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CS Agency MBS Model Documentation

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Executive Summary

The CS agency MBS model suite has navigated the recent housing cycle and market changes, by synthesizing the most updated information and introducing new and innovative modeling techniques, in order to provide users accurate, relevant and timely prepayment forecasts, valuation and risk analysis.

Model highlights

- A short term prepayment forecast framework
  - Accurate pool level forecasts and relative rankings
  - Agency universe pool level forecasts updated and available to users shortly after monthly factor release
  - Integrated in the OAS valuation framework
- Accurate pool level delinquency components
  - Combine insight from Non-Agency data analysis with GSE disclosures
  - Roll rates model integrated in the OAS valuation framework
- A new ranking based methodology to model pool level prepayment
  - Rank pools based on model forecasts to understand overall effect of pool variables
  - Superior to existing pool and cohort level model methodologies used by market participants
- Dynamic Population Approach to burnout
  - Use pseudo-subgroups to model pool attributes, then evolve these subgroup populations dynamically to model various forms of burnout
  - Consistently model pool composition changes over time, thus produce more accurate long term prepayment forecasts and valuation analysis
- Dynamic Mortgage Rate Model
  - Combine "empirical/regression approach" and "constant OAS approach"
  - Produce consistent and intuitive valuation results, better partial durations and less hedging leakage
- Interest Rate Model
  - Accurately fit volatility surface and volatility surface changes
  - Allow users to use "live" volatility for valuation

CS Agency Model Highlights – "Accurate, Relevant, Timely"

There is no standard valuation model for MBS, hence the cliché "MBS modeling is more of an art than a science." We believe the "ART" stands for "Accurate, Relevant, Timely."

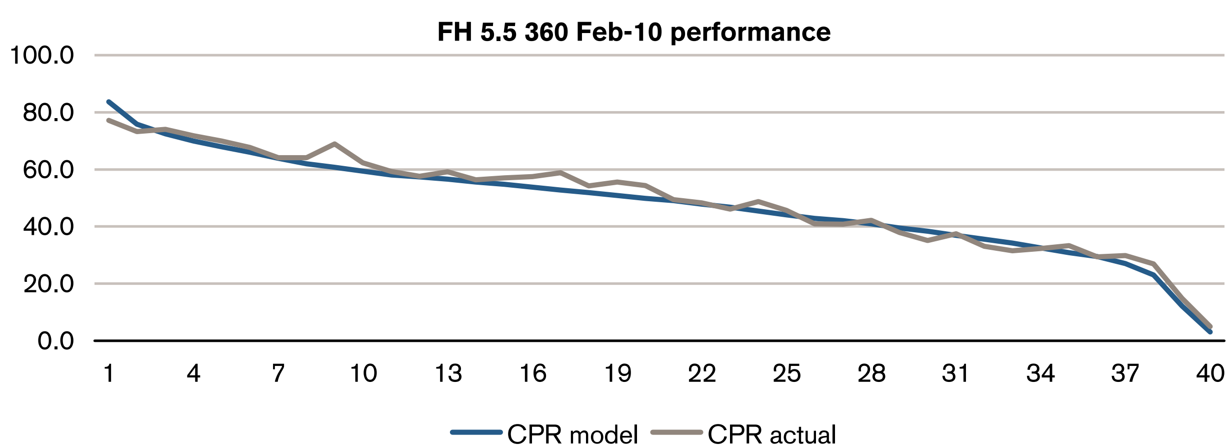
Short Term Prepayment Forecast

We developed an accurate and timely short-term pool level prepayment forecast component in the spring of 2009, in response to changing mortgage market landscape. Its success benefited from three modeling approaches and innovations.

1. **A unique pool level ranking based approach to differentiate pool level prepayment**: sometimes called "accumulative accuracy curve," we believe this is its first usage in agency prepayment modeling. When modeling pool speeds, a popular method is to error-track speeds along one dimension of a certain variable, for example, loan size. This only gives a one-dimensional snapshot. In our method, we rank all pools in a cohort, by their model speeds, and then error-track speeds along the rankings. This allows us to quickly identify relative importance of pool speed drivers, model error patterns, and trends.
2. **A unique error correction algorithm**: we adopted an error correction method ("adaptive filtering" in engineering term). The basic idea is to look at and examine past model forecast error patterns, and then construct a correction component to compensate for these errors if they are judged persistent.
3. **Using all relevant and most updated information**: pool variables, latest information on various housing and mortgage programs from government and GSEs, GSE pricing and disclosures, refinance indices, comparable mortgage performance in Non-Agency space, as well as evolving model error patterns

Exhibit 1 below shows a sample error tracking for pool level FH 30 year 5.5s February 2010 performance, based on this ranking methodology. We group pools into 40 groups based on ranking of forecasted prepayment speeds. The model was able to accurately forecast pool speeds ranging from 3 to 80 CPRs.

Exhibit 1: Sample pool level error tracking and ranking report: FH 5.5s, Feb. 2010 performance



Source: Freddie Mac, Credit Suisse

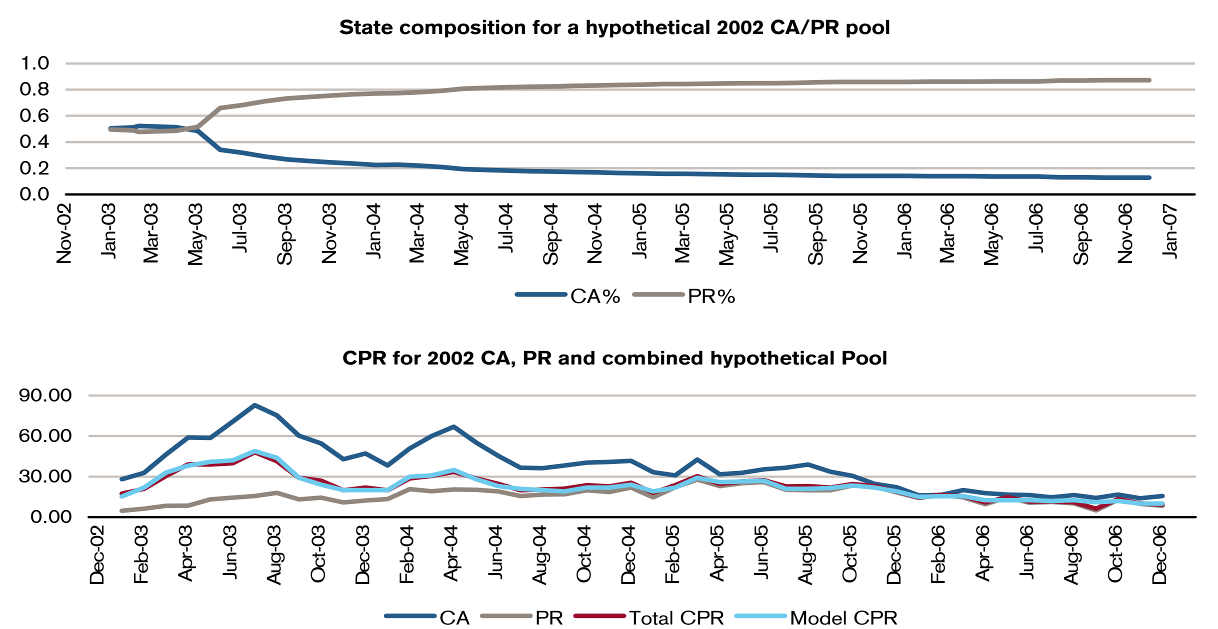
At the night of factor release, all pool level forecasts are generated and are available to users the following morning. Immediate access to accurate short-term forecasts provides an advantage in trading dollar rolls, specified pools, and CMOs (particularly Derivatives and IO/PO). Additionally, these forecasts are integrated into the OAS model framework.

Long Term Prepayment Forecast

For long term prepayment forecasts, we focus on understanding the drivers and modeling the underlying dynamics of prepayment behavior, instead of merely "fitting" (or "over-fitting") historical speeds. For example, we pioneered a "cashout" sub-model, which has been able to track and differentiate changes in base speeds and aging ramps accurately for the housing cycle since 2005.

Another dynamic process with big impact on valuation is burnout. We pioneered a "dynamic population approach" to model the evolution of pool variables and how burnout dynamically interacts with prepayment forecasts. Exhibit 2 shows an example of a hypothetical 2002 6s FN pool, which contains 50% California and 50% Puerto Rico at origination. Given the speed differences between the two groups, the pool composition transitions to 20% (CA) and 80% (PR) after one year in a refinance environment. Obviously, in order to have accurate valuation, one needs to have both an accurate pool variable based prepayment function, and also an accurate model of how these pool variables evolve over time based on prepayment projections. Our model dynamically captures these composition changes (without externally updating state information). This results in more stable and accurate long-term projections, thus increasing confidence in relative value assessments.

Exhibit 2: Prepayment and state composition dynamics for a hypothetical 2002 FN 6s pool. The dynamic population approach is able to accurately model burnout



Source: Fannie Mae, Credit Suisse

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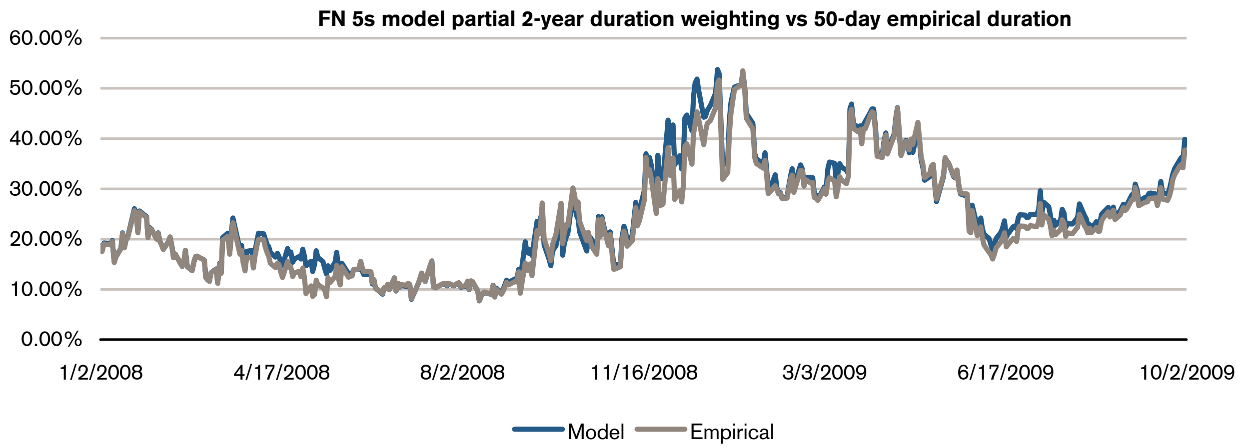
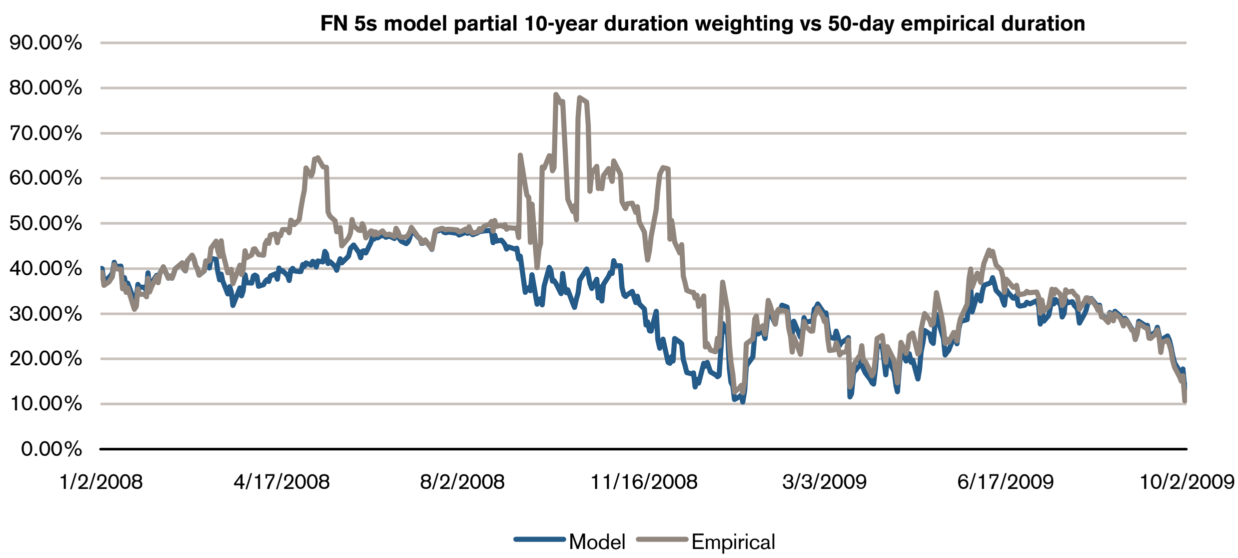
Interest Rate and Mortgage Rate Models

Our interest rate and mortgage rate models follow the same "ART" approach. The interest rate model tightly fits market option prices and tracks volatility surface changes. The forward mortgage rate model is unique, relative to others in the industry, in unifying two schools of thought: the "regression framework" which utilizes historical relationships between mortgage and swap rates, and the "risk neutral framework" which aims to maintain constant OAS or yield in forward space. This hybrid approach produces more consistent valuations and durations. Exhibit 3 below provides an example of how model partial durations mimics empirical (shown as percentage of "total" effective duration, for example, "2year partial duration/ total duration" for FN 5s.

Exhibit 3: FN 5s partial durations for 2 year and 10 year sectors, as percentage of total effective duration. Model values are very close to empirical values. 5 and 30year sectors have same behavior (not shown here)





Source: Credit Suisse

Agency Prepayment Model

This model documentation focuses on prepayment model for FN and FH 30 year TBA eligible products. Variations of the base model are constructed for other products, including:

- FN and FH 15 year, ARM products
- GNMA I and II products
- Various Non-TBA eligible FN and FH products: FNCT, FNCN, FNGL, FNCZ, FNIONP, FNJMCK, and etc.

We model agency prepayment at pool level. Cohort level prepayment forecasts are aggregations of corresponding pool level forecasts. TBA forecasts are based on pool delivery assumptions, with specified pool carve-out as well as worst-to-delivery pool rankings from model forecasts.

Model speeds are a sum of three components: (1) “turnover and cash out,” (2) “refinance” and (3) “default (buyouts)”.

The prepayment function drivers consist of two major categories: (1) macro-economic environment: including primary and secondary mortgage rates and state level house price indices (histories and projections) and (2) pool and borrower attributes, including WAC, WALA, FICO, OLTV, loan size, state distribution, loan purpose, property type, occupancy status, and etc.

Exhibit 4 shows the agency MBS prepayment regimes since 2003. The broad themes are four periods

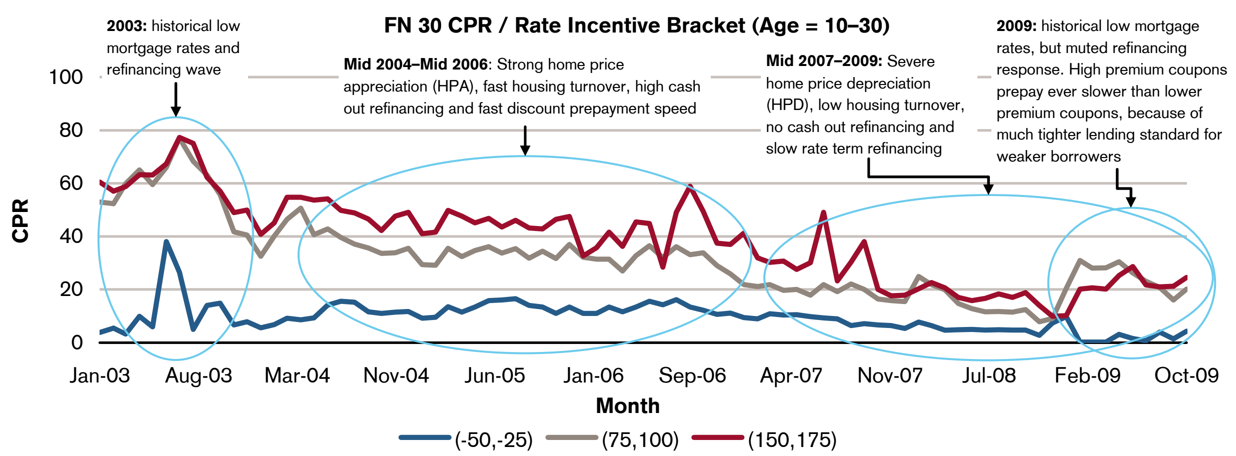
1. The 2003 historical low mortgages rates led to historical high mortgage prepayment speeds
2. Subsequent 2004-2006 period experienced high house price appreciation (HPA) and high availability of mortgage credit, which led to high turnover speeds, high cashout speeds, and high refinance activities including high fixed-to-ARM refinances
3. House price depreciation (HPD) started mid-2007, combined with subsequent financial crisis and “great recession”, led to muted turnover and refinance speeds.
4. Starting from the late 2008, when government and central bank intervened in mortgage market through various homeowner support programs and large scale MBS purchase programs, agency mortgage rates reached historical low, but various government sponsored refinance programs had varied success. In addition, following the path of non-agency mortgage performances, agency MBS delinquency rates reached historical high. In February 2010, GSEs announced plans to buyout delinquent loans from agency MBS pools.

Our modeling activities paralleled these developments

1. Version CS5 was developed and deployed in 2006. Because CS5 explicitly models cashout components and links turnover and cashout speeds to HPA (and HPA), the model was able to follow prepayment trends until 2008 without much revision
2. In March 2009, CS6 was produced, mainly to deal with various GSEs and government housing support and mortgage refinance programs. The main difficulty to model these issues is lack of performance data when the model was initially constructed. Our approach is to set up the framework to broadly cover these issues, especially relative performance among the various pool/loan level attributes. We also make the framework general enough so that we can adjust the effectiveness of these programs as performance data arrives.
3. Given the uncertainties in future long term prepayment regime, we developed a short term prepayment forecast framework in spring of 2009. This framework allows us to produce very accurate short term

forecasts at pool level and also respond to market information much quickly. In May 2010, we deployed CS6.3 to utilize the short term model in the OAS valuation framework.

