year to year volatility, creating a home price trend term that is dominated by inflation and real wage growth. Our choice of income trend is consistent with the observation that housing demand is most sensitive to changes in income that are perceived to be long term. Note that this is just a manifestation of Milton Friedman's permanent income hypothesis, and our choice of trend is commonly used in the literature[2]. The excess appreciation measure that results from detrending HPA by nominal income growth is a real variable, and so avoids spurious correlations due to inflation. To determine the effect of national home price cycles on individual regions, we estimate separate excess appreciation betas for each region.

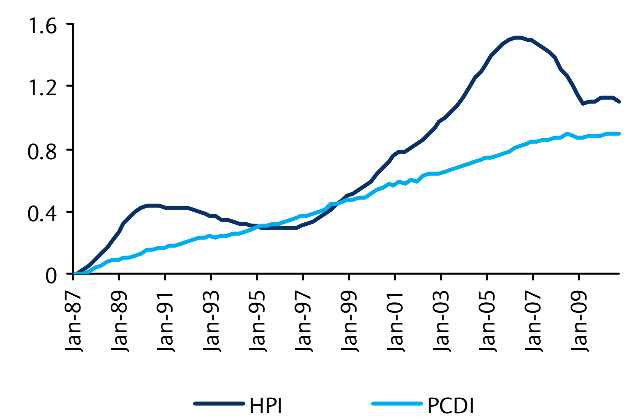
National excess appreciation includes the effects of many factors: the availability of credit, interest rates, changes in the tax code, etc. While our beta estimates do not distinguish among these factors, we notice some characteristics separating high-beta from low-beta regions. High-beta regions tend to be located on the coasts, where median home prices and incomes are higher. These are also regions where land comprises a larger fraction of the home's value. Davis and Palumbo estimate that land comprised 75% of West Coast home values at year-end 2004, whereas that fraction was only 36% in the Midwest.[3] Land prices are more volatile than construction costs, so we should expect greater sensitivity along the coasts to land-driven speculative boom/bust cycles.

**Figure 5: OH DX HPI closely tracks income growth**




Note: Log scale normalized to zero in Q1 87.
Source: CoreLogic LoanPerformance, BLS, Barclays Capital

**Figure 6: CA DX HPI has a large speculative component**




Note: Log scale normalized to zero in Q1 87.
Source: CoreLogic LoanPerformance, BLS, Barclays Capital

[2] See, for example, Alan Reichert. 1990. The impact of interest rates, income, and employment upon regional housing prices. *Journal of Real Estate Finance and Economics* 3: 373-391.
[3] Davis, Morris. A. and Michael G. Palumbo. 2008. The Price of Residential Land in Large U.S. Cities. *Journal of Urban Economics* 63(1): 352-284.

Figures 7 and 8 contrast low-beta Ohio with high-beta California. In this simple regression, which does not control for other variables used in our model, Ohio's beta of 0.29 implies that if national HPA is 10% above income growth, we should expect Ohio's home prices to grow 2.9% faster than that state's income. California's 1.58 beta would imply excess appreciation of 15.8% during such a boom period.

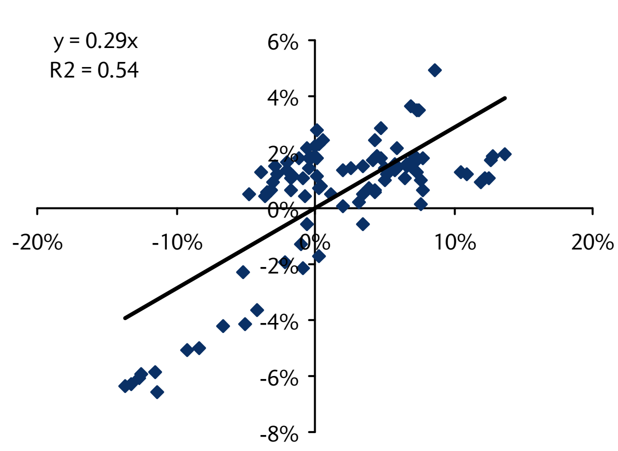
## Estimating foreclosure externalities

Distressed inventory enters our home price model in two ways: (1) the effect of distressed sales on the distressed gap between aggregate and nondistressed HPI, and (2) the suppressive effect of distressed inventory on nearby nondistressed home prices. We address the former by modeling the effect of distressed share on the convergence of aggregate HPI to nondistressed HPI, as discussed earlier. We discuss our estimation method for the latter in this section.

Defined as the suppressive effect of nearby foreclosures on voluntary sales prices, foreclosure externalities are an important determinant of regional relative performance in our model. These externalities may result for several reasons, such as an increase in supply of housing, a rise in crime due to higher vacancy rates, and diminished aesthetics of the neighborhood when foreclosed homes fall into disrepair. Several recent articles have addressed the magnitude of foreclosure externalities, typically employing a spatial, hedonic regression similar to that first used in Immergluck and Smith[4].

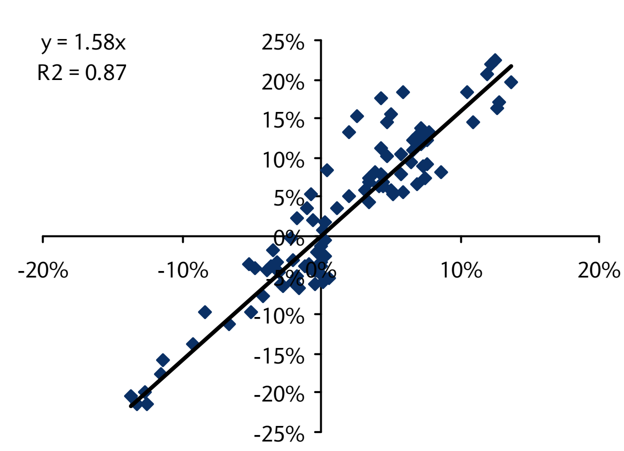
These studies estimate the discount at which a voluntary transaction occurs relative to comparable properties as a function of the number of nearby foreclosures. Immergluck and Smith, using single-family home prices in Chicago in 1999, estimate a 0.9-1.1% decline in nondistressed prices for each legal foreclosure advertisement within an eighth of a mile over the previous two years. This implies that each foreclosure imposed an average external cost of $159K. We employ a similar concept at the macro level to estimate the discount at which nondistressed HPI falls below the level it would be in the absence of distressed inventory.

**Figure 7: OH excess appreciation vs. US excess appreciation**




Note: Excess appreciation defined as y/y HPA minus y/y change in 3yr moving avg of PCDI. Source: CoreLogic LoanPerformance, BLS, Barclays Capital

**Figure 8: CA excess appreciation vs. US excess appreciation**




Note: Excess appreciation defined as y/y HPA minus y/y change in 3yr moving avg of PCDI. Source: CoreLogic LoanPerformance, BLS, Barclays Capital

[4] Immergluck, Dan and Geoff Smith. 2006. The external costs of foreclosure: The impact of single-family mortgage foreclosures on property values. *Housing Policy Debate* 17 (1): 57-79.

Defining an appropriate measure of distressed inventory requires having an idea where in the delinquency pipeline the foreclosure externality occurs: Is it when the foreclosure notice is given? At the time of foreclosure sale? When the distressed property is liquidated? Economists, John Harding and others[5] expanded on Immergluck and Smith's work to estimate the magnitude of foreclosure externality as a function of the phase of foreclosure, ranging from a year before the foreclosure sale to a year after the REO sale. They find that foreclosure externalities increase in severity leading up to the foreclosure sale, peaking at 1% per nearby foreclosure in the quarter prior to foreclosure sale, and persist for a year beyond the REO sale. This pattern is attributed to the increasing likelihood of vacancy, vandalism, and general disrepair due to the homeowner having a diminished incentive to maintain the property. Importantly, their results suggest that the foreclosure externality is not simply due to increasing visible supply, nor to the distressed discount harming "comps," ie, negative price revelation affecting similar, nearby homes. We borrow from the results of Harding et al. by defining distressed inventory as the one quarter-lagged sum of foreclosure and REO inventory as a fraction of each state's total mortgages. These estimates are derived from delinquency data provided by MBA and CoreLogic LoanPerformance.

In addition to using national excess appreciation and distressed inventory, the model seeks to explain regional excess appreciation using net migration patterns, the unemployment rate relative to the US, momentum, and mean reversion.

## Migration

Net migration, which we normalize using population and express as a percentage rate, captures changes in the relative desirability of a location. One commonality among the sand states of Florida, Arizona, and Nevada has been a multi-decade influx of retirees and those looking for work providing the services demanded by the growing population. As Figure 9 shows, net migration into those states dropped sharply after the peak in the housing market, as would-be retirees found it more difficult to sell property and move. Widespread negative equity following the housing bust further impeded migration patterns. As these effects reverse, and migration patterns revert to levels closer to historic averages, these three sand states should benefit from a pickup in housing demand and faster distressed turnover. Note that net population outflows from California appear to have been tempered by the bursting of the housing bubble in that state – underwater mortgages have likely kept homeowners from leaving the Golden State for a lower cost of living in Arizona or Nevada.

## Unemployment

A second measure of regional economic performance included in the model is the unemployment rate relative to the US. Cyclical states such as California have not only exhibited greater booms and busts in home prices, but also in unemployment rates. By including unemployment in the model, the sensitivity of regional excess appreciation to national HPA is reduced slightly in high-beta states, due to its correlation with cyclical unemployment. Including relative unemployment also controls for states that have experienced economic shocks on a different timeframe than those of the broader economy, such as has been the case for Michigan this decade. Figure 10 illustrates these two examples.

[5] Harding, John, Eric Rosenblatt, and Vincent Yao. 2009. The contagion effect of foreclosed properties. *Journal of Urban Economics* 66: 164-178.

## Momentum and Mean Reversion

The final structural feature of the model is the inclusion of momentum and mean reversion effects. Asset prices, especially home prices, exhibit a well-documented tendency of short-term serial correlation and long-term mean reversion. We estimate these effects through the inclusion of one-year (momentum) and five-year (mean reversion) cumulative error terms in our HPA regression equations.

## Estimation Results

The equation relating a given state's HPA to US HPA is of the following form:

State aggregate HPA = state income growth + state change in distressed gap + state change in foreclosure externalities + state excess appreciation

where

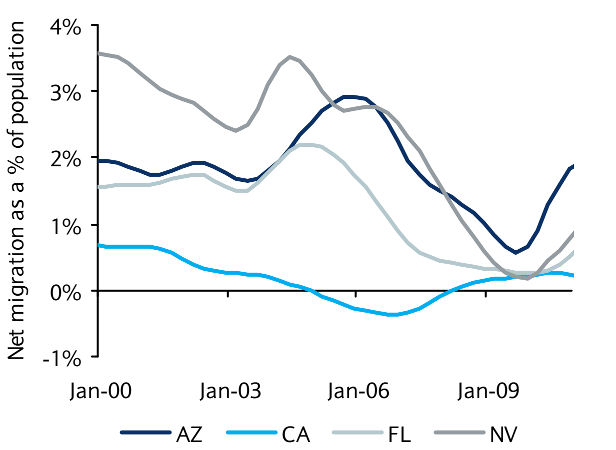
State excess appreciation = beta_state*(national aggregate HPA – national change in distressed gap – national change in foreclosure externalities – national income growth) + state alpha

Included in alpha are the contributions from economic fundamentals (migration and unemployment), momentum, and mean reversion. This functional form is analogous to the Capital Asset Pricing Model in finance, where regions are leveraged to national HPA, appreciation is detrended by a nominal rate (income), and relative performance is determined by differences in fundamentals.

Coefficients for migration, unemployment, distressed inventory, momentum, and mean reversion are held constant across states; only sensitivity to national excess appreciation is allowed to vary. When distributing national HPA to lower geographies – CBSA, county, and zip – we allow some variation around the state-level coefficient estimates for distressed inventory since the lowest level of granularity for which we have distressed inventory is at the state level. CBSA, county, and zip level distressed inventory patterns are highly correlated with their state's distressed inventory; we allow the effect to vary from the state effect to account for differences in levels across regions within a state.

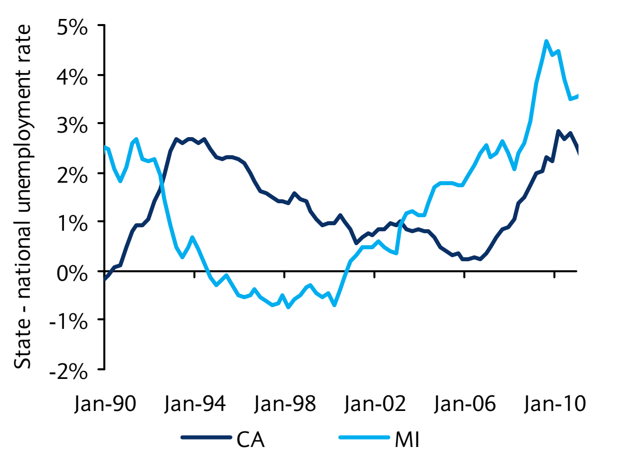
Among determinants of regional relative performance, only distressed inventory has a net effect when aggregated across states. Changes in net migration and relative unemployment

**Figure 9: Migration is down in AZ, FL, and NV**




Source: Moody's Analytics, Barclays Capital

**Figure 10: CA and MI unemployment has risen more than US**



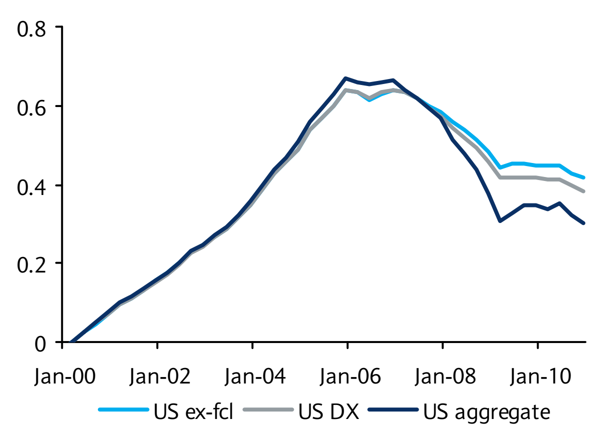

Source: Bureau of Economic Analysis, Barclays Capital are effectively zero sum – one state's gain is another's loss. We tested model specifications that consider distressed inventory relative to the US; however, such specifications have difficulty explaining home price declines in low-beta states with average foreclosure levels. For example, Ohio's distressed inventory rose less than the US from the housing peak to trough, so such a specification would suggest that prices would rise faster than income growth, rather than decline as observed (Figure 5).

Because distressed inventory has a net effect, consistent aggregation requires separating the effect of state-level foreclosures from national HPA. To get around this problem, we estimate the path of US home prices that is consistent with the observed foreclosure externality effects. This US ex-foreclosures index is calculated as the HPA path that returns the CoreLogic nondistressed HPA when state-level foreclosure externality effects are aggregated and removed from the index (Figure 11). We interpret this index as the level to which nondistressed home prices will converge as the foreclosure backlog is liquidated. Our estimates of the effect of foreclosure supply on voluntary transactions suggest that foreclosure externalities suppress nondistressed home prices by approximately 0.7% for each 1% rise in foreclosure and REO stock. Therefore, as distressed inventory rose from its long run average of 1.4% to 5.3% in 2010, foreclosure externalities pressured the national index by approximately 2.8%.

Some may find this 2.8% foreclosure externality effect surprisingly low in comparison to the attention focused on shadow inventory. It is important to remember, however, that this result excludes the effect of distressed transactions on aggregate home price indices, so represents a true externality of foreclosures on voluntary transactions (Figures 11 and 12). In addition, our estimate is consistent with other estimates of foreclosure externalities. With 2.7mn homes in distressed inventory, compared with our estimated long run average level of 700K, and \$16.5trn in residential real estate discounted by 2.8%, the implied average foreclosure externality effect is \$231K per foreclosed home. This compares with Immergluck and Smith's \$159K estimate for Chicago, which, in today's dollars, adjusted by Chicago nondistressed HPA between 1999 and 2010, is \$226K.

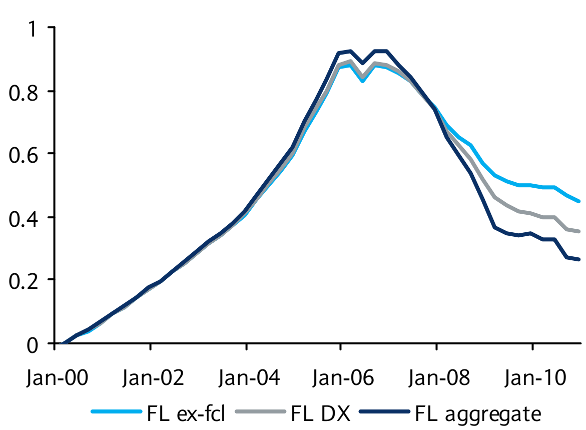
An implication of our model specification is that states with currently high foreclosures are expected to outperform in the coming years, as the suppressive effect of distressed inventory wanes. We have already begun to see this in California, the bust state with the

**Figure 11: US HPI with and without foreclosure externalities**




Note: Log index levels normalized to zero in January 2000.
Source: CoreLogic LoanPerformance, Barclays Capital

**Figure 12: FL HPI with and without foreclosure externalities**




Note: Log index levels normalized to zero in January 2000.
Source: CoreLogic LoanPerformance, Barclays Capital

earliest peak in foreclosure inventory. To see the magnitude of this effect, note that the Florida nondistressed index is 9.7% below the Florida ex-foreclosures index, implying higher expected appreciation than the national average as the state's distressed inventory of 15.7% is gradually absorbed. This outperformance will be even more pronounced in aggregate home price indices as declines in distressed share gradually reverse the compositional effects that have weighed down bust state aggregate home price indices throughout the housing crisis.