Exhibit 4: Agency MBS prepayment regimes since 2003



Source: Fannie Mae, Freddie Mac, Credit Suisse

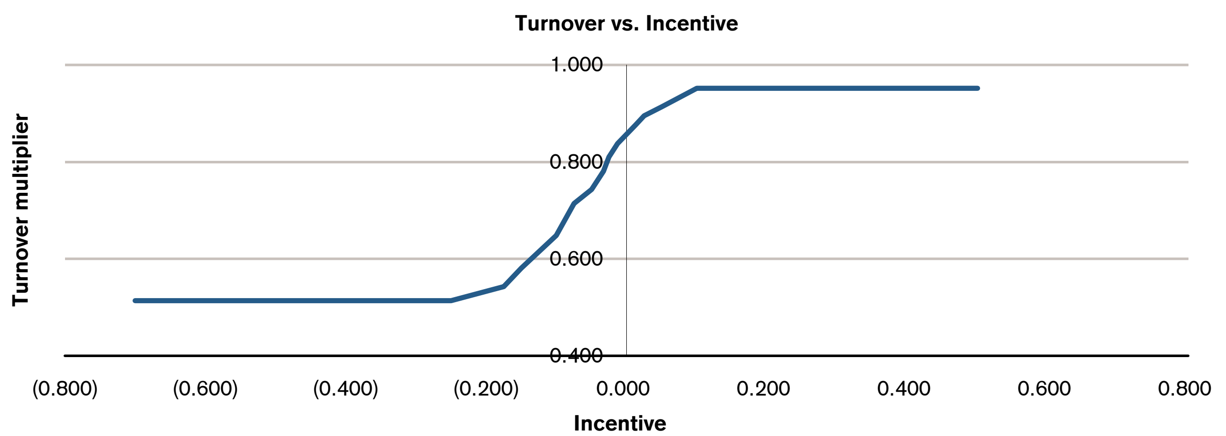
Turnover and Cashout

While other prepayment models combine turnover and cashout into one component, we explicitly model both. The shortcoming of combining the two is the need to re-calibrate turnover function frequently as cashout patterns change.

Turnover is defined as the complete pay-down of a mortgage from sale of the property. Turnover function components include:

- Turnover ramp: Due to various costs associated with home purchase/sell, borrowers who recently purchased home tend to be less likely to see the home in near future, hence the turnover speeds ramp up from low to a steady state value.
  - Drivers: WALA, "Refi percentage"
  - We use a 30-month (WALA) ramp with slightly concaved age curve
  - For refinance loans, tenure in the home is longer than loan age. The model ramp is a function of the pool variable "Refi percentage"
- Turnover lock-in: high mortgage rates reduce incentive of house sales
  - Drivers: WAC, current available mortgage rates
  - In a positive HPA environment, the turnover lock-in effect is specified as shown in Exhibit 5. (The incentive is defined as ration between monthly mortgage payments of current WAC and current available mortgage rates.)

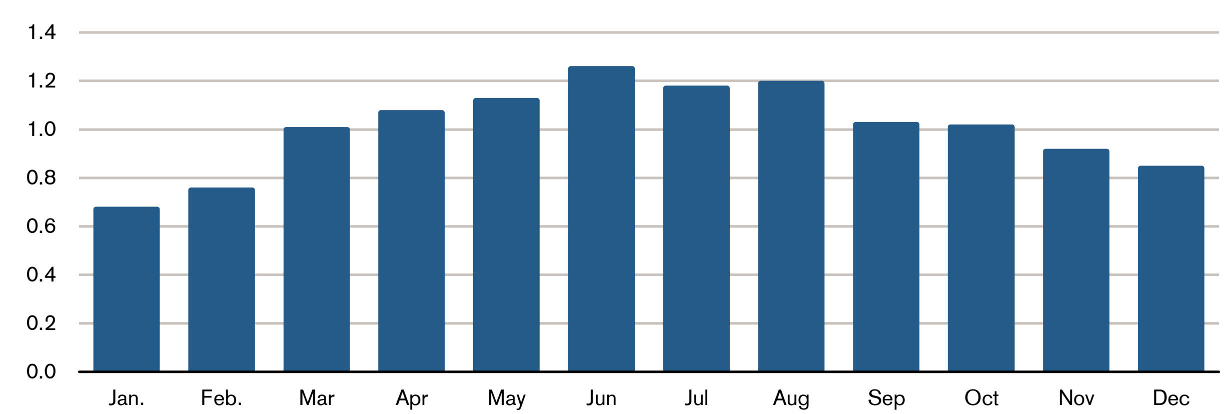
Exhibit 5: Turnover lock-in effect



Source: Credit Suisse

- Seasonality: home purchases are highly seasonal, primarily due to school year cycle
  - Model seasonality factor is presented in exhibit 6.

Exhibit 6: Turnover seasonality factor

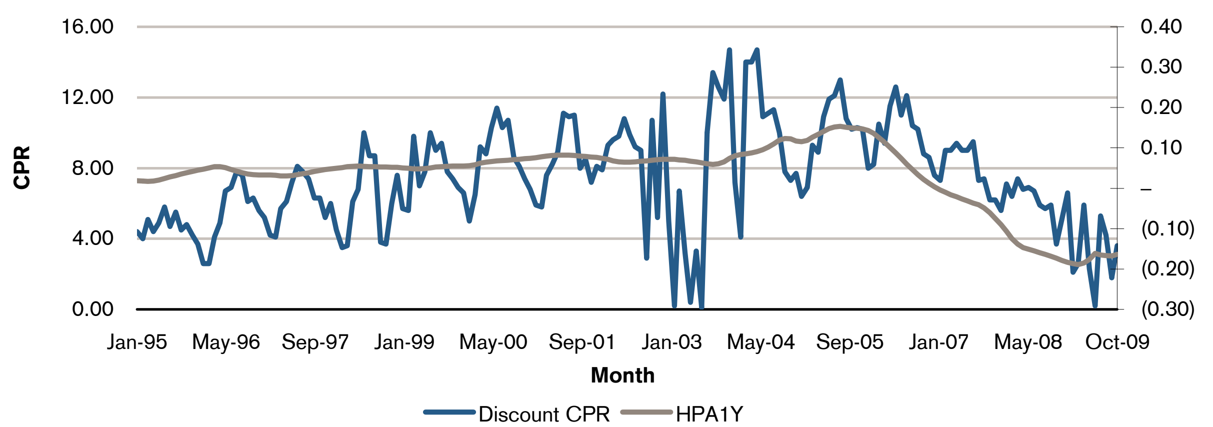


Source: Credit Suisse.

- Base turnover speeds: turnover speeds for "fully seasoned" loans
  - Drivers: HPA ("house price appreciation"), GEO ("geographical locations" or "state percentages"), Occupancy status, Property Type
  - HPA encourages housing purchase/selling, while HPD discourages. Exhibit 7 shows cohort speeds for seasoned moderately OTM ("out-the-money") FN pools, contrasted with annualized year return of HPI (house price index). The "pure" turnover speeds was around 8cpr historically, then reached 10-12cpr during the housing boom years, before crashing down to 4-6cpr depressed level. The annualized HPI is weighted

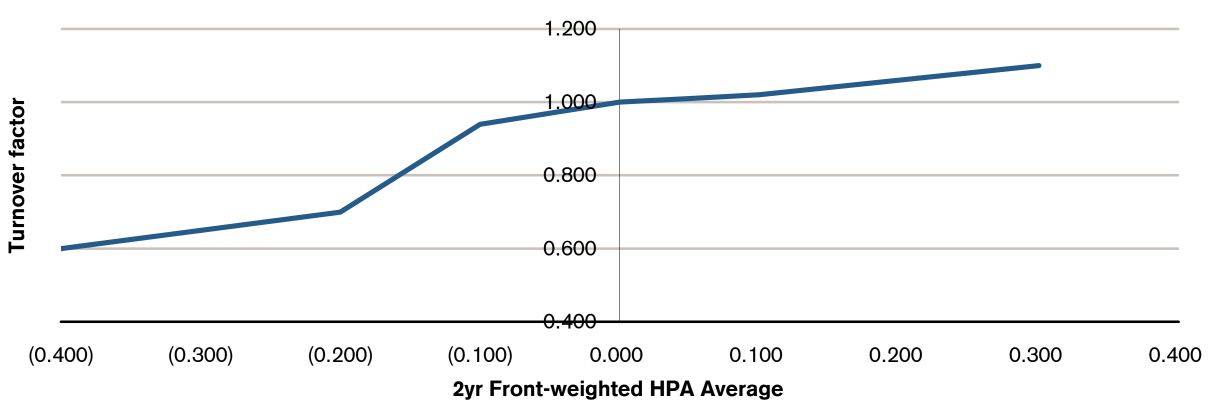
average of preceding 2 year's performance, to smooth out noise in the index. The model specification is shown in exhibit 8.

Exhibit 7: Cohort speeds for seasoned moderately OTM ("out-the-money") FN pools, contrasted with annualized year return of HPI (house price index)



Source: Fannie Mae, Credit Suisse, economy.com

Exhibit 8: Turnover Factor based on 2yr Front Weighted HPA Average



Source: Credit Suisse

- GEO ("geographical locations") also affect base turnover speeds. The GEO factors (indicated by 4 states, 6 macro-areas, and non-US/Puerto Rico) for turnover is listed in table in Exhibit 9.
- Occupancy status and Property Type also affect base turnover speeds. For example, loans for second home and investor properties as well as multi-units properties have less turnover speeds. Model specification for these factors is list in table in Exhibit 10.

Exhibit 9: Geographic location

GEO	Turnover Factor
NY	0.90
CA	1.17
FL	1.06
TX	0.94
New England	0.94
Atlantic	0.98
North	0.92
South	1.10
Pacific	1.10
Non U.S.	0.74

Exhibit 10: Occupancy and property types

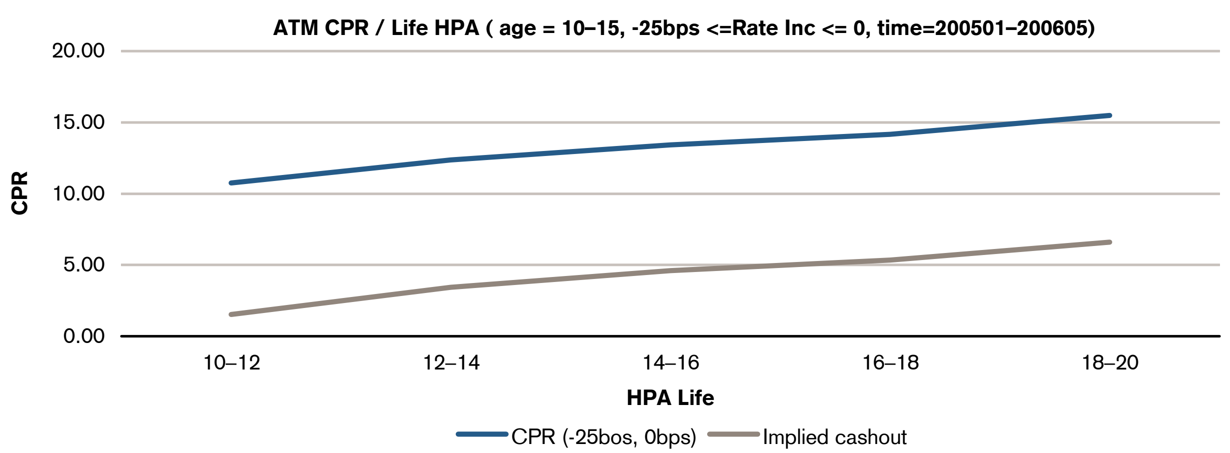
Type	Turnover Factor
Owner Occupied	1.00
Second Home	0.85
Investor	0.95
Single Unit	1.00
Multi Unit	0.85

Source: Credit Suisse

Cash-out function components:

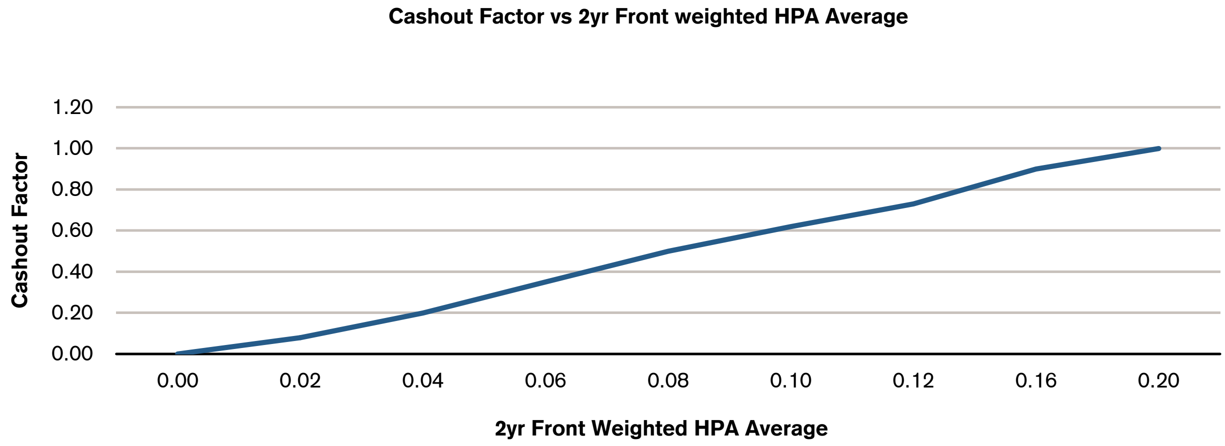
- Base Cashout speeds:
  - Drivers: pool level HPA computed at state level, FICO, OLTV, and loan size
  - The main driver for cashout is the accumulated the latest 2-year HPA, or HPA since origination if WALA is less than 24 months. The accumulated HPA for pools is computed and aggregated at state level, using "pool state percentage" and state level HPI. Exhibit 11 shows "implied" cashout levels (by subtracting model turnover from ATM/"at-the-money" cohorts speeds) for pools in housing boom years, versus their accumulated HPA amount. The model specification is shown in exhibit 12.

Exhibit 11: "Implied" cashout levels for pools in housing boom years, versus their accumulated HPA amount



Source: Credit Suisse.

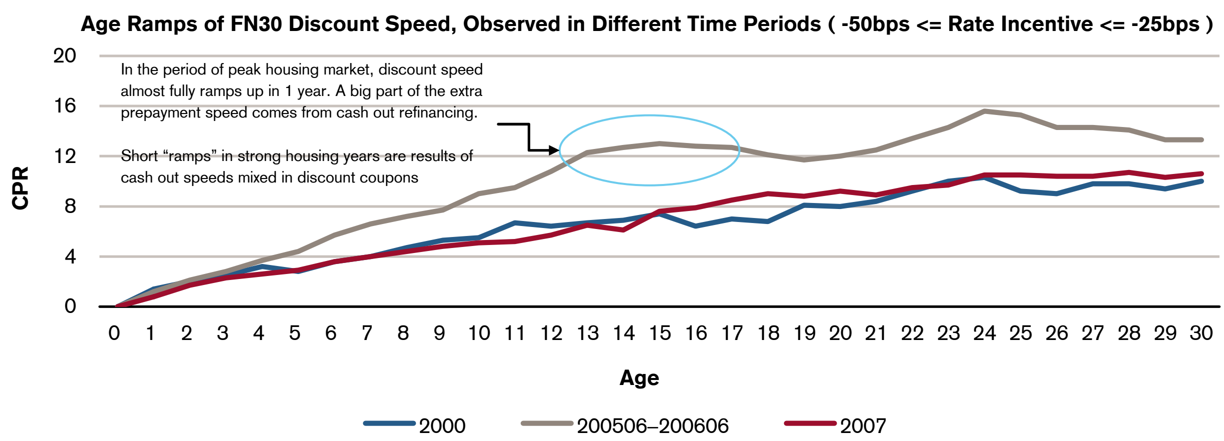
Exhibit 12: Cashout factor based on 2yr front weighted average HPA



Source: Credit Suisse

- Exhibit 13 shows the advantage of modelling turnover and cashout separately. The appearance of "short turnover ramp" during housing boom years can be explained through addition of cashout model components, which adjusting/refitting models.

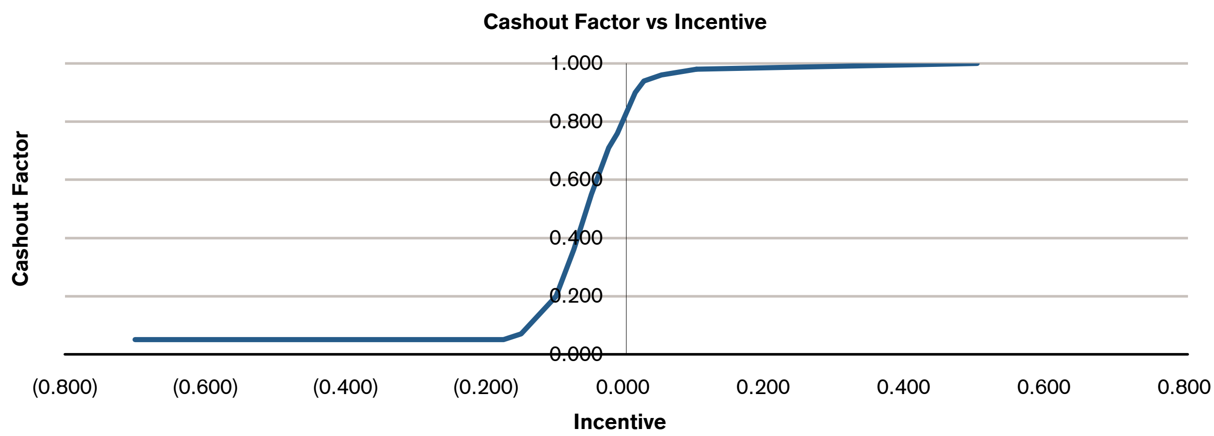
Exhibit 13: Comparisons of vintage cohort speeds. 2005/2006 vintages experienced higher speeds due to intensive cashout



Source: Credit Suisse, CPRCDR.com

- Cashout rate sensitivity: if current mortgage rates are significantly higher than borrower's existing mortgage rate, then it may be more economic to take out a HELOC (home equity line of credit) than to refinance the entire mortgage
  - Drivers: WAC, current available mortgage rates
  - Exhibit 14 shows the model specification for cashout speeds as a function of incentive. Generally, cashout becomes un-economical when rates are more than 75bps out-the-money.