Figures 13 and 14 provide a model attribution of the housing boom and bust for several states. Sensitivity to US excess appreciation (beta) is highly variable, ranging from 0.34 for Michigan and Ohio to 1.48 for California. HPA is shown as log changes, as are the constituents of HPA. Much of the variation in HPA in 2000-06 is attributed to variations in beta. US home prices grew faster than incomes, leading to a national excess appreciation of 0.38 that was distributed to states. Income growth is largely an inflation term, and exhibits little variation across states relative to excess appreciation. As originally highlighted in Figures 7 and 8, the combination of sensitivity to US excess appreciation and income growth captures the majority of state home price fluctuations. Distressed inventory declined in most of the US during the housing bubble, with Ohio and Michigan as notable exceptions, and contributed marginally to relative performance. Michigan and Ohio HPA were suppressed by 3-4% due to increases in distressed inventory, while the rest of the states were supported by 2-5%. The combined effects of unemployment, migration, momentum, and mean reversion further improved model fits, leaving unexplained HPA within a range of about 5%.

**Figure 13: Model attribution of HPA during housing boom, January 2000 – June 2006**

| | | | | Decomposition of HPA | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| State | Beta | Actual HPA | Model HPA | US excess appreciation | Income growth | Foreclosure externalities | Distressed sales | Other factors | Unexplained HPA |
| AZ | 1.24 | 0.81 | 0.81 | 0.47 | 0.29 | 0.00 | 0.03 | 0.01 | 0.00 |
| CA | 1.48 | 0.94 | 0.90 | 0.56 | 0.30 | 0.01 | 0.02 | 0.02 | 0.03 |
| FL | 1.29 | 0.95 | 0.90 | 0.49 | 0.31 | 0.01 | 0.04 | 0.04 | 0.05 |
| MI | 0.34 | 0.19 | 0.24 | 0.13 | 0.22 | -0.02 | -0.02 | -0.07 | -0.05 |
| NV | 1.17 | 0.82 | 0.80 | 0.45 | 0.28 | 0.01 | 0.01 | 0.06 | 0.02 |
| NY | 0.92 | 0.75 | 0.68 | 0.35 | 0.26 | 0.01 | 0.01 | 0.06 | 0.07 |
| OH | 0.34 | 0.20 | 0.26 | 0.13 | 0.22 | -0.02 | -0.01 | -0.06 | -0.06 |
| TX | 0.44 | 0.32 | 0.38 | 0.17 | 0.27 | 0.00 | 0.01 | -0.07 | -0.06 |
| US | | 0.69 | | 0.38 | 0.28 | 0.00 | 0.03 | | |

Note: All changes are in logs and have been seasonally adjusted. Source: CoreLogic LoanPerformance, Moody's Analytics, Barclays Capital

**Figure 14: Model attribution of HPA during housing bust, June 2006 – March 2009**

| | | | | Decomposition of HPA | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| State | Beta | Actual HPA | Model HPA | US excess appreciation | Income growth | Foreclosure externalities | Distressed sales | Other factors | Unexplained HPA |
| AZ | 1.24 | -0.59 | -0.56 | -0.39 | 0.10 | -0.06 | -0.20 | -0.01 | -0.03 |
| CA | 1.48 | -0.54 | -0.55 | -0.47 | 0.11 | -0.05 | -0.11 | -0.03 | 0.01 |
| FL | 1.29 | -0.56 | -0.55 | -0.41 | 0.10 | -0.07 | -0.14 | -0.03 | -0.01 |
| MI | 0.34 | -0.55 | -0.45 | -0.11 | 0.07 | -0.07 | -0.27 | -0.07 | -0.10 |
| NV | 1.17 | -0.65 | -0.58 | -0.37 | 0.10 | -0.08 | -0.09 | -0.13 | -0.08 |
| NY | 0.92 | -0.15 | -0.16 | -0.29 | 0.16 | -0.01 | -0.04 | 0.03 | 0.01 |
| OH | 0.34 | -0.22 | -0.17 | -0.11 | 0.10 | -0.01 | -0.12 | -0.03 | -0.04 |
| TX | 0.44 | -0.08 | -0.07 | -0.14 | 0.12 | 0.00 | -0.05 | 0.00 | -0.01 |
| US | | -0.37 | | -0.32 | 0.12 | -0.03 | -0.14 | | |

Note: All changes are in logs and have been seasonally adjusted. Source: CoreLogic LoanPerformance, Moody's Analytics, Barclays Capital

The housing bust is not a mirror image of the boom. While US excess appreciation was still an important source of regional home price movements during this period, foreclosure-related effects now account for a significant portion of the decline in home prices as well. Moreover, they also account for much of the difference across states, creating significant underperformance in bust states relative to less affected states such as New York and Texas. In the low-beta states of Michigan and Ohio, distressed sales and foreclosure externalities account for the majority of the decline in home prices. Unexplained HPA is generally lower in this shorter period, though we fail to capture the full extent of the decrease in Michigan and Nevada. Nonetheless, for boom and bust, we largely preserve the ordinal ranking of state HPA in our fits.

## Home price scenarios

### *Inputs*

We derive a set of consistent regional macroeconomic and national home price scenarios from forecasts provided by Moody's Analytics. These regional scenarios cover five macro environments, ranging from severe stress to strong recovery, and include per capita disposable income, unemployment, and net migration. Figure 15 displays our national y/y HPA changes for nondistressed prices, and Figure 16 displays these scenarios in levels.

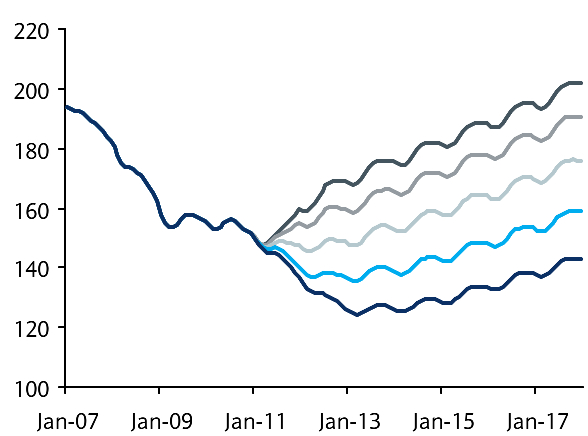
Distressed inventory forecasts are based on current delinquency pipelines and forecasts for key roll rates: current-to-delinquent, 90plus-to-foreclosure, foreclosure-to-REO, and REO-to-liquidation. Forecasts for distressed sales, which we use in our distressed share forecasts, come from this roll rate model. Distressed inventory liquidation timelines depend critically on whether the region is in a judicial or nonjudicial state. Figure 17 shows that distressed inventory (REO and foreclosures) peaked earlier in the nonjudicial states of Michigan, Nevada, Arizona, and California than they did in the judicial states of New York and Florida. New York distressed inventory is not forecasted to peak until Q1 12. Distressed share exhibits a similar pattern of convergence to its long-term average, but with much greater seasonal variation.

**Figure 15: Year/year US HPA by scenario**

| Year | Severe stress | Stress | Base | Recovery | Strong recovery |
|---|---|---|---|---|---|
| 2011 | -10.0% | -7.5% | -3.0% | 2.0% | 5.0% |
| 2012 | -7.5% | -2.5% | 1.0% | 3.0% | 6.0% |
| 2013 | 0.0% | 1.5% | 3.0% | 4.0% | 4.0% |
| 2014 | 2.0% | 3.0% | 3.5% | 3.5% | 3.5% |
| 2015 | 3.5% | 3.5% | 3.5% | 3.5% | 3.5% |
| 2016 | 3.5% | 3.5% | 3.5% | 3.5% | 3.5% |
| 2017 | 3.5% | 3.5% | 3.5% | 3.5% | 3.5% |

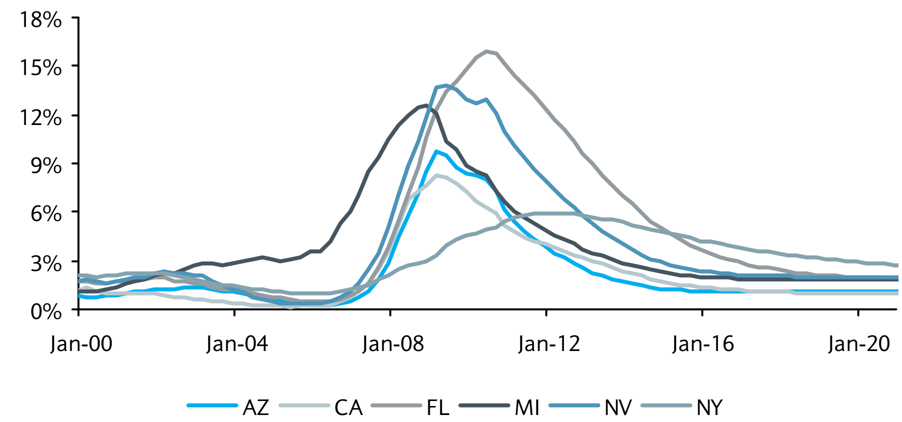
Source: Barclays Capital

**Figure 16: US HPI levels for five scenarios**




Source: Barclays Capital

**Figure 17: Distressed inventory forecasts by state**




Note: Projections after Jan 2011. Source: CoreLogic LoanPerformance, MBA, Barclays Capital

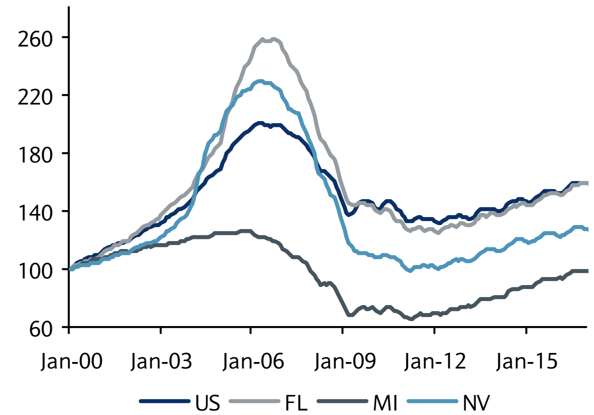
*Outputs*

For each region we forecast two home price indices: nondistressed and aggregate. Economic fundamentals, US excess appreciation, distressed inventory, momentum, and mean reversion determine nondistressed HPI, and distressed share determines the convergence rate between aggregate and nondistressed HPI. We present state-level aggregate and nondistressed forecasts for our stress, base, and recovery scenarios in Appendices 1-6.

Declining distressed inventory and distressed share should support bust state HPA in the years ahead. In Figures 18 and 19, we highlight the three bust states with the highest distressed inventory: Florida, Michigan, and Nevada. Note that each has exhibited cumulative HPA between January 2000 and December 2010 that is lower than for the US as a whole. Michigan, in particular, is down 30% since January 2000 while the US has risen by 38%. Among all states, Michigan is expected to have the highest cumulative HPA over the next 10 years (Figure 19). However, despite impressive gains through 2015, Michigan HPI is still expected to lag far behind US HPI (Figure 18).

Scenario risk is determined primarily by income growth and sensitivity to national excess appreciation. High-beta states have greater uncertainty than low-beta states. This is made clear by once again comparing California with Ohio (Figure 20). California's greater sensitivity to national excess appreciation results in a wider forecast through the end of this decade. In our severe stress scenario, California distressed excluded prices fall by a cumulative 12% over the next nine years vs. Ohio's 10% rise. In our strong recovery scenario, California prices rise by 50% versus Ohio's 38% rise. This has important implications for MBS valuations, as greater uncertainty increases both the probability that a borrower will default and prepay.

**Figure 18: Base scenario aggregate HPI for selected bust states**



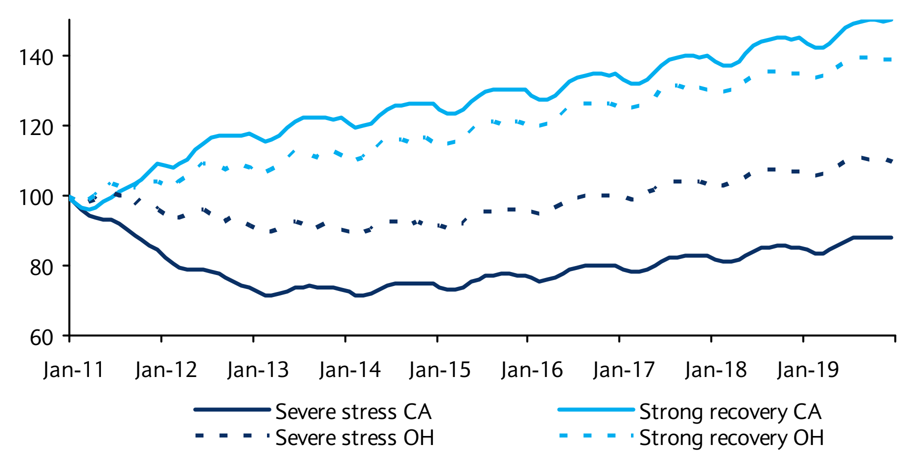

Note: Forecasts begin January 2011.
Source: CoreLogic LoanPerformance, Barclays Capital

**Figure 19: Aggregate HPA, base scenario**

| State | 2011 HPA | 2012 HPA | 2013 HPA | 2014 HPA | 2015 HPA | 2016-2020 HPA |
|---|---|---|---|---|---|---|
| US | -2.5% | 1.6% | 3.8% | 4.3% | 4.1% | 3.5% |
| FL | -2.5% | 3.4% | 5.1% | 5.0% | 4.6% | 3.9% |
| MI | 2.3% | 6.6% | 8.2% | 8.6% | 7.0% | 3.9% |
| NV | -0.3% | 4.5% | 6.9% | 5.3% | 3.8% | 3.0% |

Source: Barclays Capital

**Figure 20: CA DX HPI forecasts exhibit greater risk than OH**

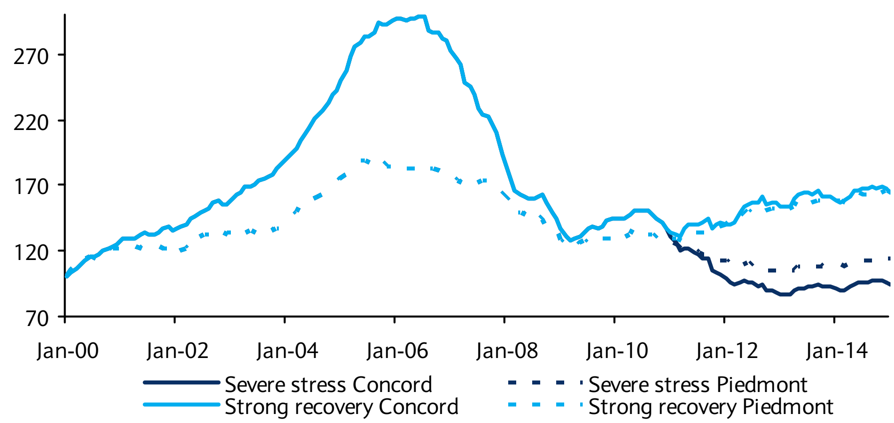



Note: HPI normalized to 100 in December 2010. Source: Barclays Capital

With 67% of subprime, alt-A, and jumbo balances coming from zip codes that we forecast, modeling within-state variation is also important . Due to differences in demographics and land scarcity, zip codes in the same MSA may exhibit markedly different HPA. In particular, prime zip codes typically experienced a less severe boom/bust than subprime. For example, zip code 94611 (Piedmont, California), an affluent zip code in the Oakland-Fremont-Heyward CBSA, with a median home price of $700K and average adjusted gross income (AGI) of $130K[6], rose by 83% between January 2000 and June 2006. In contrast, the less affluent 94519 zip code in Concord, California, with a median home value of $347K and average AGI of $49K, increased by 198% over the same period (Figure 21). Not surprisingly, we estimate a larger beta for the Concord zip code. Note that this zip code not only has greater uncertainty, but also amplified seasonality, due to its larger distressed share. Moreover, the Concord zip is estimated to have 2.4x the sensitivity to California distressed inventory as the Piedmont zip.

[6] Source: *www.city-data.com*. Home values for 2009 and income for 2004.

**Figure 21: Zip code aggregate HPI forecast variation in Oakland-Fremont-Heyward CBSA**




Note: Forecast begins January 2011. Source: CoreLogic LoanPerformance, Barclays Capital

## Regional HPA Forecasts

Our five-year base forecast is for outperformance in depressed markets, such as Florida, Michigan, and Nevada. Declining distressed inventory and distressed share should particularly support aggregate HPA in these states. Nationally, we expect relatively flat prices with limited price declines, as the market works through excess supply and housing becomes more affordable relative to disposable income. We decompose our HPA forecasts for several key states in Figure 22 and present our national forecasts in Appendices 1-6.