Exhibit 14: Cashout factor based on incentive



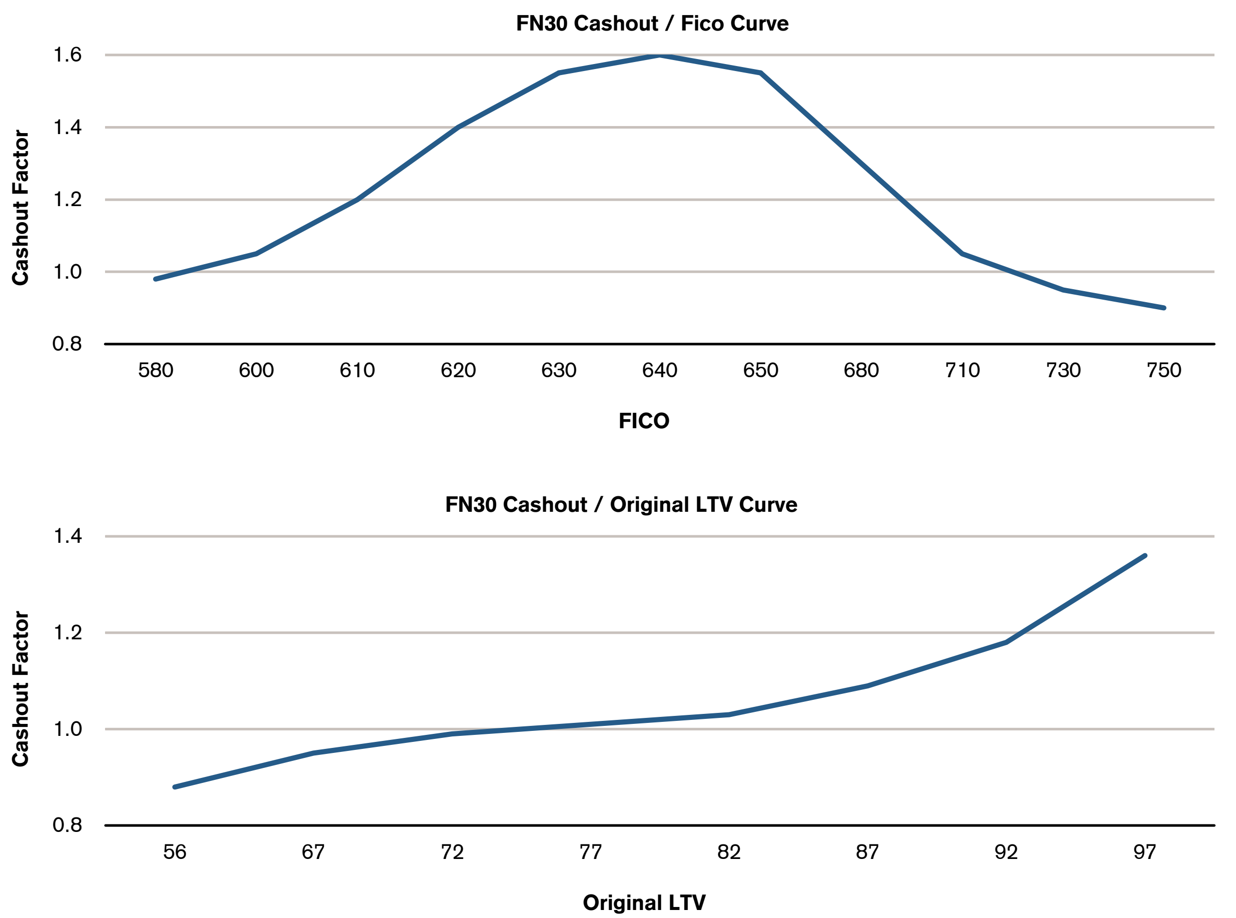
Source: Credit Suisse

- Seasonality: cashout exhibits a seasonal pattern, albeit weaker than turnover seasonality
  - Model specifies cashout seasonality at 20% level of turnover seasonality

- Seasoning: borrowers who have equity build-up but choose not to cashout have lower probability of cashout in future
  - Model cashout level diminishes after 12 months

- Dependency on pool/borrower variables
  - FICO: mid range FICO borrowers have higher tendency for cashout
  - OLTV: high OLTV borrowers have higher tendency for cashout
  - Loan Size: low loan size borrowers have higher tendency for Cashout
  - Exhibit 15 shows the model specification for these features.

Exhibit 15



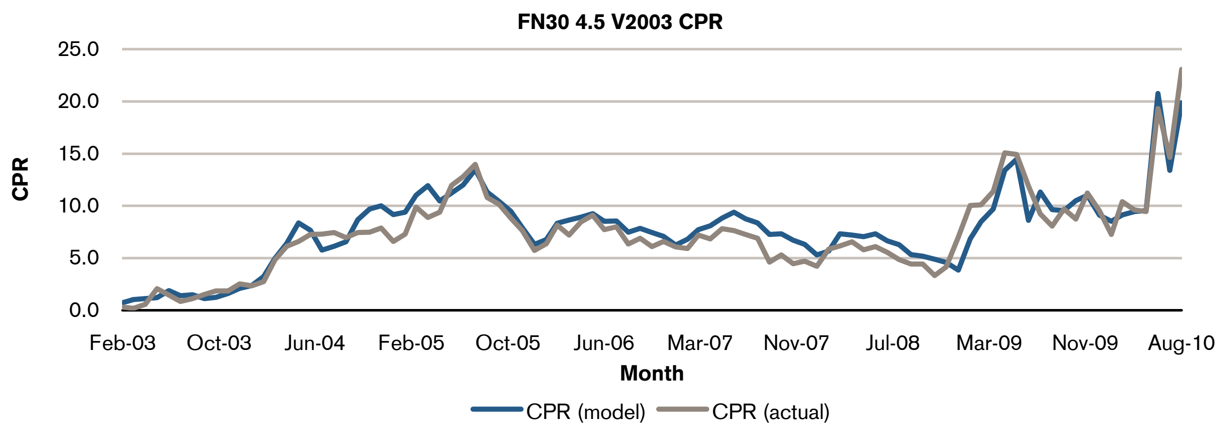
Source: Credit Suisse

Since the housing downturn, cashout speeds in the model (and in reality) are close to zero.

Exhibit 16 shows actual and model speeds tracking for 2003 FN 4.5s. Model is able to track these base speeds features well

- Seasonality
- "short ramps" during 2003-2005, due to cashout
- Base speeds as high as 14cpr, due to combination of turnover and cashout
- Base speeds drop to 6cpr during the recent housing crash

Exhibit 16: Comparisons of 2003 FN 4.5s actual and model speeds



Source: Fannie Mae, Credit Suisse.

Refinance, Burnout and a Dynamic Population Approach

Refinance motivated by incentive to lower monthly payment has two components: (1) "Rate Refi" (30 year to 30-year refinance) and (2) "Curve Refi" (30 year to ARM refinance). Refinance intensity is modeled by "Refi s-curve" -- SMM as function of rate incentive. The refinance incentive is defined as ration between monthly mortgage payments of current WAC and current available mortgage rates.

Overall Refi s-curve is driven by the availability of housing credit. Home price indices combined with various macro-economic variables are used to represent the credit environment. Loan and borrower variables that are also important drivers include: FICO, OLTV, CLTV ("Current LTV"), SATO ("Spread-at-origination"), Loan purpose, Occupancy status, Property type, GEO, etc. In addition, effects of these pool variables change when mortgage credit tightens.

Because prepayment depends on these "explicit" loan variables, pool composition changes during a refinance wave, as loans with "fast" attributes prepay at relatively higher speeds ("explicit" burnout). In addition, many undisclosed borrower attributes (e.g. financial situation and sophistication) also impact refinance intensity ("implicit" burnout).

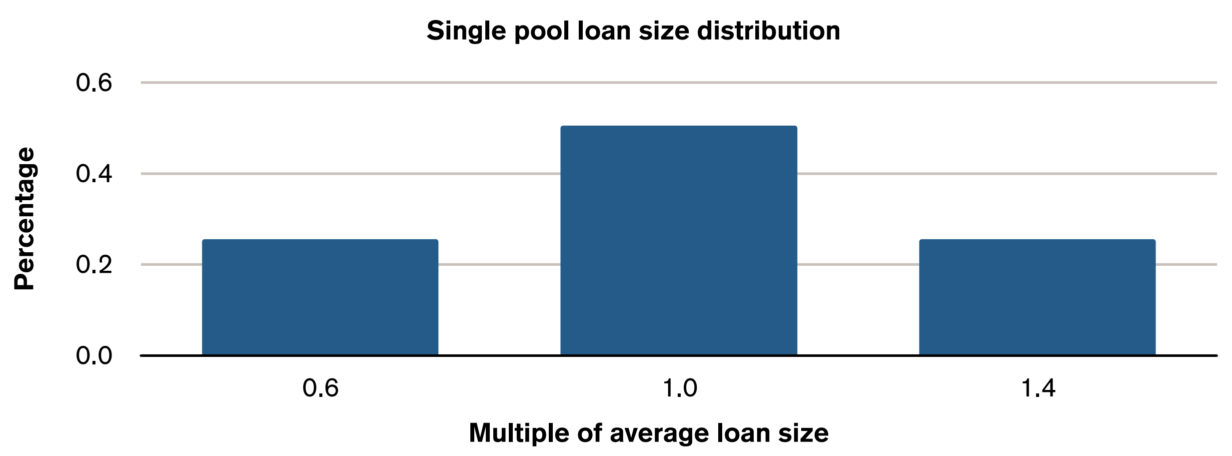
Our dynamic population approach models both implicit and explicit burnout, as well as the interaction between them, including:

- Dependency of "implicit" burnout on "explicit" pool variables. For example, implicit burnout is weaker in "state pools" (pools with high concentration in one state, for example "Puerto Rico Pools" or "new York Pools") than burnout in vintage/coupon cohorts, due to Puerto Rico pools being more homogenous. In addition, we have a consistent methodology to "add up" all the burnout for a pool.
- Impact of "implicit" burnout on "explicit" pool variable effect. For example, as pools burnout, the explicit pool variable impacts become less and less significant (i.e. As pools experience burnout, loan size effect diminishes).

The dynamic population approach uses 9 pseudo subgroups to model the basic mechanism of refinance response to rates incentive and the burnout process. The effects of macro economic environment and pool level loan/borrower variables are modelled through modification of these 9 pseudo subgroups. These model components are discussed in more detail in following sections:

- Refi-s-curves and pseudo populations
  - The basic refinance model structure uses 9 pseudo subgroups, organized along the 2 dimensions of "explicit" and "implicit" s-curve variables. Each dimension uses 3 set of values to model the underlying distribution.
  - The "explicit" dimension is mostly driven by a pseudo loan size distribution of underlying loans as illustrated by Exhibit 17. This is able to capture the average loan size drift in a pool (or pools) during a refinance wave (Exhibit 18).

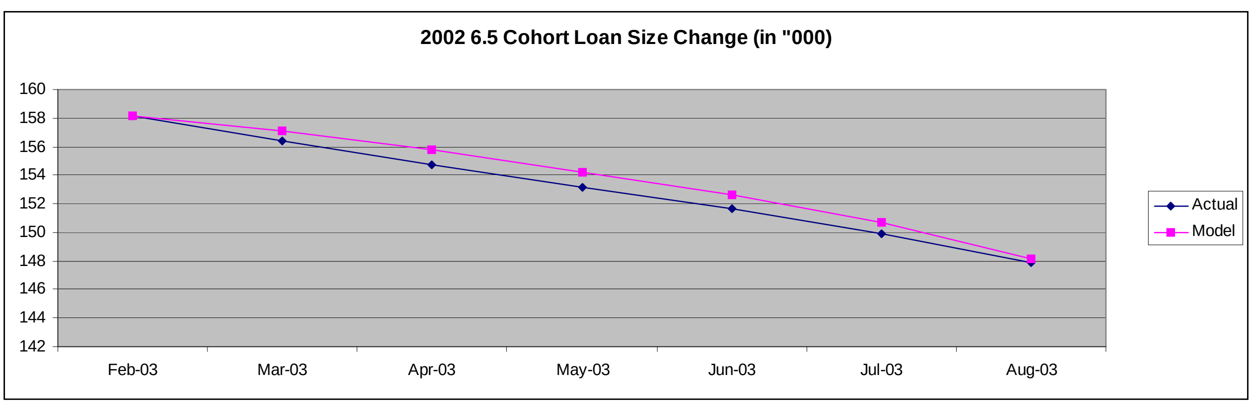
Exhibit 17: Model assumption of loan size distribution in a pool



Source: Credit Suisse.

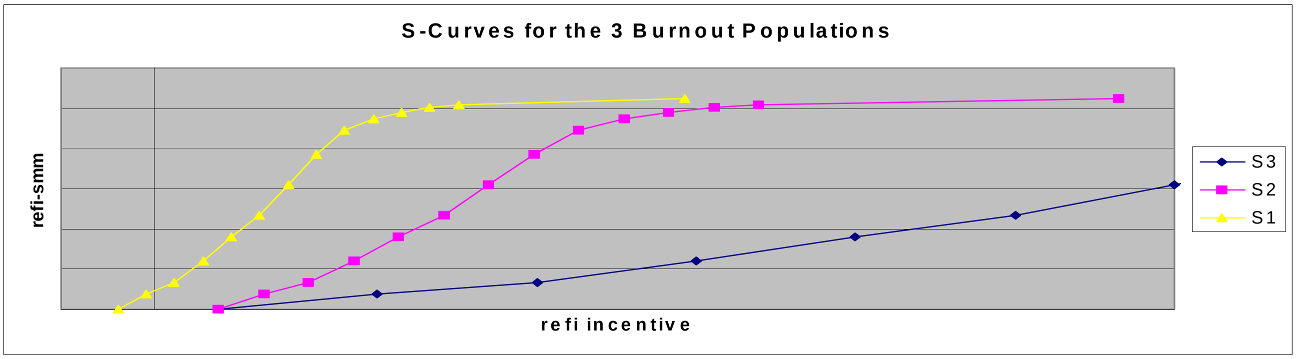
  - The "implicit" dimension is represented by three S-curves populations (Exhibit 19).

Exhibit 18: Example of average loan size drift during a refinance wave



Source: Credit Suisse.

Exhibit 19: Refi S-Curve populations



Source: Credit Suisse.

- These pseudo pools dynamically evolve based on each individual s-curve. Both “explicit” and “implicit” loan variables can be calibrated as initial distribution of the 9 subgroups, and can be additive for a pool or group of pools. We have extensively tested this approach to ensure that it models long term prepayment and valuation accurately
- Exhibit 20 shows error tracking for 2002 6.5s cohort going through the refinance wave of 2003 and 2004 and their subsequent slowing down due to burnout.
- The advantages of using this dynamic population approach are many

➢ Many models use pool factors use pool factors as proxy for burnout. That approach neglects path dependent nature of burnout. In addition it is not consistent when dealing with combination of pool variables and when dealing with multiple pools. For example, Exhibit 2 on page 5 shows the prepayment speeds for 2002 FN 6s cohort and its Puerto Rico and California “Geo” sub-cohorts going through 2003 and 2004 refinance waves. While CA sub-cohort is much faster than PR sub-cohort, (hence very different factors after each refinance wave), they both have much less burnout effect than the national cohort.

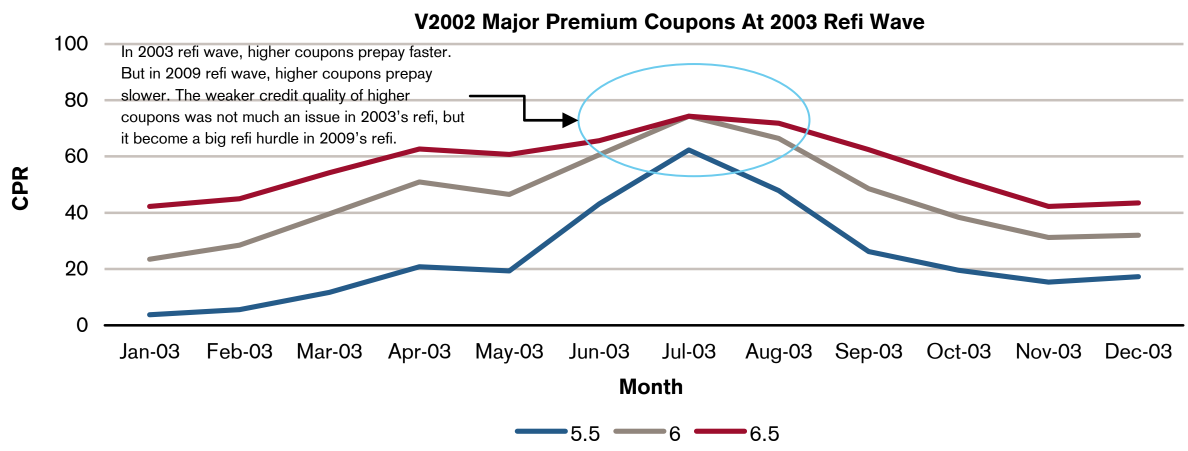
➢ Our dynamic population approach provides consistency between modelling based on current pool variables and how these variables evolve during a refinance episode.

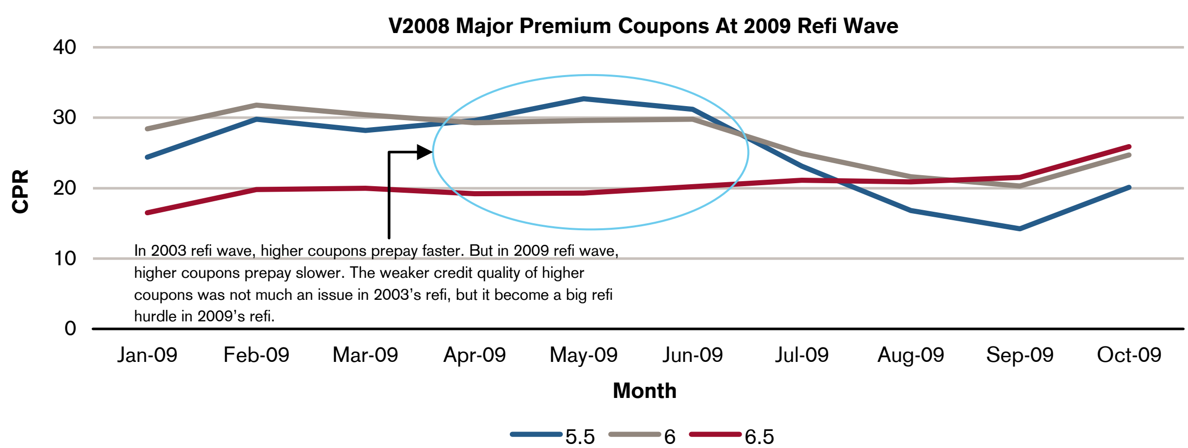
➢ This approach also allows consistently “add-up” burnout effect when dealing with multiple pool variables (for example, several states) and when combining multiple pools. This is due to the fact that the 9 subgroups are consistent across pools and pool variables.

➢ As discussed in previous sections, this approach models, in a very natural way, the interaction between “explicit burnout" and “implicit burnout”.

- Effect of House Price regime and availability of mortgage credit
  - Since the housing downturn in 2007, mortgage credit has been severely curtailed, especially to weaker borrowers. Exhibit 19 shows the overall prepayment speeds over the coupon stacks, comparing the 2003 and 2009 experiences when the prevailing mortgage rates for these two periods were similar. The 2009 refinance episode has much weaker prepayment response. The weaker response is caused by two components.

Exhibit 20: Examples of vintage cohorts experiencing burnout after refi wave



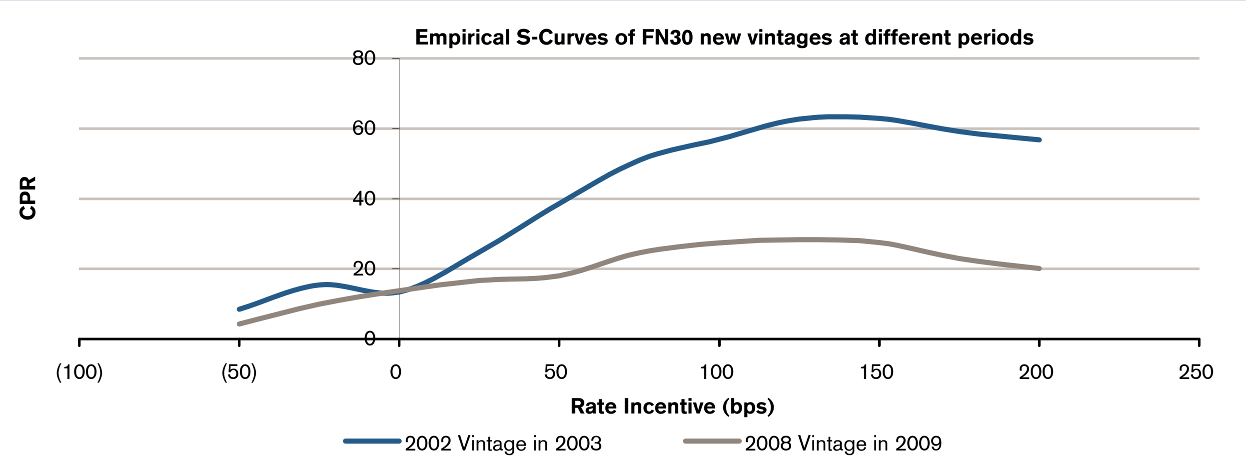


Source: Credit Suisse, CPRCDR.com.

1. Reduction in refinance propensity for strong borrowers (high FICO, low OLTV and experienced less or no HPD): Exhibit 21 compares the empirical S-curve for 2002 FN pools' performance in 2003 refinance wave, versus 2008 FN pools' performance in 2009 refinance wave. The refinance propensity is roughly reduced by half. The model applies a "refi-multiplier" based on a weighted 2 year HPA index return (Exhibit 22). The 2 year HPA index return is defined as:

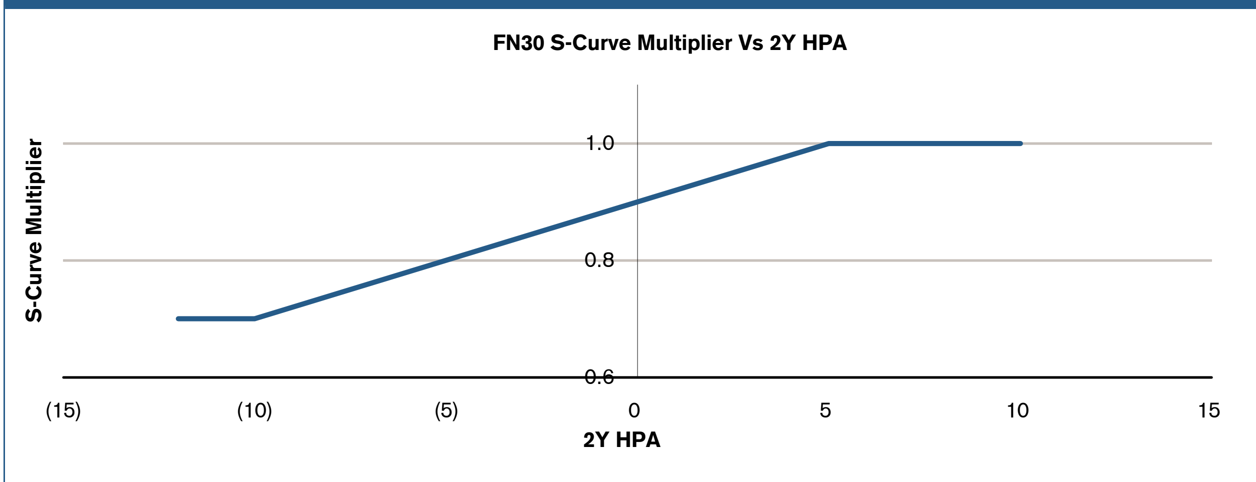
$$\mathbf{HPA\_Momentum(t) = 0.75 * min(HPA1Y(t), HPA1Y(t\text{-}1y)) + 0.25 * max(HPA1Y(t), HPA1Y(t\text{-}1y))}$$

Exhibit 21: Comparisons of FN 30yr new vintage empirical S-curves at different periods



Source: Credit Suisse, CPRCDR.com.

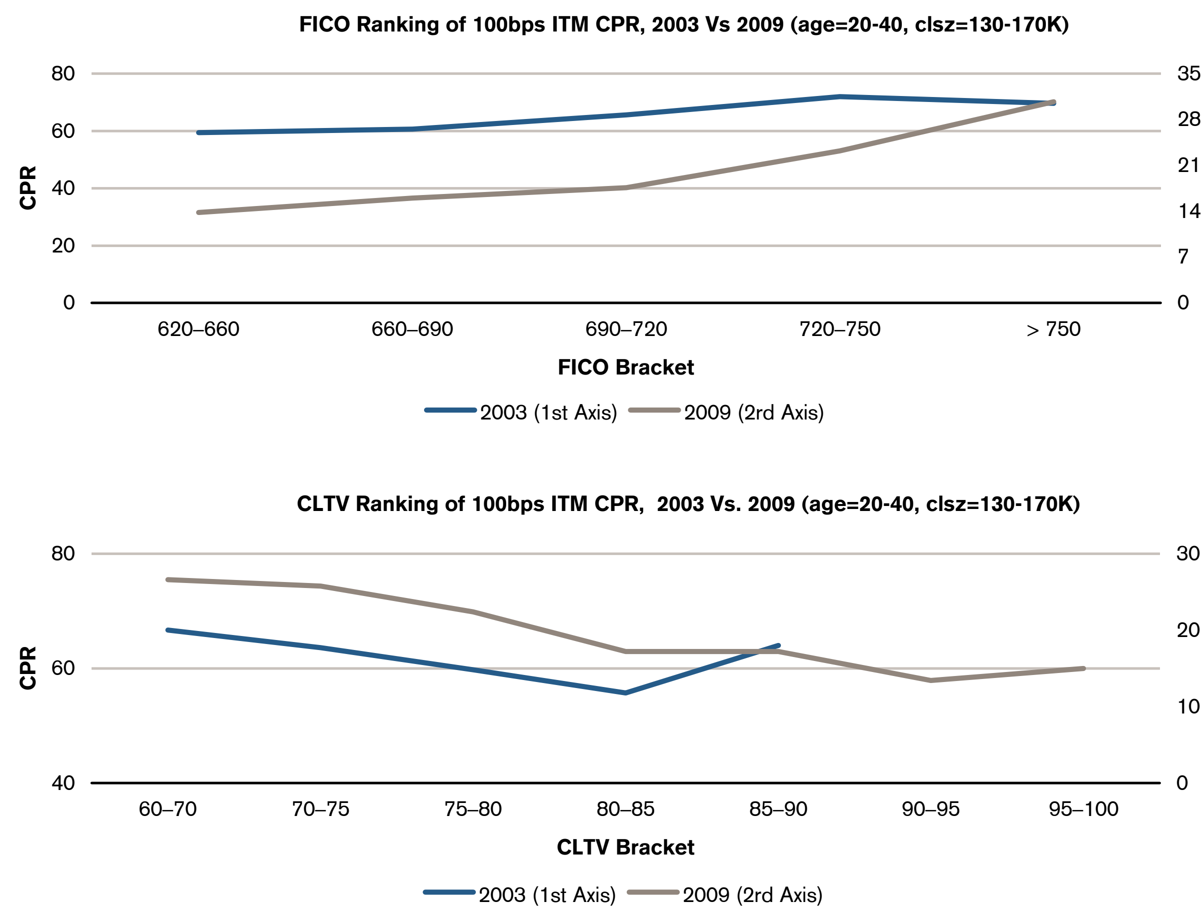
Exhibit 22: Refi factor based on 2yr front weighted average HPA



Source: Credit Suisse, CPRCDR.com.

2. Reduction in refinance propensity for weaker borrowers: the housing downturn and subsequent mortgage credit tightening leads to much bigger differentiation in refinance response between good and weaker borrowers. One example is shown in Exhibit 23. The model specification for weaker borrowers will be discussed in detail in subsequent sections for various pool variables.

Exhibit 23: Comparisons of refinance responses between strong and weak borrowers

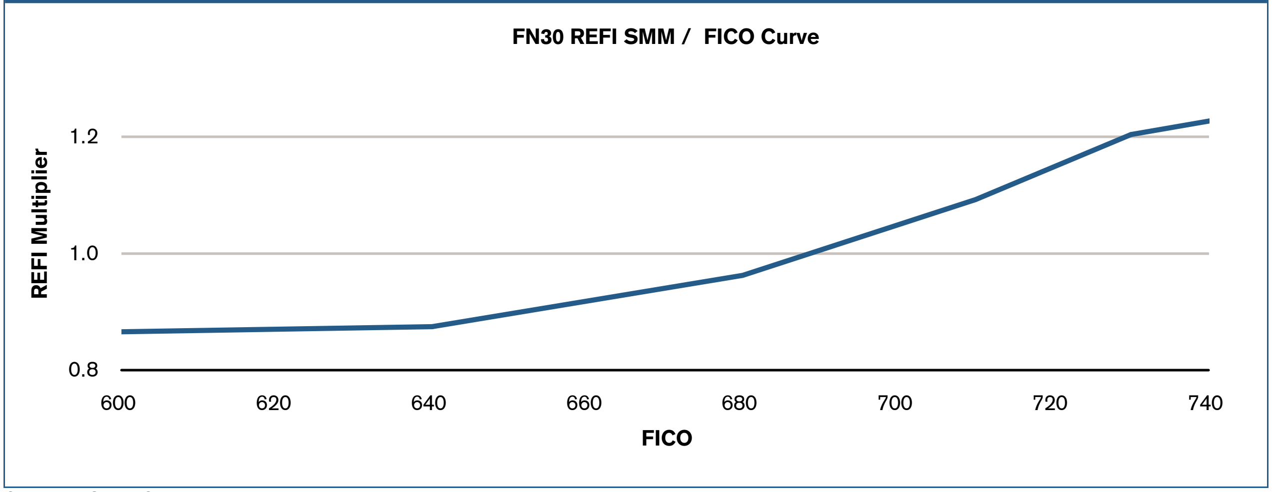


Source: Credit Suisse, CPRCDR.com.

- Additional credit environment variable: Mortgage credit tightening does not always overlap with housing downturn, especially during turning points (or perceived turning points) in housing cycle. We implement additional credit environment control variable, which we update quarterly.

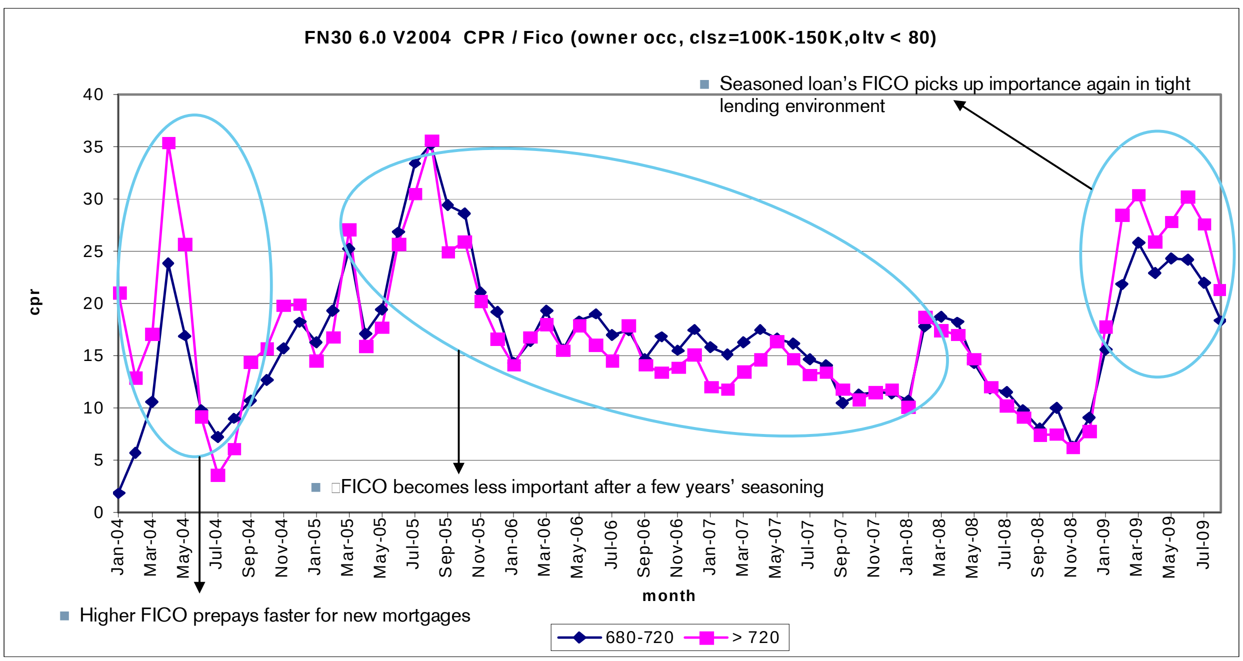
- FICO effect
  - Higher FICO loans have higher refinance intensity; the stratification of FICO effect increases during housing downtown/credit tightening.
  - Exhibit 24 shows the model specification for FICO effect; in addition, we also adopt the LLPA, the GSE's loan level pricing grid, which leads to higher effective mortgage rates for weaker FICO borrowers.
  - Exhibit 25 shows an example of the complexity of FICO effect during recent housing downturn. Some of these effects are modeller through our short term model framework. (See the "short term model" section for details.)

Exhibit 24: Refi Factor based on FICO



Source: Credit Suisse.

Exhibit 25: Complexity of FICO effect during recent housing downturn

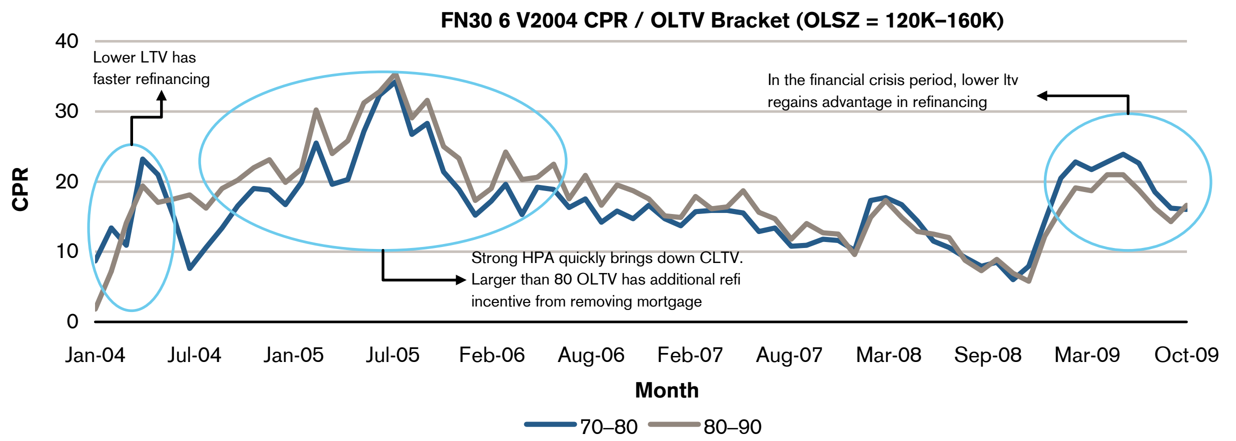


Source: Credit Suisse, CPRCDR.com.

- OLTV effect
  - In good housing environment, high OLTV loans tend to prepay faster to shed mortgage insurance; in housing downturns, high OLTV loans prepay slower due to credit constraints.
  - Exhibit 26 shows an example of OLTV effects through the housing cycle.

– Pool OLTV affects model refinance speeds mainly through the model CLTV effects, which will be explained in the next section. Some of the short term effects are modeled through short term model.

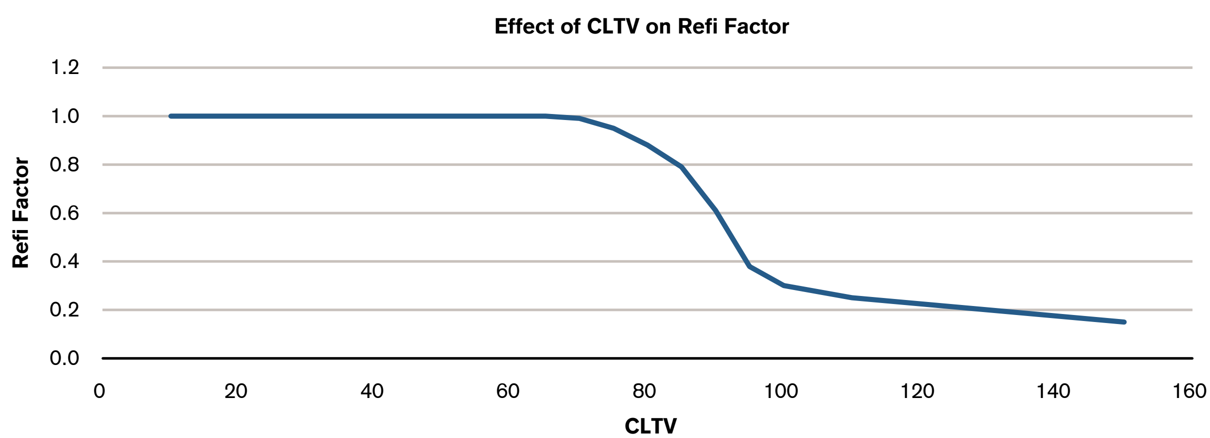
Exhibit 26: Effects of original LTV through the recent housing downturn



Source: Credit Suisse, CPRCDR.com.

- CLTV effect
  - Pool level CLTV is computed using 1) pool level OLTV 2) state level house price (indices) appreciation/depreciation since origination of the loan combined using state percentage variables 3) principle amortization
  - High CLTV is generally an impediment for refinance. Model specification of CLTV effect on refinance is shown in Exhibit 27.