**Figure 22: Constituents of aggregate HPA forecast, base scenario, December 2010 – December 2015**

| | | | | Decomposition of HPA | | | | |
|---|---|---|---|---|---|---|---|---|
| State | Beta | Aggregate HPA forecast | Nondistressed HPA forecast | US excess appreciation | Income growth | Foreclosure externalities | Distressed sales | Other factors |
| AZ | 1.24 | 0.10 | 0.03 | -0.16 | 0.13 | 0.04 | 0.06 | 0.02 |
| CA | 1.48 | 0.05 | 0.01 | -0.19 | 0.17 | 0.03 | 0.04 | 0.01 |
| FL | 1.29 | 0.15 | 0.09 | -0.17 | 0.14 | 0.09 | 0.06 | 0.03 |
| MI | 0.34 | 0.30 | 0.22 | -0.04 | 0.18 | 0.04 | 0.08 | 0.05 |
| NV | 1.17 | 0.19 | 0.16 | -0.15 | 0.12 | 0.07 | 0.04 | 0.12 |
| NY | 0.92 | 0.07 | 0.07 | -0.12 | 0.18 | 0.01 | 0.00 | 0.01 |
| OH | 0.34 | 0.10 | 0.06 | -0.04 | 0.08 | 0.02 | 0.04 | 0.01 |
| TX | 0.44 | 0.08 | 0.07 | -0.06 | 0.11 | 0.01 | 0.01 | 0.01 |
| US | | 0.11 | 0.08 | -0.13 | 0.18 | 0.03 | 0.03 | |

Note: All changes are in logs. Source: Moody's Analytics, Barclays Capital

Appendix 1: Aggregate HPA forecasts, recovery scenario

| State | 2011 | 2012 | 2013 | 2014 | 2015 | 2016-20 |
|---|---|---|---|---|---|---|
| US | 2.6% | 3.6% | 4.8% | 4.3% | 4.1% | 3.5% |
| AK | 1.5% | 1.6% | 2.1% | 2.1% | 2.6% | 3.2% |
| AL | -2.2% | 2.2% | 5.4% | 5.8% | 5.6% | 3.3% |
| AR | 3.1% | 3.9% | 4.8% | 4.4% | 3.9% | 3.1% |
| AZ | 4.8% | 4.2% | 5.0% | 4.0% | 3.5% | 3.2% |
| CA | 4.0% | 3.5% | 4.0% | 3.2% | 3.1% | 3.5% |
| CO | 3.6% | 4.7% | 5.6% | 4.6% | 4.0% | 3.1% |
| CT | 1.2% | 2.6% | 4.6% | 4.9% | 4.9% | 3.6% |
| DC | 4.2% | 2.7% | 2.1% | 1.4% | 2.0% | 3.4% |
| DE | -0.2% | 1.3% | 2.9% | 3.5% | 4.0% | 3.6% |
| FL | 4.5% | 6.3% | 6.2% | 5.2% | 4.7% | 3.9% |
| GA | 1.0% | 4.0% | 6.4% | 6.0% | 4.9% | 3.2% |
| HI | 7.4% | 6.3% | 5.9% | 4.6% | 3.8% | 3.7% |
| IA | 3.3% | 4.7% | 4.7% | 4.5% | 4.1% | 3.1% |
| ID | -0.6% | 3.5% | 5.1% | 4.5% | 4.2% | 3.2% |
| IL | 1.2% | 3.5% | 6.2% | 6.3% | 5.7% | 3.5% |
| IN | 2.6% | 4.7% | 6.4% | 5.8% | 4.9% | 3.3% |
| KS | 1.5% | 4.2% | 5.3% | 4.7% | 4.3% | 3.2% |
| KY | 2.3% | 3.7% | 5.0% | 4.9% | 4.7% | 3.3% |
| LA | 2.1% | 3.5% | 3.5% | 4.0% | 4.1% | 3.6% |
| MA | 2.8% | 3.8% | 5.5% | 5.2% | 4.9% | 3.5% |
| MD | 0.5% | 2.1% | 4.5% | 4.5% | 4.7% | 3.4% |
| ME | 1.5% | 2.9% | 4.9% | 4.7% | 4.6% | 3.4% |
| MI | 5.4% | 7.6% | 9.3% | 8.1% | 6.7% | 3.9% |
| MN | 0.7% | 2.2% | 3.0% | 3.6% | 4.1% | 3.2% |
| MO | -0.2% | 4.4% | 6.3% | 5.9% | 5.0% | 3.2% |
| MS | 3.0% | 3.3% | 3.9% | 3.5% | 3.6% | 3.1% |
| MT | -0.5% | 2.8% | 4.6% | 5.0% | 5.1% | 3.5% |
| NC | 2.2% | 3.9% | 5.3% | 4.9% | 4.5% | 3.1% |
| ND | 4.8% | 2.7% | 3.3% | 2.5% | 2.5% | 3.0% |
| NE | 2.6% | 3.8% | 4.2% | 3.8% | 3.6% | 3.1% |
| NH | 1.5% | 3.3% | 4.8% | 4.5% | 4.2% | 3.3% |
| NJ | 2.4% | 2.9% | 4.1% | 3.9% | 4.2% | 3.8% |
| NM | 1.4% | 4.3% | 6.8% | 5.8% | 4.9% | 3.3% |
| NV | 6.4% | 7.2% | 8.2% | 5.4% | 3.8% | 3.0% |
| NY | 1.9% | 3.0% | 3.8% | 3.4% | 3.5% | 3.8% |
| OH | 2.6% | 2.0% | 3.1% | 3.6% | 4.2% | 3.4% |
| OK | 0.9% | 3.0% | 3.8% | 4.2% | 4.2% | 3.3% |
| OR | 0.6% | 4.0% | 6.6% | 6.0% | 5.0% | 3.2% |
| PA | -0.3% | 1.2% | 3.1% | 3.4% | 4.6% | 3.7% |
| RI | 3.3% | 3.5% | 4.2% | 4.3% | 4.1% | 3.4% |
| SC | 2.3% | 3.2% | 4.3% | 4.4% | 3.8% | 3.3% |
| SD | -0.3% | 2.2% | 3.9% | 4.0% | 4.2% | 3.2% |
| TN | 1.6% | 4.0% | 5.1% | 4.6% | 6.6% | 3.7% |
| TX | 1.2% | 2.0% | 3.2% | 3.1% | 3.3% | 3.2% |
| UT | -0.6% | 3.4% | 4.7% | 4.2% | 4.0% | 3.1% |
| VA | 2.7% | 2.7% | 3.5% | 2.9% | 3.1% | 3.4% |
| VT | 2.4% | 2.9% | 5.2% | 6.4% | 6.3% | 4.1% |
| WA | 0.5% | 3.5% | 5.4% | 5.2% | 4.6% | 3.3% |
| WI | 1.3% | 3.5% | 5.2% | 5.2% | 4.7% | 3.3% |
| WV | 5.6% | 5.0% | 5.4% | 4.4% | 3.2% | 3.2% |
| WY | 1.1% | 2.9% | 2.2% | 2.0% | 2.6% | 3.2% |