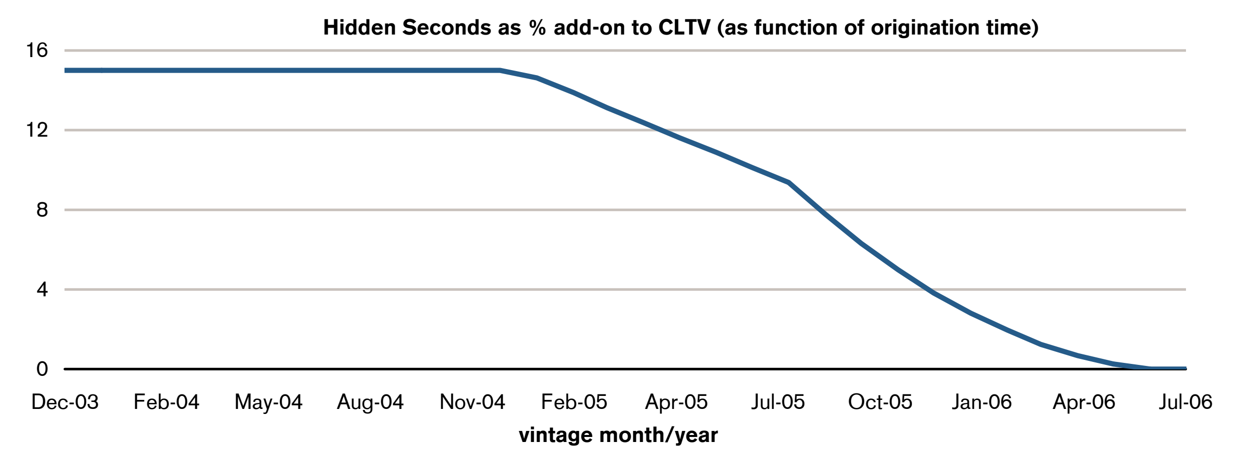
Exhibit 27: Effect of current LTV on refi factor



Source: Credit Suisse.

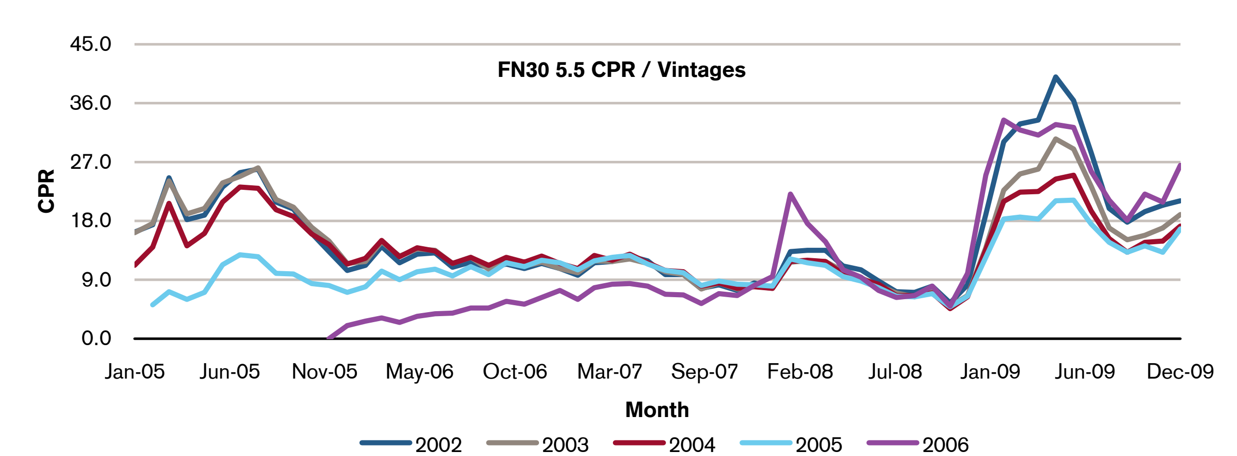
– We have fine-tuned this function dependence to take into account of several GSEs and government initiatives to help underwater borrowers in recent 2 years. These include: GSE loan level pricing and mortgage insurance (MI) requirement, the HARP program, etc.
– Given the wide spread practice of borrowers taking on simultaneous seconds, and subsequent HELOCs and other type of second liens, we apply a "CLTV add-on" based on loan/pool origination time, as shown in Exhibit 27.1. We believe the hidden seconds are mainly responsible for the slow prepayment speeds for pre-2005 vintages, even though these vintages do not suffer a big gross HPD (Exhibit 27.2)
– In addition, pool CLTV is a main factor in model's delinquency roll rates components. This will be discussed in the credit and delinquency performance section of this documentation.

Exhibit 27.1: Estimation of hidden second liens as % add-on to current LTV



Source: Credit Suisse.

Exhibit 27.2: Comparisons of FN 30yr vintage speeds

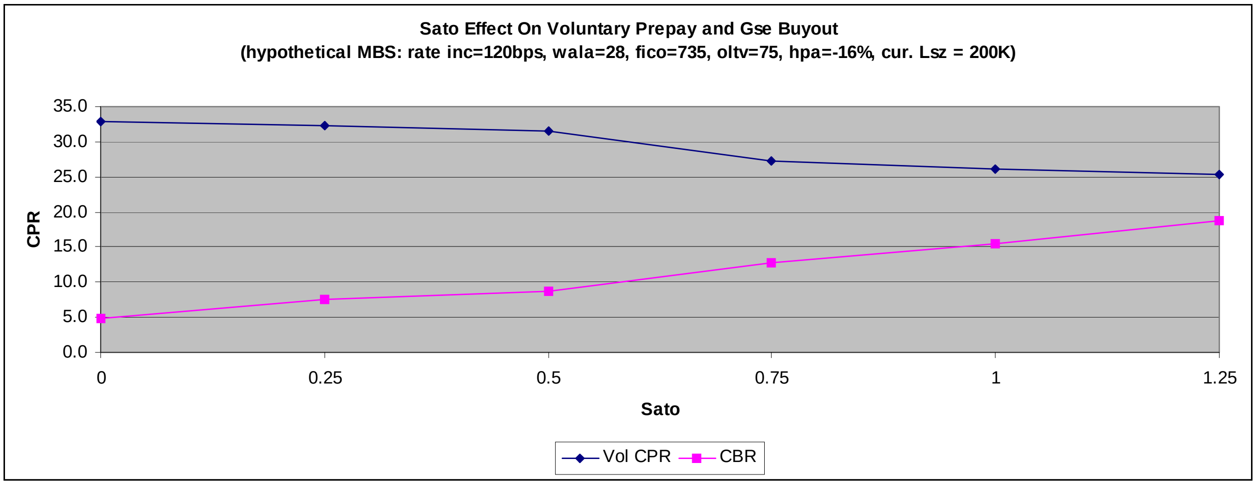


Source: Credit Suisse, CPRCDR.com.

- SATO (Spread-at-origination) effect

– Besides FICO and OLTV, there is residual credit effect due to SATO; high SATO loans tend to prepay slow, and especially so during credit tightening.
– In the current environment, high SATO suppresses voluntary prepayment, but has higher delinquency and GSE buyout speeds. The model specification for SATO effect on refinance is show in Exhibit 28.

Exhibit 28: SATO effect on voluntary prepayment and GSE buyout



Source: Credit Suisse, CDRCPR.com.

- Loan Purpose
  – "Refi loans" are more prone to refinance due to self selection

- Property Type
  – multi-unit property is less prone to rate refinance

- Occupancy Status
  – investor properties are subject to more credit constrains, especially during recent credit crunch

- Second home, investment property, and multi unit refinancing strength are suppressed more in HPD environment than single family owner occupied. The model specification for "Loan Purpose", "Property Type" and "Occupancy Status" is shown in Exhibit 29.

Exhibit 29: Relative refi factor at 6 months based on loan attributes	
Type	**Relative Refi factor at 6 months**
Purchase Loan	1.00
Refi Loan	1.10
Investment property	0.80
Second Home	1.00
Single Unit	1.00
Multi Unit	0.70

Source: Credit Suisse.

- GEO effects
  - Pools from different states have varying refinance behavior. Part of these can be explained in terms of regional differences in pool attributes, for example, loan size, house price appreciation. The residual, often significant, are modeled as "geo" effect. In addition, new and seasoned pools have difference states/"geo" effect.
  - The model casts GEO effect through the 9 pseudo subgroups by fitting the initial population distribution, s1, s2, and s3, as discussed in the "burnout" section. Exhibit 30 shows the model specification for the GEO effects for 4 major states (CA, NY, TX, and FL), 5 macro areas (Northeast/New England, Atlantic, North, South, and Pacific) and No-US (Puerto Rico). The s1/s2/s3 set of parameters models not only the refinance propensity of unseasoned underlying individual GEO portion/subgroup of the pools, but also the internal burnout of these GEO subgroups. Since the S-curves are same for the s1/s2/s3 subgroups of each GEO portion, they can be aggregated along the s1/s2/s3 labels, using the original GEO UPBs.
  - We have tested extensively this burnout scheme. As discussed on page 5 and Exhibit 2, the burnout process is accurately modelled in this "dynamic population approach".

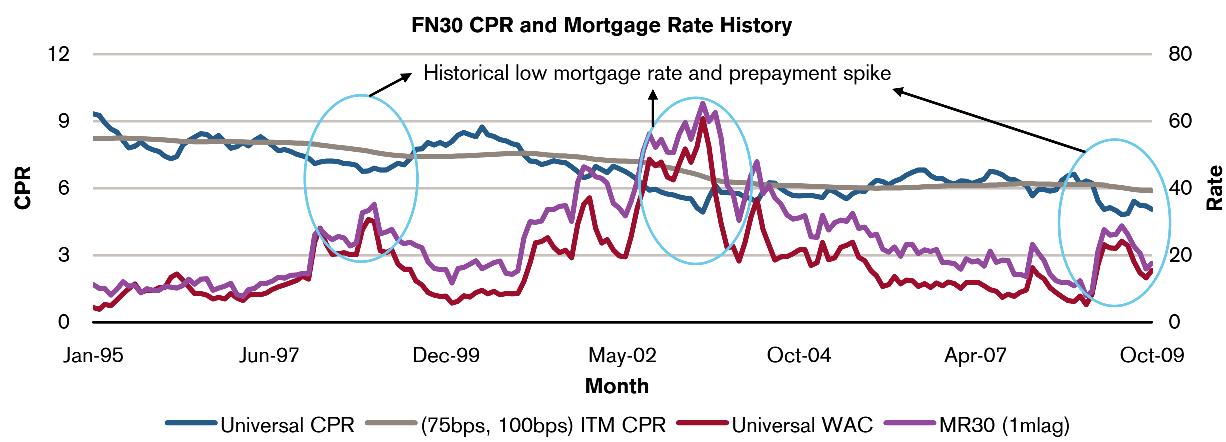
Exhibit 30: Impacts of geographic location on turnover factor and burnout S-curves

	HT	S1	S2	S3
US Average	1.0	32.5%	51.5%	16.0%
States				
NY	0.9	6.1%	41.9%	52.0%
CA	1.2	37.7%	54.9%	7.4%
FL	1.1	9.2%	40.5%	50.3%
TX	0.9	10.2%	22.6%	67.3%
Macro Regions				
New England	0.9	58.4%	25.7%	15.9%
Atlantic	1.0	26.2%	41.6%	32.2%
North	0.9	51.6%	27.3%	21.1%
South	1.1	11.1%	61.6%	27.3%
Pacific	1.1	28.4%	51.6%	20.0%
Non-US (Puerto Rico)	0.7	1.9%	5.9%	92.2%

Source: Credit Suisse.

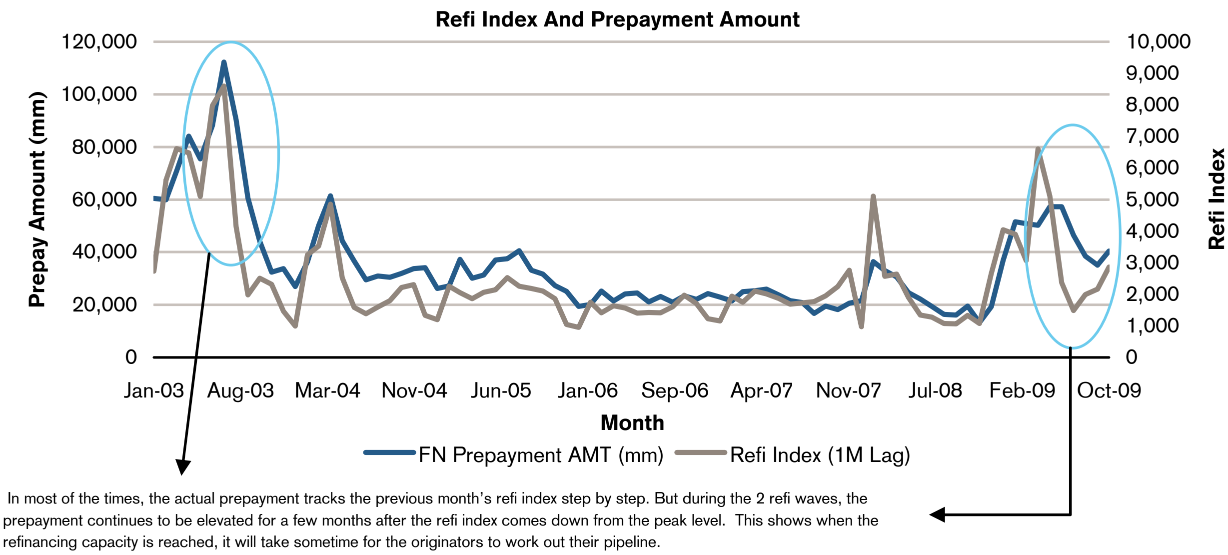
- Media effect and "Refi push out"
  - When mortgage rates hit multiyear lows, thus large part of the mortgage universe is in-the-money, there tends to be more media coverage of availability of refinance opportunities. This generally leads to a relative higher refinance response. Exhibit 31 shows the relative strength of several recent "media effect" episodes, since 1998. While the "media effect" has produced stronger and stronger prepayment speeds between 1998 and 2003, the recent historical low mortgage rates only produced a modest increase in prepayment speeds, due to the ongoing mortgage credit tightening.
  - Model compares the current mortgage rates with last 3 years average mortgage rates to determine a potential trigger of "media effect". In addition, model also limit the peak of media effect to about 4 months as prepayment tends to be less responsible after large segment of refinance eligible mortgage universe apply for refinance.
  - In addition to increase prepayment speeds, media effect also tends to push out the prepayment speeds over a longer period as originators focus on higher margin business given the high refinance application work flow. Exhibit 31.1 shows push-out for historical refinance episodes. The model specifies various categories of mortgages tor the pushout, including seasoned loans/pools, pools with low loan balance and SATOs, etc.

Exhibit 31: Relative strength of recent "media effect" episodes



Source: Credit Suisse.

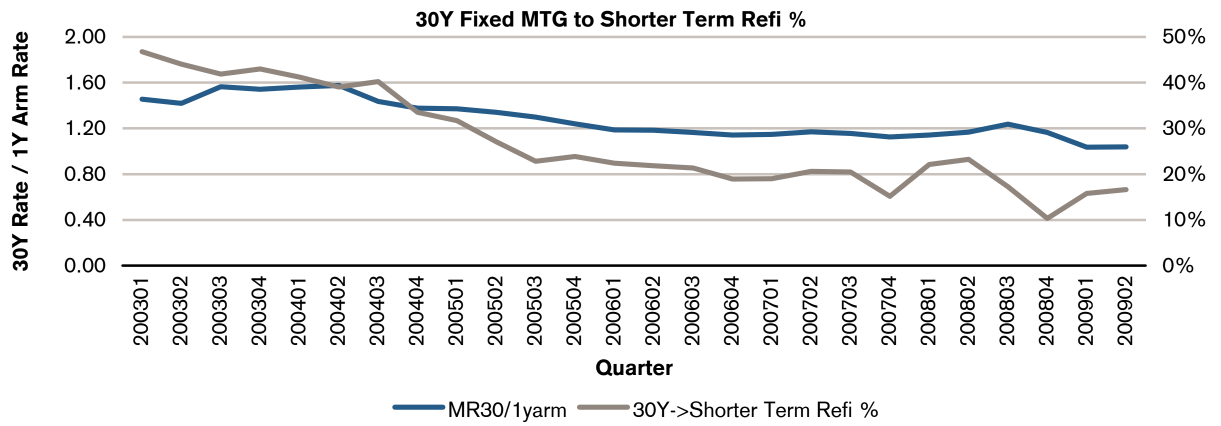
Exhibit 31.1: Evidence of speeds "pushed out" by media effect



Source: Credit Suisse, Bloomberg.

- Curve Refinance ("Fixed-to-ARM") effect
  - During the housing boom years of 2003-2005, there are considerable amount of "fixed-to-ARM" refinances, especially in 2003 when the yield curve is steep and front rates for ARMs are very low. Exhibit 32 shows the relationship between curve slope and "Fixed-to-ARM" refinance.
  - The recent housing downturn is also accompanied by very steep yield curve. However, the ARM products are not favoured by originators and GSEs and as such, the spread between actual ARM rates and 1year Libor rates has widened much, compared with historical period, thus making ARM products less attractive. In our model, we use HSH ARM rates survey to deduct this spread monthly and mean-reverting this spread to long term mean in the forward simulations. The model then compare the monthly payment saving ratio between these ARM rates and existing rates on the mortgage as refinance incentive for "Fixed-to-ARM" refinances.

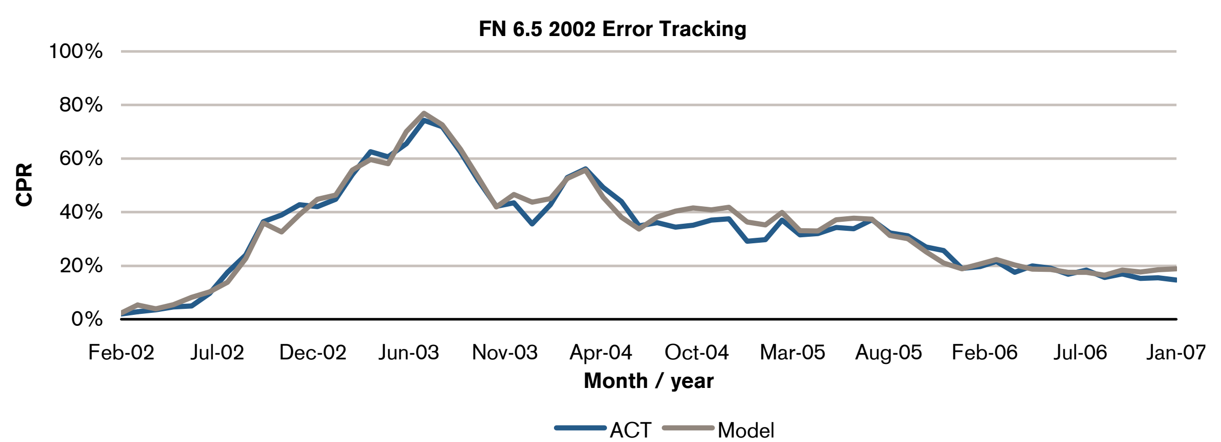
Exhibit 32: Relationship between curve slope and "Fixed-to-ARM" refinance



Source: Credit Suisse, CPRCDR.com.