Source: Barclays Capital

Appendix 2: Aggregate HPA forecasts, base scenario

| State | 2011 | 2012 | 2013 | 2014 | 2015 | 2016-20 |
|---|---|---|---|---|---|---|
| US | -2.5% | 1.6% | 3.8% | 4.3% | 4.1% | 3.5% |
| AK | -3.0% | -0.1% | 0.8% | 2.1% | 2.6% | 3.2% |
| AL | -4.5% | 1.3% | 4.6% | 5.9% | 5.7% | 3.3% |
| AR | 1.0% | 3.1% | 4.0% | 4.4% | 3.9% | 3.1% |
| AZ | -2.5% | 1.8% | 4.1% | 3.9% | 3.5% | 3.2% |
| CA | -4.1% | 0.5% | 2.8% | 3.1% | 3.0% | 3.5% |
| CO | 1.0% | 3.6% | 4.7% | 4.7% | 4.0% | 3.1% |
| CT | -3.0% | 0.8% | 3.6% | 4.9% | 4.9% | 3.6% |
| DC | -1.7% | 0.7% | 1.9% | 1.2% | 1.7% | 3.4% |
| DE | -4.3% | -0.7% | 1.8% | 3.4% | 4.0% | 3.6% |
| FL | -2.5% | 3.4% | 5.1% | 5.0% | 4.6% | 3.9% |
| GA | -1.7% | 2.6% | 5.5% | 6.1% | 5.0% | 3.2% |
| HI | 1.9% | 3.8% | 4.7% | 4.4% | 3.7% | 3.7% |
| IA | 1.9% | 3.9% | 3.8% | 4.5% | 4.2% | 3.1% |
| ID | -4.8% | 1.7% | 4.1% | 4.4% | 4.2% | 3.1% |
| IL | -2.5% | 2.1% | 5.2% | 6.5% | 5.8% | 3.5% |
| IN | 0.1% | 3.6% | 5.4% | 5.9% | 5.0% | 3.3% |
| KS | -0.9% | 3.0% | 4.4% | 4.7% | 4.3% | 3.2% |
| KY | 0.2% | 2.9% | 4.2% | 5.0% | 4.8% | 3.3% |
| LA | -1.6% | 2.3% | 2.6% | 4.1% | 4.1% | 3.6% |
| MA | -1.3% | 1.8% | 4.6% | 5.2% | 4.9% | 3.5% |
| MD | -4.5% | -0.2% | 3.4% | 4.4% | 4.6% | 3.4% |
| ME | -2.5% | 1.2% | 3.9% | 4.6% | 4.6% | 3.4% |
| MI | 2.3% | 6.6% | 8.2% | 8.6% | 7.0% | 3.9% |
| MN | -2.5% | 0.6% | 1.9% | 3.5% | 4.2% | 3.2% |
| MO | -3.2% | 3.1% | 5.4% | 5.9% | 5.1% | 3.2% |
| MS | 0.1% | 2.3% | 3.1% | 3.6% | 3.7% | 3.1% |
| MT | -3.6% | 1.4% | 3.8% | 5.0% | 5.1% | 3.5% |
| NC | 0.8% | 3.2% | 4.5% | 5.0% | 4.5% | 3.1% |
| ND | 2.9% | 1.5% | 2.4% | 2.2% | 2.5% | 3.0% |
| NE | 0.7% | 2.6% | 3.3% | 3.7% | 3.7% | 3.1% |
| NH | -2.6% | 1.4% | 3.7% | 4.3% | 4.2% | 3.3% |
| NJ | -3.2% | 0.7% | 3.0% | 3.9% | 4.1% | 3.8% |
| NM | -2.4% | 2.9% | 5.9% | 5.8% | 4.9% | 3.3% |
| NV | -0.3% | 4.5% | 6.9% | 5.3% | 3.8% | 3.0% |
| NY | -3.2% | 0.8% | 2.8% | 3.4% | 3.5% | 3.8% |
| OH | -0.1% | 1.0% | 1.9% | 3.8% | 4.4% | 3.4% |
| OK | -1.0% | 2.0% | 3.0% | 4.2% | 4.2% | 3.3% |
| OR | -2.7% | 2.8% | 5.7% | 6.2% | 5.0% | 3.2% |
| PA | -4.2% | -0.4% | 2.1% | 3.5% | 4.7% | 3.7% |
| RI | -1.6% | 1.5% | 3.1% | 4.2% | 4.1% | 3.4% |
| SC | -1.2% | 1.8% | 3.4% | 4.4% | 3.8% | 3.3% |
| SD | -1.9% | 1.1% | 3.1% | 3.9% | 4.2% | 3.2% |
| TN | -0.5% | 3.2% | 4.3% | 4.7% | 6.7% | 3.7% |
| TX | -1.5% | 0.9% | 2.3% | 3.1% | 3.3% | 3.2% |
| UT | -4.1% | 1.8% | 3.8% | 4.1% | 4.0% | 3.1% |
| VA | -3.4% | 0.1% | 2.5% | 2.6% | 2.9% | 3.4% |
| VT | -0.9% | 1.2% | 4.2% | 6.3% | 6.3% | 4.1% |
| WA | -3.4% | 2.0% | 4.5% | 5.3% | 4.6% | 3.3% |
| WI | -1.7% | 2.1% | 4.1% | 5.2% | 4.8% | 3.3% |
| WV | 0.3% | 3.2% | 4.4% | 4.4% | 3.2% | 3.2% |
| WY | -2.5% | 1.3% | 1.5% | 1.9% | 2.4% | 3.2% |

Source: Barclays Capital

Appendix 3: Aggregate HPA forecasts, stress scenario

| State | 2011 | 2012 | 2013 | 2014 | 2015 | 2016-20 |
|---|---|---|---|---|---|---|
| US | -7.0% | -1.9% | 2.3% | 3.8% | 4.1% | 3.4% |
| AK | -7.6% | -3.6% | -0.4% | 1.4% | 2.7% | 3.2% |
| AL | -6.5% | -0.4% | 3.1% | 5.2% | 5.5% | 3.3% |
| AR | -0.9% | 1.6% | 2.7% | 3.8% | 3.7% | 3.1% |
| AZ | -8.0% | -3.1% | 2.6% | 3.5% | 3.5% | 3.1% |
| CA | -11.2% | -5.0% | 1.4% | 2.9% | 3.2% | 3.4% |
| CO | -1.4% | 1.5% | 3.2% | 4.0% | 3.9% | 3.1% |
| CT | -6.8% | -2.4% | 2.0% | 4.3% | 4.8% | 3.6% |
| DC | -6.6% | -2.9% | 1.7% | 1.5% | 2.0% | 3.3% |
| DE | -8.0% | -4.0% | 0.1% | 2.7% | 3.8% | 3.5% |
| FL | -8.6% | -1.6% | 3.6% | 4.6% | 4.6% | 3.8% |
| GA | -4.3% | 0.7% | 4.0% | 5.4% | 4.9% | 3.2% |
| HI | -3.1% | -0.5% | 3.1% | 3.9% | 3.6% | 3.7% |
| IA | 0.6% | 2.5% | 2.2% | 3.5% | 3.8% | 3.1% |
| ID | -8.5% | -1.5% | 2.6% | 3.8% | 4.0% | 3.1% |
| IL | -6.2% | -0.5% | 3.5% | 5.8% | 5.7% | 3.5% |
| IN | -2.2% | 1.5% | 3.6% | 5.0% | 4.8% | 3.3% |
| KS | -3.2% | 0.8% | 2.8% | 3.9% | 4.1% | 3.1% |
| KY | -1.8% | 1.3% | 2.8% | 4.3% | 4.7% | 3.3% |
| LA | -5.0% | -0.2% | 1.2% | 3.5% | 4.1% | 3.6% |
| MA | -5.0% | -1.0% | 3.0% | 4.6% | 4.7% | 3.5% |
| MD | -8.9% | -4.1% | 1.8% | 3.8% | 4.5% | 3.4% |
| ME | -6.0% | -1.8% | 2.4% | 4.0% | 4.5% | 3.3% |
| MI | -1.0% | 4.3% | 6.2% | 7.8% | 7.1% | 3.9% |
| MN | -5.3% | -2.1% | 0.1% | 2.6% | 3.9% | 3.2% |
| MO | -6.0% | 0.7% | 3.7% | 5.2% | 5.0% | 3.2% |
| MS | -2.6% | 0.4% | 1.7% | 2.9% | 3.6% | 3.1% |
| MT | -6.4% | -1.0% | 2.5% | 4.4% | 4.9% | 3.4% |
| NC | -0.6% | 1.9% | 3.1% | 4.2% | 4.3% | 3.2% |
| ND | 1.4% | -0.3% | 0.9% | 1.3% | 2.0% | 3.0% |
| NE | -0.8% | 0.8% | 1.8% | 2.9% | 3.3% | 3.1% |
| NH | -6.1% | -2.0% | 2.0% | 3.4% | 3.9% | 3.2% |
| NJ | -8.1% | -3.2% | 1.4% | 3.4% | 4.1% | 3.7% |
| NM | -5.7% | 0.2% | 4.5% | 5.2% | 4.8% | 3.3% |
| NV | -6.1% | -0.3% | 5.5% | 4.9% | 3.8% | 2.9% |
| NY | -8.1% | -2.8% | 1.2% | 3.0% | 3.5% | 3.7% |
| OH | -2.9% | -1.1% | -0.2% | 2.7% | 4.3% | 3.4% |
| OK | -2.8% | 0.3% | 1.5% | 3.4% | 4.0% | 3.3% |
| OR | -5.9% | 0.5% | 4.1% | 5.5% | 5.0% | 3.2% |
| PA | -7.8% | -3.2% | 0.5% | 2.8% | 4.6% | 3.6% |
| RI | -5.9% | -1.9% | 1.4% | 3.5% | 4.0% | 3.4% |
| SC | -4.3% | -0.8% | 1.9% | 3.8% | 3.7% | 3.3% |
| SD | -3.3% | -0.6% | 1.6% | 3.0% | 3.8% | 3.2% |
| TN | -2.5% | 1.7% | 2.8% | 4.0% | 6.5% | 3.8% |
| TX | -4.1% | -1.2% | 1.0% | 2.5% | 3.1% | 3.2% |
| UT | -7.0% | -1.0% | 2.4% | 3.4% | 3.8% | 3.1% |
| VA | -8.5% | -4.4% | 1.0% | 2.1% | 2.7% | 3.3% |
| VT | -3.9% | -1.6% | 2.6% | 5.5% | 6.1% | 4.1% |
| WA | -7.0% | -0.9% | 2.9% | 4.7% | 4.8% | 3.2% |
| WI | -4.5% | -0.4% | 2.5% | 4.4% | 4.6% | 3.3% |
| WV | -4.4% | -0.3% | 3.0% | 3.9% | 3.1% | 3.2% |
| WY | -5.6% | -1.4% | 0.2% | 1.3% | 2.2% | 3.1% |