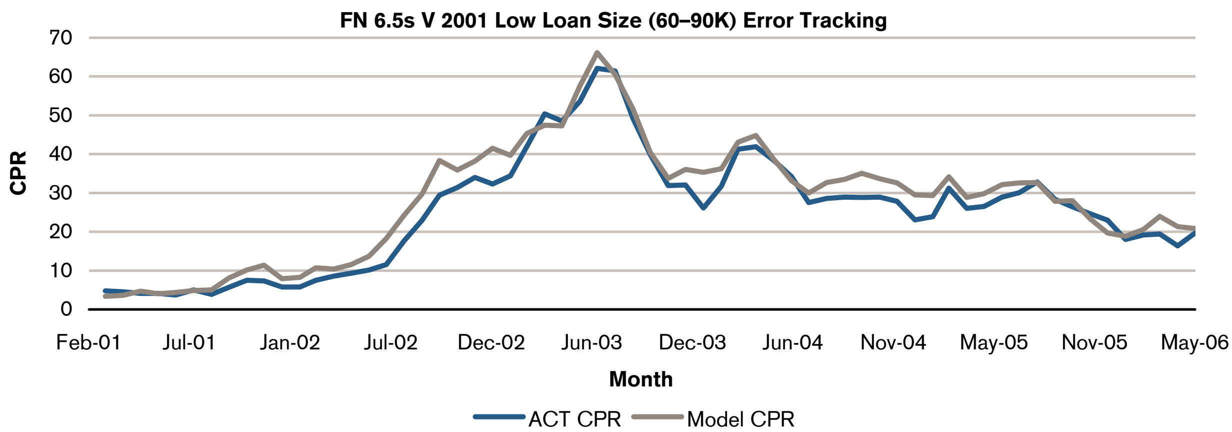
- Model Error Tracking
  - Combining the refinance models and turnover/Cashout models, we show a few samples of vintage/coupon cohorts model performance before the housing downturn.
  - Exhibit 33 shows the 2002 FN 6.5s performance over the subsequent 2 refinance waves in 2003 and 2004, and shows the model handles the refinance and burnout very well.
  - Exhibit 34 shows the model performance tracking for high/low loan size sub-cohorts for 2002 FN 6.5. Model is able to model loan size effect very well.

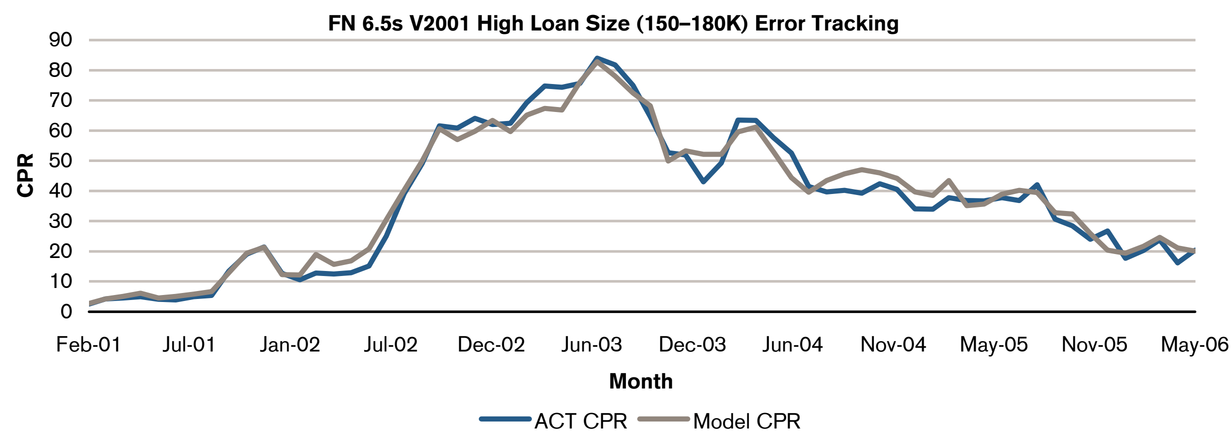
Exhibit 33: Performance of FN 30yr 6.5s 2002 vintage cohort during subsequent refinance waves



Source: Fannie Mae, Credit Suisse.

Exhibit 34: Performance of FN 30yr 6.5s 2001 vintage high/low loan size sub cohorts

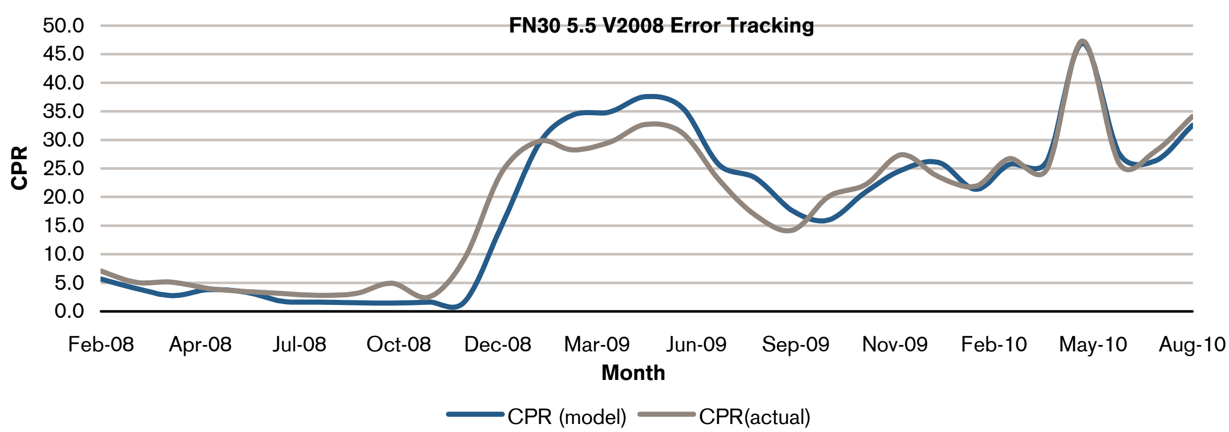




Source: Credit Suisse, CPRCDR.com.

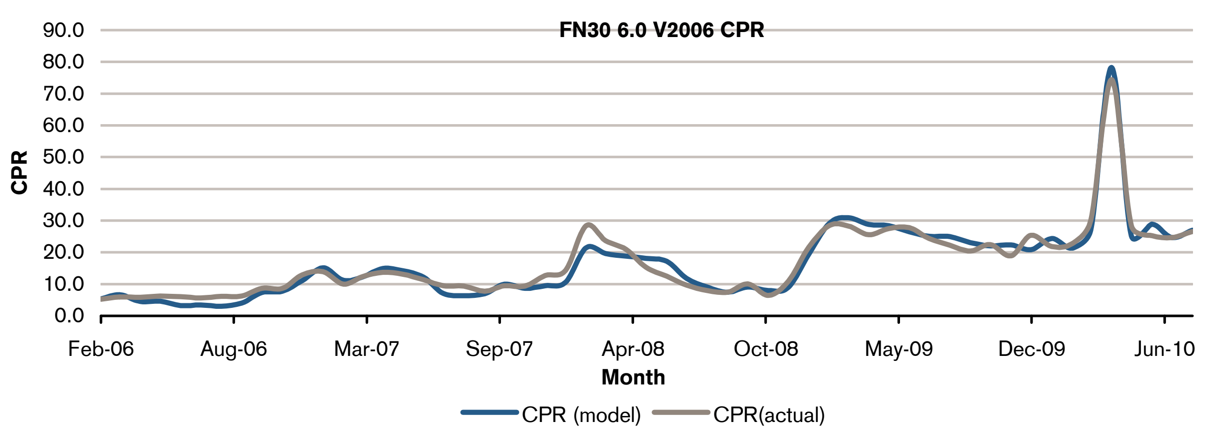
- Exhibit 34.1 shows the model performance for FN 5.5s 2008. Model is able to track the general slow down in housing turnover as well as the muted refinance in the housing downturn.
- Exhibit 34.2 shows the model performance for FN 6s 2006. Model is able to track the prepayment behaviour caused by credit impairment (for example, the CLTV issue due to 2006-2007 HPD) and the recent pool delinquency and buyout.

Exhibit 34.1: Performance of FN 30yr 5.5s 2008 vintage error tracking



Source: Credit Suisse, CPRCDR.com.

Exhibit 34.2: Performance of FN 30yr 6s 2006 vintage error tracking



Source: Credit Suisse, CPRCDR.com.

– In addition to cohort level error tracking, we also developed a ranking methodology to understand the overall effects of pool level prepayment stratifications and examine the model accuracy in differentiating pool prepayment speeds. For pools in a cohort, the methodology ranks pools based on model speeds forecasts, then subdivides the cohorts into equal sized sub-cohorts based rankings. Error tracking is performed on each sub-cohort. This ranking methodology ("Accumulative accuracy curve") can be used for TBA delivery strategy. A sample ranking report is presented in Appendix Exhibit 1.

Credit, Delinquency, Buyout

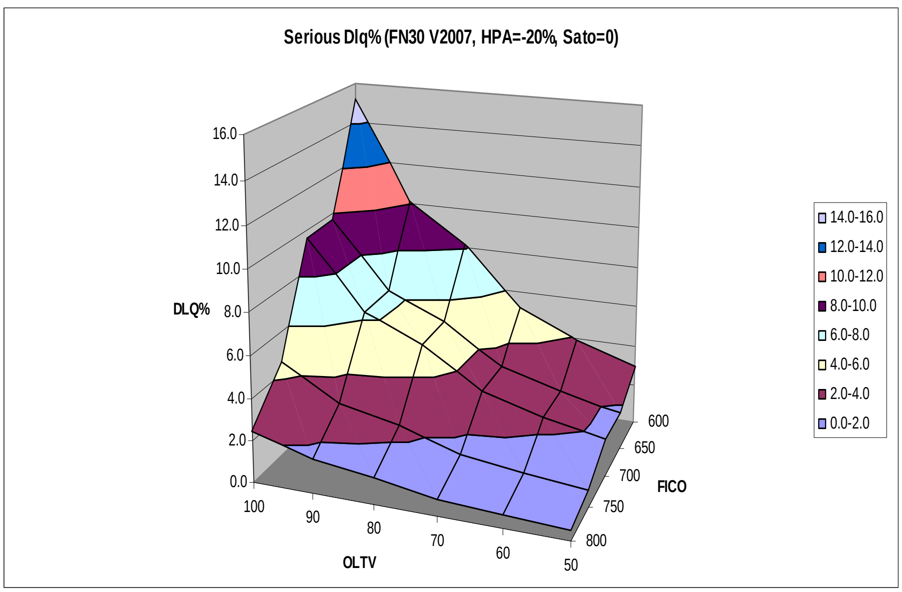
The current prepayment landscape is dominated by credit related issues. Policy initiatives with respect to the GSEs and federal programs to support borrowers (e.g. HARP, HAMP, and, etc.) are continually evolving and have widely varying success rates. Our modeling approach identifies the broad array of pools that may be affected by a particular program, and we forecast and update our forecast of the particular program's effectiveness as more performance data becomes available.

Another issue is the GSEs' voluntary buyout of delinquent loans from pools. Due to ongoing buyout risk, we have estimated roll rates and delinquency components in the latest model, version 6.3. The pool level delinquency model is estimated using Non-Agency loan level data from the Loan Performance dataset, overlaid with GSEs' disclosure of delinquency levels at vintage-coupon cohort level. Exhibit 1 (see page 4) demonstrates the accuracy of our buyout forecasts.

The delinquency roll rates model components are:

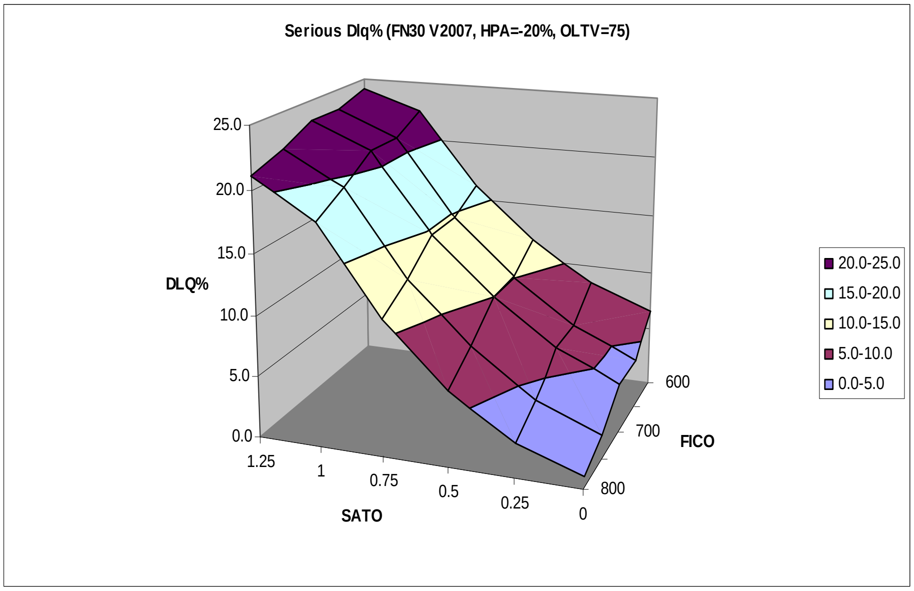
- Ramp for the overall credit performance
  - Currently, we assume that the roll rate will decline due to the improving economy and employment picture. The base line assumption is that the overall roll rates will diminish to 90% of June 2010 level by March 2011 and disappear by March 2012. This model assumption can be easily modified if our expectation changes.
- Relative performance between agency pools and vintages
  - This pool level delinquency model was originally fitted using non-agency prime data with adjustment. It uses pool FICO, OLTV, SATO, origination month/year and HPA history to model and differentiate the pool level delinquency. Model performance for recent 9 months has been extremely accurate. (See exhibit 1 for example.)
  - The function dependence on these pool variables is highly non-linear. Exhibit 35 and 36 show example of this highly non-linear function.

Exhibit 35: Delinquency as a function of FICO and original LTV



Source: Credit Suisse.

Exhibit 36: Delinquency as a function of FICO and SATO



Source: Credit Suisse.

Short Term Model Correction

Given the changes in mortgage market since the housing downtown, the prepayment regime has been "out-sample". Traditional modeling methods and techniques have been less robust. We developed a short term model approach in spring of 2009 and the model has been highly successful for the recent 16 months. The basic approach is very similar to an "error correction" model in econometrics or "filtering" in engineering.

The basic formulation is as following:

Short Term Model

Model error for pool i at time t is defined by

$$E(t) = E_c(t) + E_p(t)$$

where

$E_c(t)$ is cohort level error (free of statistical error)

$E_p(t)$ is individual pool level error.

$E_p(t)$ is defined by

$$E_p(t) = E_s(t) + \varepsilon_p(t)$$

where

$E_s(t)$ is systematic error (generally large) and

$\varepsilon_p(t)$ is statistical error.

- The statistical error is a function of the size of the pool and cannot be corrected.
- $E_c(t)$ and $E_s(t)$ are estimated and attributed to
  1. Pool variables
  2. Prevailing mortgage rates

  via a piecewise linear approach.
- In order to minimize errors, we use the following two methods:
  1. Use time series method to estimate a serial correlation of these errors so that we can forecast and cancel these errors.
  2. Multiple models: if model errors from different models are not correlated, then mixing model results tends to reduce overall model error. We have a model that uses a refinancing index to forecast overall prepayment levels.

Source: Credit Suisse.

This short term model has been very successful when dealing with various transitory prepayment phenomena, for example:

- In the summer of 2009 when low loan balance prepayment was pushed out further than high loan balance prepayment
- During the GSE buyout months, separate model errors for volunteer prepayment speeds and delinquent/buyout/HAMP speeds

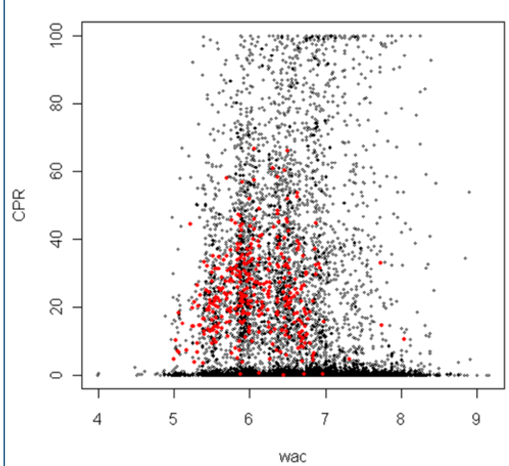
- Occasional idiosyncratic servicer behavior
- Estimate/stratify Refi-s-curve for different segment of agency universe

In addition, we have integrated the short term model in the OAS model valuation framework. The default model setting is to use 100% of the short term model forecasts for the first month, and then the mix between short term and long term models is linearly reduced to 100% for long term model at month 8. The setting can be modified by users through model dials.

Pool Level Prepayment Behaviour and Forecasting

Exhibit 37 shows a scattering diagram of April 2009 prepayment speeds for all FN pools with balance bigger than 50mm. Some of these speeds distribution come from pool level differences, for example, WALA, loan size, GEO, etc. Most are due to standard deviations.

Exhibit 37: 2009 April prepayment speeds for all FN pools with balance greater than 50 million



Source: Credit Suisse.

The prepayment model forecasts odds for prepayment for pools or loans, while the actual prepayment is digital (except curtailment). This is called "doubly stochastic process/model" in literature. Here we estimate the standard errors around our model forecasts for pools.

For a pool with N loans, and a forecast speed smm, the standard deviation for the forecast is

$$\sigma = \sqrt{\frac{smm(1-smm)}{N}} \approx \sqrt{\frac{smm}{N}}$$

The relative standard deviation is

$$\sigma_r = \frac{1}{smm}\sqrt{\frac{smm}{N}} = \frac{1}{\sqrt{N^*smm}} = \frac{1}{\sqrt{n}}$$

where n is the number of loans expected to prepay.

For example, if we have a pool(s) have 5000 loans (~1 billion $), and model forecast a 20cpr (0.02 SMM) so the numbers of loans expected to prepay for the month is 5000x0.02= 100, hence the relative standard deviation around forecast is $\frac{1}{\sqrt{100}} = 10\%$, which means: forecast is $20 \pm 2cpr$.

For a 40 million $ pool (~200 loans), if model forecast is 20cpr, the number of loans expected to prepay is 4 (actual 3.6), the relative standard error is 50%, hence the forecast is $20 \pm 10cpr$

Exhibit 38 shows a table of standard deviation for combinations of speeds forecasts and pool sizes.

Exhibit 38: Estimation of prepayment forecast standard deviation (CPR)

	Assume average loan size = 200,000	**CPR**	5	10	20	30	50	90
Pool(s) size		**SMM**	0.4%	0.9%	1.8%	2.9%	5.6%	17.5%
$ in billion	**Loan counts**							
0.05	250		4.7	6.4	8.3	9.2	9.3	3.5
0.10	500		3.3	4.5	5.9	6.5	6.5	2.5
0.50	2,500		1.5	2.0	2.6	2.9	2.9	1.1
1.00	5,000		1.1	1.4	1.9	2.1	2.1	0.8
2.00	10,000		0.7	1.0	1.3	1.5	1.5	0.6
3.00	15,000		0.6	0.8	1.1	1.2	1.2	0.5
4.00	20,000		0.5	0.7	0.9	1.0	1.0	0.4
5.00	25,000		0.5	0.6	0.8	0.9	0.9	0.3
10.00	50,000		0.3	0.5	0.6	0.7	0.7	0.2

Source: Fannie Mae, Freddie Mac, Credit Suisse.