Source: Barclays Capital

**Appendix 4: Distressed excluded HPA forecasts, recovery scenario**

| State | 2011 | 2012 | 2013 | 2014 | 2015 | 2016-20 |
|---|---|---|---|---|---|---|
| US | 2.0% | 3.0% | 4.0% | 3.5% | 3.5% | 3.3% |
| AK | 1.5% | 1.6% | 2.1% | 2.1% | 2.6% | 3.2% |
| AL | -2.2% | 2.0% | 5.1% | 5.5% | 5.4% | 3.2% |
| AR | 3.1% | 3.7% | 4.3% | 4.0% | 3.6% | 3.1% |
| AZ | 1.7% | 2.2% | 3.7% | 3.3% | 3.2% | 3.2% |
| CA | 2.7% | 2.7% | 3.1% | 2.4% | 2.6% | 3.4% |
| CO | 2.6% | 3.6% | 4.7% | 3.9% | 3.6% | 3.1% |
| CT | 1.4% | 2.6% | 4.3% | 4.1% | 4.1% | 3.3% |
| DC | 4.2% | 2.7% | 2.1% | 1.4% | 2.0% | 3.4% |
| DE | -0.2% | 1.2% | 2.6% | 3.1% | 3.6% | 3.4% |
| FL | 3.9% | 5.1% | 4.7% | 3.4% | 3.4% | 3.6% |
| GA | 0.8% | 2.9% | 4.8% | 4.5% | 4.1% | 3.1% |
| HI | 7.6% | 5.4% | 4.2% | 2.4% | 2.0% | 3.2% |
| IA | 3.3% | 4.6% | 4.4% | 4.2% | 3.9% | 3.0% |
| ID | -1.5% | 2.2% | 4.0% | 4.0% | 4.0% | 3.1% |
| IL | 0.7% | 3.0% | 5.5% | 5.3% | 4.9% | 3.3% |
| IN | 2.6% | 4.1% | 5.3% | 4.6% | 4.1% | 3.1% |
| KS | 1.4% | 3.9% | 4.7% | 4.0% | 3.8% | 3.1% |
| KY | 2.0% | 3.5% | 4.6% | 4.2% | 4.2% | 3.2% |
| LA | 2.8% | 3.5% | 3.3% | 2.7% | 3.0% | 3.3% |
| MA | 2.4% | 3.4% | 4.9% | 4.4% | 4.2% | 3.3% |
| MD | 0.6% | 2.0% | 4.1% | 4.0% | 4.2% | 3.3% |
| ME | 1.5% | 2.9% | 4.9% | 4.7% | 4.6% | 3.4% |
| MI | 2.7% | 5.3% | 7.4% | 6.5% | 5.3% | 3.1% |
| MN | -0.3% | 1.6% | 2.4% | 3.2% | 3.9% | 3.2% |
| MO | 0.1% | 3.7% | 5.3% | 4.9% | 4.5% | 3.1% |
| MS | 3.0% | 3.3% | 3.9% | 3.5% | 3.6% | 3.1% |
| MT | -0.6% | 2.2% | 3.5% | 3.9% | 4.3% | 3.3% |
| NC | 2.1% | 3.5% | 4.6% | 4.2% | 4.1% | 3.1% |
| ND | 4.7% | 2.7% | 3.2% | 2.4% | 2.5% | 3.0% |
| NE | 2.8% | 3.8% | 4.1% | 3.5% | 3.5% | 3.1% |
| NH | 1.5% | 3.3% | 4.8% | 4.5% | 4.2% | 3.3% |
| NJ | 2.3% | 2.9% | 4.0% | 3.6% | 3.7% | 3.5% |
| NM | 1.4% | 3.9% | 6.0% | 5.0% | 4.3% | 3.2% |
| NV | 5.2% | 6.1% | 7.2% | 4.7% | 3.4% | 3.0% |
| NY | 2.4% | 3.0% | 3.8% | 3.4% | 3.3% | 3.4% |
| OH | 1.5% | 1.4% | 2.2% | 2.5% | 3.4% | 3.1% |
| OK | 1.3% | 2.7% | 3.1% | 3.4% | 3.7% | 3.2% |
| OR | 0.1% | 2.9% | 5.4% | 5.1% | 4.5% | 3.1% |
| PA | 0.2% | 1.2% | 3.1% | 3.4% | 3.8% | 3.3% |
| RI | 2.8% | 3.2% | 3.7% | 3.6% | 3.5% | 3.3% |
| SC | 1.9% | 2.4% | 3.3% | 3.4% | 3.2% | 3.2% |
| SD | -0.3% | 2.2% | 3.9% | 4.0% | 4.2% | 3.2% |
| TN | 1.6% | 4.0% | 5.1% | 4.6% | 4.1% | 3.1% |
| TX | 1.4% | 2.0% | 2.6% | 2.5% | 2.9% | 3.1% |
| UT | -0.5% | 3.0% | 4.3% | 3.9% | 3.8% | 3.1% |
| VA | 2.4% | 2.1% | 2.8% | 2.3% | 2.7% | 3.3% |
| VT | 1.0% | 1.7% | 3.5% | 3.9% | 4.1% | 3.3% |
| WA | 0.6% | 3.0% | 4.6% | 4.3% | 3.9% | 3.1% |
| WI | 0.9% | 3.0% | 4.5% | 4.4% | 4.2% | 3.2% |
| WV | 6.2% | 4.7% | 4.3% | 3.2% | 2.4% | 3.1% |
| WY | 1.1% | 2.9% | 2.2% | 2.0% | 2.6% | 3.2% |