Model Error Tracking Reports

We provide series of model error tracking reports, including

- Vintage/coupon cohorts level, separate volunteer prepayment and delinquency buyout, when the delinquency data is available
- Error tracking along pool variables: Loan size, FICO, WALA, GEO, OLTV, CLTV, HPA, occupancy status, etc. often combined with vintage/cohorts
- Error tracking capability against arbitrary group of pools or against multiple (more than 2) variables is under development.
- Sample error tracking reports are listed in Appendix.

Interest Rate Model

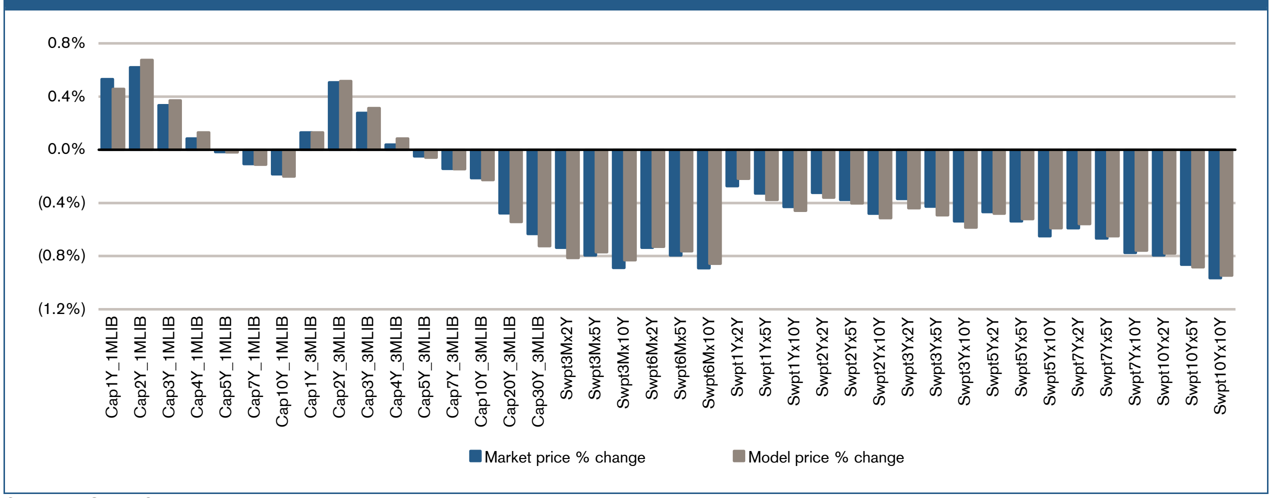
OAS models aim to price and value the prepayment option embedded in MBS against a reference curve (e.g. swap, treasury, or agency curve) and market volatility surface.

The CS6 interest rate model is a two-factor HJM model with Markov properties. The model is constructed using Monte Carlo simulations, running 250 paths as the default. The CS6 model is able to achieve statistical pricing variance accuracy of approximately 1bps OAS for TBAs.

The model construct has flexible volatility skew. Currently, the model is set close to normal skew, then gradually shifts to lognormal when rates decline towards zero. These skew assumptions are generally in line with market volatility skew since 2000. Although calibration of the volatility skew is not done on daily basis, we monitor model and market volatility skews, changing model settings if needed.

Daily calibration utilizes 26 ATM swaptions and 16 ATM caps provided by Credit Suisse's Interest Rate Products Group. To ensure accurately P&L attribution to MBS, we utilize multiple daily reports to monitor the accuracy of the calibration process, model and market volatility skew (+/-200bps OTM) (see Exhibit 39 next page) and monitor how well the model tracks daily volatility surface changes (see Exhibit 38.1 below).

Exhibit 38.1: Sample daily calibration report: model and market volatility change over one trading day



Source: Credit Suisse.

For intra-day vol, ("live vol"), we employ a very accurate numerical approximation to obtain model parameters without going through the full calibration process; hence, the "live volatility" calibration is available instantly.

Exhibit 39

ATM	3mx2	6mx2	1yx2	2yx2	3yx2	5yx2	7yx2	10yx2	3mx5	6mx5	1yx5	2yx5	3yx5	5yx5	7yx5	10yx5	3mx10	6mx10	1yx10	2yx10	3yx10	5yx10	7yx10	10yx10
Strike	1.57	1.89	2.52	3.45	4.02	4.60	4.78	4.86	2.89	3.10	3.48	4.04	4.38	4.71	4.82	4.87	3.72	3.84	4.06	4.39	4.59	4.78	4.85	4.86
Market Price	42.9	68.2	107.5	149.5	174.9	194.2	191.2	170.6	128.5	185.4	262.5	350.2	396.4	435.8	427.7	378.0	239.9	339.5	465.8	610.6	684.1	739.5	721.5	638.8
Model Price	45.6	69.2	104.2	144.8	169.5	192.9	187.7	169.5	125.0	186.4	271.2	351.8	402.0	442.2	425.7	382.1	225.3	334.7	478.8	610.7	689.7	750.9	719.9	643.9
Model - Market	2.7	1.0	(3.3)	(4.7)	(5.3)	(1.4)	(3.5)	(1.1)	(3.5)	1.1	8.7	1.5	5.6	6.4	(2.0)	4.1	(14.6)	(4.8)	13.0	0.1	5.6	11.4	(1.6)	5.1
△• (bps/yr)	6.9	1.7	(4.2)	(4.5)	(4.3)	(0.9)	(2.2)	(0.7)	(3.7)	0.8	4.8	0.6	1.9	1.9	(0.5)	1.1	(8.6)	(2.0)	4.0	0.0	1.1	1.9	(0.2)	0.7

ATM + 100bps	3mx2	6mx2	1yx2	2yx2	3yx2	5yx2	7yx2	10yx2	3mx5	6mx5	1yx5	2yx5	3yx5	5yx5	7yx5	10yx5	3mx10	6mx10	1yx10	2yx10	3yx10	5yx10	7yx10	10yx10
Strike	2.57	2.89	3.52	4.45	5.02	5.60	5.78	5.86	3.89	4.10	4.48	5.04	5.38	5.71	5.82	5.87	4.72	4.84	5.06	5.39	5.59	5.78	5.85	5.86
Market Price	6.3	23.2	54.2	90.7	117.3	139.4	140.1	124.6	20.6	59.9	125.7	207.4	257.1	304.6	305.2	268.5	38.4	105.5	212.9	351.0	431.8	502.8	501.3	442.4
Model Price	2.7	12.7	38.8	68.8	96.1	124.8	124.6	116.6	12.5	42.1	108.8	171.0	226.5	284.7	281.2	259.5	22.4	74.1	187.4	290.0	380.4	473.0	466.2	426.9
Model - Market	(3.6)	(10.5)	(15.4)	(21.9)	(21.2)	(14.6)	(15.5)	(8.1)	(8.1)	(17.7)	(16.9)	(36.4)	(30.6)	(19.8)	(24.0)	(9.1)	(16.0)	(31.4)	(25.5)	(61.0)	(51.4)	(29.8)	(35.1)	(15.5)
△• (bps/yr)	0.0	(34.3)	(25.6)	(23.7)	(18.6)	(10.5)	(10.3)	(5.1)	(22.7)	(21.5)	(11.4)	(16.6)	(11.4)	(6.1)	(6.8)	(2.5)	(24.9)	(21.3)	(9.7)	(15.6)	(10.8)	(5.2)	(5.6)	(2.4)

ATM -100bps	3mx2	6mx2	1yx2	2yx2	3yx2	5yx2	7yx2	10yx2	3mx5	6mx5	1yx5	2yx5	3yx5	5yx5	7yx5	10yx5	3mx10	6mx10	1yx10	2yx10	3yx10	5yx10	7yx10	10yx10
Strike	0.57	0.89	1.52	2.45	3.02	3.60	3.78	3.86	1.89	2.10	2.48	3.04	3.38	3.71	3.82	3.87	2.72	2.84	3.06	3.39	3.59	3.78	3.85	3.86
Market Price	0.0	2.3	22.3	60.1	84.6	109.4	114.0	105.6	4.5	22.8	68.7	145.6	192.5	244.3	253.6	232.2	11.6	48.9	127.0	252.0	327.5	406.3	418.7	383.7
Model Price	2.3	11.0	35.7	63.9	90.9	115.3	116.6	108.4	11.9	40.5	106.9	161.1	216.5	262.3	261.3	241.1	20.8	73.1	184.9	272.9	362.6	433.6	427.7	394.7
Model - Market	2.2	8.7	13.4	3.8	6.3	6.0	2.6	2.8	7.4	17.7	38.2	15.5	24.1	18.1	7.6	8.9	9.2	24.2	57.9	20.9	35.1	27.3	8.9	11.0
△• (bps/yr)	0.0	29.9	22.7	4.1	5.6	4.3	1.7	1.8	21.3	21.8	25.9	7.1	9.0	5.6	2.2	2.4	14.9	16.5	22.0	5.4	7.4	4.8	1.4	1.7

Cap/Floor (1m LIBOR - by Terms)

ATM	1y	2y	3y	4y	5y	7y	10y
Strike	0.61	1.29	1.88	2.33	2.68	3.15	3.55
Market Price	23.6	110.8	229.1	355.7	484.1	734.9	1,071.1
Model Price	21.9	99.0	220.3	351.3	486.1	746.2	1,097.5
Model - Market	(1.7)	(11.8)	(8.8)	4.4	2.0	11.3	26.4
△• (bps/yr)	(8.1)	(20.7)	(8.2)	2.6	0.9	2.9	4.2

ATM + 100	1y	2y	3y	4y	5y	7y	10y
Strike	1.61	2.29	2.88	3.33	3.68	4.15	4.55
Market Price	10.9	66.5	149.4	242.0	338.0	527.5	781.2
Model Price	3.8	43.9	128.1	220.6	318.5	507.7	766.1
Model - Market	(7.2)	(22.6)	(21.3)	(21.4)	(19.5)	(19.8)	(15.0)
△• (bps/yr)	(68.3)	(45.5)	(20.7)	(13.1)	(8.5)	(5.2)	(2.4)

ATM + 200	1y	2y	3y	4y	5y	7y	10y
Strike	2.61	3.29	3.88	4.33	4.68	5.15	5.55
Market Price	6.3	42.3	101.0	169.9	242.8	387.9	582.4
Model Price	0.3	16.2	70.3	131.7	199.8	333.3	517.6
Model - Market	(6.0)	(26.1)	(30.7)	(38.2)	(43.1)	(54.6)	(64.9)
△• (bps/yr)	(329.7)	(82.7)	(37.0)	(27.4)	(21.3)	(16.1)	(11.6)

ATM - 100	1y	2y	3y	4y	5y	7y	10y
Strike	(0.39)	0.29	0.88	1.33	1.68	2.15	2.55
Market Price	0.0	7.4	67.9	144.9	225.9	388.2	608.4
Model Price	0.0	11.4	71.1	151.7	239.3	414.6	654.5
Model - Market	0.0	4.0	3.2	6.8	13.4	26.4	46.1
△• (bps/yr)	0.0	12.7	3.8	4.8	6.5	7.6	8.0

ATM - 200	1y	2y	3y	4y	5y	7y	10y
Strike	(1.39)	(0.71)	(0.12)	0.33	0.68	1.15	1.55
Market Price	0.0	0.0	0.0	13.4	51.6	142.5	272.9
Model Price	0.0	0.0	0.0	24.1	66.3	166.9	313.8
Model - Market	0.0	0.0	0.0	10.7	14.7	24.4	40.8
△• (bps/yr)	0.0	0.0	0.0	16.2	11.7	9.6	8.9

Cap/Floor (3m L1BOR - by Terms)

ATM	1y	2y	3y	4y	5y	7y	10y	20y	30y
Strike	0.68	1.38	1.98	2.43	2.77	3.24	3.63	4.08	4.15
Market Price	17.5	95.6	205.5	324.9	447.5	689.9	1,017.6	1,817.9	2,331.4
Model Price	18.6	88.4	197.6	318.3	445.2	692.0	1,027.4	1,820.8	2,266.1
Model - Market	1.1	(7.2)	(8.0)	(6.6)	(2.3)	22.0	9.8	2.9	(65.3)
△• (bps/yr)	5.9	(13.5)	(7.8)	(4.1)	(1.0)	0.6	1.6	0.2	(3.1)

ATM + 100	1y	2y	3y	4y	5y	7y	10y	20y	30y
Strike	1.68	2.38	2.98	3.43	3.77	4.24	4.63	5.08	5.15
Market Price	6.5	53.7	129.2	215.6	306.7	489.3	736.3	1,333.6	1,724.2
Model Price	2.8	36.9	108.8	190.5	282.6	461.0	704.2	1,261.8	1,556.8
Model - Market	(3.7)	(16.8)	(20.4)	(25.1)	(24.1)	(28.3)	(32.1)	(71.8)	(167.4)
△• (bps/yr)	(44.0)	(37.1)	(21.3)	(16.2)	(10.9)	(7.7)	(5.3)	(5.2)	(8.3)

ATM + 200	1y	2y	3y	4y	5y	7y	10y	20y	30y
Strike	2.68	3.38	3.98	4.43	4.77	5.24	5.63	6.08	6.15
Market Price	3.2	32.1	84.3	147.9	216.7	356.2	545.6	1,002.4	1,308.8
Model Price	2.0	12.4	55.1	107.5	170.9	294.5	465.3	844.0	1,028.3
Model - Market	(3.0)	(19.7)	(29.3)	(40.4)	(45.9)	(61.7)	(80.3)	(158.3)	280.5
△• (bps/yr)	0.0	(73.0)	(39.3)	(31.4)	(24.1)	(19.0)	(14.8)	(12.7)	(15.5)

ATM - 100	1y	2y	3y	4y	5y	7y	10y	20y	30y
Strike	(0.32)	0.38	0.98	1.43	1.77	2.24	2.63	3.08	3.15
Market Price	0.0	7.5	59.8	129.0	203.6	356.6	567.4	1,092.2	1,429.3
Model Price	0.0	125.0	64.1	135.6	215.3	376.3	600.0	1,086.0	1,302.6
Model - Market	0.0	50.0	43.0	66.0	116.0	19.7	32.6	(6.2)	(126.7)
△• (bps/yr)	0.0	15.7	5.3	4.9	5.9	5.9	5.8	(0.5)	(6.6)

ATM - 200	1y	2y	3y	4y	5y	7y	10y	20y	30y
Strike	(1.32)	(0.62)	(0.02)	0.43	0.77	1.24	1.63	2.08	2.15
Market Price	0.0	0.0	0.0	13.5	46.1	127.3	248.1	566.6	774.5
Model Price	0.0	0.0	0.0	24.2	61.5	149.8	281.9	569.9	689.6
Model - Market	0.0	0.0	0.0	10.8	15.4	22.4	33.8	3.4	84.8
△• (bps/yr)	0.0	0.0	0.0	16.2	12.5	9.2	7.6	0.3	(5.5)

Summary (RMS Error)

Swaption	△p/p (%)	△• (bps/yr)
ATM	2.5	3.3
ATM + 100bps	13.8	12.8
ATM -100bps	23.0	10.6

Cap	△p/p (%)	△• (bps/yr)
ATM	4.7	8.0
ATM + 100bps	15.7	20.6
ATM + 200bps	22.3	25.8
ATM -100bps	25.6	8.0
ATM - 200bps	39.5	10.6

Source: Credit Suisse.

Mortgage Rate Model

The CS6 mortgage rate model consists of three components: (1) primary/secondary mortgage rate spread, (2) mortgage/swap spread and (3) a current coupon model which is a non-linear function of future swap rates of various maturities.

Market participants generally have two types of current coupon models:

1. An empirical approach, often involving regression between current coupon rates and a set of swap rates to minimize the volatility of historical current coupon basis. The shortcomings of this approach include:

- Due to the collinearity between swaps rates, regression results may appear arbitrary
- Relationship between current coupon and swap rates are non-linear
- Generally unreasonable partial duration results that lead to hedging leakage for CMOs

2. A "constant OAS" approach, which often involves backward induction to solve for current coupon rates along the future space. It is computationally expensive and results may not be intuitive due to either numerical issues or prepayment model issue.

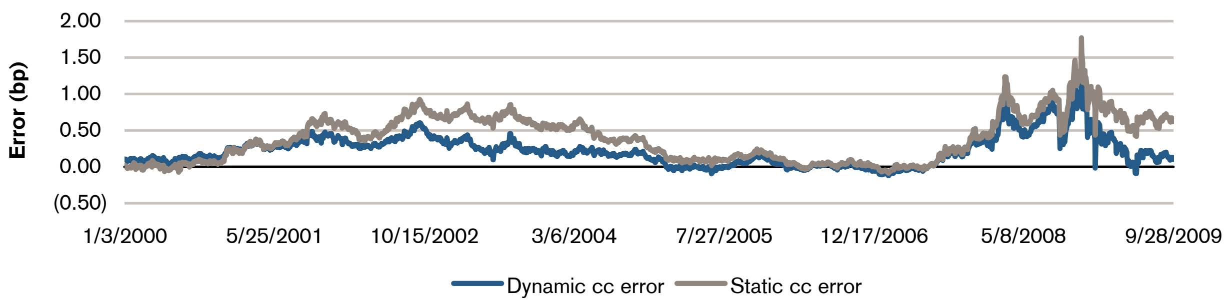
Our model incorporates the merits of both approaches, through a global optimization scheme and validated through both TBA valuation test (the "Constant OAS" idea, see exhibit 40 below) and statistical analysis of both mortgage basis and current coupon OASs ("the Empirical Behavior" idea, see exhibit 41 below). As a result, our model partial duration weight is very close to empirical ones (see Exhibit 3 on page 6), which leads to more accurate hedging.

Exhibit 40: Sample test of "Constant OAS" under curve level and slope shocks: CS6 "Dynamic" mortgage rate model vs. a "Static" regression based model

(5/4/2006)	CC OAS		OAS difference	
Scenario	**Dynamic**	**Static**	**Dynamic**	**Static**
Base case	(7.1)	(8.2)	–	–
Up 25bp	(6.0)	(5.9)	(1.2)	(2.3)
Dn 25bp	(7.1)	(9.3)	–	1.1
Flattener	(9.0)	(13.5)	1.9	5.3
Steepener	(5.4)	(3.0)	(1.7)	(5.2)
Variance			2.5	20.5

Source: Credit Suisse.