Source: Barclays Capital

## Appendix 5: Distressed excluded HPA forecasts, base scenario

| State | 2011 | 2012 | 2013 | 2014 | 2015 | 2016-20 |
|---|---|---|---|---|---|---|
| US | -3.0% | 1.0% | 3.0% | 3.5% | 3.5% | 3.3% |
| AK | -3.0% | -0.1% | 0.8% | 2.1% | 2.6% | 3.2% |
| AL | -4.5% | 1.1% | 4.3% | 5.6% | 5.4% | 3.2% |
| AR | 1.1% | 2.8% | 3.6% | 4.0% | 3.6% | 3.1% |
| AZ | -5.4% | -0.2% | 2.7% | 3.1% | 3.2% | 3.2% |
| CA | -5.3% | -0.4% | 2.0% | 2.3% | 2.5% | 3.4% |
| CO | 0.1% | 2.5% | 3.8% | 4.0% | 3.7% | 3.1% |
| CT | -2.8% | 0.8% | 3.2% | 4.1% | 4.1% | 3.3% |
| DC | -1.7% | 0.7% | 1.9% | 1.2% | 1.7% | 3.4% |
| DE | -4.3% | -0.8% | 1.5% | 3.0% | 3.6% | 3.4% |
| FL | -3.2% | 2.3% | 3.6% | 3.2% | 3.3% | 3.6% |
| GA | -1.8% | 1.5% | 4.0% | 4.7% | 4.2% | 3.1% |
| HI | 2.0% | 2.9% | 3.0% | 2.3% | 1.9% | 3.2% |
| IA | 1.9% | 3.7% | 3.6% | 4.2% | 4.0% | 3.1% |
| ID | -5.7% | 0.4% | 3.1% | 3.9% | 3.9% | 3.1% |
| IL | -3.0% | 1.6% | 4.4% | 5.5% | 5.0% | 3.3% |
| IN | 0.1% | 2.9% | 4.3% | 4.7% | 4.2% | 3.1% |
| KS | -1.1% | 2.6% | 3.7% | 4.0% | 3.8% | 3.1% |
| KY | -0.1% | 2.6% | 3.7% | 4.4% | 4.3% | 3.2% |
| LA | -0.9% | 2.3% | 2.4% | 2.8% | 3.0% | 3.3% |
| MA | -1.7% | 1.4% | 4.1% | 4.4% | 4.2% | 3.3% |
| MD | -4.4% | -0.3% | 3.1% | 3.8% | 4.1% | 3.3% |
| ME | -2.5% | 1.2% | 3.9% | 4.6% | 4.6% | 3.4% |
| MI | -0.4% | 4.3% | 6.2% | 6.9% | 5.6% | 3.1% |
| MN | -3.4% | 0.0% | 1.3% | 3.1% | 3.9% | 3.2% |
| MO | -3.0% | 2.3% | 4.3% | 4.9% | 4.6% | 3.1% |
| MS | 0.1% | 2.3% | 3.1% | 3.6% | 3.7% | 3.1% |
| MT | -3.8% | 0.8% | 2.8% | 3.8% | 4.3% | 3.3% |
| NC | 0.7% | 2.7% | 3.8% | 4.3% | 4.1% | 3.1% |
| ND | 2.9% | 1.5% | 2.4% | 2.2% | 2.5% | 3.0% |
| NE | 1.0% | 2.6% | 3.2% | 3.4% | 3.5% | 3.1% |
| NH | -2.6% | 1.4% | 3.7% | 4.3% | 4.2% | 3.3% |
| NJ | -3.2% | 0.7% | 2.9% | 3.5% | 3.7% | 3.5% |
| NM | -2.4% | 2.4% | 5.2% | 5.0% | 4.3% | 3.2% |
| NV | -1.4% | 3.4% | 5.9% | 4.6% | 3.4% | 3.0% |
| NY | -2.7% | 0.8% | 2.8% | 3.4% | 3.3% | 3.4% |
| OH | -1.2% | 0.3% | 1.0% | 2.6% | 3.6% | 3.1% |
| OK | -0.6% | 1.7% | 2.3% | 3.4% | 3.7% | 3.2% |
| OR | -3.2% | 1.7% | 4.6% | 5.3% | 4.6% | 3.1% |
| PA | -3.7% | -0.4% | 2.1% | 3.4% | 3.9% | 3.3% |
| RI | -2.1% | 1.2% | 2.6% | 3.5% | 3.5% | 3.3% |
| SC | -1.6% | 1.0% | 2.3% | 3.4% | 3.2% | 3.2% |
| SD | -1.9% | 1.1% | 3.0% | 3.9% | 4.2% | 3.2% |
| TN | -0.5% | 3.2% | 4.3% | 4.7% | 4.2% | 3.1% |
| TX | -1.3% | 0.9% | 1.8% | 2.5% | 2.9% | 3.1% |
| UT | -4.0% | 1.4% | 3.4% | 3.7% | 3.8% | 3.1% |
| VA | -3.7% | -0.6% | 1.8% | 2.0% | 2.6% | 3.3% |
| VT | -2.3% | 0.1% | 2.5% | 3.8% | 4.1% | 3.3% |
| WA | -3.4% | 1.5% | 3.7% | 4.4% | 4.0% | 3.1% |
| WI | -2.1% | 1.6% | 3.4% | 4.4% | 4.3% | 3.2% |
| WV | 0.9% | 2.8% | 3.3% | 3.2% | 2.4% | 3.1% |
| WY | -2.5% | 1.3% | 1.5% | 1.9% | 2.4% | 3.2% |

Source: Barclays Capital

**Appendix 6: Distressed excluded HPA forecasts, stress scenario**

| State | 2011 | 2012 | 2013 | 2014 | 2015 | 2016-2020 |
|---|---|---|---|---|---|---|
| US | -7.5% | -2.5% | 1.5% | 3.0% | 3.5% | 3.2% |
| AK | -7.6% | -3.6% | -0.4% | 1.4% | 2.7% | 3.2% |
| AL | -6.5% | -0.5% | 2.8% | 4.9% | 5.3% | 3.3% |
| AR | -0.8% | 1.4% | 2.3% | 3.3% | 3.4% | 3.1% |
| AZ | -10.8% | -4.9% | 1.3% | 2.7% | 3.2% | 3.1% |
| CA | -12.3% | -5.8% | 0.6% | 2.1% | 2.7% | 3.3% |
| CO | -2.3% | 0.5% | 2.2% | 3.3% | 3.5% | 3.1% |
| CT | -6.6% | -2.4% | 1.6% | 3.5% | 4.0% | 3.3% |
| DC | -6.6% | -2.9% | 1.7% | 1.5% | 2.0% | 3.3% |
| DE | -7.9% | -4.1% | -0.1% | 2.3% | 3.4% | 3.4% |
| FL | -9.2% | -2.7% | 2.1% | 2.8% | 3.3% | 3.5% |
| GA | -4.5% | -0.4% | 2.5% | 4.0% | 4.1% | 3.1% |
| HI | -2.9% | -1.3% | 1.4% | 1.7% | 1.8% | 3.1% |
| IA | 0.6% | 2.4% | 1.9% | 3.2% | 3.6% | 3.1% |
| ID | -9.4% | -2.7% | 1.6% | 3.2% | 3.8% | 3.1% |
| IL | -6.7% | -1.0% | 2.7% | 4.9% | 5.0% | 3.3% |
| IN | -2.3% | 0.8% | 2.6% | 3.9% | 4.0% | 3.1% |
| KS | -3.3% | 0.5% | 2.2% | 3.3% | 3.6% | 3.1% |
| KY | -2.1% | 1.1% | 2.3% | 3.6% | 4.2% | 3.2% |
| LA | -4.3% | -0.2% | 1.0% | 2.2% | 2.9% | 3.3% |
| MA | -5.4% | -1.3% | 2.5% | 3.8% | 4.0% | 3.2% |
| MD | -8.8% | -4.1% | 1.5% | 3.2% | 4.0% | 3.2% |
| ME | -6.0% | -1.8% | 2.4% | 4.0% | 4.5% | 3.3% |
| MI | -3.6% | 2.0% | 4.3% | 6.2% | 5.8% | 3.1% |
| MN | -6.2% | -2.7% | -0.4% | 2.1% | 3.6% | 3.2% |
| MO | -5.8% | -0.1% | 2.7% | 4.2% | 4.4% | 3.1% |
| MS | -2.6% | 0.4% | 1.7% | 2.9% | 3.6% | 3.1% |
| MT | -6.6% | -1.6% | 1.5% | 3.2% | 4.1% | 3.3% |
| NC | -0.7% | 1.5% | 2.5% | 3.6% | 3.9% | 3.1% |
| ND | 1.3% | -0.4% | 0.9% | 1.3% | 2.0% | 3.0% |
| NE | -0.6% | 0.8% | 1.7% | 2.6% | 3.1% | 3.1% |
| NH | -6.1% | -2.0% | 2.0% | 3.4% | 3.9% | 3.2% |
| NJ | -8.1% | -3.2% | 1.3% | 3.0% | 3.6% | 3.4% |
| NM | -5.8% | -0.2% | 3.8% | 4.4% | 4.2% | 3.1% |
| NV | -7.1% | -1.3% | 4.5% | 4.1% | 3.4% | 2.9% |
| NY | -7.6% | -2.8% | 1.2% | 3.0% | 3.4% | 3.3% |
| OH | -3.9% | -1.8% | -1.1% | 1.6% | 3.4% | 3.2% |
| OK | -2.5% | 0.0% | 0.8% | 2.6% | 3.5% | 3.2% |
| OR | -6.3% | -0.6% | 3.0% | 4.6% | 4.5% | 3.1% |
| PA | -7.3% | -3.2% | 0.5% | 2.8% | 3.8% | 3.3% |
| RI | -6.4% | -2.3% | 0.9% | 2.8% | 3.4% | 3.2% |
| SC | -4.7% | -1.6% | 0.9% | 2.8% | 3.1% | 3.2% |
| SD | -3.3% | -0.6% | 1.6% | 3.0% | 3.8% | 3.2% |
| TN | -2.5% | 1.7% | 2.8% | 4.0% | 4.0% | 3.2% |
| TX | -3.9% | -1.2% | 0.5% | 1.9% | 2.7% | 3.1% |
| UT | -7.0% | -1.4% | 2.0% | 3.1% | 3.6% | 3.1% |
| VA | -8.8% | -5.0% | 0.4% | 1.5% | 2.4% | 3.2% |
| VT | -5.2% | -2.6% | 0.9% | 3.0% | 3.9% | 3.3% |
| WA | -7.0% | -1.4% | 2.1% | 3.7% | 4.1% | 3.1% |
| WI | -4.9% | -0.9% | 1.8% | 3.6% | 4.1% | 3.2% |
| WV | -3.8% | -0.6% | 1.9% | 2.6% | 2.4% | 3.0% |
| WY | -5.6% | -1.4% | 0.2% | 1.3% | 2.2% | 3.1% |

Source: Barclays Capital

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