Exhibit 41: Empirical Behavior: using 1/2/2007 as base, compare mortgage rate forecasting errors between CS6 "Dynamic" mortgage rate model vs. a "Static" regression based model

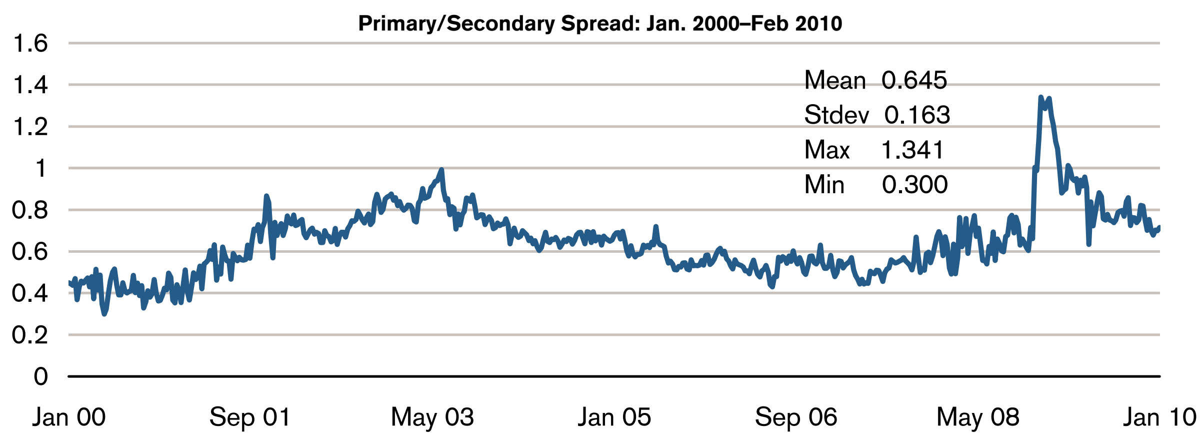


Source: Credit Suisse.

Exhibit 42 shows the history of primary/secondary spread. The historical average level is about 55bps, with highs reaching 115bps during recent refinance episode. In the OAS model, we employ a mean-reversion scheme to produce forward values for this spread. The spread starts with most recent value, then mean-reversion to long term mean of 55bps in 6 months.

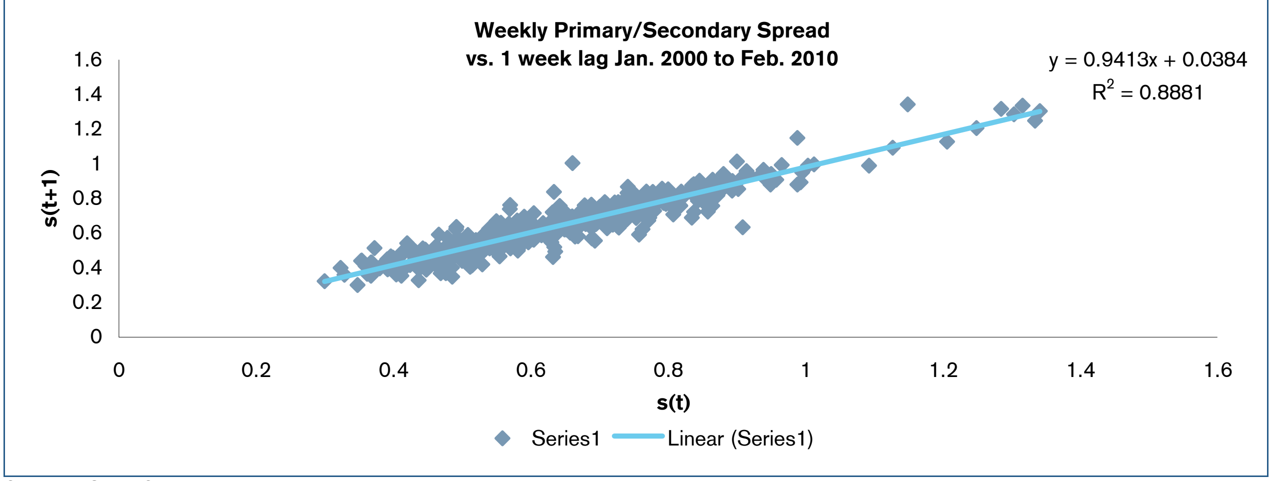
Exhibit 43 shows the scattering diagram between weekly series of this spread and 1 week lagged spread. The 1 week lagged serial correlation is around 0.94, which leads to an estimation of mean-reversion speeds of 6 months. (In a mean reversion model, the serial correlation between T-time lag is equal to exp(-T/mean-reversion-time-scale))

Exhibit 42: Historical primary/second mortgage rate spread



Source: Freddie Mac, Credit Suisse.

Exhibit 43: Weekly primary/second mortgage rate spread vs. 1 week lagged spread



Source: Credit Suisse.

Both mean reversion speeds and levels can be changed by users via model dials.

Discussion about Model Uncertainties

The models are either produced from statistical analysis of historical data and/or economics understanding of underlining process. Implicitly assumed is that the economic and business rationale that give rise to these rules will continue to exist in the future. Model uncertainties arise when these assumptions are in doubt. Here we list a few model features that may need continued scrutiny.

- Prepayment Model
  - Future "opening of credit Box" which may lead to fast prepayment for credit impaired loans
  - Long term prepayment regime: this will depend on how efficient future mortgage origination business will be, how much borrowers can save from refinance and how much and how easily mortgage/housing credit will be available
  - Credit underwriting: this will impact most of the pool variables effect discussed in this document
- Mortgage Rate Model
  - Primary-secondary spread: depend on future GSE's guarantee fee level as well as landscape of mortgage origination business
  - Mortgage swap spread: depend on supply and demand of MBS investor base
- Interest Rate Model
  - Volatility skew: at very low level levels, volatility skew will move away from current normal setting
  - Volatility regimes and levels: major demand for volatility came from mortgage servicers and GSEs portfolio hedging. Without these demand sources, implied volatility may rest at a substantially lower level
  - Benchmark curve: both libor/swap curves and Treasury curves can be candidates as benchmark curve for MBS valuation

Appendix: Sample Error Tracking Reports

Appendix exhibit 1: pool level error tracking, ranking and forecasts report for FH 5.5s floats, Feb. 2010 performance

CREDIT SUISSE

Short Term Model for FH floats cohort

Feb-2010 FH 5.5 360

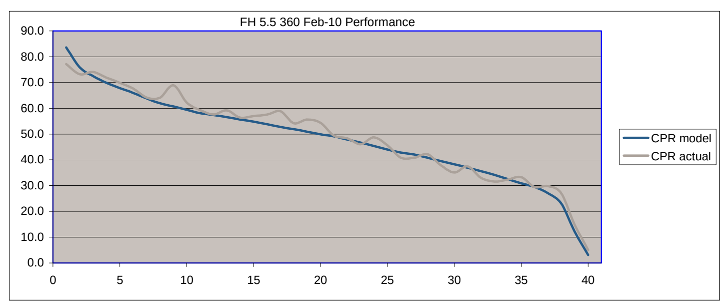
Mortgages
MSTAR

Sorted by model speeds

	Error tracking		Forcasts														
	Feb-10		Feb-10														
Group	CPR model	CPR actual	Float amt (mm)	CPR model	Float%	Loan size (StDv)	FICO (StDv)	WALA (StDv)	WAC (StDv)	CLTV (StDv)	Refi% (StDv)	Invest% (StDv)	SecHome% (StDv)	OneUnit% (StDv)	NY% (StDv)	CA% (StDv)	FL% (StDv)
1	83.6	77.1	5,831	34.1	95%	202,017 (44,534)	704 (15)	37 (4)	6.24 (.16)	104 (8)	46.1 (26)	3.1 (5)	2.8 (3)	97.4 (4)	3.7 (11)	9.4 (8)	6.9 (5)
2	75.8	73.2	5,823	30.4	90%	221,099 (35,974)	714 (14)	37 (5)	6.23 (.11)	100 (8)	56.1 (20)	2.8 (6)	5.2 (3)	97.5 (4)	3.5 (9)	13.0 (9)	8.9 (8)
3	72.5	74.0	5,910	28.7	92%	217,508 (36,145)	716 (16)	37 (6)	6.18 (.13)	100 (8)	45.2 (22)	2.5 (4)	4.1 (4)	97.5 (4)	3.6 (8)	13.5 (9)	8.8 (8)
4	69.9	71.8	5,823	27.5	88%	218,252 (34,977)	719 (11)	37 (6)	6.18 (.11)	98 (7)	54.4 (17)	2.6 (4)	5.3 (3)	97.4 (3)	3.0 (7)	12.4 (8)	8.5 (8)
5	67.9	69.9	5,806	26.7	84%	223,274 (39,489)	719 (15)	36 (9)	6.17 (.11)	98 (8)	55.8 (17)	3.6 (4)	5.8 (4)	96.8 (4)	4.4 (13)	15.1 (12)	8.3 (9)
6	66.0	67.6	5,921	26.1	82%	218,235 (45,805)	720 (15)	38 (9)	6.18 (.13)	96 (9)	52.3 (19)	3.7 (7)	5.2 (4)	95.7 (7)	7.0 (19)	13.9 (11)	8.6 (10)
7	63.8	64.1	5,836	25.5	79%	215,145 (53,600)	720 (15)	35 (11)	6.17 (.13)	95 (10)	51.4 (18)	4.2 (6)	5.8 (4)	95.3 (7)	7.4 (20)	13.6 (16)	7.6 (10)
8	62.0	64.1	5,686	25.0	83%	218,738 (48,091)	721 (14)	36 (11)	6.16 (.16)	94 (9)	53.5 (20)	4.6 (7)	5.8 (3)	95.7 (6)	6.5 (17)	14.9 (15)	8.7 (10)
9	60.7	68.9	6,505	24.6	84%	226,089 (50,614)	723 (13)	35 (11)	6.17 (.16)	97 (10)	50.4 (17)	3.5 (6)	6.0 (4)	96.4 (5)	5.8 (16)	17.3 (16)	9.8 (12)
10	59.4	62.3	5,837	24.3	82%	217,086 (49,391)	722 (14)	37 (12)	6.09 (.14)	93 (9)	54.1 (15)	4.1 (7)	5.3 (3)	95.6 (6)	6.2 (19)	14.8 (15)	7.6 (12)
11	58.1	59.3	5,136	24.0	80%	217,342 (42,078)	725 (14)	40 (12)	6.11 (.13)	92 (9)	54.4 (17)	4.0 (7)	5.8 (4)	96.1 (6)	6.1 (15)	15.9 (12)	8.5 (11)
12	57.4	57.6	6,311	23.6	88%	230,656 (42,007)	729 (13)	36 (9)	6.08 (.09)	94 (8)	54.3 (17)	3.3 (4)	5.2 (3)	96.5 (5)	7.2 (19)	14.6 (10)	7.4 (7)
13	56.6	59.2	6,715	23.4	84%	218,575 (45,726)	726 (11)	36 (12)	6.09 (.12)	93 (8)	55.6 (15)	3.6 (5)	5.8 (3)	96.8 (4)	6.0 (18)	14.2 (12)	8.1 (12)
14	55.6	56.4	6,133	23.1	86%	224,272 (44,846)	728 (14)	37 (14)	6.09 (.13)	91 (8)	53.8 (16)	2.5 (5)	6.1 (3)	97.0 (4)	5.6 (15)	14.0 (11)	9.0 (14)
15	54.8	57.0	6,144	22.9	83%	219,806 (46,324)	728 (11)	38 (12)	6.03 (.13)	92 (7)	54.3 (13)	2.3 (5)	6.2 (4)	97.1 (4)	4.8 (13)	16.9 (14)	8.1 (8)
16	53.8	57.5	5,826	22.6	78%	210,790 (48,557)	728 (14)	38 (13)	6.08 (.13)	92 (10)	56.4 (15)	2.5 (4)	6.1 (3)	96.8 (4)	6.4 (17)	17.1 (15)	11.2 (17)
17	52.8	58.9	5,922	22.5	82%	209,045 (52,912)	728 (13)	40 (14)	6.06 (.14)	91 (9)	52.6 (15)	2.4 (5)	6.2 (3)	97.0 (4)	4.7 (13)	14.3 (15)	8.8 (12)
18	51.9	54.2	5,509	22.3	78%	207,938 (54,342)	727 (17)	38 (15)	6.02 (.12)	89 (9)	51.8 (18)	3.0 (6)	6.1 (4)	96.7 (5)	6.4 (17)	12.5 (11)	8.3 (11)
19	50.9	55.6	6,258	22.0	74%	217,452 (54,514)	730 (13)	35 (15)	6.06 (.14)	89 (10)	51.8 (15)	4.0 (6)	6.4 (4)	95.7 (5)	9.4 (22)	15.5 (13)	7.7 (8)
20	49.9	54.4	5,927	21.8	81%	212,514 (57,867)	733 (14)	35 (15)	6.04 (.11)	90 (10)	52.0 (17)	2.7 (6)	7.0 (4)	97.1 (5)	5.8 (16)	14.4 (12)	7.9 (9)
21	49.1	49.4	5,788	21.5	72%	202,878 (55,652)	728 (15)	44 (15)	5.98 (.13)	86 (8)	55.6 (13)	3.6 (7)	5.8 (4)	96.0 (5)	6.5 (17)	13.0 (12)	6.9 (12)
22	47.9	48.4	5,883	21.2	70%	195,474 (55,998)	731 (16)	41 (18)	5.98 (.12)	85 (10)	53.1 (20)	4.2 (7)	4.9 (4)	96.5 (5)	5.8 (15)	12.3 (11)	7.1 (11)
23	46.7	46.1	5,833	21.0	76%	194,813 (57,970)	731 (14)	40 (17)	6. (.14)	86 (10)	54.8 (15)	3.4 (5)	5.6 (4)	96.8 (5)	5.9 (16)	13.6 (13)	6.3 (9)
24	45.4	48.7	5,816	20.7	66%	205,013 (62,141)	731 (17)	42 (19)	5.99 (.16)	84 (11)	56.3 (17)	4.3 (7)	5.8 (4)	96.4 (4)	6.5 (16)	16.7 (15)	7.7 (11)
25	44.0	45.7	5,899	20.4	67%	189,120 (56,971)	730 (17)	41 (18)	5.96 (.12)	83 (9)	56.8 (16)	3.7 (5)	5.6 (4)	96.6 (5)	5.8 (17)	11.0 (10)	6.8 (9)
26	42.8	40.9	5,867	20.1	67%	191,277 (55,256)	728 (15)	44 (20)	5.94 (.14)	83 (9)	59.8 (17)	3.9 (4)	5.1 (3)	96.6 (4)	5.5 (14)	13.5 (12)	5.0 (6)
27	42.1	40.8	5,218	19.8	62%	199,608 (59,378)	734 (18)	40 (21)	5.95 (.16)	82 (9)	55.6 (16)	3.8 (6)	5.8 (4)	96.1 (5)	7.2 (17)	14.9 (13)	6.5 (9)
28	40.9	42.2	6,379	19.5	67%	195,307 (57,379)	732 (13)	41 (21)	5.94 (.11)	82 (9)	57.7 (14)	3.1 (4)	5.5 (3)	97.0 (4)	5.3 (14)	13.1 (13)	6.6 (7)
29	39.5	37.9	5,491	19.2	67%	182,507 (58,580)	732 (13)	40 (23)	5.96 (.13)	79 (10)	58.9 (17)	4.0 (4)	5.4 (3)	96.8 (4)	4.9 (10)	11.7 (11)	5.5 (6)
30	38.3	35.1	6,703	18.9	66%	187,558 (54,062)	733 (13)	35 (21)	5.95 (.13)	82 (9)	59.6 (15)	4.1 (8)	5.3 (3)	97.0 (4)	4.7 (11)	11.6 (11)	4.7 (6)
31	36.9	37.5	5,871	18.5	59%	193,160 (59,926)	735 (17)	40 (24)	5.96 (.13)	79 (9)	55.0 (16)	3.5 (6)	5.8 (4)	96.9 (4)	4.2 (10)	13.0 (12)	6.3 (9)
32	35.6	33.1	5,769	18.0	64%	194,010 (51,739)	736 (14)	42 (25)	5.93 (.09)	78 (10)	56.9 (15)	3.0 (4)	5.6 (3)	96.9 (3)	5.0 (9)	13.4 (11)	5.1 (7)
33	34.2	31.6	6,201	17.5	53%	178,094 (57,734)	734 (16)	45 (27)	5.93 (.11)	75 (10)	54.2 (15)	2.7 (3)	5.8 (3)	97.5 (3)	5.7 (8)	11.5 (10)	6.0 (6)
34	32.6	32.3	5,826	16.9	55%	192,987 (52,241)	739 (15)	40 (26)	5.93 (.13)	77 (9)	55.1 (15)	2.5 (5)	5.9 (4)	97.6 (3)	3.4 (9)	13.1 (11)	4.8 (6)
35	30.9	33.3	6,010	16.2	66%	187,882 (59,759)	737 (16)	41 (27)	5.93 (.09)	76 (9)	51.9 (15)	3.0 (3)	6.1 (3)	97.1 (4)	5.5 (7)	15.3 (13)	5.6 (9)
36	29.5	29.5	6,120	15.4	52%	168,577 (56,443)	735 (14)	54 (27)	5.91 (.1)	72 (9)	59.1 (19)	2.8 (3)	5.4 (3)	97.0 (4)	5.6 (9)	13.0 (13)	4.6 (5)
37	27.1	29.8	5,644	14.5	47%	164,196 (50,877)	736 (13)	53 (30)	5.92 (.1)	70 (10)	63.2 (17)	2.8 (3)	4.5 (3)	97.3 (3)	4.4 (7)	14.0 (12)	4.2 (5)
38	23.1	27.0	6,063	13.0	34%	150,426 (57,414)	737 (15)	52 (35)	5.95 (.12)	68 (11)	61.2 (20)	3.5 (6)	4.5 (4)	97.5 (4)	3.5 (9)	12.9 (13)	4.5 (6)
39	12.2	14.9	5,999	10.3	85%	183,349 (70,909)	733 (17)	13 (21)	5.95 (.13)	74 (8)	61.4 (17)	17.1 (21)	4.8 (4)	94.4 (7)	4.9 (6)	15.3 (13)	5.3 (6)
40	3.1	5.1	2,045	4.6	100%	141,453 (71,703)	728 (23)	4 (3)	5.92 (.09)	75 (11)	72.1 (21)	28.7 (31)	3.8 (4)	93.0 (12)	3.8 (6)	12.2 (12)	7.2 (6)
Total	**51.2**	**52.4**	**233,284**	**21.6**	**71%**	**202,128 (55,929)**	**728 (16)**	**39 (19)**	**6.04 (.16)**	**87 (13)**	**55.1 (18)**	**3.9 (8)**	**5.5 (4)**	**96.6 (5)**	**5.5 (14)**	**13.8 (12)**	**7.1 (9)**

Total upb (mm)	Total float (mm)	float%
330,806	233,284	71%

Note: Std Dev of each variable for each group is reported in ( )



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